Editor's Overview

The 37th issue of the International Productivity Monitor contains seven articles. The topics are a comparison of the productivity growth slowdown between Europe and the United States; firm-level evidence on the impact of digitalization on productivity; the impact of the China shock on innovation and productivity in Canadian manufacturing; productivity dispersion at the firm level in Canada; the role of R&D in productivity improvement; consistency issues on the construction of productivity indices; and the state of productivity research.

Productivity comparisons between countries have the potential to offer significant insight into the explanation of productivity developments. In the lead article, **Robert J. Gordon** from Northwestern University and **Hassan Sayed** from Princeton University provide a detailed examination of productivity trends by industry in the United States and Europe. Their analysis sheds much light on the phenomenon of slower productivity growth. The key finding is that productivity growth in EU-10 countries, at both the aggregate and industry level, has followed that in the United States with a 20 year lag. Indeed, the total economy labour productivity of slowdown of 1.67 percentage points in the United States between 1950-1972 and 2005-2015 was virtually identical to that in Europe between 1972-1995 and 2005-2015 (1.68 points). The authors argue that these transatlantic developments support the view that the productivity slowdown is due to a slowing of the pace of technical change that has affected the same industries, by the same magnitude on both sides of the Atlantic.

The slowdown in productivity growth observed in the world economy has taken place in a period of rapid development of digital technologies. This is paradoxical as many believe the adoption of these technologies should have a positive impact on productivity. In the second article, **Peter Gal**, **Giuseppe Nicoletti**, **Christina von Rüden** and **Stéphanie Sorge** from the OECD and **Théodore Renault** from the Graduate Institute of International and Development Studies examine the impact of digitalization on productivity in Europe. They find robust evidence that digital adoption is in fact associated with productivity gains at the firm level, especially in manufacturing, and for routine-intensive activities and the more productive firms. They note that compared to earlier waves of innovation, digital technologies appear more difficult to implement for less productive firms because of the increased importance of intangible capital and skills. This has in turn has led to a slower pace of diffusion for these firms and increased dispersion of productivity growth among firms and may in part explain slower aggregate productivity growth.

The rise of China has had a major effect on many aspects of the global economy, including productivity. In the third article, **Myeongwan Kim** from the Centre for the Study of Living Standards looks at the impact of the China shock on innovation and productivity in Canadian manufacturing at the firm level. He finds that increased import competition from China reduced profitability, especially in smaller firms, and consequently decreased R&D expenditures and total factor productivity growth within firms. But the exit from the market of many smaller less productive firms because of Chinese imports had a positive reallocation effect on TFP, more than offsetting the negative direct effect. Had there been no increase in Chinese import penetration, TFP growth in Canadian manufacturing would have been 0.2 percentage points per year lower in 2005-2010.

Productivity researchers have greatly benefited from the increased public availability of firm-level data in recent years. These data have provided many new insights, especially on the dispersion of productivity and productivity growth across firms. In the fourth article, **Wulong Gu** from Statistics Canada presents data for the firm time on the productivity of frontier firms, the most productive 10 per cent of all firms, and non-frontier firms in Canada. He finds that labour productivity growth was indeed faster for the former than the latter in the 1991-2015 period. But because non-frontier firms account for 90 per cent of total employment, these firms also accounted for the lion's share of the post-2000 productivity slowdown in Canada.

Research and development (R&D) has long been considered a key driver of technological innovation and productivity growth. But is R&D alone enough to improve productivity or are complementary co-investments also needed for a productivity payoff from R&D? In the fifth article, **Jianmin Tang** from Innovation, Science and Economic Development Canada and **Weimin Wang** from Statistics Canada examine this issue by estimating a stochastic frontier model based on firm-level data for Canadian manufacturing. They find that R&D does improve multifactor productivity, but that the actual impact depends of R&D efficiency. This in turn is related to factors internal to the firm, including management practices, ICT investment, a skilled workforce, firm size and market power, and business strategy.

Many national statistical offices produce both quarterly and annual estimates of productivity in index form based on the same data sources. This raises the question of whether consistency between the two series can be expected. In the sixth article, **Bert M. Balk** from Erasmus University explores this issue from a theoretical perspective, concluding that consistency is in fact unattainable. He then lays out the choices open to statistical offices to deal with the inconsistency, stressing the importance of communicating clearly to data users that there is at best an approximate relationship between annual and sub-annual productivity series.

The literature on productivity topics has burgeoned in recent years, making it increasingly difficult for researchers to keep up with the progress in the field. Fortunately, the publication of the *Oxford Handbook of Productivity Analysis*, edited by Emili Grifell-Tatjé, Knox Lovell, and Robin Sickles, will make keeping abreast of new developments easier. In the final article in the issue, **Marshall Reinsdorf** from the International Monetary Fund provides a review article of the book, concluding that the *Handbook* is an extremely valuable reference as both a general introduction to the productivity field and as a source of authoritative articles on key productivity topics.

Table of Contents

International Productivity Monitor NUMBER 37, FALL 2019

The Industry Anatomy of the Transatlantic Productivity Growth Slowdown: Europe Chasing the American Frontier

Robert J. Gordon
Northwestern University and NBER
Hassan Sayed
Princeton University[1]

Abstract

By merging KLEMS data covering 16 industry groups within the total economy and 11 manufacturing sub-industries, we compare and contrast productivity growth from 1950 to 2015 in the United States with an aggregate of the ten largest European nations (EU-10) from 1972 to 2015. We interpret the EU-10 performance as catching up to the United States in stages. Strikingly, the total economy "early-to-late" productivity growth slowdown from 1972-1995 to 2005-2015 in the EU-10 (-1.68 percentage points) was almost identical to the U.S. slowdown from 1950-1972 to 2005-2015 (-1.67 percentage points). There is a very high EU-U.S. correlation in the magnitude of the early-to-late slowdown in each industry, suggesting that the productivity growth slowdown from the early postwar years to the most recent decade was due to a retardation in technical change that affected the same industries by roughly the same magnitudes on both sides of the Atlantic.

Slowing labour productivity growth for any given income share of labour directly limits the growth rate of real wages and of a nation's standard of living. Each percentage point by which labour productivity growth declines from its previous value translates into a one percentage-point reduction in the growth rate of potential output, which in turn reduces the capacity of a nation to finance national security, education, health care, and old-age pensions. Taking real GDP per hour worked as the broadest measure of labour productivity, its growth rate in the United States has

1 Robert J. Gordon is the Stanley G. Harris Professor of the Social Sciences at Northwestern University and a Research Associate with the National Bureau of Economic Research. Hassan Sayed is a PhD student in economics at Princeton University. This research was supported by the Smith-Richardson Foundation. The authors are grateful to Dale Jorgenson and co-authors for their role in extending the U.S. KLEMS data back to 1947, an essential ingredient in making possible much of our analysis. We are also grateful to the editor and to three anonymous referees for their many constructive criticisms and suggestions. Email: rjg@northwestern.edu.

declined from 2.7 per cent per year during 1950-1972, to 1.9 per cent during 1972-2005, to 1.1 per cent during 2005-2017. In this article we will examine the behavior of 10 of the 15 Western European members of the European Union prior to its 2004 enlargement (the "EU-10"). For this group of ten Western European countries, including all the large ones, the same growth measure declined even more sharply from 4.9 per cent per year during 1950-1972, to 2.3 per cent during 1972-2005, to a mere 0.7 per cent during 2005-2017.[2]

This article provides a comprehensive examination and comparison of labour productivity growth by industry in the United States back to 1950 and in the EU back to 1972, using KLEMS data that imposes uniform definitions and concepts on productivity and related data in each nation that is included. Our data allow a standard growth accounting decomposition of productivity into its three contributions of capital deepening, labour composition, and multifactor productivity (MFP). Beyond that, we can identify which industries grew rapidly and slowly in each subperiod and can create measures of the relative contribution to overall productivity growth of individual industries. Further, the data allow a growth accounting decomposition at the industry level, so that we can identify industries in which a slowdown in capital deepening or in MFP was particularly important.

The use of KLEMS data offers two advantages beyond consistent concepts and definitions. First, in contrast to the recent studies at the industry level limited to the United States, our data allow a detailed comparison with the EU. Second, in contrast to recent U.S. research (e.g., Baily and Montalbano, 2016, and Murray, 2018) based on the industry data base of the Bureau of Labor Statistics, which is currently available only back to 1987, we have been able to merge different vintages of KLEMS data into a single U.S. industry database that extends from 1950 to 2015.[3] For the EU we have merged two data sets that allow our analysis to extend from 1972 to 2015 and to cover ten[4] of the 15 nations of the EU-15, including all the largest nations, hereafter the EU-10.

There are two important differences in the timing and pace of the productivity growth slowdown in the United States and EU-10.[5] The first, already identified above, is that the post-1972 slowdown in the EU was much sharper than in the United States. The second is that the United States enjoyed a temporary productivity

2 The labour productivity growth rates for the United States and EU-10 in this paragraph come from the Conference Board Total Economy Database.

3 As indicated below, the U.S. data extend back to 1947 but we exclude 1947-1950 due to implausible behavior in the KLEMS data for public sector administration.

4 The ten included nations are Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Spain, Sweden, and the U.K. The nations in the EU-15 that are omitted are all small — Finland, Greece, Ireland, Luxembourg, and Portugal. Their combined GDP in 2017 was only 7 per cent of the GDP of the EU-15 (Source: Conference Board Total Economy Database).

5 For the remainder of the article the term "productivity growth" refers to labour productivity, while the abbreviation MFP refers to multi-factor productivity growth. Also, all growth rates cited in this article are annual growth rates calculated with logarithms.

growth revival between 1995 and 2005 that is missing in the EU experience. Dividing up the postwar into periods delineated by 1972, 1995, and 2005, the EU experienced a continuous deceleration from 1950-1972 to 1972-1995 to 1995-2005 to 2005-2015, whereas the United States experienced a slowdown from 1950-1972 to 1972-1995, then a marked but temporary growth revival in the 1995-2005 interval, followed by another slowdown after 2005.

Despite these differences, this article provides a new interpretation that points to similarities between the United States and EU-10 experience both in the aggregate and in the identity of those industries that made the largest contributions to changes in productivity growth over the intervals divided at 1972, 1995, and 2005. In our interpretation the EU was playing catchup to the United States over the entire period from 1950 to 1995, i.e., it was performing consistently with the convergence hypothesis. Starting in 1950 at a productivity level only 50 per cent of the United States, the EU caught up to 81 per cent by 1972, growing much more rapidly as it rebuilt after the war and implemented the large backlog of inventions and innovations that had propelled U.S. growth in the first half of the 20^{th} century. After 1972 it continued to converge but at a slower pace, and we show that EU productivity growth in 1972-1995 was a mirror image of U.S. growth in the prior 1950-1972 interval, not only in the sense that the growth rates of productivity were identical, but also that there is a high correlation across industries between the EU 1972-1995 and the United States 1950-1972 in the industry-by-industry productivity growth rates.

By linking the U.S. experience in 1950-1972 to the EU-10 growth pattern of 1972-1995, we are able to point to another striking similarity. The productivity growth slowdown from these early periods to the most recent 2005-2015 interval was almost identical: -1.68 percentage points for the EU-10 and -1.67 points for the United States. Further the industry-by-industry composition of the slowdown was very similar, with a high correlation across industries in the extent of the early-to-late slowdown.[6] These similarities shed new light on the frequent claim that the EU suffers from "Eurosclerosis." Viewed in this new light, the productivity growth experience of the EU-10 reflects an extended period of catch-up with an endpoint in the 2005-2015 interval that mimicks the U.S. experience over the same interval.

Throughout the article we distinguish between industries producing commodities and those producing services. We show that the 1972-1995 U.S. productivity growth slowdown occurred entirely within the commodities sector, with no slowdown at all for services, while most of the 1995-2005 U.S. revival likewise occurred in commodities. The post-2005 U.S. slowdown occurred equally in commodities and services industries. For the EU-10 the contrast is not as sharp, but the early-to-late EU slowdown was twice as great in com-

6 The "early-to-late" slowdown refers to the change in U.S. productivity growth from 1950-1972 to 2005-2015 and to the change in EU-10 productivity growth from 1972-1995 to 2005-2015.

modities as in services. Part of our interpretation is that the technological innovations of the first half of the century and the early postwar years disproportionately benefitted commodities, and so commodities had "further to fall" when the exploitation of those technological advances ran its course. A more surprising conclusion is the large role of commodities in the 1995-2005 U.S. productivity revival, given the emphasis in the literature on the role of the digital revolution in changing business practices in the services sector.

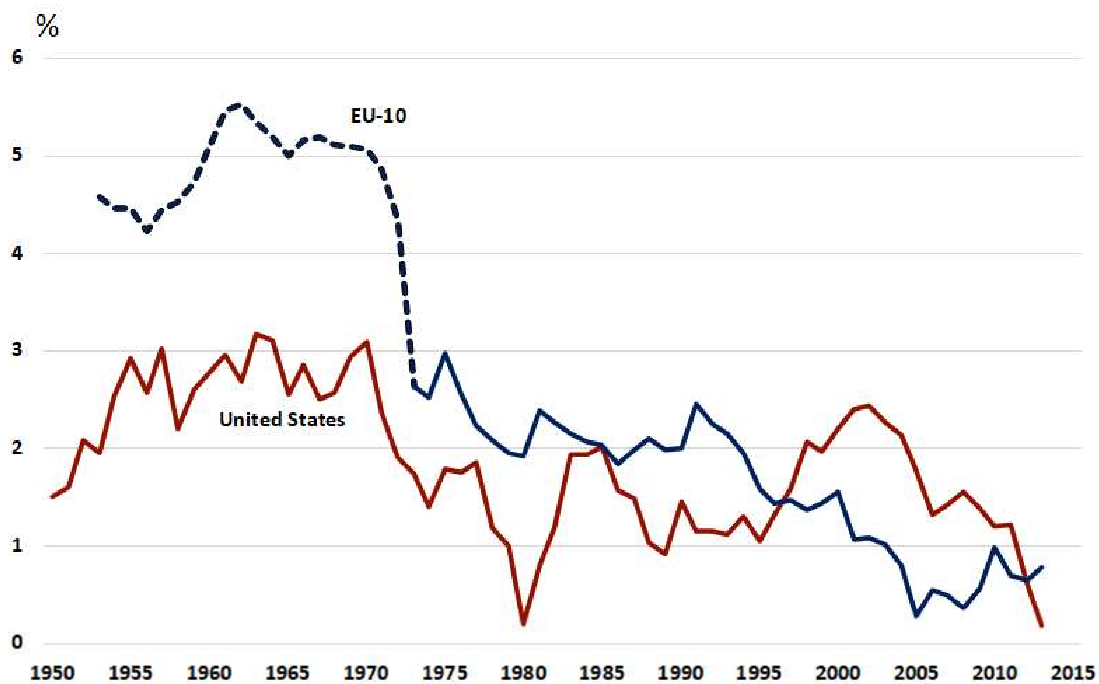
We also perform a calculation of sources of growth over each time interval, decomposing labour productivity growth. We show that MFP changes dominated the post-1972 U.S. slowdown and 1995-2005 U.S. revival, whereas declines in the respective contributions of MFP and capital deepening share roughly equal responsibility for the post-2005 U.S. slowdown as well as the early-to-late EU-10 slowdown. The role of the KLEMS measure of changes in labour composition is trivial in all the transitions across time intervals. The sources-of-growth analysis includes a ranked display by industry of the MFP contributions to the overall slowdown and points to a largely similar cast of characters in the industries that exhibit the largest overall slowdowns in their MFP contribution, again pointing to a technological explanation of the overall slowdown.

Despite these similarities between the United States and EU-10, the 1995-2005 U.S. revival contrasts sharply with the post-1995 EU slowdown. The ratio of the level of EU-10 productivity to that of the United States fell from 106 per cent in 1995 to 90 per cent in 2005. We show that the ranking of industries in their 1995-2005 growth rates was similar in the United States and EU-10 but that for most industries European growth was only about half that in the United States. An extreme outlier was the electric machinery industry, where the production of information-communication technology (ICT) equipment is located in our KLEMS data. That industry achieved an annual growth rate of productivity for 1995-2005 of 17.6 per cent in the United States compared to 4.8 per cent in the EU-10.

One of the ironies of our overall conclusions is that the EU-10 was very successful in catching up to the United States pre-1950 performance in 1950-1972 and to the United States 1950-1972 performance during 1972-1995. But the EU-10 utterly failed to catch up to the U.S. revival of 1995-2005, either before or after 2005.

The paper begins in Part 2 with the basic facts about the evolution of labour productivity growth in the U.S. and EU-10. Parts 3 and 4 examine the industry anatomy of productivity growth in the U.S. over four time intervals, both for the 16 major sectors of the economy and for the 11 components of manufacturing. Parts 5 and 6 examine the same industry decomposition for the EU-10 and provide comparisons and correlations across industries and time periods with the U.S. Part 7 provides a sources-of-growth decomposition to examine the extent to which the slowdown in labour productivity growth was caused by declining TFP growth or a decline in capital-deepening. Part 8 examines alternative hypotheses to explain U.S. vs. EU-10 differences, and Part 9 concludes.

Chart 1: United States vs. EU-10 Labour Productivity Growth 1950-2015, Centered Five Year Moving Averages, Total Economy



Source: KLEMS data as described in Data Appendix, except for EU-10 1950-1972 for the Total Economy, which is GDP per hour from the Conference Board Total Economy Database, weighted together for the 10 EU nations using real GDP weights.

The Economy-wide Growth Experience

Before examining data at the level of individual industries, we provide a depiction of labour productivity growth and its major contributing factors for the total economy and several of its main sectors. Chart 1 compares the rate of labour productivity growth for the total economy (not the "business" or "market" sector) in the United States and EU-10 from the KLEMS data. To smooth out sharp changes from year to year, the data are plotted as centered five-year moving averages of annual growth rates. Shown for the United States is the growth rate for 1947-2015, implying that the centered five-year moving averages extend from 1949 to 2013. For the EU-10 the same series is based on data from 1972 to 2015. To extend the EU-10 data backwards before 1972 for comparison with the United States, we use real GDP per hour from the Conference Board Total Economy Database.[7]

Turning first to the U.S. growth rate in Chart 1, we note that the five-year moving averages do not remove all of the cycli-

7 In Chart 1, Table 1, and the subsequent analysis, growth rates for the EU-10 aggregate are calculated by taking the growth rates for an individual country and weighting that growth rate by the share of its real GDP in total EU-10 real GDP, where the GDP data come from the Conference Board Total Economy Database.

cal movements. There are sharp troughs in 1980 and 2013. Observing longer-term trends, we note that U.S. productivity growth was relatively rapid in the 1950s and 1960s, slowed appreciably from the early 1970s through the mid-1990s, exhibited a revival between 1995 and 2005, then during 2006-11 returned to the rates of the 1970s and 1980s before plummeting toward zero in the last two years. This alternation between fast and slow periods of growth characterizes the U.S. postwar experience, and as we shall see the most important contributors to this zig-zag pattern are industries that produce commodities, not industries that produce services.

The evolution of the centered five-year moving averages for the EU-10 is smoother than for the United States, with no sharp troughs. This may reflect the fact that the EU-10 growth rates are weighted averages across 10 different nations, each of which may have experienced different cyclical peaks and troughs. Unlike the United States with its late 1990s revival, the EU-10 experience appears to be a continuous slowdown in stages. Productivity growth was greater than 5 per cent per annum between 1960 and 1971, then slowed sharply to the range of 2 to 3 per cent during 1973-96, then slowed further to the range of one to two per cent during 1997-2007, and remained below 1 per cent per year after 2007.

The trends of average annual productivity growth rates over sub-intervals divided at 1972, 1995, and 2005 are shown in Table 1 for the United States and EU-10, and for the total, market, and non-market sectors[8]. The market economy is subdivided between the commodity-producing (CP) industries and the service-producing (SP) industries. For the U.S. total economy, the growth rates alternate between high and low. The difference between the high and low periods is greater for the market economy than for the total, reflecting the fact that the non-market economy exhibits the opposite pattern by growing faster in 1972-1995 and 2005-2015 than in 1950-1972 or 1995-2005. The 1995-2005 revival in the market economy brought its growth rate up to 2.89 per cent per year, close to the 3.05 per cent per year registered for 1950-1972, while the final interval of 2005-2015 experienced a growth rate of 0.86 per cent, lower than the previous slow period of 1972-1995 when market productivity growth was 1.66 per cent.

The decomposition of the market economy into the CP and SP sub-sectors reveals a surprising fact that has escaped comment in most of the recent literature on the U.S. productivity revival and slowdown. Virtually all of the post-1972 slowdown and most of the 1995-2005 revival occurred within the CP industries, with no difference in the productivity growth rate of the SP industries when 1950-1972 is compared to 1972-1995 and only a relatively small SP revival in 1995-2005. However, the CP and SP industries experienced a similar post-2005 slowdown; when compared to 1995-2005 the CP slowdown was 2.33 percentage

8 The distinction between the market and non-market sectors follows the KLEMS convention and is outlined in Timmer *et al.* (2007)

Table 1: Annual Average Growth Rates of Labour Productivity by Sector, Selected Intervals, 1950-2015

	1950-72	1972-95	1995-2005	2005-15	Slowdown in 2005-15 from 1950-72	Slowdown in 2005-15 from 1972-95
U.S.						
Total	2.54	1.25	2.17	0.87	**-1.67**	
Market	3.05	1.66	2.89	0.86	**-2.19**	
Commodities	3.39	1.45	3.60	1.27	**-2.13**	
Services	2.19	2.20	2.84	0.90	**-1.29**	
Non-market	0.07	0.83	0.63	0.88	**0.81**	
EU-10						
Total	4.86	2.31	1.26	0.63		**-1.68**
Market	N/A	2.47	1.61	0.72		**-1.75**
Commodities	N/A	3.11	2.26	0.95		**-2.15**
Services	N/A	1.69	1.23	0.64		**-1.05**
Non-market	N/A	0.56	0.26	0.19		**-0.37**

Note: All cells are computed from the merged KLEMS data base as described in the Data Appendix except for the EU-10 in 1950-72, which comes from the Conference Board Total Economy Database.

points in comparison to the SP slowdown of 1.94 points.[9]

The story is simpler for the EU-10, where total economy productivity growth decreased in each period, most sharply between 1950-1972 and 1972-1995. Growth in the market sector was modestly faster than in the total economy in each interval, while growth in the non-market sector was slower and exhibited a steady slowdown in contrast to the alternation visible in the non-market data for the United States. For the total economy trend growth in the EU-10 started out at double the rate of the United States in the initial 1950-1972 interval and gradually decreased until in 2005-2015 it was virtually identical. EU-10 growth in the non-market sector was substantially slower than in the United States in the last two intervals following 1995. The distinction between the CP and SP industries is also more straightforward for the EU-10 than for the United States. CP productivity growth started out in 1972-1995 roughly double that of the SP industries and then slowed down more rapidly, so that by 2005-2015 CP and SP growth were little different. This reinforces our emphasis on the importance of the CP industries as contributors to the overall slowdown between the early and late time intervals in both the United States and the EU-10.

The fact that the EU-10 had more rapid productivity growth than the United States prior to 1995 but slower growth after 1995 implies that the *level* of EU-10 labour productivity caught up to that of the United States prior to 1995 and then fell back after 1995. In the pre-1995 interval the EU-10 more than caught up to the United States, with the ratio of its productivity level rising from 50 per cent in 1950 to 81 per cent

9 The accentuated slowdown of the market sector relative to its sub-industries in commodities and services production between 1950-1972 and 2005-2015 is due to a compositional shift towards the services sector.

10 The ratio of EU-10 to U.S. labour productivity is based on a comparison of GDP per hour, with EU-10 GDP in purchasing-power-parity dollars aggregated and divided by hours. Source: Conference Board Total Economy Database.

in 1972 to 106 per cent in 1995.[10] Thus, despite suggestions in the literature that the European economy suffers from "Eurosclerosis," structural flaws that prevent it from achieving the U.S. level of productivity, Europe actually exceeded the U.S. level from 1989 to 2000 before retreating as a result of its failure to duplicate the U.S. 1995-2005 growth revival. The ratio of the EU-10 to the U.S. productivity level declined from 106 per cent in 1995 to 90 per cent in 2005 and slightly further to 86 per cent in 2015.

An interesting feature of Table 1 is the close similarity of the U.S. growth rates in 1950-1972 with the EU-10 growth rates in 1972-1995, and the close similarity of the U.S. growth rates in 1972-1995 to the EU-10 growth rates in 1995-2005. In this sense the entire period from 1972 to 2005 can be characterized as "the EU-10 lagged 20 years behind the productivity performance of the United States."

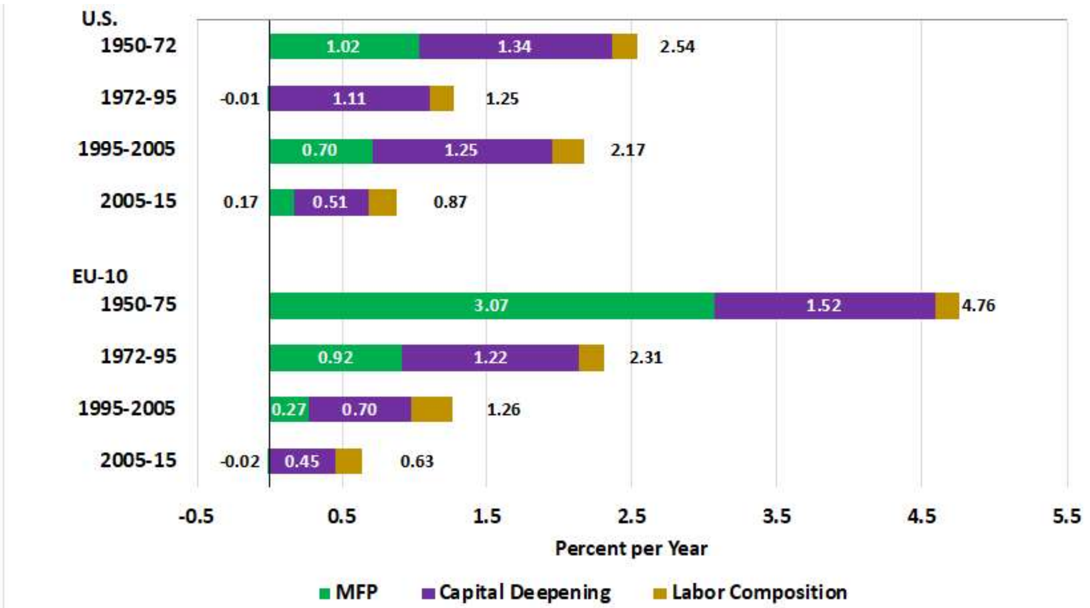
The rapid EU growth of 1950-1972 can also be interpreted as "catch-up"[11] growth after the economic dislocations of the two world wars and the interwar period, when the United States leaped ahead of the EU in its level of labour productivity. As noted, in 1950 the level of EU-10 labour productivity was only 50 per cent of the U.S. level, implying substantial room for catch-up. By 1972 Europe had time to adopt most of the inventions of the late nineteenth and early twentieth century that had become common in the United States before World War II, and so after 1972 EU-10 productivity growth slowed down to a rate very similar to the U.S. rate in the early postwar years, 1950-1972. When we interpret 1950-1972 for the United States as being comparable to 1972-1995 for the EU-10, a remarkable fact emerges from Table 1, as shown in the two right-hand columns. For the total economy *the slowdown in labour productivity growth from these comparable periods to 2005-2015 was exactly the same, -1.67 points for the United States and -1.68 points for Europe.*

Within the market economy this measure of slowdown was also quite similar, and again the slowdown for the CP industries in Europe (-2.15 points) was exactly the same as in the United States (-2.13 points). The slowdown in the SP industries in the United States was slightly greater in the United States than in Europe (-1.29 vs. -1.05 points). The measure of slowdown was quite different in the non-market sector, reflecting the unusually slow growth for the non-market sector in the United States in the early postwar years.

The standard sources-of-growth decomposition divides growth in labour productivity among the contributions of multifactor productivity (MFP), capital deepening, and changes in labour composition. Chart 2 provides for the same time intervals as Table 1 a graphical depiction of these three respective contributions to total economy labour productivity growth as green, purple, and gold slices in the horizontal bars, the total width of which represents labour productivity growth. Here we notice interesting differences between

11 Timmer *et al.* (2011) provide a similar diagnosis, arguing that from 1950 to 1973, European productivity was playing "catch up" with the United States — specifically through "technology imitation" and "new institutions." They also concur that from 1973 to 1995 growth slowed as the EU "caught up."

Chart 2: Decomposition of Labour Productivity Growth Between MFP, Capital Deepening, and Labour Composition, Selected Periods, 1950-2015



Source: All data except EU-10 for 1950-1975 are taken from the KLEMS series decribed in the Data Appendix. The EU-10 numbers from 1950-1975 are taken from Bergeaud, Cette, and Remy (2017: Table 1), which provides the data separately from the UK and Eurozone. These are weighted together by average 1950-1975 GDP of the listed nations from the Conference Board Total Economy Database. Unlike the other intervals for the EU-10, the series shown for 1950-1975 include Finland and Portugal, while excluding Austria, Denmark, and Sweden.

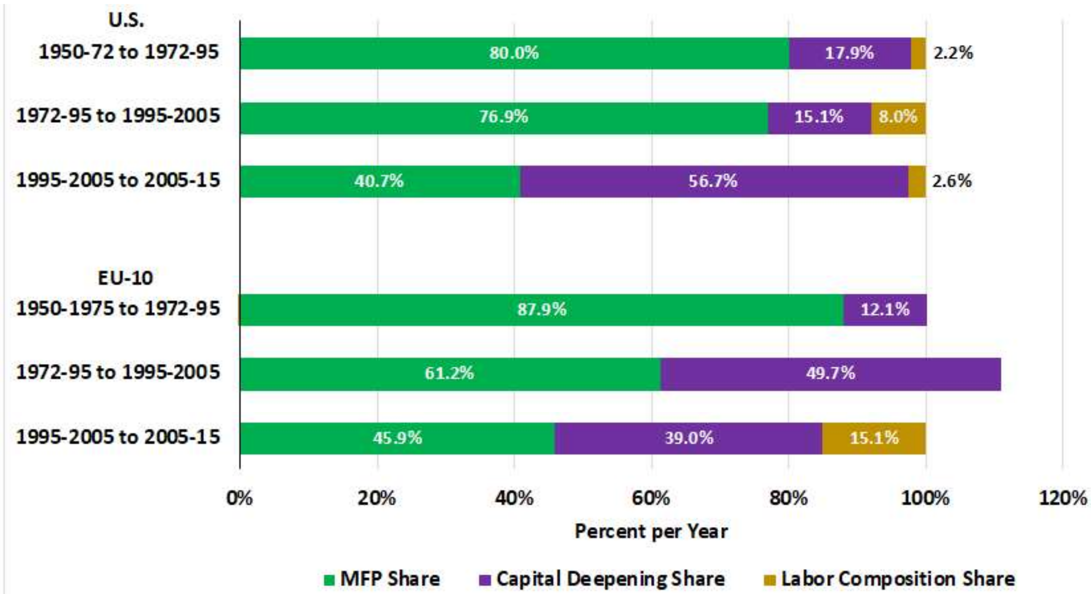
the United States and EU-10. For the United States the contribution of capital deepening was virtually the same in the first three periods — 1.34, 1.11, and 1.25 percentage points respectively, indicating that virtually all of the 1972-1995 productivity growth slowdown and 1995-2005 revival was due to variations in average MFP growth.

In contrast a reduction in the contribution of capital deepening accounted for more of the post-2005 productivity growth slowdown than the slowdown in the MFP contribution. [12] Based on a separate calculation that is not included in Chart 2, during 2005-2010, U.S. capital deepening continued at a 1.11 per cent growth rate, similar to that observed before 2005, while MFP growth fell from 0.71 per cent in 1995-2005 to a negligible 0.21 per cent in 2005-2010. Then in 2010-2015 MFP growth continued at the even slower rate of 0.14 per cent while capital deepening growth plummeted to a negative -0.10 per cent rate. In this sense the slowdown was led by MFP, while capital deepening followed along with a lag.

For the EU-10 the relative roles of MFP and capital deepening were different than in the United States. In each of the transitions the slowdown in the growth rate of labour productivity is explained by a

12 It is interesting to note that the first and last halves of the 2005-2015 interval were quite different for the United States (although not for the EU-10).

Chart 3: Percent Decomposition of Labour Productivity Change Between MFP, Capital Deepening, and Labour Composition, Selected Periods, 1950-2015



Source: All data except EU-10 for 1950-1975 is taken from the KLEMS series decribed in the Data Appendix. The EU-10 numbers from 1950-1975 are taken from Bergeaud, Cette, and Remy (2017: Table 1), which provides the data separately from the UK and Eurozone. These are weighted together by average 1950-1975 GDP of the listed nations from the Conference Board Total Economy Database. Unlike the other intervals for the EU-10, the series shown for 1950-1975 include Finland and Portugal, while excluding Austria, Denmark, and Sweden.

slowdown in both the contribution of MFP and of capital deepening.[13] In the first post-1972 transition the MFP contribution was substantially more important, but in the post-1995 and post-2005 transitions the MFP and capital deepening contributions were of roughly equal importance. The impact of the labour composition contribution was small and notably reversed sign toward a higher contribution in 1995-2005 than in the second and fourth intervals.

Chart 3 shows the relative importance of the contributions in explaining each of the transitions of Chart 2. Each horizontal bar sums to 100 per cent, and the same colors as in Chart 2 indicate the share of the MFP, capital deepening, and labour composition contributions to the transitions between time intervals. For the United States the large green segments show the dominant role of MFP in causing the down and up of labour productivity growth in the 1972-1995 slowdown and 1995-2005 revival, while the large purple segment indicates the predominant role of capital deepening in the post-2005 slowdown. For the EU-10 the green MFP area indicates its major responsibility for the first 1972-1995 slowdown, while the roughly equal green and purple areas show joint responsibility in the 1995-2005 and post-2005 slowdowns. Note that the sum of the green and purple EU

13 Charts 2 and 3 reach the same conclusion as Giombini *et al.* (2017), who concur that EU productivity slowed both because of smaller contributions of both MFP and capital deepening

bars for the post-1995 transition sums to more than 100 per cent, because the contribution of labour composition goes in the opposite direction (up) from the direction of the MFP and capital deepening contributions (down).

The green and purple shares in Chart 3 help to focus our attention on the underlying causes of the changes in labour productivity growth over these intervals. Viewed in this way, the U.S. 1972-1995 slowdown and 1995-2005 revival were largely a story of the shifting role of innovation, while the post-2005 slowdown combined the impact of innovation with a depressed contribution of investment. For the EU-10 innovation dominated in the first 1972-1995 slowdown, while innovation and investment shared responsibility for the further 1995-2005 and post-2005 growth slowdowns.

Industrial Sector Behavior for the United States

In contrast to the EU-10, which experienced a steady slowdown in labour productivity growth from one time interval to the next, the United States alternated between a 1972-1995 slowdown, a 1995-2005 revival, and a second post-2005 slowdown. In this section we examine the industry breakdown of the three U.S. transitions and turn in the next section to the EU-10 slowdown and the contrast between its industry makeup and that of the United States.

Previous analyses of U.S. industry data have been based on the BLS data that are available for 60 different industries and have focused primarily on the 1995-2005 revival (Stiroh, 2002) or post-2005 slowdown (Murray, 2018) or both (Baily and Montalbano, 2016). With so many industries behaving in different ways, it has been difficult for these studies to emerge with firm conclusions regarding the industry anatomy of these transitions. Here we begin with 27 industry groups from the KLEMS data and reduce that number to 16 by combining the 11 two-digit subindustries of manufacturing into a single manufacturing sector (later we shall look at the manufacturing sub-industries separately). By aggregating into a smaller number of industries than the BLS data, the KLEMS data makes it more feasible to highlight the behavior of particular industries.

Table 2 presents labour productivity growth rates for the United States in our four time periods divided by 1972, 1995, and 2005. The industries are presented in the order of the KLEMS industrial classification, which places five commodity-producing industries first (agriculture, mining, manufacturing, utilities, and construction), followed by seven service-producing industries. Growth rates for five aggregates — total, market, nonmarket, commodities, and services — are shown in bold and are identical to the same growth rates presented above in Table 1.

In the initial 1950-1972 interval for the market sector, six industries registered above average growth rates. These were the first four listed commodity-producing (CP) industries, plus wholesale/retail and information/communication. All the industries with below-average growth were in the SP sector except for construction — notably two of the SP industries had productivity growth of near zero, and another two had negative productivity growth. Growth

Table 2: Annual Labour Productivity Growth Rates by Industry Group, U.S., Selected Intervals, 1950-2015

Industry	1950-72	1972-95	1995-2005	2005-15
Total	**2.54**	**1.25**	**2.17**	**0.87**
Market	**3.05**	**1.66**	**2.89**	**0.86**
Commodities	**3.39**	**1.45**	**3.60**	**1.27**
Agriculture	4.68	3.72	7.27	1.05
Mining	2.97	-0.27	-1.87	2.98
Manufacturing	3.41	2.43	5.53	1.90
Utilities	4.56	-1.24	1.20	-0.03
Construction	1.89	-1.44	-1.02	-0.92
Services	**2.19**	**2.20**	**2.84**	**0.90**
Wholesale & Retail	3.55	3.18	4.33	0.79
Transportation	2.37	1.43	1.48	-0.69
Hotels & Restaurants	-1.74	-0.67	1.81	-0.67
Information & Communications	4.33	5.46	4.04	3.05
Finance & Insurance	-0.19	3.65	3.77	0.80
Professions & Administrative	-	-0.60	1.20	1.07
Arts & Entertainment	-1.09	-0.14	-0.05	-0.10
Nonmarket	**0.07**	**0.83**	**0.63**	**0.88**
Real Estate	2.16	0.09	0.96	1.91
Public Sector	-0.93	1.47	0.55	0.33
Education	2.47	0.80	0.87	0.99
Health	0.06	-0.29	-0.25	0.34

Source: KLEMS Database.

in the nonmarket sector was negative, pulled down by the substantial negative growth rate of public sector administration. Since output in many parts of the public sector is measured by employment, this 1950-1972 negative rate of public sector productivity growth may be spurious in the underlying KLEMS data for this early time interval.

In the next interval — 1972-1995 — labour productivity growth declined by half in the total economy (from 2.54 to 1.25 per cent) and by almost half in the market sector (from 3.05 to 1.66 per cent). Which industries accounted for the slowdown? As shown in Table 2 all of the slowdown was concentrated in the CP industries, since growth in the SP industries was exactly the same after 1972. In the market sector eight of the 12 industries registered slower growth after 1972, and seven of these were those listed at the top of the table (from agriculture down through transportation services). The other was professional/administrative, which went from zero to negative growth. The remaining four industries experienced faster productivity growth, or in the case of hotels/restaurants and arts/entertainment a smaller negative growth rate. In the nonmarket sector there was a sharp turnaround in public administration from negative to positive growth, while the other three industries experienced slower growth. Overall, 11 of the 16 industries experienced slower growth.

Productivity growth revived from 1972-1995 to 1995-2005 in the total economy from 1.25 to 2.17 per cent and in the market sector from 1.66 to 2.89 per cent. Once again we see that the transition was dominated by the CP industries, which witnessed productivity growth more than double from 1.45 to 3.60 per cent, while the revival for the SP industries was only from 2.20 to 2.84 per cent. Thus the CP industries grew faster than the SP industries in the first and third period but slower in the second period. This strong contribution of the CP industries to the 1972-1995 slowdown and 1995-2005 revival has received relatively little comment in the literature.

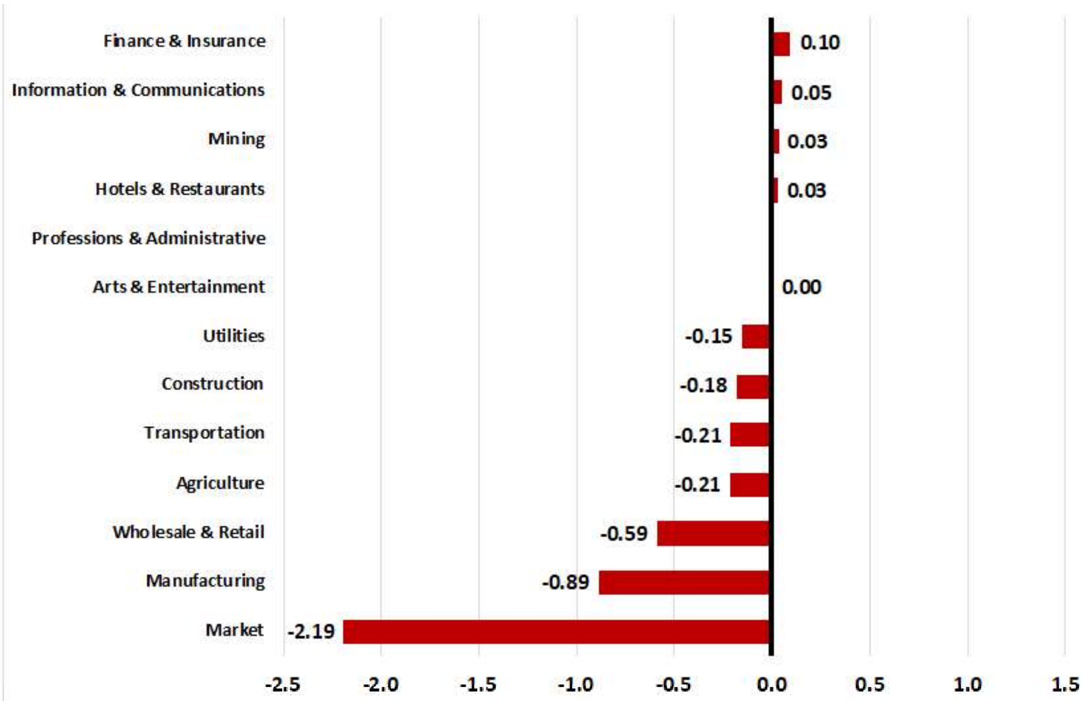
Six industries experienced an increase in productivity growth of more than 1 percentage point after 1995, and four of these achieved a growth rate faster than in the initial 1950-1972 period (agriculture, manufacturing, wholesale/retail, and professional/administrative). The sharpest changes in the 1995-2005 transition were for agriculture (3.55 percentage points), manufacturing (3.10), hotels/restaurants (2.48), and utilities (2.44). The remaining six industries experienced increases of less than one per cent or a decline in the case of mining and information/communication. Mining, construction, and arts/entertainment recorded negative productivity growth during 1995-2005. Productivity growth changed little on balance in the nonmarket sector, with little change in education and health, and with an increase in real estate offset by a decline in public administration.

The second episode of slower productivity growth occurred after 2005, slowing from 2.17 per cent to 0.87 per cent in the total economy and from 2.89 to 0.86 per cent in the market sector. The decline of more than 2 percentage points in the market sector was greater than the previous slowdown from 1950-1972 to 1972-1995. Within the market sector the CP and SP industries recorded roughly similar slowdowns of -2.33 and -1.94 per cent respectively, as shown in Table 2. Six industries experienced a decline of more than one percentage point *and* recorded lower productivity growth than in the previous slowdown period of 1972-1995. In descending order of the extent of the slowdown, these were agriculture (-6.22 percentage points), manufacturing (-3.63), wholesale/retail (-3.54), finance/insurance (-2.97), transportation services (-2.17), and information/communication (-0.99). Hotels/restaurants had a decline of -2.48 points to negative growth which exactly matched the negative growth of 1972-1995. Utilities experienced a slowdown of -1.23 points but grew faster than in 1972-1995. Mining was the notable outlier, experiencing a sharp growth revival of 4.85 per cent. The remaining industries in the market sector grew slowly and exhibited little change in the post-2005 transition. The nonmarket sector grew slightly faster after 2005, with a one point revival in real estate but little change otherwise.

Across the columns in Table 2, there is a relatively high correlation coefficient of 0.79 across market industries between the productivity growth rates of 1972-1995 and 1995-2005. This means that the industries that grew the fastest between 1972 and 1995 also grew the fastest between 1995 and 2005. The regression constant is 1.11 percentage points and the slope coefficient is a highly significant 0.92.

Perhaps most interesting is the strong negative correlation coefficient of -0.69 across the market industries between the 1995-2005 revival and the post-2005 slowdown. Those industries that experienced the largest revivals after 1995 also experienced the greatest slowdowns after 2005, particularly agriculture, manufac-

Chart 4: Value-Added Weighted Contributions of Market Industries to U.S Labour Productivity Growth, 1950-1972 to 2005-2015 Transition



Source: KLEMS Database.

turing, utilities, wholesale/retail, and hotels/restaurants.[14] The regression line has a constant term of -0.22 and a slope of -1.10. The high negative correlation is also supported by the turnaround in mining from a negative post-1995 change to a sharp positive post-2005 change. This correlation pattern is consistent with the hypothesis that the U.S. market economy experienced a temporary positive technological shock in 1995-2005 that dissipated after 2005, and this interpretation, consistent with much of the previous literature, is supported by the dominant role of MFP relative to capital deepening in explaining the 1995-2005 revival.

Which were the main industries that contributed to the overall decline from the first 1950-1972 interval to the final 2005-2015 interval? We can calculate the contributions of each industry to the total change in productivity growth over this transition. This is done by multiplying the change in productivity growth between time intervals by the average share in value-added of the particular industry over that time period. The results are displayed graphically in Chart 4 and focus on the market sector, omitting the four industries of the nonmarket sector to simplify the discussion.

Chart 4 displays as the bottom red bar the total change in the market sector of -

14 A graph illustrating this negative correlation appears in Baily and Montalbano (2016: Figure 9).

2.19 percentage points. Interestingly all of this contribution can be explained by the six industries listed at the bottom, while the six industries at the top made virtually no contribution to this overall change. Moving up from the bottom, in descending order of negative contributions, the industries making the largest contributions were manufacturing, wholesale/retail, agriculture, construction, transportation services, and utilities. Note that four of these produce commodities while the others produce services. The small role of services in this list suggests that the overall productivity growth slowdown over the postwar years has been heavily influenced by diminishing returns to innovations earlier in the 20th century that boosted productivity growth in the CP industries during 1950-1972 but faded out in importance after 1972.[15]

Industrial Sector Behavior Within U.S. Manufacturing

So far we have considered only the behavior of the manufacturing sector as a whole. But the KLEMS data allow us to differentiate between 11 sub-industries within manufacturing, and Table 3 displays their growth rates of labour productivity in the same format as Table 2. Productivity growth was robust in the initial 1950-1972 interval, with seven of the eleven sub-industries displaying growth rates of 3.5 per cent or above. The metals sub-industry was an outlier, with growth of only 1.14 per cent, and indeed experienced relatively slow growth in all four of the time intervals.

In the post-1972 transition productivity growth declined by 0.98 percentage points for total manufacturing and by more than 2 percentage points in 5 of the 11 sub-industries, with particularly sharp declines of more than 5 per cent in petroleum, chemicals, and machinery n.e.c. ("not elsewhere classified"). This response of petroleum and chemicals may reflect the influence of the oil price shocks of the 1970s, which raised the price of crude oil from \$3.56 in mid-1972 to \$39.50 in mid-1980.[16] The reason that the post-1972 decline for manufacturing as a whole was more modest than for most of the individual industries reflects the giant jump in the electric machinery industry from 4.24 to 13.49 per cent per year, reflecting the growing importance in this sector of the manufacture of ICT equipment.

As previously displayed in Table 2, the manufacturing sector enjoyed a sharp 1995-2005 revival in productivity growth from 2.43 to 5.53 per cent per year, or an increase of 3.10 percentage points. This increase as shown in Table 3 was consistent across sub-industries, as 6 of the 11 sub-industries experienced a productivity growth revival of 2 per cent or more, led by the enormous 8.58 percentage point revival for petroleum, and revivals of 3.5 percentage points or more for electrical machinery

15 Baily and Montalbano (2016) also highlight the role of agriculture, manufacturing, and retail/wholesale in the 1995-2005 productivity growth revival and post-2005 slowdown.

16 Source: Spot crude oil price, West Texas Intermediate, from FRED.

Table 3: Annual Labour Productivity Growth Rates by Industry Group, U.S. Manufacturing, Selected Intervals, 1950-2015

Industry	1950-72	1972-95	1995-2005	2005-15
Total Manufacturing	**3.41**	**2.43**	**5.53**	**1.90**
Food	3.47	0.87	0.05	-0.43
Textiles & Apparel	4.55	4.72	3.63	1.20
Wood & Paper	2.10	0.27	2.15	1.46
Petroleum	8.24	2.41	10.99	-1.08
Chemicals	4.55	0.41	3.22	1.37
Rubber & Plastics	2.65	1.02	3.19	-0.78
Metals	1.14	1.05	2.25	0.50
Electrical Machinery	3.87	13.49	17.57	7.07
Machinery NEC	5.28	-0.60	3.02	0.64
Transportation Equipment	2.35	0.78	4.63	2.26
Other Manufacturing	5.16	2.91	3.32	1.79

Source: KLEMS Database.

(which reached a stunning growth rate of 17.6 per cent), machinery n.e.c., and transportation machinery. In four of these six industries with a revival of two per cent or more, productivity growth in 1995-2005 was faster than in the initial interval of 1950-1972, with an enormous margin for electrical machinery, while transportation equipment registered double the productivity growth in 1995-2005 as in 1950-1972. Only food and textiles/apparel experienced a productivity growth slowdown after 1995.

After 2005 overall manufacturing productivity growth slowed from 5.53 to 1.90 per cent, for a slowdown of 3.63 points. 6 of the eleven sub-industries experienced growth slowdowns of 2 per cent or more, led by the enormous declines of petroleum (-12 points) and electrical machinery (-10.5 per cent).[17] Seven industries display growth rates in 2005-2015 that are below their growth rates in the initial slowdown period of 1972-1995. Not a single manufacturing sub-industry recorded faster growth in 2005-2015 than in the prior period of 1995-2005.

To summarize the experience of the eleven sub-industries within manufacturing we can divide them into groups. Electrical machinery is in a category by itself, with rapid growth in all periods, double-digit growth in the two middle periods, and a sharp post-2005 slowdown to a growth rate of 7.07 per cent that was still relatively high. Next comes the majority of industries (seven of 11) that experienced a zigzag from high growth in 1947-1972 to lower growth in 1972-1995, followed by a revival in 1995-2005 and a second slowdown after 2005. This group includes wood and paper, petroleum, chemicals, rubber and plastics, machinery n.e.c., transportation equipment, and other manufacturing. The three remaining industries display unique patterns — food slowed after 1972 with no 1995-2005 revival at all; textiles and

17 Brill *et al.* (2018) in their analysis of BLS data conclude that most of the post-1995 and the post-2004 speedup/slowdown in manufacturing can be attributed to ICT producing industries. These authors also highlight the Petroleum industry as making a massive negative contribution, as is evident in Table 3.

apparel remained strong throughout until 2005 with no 1972-1995 slowdown; and metals registered slow growth throughout interrupted by a slight improvement in 1995-2005.

Industrial Sector Behavior for the EU-10 and EU-U.S. Comparisons

The industrial breakdown of the EU-10 reveals a steady decline in productivity growth rather than the alternation of slowdown-revival-slowdown that we have observed for the United States. Table 4 displays EU-10 productivity growth for the same industries and same format as Table 2, but here we have three periods rather than four. Productivity growth slowed steadily across the intervals for the total economy, market economy, CP industries, SP industries, and the non-market sector.

In the initial 1972-1995 interval five of the 12 industrial sectors in the market sector exhibited growth of more than 2.5 per cent, and four of these five were CP industries, while the fifth was transportation services. Only one industry, hotels and restaurants, experienced negative productivity growth. As in the U.S. non-market productivity growth was slow, with negative growth in real estate.

When the 1995-2005 interval is compared with 1972-1995, all of the CP industries except for utilities experienced slower productivity growth. However, in the SP industries two of the seven achieved faster productivity growth, namely information/communications and finance/insurance. These are two of the industries that we would expect to be most influenced by the ICT revolution of the 1990s. While information/communications experienced somewhat slower post-1995 growth in the United States, the transition was from a much higher growth rate (5.46 per cent to 4.04 per cent for the United States, 2.11 per cent to 3.84 per cent for the EU-10). Growth in the non-market sector slowed modestly in each industry except real estate, where productivity growth became slightly less negative.

Comparing Tables 2 and 4, we see that the EU-10 had faster productivity growth during 1972-1995 than the United States in eight of the 12 industries, including all five of the CP industries. The pattern was reversed for the 1995-2005 interval, with the United States having faster productivity growth than the EU-10 in seven of the 12 industries. However, while the EU had excelled in producing commodities in the earlier interval, the United States in 1995-2005 excelled in services, with five out of its seven SP industries having more rapid productivity growth than the EU-10. In the non-market sector productivity growth was virtually the same in the United States and EU-10, with small positive or negative numbers except for growth slightly above one per cent in EU-10 public administration.[18]

One of the most notable differences between the EU-10 and the United States

18 The predominant theme of the previous literature on the EU productivity growth slowdown is to emphasize the role of market services in the shortfall relative to the United States. Among these papers are Uppenberg *et al.* (2010), Timmer *et al.* (2011), Inklaar *et al.* (2005), Van Ark *et al.* (2008), and Inklaar *et al.*(2007).

Table 4: Annual Labour Productivity Growth Rates by Industry Group, EU-10, Selected Intervals, 1972-2015

Industry	1972-95	1995-05	2005-15
Total	**2.31**	**1.26**	**0.63**
Market	**2.47**	**1.61**	**0.72**
Commodities	**3.11**	**2.26**	**0.95**
Agriculture	4.76	3.47	1.37
Mining	3.70	-0.72	-0.29
Manufacturing	3.46	2.87	1.84
Utilities	2.78	3.21	-1.38
Construction	1.12	-0.10	-0.30
Services	**1.69**	**1.23**	**0.64**
Wholesale & Retail	2.03	1.81	1.29
Transportation	3.44	2.46	0.42
Hotels & Restaurants	-0.53	-0.52	-0.58
Information & Communications	2.11	3.84	2.26
Finance & Insurance	1.49	2.14	1.14
Professions & Administrative	0.94	-1.03	-0.24
Arts & Entertainment	0.64	0.40	-0.51
Non-market	**0.60**	**0.26**	**0.19**
Real Estate	-0.40	-0.21	0.58
Public Sector	1.59	1.26	1.11
Education	0.72	-0.19	-0.70
Health	0.42	0.36	0.22

Source: KLEMS Database.

is the failure of the EU to mimic the 1995-2005 growth revival enjoyed by the United States. Yet the best-performing EU-10 industries during 1995-2005 were in most cases the same as in the United States, sufficient to create a correlation coefficient across industries of 0.71 between the 1995-2005 productivity growth rates in the EU vs. United States. The top-performing industries were similar — agriculture, manufacturing, information/communication, and finance/insurance. But in each of these cases EU growth fell short of U.S. growth, and in other industries the EU did poorly and lagged by a substantial margin, especially in wholesale/retail, hotels/restaurants, and professional/administrative. There is only a 0.08 correlation across industries between EU 1995-2005 growth and the *difference* by industry between United States and EU growth.

After 2005 EU-10 productivity growth slowed to 0.63 per cent per year in the total economy, little different than the sluggish 0.87 per cent pace registered by the United States. The post-2005 slowdown in the United States was greater than in the EU-10, because the United States during 1995-05 had achieved faster growth. Fully ten of the 12 EU-10 market industries experienced slower growth after 2005. Only five of the 12 industries in the market sector registered productivity growth above 1.0 per cent after 2005, while six recorded negative productivity growth — three of these were CP industries and the other three were SP industries.

Because productivity growth in the EU-10 slowed both after 1995 and again after 2005, we can examine the industry composition of the slowdown most efficiently by combining the two slowdowns. Accordingly the left column of Table 5 compares EU-10 productivity growth by industry for 2005-2015 with that for 1972-1995. Four of the 12 industries in the market sector experienced slowdowns of more than 3.0 percentage points, three of which were CP-industries (agriculture, mining, and utilities) while one was a SP industry (transportation services). Overall the average slowdown for the CP industries (-2.15 percentage points) was more than double the slowdown for the SP industries (-1.05 percentage points).

Almost all the industries in the non-market sector experienced slower productivity growth, although for most the declines were small because growth in the initial 1972-1995 interval was relatively slow. In fact there is a general tendency for the industries that grew the fastest in the initial 1972-1995 interval to have the largest growth slowdowns to 2005-2015. The correlation coefficient between 1972-1995 growth rates and the slowdown shown for the EU-10 market sector in Table 5 is -0.72 and rises to -0.78 when the non-market sector is included.

In our discussion of Table 1 above, we noted that for the total economy the EU-10 experienced almost exactly the same slowdown (-1.68 points) from 1972-1995 to 2005-2015 as the United States experienced from the earlier 1950-1972 period to 2005-2015 (-1.67 points). To further explore this close similarity between the two overall slowdowns, Table 5 adds an additional column that shows the change for each industry in U.S. productivity growth from 1950-1972 to 2005-2015. Several similarities stand out, including the large slowdowns in both columns for agriculture, manufacturing, utilities, and transportation services. The U.S. experienced greater slowdowns in retail/wholesale, hotels/restaurants, and information/communication. In the opposite direction the United States had no slowdown at all in mining, one of the worst-performing EU sectors, and the United States experienced an overall rise in productivity growth compared to a EU slowdown in finance/insurance and arts/entertainment.[19]

How closely related are the EU-10 vs. U.S. slowdowns shown in Table 5? Leaving aside the professional/administrative industry, the correlation coefficient in the market sector between the EU and U.S. slowdowns is 0.54 and the rank correlation is 0.70. When mining and arts/entertainment are removed the correlation rises to 0.81 and the rank correlation to 0.90. The major exception of mining can be explained by the development of the fracking revolution after 2005 in the United States but not in the EU-10. With the exception of mining we can conclude that the industrial composition of the EU and U.S. productivity growth slowdowns is highly correlated when the early and late intervals are compared as in Table 5.

The close correlation between the EU and U.S. slowdowns extends further to the close 0.79 correlation across industries in

19 The U.S. cell for professional/administrative is empty because data for that industry are missing for part of the 1950-1972 interval.

Table 5: **Labour Productivity Changes by Industry Group, Full Period Slowdowns for EU-10 and United States (percentage points per year)**

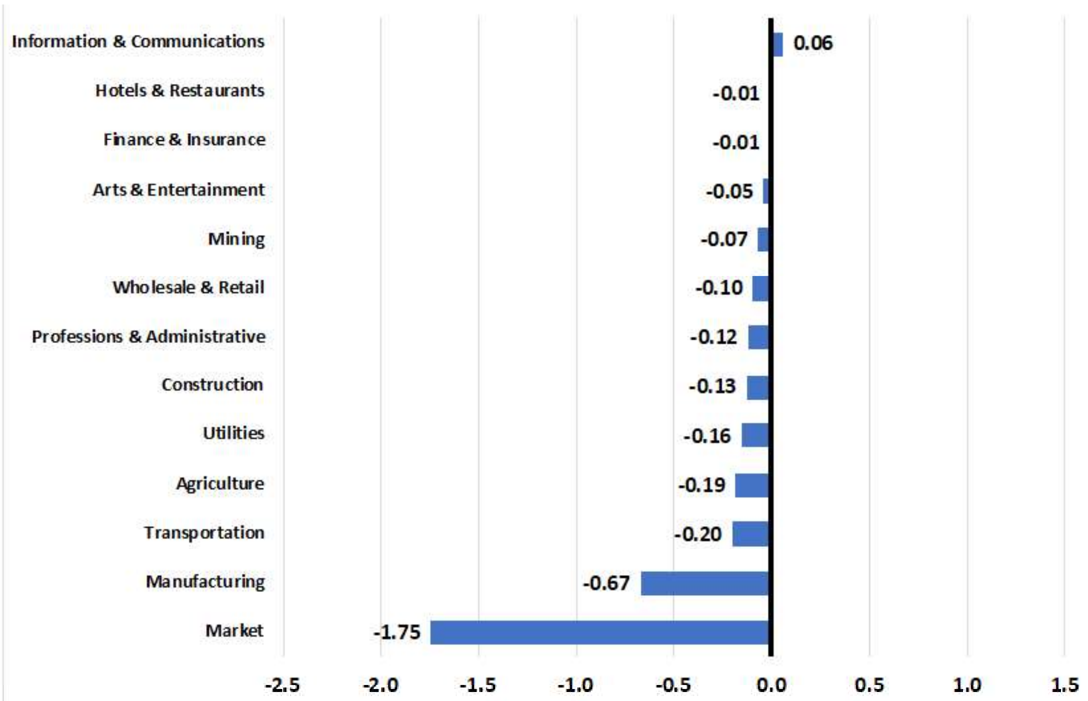
Industry	EU-10 1972-1995 to 2005-15	United States 1950-72 to 2005-15
Total	**-1.68**	**-1.67**
Market	**-1.75**	**-2.19**
Commodities	**-2.15**	**-2.13**
Agriculture	-3.39	-3.63
Mining	-4.00	0.00
Manufacturing	-1.62	-1.51
Utilities	-4.16	-4.59
Construction	-1.41	-2.81
Services	**-1.05**	**-1.29**
Wholesale & Retail	-0.74	-2.76
Transportation	-3.02	-3.06
Hotels & Restaurants	-0.04	1.07
Information & Communications	0.15	-1.28
Finance & Insurance	-0.35	0.99
Professions & Administrative	-1.18	-
Arts & Entertainment	-1.15	0.99
Non-market	**-0.41**	**0.81**
Real Estate	0.98	-0.26
Public Sector	-0.47	1.26
Education	-1.41	-1.48
Health	-0.20	0.28

Source: KLEMS Database.

the productivity growth rate achieved during 1950-1972 for the United States with that recorded for the EU-10 during 1972-1995. This reflects the pattern that cross-industry differences in productivity growth in the earlier periods differed more than in the final interval, and that the industries that grew fastest in the earlier periods experienced the greatest slowdowns when the earlier periods are compared to the final period. Furthermore, four of the five fastest-growing EU-10 industries in 1972-1995 were producing commodities. For the United States the same four CP industries were among the six fastest growing industries. In both the EU-10 and in the United States the construction industry was the only CP industry that failed to achieve productivity growth in the top performing group.

Just as Chart 4 displayed the contribution by industry for the United States between the early 1950-1972 and late 2005-2015 periods to the slowdown in market sector productivity growth, so Chart 5 displays the same contributions for the EU-10 between its early 1972-1995 interval and 2005-2015. With the exception of professional/administrative, for which there are no early data for the United States, the list of the six most important industries contributing to the slowdown is the same for the United States and EU-10. The contributions are in roughly the same order, as evidenced by the remarkably high 0.85 correlation across industries in the contributions displayed in Chart 4 compared with Chart 5. This supports our theme that the overall slowdown from the early postwar years to the most recent decade was due

Chart 5: Value-Added Weighted Contributions of Market Industries to Labour Productivity Growth Slowdown, EU-10, 1972-1995 to 2005-2015 Transition (percentage points per year)



Source: KLEMS Database.

to a retardation in technical change that affected the same industries by roughly the same magnitudes in the United States and in the EU-10. The most important difference is that wholesale/retail was in second rank for the United States with its contribution of -0.59 points, whereas that industry was in seventh place for the EU-10 with a much smaller contribution of -0.10 points.

Industrial Sector Behavior Within EU-10 Manufacturing and EU-U.S. Comparisons

We now turn to the performance for the EU-10 of the 11 sub-industries within manufacturing, where productivity growth rates are shown for the three intervals in Table 6. In the initial 1972-1995 interval productivity growth was robust across manufacturing, with eight of the 11 sub-industries reporting growth of more than 2.5 per cent. Only petroleum fell short, with growth below 1.0 per cent, which is interesting because the U.S. petroleum refining sector also suffered a severe growth slowdown after 1972. This similarity of slow productivity growth in the United States and EU-10 petroleum refining industry may reflect the influence of the oil price shocks of 1973-1975 and 1979-1981.

Growth in total EU-10 manufacturing declined modestly after 1995 from 3.46 per cent in 1972-1995 to 2.87 per cent in 1995-2005. The pattern of slower growth was quite uniform, as nine of the 11 sub-industries experienced slower growth, and only two (food and chemicals) experienced

Table 6: Annual Labour Productivity Growth Rates by Industry Group, EU-10 Manufacturing, Selected Intervals, 1950-2015

Industry Name	1972-95	1995-2005	2005-15
Total Manufacturing	**3.46**	**2.87**	**1.84**
Food	2.36	0.92	0.42
Textiles & Apparel	3.47	2.99	2.11
Wood & Paper	2.59	2.38	2.02
Petroleum	0.43	-0.39	-3.53
Chemicals	5.41	4.05	1.94
Rubber & Plastics	3.24	2.42	1.42
Metals	3.00	2.01	1.62
Electrical Machinery	5.47	4.78	2.95
Machinery NEC	2.66	2.86	0.97
Transportation Equipment	3.61	2.58	3.15
Other Manufacturing	1.31	2.82	1.12

Source: KLEMS Database.

a growth slowdown of more than 1.0 per cent. Two industries registered faster productivity growth, machinery n.e.c. and other manufacturing. Industries remained in roughly the same rank from fastest to slowest growing, with the correlation coefficient across industries of growth rates for 1972-1995 versus 1995-2005 a high 0.84.

There was a larger slowdown after 2005, from 2.87 to 1.84 per cent per year for total manufacturing. Four industries — petroleum, chemicals, electrical machinery, and machinery n.e.c. — experienced a slowdown of more than 1.8 percentage points. Only transportation equipment enjoyed an increase, albeit small, in productivity growth. Industries retained roughly the same rank from fastest to slowest growing, with a correlation coefficient of 0.82 across industries of growth rates for 1995-2005 and 2005-2015. The correlation between growth rates in the first and last periods is 0.75. However, there is no association between the cross-industry slowdowns after 1995 and after 2005, with a small correlation coefficient of -0.20.

We can extract from Tables 3 and 6 a comparison of the EU-10 slowdown from the first (1972-1995) to last period with the U.S. slowdown from its first (1950-1972) to last period. On one hand, the slowdowns for total manufacturing are similar, -1.62 for the EU-10 and -1.51 for the United States, and these magnitudes are quite similar to the -1.67 and -1.68 slowdowns for the total economy over the same time comparison. However, the pattern is somewhat different, as several industries experience substantially greater slowdowns in the United States than in the EU-10, particularly petroleum. Food, textiles, machinery n.e.c., and other manufacturing also experienced substantially greater slowdowns in the United States. Partly offsetting these slowdowns are the totally different behavior of electrical machinery, which (despite a big slowdown from 1995-05 to 2005-2015) grew substantially faster in the final period than before 1972 in the United States, whereas growth for the EU-10 electrical machinery industry in 2005-2015 was slower than in 1972-1995. The correlation across industries for the early-to-late slowdowns is 0.43 for the 11 industries but jumps to 0.73 when the electrical machinery industry is excluded.

Was Slowing Innovation or Flagging Investment Responsible for the Slowdown?

In Charts 2 and 3 we decomposed labour productivity growth in our four intervals in both the United States and EU-10 into the respective contributions of MFP growth, capital deepening, and changes in labour composition. Now we look at these contributions by industry and focus on the early-to-late slowdowns that were previously illustrated for labour productivity growth in Charts 4 and 5. Panel A of Chart 6 shows contributions by industry for the market economy to the U.S. slowdown between 1950-1972 and 2005-2015. Green segments measure the contribution of MFP, purple segments the contribution of capital deepening, and gold segments the contribution of changes in labour composition. The industries are ranked in order of the MFP contributions, ranked from mining at the top with a positive 4.72 point contribution down to utilities with its -3.41 point contribution.

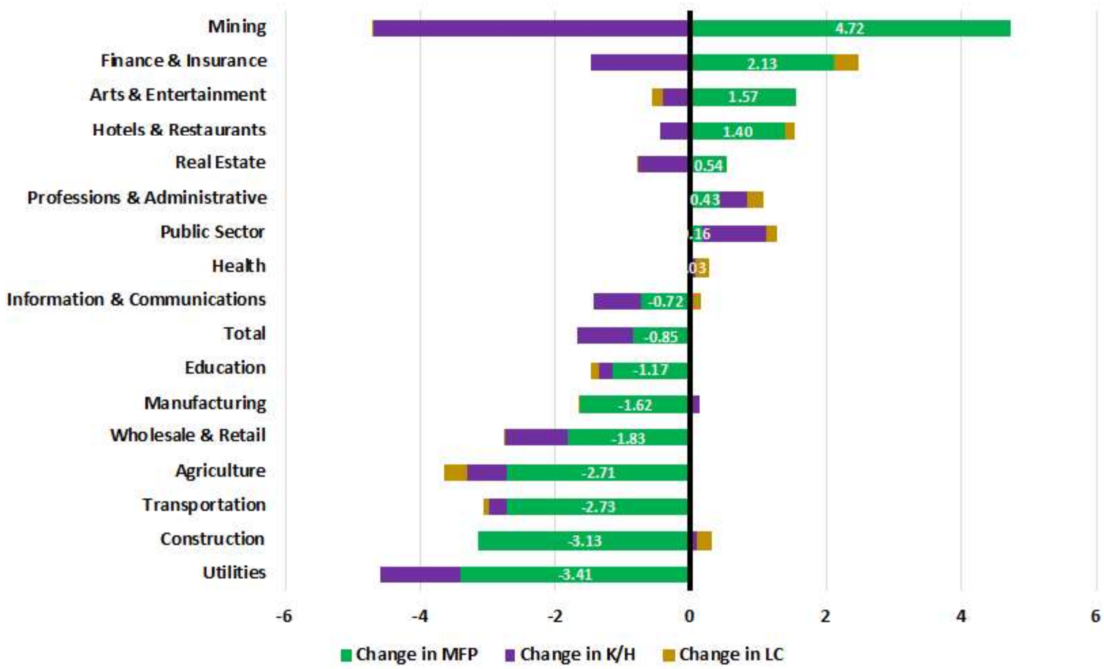
The total economy appears in the middle with a -0.85 point negative contribution of MFP growth. This contribution is almost exactly the same length as the purple bar indicating a -0.83 point negative contribution of capital deepening. The five top-listed industries with a positive MFP contribution all show a negative capital deepening contribution, and for mining the purple bar indicating a negative -4.70 point contribution of capital deepening almost exactly offsets the positive mining MFP contribution, resulting in a change in labour productivity growth of almost exactly zero (mining productivity growth in Table 2 was 2.97 per cent during 1950-1972 and 2.98 per cent during 2005-2015). Most of the industries at the bottom listed underneath the bar for the total economy display increasingly negative MFP contributions with small additional negative contributions of capital deepening.

Overall the industries are split on their MFP contributions, with eight registering positive contributions and eight recording negative contributions. The negative contributions are on balance larger and the industries more important (notably manufacturing and wholesale/retail), explaining why for the total economy the MFP contribution is on balance -0.85 per cent. A particularly important finding is that the slowdown of -1.51 points in manufacturing is overexplained by a decline of -1.62 points for the MFP contribution, with a 0.11 point positive contribution for capital deepening. As we shall see below, virtually all of the 11 manufacturing sub-industries had a negative MFP contribution to the overall slowdown, strengthening the case for a largely technological explanation. The contributions of changing labour composition are split evenly between positive and negative and range from a positive 0.35 for finance/insurance to a negative 0.33 in agriculture.

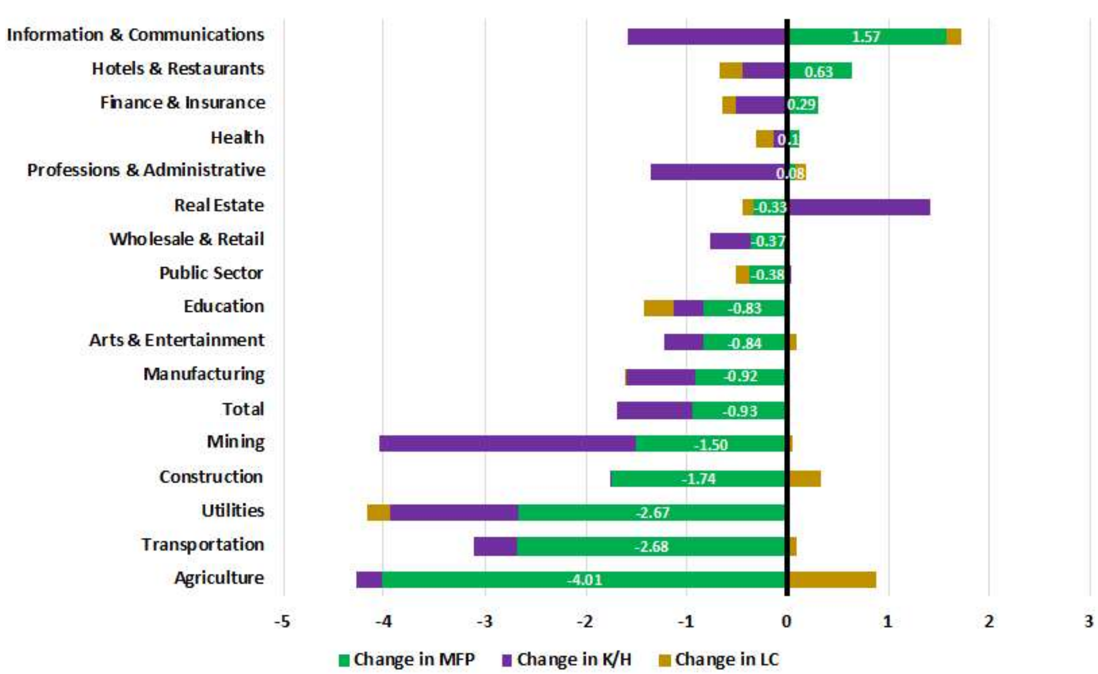
Panel B in Chart 6 displays in the same format the contributions to the EU-10 productivity slowdown from 1972-1995 to 2005-2015. Here there is a greater preponderance of industries with negative MFP contributions, 11 out of the 16 industries. Fully 14 of the 16 have negative

Chart 6: Decomposition of Labor Productivity Change

Panel A: Decomposition of Labour Productivity Change for U.S. Total Economy, 1950-1972 to 2005-2015, Ranked in Order of Change in MFP Contribution



Panel B: Decomposition of Labour Productivity Change for EU-10 Total Economy, 1972-1995 to 2005-2015, Ranked in Order of Change in MFP Contribution



Source: KLEMS Database.

capital deepening contributions. For the total economy the contribution of MFP of -0.93 points slightly exceeds that of capital deepening which is -0.77 points. The contribution of changing labour composition for the total economy is a negligible 0.02 points. The industry displayed as the top bar, information/communications, shows the same combination of a positive MFP contribution offset by a negative capital deepening contribution that we noted for mining in the case of the United States., but here the positive and negative numbers are less than half as large.

How similar are the United States versus EU-10 lists of industries experiencing the greatest slowdowns in the MFP contribution? Remarkably five of the bottom six industries are the same (although not in the same order) — agriculture, transportation, utilities, construction, and manufacturing. Mining appears in the bottom six on the EU-10 list while wholesale/retail appears in the bottom six on the U.S. list. The correlation of the MFP contributions across industries is 0.47 for all 16 industries but rises to 0.70 when mining is excluded.

We can carry out the same analysis of MFP vs. capital deepening contributions for the 11 individual sub-industries within manufacturing. For the United States all sub-industries except for electrical machinery and transportation equipment had negative MFP contributions between 1950-1972 and 2005-2015. The contributions of capital deepening are generally small and for total manufacturing is a slightly positive 0.11 points, so as pointed out above the MFP growth slowdown overexplains the labour productivity growth slowdown. The seven lowest-ranked industries all have negative MFP contributions of greater than -3.0 percentage points, and the contribution of MFP in petroleum is an enormous -10.47 points. Capital deepening contributions are generally small. Thus manufacturing is the sector of the economy in which the case for a technological explanation of the productivity growth slowdown is the strongest.

For the EU-10 capital deepening plays a larger role in explaining the "early-to-late" slowdown within manufacturing. For total EU manufacturing the MFP contribution of -0.92 points and the capital deepening contribution of -0.68 points are sufficient to explain the productivity slowdown of -1.62 points, with a negligible contribution from labour composition. Nine of the 11 EU sub-industries had a negative MFP contribution and neither of the others had a significant positive contribution. Each of the 11 sub-industries had a negative capital deepening contribution, and the largest of these were -1.40 points in petroleum and -1.89 points in electrical machinery. It is notable that electrical machinery performed so poorly in Europe, in contrast to the United States where that industry was the only one to record a sizeable positive change in the MFP contribution.

Beyond the difference in electrical machinery, how similar between the United States and EU-10 were the sub-industries experiencing the worst slowdowns in the MFP contribution? Four of the worst six are shared in common — chemicals, petroleum, food, and machinery n.e.c. The correlation across sub-industries in the magnitude of the MFP contribution change is 0.67 for all 11, which rises to 0.75 when electrical machinery is excluded and to 0.82

when the metals sub-industry is also excluded. This compares to a correlation for the total economy from Panel A and Panel B of Chart 6 of 0.70 for the total economy when mining was excluded. Thus we can conclude that the process of a slower MFP contribution, which reflects largely a smaller impact of innovation, originated in roughly the same set of industries in the EU-10 as in the United States.

How closely related between the EU and United States are the industries making the largest contributions to productivity growth and the growth slowdown? The first row and first column of Table 7 report for the total economy a regression of productivity growth by industry in the EU-10 during 1972-1995 on U.S. productivity growth by industry during the earlier time interval 1950-1972. The constant is a significant 0.90 and the coefficient a highly significant 0.49. The data points and the regression line are plotted in Panel A of Chart 7, along with a 45 degree line that indicates equal growth rates. There are four industries on the right side of the diagram lying above the regression line and on or above the 45 degree line, indicating 1972-1995 EU-10 performance superior to that in the United States during 1950-1972 — namely, agriculture, manufacturing, mining, and transportation services.

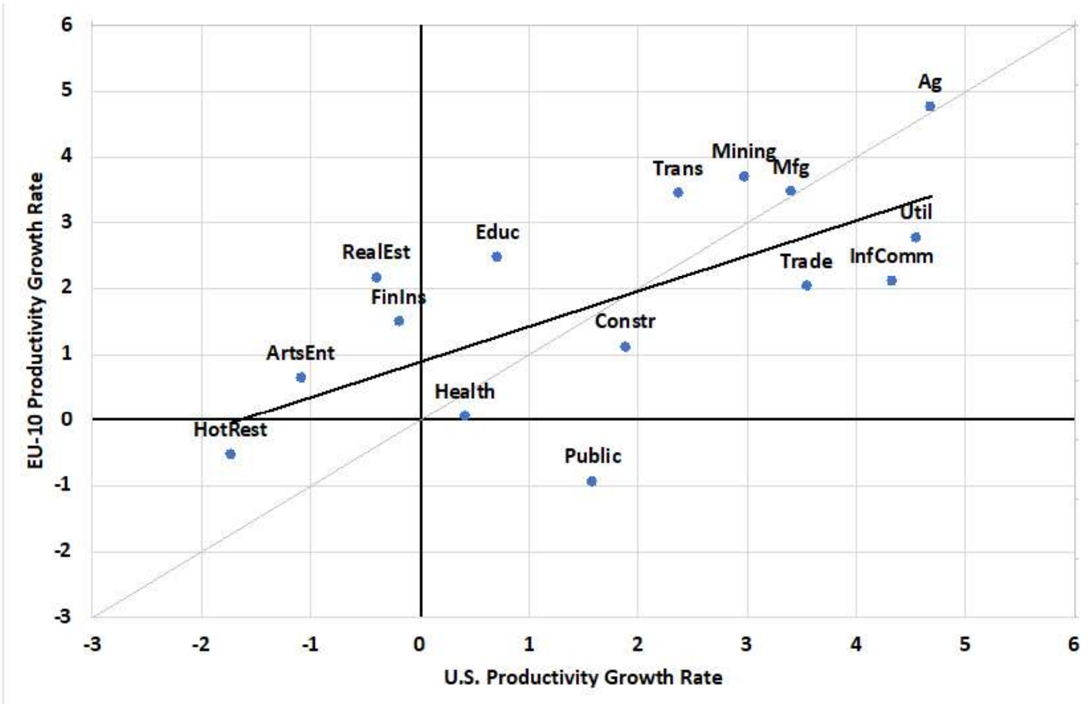
The second column of the top row in Table 7 reports that for the 11 sub-industries within manufacturing, the regression coefficient is negative rather than positive, although the relationship is weak. Removing the chemicals and electric machinery industries raises the R^2 from 0.08 to 0.51 but does not change the negative coefficient within manufacturing.

In light of the fact that the United States enjoyed a productivity growth revival after 1995 but the EU did not, the second row of Table 7 asks whether, despite this divergence, there was a relationship between the faster growing and slower growing EU industries and their U.S. counterparts during the 1995-2005 interval. For the total economy in the first column the coefficient is a highly significant 0.48, indicating that on average EU industries during 1995-2005 grew roughly half as fast as in the United States Panel B of Chart 7 illustrates this relationship, showing that agriculture, manufacturing, and finance/insurance lie right along the regression line, with trade a bit below, while information/communication lies on the 45 degree line, indicating equal growth rates in the EU-10 and United States.

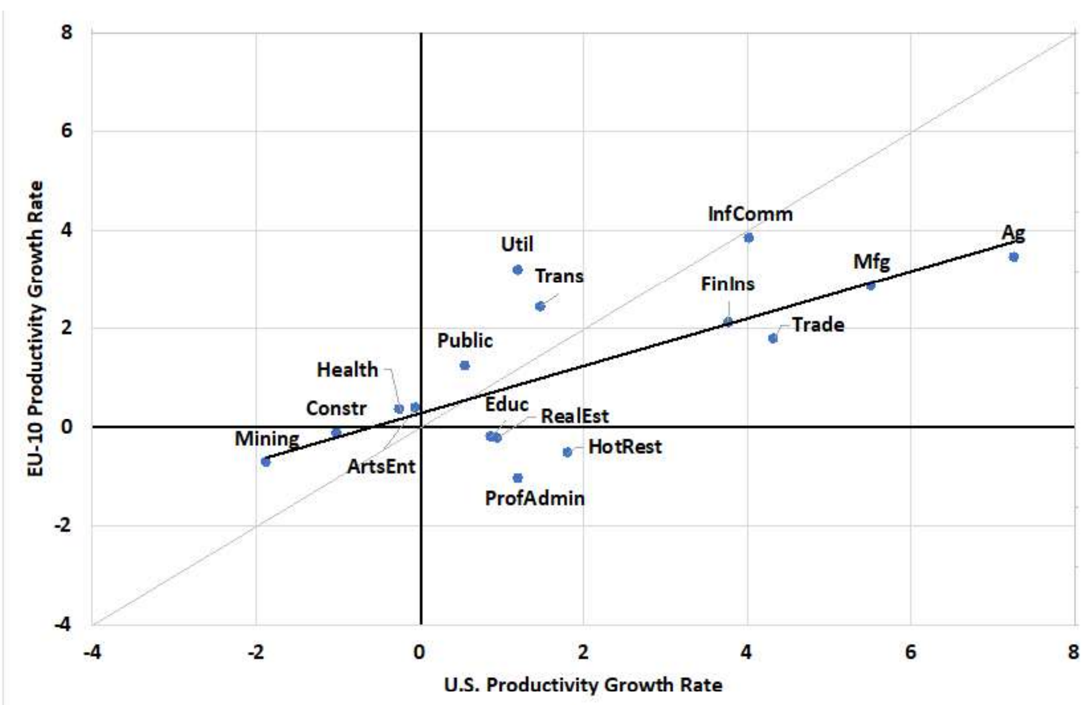
Finally, we have noted above that there is a relatively strong relationship between the industries in the EU-10 in the magnitude of its early-to-late growth slowdowns (from 1972-1995 to 2005-2015) and the industries in the United States in its early-to-late slowdown (1950-1972 to 2005-2015). For the total economy the coefficient is a significant 0.49. For manufacturing the coefficient is an insignificant 0.16, but this rises to a highly significant 0.34 with a R^2 of 0.89 when the electrical machinery, other manufacturing, and chemicals industries are excluded. The relationship for the total economy is plotted in Chart 8, showing that six industries lie along the 45 degree line, indicating almost exactly the same extent of the early-to-late change in productivity growth in the EU-10 as in the United States — agriculture, manufacturing, utilities, transportation services, edu-

Chart 7: Regression of EU-10 Labour Productivity Growth on U.S. Labour Productivity Growth (Two Periods)

Panel A: Regression of EU-10 1972-1995 Labour Productivity Growth on U.S. 1950-1972 Labour Productivity Growth



Panel B: Regression of EU-10 1995-2005 Labour Productivity Growth on U.S. 1995-2005 Labour Productivity Growth



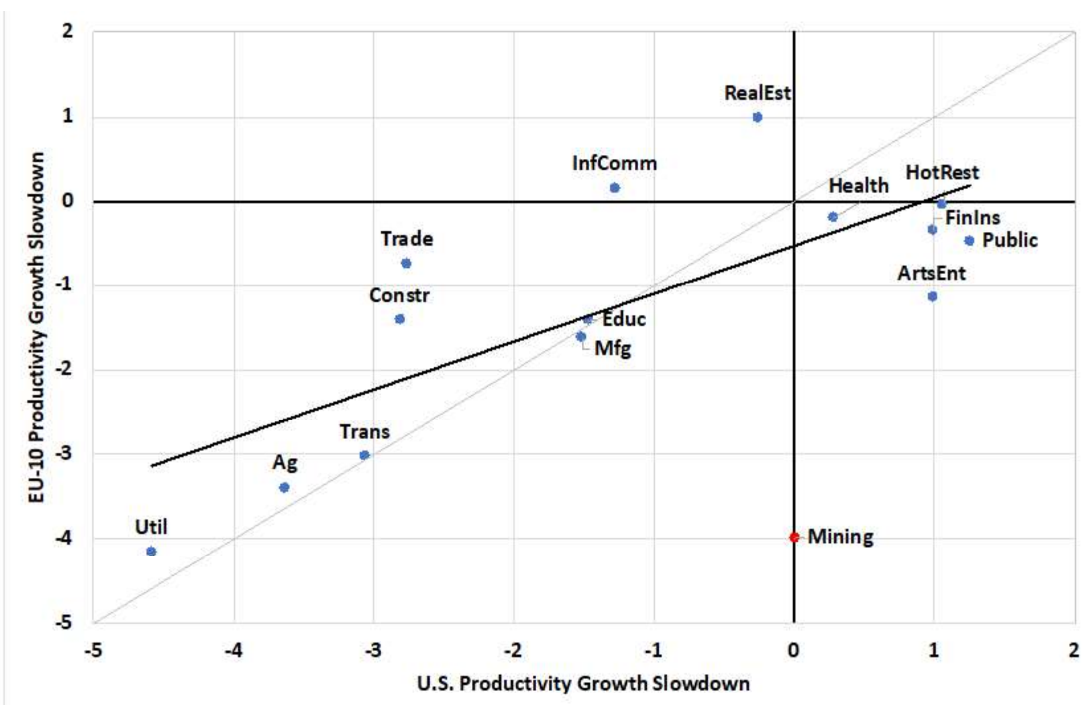
Source: KLEMS Database.

Table 7: Regressions of EU-10 Growth on U.S. Growth by Industry, Selected Intervals

		All Major Industrial Sectors		Manufacturing Sub-Industries			
				All		Selected Exclusions*	
		Coef.	**Prob > t**	**Coef.**	**Prob > t**	**Coef.**	**Prob > t**
a) EU-10 1972-95 on U.S. 1950-72	U.S. Variable	0.49	0.01	-0.32	0.20	-0.36	0.02
	Constant	0.90	0.05	4.31	0.00	3.93	0.00
	NOBS	15		11		9	
	Adj R^2	0.41		0.08		0.51	
b) EU-10 1995-2005 on U.S. 1995-2005	U.S. Variable	0.48	0.00	0.07	0.49	0.18	0.00
	Constant	0.30	0.44	2.17	0.01	1.85	0.00
	NOBS	16		11		9	
	Adj R^2	0.49		-0.05		0.78	
c) EU-10 Full Slowdown on U.S. Full Slowdown	U.S. Variable	0.49	0.02	0.16	0.18	0.34	0.00
	Constant	-0.84	0.05	-1.32	0.02	-0.53	0.04
	NOBS	15		11		8	
	Adj R^2	0.31		0.10		0.89	

Note: *Selected manufacturing exclusions include Chemicals and Electrical Machinery for panel a); Petroleum and Chemicals for panel b); Electrical Machinery, Other Manufacturing, and Chemicals for panel c). Data for the "Professions & Administrative" industry are unavailable for the U.S. from 1950-72.
Source: KLEMS Database.

Chart 8: Regression of EU-10 1972-1995 to 2005-2015 Productivity Slowdown on U.S. 1950-1972 to 2005-2015 Productivity Slowdown (percentage points)



Source: KLEMS Database.

cation, and health.

These results indicate that, at least for the total economy, if in 1972 one had known the rate of productivity growth by industry achieved in 1950-1972 for the United States, one would have been able to do a quite a good job of predicting productivity growth by industry in the EU-10 in the subsequent 1972-1995 period. There was also a significant positive relationship for the total economy between EU and U.S. growth by industry within the 1995-2005 interval, as well as in the magnitude of the early-to-late interval productivity growth slowdown. The results are much weaker within manufacturing and indeed show a negative relationship between the U.S. 1950-1972 growth rates and those in the EU-10 for 1972-1995. But even for manufacturing there is quite a strong positive relationship across industries in the magnitude of the early-to-late slowdown when three outlier industries are excluded.

A Consideration of Alternative Hypotheses

Throughout the article we have pointed to the high correlations between the United States and EU-10 in the industry composition of productivity growth and its slowdown, both within and across time periods. This is consistent with a technological interpretation of the growth slowdown, that industry-specific innovations were achieved in common across the Atlantic and determined the pace of productivity growth in each industry, with Europe's adoption of technologies lagging roughly 20 years behind the United States from the early postwar years to 2005. The strong role of MFP in the growth-accounting decomposition of the sources of labour productivity growth is also consistent with a prominent role in the slowdown for a waning of the impact of earlier innovations. To use a frequently-used analogy, "the low-hanging fruit had been picked." In another analogy, the level of productivity when plotted on a logarithmic scale has the appearance of an "S" on its side, the so-called "S curve," rising slowly at the beginning, then rapidly in the middle, and more slowly at the end. This phenomenon was illustrated for numerous products and industries by Lapp (1973).

In a phenomenon as important and complex as the productivity growth slowdown, other factors may have also made a contribution. We consider briefly reverse feedback from innovation to investment and mismeasurement of output. We then examine two potential explanatory factors beyond innovation that may have played a role in the convergence of the EU-10 productivity level to the U.S. level between 1995 — the role of education and of the differing trajectory of hours per employee.

The standard growth accounting decomposition of labour productivity growth between MFP and capital deepening implicitly treats the sources of changes in MFP and of capital deepening, i.e., growth in capital per labour hour, as two independent sources of growth. Innovation, including large and small inventions as well as incremental tinkering that makes previous inventions more efficient, are assumed to be the drivers of MFP growth. Factors such as interest rates and taxation are usually cited as the major determinants of the level of investment that in turn drives the growth in capital per labour hour.

However this decomposition ignores the response of capital per hour growth to productivity growth. In the standard Solow growth model, long run capital per hour growth equals output per hour growth and the capital-output ratio is constant. Thus anything that reduces growth in output per hour, including a diminished impact of innovation or a slowing rate of change of educational achievement, will reduce investment and cause slower growth in capital per hour. This reverse feedback from innovation to investment can occur, so that the split between MFP growth and changes in capital deepening as sources of productivity growth tends to understate the importance of slowing innovation. In this context we noted above that the 2005-2015 slowdown in U.S. productivity growth was led by a sharp slowdown in MFP growth during 2005-10 while capital deepening continued at the previous pre-2005 rate, while during 2010-15 capital deepening growth followed along with a sharp plunge to a negative value.

Measurement error is sometimes suggested as an explanation for declining productivity growth. The dominant role of commodity-producing industries in causing the U.S. post-1972 slowdown and 1995-2005 revival, together with their disproportionate role in the overall EU-10 slowdown, leads to skepticism about a measurement explanation of the trajectory of productivity growth over the postwar period. Of our five commodity-producing industries — agriculture, mining, manufacturing, utilities, and construction — the first four are considered relatively well measured as they produce tangible objects such as bushels of wheat, tons of coal, gallons of refined petroleum, and kilowatt hours of electricity. Construction is the exception and has long been considered "hard to measure" due to its output deflators based on input costs. Assessing the manufacturing sector as relatively well measured is subject to the qualification that price indexes for manufactured goods have long been subject to an upward bias, but this bias is relatively consistent without prolonged episodes of worsening or improving bias. To explain the postwar trajectory of productivity growth in commodity-producing industries by measurement error would require that error to be absent during 1950-1972, emerge after 1972, disappear between 1995 and 2005, and then become even worse after 2005 than it was during 1972-1995.

While commodities dominated the post-1972 U.S. slowdown and 1995-2005 revival, as well as the post-1995 EU slowdown, both services and commodities have contributed roughly equally to the post-2005 slowdown on both sides of the Atlantic. Since output in several service sectors is hard to measure, could mismeasurement explain the more recent post-2005 slowdown? This question has been carefully considered in the recent literature on the United States, particularly in papers by Byrne *et al.* (2016) and Syverson (2017). They both conclude that the role of mismeasurement, primarily in the undercounting of free internet services, cannot plausibly be large enough to explain more than a small fraction of the post-2005 U.S. slowdown. The details of their arguments go beyond the scope of this article, but we might add that several of the industries with the largest post-2005 slowdowns, such as agriculture and transportation services, and within manufacturing petroleum refining and rubber/plastics, are relatively easy to measure, whereas several hard-to-measure sectors such as education and healthcare services experienced either small slowdowns after 2005 or, in the case of U.S. healthcare, an actual increase in productivity growth.

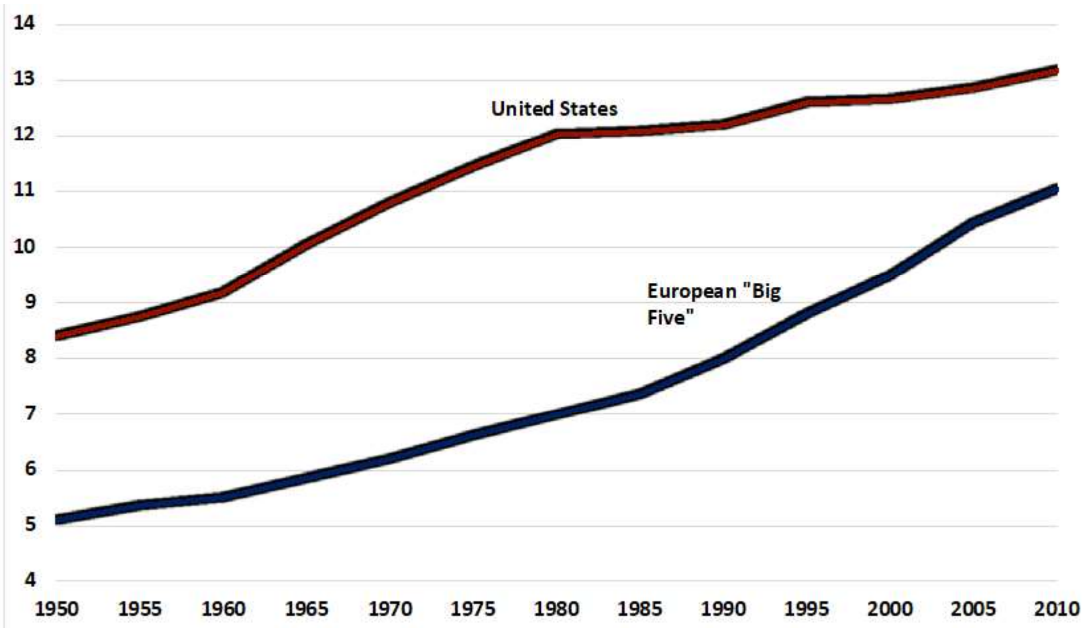
Turning to the explanation of European convergence to the U.S. productivity level between 1950 and 1995, the most convincing reason is the lag behind the United States in the adoption by Europe of the major innovations that had propelled the United States by 1950 to double the level of labour productivity as the EU-10 average. It is plausible that other explanations also made a contribution to the European convergence. One possibility is educational attainment, which also lagged in the EU-10 substantially below the U.S. level. Chart 9 shows average years of school completed during 1950-2010 for the United States as the upper line and the average for the five largest members of the EU-10 (France, Germany, Italy, Spain, U.K., making up 85 per cent of EU-10 GDP) as the lower line labelled "EU-5".

The trajectory of the lines in Chart 9 weakens the case for a major role of education in the European convergence. By far the period of most rapid European catch-up of the productivity level occurred during 1950-1972, but Chart 9 shows that the gap between the United States and the EU-5 widened from 3.3 years in 1950 to 4.8 years in 1975 and continued to widen further to 5.2 years in 1980. Yet by then the level of productivity in Europe had completed most of its convergence, reaching 100 per cent of the U.S. level in 1989. The catching up of the EU-5 educational level occurred between 1980 and 2010, with the gap declining from 5.2 years in 1980 to 2.2 years in 2010. Yet the level of European productivity relative to the United States was actually lower in 2010 than in 1980. One aspect of the education hypothesis does, however, appears suggestive, and this is the role of the slow growth of U.S. educational achievement in 1995-2010 in contributing the slow U.S. productivity growth after 2005.

Another hypothesis that has been suggested to explain the European convergence to the U.S. productivity level is the decline in hours per employee illustrated in Chart 10. Over the period 1950-2015 hours per employee in the EU-10 declined sharply from 2250 hours to 1560 hours, a (log) decline of 37 per cent. In contrast hours per employee in the United States declined only from 2020 to 1780, a (log) decline of 12 per cent. Hours per employee in Europe were higher than in the United States from 1950 to 1975 and have been lower since 1975. The hypothesis of diminishing returns to added hours of work by an individual employee suggests that declining hours should raise productivity. If all else were equal, productivity in the EU-10 should have caught up to the U.S. level in 1975 and exceeded it thereafter. But other factors were notn equal — Europe caught up to the U.S. productivity level in 1989 and exceeded it until 2000.

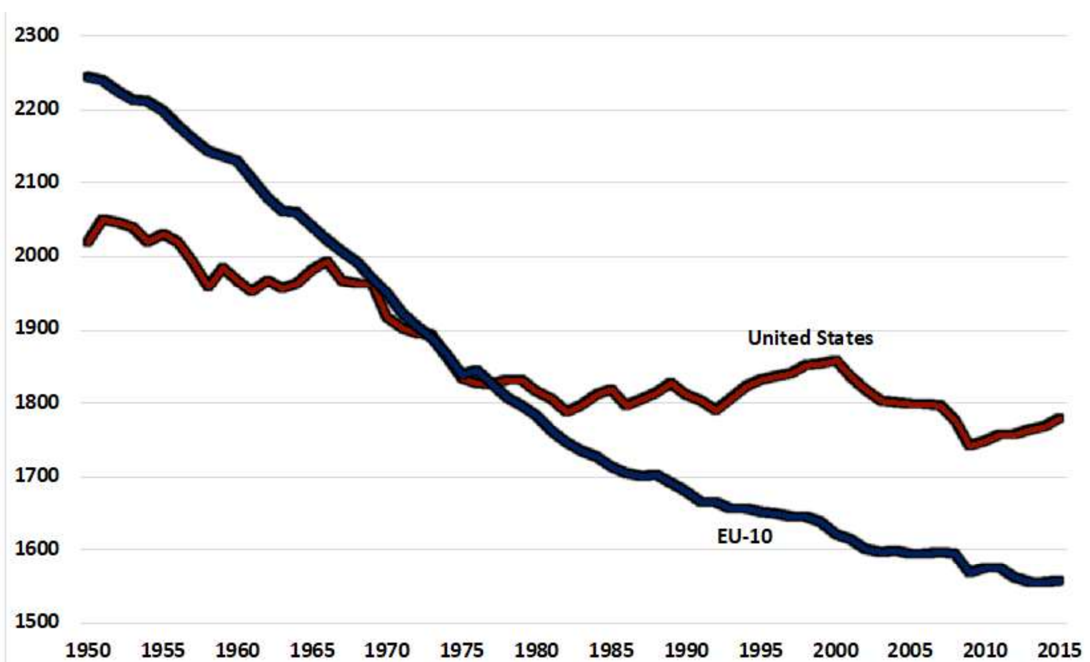
This section has thus far ignored the big exception to the result that Europe lagged 20 years behind, and this was the fact that U.S. productivity growth surged ahead during 1995-2005 without any echo

Chart 9: Average Years of Schooling Completed by Population Aged 15 and Over, United States vs. Geometric Average of European "Big Five," 1950-2010



Source: Five-year data on average years of total schooling for population aged 15 and up from Barro-Lee Educational Dataset, last updated July 2, 2018. The European "Big Five," comprised of France, Germany, Spain, Italy, and the United Kingdom, stably account for approximately 85 per cent of the EU-10 GDP between 1950 and 2015.

Chart 10: Total Hours Worked per Employed Person, United States vs. EU-10, 1950-2015



Source: Conference Board Total Economy Database. Hours per Employee for the EU-10 are calculated as the sum of total divided by the sum of total employed persons for the relevant countries.

effect in Europe either at the same time or ten years later. As a result the level of European productivity relative to the United States fell back from a peak of 106 per cent in 1995 to just 86 per cent in 2015. Chart 7 Panel B above plots the 1995-2005 growth rate of each major European industry against its American counterpart. The correlation across industries is high but on average each European growth rate is about half of the corresponding U.S. growth rate.

The consensus in the American literature is that the 1995-2005 revival in U.S. productivity growth was driven by both an increase of investment in information-communication technology (ICT) hardware and the effect of ICT hardware and software in industries that are heavy users of ICT (Oliner and Sichel, 2000). Europe failed to achieve the same productivity gains, and this is evident above in the much slower rate of productivity growth in the electrical machinery industry (home of ICT hardware) in Table 6 for the EU-10 than in Table 3 for the United States. We have carried out a detailed analysis of the differing contribution of ICT hardware and software to productivity growth in the EU-10 as compared to the United States, to be published in the next issue of this journal.

Conclusion

This article examines the industry origins of the slowdown in labour productivity growth for the United States going back to 1950 and for the EU-10 back to 1972. A novel contribution of the article is to merge several different KLEMS data sets and perform a year-by-year aggregation across European countries that allows us to analyze aggregate and industry productivity performance in the EU-10 in contrast to previous studies which limited their analysis to an array of individual countries.

As suggested by Shackleton (2013) and a large previous literature, productivity growth in the United States soared between 1920 and 1972 as a result of key inventions such as electricity, the internal combustion engine, chemicals and plastics, information and communications, and an expansion of infrastructure. Due to the disruption of the two world wars and the interwar period, Europe missed out on many of the benefits of this wave of innovation, in 1950 having a ratio of its productivity *level* to the United States of only 50 per cent. Europe rapidly caught up in 1950-1972, by 1972 reaching a level ratio of 81 per cent, and in 1972-1995 more than caught up, reaching 106 per cent of the U.S. level in 1995.

From 1972-1995 the characteristics of EU-10 productivity growth were surprisingly similar both in overall pace and also in industry composition to that achieved by the United States in the prior 1950-1972 time period. A novel aspect of the article is to take the 1972-1995 period in the EU-10 as equivalent to the 1950-1972 interval in the United States and to calculate an "early-to-late" slowdown from these two different starting points to a common end interval, the decade between 2005 and 2015.

Contrary to the "Eurosclerosis" literature that laments European shortcomings in the scope and application of innovation and structural arthritis in its product and labour markets, one of the most striking results of this article is that the slowdown in EU-10 productivity growth from the 1972-1995 average growth rate to 2005-2015 was exactly the same (-1.68 percentage points) as the slowdown in U.S. productivity growth from its 1950-1972 average growth rate to 2005-2015 (-1.67 percentage points).

Even more striking about this "early-to-late change" is that there is a correlation coefficient of 0.81 across industries between the United States and EU-10 in the magnitude of their growth slowdowns. Thus the productivity growth slowdown is a trans Atlantic disease, not only in its overall magnitude but in the composition of industries making the biggest contributions. This supports our overall theme that the productivity growth slowdown from the early postwar years to the most recent decade was due to a retardation in technical change that affected the same industries by roughly the same magnitudes in the United States and in the EU-10. From the early postwar years until 2005 the EU-10 can be characterized as lagging about 20 years behind the United States in its adoption of technology.

We emphasize the distinction between commodity-producing industries and those producing market services. In both the United States and EU-10, the early-to-late slowdown was more than twice as large in commodities as in services. This dominant role of commodities in driving the slowdown on both sides of the Atlantic reflects the fact that in the early periods (1950-1972 for the United States and 1972-1995 for the EU-10) productivity growth in commodities was faster and thus had further to fall. This reflects the role of inventions and innovations earlier in the 20th century that had a greater impact on commodity-producing industries than those producing market services.[20]

The best-known difference between productivity behavior in the United States and Europe, going beyond Europe's catch-up lag between 1950 and 1995, is the failure of Europe to enjoy a productivity growth revival during 1995-2005 as did the United States. We show that there was a high correlation across industries between the United States and EU-10 in 1995-2005 growth rates, indicating that the industries that did best in the United States also did best in the EU-10. The problem was that for all the best-performing EU industries the productivity growth rate was about half of their U.S. counterparts during 1995-2005.

We carry out a sources-of-growth calculation which decomposes labour productivity growth into the respective contributions of multi-factor productivity (MFP), capital deepening, and changes in labour composition. For the United States MFP makes the dominant contribution to the post-1972 productivity growth slowdown and 1995-2005 revival, while MFP and capital deepening jointly share responsibility for the post-2005 slowdown. In the EU-10 the contributions of MFP and capital deepening are evenly divided in explaining the slowdown. To the extent that the MFP contri-

20 The analysis of the Canadian productivity growth slowdown by Sharpe and Tsang (2018) finds many patterns similar to those highlighted in this article, including the major role of manufacturing.

bution measures the impact of innovation, we could conclude that flagging innovation deserves half the blame for the early-to-late slowdown in both the United States and the EU-10. The high correlation between the United States and EU-10 in the list of industries contributing the largest early-to-late slowdowns in the MFP contribution also support the theme of a common cause, the diminishing impact and depreciation of the innovations that had driven early post-war growth, particularly in the commodity-producing industries.

But it would be a mistake to limit the role of innovation to the MFP contribution. As suggested by the long-run dynamics of the standard Solow growth model, reductions in growth of output per hour, including those due to slowing innovation, simultaneously diminish capital deepening's contribution to productivity. Thus while the contribution of MFP to the early-to-late productivity growth slowdown is 50 per cent of the total in the United States and 55 per cent for the EU-10, the true contribution of flagging innovation is greater than that, perhaps three-quarters. The case for a technological explanation is particularly strong in U.S. manufacturing, where the early-to-late slowdown in nine of 11 subindustries is dominated by a declining MFP contribution, and where for the manufacturing sector total MFP overexplains the overall decline in labour productivity growth.

This article is only a start at the enormous task of understanding the slow rate of productivity growth experienced on both sides of the Atlantic since 2005. We have emphasized the role of MFP and innovation, as well as the dominant role of the commodity-producing industries in driving the earlier slowdowns and 1995-2005 U.S. revival. Further insight into the sources of the productivity slowdown will need to be fought in the trenches of detailed studies of individual industries, and the research reported here has helped to point to those particular industries that are most in need of further insight and evaluation. This process will begin with a second article in the next issue of this journal on the role of the production and use of information-communication technology (ICT) equipment in the United States and EU-10 in achieving productivity growth in the aggregate and at the level of individual industries.

References

Baily, Martin N. and Nicholas Montalbano (2016) "Why is US Productivity Growth So Slow? Possible Explanations and Policy Responses," Brookings Institution Hutchins Center Working Paper, September, pp. 1-29.

Bergeaud, Antonin, Gilbert Cette and Rémy Lecat (2017) "Total Factor Productivity in Advanced Countries: A Long-term Perspective," *International Productivity Monitor*, No. 32, pp. 6-24, http://www.csls.ca/ipm/32/Bergeaud_Cette_Lecat%20Version%202.pdf.

Brill, Michael, Brian Chansky and Jennifer Kim (2018) "Multifactor Productivity Slowdown in US Manufacturing," *Monthly Labor Review* June, pp. 1-15.

Byrne, David M., John G. Fernald and Marshall B. Reinsdorf (2016) "Does the United States Have a Productivity Slowdown or a Measurement Problem?" *Brookings Papers on Economic Activity,* Vol. 47, No. 1, Spring, pp. 109-182.

Byrne, David, Stephen D. Oliner and Daniel E. Sichel (2017) "Prices of High-tech Products, Mismeasurement, and the Pace of Innovation," *Business Economics*, No. 2, pp. 103-113.

Cobet, Aaron E. and Gregory A. Wilson (2002) "Comparing 50 years of Labor Productivity in US and Foreign Manufacturing," *Monthly Labor Review* June, pp. 51-65.

Giombini, Germana, Francesco Perugini and Giuseppe Travaglini (2017) "The Productivity Slowdown Puzzle of European Countries: a Focus on Italy," *Argomenti*, No. 6, pp. 1-20.

Gordon, Robert J. and Hassan Sayed (2020) "Transatlantic Technologies: Rethinking the Role of ICT Innovation in the post-1995 Productivity Growth Revival," *International Productivity Monitor,* Spring, forthcoming.

Inklaar, Robert, Mary O'Mahony and Marcel Timmer (2005) "ICT and Europe's Productivity Performance: Industry-Level Growth Account Comparisons with the United States," *Review of Income and Wealth*, Vol. 51, No. 4, pp. 505-536.

Inklaar, Robert, Marcel P. Timmer and Bart Van Ark (2007) "Mind the Gap! International Comparisons of Productivity in Services and Goods Production," *German Economic Review,* Vol. 8, No. 2, pp. 281-307.

Jorgenson, Dale W. and Kevin J. Stiroh (2000) "Raising the Speed Limit: U.S. Economic Growth in the Information Age," *Brookings Papers on Economic Activity,* No. 1, pp. 125-211.

Murray, Alexander (2018) "What Explains the Post-2004 U.S. Productivity Slowdown?," *International Productivity Monitor*, No. 34, pp. 81-109, http://www.csls.ca/ipm/34/murray.pdf.

Lapp, Ralph K. (1973) *The Logarithmic Century* (New York: Prentice-Hall).

Oliner, Stephen D. and Daniel E. Sichel (2000) "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives*, Vol. 14, No. 4, pp. 3-22.

Shackleton, R. (2013) "Total Factor Productivity Growth in Historical Perspective," Congressional Budget Office Working Paper, No. 2013-01.

Sharpe, Andrew and John Tsang (2018) "The Stylized Facts about Slower Productivity Growth in Canada," *International Productivity Monitor*, No. 35, pp. 52-72, http://www.csls.ca/ipm/35/IPM-35-Sharpe-Tsang.pdf.

Syverson, Chad (2017) "Challenges to Measurement Explanations for the U.S. Productivity Slowdown," *Journal of Economic Perspectives*, Vol. 31, No. 2, pp. 165-86.

Timmer, Marcel, P., Robert Inklaar, Mary Mahoney and Bart Van Ark (2011) "Productivity and Economic Growth in Europe: A Comparative Industry Perspective," *International Productivity Monitor,* No. 21, pp. 3-23, http://www.csls.ca/ipm/21/IPM-21-Timmer-et-al.pdf.

Uppenberg, Kristian and Hubert Strauss (2010) "Innovation and Productivity Growth in the EU Services Sector," Luxembourg: European Investment Bank.

Van Ark, Bart, Mary O'Mahony and Marcel Timmer (2008) " The Productivity Gap between Europe and the United States: Trends and Causes," *Journal of Economic Perspectives*, Vol. 22, No. 1, pp. 25-22.

Online Appendix to "The Industry Anatomy of the Transatlantic Productivity Growth Slowdown: Europe Chasing the American Frontier"

Robert J. Gordon
Northwestern University and NBER
Hassan Sayed
Princeton University[1]

Datasets Utilized

The vintages of the annual data used in this project were downloaded between May, June, and early July of 2018, and consist of the 2012 and 2017 releases of the EUKLEMS datasets. These data includes quantities, indices, and pre-calculated growth rates of output, capital, labor, and productivity, among other variables. With the exception of value added and a handful of indices (usually labor and capital services), labor productivity and growth rate data generally start post-1995 in the 2017 release. However, these data were also available in the 2012 releases, which estimated values back until 1970. To gain a full picture of the data for each country and industry back us far as possible, it was necessary to link the older release of the KLEMS from 2012 with the 2017 dataset.

Towards the end of July, EUKLEMS revised the 2017 release, in the process eliminating many pre-1995 datapoints. Since we downloaded the data prior to this revision, we have retained many of the now-missing pre-1995 values from the 2017 release, though these are likely available to some extent in the 2012 releases.

Merging the KLEMS Data Old to New

The primary method of merging was ratio linking, which was used for merging indices and quantities. For each variable in a given industry and country, we took the earliest value available in the 2017 data and identified the observation in the older dataset corresponding to the same variable.

1 The main article is available at http://www.csls.ca/ipm/37/Gordon.pdf.

We then computed the ratio of the 2017 datapoint to the 2012 datapoint for that year and multiplied all prior observations by this ratio. The consequence of using this procedure was that growth rates were preserved across the old and new data without any jumps or discontinuities at the point of merging.

In the case of pre-calculated growth rates, datapoints were simply appended. That is, if time t were the last year that the growth rate for a variable was available in the 2017 data, then at time *t-1* and earlier, the growth rates for 2012 were used without any transformation. This method of appending growth rates is equivalent to ratio-linking indices, since ratio-linking ultimately multiplies the earlier subset of data by a uniform constant, preserving growth rates.

Growth Accounting and Capital/Hour Contributions

The EUKLEMS data provide a handful of pre-calculated growth rates in its releases. These include:

1. *VA_Q*, growth rate of real value added;
2. *VAConTFP*, contribution of TFP growth to real value added growth;
3. *VAConLC*, contribution of labor composition growth to *VA_Q*;
4. *VAConH*, contribution of hours growth to *VA_Q*;
5. *VAConKIT*, contribution of ICT capital services growth to *VA_Q*;
6. *VAConKNIT*, contribution of non-ICT capital services growth to *VA_-Q*;
7. *VAConK*, contribution of capital services growth to *VA_Q*, which is the sum of *VAConKIT* and *VA-ConKNIT*;
8. and *LP1_Q*, the growth rate of value added per hour as calculated by the sum of contributions

These contributions to value added per hour are governed by the following equation:

$$VAQ_t = VAConTFP_t + VAConLC_t + VAConH_t + VAConKIT_t + VAConKNIT_t \quad (1)$$

Let s^{IT} be the share of ICT capital services in production, s^{NIT} the share of non-ICT capital, y value added growth, lc labor composition growth, h hours growth, k^{IT} ICT capital growth, and k^{NIT} non-ICT capital growth. Then, this equation can also be written as:

$$y_t = tfp_t + (1 - s^{IT} - s^{KIT})(lc_t) + (1 - s^{IT} - s^{KIT})(h_t) + s^{IT}k_t^{IT} + s^{NIT}k_t^{NIT} \quad (2)$$

Extensive *VAConKIT* and *VAConKNIT* data were not available for the U.S., so we primarily utilized *VAConK* by adding together *VAConKIT* and *VAConKNIT*. For consistency, we also did this with the Europe data. Because of the identity above, this equation can be simplified to:

$$y_t = tfp_t + (1 - s)(lc_t) + (1 - s)(h_t) + sk_t \quad (3)$$

where s is defined so that $sk_t = s^{IT}k_t^{IT} + s^{NIT}k_t^{NIT}$.

On the other hand, *LP1_Q* (or *lp*), which is value added per hour, can be written as:

$$LP1Q_t = lp_t = y_t - h_t = tfp_t + (1-s)(lc_t) + (1-s)(h_t) + sk_t - h_t = tfp_t + (1-s)(lc_t) + s(k_t - h_t) = VAQ_t - h_t = VAConTFP_t + VAConLC_t + s(k_t - h_t) \quad (4)$$

Concretely, labor productivity growth is TFP growth + the contribution of labor composition + the contribution of capital per hour, i.e. capital's share multiplied by the growth rate of capital less the growth rate of hours. The contribution of capital per hour will be denoted by *ConK/H*.

One way to calculate *ConK/H* is to use nominal expenditure on labor and capital to retrieve labor's share, multiply the contributions of hours by $\frac{s}{1-s}$, and subtract this from VAConK. However, since *LP1_Q*, *VAConTFP*, and *VAConLC* are already given by KLEMS, we can simply calculate ConK/H as a residual. That is,

$$LP1Q_t - VAConTFP_t - VAConLC_t = ConK/H_t \quad (5)$$

We indeed employ this method in the data to calculate the contribution of capital per hour. Not only does this satisfy the identity above and allow the given contributions to add up to labor productivity, it also prevents any error related to computing *ConK/H* by hand using labor's share.

Calculating Earlier LP1_Q Values

There are two labor productivity variables of interest available in the KLEMS data: "*LP1_Q*" and "*LP_I*" — while the former is a growth rate calculated bottom-up as a sum of contributions, the latter is an index that directly divides value added by the hours index. The former is available only in the 2017 release, while the latter is available in both the 2012 and 2017 datasets. Since this project is concerned with breaking down labor productivity growth into its components, we utilize *LP1_Q* instead of *LP_I*.

However, since *LP1_Q* is unavailable in the 2012 data, we use the growth of the *LP_I* index to proxy for any earlier years where *LP1_Q* is unavailable — we append the growth rate of *LP_I* to any data points prior to the earliest year where *LP1_Q* is available.

A Note on Anomalous UK Data

Upon a cursory observation of the UK KLEMS series for *LP1_Q*, the year 1995 sticks out as an anomaly: the data source has labor productivity growth for the total economy listed at 23.5 percent, mining at 58 percent, and much of manufacturing above 15 percent. Although this result is likely due to an error in the original dataset, the data cannot be properly corrected if the source of that error is unknown. To correct for this problem, we calculate the level of UK labor productivity in 1995 as the average of the values in 1994 and 1996.

Aggregating the Commodities and Services industries

The KLEMS data are divided into two types of industries: commodities producing, alphanumeric industries A through F (Agriculture through Construction) and services producing industries G through S (Wholesale & Retail through Arts & Entertainment). To examine trends within both of these types of industries, we create aggregates for "Commodities" and "Services" by combining data from different subindustries into a single aggregate. In the case of nominal variables like gross output and value added, we simply add the values of each sub-industry. For indices and growth rates, we compute a weighted sum of the values of each sub-industry's index or growth rate, where the weights are the shares of nominal value added of that industry in the entire value added of an aggregate. For example, the weight for the commodities producing "Agriculture" industry would be the value-added of Agriculture divided by the sum of value added for industries Agriculture through Construction, i.e. the total value-added of commodities.

Creating the EU-10 Aggregate

To examine productivity behavior in a European aggregate, we use the same weighting technique as described above for Commodities and Services. In this case, the source of our weights are the real PPP-adjusted GDPs of European countries, taken from the Conference Board Total Economy (TED) database, divided by the sum of those GDPs. We utilize a procedure of moving weights; since the data for different European variables start at different times, we take account of whether those countries are available in the dataset before assigning weights. For example, for the year 1974, only Germany, Italy, and the UK have data available for TFP growth. Because of this, we take the weight for Germany in 1974 to be the GDP for Germany divided by the sum of the GDPs of Germany, Italy, and the UK (rather than the entirety of the EU-10). As more countries enter into the dataset, we incorporate these new countries into the weights: when the Netherlands enters the dataset in 1980, for example, the weight for Germany is the GDP for Germany divided by the sum of the GDPs of Germany, Italy, the UK, and the Netherlands.

European Value Added

Although it is straightforward to convert growth rates or indices to aggregates with the TED GDP weights, calculating nominal value added poses a challenge, as the EU KLEMS country-level datasets are all in terms of millions of national currency. To circumvent this issue, we used the TED GDP data as representative of the KLEMS Total Economy aggregate ("TOT") and normalized each country's industry's value-added to TED PPP units.

To calculate PPP adjusted value added for country j and industry i, we took the industry's share of TOT value added and multiplied it by the TED GDP for that country:

$$VA_{i,j}^{adj} = \frac{VA_{i,j}^{KLEMS}}{VA_{TOT,j}^{KLEMS}} GDP_j^{TED}$$

Then calculating aggregate value-added for the EU-10 only required summing up the VA terms of each individual country.

Extending the US Further: The WorldKLEMS Dataset

Although EUKLEMS mostly has U.S. growth rates back until 1977 (and some nominal indices back to 1970), a dataset from Dale Jorgensen and his collaborators on the WorldKLEMS website provides detailed data on the US back until 1947 in a similar format to the EUKLEMS data. We use the 2013 release of the data; the vintage was downloaded in mid-July of 2018. The range of this data is from 1947-2010. Instead of linking these data directly to the 2017 release of EUKLEMS, we first linked the earliest data in the 2017 release to the earliest points in the 2012 release, and then linked the WorldKLEMS data to the earliest point of the 2012 data.

The primary limitation of this WorldKLEMS data is that the industry categories use an older revision of the ICIS (Rev 3), while the EUKLEMS data uses Rev 4. Hence, we have linked older industry categories into the newer ones. Table A1 details those re-classifications of data — some were left unlinked, while others were formed by aggregation. Aggregation of smaller industries into larger ones was done in the same way as the commodities and services aggregates discussed above, using value added weights for indices and growth rates and direct addition for nominal quantities.

The only industries that were could not be successfully merged were 58-60, 61, 62-63, M-N, R, and S, indicated in orange in Table A1. Of these, the only unmarked industry which was consequential to our analysis was M-N, Professional Services. For that reason the Professional Services industry is omitted for the period 1950-72 in several of the tables and figures.

Table A1: WorldKLEMS Industries and Merges with EUKLEMS Data

WorldKLEMS Data	EUKLEMS Data	
WorldKLEMS Code	**EUKLEMS Code**	**Industries Merged from WorldKLEMS**
TOT	TOT	TOT
MARKT	MARKT	MARKT
AtB	A	AtB
C	B	C
D	C	D
15t16	10-12	15t16
17t19	13-15	17t19
20	16-18	20, 21t22
21t22	19	23
23t25	20-21	24
23	22-23	25, 26
24	24-25	27t28
25	26-27	30t33
26	28	29
27t28	29-30	34t35
29	31-33	36t37
30t33	D-E	E
34t35	F	F
36t37	G	G
E	45	50
F	46	51
G	47	52
50	H	60t63
51		
52		
H	I	H
I	J	64
60t63	58-60	
64	61	
JtK	62-63	
J	K	J
K	L	K
70	M-N	
71t74	O-U	LtQ
LtQ	O	L
L	P	M
M	Q	N
N	R-S	O
O	R	
	S	

Digitalization and Productivity: In Search of the Holy Grail – Firm-level Empirical Evidence from European Countries

Peter Gal, Giuseppe Nicoletti, Christina von Rüden, Stéphane Sorbe
OECD
Théodore Renault
Graduate Institute of International and Development Studies[1]

Abstract

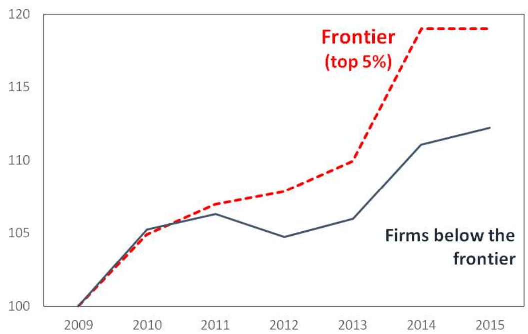
This article assesses how the adoption of a range of digital technologies affects firm productivity. It combines cross-country firm-level data on productivity and industry-level data on digital technology adoption in an empirical framework that accounts for firm heterogeneity. The results provide robust evidence that digital adoption in an industry is associated to productivity gains at the firm level. Effects are relatively stronger in manufacturing and routine-intensive activities. They also tend to be stronger for more productive firms and weaker in the presence of skill shortages, which may relate to the complementarities between digital technologies and other forms of capital (e.g. skills, organisation, or other intangibles). As a result, digital technologies may have contributed to the growing dispersion in productivity performance across firms. Hence, policies to support digital adoption should go hand in hand with creating the conditions to enable the catch-up of lagging firms, notably by easing access to skills.

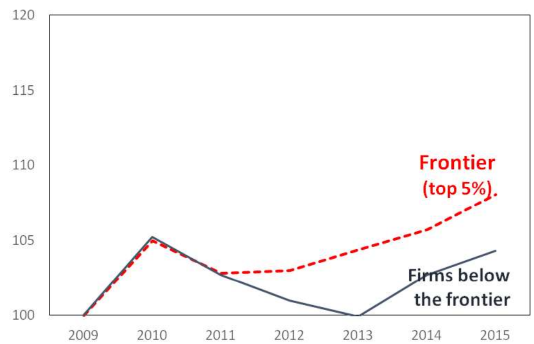
Why is innovation everywhere except in productivity statistics? This famous 1987 question by Robert Solow was recently revived and adapted to the digital era by Brynjolfsson *et al.* (2017). There are good reasons to believe that investment in digital technologies should have strong positive effects on productivity (Syverson, 2011;

1 Peter Gal is Senior Economist, Giuseppe Nicoletti is Head of Division, Christina von Rüden is Economist and Stéphane Sorbe is Senior Economist in the OECD Economics Department. Théodore Renault is PhD candidate at the Graduate Institute of International and Development Studies, Geneva. The authors would like to thank Carlo Altomonte, Laurence Boone, Chiara Criscuolo, Luiz de Mello, Alain de Serres, Alexander Himbert and Nicolas Ruiz for their valuable comments, as well as participants to workshops organised by the European Commission, the European Central Bank, the European Investment Bank, Banque de France, and an internal OECD seminar. The authors also thank two anonymous referees for useful comments. The opinions expressed and arguments employed are those of the author(s), and they should not be reported as representing the official views of the OECD or of its member countries. Emails: peter.gal@oecd.org, giuseppe.nicoletti@oecd.org, christina.vonrueden@oecd.org, stephane.sorbe@oecd.org, theodorerenault@gmail.com.

Chart 1: MFP at the Productivity Frontier and for the Average Non-frontier Firm, 2009-2015 (2009=100)

Panel A: High Digital Intensity Industries **Panel B: Low Digital Intensity Industries**





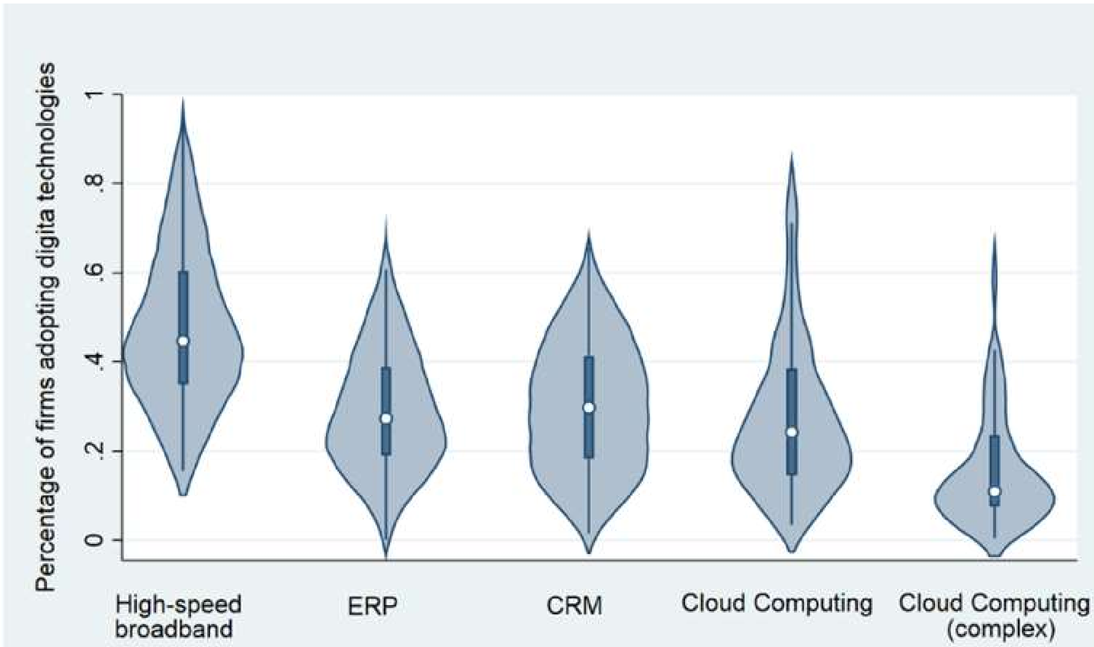
Note: The "frontier" is measured by the average of log multi-factor productivity, based on the Wooldridge (2009) methodology, for the top 5 per cent of companies with the highest productivity levels in each 2-digit industry and year, across 24 countries. The "firms below the frontier" lines capture the averages of the log-productivity distribution in each industry and year (excluding the top 5 per cent). The values obtained for the detailed 2-digit industries are averaged to industry groups that are classified either as having "high" or "low" digital intensities according to the methodology in Calvino *et al.* (2018). The series are normalized to 100 in the starting year (2009=100).
Source: Calculations using Orbis data of Bureau van Dijk, following the methodology in Andrews *et al.* (2016).

Brynjolfsson and McAfee, 2014). Yet, the empirical evidence at the industry and firm levels has been more nuanced (Acemoglu *et al.*, 2014; Bartelsman *et al.*, 2017; DeStefano *et al.*, 2018; Cette *et al.*, 2017), and aggregate productivity has generally been slowing down over the past decade, partly reflecting increasing dispersion in productivity performance across firms (Berlingieri *et al.*, 2017; Decker *et al.*, 2018). Notably, Andrews *et al.* (2016) and Berlingieri *et al.* (2018) have shown that aggregate patterns mask a widening productivity gap between a handful of frontier firms and a mass of laggard firms, especially in highly digitalized industries (Chart 1).

At the same time, cross-country data on firm-level adoption of digital technologies suggest that dispersion of adoption across firms is also wide and differs significantly across countries (Hagsten *et al.*, 2013; DeStefano, De Backer and Moussiegt, 2017), as shown in Chart 2. For instance, adoption of cloud computing is more than twice more common in large firms than in small firms in the average OECD country (OECD, 2017). Andrews *et al.* (2018) have related this dispersion to adoption obstacles that depend crucially on capabilities and incentives, whose strength differs across firms, industries and countries.

This article uses cross-country firm-level data to assess the productivity effects of industry-level digital adoption. We find strong evidence that operating in a digitalized environment benefits productivity, though not to the same extent across firms and industries, and explore some of the reasons why these benefits may have been disappointing at the aggregate level. We argue that the heterogeneity of adoption

Chart 2: Dispersion of Digital Technologies Across Countries, 2017 (Kernel densities based on the percentage of enterprises with at least 10 employees adopting digital technologies by country)



Note: This figure offers a visualisation of the distribution of digital adoption rates in 2017 across countries using a rotated kernel density plot (outer shape) and a boxplot (inner figure) indicating the median (white dot), the 25^{th} and the 75^{th} percentile of the distribution (top and bottom of the bar). The graph is based on country-year observations of the overall share of firms adopting a certain technology, where *high-speed broadband* refers to access to high-speed broadband (>30Mbits); *ERP* stands for the adoption of Enterprise resource planning systems, a software-based tool that can integrate the management of internal and external flows, from material and human resources to finance, accounting and customer relations; *CRM* stands for Customer Relationship Management software; *Cloud Computing* refers to ICT services used over the internet as a set of computing resources; and *Cloud Computing (complex)* is a subset of relatively more complex uses of Cloud Computing (e.g. accounting applications, CRM software, or computing power). See Annex D of Andrews *et al.* (2018) for a detailed description of each technology.
Source: Eurostat, Digital Economy and Society Statistics, comprehensive database

rates and adoption effects across firms and industries may contribute to explain why aggregate gains from digitalization have been disappointing and too weak to offset other factors contributing to the productivity slowdown. Econometrically, identifying causal effects of digital adoption on firm productivity poses multiple challenges. A first issue is reverse causality — does productivity increase due to adoption or is adoption just easier for high-productivity growth firms? Related to this, firm performance and adoption are likely to be driven by a number of common factors (e.g. skills or competitive pressures). Spillovers also pose identification issues: is productivity increasing due to within-firm adoption or due to the benefits of operating in a highly digitalized industry? Studies have shown that spillover effects across firms can be important (Syverson, 2011) and pure firm-level analysis obviously tends to miss them. Industry-level studies cover such spillovers, but they are by nature unable to account for the heterogeneous firm-level patterns that characterize adoption and its productivity effects.

In this article, we address some of these issues by combining industry-level cross-country data on adoption of a range of digital technologies with firm-level cross-country data on multifactor productivity in an empirical framework allowing for productivity heterogeneity across firms. Relying on adoption rates at industry rather than firm level is a way to mitigate endogeneity issues and to account for spillover effects from early adopters to other firms in the industry. This is because industry-level adoption rates will reflect both the adoption propensity (i) of the firm whose productivity is being assessed (direct effect), and (ii) of other firms in the same industry (spillover effect). As a result, industry-level adoption is less likely than firm-level adoption to be endogenous to firm-level productivity performance, though clearly other sources of endogeneity persist and need to be controlled for in estimates. Moreover, focusing on firm-level productivity performance helps identifying which categories of firms benefit most from adoption, for example depending on their size or productivity, and allows controlling for the effects of catching up to the technological frontier. Finally, looking at specific digital technologies instead of an aggregate ICT index accounts for the different effects they can have on productivity.

We rely on two main sources of data, the Eurostat Digital Economy and Society database for digital adoption and the Orbis database for firm-level productivity and other characteristics. We cover five major digital technologies (high-speed broadband internet, simple and complex cloud computing services, Enterprise Resource Planning and Customer Relationship Management softwares) in 19 EU countries and Turkey and 22 industries over 2010-15, which corresponds to the period sufficiently well covered by the Eurostat adoption rates and is also an important period for the adoption of these technologies (OECD, 2017). Both datasets are restricted to firms with at least 10 employees.

These technologies have been selected for their potential to improve firm productivity. For example, cloud computing gives firms flexibility to scale up or down their operations without incurring the cost of building and maintaining IT infrastructure, while also offering the possibility to access documents and software from anywhere in real time. Enterprise resource planning (ERP) software integrates and automates various functions, such as planning, purchasing, inventory, sales, marketing, finance and human resources into a single system, which can improve the speed and reliability of information exchanges within firms as well as with suppliers and customers. For more details, see Andrews *et al.*, (2018)

Our main result is that industry-level digital adoption is associated with significant productivity returns at the firm level. While the data do not permit to disentangle whether these are mainly driven by within-firm adoption or spillovers from other digitalized firms, our attempts to control for within-firm investment (in tangible or intangible assets) tentatively suggest that both channels may play a role. Our results are little affected by the inclusion of potential common drivers of adoption and productivity (such as skills and the regulatory environment), suggesting that they are not driven by the omission of these factors. Results are also robust to using adoption rates lagged by one year, or alternatively adoption rates at the beginning of the sample period, suggesting that they are not primarily driven by reverse causality.

Interestingly, we find that productivity gains are strongest for high productivity firms, suggesting that digital adoption in an industry has contributed to the increasing productivity dispersion across firms of this industry. This is in line with recent evidence showing that the catch-up of laggard firms is weaker in industries that rely more on ICT specialists (Berlingieri *et al.*, 2018). In contrast, productivity gains do not systematically depend on firm size. Different technologies have different effects in this respect. For example, Enterprise Resource Planning is more beneficial for larger firms and cloud computing for smaller ones, which is consistent with the idea that cloud computing is attractive for small firms as a means to avoid investing in a large IT infrastructure, in line with a recent finding by Bloom and Pierri (2018) for the United States. Further, we find that the productivity benefits of adoption are significantly thwarted by skill and occupational shortages, pointing to synergies between digitalization and other kinds of intangibles. Finally, we find that digitalization is on average more beneficial in manufacturing than service firms, and more broadly in industries involving a high share of routine tasks, which is consistent with previous findings (Akerman *et al.*, 2013; Dhyne *et al.*, 2018).

While further research is needed to identify the firm-level sources of the estimated productivity benefits, our evidence is consistent with three drivers. First, the fact that highly productive firms benefit most from digital technologies and that skill shortages reduce these benefits points to the existence of important complementarities between these technologies and other intangible investments that raise productivity, such as managerial competence or worker skills. This echoes earlier results by Andrews *et al.*, (2018), who found a strong association between the propensity to adopt digital technologies and access to such intangibles at the industry level. Second, interactions with digitalized firms (within an industry or more broadly in global value chains) can generate positive spillovers, for example thanks to back and front office digital integration with suppliers and customers. Third, a strong incidence of routine tasks may generate scope for taking advantage of digital technologies by streamlining production processes.

Our results point to both opportunities and challenges for policies aimed at enhancing aggregate productivity via wider technology adoption. The generally positive effects of digital adoption and the importance of complementarities suggest that broad-based policies that support the diffusion of digital technology, such as the roll out of high-speed broadband and the upgrade of the skill pool, can bring important aggregate productivity benefits (Sorbe *et al.*, 2019). However, an important characteristic of digitalization is that high-productivity firms have tended to benefit more from it than less productive ones. This probably reflects a combination of (i) a higher propensity to adopt digital technologies, (ii) greater productivity benefits from adoption thanks to higher endowment in skills and organizational capital, and (iii) more positive spillovers from interacting with digitalized peers (the empirical analysis in this article cannot disentangle these three factors). In turn, the higher productivity gains enjoyed by more productive firms may have compounded productivity dispersion across firms, a phenomenon that has been shown to underlie some of the productivity slowdown (Andrews *et al.*, 2016; Decker *et al.*, 2018). Moreover, to the extent that some of the benefits of digitalization depend on the ability of adopting firms to automate routine tasks (including by shedding labour), policies may also have to deal with the potential labour market implications of widespread adoption of digital technologies.

The article is organised as follows. In the first major section, we relate our work to previous research and highlight the issues involved in estimating the productivity effects of digitalization. The second section describes the empirical methodology and the data. We then present the results for the average firm and explore the heterogeneity of the digital-productivity link across industries and firms. We conclude discussing open research issues and policy implications.

Digitalization and Productivity: A Complex Link

A number of firm- and industry-level studies provide evidence of positive links between investment in digital technologies and productivity performance.[2] Digital technologies enable firms to innovate, for example by improving business processes, and to automate certain routine tasks; they also reduce the costs of interacting with suppliers and customers (Bartel *et al.*, 2007; Brynjolfsson *et al.*, 2008; Akerman *et al.*, 2013). However, three recent studies contrast with this literature. Acemoglu *et al.* (2014) find no effect of IT intensity on manufacturing productivity except in the computer-producing industry, using US firm-level data over 1977-2007. Bartelsman *et al.* (2017) find no significant effect of broadband access on within-firm productivity, but still a positive effect at the aggregate level, which may indicate positive effects from reallocation (i.e. more productive firms growing in size relatively to less productive firms), firm entry and exit, or spillovers across firms. Similarly, DeStefano *et al.* (2018) find that broadband ADSL positively affected firm size but not firm productivity, based on UK data for the early 2000s. In a context of slow global productivity growth, these papers have led to renewed discussions about Robert Solow's 1987 productivity paradox.

This overall puzzling picture reflects the fact that links between adoption of digital technology and productivity are complex and their empirical identification challenging. The key reason is that digital technologies typically support productivity in combination with other factors. Indeed, past studies have shown strong complementarities of digital technologies with organizational capital and management skills (Brynjolfsson and Hitt, 2000; Basu *et al.*, 2003; Bloom *et al.*, 2012; Aral

2 See for example reviews in Dedrick *et al.* (2003), Draca *et al.* (2009), Syverson (2011), Munch *et al.* (2018). Refer to the online Appendix C for an overview of the main studies and their results at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

et al., 2012), R&D and intangible investments (Corrado *et al.*, 2017; Mohnen *et al.*, 2018),[3] human capital and ICT-related skills (Bugamelli and Pagano, 2004) and a regulatory environment that enables the efficient reallocation of resources (Gust and Marquez, 2004; Conway *et al.*, 2006; Bartelsman, 2013). There are also complementarities between different digital technologies, for example between high-speed broadband and cloud computing (DeStefano *et al.*, 2019) or supply-chain management and customer-relationship software (Wieder *et al.*, 2006; Aral *et al.*, 2006; Engelstätter, 2009; Bartelsman *et al.*, 2017). Another complication is that productivity gains tend to materialize with a certain lag, as digital adoption can disrupt production processes in the short term and require organizational adjustments to fulfill their potential (Van Ark and Inklaar, 2006; Brynjolfsson, Rock and Syverson, 2017). This in turn can result in productivity mismeasurement that may lead to a productivity J-curve if complementary intangible investments are imperfectly measured (Brynjolfsson *et al.*, 2018).

Beyond these factors, a number of more technical reasons complicate the econometric identification of the productivity effects of digital technologies. A key one is endogeneity, which can result from both reverse causality and common factors influencing productivity and adoption. Reverse causality arises from the fact that digital adoption may be easier for high-productivity firms, because their high productivity can give them the financial means to invest in new digital technologies. In addition, certain potential drivers of digital adoption (e.g. managerial skills, organizational capital, favourable business and regulatory environment) can also support productivity directly, i.e. beyond their impact through digital adoption. If not properly addressed, this endogeneity can bias estimates upwards.

Another issue is the level of aggregation used in the analysis. Both the firm and the industry levels have advantages and downsides. Firm-level analyses are typically more subject to the endogeneity issues discussed above, although certain studies have developed original instrumentation techniques to overcome them (De Stefano *et al.*, 2014). In addition, firm-level studies can miss the positive spillovers generated by adoption by other firms, which past research has shown to be significant (Syverson, 2011). In contrast, industry-level studies take into account both within-firm and spillover effects (typically without being able to disentangle them), but they do not take into account the firm-level heterogeneity in productivity drivers and performance. This can lead to less accurate specifications and hinder the identification of heterogeneous effects of adoption across firms.

Finally, the way to measure digital adoption also opens a number of questions. A number of papers rely on broad measures of digital intensity (e.g. spending on ICT, number of computers per worker), while

3 In contrast, Hall *et al.* (2012) find no evidence of complementarity between ICT and R&D investment on firm-level Italian data over 1995-2006.

others focus on adoption of specific technologies, such as Enterprise Resource Planning software (Hunton *et al.*, 2003). Certain studies cover several specific technologies, but they tend to focus only on single countries (Aral *et al.*, 2006; Engelstätter, 2009). Overall, broad measures of digital intensity offer more general results, but may rely on less precise identification and cannot assess heterogeneous effects of technologies across firms (e.g. small firms may benefit relatively more from certain technologies, such as cloud computing) or complementarities between technologies.

This article aims to address some of these issues to provide robust cross-country evidence on the links between digital adoption and productivity. The combination of industry-level data on adoption and firm-level data on productivity is a way to mitigate endogeneity concerns, as discussed below, while it allows to cover both within-firm and spillover effects of adoption. In addition, it permits accounting for firm heterogeneity and assessing how different industries and types of firms (e.g. in terms of size or productivity) benefit from digital technologies — an area that has been relatively little explored, especially in a cross-country perspective. The joint focus on several specific digital technologies, which is relatively new for a cross-country analysis, allows for a more refined identification. Finally, complementarities between technologies are explored by testing the effect of the first principal component of the adoption variables considered.

Nevertheless, the approach in this article has a number of limitations, as further discussed below. While it covers both within-firm effects of adoption and within-industry spillovers, it leaves aside reallocation effects as well cross-industry spillovers, and in this respect probably underestimates productivity gains from adoption. In addition, it cannot directly disentangle within-firm and spillover effects, although it explores indirect ways to do so. Another limitation is that the measure of digital adoption used in this article is binary at the firm level (surveyed firms report using the technology or not) hence it does not take into account the changing firm-level intensity in the use of technologies.

Empirical Approach and Data

Model Specification

The empirical specification takes the neo-Schumpeterian growth approach to technology diffusion and innovation by Aghion and Howitt (1997) and Acemoglu *et al.* (2006), which has been implemented in a number of empirical studies at the firm (Griffith *et al.*, 2006; Arnold *et al.*, 2011; Andrews and Criscuolo, 2013; Andrews *et al.*, 2016; Adalet McGowan *et al.*, 2017) and industry levels (Nicoletti and Scarpetta, 2003; Bourlès *et al.*, 2013). Multifactor productivity (MFP) is assumed to follow an error correction model of the form:[4]

4 See Bourlès *et al.* (2013) for a derivation of a similar specification from a co-integrating relationship in levels relating MFP to frontier MFP.

$$\Delta MFP_{f,s,c,t} = \alpha_1 \Delta MFP_{Frontier\ s,t} + \alpha_2 Gap_{f,s,c,t-1} + \beta\ Dig\_adopt_{s,c,\bar{t}} + \gamma X_{f,sc,t} + \delta_{c,t} + \delta_i + \varepsilon_{c,t} \quad (1)$$

$\Delta MFP_{f,sc,t}$ is the change in the logarithm of multi-factor productivity (MFP) of firm f, which operates in sector s and country c, in year t, estimated with the Wooldridge (2009) method. MFP growth of firm f is assumed to depend on MFP growth of the productivity frontier ($\Delta MFP_{Frontier\ s,t}$), which is defined as the average MFP among the 5 per cent most productive firms in sector *s* and year t across the countries in the sample,[5] and on the lagged distance to the frontier ($Gap_{f,sc,t-1} = MFP_{Frontie\ r\ s,t-1} - MFP_{f,s,t-1}$). Frontier firms are excluded from the sample to avoid endogeneity issues.

Based on economic theory and previous estimations of this model, one should expect α_1 to be positive but below 1, indicating that innovation at the frontier benefits other firms but only partially so, and α_2 to be positive, indicating that firms below the frontier benefit from a catch-up effect. However, the speed of frontier growth, the variance of non-modelled productivity shocks and the nature of firm entry and exit (productivity enhancing or not) can either lead to productivity convergence or divergence across firms. In practice, divergence has generally been prevailing over recent years at the OECD level (Chart 1), although not necessarily within each country.

The main coefficient of interest is β, which captures the effect of industry-level digital adoption on firm-level productivity growth. $Dig\_adopt_{s,c,\bar{t}}$ represents the share of firms in sector s and country c that report using a specific digital technology (e.g. high-speed broadband internet connection, cloud computing) averaged over the period 2010-15. The effect of different digital technologies is assessed in separate identical regressions (i.e. one regression per technology). In addition, their combined effect is assessed using a composite indicator of adoption, which is constructed as the principal component of five variables representing the adoption of different digital technologies (high-speed broadband, simple and complex cloud computing, ERP and CRM software), in the spirit of Andrews *et al.* (2018).

As digital adoption is typically observed only for two or three years in the period of interest, the regression relies on the average of the digital adoption variable over the available years ($Dig\_adopt_{sc,\bar{t}}$), meaning that adoption does not vary over time in our regression framework. While this may hinder identification, it also mitigates potential endogeneity issues (e.g. if adoption and productivity in a specific year were driven by a common factor) and can help capturing lagged benefits of adoption. Since the digital adoption variable only varies at the country-industry level (and

5 In line with Andrews *et al.* (2016) and others, we define the frontier as the top 5 per cent percent of firms and use the global industry frontier as opposed to the national frontier. In theory, both can be relevant to productivity catch-up, but the global frontier is likely to be measured more consistently and with less noise in our dataset.

not across firms in an industry or over time) standard errors are clustered at the country-industry level to address potential correlation of residuals.

Longer time series are available in the data only for the adoption of ERP software. This allows the estimation of alternative specifications less subject to potential endogeneity issues. Two options are considered: using (i) adoption rates lagged by one year, or (ii) adoption rates in the first year of the sample period (2010).

The baseline specification also includes a vector of control variables ($X_{fsc,t}$), including firm size (measured as the log of employment[6]) and age, as well as industry and country-year fixed effects.[7] In alternative specifications, additional controls are included to account for potential common determinants of productivity and digital adoption at the industry level, such as skill shortage and regulatory environment indicators. In an attempt to disentangle the within-firm effect of digital adoption from spillovers resulting from digital adoption by other firms in the industry, we also control in a separate specification for firm-level investment (tangible or intangible) as a proxy for firm-level digital adoption. With this additional control capturing within-firm effects, the estimated β coefficient should only reflect spillover effects. However, these proxies are clearly imperfect (but the only ones available in our dataset) and corresponding results should be considered as illustrative.

Overall, this empirical framework offers the benefit of taking account of firm heterogeneities and firm-specific drivers of productivity, making it richer and more robust than an industry-level framework. In addition, the use of industry-level adoption as a determinant of firm-level adoption addresses certain endogeneity concerns since industry-level adoption is less likely than firm-level adoption to be influenced by firm-level productivity.

Still, one should keep in mind a number of caveats. First, it is possible that some endogeneity still persists despite the benefits of the general approach combining industry and firm-level data and the additional control variables introduced (and, in the case of ERP, the use of lagged and initial digital adoption rates). This would be the case if unobserved factors were affecting simultaneously adoption levels in an industry and productivity growth rates of the firms in this industry in a way that is not captured by industry and country-year fixed effects and by the additional control variables. Second, it is possible that the productivity catch-up of lagging firms is achieved via the adoption of digital technologies that more advanced firms have already adopted, in which case this effect may be captured (at least partially) by the productivity gap variable rather than the digital adoption variable. Results are robust to dropping the catch-up term in the regression, suggesting that this is not an

6 Regressions using turnover instead of employees as a measure of size yield quantitatively similar results as the baseline specification.

7 Results are also robust to including industry-year fixed effects.

issue.[8]

Third, another potential concern is that dropping the firms at the productivity frontier (i.e. the top 5 per cent in each industry) may lead to underestimating the effect of relatively new technologies that they may be the first ones to adopt (e.g. complex cloud computing services).[9] Fourth, in the absence of firm-level adoption rates coupled with information on firm entry/exit, estimations may fail to account for missed adoption opportunities and unsuccessful adoption processes forcing firms to exit the market, and symmetrically for successful entry of digital-natives highly productive firms. Finally, as shown by past research, reaping the benefits of digital adoption generally requires broader organizational changes, which are likely to be per se productivity-enhancing. Given that the estimates encompass a combination of the effect of adoption and such concomitant reorganisations, they reflect the productivity gains from digitalization in a broad sense (i.e. including the effect of these reorganisations).

In addition to the specifications described above, a number of refinements of the baseline specification are introduced to assess which industries and firms benefit most from digitalization and what are the potential complementarities with other factors:

- to assess which industries benefit more from digital adoption, we interact the digital adoption variable with (i) a categorical variable separating manufacturing and service industries, (ii) a variable capturing the average routine intensity of tasks in each industry, with the idea that industries with higher routine intensity may benefit more from digitalization through the automation of routine tasks;
- to assess which firms benefit more from the diffusion of digital technologies, the digital adoption variable is successively interacted with two categorical variables splitting the sample into (i) four size classes (from smallest to largest firms) and (ii) four productivity classes (from least to most productive). As a different way to test if productivity effects of digitalization vary according to productivity levels, the digital adoption variable is also interacted with lagged distance to the frontier; and
- to better understand complementarities of digital technologies with skills, we explore if skill shortages in ICT-related areas affect the adoption-productivity link by interacting industry and country level measures of skill shortages with the digital adoption variable.

8 That results are robust to omitting the productivity gap variable is also an indication that they are not subject to a potential bias that may result from including a transformation of the lagged level of the dependent variable as an explanatory variable.

9 Indeed, regressions including the top 5 per cent firms display slightly higher coefficient estimates for digital adoption rates than our baseline preferred specification.

Combining Firm and Industry-level Data

We combine various industry-level sources on digital adoption, routine intensity and occupational or skill shortages with firm-level information on productivity. Digital adoption data are drawn from the Eurostat "community survey on ICT usage and e-commerce in enterprises" and have country and industry dimensions and, for a subsample of technologies, also a time dimension. The survey provides a compilation of data on the use of various types of information and communication technologies in enterprises with at least 10 employees. To the best of our knowledge, this dataset is the only source of comparable cross-country data on digital adoption rates at the industry level.

Our analysis focuses on a subset of five indicators selected from a list of several hundred variables available in the Eurostat dataset. The selected indicators are the availability of high-speed broadband internet access, use of simple or complex cloud computing (CC, CC_HI), and the use of front or back office applications — customer relationship management (CRM), and enterprise resource planning (ERP). Technologies were selected based on their potential to improve productivity within the firm, but also via spillovers. These spillovers include potential network effects on other firms (e.g. ERP systems, the utility of which might increase with the number of clients and business partners working with it). These technologies also have possible complementarities between themselves (e.g. broadband access with other technologies, or Cloud Computing with ERP). An additional selection criterion was to maximize cross-country, cross-industry coverage.[10]

Since adoption rates of different technologies are positively correlated[11] and there could be complementarities from adopting them jointly, we also combine them into a single index using their first principal component (i.e. the linear combination of adoption rates that accounts for the largest fraction of their total variance). The first principal component explains a high fraction (more than 60 per cent) of the overall variation in the digital adoption indicators,[12] and the weights assigned to them are relatively close to each other,[13] implying that all technologies are important contributors to the first principal component. More broadly, this index may capture a general tendency of digital technology adoption in a given country-industry cell, in which case it is possible that it captures to some extent the adoption of other digital technologies not covered in this article.

10 For more details see a companion paper examining the drivers of digital adoption by Andrews *et al.* (2018) where the same set of indicators are used.

11 Refer to Table 4 in the online Appendix A for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

12 Refer to Panel A of Table 5 in the online Appendix A for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

13 Refer to Panel B of Table 5 in the online Appendix A for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Productivity and other firm-level variables come from Orbis, a widely used harmonized cross-country longitudinal firm-level database, building on the data construction steps described in Gal (2013), Andrews *et al.* (2016), and Gopinath *et al.* (2017).[14] The underlying data are sourced from annual balance sheet and income statements, collected by Bureau van Dijk (BvD) — an electronic publishing firm — using a variety of underlying sources ranging from credit rating agencies (e.g. Cerved in Italy) to national banks (e.g. National Bank of Belgium). It is the largest available cross-country firm-level database for economic and financial research, which contains not only publicly listed but also privately owned companies. However, important processing and cleaning work needs to be undertaken to transform the financial information to a database suited for economic analysis.

This involves three broad steps: (i) ensuring comparability of nominal variables across countries and over time (industry-level PPP conversion and deflation based on Inklaar and Timmer (2014) and the OECD STAN database, respectively); (ii) deriving new variables that are used in the analysis (real capital stock, productivity); and (iii) keeping only company accounts with valid and relevant information for our present purposes (filtering and cleaning).[15] We obtain productivity as a residual from estimating value-added based production functions, separately for each detailed industry, using the control function approach based on intermediate inputs to mitigate the endogeneity of input choices (Wooldridge, 2009).[16] We restrict the sample to firms that have an average of at least 10 employees (over our sample period) to match the reference group of the industry level digital adoption variable.

Concerning control variables at the industry level, we utilize a recently developed indicator for the routine content intensity of tasks in each industry (Marcolin *et al.*, 2016). This indicator provides a measure of the routine content of occupations, based on data from the OECD Survey of Adult Skills (PIAAC). It measures the degree of independence and freedom in planning and organizing the tasks to be performed on the job as a proxy for non-routine content. The occupation-level index is translated into an industry-level index by constructing the weighted average of the occupation-based index by industry,

14 The version used throughout this article was made available to the OECD by BvD in March 2017.

15 We prefer unconsolidated accounts in case a firm reports both unconsolidated and consolidated accounts so as to ensure that the covered economic activity refers to the local, domestic markets and does not reflect global activities in case of multinational firms. Further, we drop firms that report extreme growth rates in productivity and employment, i.e. which are in the top or bottom 1 per cent of the growth distribution within each country and industry. This step also serves to mitigate the risk of retaining company accounts that are affected by abrupt and large changes resulting from mergers, acquisitions or split-ups.

16 A number of limitations that commonly affect productivity measurement should be noted. First, differences in the quality and utilisation of capital and labour inputs cannot be accounted for as the capital stock is measured in book values and labour input by the number of employees. Secondly, measuring outputs and inputs in internationally comparable price levels remains an important challenge. Finally, similar to most firm-level datasets, Orbis contains variables on outputs and inputs in nominal values and no additional separate information on firm-specific prices and quantities. For further details, see Andrews *et al.* (2016).

Table 1: Descriptive Statistics

	Mean	Median	Bottom decile	Top decile	Standard deviation**	Observations
Digital variables (percentage of firms)						
High-speed broadband	0.359	0.301	0.155	0.650	0.182	401
Enterprise Resource Planning	0.329	0.305	0.107	0.585	0.179	417
Customer Relationship Management	0.327	0.288	0.143	0.575	0.170	409
Cloud Computing (all uses)	0.244	0.198	0.075	0.482	0.162	391
Cloud Computing (complex)	0.138	0.105	0.034	0.286	0.114	380
First principal component	0.853	0.351	-1.637	4.341	2.381	349
Firm-level variables						
MFP growth per year all firms	0.010	0.010	-0.255	0.276	0.264	1,803,155
MPF Frontier growth	0.019	0.019	-0.032	0.075	0.045	2,449,946
Gap to frontier (lagged)	1.711	1.619	0.860	2.614	0.772	1,737,330
Age	21.967	18.000	43.000	4.000	17.809	3,318,977
Employees (log)	3.534	3.219	2.485	4.977	1.075	3,367,107
Capex (log)	11.275	11.225	8.437	14.200	2.332	809,083
Intangibles (log)	11.276	11.364	7.317	15.194	3.263	2,627,018
Other (industry-level)						
Routine intensity	-0.101	0.024	-0.730	0.315	0.369	22
Knowledge intensity	0.423	0.380	0.260	0.620	0.167	22
Skill shortages	-0.053	-0.037	-0.233	0.131	0.156	1577
Resource management skills	0.005	0.007	-0.028	0.040	0.029	1577
Management of personnel resources	0.006	0.007	-0.035	0.048	0.034	1577
Computer and electronics	0.017	0.010	-0.032	0.081	0.044	1577
Technical skills	-0.002	-0.001	-0.019	0.016	0.017	1577
Regulatory impact	0.119	0.072	0.027	0.337	0.113	339

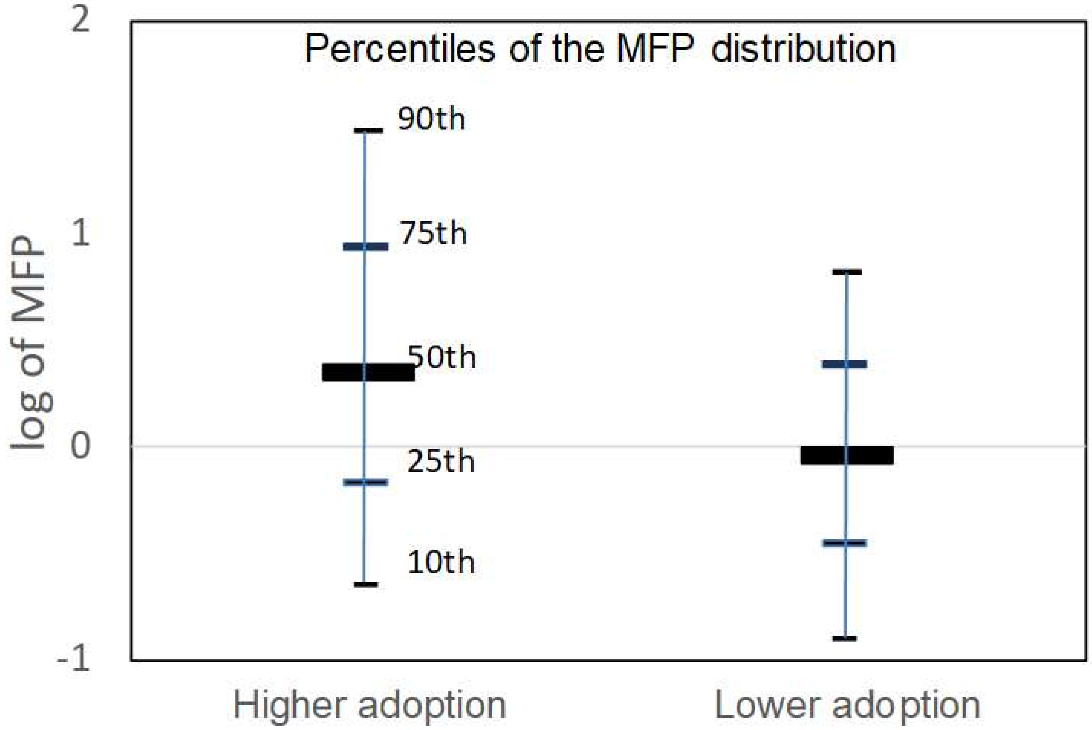
Note: MFP is measured in logarithms, based on the Wooldridge (2009) methodology. The top decile excludes firms in the top 5 per cent. The first principal component (i.e. the one associated with the largest eigenvalue) is obtained from the five digital adoption indicators. For a detailed description of each indicator, please refer to Table 1 in online Appendix A at http://www.csls.ca/ipm/37/OECD_appendix.pdf.
Source: OECD calculations.

with the occupational weights by industry obtained from the European Labour Force Survey (1995-2015).

Occupational and skill shortages rely on the OECD Skills for Jobs database, which uses labour market signals at the occupation level — in particular, relative wages, hours worked, employment and unemployment as well as qualification mismatches — to derive indicators of skill shortages in an industry (OECD, 2018). The indicators cover a rich set of skills, of which we use the following ones: *i)* resource management skills, which capture the ability to allocate resources efficiently; *ii)* management of personnel resources, which identifies how well managers motivate, develop and direct people as they work, and identify the best people for each job; *iii)* computer and electronics skills, which refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; and *iv)* technical skills, which are associated with workers' capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems.

Our combined dataset contains about 1.5 million firm-year observations in the baseline specification, spanning across 20 OECD countries (all from the European Union plus Turkey) and 22 industries over

Chart 3: MFP Distribution in Industries with High and Low Digital Adoption Rates



Note: "Higher adoption" and "lower adoption" denotes industries that are above and below, respectively, of the median industry in terms of the first principal component (i.e. the one associated with the largest eigenvalue) of the five digital adoption indicators. The percentiles are calculated within each industry and then averaged to the two industry groups, and are shown in relative terms to the median across firms with lower adoption.
Source: Orbis database of Bureau van Dijk; Eurostat, Digital Economy and Society Statistics, comprehensive database.

2010-2015 (Table 1).[17] A simple descriptive chart (Chart 3) suggests that firms tend to have higher productivity when they operate in industries where digital adoption rates are higher, but also that they exhibit higher dispersion in productivity, which is consistent with the evidence presented in Chart 1 that uses a broader classification of digital intensity following Calvino *et al.* (2018).

Results

Digital Adoption and Productivity in the Average Firm

Table 2 shows the results of estimating the baseline MFP model by ordinary least squares (OLS). All coefficients have the expected sign and significance. Roughly 20 percent of increases in frontier growth are passed to the average firm and 10 percent of the gap with frontier is filled each year

17 The set of countries are as follows: Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, the Netherlands, Poland, Portugal, Slovenia, Spain, Sweden, Turkey and the United Kingdom. The industries covered range from manufacturing to administrative and other support services, excluding the financial sector (i.e. 2-digit codes between 10 and 82, excluding 64-66).

Table 2: Baseline Results
Dependent Variable: MFP Growth

	Basic	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.218***	0.222***	0.212***	0.218***	0.215***	0.230***	0.236***
	(0.0353)	(0.0383)	(0.0374)	(0.0378)	(0.0377)	(0.0381)	(0.0394)
Gap to frontier	0.105***	0.104***	0.104***	0.105***	0.104***	0.107***	0.107***
(lagged	(0.0106)	(0.0118)	(0.0114)	(0.0117)	(0.0114)	(0.0118)	(0.0126)
Age	-0.0002***	-0.0003***	-0.0003***	-0.0002***	-0.0003***	-0.0003***	-0.0003***
	(5.19e-05)	(5.89e-05)	(5.53e-05)	(5.78e-05)	(5.67e-05)	(5.75e-05)	(6.24e-05)
Employees	0.0224***	0.0216***	0.0216***	0.0220***	0.0217***	0.0233***	0.0233***
(log)	(0.00252)	(0.00275)	(0.00266)	(0.00272)	(0.00268)	(0.00277)	(0.00295)
Digital		0.143***	0.101**	0.187***	0.0864**	0.0419	0.0161***
Technology		(0.0343)	(0.0402)	(0.0347)	(0.0437)	(0.0555)	(0.00391)
Observations	1,681,981	1,453,519	1,503,462	1,485,781	1,505,867	1,435,145	1,348,670
R-squared	0.063	0.062	0.062	0.063	0.062	0.064	0.064

Note: This table reports the estimates of the baseline equation where firm-level multifactor productivity (MFP) growth is regressed on average MFP growth of the 5 per cent firms with highest MFP in each sector-year cell, the firm's lagged gap to this productivity frontier, age and size (measured by the number of employees), and the average country-sector level adoption rates of individual digital technologies. The last column shows results for the 1^{st} principal component of the five technologies. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

via catch-up (column 1). These are standard magnitudes at the firm level and consistent with an overall pattern of productivity dispersion (Andrews *et al.*, 2016). The main result is that an industry environment characterized by high digital adoption rates is associated with higher MFP growth in the average firm. With the exception of complex cloud computing, all digital technologies are positively and significantly associated with MFP growth. This is also the case for the first principal component of the five digital technologies (last column), which captures the simultaneous covariation and potential complementarities of several technologies.[18]

These results are robust to using (i) digital adoption rates lagged by one year, or (ii) adoption rates at the beginning of the sample period.[19]. While this could only be tested for ERP software (the only technology in our sample with sufficient time coverage in the data), it nevertheless suggests that results are not primarily driven by reverse causality.[20]

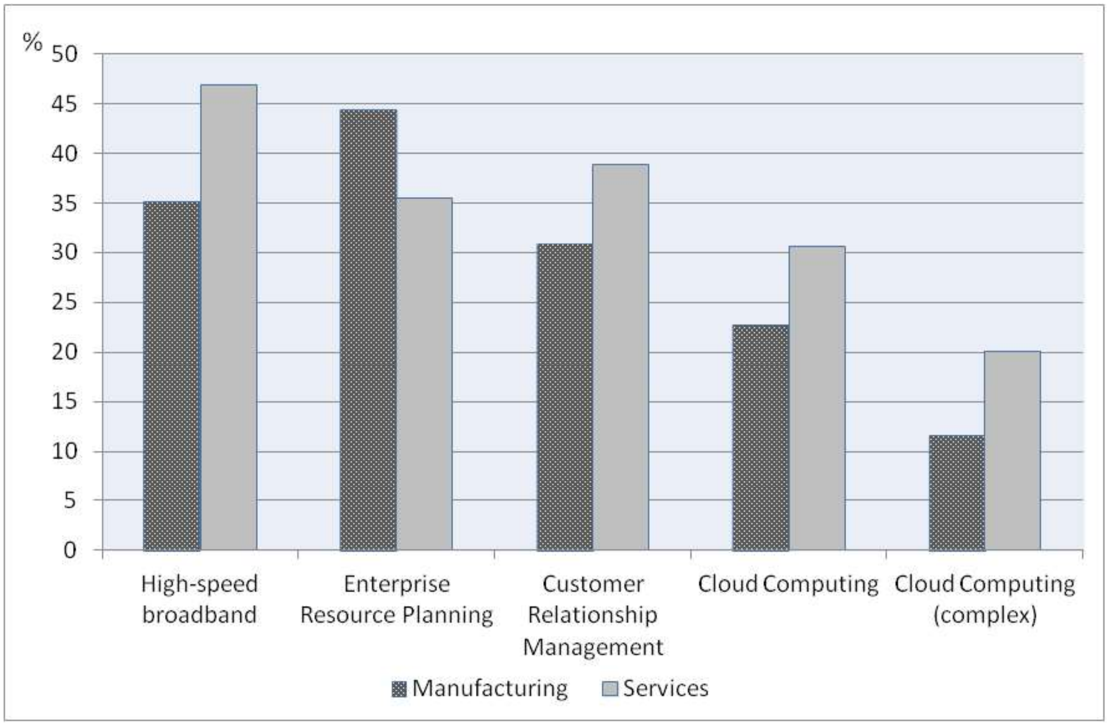
If one interprets the results as causal, they imply that a 10 percentage point increase in adoption of high-speed broadband (or cloud computing) would translate into an instantaneous increase in MFP growth by 1.4 percentage points (or 0.9 percentage point). After 5 years, this would im-

18 Refer to the online Appendix A for details http://www.csls.ca/ipm/37/OECD_appendix.pdf. An alternative approach would consist of including the adoption rates of different technologies separately in the same regression, but their individual coefficients could be difficult to interpret as the non-negligible correlation between the adoption of different technologies could give rise to multicollinearity.

19 Refer to Table 2 in the online Appendix B for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

20 Results are also robust to restricting the estimation period of the baseline regression to the years 2014-15, a period for which all digital technology variables are available (Refer to Table 1 in online Appendix B for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf).

Chart 4: The Diffusion of Digital Technologies Across Sectors, Selected Technologies, 2016 (or latest available)



Note: This figure shows the average adoption rate of selected digital technologies in the manufacturing sector (NACE Rev.2 10-33) and the services sector (NACE Rev.2 45-82) of the 20 countries included in this analysis.
Source: OECD calculations based on Eurostat, Digital Economy and Society Statistics, comprehensive database.
Source: OECD calculations based on Eurostat, Digital Economy and Society Statistics, comprehensive database.

ply a 5.8 per cent (or 3.5 per cent) higher MFP level for the average firm.[21] Effects found for other technologies are of the same order of magnitude, but as shown below exhibit different patterns across industries and firms, underlining the importance of distinguishing their respective association with productivity rather than bundling all technologies in a single ICT aggregate. Overall, results suggest that at least on average there is no apparent productivity paradox at the firm level: the digitalization of an industry is indeed linked to better productivity performance of its firms.

Sectoral Differences and Routine Tasks

Economy-wide coefficient estimates may nonetheless mask differences in the covariation of productivity and adoption in different parts of the economy. Indeed, the take-up of digital technologies varies significantly across industries (Chart 4 and Table

21 The effect after 5 years results from cumulated annual increases in MFP growth combined with weaker catch-up due to progressively higher MFP levels.

22 Appendix A is available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

3 of online Appendix A)[22] and is generally higher in services than in manufacturing.[23] However, the association of digital adoption with higher firm-level productivity is much stronger in manufacturing than services for most technologies, with the notable exception of high-speed broadband (Table 3).

One relevant factor for the effect of digital adoption is the intensity in routine tasks, which digital technologies can presumably replace or streamline (Akerman *et al.*, 2013). We therefore augment our baseline specification with the interaction between digital technology adoption and the indicator of sectoral routine task intensity proposed by Marcolin *et al.* (2016).[24] Results (Table 4), consistent with Chevalier and Luciani (2018), show that digital adoption is more closely associated with productivity gains in sectors highly intensive in routine tasks than elsewhere, perhaps reflecting a wider scope for substitution between technology and labour in these sectors. If one assumes that these effects are causal, Chart 5 shows for instance that the productivity benefits of raising adoption in a high routine-intensive sector are significantly higher than in other industries.

Channels and Robustness to Omitted Variable Bias

While our estimates are suggestive of a positive link between digital adoption and productivity performance, they suffer from a number of limitations already mentioned. Here, we attempt to identify the channels underlying the links (within-firm adoption versus spillovers from other firms) and the potential role of omitted variables.

To try disentangling the effects of the spillovers versus within firm, we run regressions including total firm-level capital expenditure or expenditure on intangible assets, which are available in the Orbis database (Table B.5, Panels A and B).[25] Coefficient estimates barely change for most of the digital technologies, save for cloud computing whose coefficient either declines (when including intangible investment) or loses significance (when including total capital expenditure). It would seem, therefore, that for most technologies the effects captured reflect either mainly sector-wide spillovers or benefits from within-firm adoption that cannot be controlled for using the available set of information from company accounts.

A potential source of concern is that sector-level adoption rates may capture the effects of other sectoral drivers of productivity that are correlated with adoption. For instance, Andrews *et al.* (2018) find

23 This is consistent with findings in previous research, such as Dhyne *et al.* (2018).

24 We use the indicator for the United States, under the assumption that it reflects structural sectoral features in a relatively frictionless economy, which would be common in all countries. This also avoids possible endogeneity issues between adoption rates and routine intensity. Results are also robust to replacing the Marcolin *et al.*'s indicator of sectoral routine intensity with the indicator of sectoral knowledge intensity used in Andrews *et al.*, (2018). Table 3 of Appendix B is available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

25 Refer to Panels A and B in Table 5 of online Appendix B at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Table 3: Differentiating Between Manufacturing and Services
Dependent variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.184***	0.170***	0.178***	0.179***	0.182***	0.189***
	(0.0413)	(0.0400)	(0.0410)	(0.0409)	(0.0421)	(0.0443)
Gap to frontier	0.127***	0.125***	0.126***	0.126***	0.128***	0.129***
(lagged)	(0.00540)	(0.00508)	(0.00512)	(0.00522)	(0.00523)	(0.00561)
Age	-0.000204***	-0.000215***	-0.000203***	-0.000219***	-0.000282***	-0.000270***
	(5.38e-05)	(5.04e-05)	(5.31e-05)	(5.17e-05)	(4.97e-05)	(5.30e-05)
Employees (log)	0.0256***	0.0254***	0.0257***	0.0258***	0.0271***	0.0273***
	(0.00201)	(0.00194)	(0.00195)	(0.00199)	(0.00207)	(0.00217)
Digital technology	0.119**	0.113***	0.211***	0.189***	0.359***	0.0264***
(Manufacturing)	(0.0535)	(0.0419)	(0.0481)	(0.0524)	(0.115)	(0.00517)
Digital technology	0.173***	0.0526	0.158***	0.0589	0.0644	0.0140***
(Services)	(0.0329)	(0.0578)	(0.0384)	(0.0509)	(0.0574)	(0.00395)
Observations	1,223,625	1,273,088	1,256,137	1,275,982	1,221,521	1,135,046
R-squared	0.073	0.073	0.073	0.073	0.074	0.074

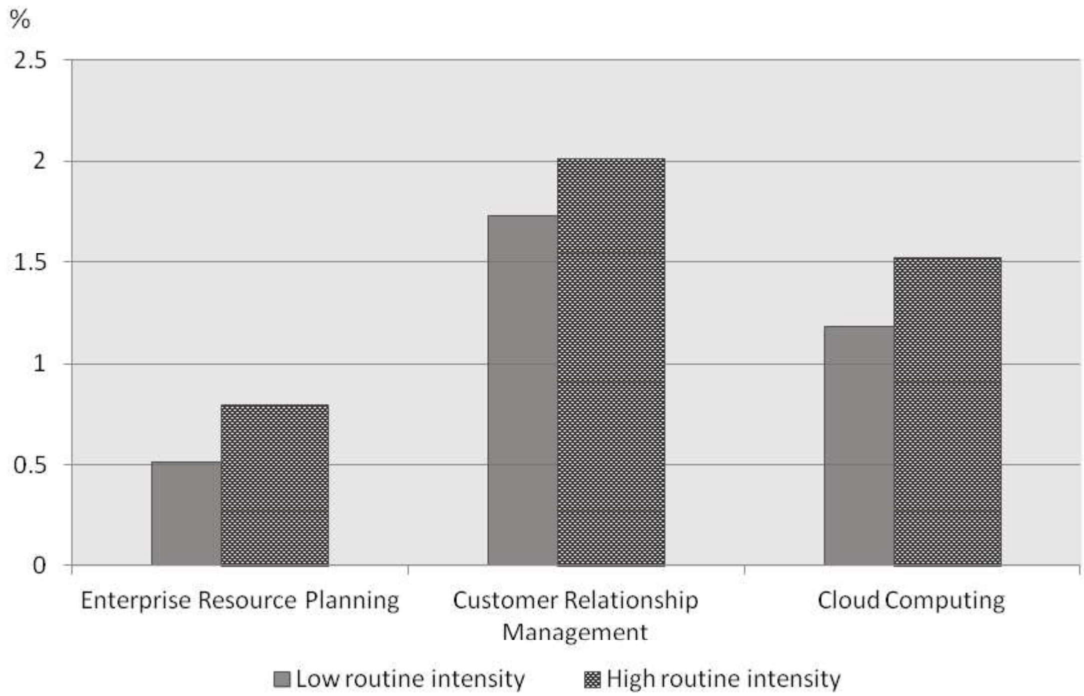
Note: Colum 1-6 of this table show the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), and the interaction between digital technology adoption rates and a dummy for the sector. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the first principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 20 manufacturing and market services sectors (NACE Rev 2, 10-82, excl. sectors 35-43) over the period 2010-15 for firms with at least 10 employees. To maximize coverage, unweighted averages of each digital technology variable are used over the period. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table 4: Differentiating According to Sector Routine Intensity
Dependent variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.236***	0.235***	0.239***	0.234***	0.267***	0.264***
	(0.0483)	(0.0480)	(0.0478)	(0.0481)	(0.0472)	(0.0474)
Gap to frontier	0.101***	0.101***	0.102***	0.101***	0.105***	0.107***
(lagged)	(0.0152)	(0.0150)	(0.0154)	(0.0153)	(0.0161)	(0.0166)
Age	-0.000286***	-0.000286***	-0.000284***	-0.000278***	-0.000319***	-0.000323***
	(6.28e-05)	(6.28e-05)	(6.33e-05)	(6.29e-05)	(7.21e-05)	(7.47e-05)
Employees (log)	0.0195***	0.0194***	0.0200***	0.0194***	0.0206***	0.0213***
	(0.00317)	(0.00314)	(0.00323)	(0.00318)	(0.00332)	(0.00345)
Digital technology	0.168***	0.0551	0.177***	0.123**	0.185*	0.0229***
	(0.0580)	(0.0517)	(0.0470)	(0.0593)	(0.101)	(0.00564)
Digital technology	0.0177	0.136**	0.133*	0.162**	0.286**	0.0222***
X routine intensity	(0.0658)	(0.0617)	(0.0777)	(0.0653)	(0.128)	(0.00569)
Observations	1,137,711	1,142,895	1,138,659	1,138,021	1,070,569	1,052,191
R-squared	0.063	0.062	0.063	0.063	0.065	0.065

Note: This table reports estimates of the baseline equation augmented with an interaction between digital technologies and the intensity of routine tasks (see Marcolin et al., 2016, for a description of the indicator). All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the 1st principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with at least 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15 and routine intensity refers to the average over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Chart 5: Multifactor Productivity Gains for the Average Firm Associated with a 10 Percentage Point Increase in Industry-level Adoption



Note: Estimates are derived from the baseline equation augmented with an interaction between digital technologies and the country-sector-level intensity of routine tasks (Marcolin *et al.*, 2016) (Table 4). High (low) routine intensity represents the 75^{th} (25^{th}) percentile of the distribution in this classification.

that digital adoption rates are influenced by a number of sector-level structural and policy factors affecting firm-level capabilities and incentives to adopt. A number of these factors, such as the regulatory environment and the availability of skills may also directly affect firm-level productivity growth (Arnold *et al.*, 2011; Andrews *et al.*, 2016).

Omitting these factors could artificially inflate the estimated effects of sector-level digital adoption rates. To control for this possibility, we extend the model with two additional control variables: (i) the OECD indicator of the impact of upstream anti-competitive regulations in each sector (Conway and Nicoletti, 2006; Égert and Wanner, 2016), and (ii) a new indicator of sectoral occupational shortages recently published in the OECD Skills for Jobs Database (2018). Reassuringly, while both regulatory burdens and lack of skills have the expected negative association with productivity performance,[26] the finding that higher digital adoption rates are associated with higher MFP growth remains largely unaffected when we account for the direct influence of these variables.[27]

---

26 The lack of significance of the regulatory impact indicator is most likely related to the relatively short time period spanned, as most of the variation in this indicator is within country-industry in the sample of relatively homogeneous EU countries mostly covered by our analysis.

27 Refer to Panel in C Table 5 of online Appendix B at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

The Role of Skills

The likely complementarity between digital technologies and other intangible investments suggests that skill shortages in a sector could impede digital adoption from yielding its full productivity benefits. We test this conjecture by further extending the baseline model to include the interaction between digital adoption and skill shortages. One concern with this approach could be that industries in which adoption is high (or low) may cause (or suffer from) skill shortages, and this endogeneity could bias estimates in unpredictable ways. However, there appears to be no systematic correlation between adoption and shortages in the data.[28] Since the OECD Skills for Jobs database includes a large number of skills (captured through occupations), we concentrate first on general shortages and subsequently focus more specifically on skills that are likely to be most complementary to digital adoption (managerial, computer and electronics, and technical).[29]

Consistent with the idea that digital technologies are complementary to organizational and human capital, we find that general occupational shortages in an industry curb the linkage between adoption rates and productivity performance (Table 5) for specific technologies (such as high-speed broadband, CRM and cloud computing) and for all technologies combined (first principal component).[30]

Since a lack of skill shortages are found to be correlated with a higher automation risk (OECD, 2018) we implement a further test to rule out that our results on skill shortages are merely a reflection of a greater capacity for productivity-enhancing automation in industries with low skill shortages. In particular, we include interactions of digital technologies not only with skill shortages but also with routine intensity — to capture automation risk — in the same regressions. As shown in Table 4 of online Appendix B, the results on both channels remain robust to this specification.

Digging deeper (Table B.6), shortages in managerial, electronic and technical skills all inhibit the ability of firms to reap the productivity benefits of higher sector-level adoption rates.[31] The damaging effects of skill shortages on the productivity gains from adoption are substantive (Chart 6, Panel A). For instance, moving from rel-

28 Refer to Table 6 of online Appendix A at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

29 "Occupational shortages" pools shortages in all occupational categories covered by the OECD dataset; managerial shortages covers "Resource management skills" (ability to allocate resources efficiently) and "Management of personnel resources" (how well managers motivate, develop and direct people and identify best people for each job); "Computer and electronics" refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; "Technical skills" are associated with workers' capacity to design, set up, operate and correct malfunctions, involving application of machines or technological systems. See OECD (2018) for details.

30 Since skill shortages are constructed by relying among other factors on differences in wage dynamics across occupations, they could also capture to some extent differences in industry productivity, which in turn are related to average firm productivity. However, this is mitigated by the fact that wages enter only with a small weight (20 per cent) into the skill shortage indicator (see subsection Combining Firm and Industry-level Data and OECD (2018)).

31 Refer to Table 6 of online Appendix B athttp://www.csls.ca/ipm/37/OECD_appendix.pdf.

Table 5: Assessing the Effects of Skill Shortages, Dependent Variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.154***	0.128***	0.141***	0.133***	0.133***	0.145***
	(0.0372)	(0.0378)	(0.0373)	(0.0374)	(0.0374)	(0.0375)
Gap to frontier	0.105***	0.104***	0.106***	0.104***	0.105***	0.106***
(lagged)	(0.0133)	(0.0126)	(0.0130)	(0.0126)	(0.0126)	(0.0136)
Age	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0004***
	(6.30e-05)	(6.13e-05)	(6.25e-05)	(6.12e-05)	(6.15e-05)	(6.67e-05)
Employees (log)	0.0228***	0.0224***	0.0230***	0.0225***	0.0228***	0.0231***
	(0.00303)	(0.00290)	(0.00298)	(0.00290)	(0.00291)	(0.00311)
Occupational	-0.0363***	-0.0264*	-0.0316***	-0.0232	-0.0232	-0.0309**
shortage	(0.0128)	(0.0140)	(0.0110)	(0.0142)	(0.0141)	(0.0124)
Digital technology	0.170***	0.0465	0.201***	0.0957**	0.0247	0.0163***
	(0.0420)	(0.0468)	(0.0408)	(0.0478)	(0.0664)	(0.00411)
Occupational shortage	-0.287***	-0.121	-0.274***	-0.0411	-0.170**	-0.0186***
X digital technology	(0.0851)	(0.105)	(0.0935)	(0.0649)	(0.0802)	(0.00534)
Observations	1,106,487	1,142,249	1,128,495	1,149,976	1,151,662	1,080,849
R-squared	0.062	0.061	0.062	0.062	0.062	0.062

Note: This table reports the estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 per cent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), average country-sector level adoption rates of individual digital technologies, an index capturing sector-level general occupational shortages, and their interaction with the digital adoption variable. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the first principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2011-15 for firms with at least 10 employees. To maximize coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

atively low to high shortages would reduce the estimated firm-level productivity growth gains from an increase in high-speed broadband internet diffusion by more than a quarter; a similar reduction in productivity gains due to shortages is estimated for CRM. Focusing on specific skills, the strongest downward effects of shortages on productivity gains from wider sector-level adoption rates (of all technologies combined) are found for electronic and technical skills (Chart 6, Panel B).

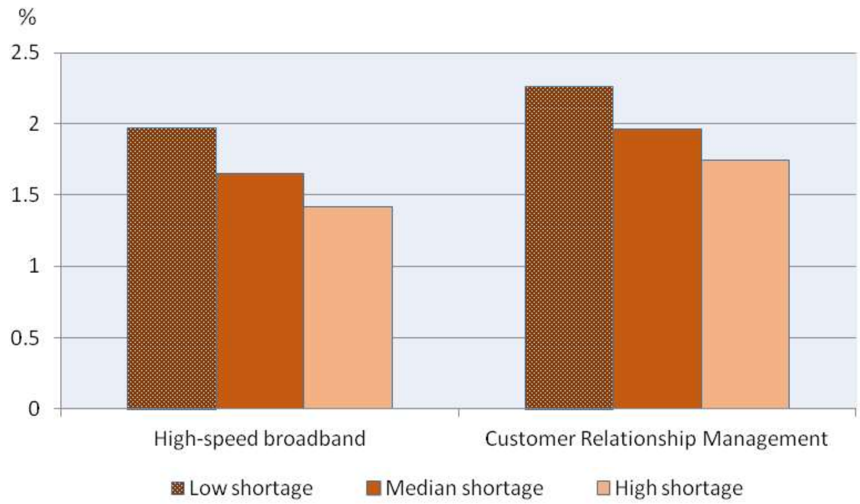
Which Firms Benefit Most from Adoption?

To study the link between digitalization and productivity growth across the firm productivity distribution, we test two approaches (Table 6). First, we introduce dummy variables that divide the sample according to productivity quartiles in each industry, from lowest to highest initial productivity levels (columns 1 to 6).[32] Second, we interact digital adoption rates with the gap to the productivity frontier variable (column 7). The results of both approaches are consistent and strongly suggest that the positive association between

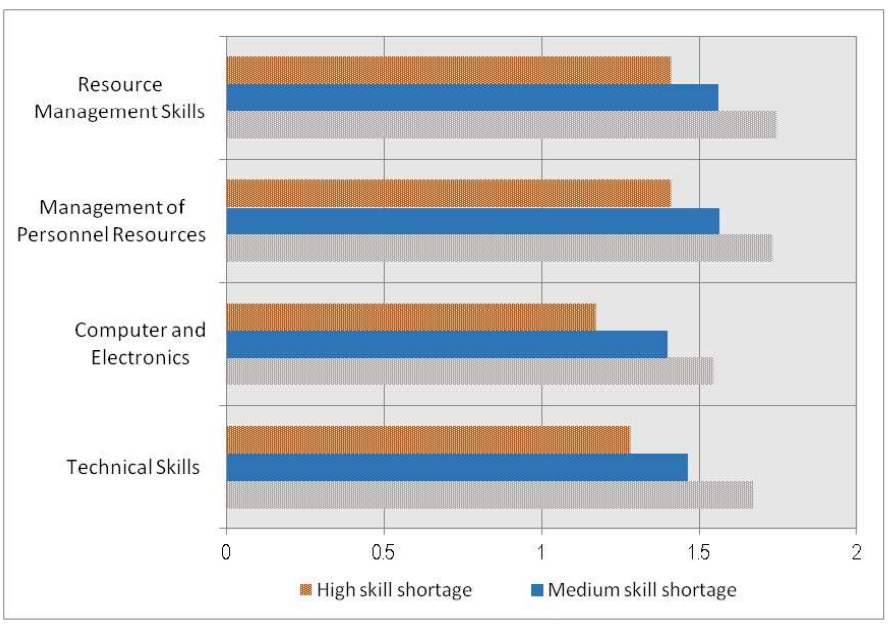
32 Given that these dummies could duplicate the information conveyed by the gap to frontier variable, we also ran the same regression omitting the gap. The results remained unchanged. See Table 8 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Chart 6: Skill Shortages and the Returns from Digitalization

Panel A: Increase in MFP Growth Associated with a Ten Percentage Point Increase in the Diffusion of Digital Technologies in the Presence of General Occupational Shortages



Panel B: Increase in MFP Growth Associated with a Ten Percentage Point Increase in the Diffusion of High-speed Broadband, for Specific Skill Shortages



Note: These figures show the ceteris paribus impact of a ten percentage point increase in the diffusion of high-speed broadband or customer relationship management in a labour market environment characterized by a low (25th percentile of the distribution), medium (median of the distribution) or high (75th percentile of the distribution) shortage in occupations (Panel A) or specific skills Appendix Table B.5 (Panel B). Calculations are based on estimates from Table 5 (Panel A) and Table B5 (Panel B). Resource management skills capture the ability to allocate resources efficiently; management of personnel resources identifies how well managers motivate, develop and direct people as they work, and identify the best people for each job; computer and electronics refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; and technical skills are associated with worker's capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems. See OECD (2018) for more information.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, OECD (2018).

Table 6: The Heterogeneous Effects of Digitalization Across Productivity Quartiles Dependent variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component	First principal component
Frontier growth	0.206***	0.197***	0.203***	0.201***	0.216***	0.220***	0.235***
	(0.0388)	(0.0377)	(0.0382)	(0.0382)	(0.0387)	(0.0399)	(0.0394)
Gap to frontier (lagged)	0.0741***	0.0760***	0.0762***	0.0758***	0.0807***	0.0780***	0.108***
	(0.0197)	(0.0191)	(0.0195)	(0.0193)	(0.0205)	(0.0208)	(0.0120)
Age	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(4.96e-05)	(4.75e-05)	(4.86e-05)	(4.84e-05)	(4.89e-05)	(5.16e-05)	(5.94e-05)
Employees (log)	0.0198***	0.0197***	0.0202***	0.0198***	0.0212***	0.0216***	0.0235***
	(0.00185)	(0.00178)	(0.00183)	(0.00183)	(0.00193)	(0.00202)	(0.00288)
Quartile 2 (dummy)	-0.0636***	-0.0662***	-0.0577***	-0.0312**	-0.0331**	-0.0392***	
	(0.0124)	(0.0134)	(0.0148)	(0.0140)	(0.0135)	(0.0119)	
Quartile 3 (dummy)	-0.0704***	-0.0710***	-0.0672***	-0.0358*	-0.0363*	-0.0437**	
	(0.0183)	(0.0199)	(0.0215)	(0.0208)	(0.0207)	(0.0194)	
Quartile 4 (dummy)	-0.0852***	-0.0859***	-0.0841***	-0.0457	-0.0459	-0.0554*	
	(0.0263)	(0.0290)	(0.0304)	(0.0298)	(0.0298)	(0.0287)	
Digital technology (Quartile 1)	0.0845***	-0.00483	0.100**	0.122**	0.0668	0.0107**	
	(0.0326)	(0.0452)	(0.0444)	(0.0590)	(0.0741)	(0.00425)	
Digital technology (Quartile 2)	0.170***	0.0898**	0.166***	0.0862*	0.0373	0.0150***	
	(0.0332)	(0.0395)	(0.0330)	(0.0449)	(0.0606)	(0.00382)	
Digital technology (Quartile 3)	0.179***	0.0933**	0.182***	0.0905**	0.0478	0.0156***	
	(0.0358)	(0.0390)	(0.0315)	(0.0410)	(0.0555)	(0.00347)	
Digital technology (Quartile 4)	0.191***	0.109***	0.202***	0.0888**	0.0473	0.0164***	
	(0.0424)	(0.0386)	(0.0347)	(0.0422)	(0.0523)	(0.00365)	
Digital technology							0.0139***
							(0.00394)
Digital technology X gap to frontier (lagged)							-0.00763**
							(0.00323)
Observations	1,403,093	1,451,507	1,434,364	1,453,557	1,383,623	1,299,953	1,348,670
R-squared	0.062	0.062	0.062	0.061	0.062	0.063	0.065

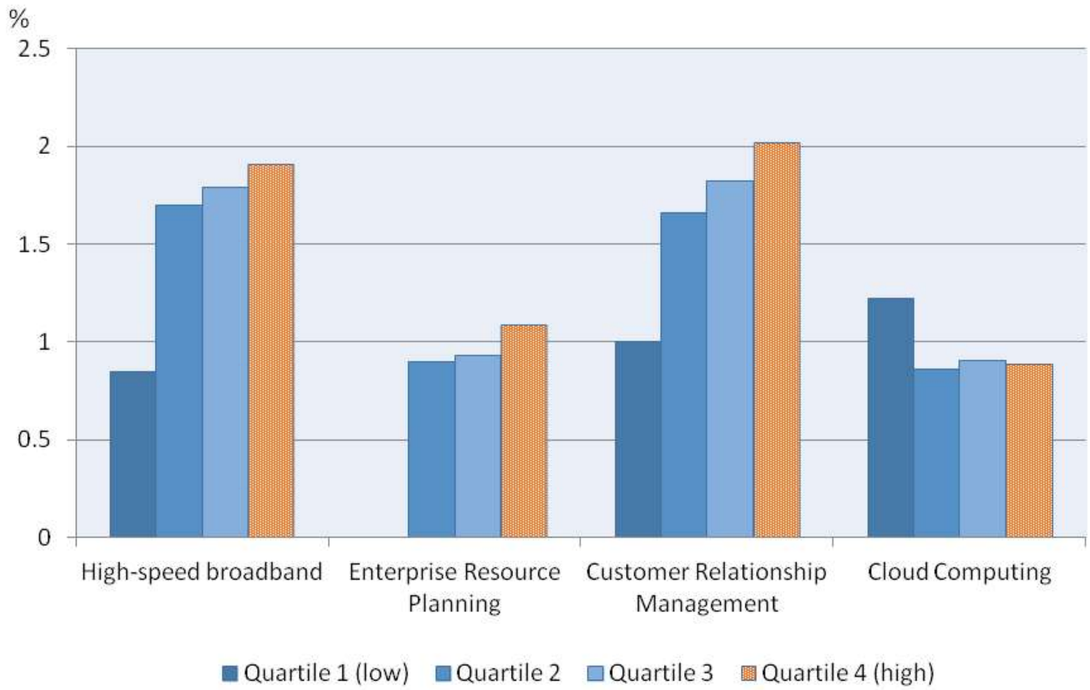
Note: Colum 1-6 of this table show the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 per cent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), a dummy for each productivity quartile (omitting the first quartile for reference), and the interaction between digital technology adoption rates and a dummy for each productivity quartile. Quartile 1 refers to the bottom of the distribution (i.e. low productive firms), quartile 4 to the top. Alternatively, the last column displays results of the baseline equation augmented by an interaction term between digital technologies and the lagged gap to the frontier. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. In all cases, the coefficient estimates of quartile 1 and 4 are statistically different. The 1st principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with at least 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

sector-level diffusion of digital technologies and productivity growth is strongest for high productivity firms (or firms close to the frontier).[33]

For instance, if one assumes that the results are causal, the estimated productivity gains from raising adoption rates by 10 percentage points are more than doubled for high productivity relative to low productivity firms in the case of high-speed broadband and CRM (Chart 7). Interestingly, cloud computing is the only technology for which low-productivity firms tend to benefit more, consistent with the idea that it may be less demanding than other technologies (e.g. ERP and CRM) in terms

33 For brevity, we only report results for the 1st principal component in the case of interaction with distance to the frontier. More detailed results can be found in Table B.7. Results by productivity quartile for ERP are also robust to using lagged or initial adoption rates, suggesting that they are not primarily driven by reverse causality. See Table 2 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Chart 7: Multifactor Productivity Gains from a 10 Percentage Point Increase in the Industry-level Diffusion of Specific Technologies, by Productivity Quartiles, after 1 year



This chart shows the ceteris paribus increase in multifactor productivity growth from increasing the diffusion of digital technologies by ten percentage points across different productivity quartiles. Quartile 1 refers to the bottom of the distribution (i.e. low productive firms), quartile 4 to the top of the distribution (i.e. high productive firms). Results for ERP for the least productive firms are not statistically significant. Calculations are based on estimates from Table 6, column 1-4. Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

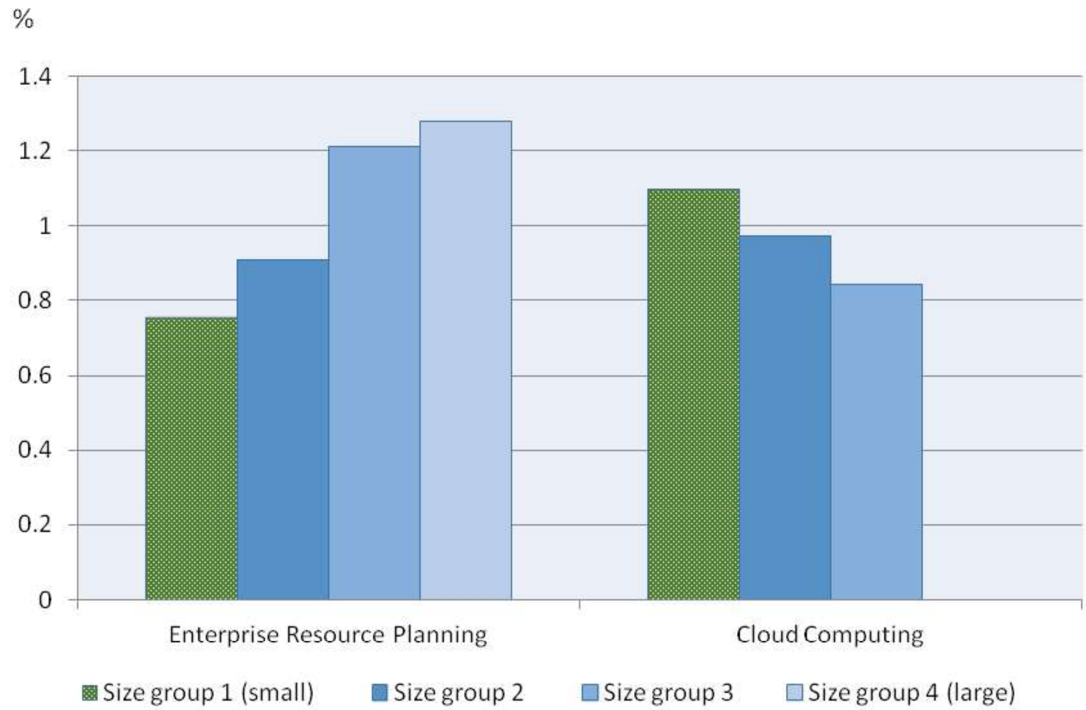
of complementary investments in organizational capital.

Regressions that differentiate firms by size suggest that size matters less than productivity in terms of gains from digital adoption (Chart 8 and Table 9 in online Appendix B).[34] Interestingly, the effect of size depends on the technology. As expected, cloud computing has the strongest positive association with productivity performance for the smallest firms, which are for instance able to avoid the fixed costs of investing in data storage and processing facilities, which is a way to acquire "scale without mass" (Bloom and Pierri, 2018). The opposite is found for Enterprise Resource Planning, which is most strongly associated with productivity improvements in the largest firms, due to the well-known economies of scope and scale characterizing this technology. Confirming that productivity is the key determinant, crossing the size and productivity criteria shows that, independent of the technology, it is always

34 Appendix B is available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

35 Refer to Table 10 from online Appendix B at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Chart 8: Multifactor Productivity Gains from a 10 Percentage Point Increase in Diffusion of Digital Technologies, by Firm Size, after 1 year



This graph shows the ceteris paribus increase in multifactor productivity growth from increasing the diffusion of digital technologies by ten percentage points across different size groups. Size group 1 captures firms with 10-20 employees, size group 2 firms with 21-50 employees, size group 3 firms with 51-250 employees, and size group 4 capture very large firms with more than 250 employees. Results for cloud computing for the largest firms are not significant. Calculations are based on estimates from Table 9 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf. // Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

the highest productivity firms that benefit most.[35]

The finding that sector-level digital adoption is most closely associated with productivity increases in the best performing firms would point to an inherent tendency of digitalization to increase productivity dispersion as digital technologies spread out. This is consistent with evidence pointing to a rising dispersion in productivity within narrowly-defined sectors (Syverson, 2011) and a rising gap between productivity growth in the best firms and the rest, especially in highly digitalized sectors (Andrews *et al.*, 2016; Berlingieri *et al.*, 2017). It is also in line with recent findings on the speed of catch-up of laggard firms, which is shown to be weaker in industries that rely more on ICT specialists (Berlingieri *et al.*, 2018).

A simple back-of-the-envelope calculation suggests that the simultaneous increase in the take-up of all five digital technologies considered in this article could explain about 0.28-0.35 log point per year out of the 0.64 log point annual observed divergence in productivity between the top and bottom quartiles over 2010-15, i.e. about half of the total divergence.[36]

One potential explanation for the higher gains of high-productivity firms is that adopting digital technologies and exploiting them efficiently requires other endowments, such as managerial ability, know-how or technical skills. It is likely that these endowments are more present in high productivity firms than elsewhere. Consistent with this, additional regressions suggest that skills shortages at the industry level reduce the gains from digitalization relatively more in less productive firms than in more productive ones, suggesting that it is relatively more difficult for less productive firms to attract workers with relevant skills.[37]

Conclusion

Our findings support the idea that the adoption of digital technologies is generally associated with substantially higher firm-level productivity. These results hold for a range of different technologies (high-speed broadband access, simple and complex cloud computing, CRM and ERP software). This association is stronger in manufacturing industries and more generally in industries that are intensive in routine tasks, suggesting that digital adoption can streamline production processes and to some extent act as a substitute for routine labour input.

The association between the adoption of digital technologies and productivity is also stronger for firms that are already highly productive, hence likely to benefit from complementary organizational and technical skills. This evidence is consistent with a potential for digitalization to exacerbate dispersion in firm-level performance outcomes (Brynjolfsson and McAfee, 2011). Compared to past innovation waves, gains from digital technologies may have been less easy to reap for less productive firms, because these gains depend crucially on firm-specific intangible assets and skills (e.g. data, tacit knowledge, organizational capital) and complementary additional investments in these factors, which are harder to implement in these firms. This is in line with recent evidence at the macroeconomic level that shows a slower penetration of the latest technologies within countries — even though their initial diffusion across countries is now faster than in the past (Comin and Mestieri, 2018).

This sheds some light on the so-called "modern productivity paradox". Overall gains from digitalization may appear disappointing compared to past innovation waves or to the potential offered by these technologies since this potential, albeit important, is fully realised only by the most

36 These results are obtained by using the estimated coefficients on the first principal component from Table 6 (last column) and combining average changes in adoption with the weight of each technology in the first principal component. The average adoption rates in 2010 (2015) are the following: for ERP, 25 per cent (35 per cent), for CRM, 31 per cent (34 per cent). For the other two variables where no data are available in 2010 — cloud computing and high speed broadband — we assumed zero prevalence, with 2015 values being 24 per cent (cloud computing simple), 13 per cent (cloud computing complex) and 35 per cent (high speed broadband). For high-speed broadband, as alternative, we also assumed 20 per cent in the initial year, leading to the two values that define the interval of the final result.

37 Refer to Table 11 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

productive firms. A key question is the counterfactual scenario to which one compares current trends. Overall, our results suggest that current productivity growth is clearly stronger (especially among the more productive firms) than in a hypothetical scenario without digitalization, but weaker than in a scenario where all firms would reap the full benefits from digital technologies.

While this finding contributes to explaining disappointing productivity growth, it does not explain by itself the broad-based productivity slowdown observed since the mid-2000s in OECD countries. This suggests either that a first, more significant wave of ICT adoption — leading to productivity gains in manufacturing and certain services such as distribution or finance, especially in the United States (Cette *et al.*, 2016; Van Ark *et al.*, 2008) — has run its course, or that other negative factors may have masked the productivity gains from digitalization. For example, weakening business dynamism (Decker *et al.*, 2016; Calvino *et al.*, 2018) and legacies of the global financial crisis (Adler *et al.*, 2017) have been drags on overall productivity growth.

More broadly, the ability of less productive firms to catch up has apparently diminished, resulting in an increasing dispersion in productivity outcomes (Andrews *et al.*, 2016; Berlingieri *et al.*, 2017; Berlingieri *et al.*, 2018). As discussed in this article, digitalization is a factor that has contributed to this divergence — a back-of-the-envelope calculation suggests that it could have contributed to about half of the observed divergence between the top and bottom productivity quartiles in each industry over 2010-15. Our findings suggest that shortages in technical and managerial skills in an industry tend to amplify this divergence, since they affect predominantly less productive firms.

Looking ahead, there is a risk that a wide and enduring productivity gap across firms is not only a reflection of weaker diffusion of innovation, business dynamism and potentially competition, but may in itself fuel a further weakening of these factors. For example, the most productive firms may become more difficult for other firms to challenge because they benefit from firm-specific intangible assets and can attract the most skilled workers. Andrews *et al.* (2016) find that industries where productivity dispersion widens more also tend to have weaker aggregate productivity growth. Mounting evidence of rising mark-ups — especially in digitally intensive industries — and sector concentration (Calligaris *et al.*, 2018; Bajgar *et al.*, 2019), as well as declining firm entry and exit rates (Calvino *et al.*, 2015; Adalet McGowan *et al.*, 2017) — again, especially in highly digitalized sectors (Calvino and Criscuolo, 2018) — are consistent with this picture.

These findings raise challenges and opportunities for policies aimed at making the best of digital technologies. Policies encouraging digital adoption are warranted given the intrinsic potential of these technologies to support productivity, but should be accompanied by efforts to create the conditions enabling the catch-up of productivity laggards and the efficient reallocation of resources in the economy (Sorbe *et al.*, 2019). This includes smoothing the costs of the digital transition for displaced workers and maximising their reemployment potential.

As shown by Andrews *et al.* (2018), both capabilities (e.g. enhancing managerial and digital-friendly skills) and incentives (e.g. reducing entry and exit barriers) are relevant to stimulate digital adoption. Moreover, certain drivers of digital adoption identified by Andrews *et al.* (2018) are also likely to support the performance of lagging firms (e.g. widening the skill pool, improving access to financing, reducing entry barriers to certain markets). Enhancing skills is particularly important in this respect, as lagging firms are more affected by skill shortages than more productive firms. In addition, further efforts may be needed to ensure that large incumbents do not create barriers to the entry and growth of competitors and the diffusion of innovation in the economy (Berlingieri *et al.*, 2018).

Further research is needed to improve our understanding of the links between digital adoption and productivity. More specifically, two issues that were not covered in this article due to data limitations would deserve further attention. First, better disentangling the benefits of within-firm digital adoption from the positive spillovers via adoption in other firms (a question this article could only explore tentatively) would be useful. Second, it would be interesting to broaden the perspective to account for reallocation effects (does digital adoption enable more productive firms to grow faster than less productive ones?) as well as the propensity for entry and exit of firms in a more digitalized environment.

More broadly, the benefits of digitalization could be assessed beyond the scope of firm productivity. Indeed, households and governments also likely benefit from the use of digital technologies, and from a more digitalized environment in general. There are probably important complementarities to be explored between digital adoption in firms, households and governments, as joint increases in adoption can facilitate interactions between them as well as skill upgrades.

References

Acemoglu, D., P. Aghion and F. Zilibotti (2006) "Distance to Frontier, Selection, and Economic Growth," *Journal of the European Economic Association*, Vol. 4, No. 1, pp. 37-74.

Acemoglu, D., David Autor, David Dorn, Gordon H. Hanson and Brendan Price (2014), "Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing," *American Economic Review*, Vol. 104, No. 5, pp. 394-399.

Acharya, R. (2016) "ICT Use and Total Factor Productivity Growth: Intangible Capital or Productive Externalities?", *Oxford Economic Papers,* Vol. 68, pp. 16-39.

Adalet McGowan, M., D. Andrews and V. Millot (2017) "Insolvency Regimes, Technology Diffusion and Productivity Growth: Evidence from Firms in OECD Countries," OECD Economics Department Working Papers, No. 1425, OECD Publishing, Paris, http://dx.doi.org/10.1787/36600267-en.

Adalet McGowan, M., D. Andrews and V. Millot (2017) "The Walking Dead? Zombie Firms and Productivity Performance in OECD Countries," OECD Economics Department Working Papers, No. 1372, OECD, http://dx.doi.org/10.1787/18151973.

Adler, Gustavo, Romain A. Duval, Davide Furceri, Sinem Kilic Celik, Ksenia Koloskova and Marcos Poplawski-Robeiro (2017) "Gone with the Headwinds: Global Productivity," IMF Staff Discussion Note, No. SDN/17/04, International Monetary Fund.

Aghion, P. and P. Howitt (1997) *Endogenous Growth Theory*, (Cambridge MIT Press).

Akerman, A., I. Gaarder and M. Mogstad (2013) "The Skill Complementarity of Broadband Internet," Discussion Paper, No. 7762, IZA Institute for the Study of Labor, Bonn, http://ftp.iza.org/dp7762.pdf.

Andrews, D. and C. Criscuolo (2013) "Knowledge-Based Capital, Innovation and Resource Allocation," OECD Economics Department Working Papers, No. 1046, OECD, Paris, http://dx.doi.org/10.1787/18151973.

Andrews, D., C. Criscuolo and P. Gal (2016) "The Best Versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy," OECD Productivity Working Papers, No. 5, OECD, Paris, http://dx.doi.org/10.1787/24139424.

Andrews, D., G. Nicoletti and C. Timiliotis (2018) "Digital Technology Diffusion: A Matter of Capabilities, Incentives or Both?," OECD Economics Department Working Papers, No. 1476, OECD Publishing, Paris, http://dx.doi.org/10.1787/7c542c16-en.

Aral, S., E. Brynjolfsson and D. Wu (2006) "Which Came First, it or Productivity? Virtuous Cycle of Investment and Use in Enterprise Systems," *SSRN Electronic Journal*, http://dx.doi.org/10.2139/ssrn.942291.

Aral, S., E. Brynjolfsson and L. Wu (2012) "Three-Way Complementarities: Performance Pay, Human Resource Analytics, and Information Technology," *Management Science*, Vol. 58, No. 5, pp. 913-931, http://dx.doi.org/10.1287/mnsc.1110.1460.

Arnold, J., G. Nicoletti and S. Scarpetta (2011) "Regulation, Resource Reallocation and Productivity Growth," *Nordic Economic Policy Review*, Vol. 2.

Bajgar, Matej, Giuseppe Berlingieri, Sara Calligaris, Chiara Criscuolo and Jonathan Timmis (2019) "Industry Concentration in Europe and North America," OECD Productivity Working Papers, No. 18.

Bartel, A., C. Ichniowski and K. Shaw (2007) "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills," *Quarterly Journal of Economics*, Vol. 122, No. 4, pp. 1721-1758, https://www.jstor.org/stable/pdf/25098887.

Bartelsman, E. (2013) "ICT, Reallocation and Productivity," *Economic Papers*, No. 486, European Commission, http://dx.doi.org/10.2765/42751.

Bartelsman, E., G. Van Leeuwen and M. Polder (2017) "CDM Using a Cross-country Micro Moments Database," *Economics of Innovation and New Technology,* Vol. 26, No. 1-2, pp. 168-182, http://dx.doi.org/10.1080/10438599.2016.1202517.

Basu, S. et al. (2003) "The Case of the Missing Productivity Growth, or Does Information Technology Explain Why Productivity Accelerated in the United States but Not in the United Kingdom?,"NBER Working Papers 11441, https://www.nber.org/chapters/c11441.pdf.

Berlingieri, G. et al. (2017) "Firm-level Productivity Differences: Insights from the OECD's MultiProd Project," *International Productivity Monitor*, Vol. 32, http://www.csls.ca/ipm/32/Berlingieri_Blanchenay_Calligaris_Criscuolo%20Version%202.pdf.

Berlingieri, G. et al. (2018) "Last but not Least: Laggard Firms, Technology Diffusion and its Structural and Policy Determinants," OECD Directorate for Science, Technology and Innovation, https://one.oecd.org/document/DSTI/CIIE(2018)11/en/pdf.

Black, S. (2001) "How to Compete: The Impact of Workplace Practices and Information Technology on Productivity," *Review of Economics and Statistics,* Vol. 83, No. 3, pp. 434-445.

Bloom, N. (2017) "What Drives Differences in Management?" *American Economic Review*, Vol. 104 no. 5, pp. 394-99,.

Bloom, N. and N. Pierri (2018) "Research: Cloud Computing Is Helping Smaller, Newer Firms Compete," *Harvard Business Review.*

Bloom, N., R. Sadun and J. Van Reenen (2012) *Americans do IT Better: US Multinationals and the Productivity Miracle*, http://dx.doi.org/10.1257/aer.102.1.167.

Bourlès, R. et al. (2013) "Do Product Market Regulations in Upstream Sectors Curb Productivity Growth? Panel Data Evidence for OECD Countries," *The Review of Economics and Statistics*, Vol. 95, No. 5, pp. 1750–1768, http://dx.doi.org/10.1162/REST_a_00338.

Brynjolffson, E. (1996) "Paradox Lost? Firm-level Evidence on the Returns to Information Systems Spending," *Management Science*, Vol. 42.

Brynjolfsson, E. and L. Hitt (2000) "Beyond Computation: Information Technology, Organizational Transformation and Business Performance", *Journal of Economic Perspectives*, Vol. 14, No. 4, pp. 23-48.

Brynjolfsson, E. and A. McAfee (2011) *Race Against the Machine : How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*, Digital Frontier Press.

Brynjolfsson, E. and A. McAfee (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, (New York: W. W. Norton Company).

Brynjolfsson, E. et al. (2008) "Scale without Mass: Business Process Replication and Industry Dynamics," Harvard Business School Technology Operations Mgt. Unit Research Paper, No. 07-016, http://ssrn.com/abstract=980568.

Brynjolfsson, E., D. Rock and C. Syverson (2017) "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics," NBER Working Paper, No. 24001, National Bureau of Economic Research, Cambridge, MA, http://dx.doi.org/10.3386/w24001.

Brynjolfsson, E., D. Rock and C. Syverson (2018) "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies," NBER Working Paper, No. 25148, http://www.nber.org/papers/w25148.

Bugamelli, M. and P. Pagano (2004) "Barriers to Investment in ICT," *Applied Economics*, Vol. 36, pp. 2275–2286.

Calligaris, S., C. Criscuolo and L. Marcolin (2018) "Mark-ups in the Digital Era," OECD Science, Technology and Industry Working Papers, No. 2018/10, OECD Publishing, Paris, http://dx.doi.org/10.1787/4efe2d25-en.

Calvino, F. and C. Criscuolo (2018) "Business Dynamics and Digitalisation," No. DSTI/CIIE(2018)14.

Calvino, F. et al. (2018) "A Taxonomy of Digital Intensive Sectors," OECD Science, Technology and Industry Working Papers, No. 2018/14, OECD Publishing, Paris, http://dx.doi.org/10.1787/f404736a-en.

Calvino, F., C. Criscuolo and C. Menon (2015) "Cross-country Evidence on Start-up Dynamics," OECD Science, Technology and Industry Working Papers, No. 2015/6, OECD Publishing, Paris, http://dx.doi.org/10.1787/5jrxtkb9mxtb-en.

Calvino, F., C. Criscuolo and R. Verlhac (2018) "Declining Business Dynamism: Evidence and Causes," No. DSTI/CIIE/WPIA(2018)6, OECD Directorate for Science, Technology and Innovation.

Castiglione, C. (2012) "Technical Efficiency and ICT Investment in Italian Manufacturing Firms," *Applied Economics 44*, Vol. 14.

Cette, G., J. Fernald and B. Mojon (2016) "The Pre-Great Recession Slowdown in Productivity," *European Economic Review*, http://dx.doi.org/10.1016/j.euroecorev.2016.03.012.

Cette, G., J. Lopez and J. Mairesse (2017) "Upstream Product Market Regulations, ICT, R&D and Productivity," *Review of Income and Wealth*, http://dx.doi.org/10.1111/roiw.12252.

Chevalier, C. and A. Luciani (2018) "Computerization, Labor Productivity and Employment: Impacts Across Industries Vary with Technological Level," *Documents de travail de la Direction des Études et Synthèses Économiques*, No. G2018/02, Institut National de la Statistique et des Études Économiques, http://www.epsilon.insee.fr/jspui/bitstream/1/77075/1/g1802.pdf.

Comin, D. and M. Mestieri (2018) "If Technology Has Arrived Everywhere, Why Has Income Diverged?" *American Economic Journal: Macroeconomics*, Vol. 10, No. 3, pp. 137-178.

Conway, P. et al. (2006) "Regulation, Competition and Productivity Convergence," OECD Economics Department Working Papers, No. 509, OECD Publishing, Paris, http://dx.doi.org/10.1787/431383770805.

Conway, P. and G. Nicoletti (2006) "Product Market Regulation in the Non-Manufacturing Sectors of OECD Countries: Measurement and Highlights," OECD Economics Department Working Papers, No. 530, OECD Publishing, Paris, http://dx.doi.org/10.1787/362886816127.

Corrado, C., J. Haskel and C. Jona-Lasinio (2017) "Knowledge Spillovers, ICT and Productivity Growth," *Oxford Bulletin of Economics and Statistics*, Vol. 79, No. 4, pp. 592-618.

De Stefano, T., R. Kneller and J. Timmis (2014) "The (Fuzzy) Digital Divide: The Effect of Broadband Internet Use on UK Firm Performance," Discussion Papers, No. 14, No. 6, University of Nottingham, School of Economics, https://www.nottingham.ac.uk/economics/documents/discussion-papers/14-06.pdf.

Decker, R. et al. (2018) "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," Finance and Economics Discussion Series, No. 2018-007, : Board of Governors of the Federal Reserve System, Washington D.C., http://dx.doi.org/10.17016/FEDS.2018.007.

Decker, R. et al. (2016) "Declining Business Dynamism: Implications for Productivity?".

Dedrick, J., V. Gurbaxani and K. Kraemer (2003) "Information Technology and Economic Performance: A Critical Review of the Empirical Evidence," *ACM Computing Surveys*, Vol. 35, No. 1, pp. 1-28.

DeStefano, T., K. De Backer and L. Moussiegt (2017) "Determinants of Digital Technology Use by Companies," OECD Science, Technology and Innovation Policy Papers, No. 40, OECD, https://www.oecd-ilibrary.org/docserver/a9b53784-en.pdf.

DeStefano, T., R. Kneller and J. Timmis (2019) *Cloud Computing and Firm Growth*, forthcoming.

DeStefano, T., R. Kneller and J. Timmis (2018) "Broadband Infrastructure, ICT Use and Firm Performance: Evidence for UK Firms," *Journal of Economic Behavior Organization*, Vol. 155, pp. 110-139.

Dhyne, E. et al. (2018) "IT and Productivity : A Firm Level Analysis", *Working Paper Research*, No. 346, National Bank of Belgium, https://www.nbb.be/doc/oc/repec/reswpp/wp346en.pdf.

Dinlersoz, E. (2018) "The Productivity Gap between Europe and the United States: Trends and Causes," U.S. Census Bureau, Center for Economic Studies Working Paper.

Draca, M., R. Sadun and J. Van Reenen (2009) "Productivity and ICTs: A Review of the Evidence," in *The Oxford Handbook of Information and Communication Technologies*, http://dx.doi.org/10.1093/oxfordhb/9780199548798.003.0005.

Égert, B. and I. Wanner (2016) "Regulations in Services Sectors and Their Impact on Downstream Industries: The OECD 2013 Regimpact Indicator," OECD Economics Department Working Papers, No. 1303, OECD Publishing, Paris, http://dx.doi.org/10.1787/5jlwz7kz39q8-en.

Engelstätter, B. (2009) "Enterprise Systems and Labor Productivity: Disentangling Combination Effects," *ZEW Discussion Papers*, No. 09-040, Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim, https://www.econstor.eu/bitstream/10419/27764/1/607848766.PDF.

Evangelista, R., P. Guerrieri and V. Meliciani (2014) "The Economic Impact of Digital Technologies in Europe," *Economics of Innovation and New Technology*, Vol. 23, No. 8, pp. 802-824.

Gal, P. (2013) "Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS," OECD Economics Department Working Papers, No. 1049, OECD Publishing, Paris, http://dx.doi.org/10.1787/5k46dsb25ls6-en.

Gopinath, G. et al. (2017) "Capital Allocation and Productivity in South Europe," *Quarterly Journal of Economics*, Vol. 132, No 4, pp. 1915-1967.

Griffith, R., S. Redding and H. Simpson (2006) "Technological Catch-up and the Role of Multinationals," CEPR Discussion Paper, No. 3765, http://www.princeton.edu/~reddings/papers/GriffithReddingSimpson.pdf.

Gust, C. and J. Marquez (2004) "International Comparisons of Productivity Growth: The Role of Information Technology and Regulatory Practices," *Labour Economics*, Vol. 11, No. 1, pp. 33-58.

Hagsten, E. et al. (2013) "The Multifaceted Nature of ICT: Final Report of the ESSnet on Linking of Microdata to Analyse ICT Impact," Statistics Sweden and Eurostat, https://ec.europa.eu/eurostat/documents/341889/725524/2013-esslait-final-report-final.pdf.

Hall, B., F. Lotti and J. Mairesse (2012) "Evidence on the Impact of R&D and ICT Investment on Innovation and Productivity in Italian Firms," NBER Working Paper, No. 18053, http://www.nber.org/papers/w18053.

Hunton, J., B. Lippincott and J. Reck (2003) "Enterprise Resource Planning Systems: Comparing Firm Performance of Adopters and Non-adopters," *International Journal of Accounting Information Systems*, Vol. 4, pp. 165-184.

Inklaar, R. and M. Timmer (2014) "The Relative Price of Services," *Review of Income and Wealth*, http://dx.doi.org/10.1111/roiw.12012.

Marcolin, L., S. Miroudot and M. Squicciarini (2016) "The Routine Content of Occupations: New Cross-country Measures Based on PIAAC," OECD Science, Technology and Industry Working Papers, No. 2016/2, OECD Publishing, Paris, http://dx.doi.org/10.1787/5jm0q1dhszjg-en.

Mohnen, P., M. Polder and G. Van Leeuwen (2018) "R&D and Organizational Innovation: Exploring Complementarities in Investment and Production," NBER Working Paper, No. 25044, http://www.nber.org/papers/w25044.

Munch, J. et al. (2018), Technological Change and Its Implications for the Labor Market, Productivity and the Nature of Work, Mimeo.

Nicolau, A. (2005) "Organizational Performance Effects of ERP Systems Usage: The Impact of Post-implementation Changes", *International Journal of Accounting Information Systems*, Vol. 7, pp. 18-35.

Nicolau, A. (2005) "Organizational Performance Effects of ERP Systems Usage: The Impact of Post-implementation Changes," *International Journal of Accounting Information Systems*, Vol. 7, pp. 18-35.

Nicoletti, G. and S. Scarpetta (2003) "Regulation, Productivity and Growth: OECD Evidence," *Economic Policy*, Vol. 18, No. 36, pp. 9-72.

OECD (2017) *OECD Digital Economy Outlook 2017*, OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264276284-en.

OECD (2018) *Skills for Jobs database*, OECD Publishing, Paris.

Pellegrino, B. (2017) "Diagnosing the Italian Disease," NBER Working Paper, Vol. 23964.

Sorbe, S. et al. (2019) "Digital Dividend: Policies to Harness the Productivity Potential of Digital Technologies," OECD Economic Policy Papers, No. 26, OECD Publising, Paris.

Syverson, C. (2011) "What Determines Productivity?" *Journal of Economic Literature*, http://dx.doi.org/10.1257/jel.49.2.326.

Van Ark, B. (2008) "The Productivity Gap between Europe and the United States: Trends and Causes," *Journal of Economic Perspectives*, Vol. 22, No. 1, pp. 25-44.

Van Ark, B. and R. Inklaar (2006) "Catching up or Getting Stuck? Europe's Trouble to Exploit ICT's Productivity Potential," Research Memorandum, No. GD-79, University of Groningen, https://www.rug.nl/research/portal/files/2856698/gd79online.pdf.

Van Ark, B., M. O'Mahony and M. Timmer (2008) "The Productivity Gap between Europe and the United States: Trends and Causes," *Journal of Economic Perspectives*, http://dx.doi.org/10.1257/jep.22.1.25.

Wieder, B. et al. (2006) "The Impact of ERP Systems on Firm and Business Process Performance," *Journal of Enterprise Information Management*, Vol. 19, No. 1, pp. 13-29.

Wooldridge, J. (2009) "On Estimating Firm-level Production Functions Using Proxy Variables to Control for Unobservables", *Economics Letters*, Vol. 104, No. 3, pp. 112-114.

Online Appendix for "Digitalization and Productivity: In Search of the Holy Grail Firm-level Empirical Evidence from European Countries"

Peter Gal, Giuseppe Nicoletti, Christina von Rüden, Stéphane Sorbe
OECD
Théodore Renault
Graduate Institute of International and development Studies[1]

1 The main article is available at http://www.csls.ca/ipm/37/OECD.pdf.

Appendix A. Description of the data and variables used

Table A1: Description of variables and sources

	Description	Coverage	Dimension used in analysis	Source	Link
Digital Technologies					
High-speed Broadband	Maximum contracted download speed of the fastest internet connection is at least 30 Mb/s (e_ispdf_ge30)	2014-2016	Sector, Country	Eurostat - Digital economy and society statistics - households and individuals	http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
CC	Buy cloud computing services used over the internet (E_CC)	2014-2016	Sector, Country	Eurostat - Digital economy and society statistics - households and individuals	http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
ERP	Enterprises who have ERP software package to share information between different functional areas (E_ERP1)	2010; 2012-15	Sector, Country, (Time)	Eurostat - Digital economy and society statistics - households and individuals	http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
CRM	Enterprises using software solutions like Customer Relationship Management (CRM)	2010; 2014-2015	Sector, Country	Eurostat - Digital economy and society statistics - households and individuals	http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
CC complex	Buy high CC services (accounting software applications, CRM software, computing power)(E_CC_HI)	2014-2016	Sector, Country	Eurostat - Digital economy and society statistics - households and individuals	http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
SCM	Automatic linking of enterprises to their suppliers and/or customers application	2010-15	Sector, Country, Time	Eurostat - Digital economy and society statistics - households and individuals http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database	
Firm-level variables					
Frontier growth	Average growth of the top 5 percent firms in each sector-year cell	2009-2015	Sector, Time	ORBIS, based on Bureau van Dijk (BvD)	N.A.
Gap to frontier	Firms' lagged distance to the frontier	2009-2015	Firm, Sector, Country, Time	ORBIS, based on Bureau van Dijk (BvD)	N.A.
Age	Firms' age	2009-2015	Firm, Sector, Country, Time	ORBIS, based on Bureau van Dijk (BvD)	N.A.
Employees	Firms' number of employees (log)	2009-2015	Firm, Sector, Country, Time	ORBIS, based on Bureau van Dijk (BvD)	N.A.
Intangibles	Stock of intangible capital (log)	2009-2015	Firm, Sector, Country, Time	ORBIS, based on Bureau van Dijk (BvD)	N.A.
Capex	Capital expenditures (log)	2009-2015	Firm, Sector, Country, Time	ORBIS, based on Bureau van Dijk (BvD)	N.A.
Other					
Routine tasks	Routine content intensity (US)	2010-15	Sector	Marcolin et al. (2016), based on the OECD Programme for the International Assessment of Adult Competencies (PIAAC) and European Labour Force Survey (1995-2015).	
Knowledge Intensity	Share of labour compensation of personnel with tertiary education (US)	1995-2000	Sector	OECD (2013)	http://dx.doi.org/10.1787/9789264193307-en
Occupational shortages	General skill shortage	2011-15	Sector, Country	OECD, 2018	http://dx.doi.org/10.1787/9789264277878-en.
Resource management skills	Ability to allocate resources efficiently	2011-15	Sector, Country	OECD, 2018	http://dx.doi.org/10.1787/9789264277878-en.
Management of personnel resources	Ability of managers to motivate, develop and direct people as they work, and identify the best people for each job	2011-15	Sector, Country	OECD, 2018	http://dx.doi.org/10.1787/9789264277878-en.
Computer and electronics	Knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming	2011-15	Sector, Country	OECD, 2018	http://dx.doi.org/10.1787/9789264277878-en.
Technical skills	Worker's capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems	2011-15	Sector, Country	OECD, 2018	http://dx.doi.org/10.1787/9789264277878-en.

Table A2: Country coverage

Austria	Belgium	Denmark	Estonia	Finland
France	Germany	Greece	Hungary	Ireland
Italy	Latvia	Netherlands	Poland	Portugal
Slovenia	Spain	Sweden	Turkey	United Kingdom

Table A3: Average adoption rates by sector (2010-2016)

NACE Rev 2	Description	ERP	CRM	CC	CC (complex)
10-12	Manufacture of beverages, food and tobacco products	0.271245	0.188223	0.179248	0.099456
13-15	Manufacture of textiles, wearing apparel, leather and related products	0.308204	0.212234	0.181328	0.084579
16-18	Manufacture of wood & products of wood & cork, except furniture; articles of straw & plaiting materials; paper & paper products; printing & reproduction of recorded media	0.291412	0.26719	0.188538	0.090067
19-23	Manufacture of coke, refined petroleum, chemical & basic pharmaceutical products, rubber & plastics, other non-metallic mineral products	0.42955	0.326845	0.227648	0.112065
24-25	Manufacture of basic metals & fabricated metal products excluding machines & equipments	0.333373	0.248728	0.178942	0.080149
26	Manufacture of computer, electronic and optical products	0.556172	0.447013	0.278731	0.147594
27-28	Manufacture of electrical equipment, machinery and equipment n.e.c.	0.455789	0.352506	0.187869	0.086747
29-30	Manufacture of motor vehicles, trailers and semi-trailers, other transport equipment	0.501986	0.276797	0.212032	0.095408
31-33	Manufacture of furniture and other manufacturing; repair and installation of machinery and equipment	0.272652	0.228846	0.191396	0.094772
35_39	Electricity, gas, steam, air conditioning and water supply	0.341647	0.32225	0.259049	0.133773
41_43	Construction	0.156103	0.144789	0.199024	0.112612
45	Trade of motor vehicles and motorcycles	0.301579	0.427382	0.182405	0.115079
46	Wholesale trade, except of motor vehicles and motorcycles	0.402495	0.393588	0.235896	0.130059
47	Retail trade, except of motor vehicles and motorcycles	0.22922	0.238353	0.177975	0.103962
49_53	Transportation and storage	0.198024	0.203841	0.195679	0.103173
55_56	Accommodation and Food and beverage service activities	0.111989	0.16216	0.165641	0.104095
58-60	Publishing activities; motion picture, video & television programme production, sound recording & music publishing; programming & broadcasting	0.330037	0.42285	0.385612	0.247627
61	Telecommunications	0.480137	0.659599	0.389523	0.254364
62-63	Computer programming, consultancy and related activities, information service activities	0.445565	0.605442	0.555143	0.402173
68	Real estate activities	0.225138	0.284749	0.256101	0.153134
69-74	Professional, scientific and technical activities	0.256945	0.333358	0.337497	0.203696
77-82	Administrative and support service activities	0.199038	0.279514	0.250756	0.161046

This table reports average adoption rates across industries for a set of 20 countries over the time period 2010-2016 (depending on data availability).
Source: based on Eurostat, Digital Economy and Society (database), http://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensivedatabase (accessed September 2017).

Table A4: Correlations across digital technologies

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)
High-speed broadband	1				
Enterprise Resource Planning	0.152***	1			
Customer Relationship Management	0.3252***	0.5318***	1		
Cloud Computing	0.2312***	0.0744***	0.4108***	1	
Cloud Computing (complex)	0.1331***	0.0791***	0.4582***	0.762***	1

Note: ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively. Estimates are purged of country and industry fixed effects.

Table A5: Principal Component Analysis

Panel A: Eigenvalue

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.05223	1.93051	0.6104	0.6104
Comp2	1.12172	0.547131	0.2243	0.8348
Comp3	0.574586	0.375566	0.1149	0.9497
Comp4	0.19902	0.146568	0.0398	0.9895
Comp5	0.0524514	.	0.0105	1

Panel B: Eigenvector

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)
1st principal component	0.4207	0.3088	0.4816	0.4917	0.5039

Table A6: The correlation between skill shortages and digital adoption

	Computer skills	Technical skills	Management of Personnel Resources	Resource Management skills
High-speed broadband	0.0645***	0.079***	0.0894***	0.0932***
Enterprise Resource Planning	-0.0807***	-0.0918**	-0.0602***	-0.0557***
Customer Relationship Management	-0.0484***	-0.0399***	-0.04***	-0.036***
Cloud Computing	0.0529***	0.0555***	0.0413***	0.0415***
Cloud Computing (complex)	0.0097***	-0.0096***	-0.023**	-0.0208***

Note: ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively. Estimates are purged of country and industry fixed effects.

Appendix B. Additional regression results

Table B1: Cross-sectional regression (2014-15)

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.0485	0.0543	0.0554	0.0626	0.0711	0.0598
	(0.0435)	(0.0431)	(0.0432)	(0.0442)	(0.0452)	(0.0453)
Gap to frontier	0.102***	0.102***	0.103***	0.0995***	0.102***	0.102***
(lagged)	(0.0126)	(0.0126)	(0.0126)	(0.0120)	(0.0121)	(0.0129)
Age	-0.000350***	-0.000357***	-0.000342***	-0.000315***	-0.000356***	-0.000358***
	(6.30e-05)	(6.22e-05)	(6.27e-05)	(5.79e-05)	(6.14e-05)	(6.53e-05)
Employees (log)	0.0202***	0.0203***	0.0205***	0.0195***	0.0208***	0.0211***
	(0.00287)	(0.00287)	(0.00287)	(0.00272)	(0.00274)	(0.00290)
Digital	0.175***	0.119***	0.195***	0.158***	0.0668	0.0167***
Technologies	(0.0454)	(0.0364)	(0.0327)	(0.0455)	(0.0494)	(0.00347)
Observations	470,813	474,425	476,635	476,480	467,091	443,077
R-squared	0.059	0.059	0.060	0.057	0.058	0.059

Note: This table reports the estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), and the average country-sector level adoption rates of individual digital technologies. The last column shows results for the 1st principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2014-15 for firms with more than 10 employees. Unweighted averages of each digital technology variable are used over the period 2014-15. ***, ** and * represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B2: Robustness to endogeneity concerns

Dependent variable: MFP growth. Digital technology: ERP software				
	Lagged adoption rate	Initial (2010) adoption rate	Lagged adoption rate (by prod. quartile)	Initial adoption rate (by prod. quartile)
Frontier growth	0.118**	0.124***	0.109**	0.110***
	(0.0500)	(0.0352)	(0.0495)	(0.0351)
Gap to frontier (lagged)	0.0931***	0.0990***	0.0723***	0.0725***
	(0.00508)	(0.0116)	(0.00871)	(0.0191)
Age	-0.000341***	-0.000335***	-0.000324***	-0.000324***
	(3.29e-05)	(5.88e-05)	(3.04e-05)	(5.13e-05)
Employees (log)	0.0170***	0.0199***	0.0180***	0.0179***
	(0.00119)	(0.00261)	(0.000908)	(0.00171)
ERP	0.0410**	0.0479**		
	(0.0197)	(0.0228)		
Quartile 2 (dummy)			-0.0608***	-0.0585***
			(0.00630)	(0.0126)
Quartile 3 (dummy)			-0.0659***	-0.0627***
			(0.00930)	(0.0192)
Quartile 4 (dummy)			-0.0799***	-0.0744***
			(0.0133)	(0.0281)
ERP (Quartile 1)			-0.0424*	-0.0330
			(0.0248)	(0.0305)
ERP (Quartile 2)			0.0438**	0.0574**
			(0.0214)	(0.0232)
ERP (Quartile 3)			0.0529***	0.0644**
			(0.0205)	(0.0251)
ERP (Quartile 4)			0.0698***	0.0746***
			(0.0200)	(0.0265)
Observations	1,182,855	1,226,046	1,182,855	1,184,608
R-squared	0.055	0.058	0.058	0.057

Note: This table reports estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees) and a digital adoption variable. The adoption variable in this table always relates to ERP software (time variation not being available for the other variables in the sample). Results are presented for the the adoption rate lagged by one year (column 1) and the initial adoption rate in the sample (year 2010, column 2). In the last two columns, the digital adoption variable is interacted with a dummy for each productivity quartile, as in Table 6. All regressions include sector and country-year fixed effects and are clustered at the country-sector level (except columns 1 and 3, which are clustered at the country-industry-year level since the digital variable varies at this level in these cases). Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B3: Replacing routine intensity with knowledge intensity

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.222***	0.212***	0.218***	0.213***	0.230***	0.235***
	(0.0382)	(0.0374)	(0.0379)	(0.0373)	(0.0381)	(0.0392)
Gap to frontier (lagged)	0.104***	0.104***	0.105***	0.104***	0.107***	0.108***
	(0.0118)	(0.0114)	(0.0117)	(0.0115)	(0.0118)	(0.0127)
Age	-0.000304***	-0.000306***	-0.000295***	-0.000303***	-0.000372***	-0.000373***
	(5.89e-05)	(5.49e-05)	(5.86e-05)	(5.63e-05)	(5.75e-05)	(6.24e-05)
Employees (log)	0.0216***	0.0216***	0.0221***	0.0218***	0.0233***	0.0235***
	(0.00275)	(0.00267)	(0.00274)	(0.00269)	(0.00277)	(0.00297)
Digital technology	0.114*	0.121*	0.282***	0.202***	0.113	0.0309***
	(0.0642)	(0.0719)	(0.0625)	(0.0708)	(0.134)	(0.00633)
Digital technology	0.0476	-0.0554	-0.234*	-0.232**	-0.121	-0.0263***
# knowledge intensity	(0.0920)	(0.144)	(0.129)	(0.109)	(0.199)	(0.00892)
Observations	1,453,519	1,503,462	1,485,781	1,505,867	1,435,145	1,348,670
R-squared	0.062	0.062	0.063	0.062	0.064	0.064

Note: This table reports estimates of the baseline equation augmented with an interaction between digital technologies and knowledge intensity, defined as the share of labour compensation of personnel with tertiary education (see Annex A). All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the 1st principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15 and routine intensity refers to the average over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B4: Assessing the effects of skill shortages and routine intensity simultaneously

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.162***	0.133***	0.147***	0.142***	0.138***	0.150***
	(0.0377)	(0.0385)	(0.0380)	(0.0382)	(0.0381)	(0.0382)
Gap to frontier (lagged)	0.107***	0.105***	0.107***	0.106***	0.106***	0.107***
	(0.0137)	(0.0131)	(0.0134)	(0.0131)	(0.0130)	(0.0141)
Age	-0.000391***	-0.000394***	-0.000395***	-0.000394***	-0.000404***	-0.000404***
	(6.31e-05)	(6.21e-05)	(6.33e-05)	(6.17e-05)	(6.26e-05)	(6.79e-05)
Employees (log)	0.0230***	0.0227***	0.0234***	0.0228***	0.0229***	0.0233***
	(0.00312)	(0.00298)	(0.00308)	(0.00299)	(0.00297)	(0.00321)
Occupational shortage	-0.0372***	-0.0234	-0.0247**	-0.0223	-0.0215	-0.0269**
	(0.0130)	(0.0148)	(0.0117)	(0.0142)	(0.0145)	(0.0126)
Digital technology	0.147***	0.0310	0.207***	0.118**	0.0487	0.0216***
	(0.0491)	(0.0501)	(0.0429)	(0.0507)	(0.0848)	(0.00478)
Occupational shortage X digital technology	-0.306***	-0.110	-0.228**	0.00283	-0.158	-0.0129**
	(0.0861)	(0.111)	(0.0940)	(0.0663)	(0.0995)	(0.00537)
Routine intensity x digital technology	-0.130*	0.334***	0.369***	0.198**	0.0397	0.0199**
	(0.0706)	(0.102)	(0.114)	(0.0855)	(0.154)	(0.00780)
Observations	1,090,287	1,125,495	1,112,295	1,133,648	1,134,856	1,065,403
R-squared	0.063	0.062	0.063	0.063	0.062	0.063

Note: This table reports the estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), average country-sector level adoption rates of individual digital technologies, an index capturing sector-level general occupational shortages, their interaction with the digital adoption variable, and an interaction between digital technology and routine intensity. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the 1st principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2011-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database

Table B5: Baseline estimates controlling for additional variables

Panel A: controlling for intangible capital

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.220***	0.211***	0.218***	0.214***	0.231***	0.238***
	(0.0384)	(0.0373)	(0.0378)	(0.0377)	(0.0383)	(0.0394)
Gap to frontier (lagged)	0.103***	0.103***	0.104***	0.103***	0.107***	0.107***
	(0.0131)	(0.0127)	(0.0129)	(0.0127)	(0.0132)	(0.0140)
Age	-0.000292***	-0.000292***	-0.000279***	-0.000291***	-0.000358***	-0.000358***
	(6.21e-05)	(5.83e-05)	(6.11e-05)	(5.98e-05)	(6.12e-05)	(6.63e-05)
Employees (log)	0.0198***	0.0198***	0.0201***	0.0198***	0.0218***	0.0221***
	(0.00289)	(0.00279)	(0.00285)	(0.00281)	(0.00288)	(0.00307)
Digital technology	0.139***	0.111***	0.172***	0.0795*	0.0404	0.0161***
	(0.0342)	(0.0371)	(0.0349)	(0.0427)	(0.0542)	(0.00382)
Intangible capital stock (log)	0.00159***	0.00155***	0.00154***	0.00165***	0.00148***	0.00136***
	(0.000413)	(0.000402)	(0.000404)	(0.000404)	(0.000437)	(0.000457)
Observations	1,229,670	1,269,595	1,255,462	1,270,278	1,203,570	1,136,071
R-squared	0.062	0.062	0.062	0.062	0.064	0.064

Panel B: controlling for capital expenditures

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.201***	0.195***	0.201***	0.198***	0.216***	0.219***
	(0.0433)	(0.0420)	(0.0424)	(0.0426)	(0.0430)	(0.0441)
Gap to frontier (lagged)	0.102***	0.102***	0.103***	0.102***	0.106***	0.106***
	(0.0138)	(0.0135)	(0.0138)	(0.0135)	(0.0139)	(0.0147)
Age	-0.000399***	-0.000392***	-0.000383***	-0.000395***	-0.000494***	-0.000495***
	(7.94e-05)	(7.55e-05)	(7.83e-05)	(7.71e-05)	(8.20e-05)	(8.79e-05)
Employees (log)	0.0183***	0.0181***	0.0186***	0.0181***	0.0198***	0.0200***
	(0.00269)	(0.00261)	(0.00267)	(0.00264)	(0.00270)	(0.00284)
Capital expenditures (log)	0.00207***	0.00220***	0.00214***	0.00226***	0.00240***	0.00225***
	(0.000651)	(0.000632)	(0.000638)	(0.000641)	(0.000679)	(0.000698)
Digital technology	0.137***	0.110***	0.182***	0.0638	0.0137	0.0149***
	(0.0392)	(0.0401)	(0.0359)	(0.0473)	(0.0651)	(0.00404)
Observations	512,728	528,586	523,247	528,936	497,239	470,143
R-squared	0.065	0.065	0.066	0.065	0.068	0.068

Panel C: controlling for omitted variables bias

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.169***	0.152***	0.161***	0.161***	0.163***	0.171***
	(0.0436)	(0.0432)	(0.0430)	(0.0436)	(0.0437)	(0.0444)
Gap to frontier (lagged)	0.102***	0.102***	0.103***	0.102***	0.103***	0.103***
	(0.0166)	(0.0162)	(0.0166)	(0.0162)	(0.0162)	(0.0171)
Age	-0.000492***	-0.000473***	-0.000479***	-0.000482***	-0.000501***	-0.000502***
	(9.56e-05)	(9.35e-05)	(9.53e-05)	(9.27e-05)	(9.44e-05)	(0.000101)
Employees (log)	0.0213***	0.0210***	0.0216***	0.0211***	0.0217***	0.0216***
	(0.00329)	(0.00325)	(0.00335)	(0.00325)	(0.00322)	(0.00341)
Regulatory impact	0.0114	0.0132	0.0303	0.0471	0.0224	0.0397
	(0.0454)	(0.0485)	(0.0424)	(0.0530)	(0.0503)	(0.0484)
Occupational shortage	-0.0353***	-0.0311**	-0.0266**	-0.0344**	-0.0318**	-0.0333**
	(0.0132)	(0.0136)	(0.0127)	(0.0138)	(0.0143)	(0.0132)
Capex (log)	0.00164**	0.00175**	0.00167**	0.00178**	0.00176**	0.00170**
	(0.000767)	(0.000748)	(0.000756)	(0.000751)	(0.000754)	(0.000785)
Digital Technology	0.164***	0.0695	0.214***	0.0861*	-0.0458	0.0162***
	(0.0533)	(0.0508)	(0.0510)	(0.0487)	(0.0848)	(0.00494)
Observations	343,890	352,794	348,719	355,672	354,379	335,739
R-squared	0.067	0.067	0.068	0.067	0.067	0.067

Note: These tables report estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), augmented with the firm-level stock of intangible capital (Panel A), firm-level capital expenditures (Panel B), or a set of control variable accounting for the potential omitted variables bias (i.e. impact of regulatory barriers to competition, firm-level capital expenditures, and occupational shortages). The indicator of regulatory impact quantifies the potential costs of anti-competitive regulations in non-manufacturing sectors on all industries the United States that use the output of these sectors as intermediate inputs (see Égert and Wanner, 2016). The 1^{st} principal component is based on the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database and the OECD Indicators of Product Market Regulations.

Table B6: Digital technology productivity benefits are diminished by technical and managerial skill shortages

Panel A: Testing for the effect of different skill shortages on the returns from high speed broadband

Dependent variable: MFP growth	Resource Management Skills	Management of Personnel Resources	Computers and Electronics	Technical Skills
Frontier growth	0.159***	0.160***	0.155***	0.152***
	(0.0372)	(0.0373)	(0.0368)	(0.0369)
Gap to frontier (lagged)	0.105***	0.105***	0.105***	0.105***
	(0.0133)	(0.0133)	(0.0132)	(0.0132)
Age	-0.000392***	-0.000392***	-0.000393***	-0.000394***
	(6.31e-05)	(6.31e-05)	(6.32e-05)	(6.30e-05)
Employees (log)	0.0227***	0.0227***	0.0227***	0.0227***
	(0.00303)	(0.00303)	(0.00303)	(0.00301)
High-speed broadband	0.164***	0.164***	0.149***	0.151***
	(0.0435)	(0.0429)	(0.0446)	(0.0443)
Skill shortage	-0.273***	-0.227***	-0.197***	-0.339***
	(0.0724)	(0.0597)	(0.0539)	(0.124)
Skill shortage	-1.020**	-0.898**	-0.705**	-2.236***
# High-speed broadband	(0.435)	(0.371)	(0.318)	(0.645)
Observations	1,106,487	1,106,487	1,106,487	1,106,487
R-squared	0.062	0.062	0.062	0.062

Panel B: The role of knowledge about computers and electronics for productivity returns

Dependent variable: MFP growth	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.155***	0.134***	0.145***	0.142***	0.142***	0.152***
	(0.0368)	(0.0374)	(0.0369)	(0.0376)	(0.0374)	(0.0374)
Gap to frontier (lagged)	0.105***	0.104***	0.106***	0.105***	0.105***	0.106***
	(0.0132)	(0.0126)	(0.0130)	(0.0126)	(0.0126)	(0.0135)
Age	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0004***
	(6.32e-05)	(6.16e-05)	(6.27e-05)	(6.12e-05)	(6.15e-05)	(6.69e-05)
Employees (log)	0.0227***	0.0224***	0.0230***	0.0226***	0.0229***	0.0231***
	(0.00303)	(0.00289)	(0.00298)	(0.00289)	(0.00290)	(0.00310)
Digital Technology	0.149***	0.0584	0.195***	0.103**	0.0252	0.0166***
	(0.0446)	(0.0438)	(0.0406)	(0.0436)	(0.0668)	(0.00419)
Computers and electronics	-0.197***	-0.180***	-0.164***	-0.186***	-0.169***	-0.176***
skill shortage	(0.0539)	(0.0581)	(0.0508)	(0.0656)	(0.0635)	(0.0611)
Computers and electronics	-0.705**	0.141	-0.689*	0.0250	-0.287	-0.0363**
skill shortage	(0.318)	(0.360)	(0.352)	(0.202)	(0.244)	(0.0163)
# Digital Technology						
Observations	1,106,487	1,142,249	1,128,495	1,149,976	1,151,662	1,080,849
R-squared	0.062	0.062	0.062	0.062	0.062	0.062

Note: These tables reports the estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), average country-sector level adoption rates of individual digital technologies, an index capturing sector-level skill shortages, and their effect on the productivity returns from digitalisation. *Resource management skills* refer the ability to allocate resources efficiently; *management of personnel resources* identifies how well managers motivate, develop and direct people as they work, and identify the best people for each job; *computer and electronics* refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; and *technical skills* are associated with worker's capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems (see OECD (2018), for more information). Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2011-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B7: Interacting lagged gap with digital technologies

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.222***	0.211***	0.215***	0.215***	0.229***	0.235***
	(0.0382)	(0.0375)	(0.0382)	(0.0372)	(0.0381)	(0.0394)
Gap to frontier	0.104***	0.103***	0.103***	0.106***	0.107***	0.108***
(lagged)	(0.0114)	(0.0111)	(0.0113)	(0.00992)	(0.0116)	(0.0120)
Age	-0.000301***	-0.000308***	-0.000289***	-0.000294***	-0.000366***	-0.000355***
	(6.42e-05)	(5.45e-05)	(5.59e-05)	(5.42e-05)	(5.57e-05)	(5.94e-05)
Employees (log)	0.0216***	0.0214***	0.0219***	0.0222***	0.0234***	0.0235***
	(0.00273)	(0.00262)	(0.00268)	(0.00246)	(0.00272)	(0.00288)
Digital technology	0.149***	0.0761*	0.157***	0.0757*	0.0155	0.0139***
	(0.0425)	(0.0416)	(0.0361)	(0.0434)	(0.0593)	(0.00394)
Digital technology	-0.0192	-0.0827**	-0.0933**	-0.0853	-0.0816	-0.00763**
# Lagged gap	(0.0494)	(0.0378)	(0.0393)	(0.0523)	(0.0652)	(0.00323)
Observations	1,453,519	1,503,462	1,485,781	1,505,867	1,435,145	1,348,670
R-squared	0.062	0.063	0.064	0.063	0.064	0.065

Note: This table shows the results of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), augmented by an interaction term between digital technologies and the lagged gap to the frontier. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The 1^{st} principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B8: By productivity quartile without gap

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.174***	0.164***	0.170***	0.168***	0.181***	0.186***
	(0.0367)	(0.0358)	(0.0363)	(0.0363)	(0.0372)	(0.0384)
Age	-0.000309***	-0.000326***	-0.000312***	-0.000323***	-0.000398***	-0.000388***
	(4.75e-05)	(4.72e-05)	(4.75e-05)	(4.73e-05)	(4.75e-05)	(5.02e-05)
Employees (log)	0.0178***	0.0176***	0.0180***	0.0177***	0.0188***	0.0192***
	(0.00141)	(0.00136)	(0.00138)	(0.00140)	(0.00147)	(0.00154)
Quartile 2	-0.110***	-0.115***	-0.108***	-0.0767***	-0.0827***	-0.0879***
(dummy)	(0.00934)	(0.00779)	(0.00887)	(0.00682)	(0.00650)	(0.00492)
Quartile 3	-0.143***	-0.144***	-0.142***	-0.109***	-0.116***	-0.123***
(dummy)	(0.0113)	(0.0106)	(0.0114)	(0.00819)	(0.00786)	(0.00610)
Quartile 4	-0.207***	-0.210***	-0.208***	-0.170***	-0.178***	-0.186***
(dummy)	(0.0139)	(0.0143)	(0.0153)	(0.0111)	(0.0105)	(0.00803)
Digital (Quartile 1)	0.0694**	-0.0275	0.0780*	0.146***	0.108	0.00981**
	(0.0300)	(0.0412)	(0.0410)	(0.0531)	(0.0681)	(0.00387)
Digital (Quartile 2)	0.155***	0.0699*	0.154***	0.102**	0.0709	0.0142***
	(0.0305)	(0.0366)	(0.0316)	(0.0427)	(0.0585)	(0.00354)
Digital (Quartile 3)	0.155***	0.0559	0.152***	0.0962**	0.0673	0.0136***
	(0.0323)	(0.0347)	(0.0282)	(0.0396)	(0.0538)	(0.00311)
Digital (Quartile 4)	0.161***	0.0701**	0.165***	0.0914**	0.0593	0.0140***
	(0.0358)	(0.0336)	(0.0297)	(0.0401)	(0.0507)	(0.00314)
Observations	1,419,356	1,468,278	1,450,888	1,470,164	1,398,222	1,313,619
R-squared	0.057	0.056	0.057	0.056	0.056	0.057

Note: This table shows the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, age and size (measured by the number of employees), a dummy for each productivity quartile (omitting the first quartile for reference), and the interaction between digital technology adoption rates and each productivity quartile. Compared with the baseline equation the gap to the frontier is omitted from this regression. Quartile 1 refers to the bottom of the distribution (i.e. low productive firms), quartile 4 to the top. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The coefficient estimates of quartile 1 and 4 are always statistically different. The 1^{st} principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B9: The effects of digital adoption on productivity by size group

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.222***	0.211***	0.218***	0.215***	0.229***	0.236***
	(0.0383)	(0.0373)	(0.0378)	(0.0376)	(0.0381)	(0.0393)
Gap to frontier (lagged)	0.103***	0.103***	0.104***	0.103***	0.106***	0.107***
	(0.0116)	(0.0112)	(0.0115)	(0.0112)	(0.0116)	(0.0124)
Age	-0.000283***	-0.000288***	-0.000269***	-0.000281***	-0.000348***	-0.000346***
	(5.89e-05)	(5.57e-05)	(5.82e-05)	(5.71e-05)	(5.79e-05)	(6.30e-05)
Size class 2 (dummy)	0.0157***	0.0133***	0.0159***	0.0206***	0.0212***	0.0186***
	(0.00343)	(0.00424)	(0.00398)	(0.00349)	(0.00316)	(0.00275)
Size class 3 (dummy)	0.0490***	0.0318***	0.0451***	0.0516***	0.0558***	0.0486***
	(0.00727)	(0.00776)	(0.00800)	(0.00696)	(0.00656)	(0.00576)
Size class 4 (dummy)	0.0756***	0.0517***	0.0735***	0.0844***	0.0836***	0.0716***
	(0.00920)	(0.00831)	(0.00925)	(0.00927)	(0.00816)	(0.00724)
Digital (Size class 1)	0.142***	0.0753*	0.184***	0.110**	0.0906	0.0172***
	(0.0343)	(0.0425)	(0.0365)	(0.0463)	(0.0600)	(0.00409)
Digital (Size class 2)	0.149***	0.0909**	0.191***	0.0974**	0.0658	0.0169***
	(0.0347)	(0.0411)	(0.0347)	(0.0444)	(0.0559)	(0.00392)
Digital (Size class 3)	0.128***	0.121***	0.188***	0.0842*	0.0191	0.0156***
	(0.0359)	(0.0370)	(0.0351)	(0.0447)	(0.0572)	(0.00387)
Digital (Size class 4)	0.113***	0.128***	0.167***	0.0349	-0.0278	0.0126***
	(0.0385)	(0.0375)	(0.0360)	(0.0439)	(0.0565)	(0.00382)
Observations	1,453,519	1,503,462	1,485,781	1,505,867	1,435,145	1,348,670
R-squared	0.062	0.062	0.063	0.062	0.064	0.064

Note: This table shows the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, age and size (measured by the number of employees), a dummy for each size group (omitting the first group for reference), and the interaction between digital technology adoption rates and each size group. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. Compared with the baseline equation the gap to the frontier is omitted from this regression. Size group 1 captures firms with 10-20 employees, size group 2 firms from 21-50 employees, size group 3 firms with 51-250 employees, and size group 4 capture very large firms with more than 250 employees. In all cases, the coefficient estimates of size group 1 and 4 are statistically different. The 1^{st} principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B10: The effects of digital adoption on productivity by productivity quartile and size group

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.220***	0.205***	0.213***	0.210***	0.224***	0.231***
	(0.0391)	(0.0393)	(0.0400)	(0.0402)	(0.0404)	(0.0409)
Gap to frontier (lagged)	0.0985***	0.102***	0.102***	0.102***	0.107***	0.104***
	(0.0253)	(0.0251)	(0.0252)	(0.0248)	(0.0263)	(0.0270)
Age	-0.000503***	-0.000554***	-0.000518***	-0.000541***	-0.000684***	-0.000666***
	(9.24e-05)	(8.72e-05)	(8.91e-05)	(9.02e-05)	(9.46e-05)	(0.000101)
Employees (log)	0.00851***	0.00813***	0.00849***	0.00829***	0.0107***	0.0105***
	(0.00281)	(0.00266)	(0.00279)	(0.00280)	(0.00308)	(0.00312)
Dummy	-0.0650*	-0.0724*	-0.0817**	-0.0221	-0.0241	-0.0245
(High productive; Small)	(0.0352)	(0.0388)	(0.0389)	(0.0367)	(0.0367)	(0.0363)
Dummy	0.113***	0.0720***	0.109***	0.122***	0.119***	0.0852***
(Low productive; Large)	(0.0148)	(0.0174)	(0.0154)	(0.0122)	(0.0116)	(0.00720)
Dummy	-0.00980	-0.0287	-0.0156	0.0227	0.0213	0.0139
(High productive; Large)	(0.0337)	(0.0345)	(0.0366)	(0.0361)	(0.0364)	(0.0358)
Digital technology	0.126***	0.0236	0.0965**	0.0277	0.0165	0.00789
(Low productive; Small)	(0.0339)	(0.0514)	(0.0456)	(0.0758)	(0.0793)	(0.00490)
Digital technology	0.279***	0.205***	0.299***	0.0350	0.0898	0.0193***
(High productive; Small)	(0.0673)	(0.0573)	(0.0522)	(0.0624)	(0.0658)	(0.00468)
Digital technology	0.0352	0.0706	0.0110	-0.134	-0.316**	-0.00413
(Low productive; Large)	(0.0501)	(0.0811)	(0.0719)	(0.0985)	(0.137)	(0.00639)
Digital technology	0.216***	0.185***	0.210***	0.00977	-0.00122	0.0137***
(High productive; Large)	(0.0553)	(0.0455)	(0.0440)	(0.0565)	(0.0598)	(0.00448)
Observations	292,650	307,626	301,775	309,532	297,656	272,312
R-squared	0.083	0.084	0.084	0.082	0.084	0.085

Note: This table shows the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, age and size (measured by the number of employees), a dummy for each four different size/productivity groups (low productive and small; high productive and small; low productive and large; high productive and large),omitting the first group for reference, and the interaction between digital technology adoption rates and each group. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The 1^{st} principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table B11: Skill shortages disproportionately curb the returns from digitalisation in low productive firms

	Dependent variable: MFP growth					
	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	1st principal component
Frontier growth	0.136***	0.115***	0.125***	0.117***	0.119***	0.125***
	(0.0366)	(0.0372)	(0.0366)	(0.0370)	(0.0371)	(0.0385)
Gap to frontier (lagged)	0.0777***	0.0777***	0.0788***	0.0788***	0.0795***	0.0770***
	(0.0217)	(0.0206)	(0.0212)	(0.0209)	(0.0211)	(0.0216)
Age	-0.000355***	-0.000374***	-0.000366***	-0.000371***	-0.000387***	-0.000386***
	(5.09e-05)	(5.12e-05)	(5.09e-05)	(4.98e-05)	(5.08e-05)	(5.50e-05)
Employees (log)	0.0207***	0.0200***	0.0208***	0.0201***	0.0205***	0.0212***
	(0.00194)	(0.00186)	(0.00190)	(0.00183)	(0.00191)	(0.00203)
Digital (Quartile 1)	0.0969***	-0.0717	0.121**	0.168**	0.140	0.00602
	(0.0364)	(0.0519)	(0.0537)	(0.0695)	(0.108)	(0.00515)
Digital (Quartile 2)	0.208***	0.0470	0.201***	0.0839*	0.0336	0.0144***
	(0.0375)	(0.0448)	(0.0373)	(0.0464)	(0.0696)	(0.00407)
Digital (Quartile 3)	0.208***	0.0433	0.204***	0.0804*	0.0247	0.0157***
	(0.0425)	(0.0441)	(0.0377)	(0.0440)	(0.0660)	(0.00391)
Digital (Quartile 4)	0.239***	0.0648	0.234***	0.0961**	0.0519	0.0180***
	(0.0534)	(0.0431)	(0.0430)	(0.0471)	(0.0724)	(0.00432)
Digital (Quartile 1)	-0.269***	-0.153*	-0.213**	-0.307***	-0.581**	-0.00877
X Occupation shortage	(0.0730)	(0.0870)	(0.0912)	(0.116)	(0.244)	(0.0141)
Digital (Quartile 2)	-0.215***	-0.174***	-0.187***	-0.155***	-0.334***	-0.0210**
X Occupation shortage	(0.0401)	(0.0424)	(0.0356)	(0.0443)	(0.0890)	(0.00815)
Digital (Quartile 3)	-0.102**	-0.0461	-0.0451	-0.0327	-0.116	-0.0177***
X Occupation shortage	(0.0404)	(0.0494)	(0.0481)	(0.0587)	(0.105)	(0.00660)
Digital (Quartile 4)	0.0854	0.0933	0.122*	0.142*	0.239	-0.0160
X Occupation shortage	(0.0535)	(0.0674)	(0.0682)	(0.0794)	(0.146)	(0.0120)
Observations	1,067,412	1,102,176	1,088,798	1,109,472	1,110,981	1,042,252
R-squared	0.063	0.062	0.062	0.061	0.061	0.061

Note: This table shows the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, age and size (measured by the number of employees), an interaction between each productivity quartile and digital technologies, and the interaction between the latter and occupational shortages. Quartile 1 refers to the bottom of the distribution (i.e. low productive firms), quartile 4 to the top. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The 1^{st} principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table C1: Literature review

Focus	Author and year	Title	Measure of ICT	Time	Country coverage	Main source of data	Main finding
US-studies	(Brynjolffson, 1996)	Paradox Lost? Firm-level Evidence on the Returns to Information Systems Spending	Computer Capital; Information System Staff	1987-1991;	United States	Firm level data; International Data Group (IDG) annual survey of IT spending; Compustat.	IT capital and labour are significantly related to output, and their marginal products are larger than their non-IT counterparts. (Black, 2001)
US-studies	(Brynjolfsson and Hitt, 2000)	Computing Productivity: Firm-Level Evidence,	Computer equipment	1987-1994;	United States	Firm-level data; Computer Intelligence InfoCorp (CII), Compustat.	IT capital makes a significant contribution to productivity and output growth in the short run (1 year lag), but the contribution is five times larger in the long run (5-7 years lag).
US-studies	(Black, 2001)	How to Compete. The impact of Workplace Practices and Information Technology on Productivity	Share of workers using computers	1987-1993	United States	Plant-level data; Bureau of the Census' Longitudinal Research Database (LRD)	The greater the proportion of non-managerial workers using computers, the higher plant productivity.
US-studies	(Hunton, Lippincott and Reck, 2003)	Enterprise resource planning systems: comparing firm performance of adopters and non-adopters	Enterprise Resource Planning (ERP)	1990-1998	United States	Firm-level data; Compustat; Hayes DC,	Return on assets (ROA), return on investment (ROI), and asset turnover (ATO) were significantly better over a 3-year period for adopters, as compared to nonadopters.
US-studies	(Nicolau, 2005)	Organizational performance effects of ERP systems usage: The impact of post-implementation changes	Enterprise Resource Planning (ERP)	2004	United States	Firm-level data; Lexis/Nexis database	Subsequent changes in ERP systems often help resolve or surface implementation issues that affect subsequent use of and success from the use of such systems. Specific findings indicate that ERP-adopting firms, which initiate early enhancements in the form of either add-ons or upgrades, may enjoy superior differential financialperformance in comparison to other ERP-adopting firms' differential performance.
US-studies	(Aral, Brynjolfsson and Wu, 2006)	"Which Came First, IT or Productivity? Virtuous Cycle of Investment and Use in Enterprise Systems"	Enterprise Resource Planning (ERP), Customer Relationship Management Systens (CRM), Supply Chain Management Systems (SCM).	1998-2005;	United States	Firm-level data; HCM vendor data; Compustat	Firms that successfully implement IT, react by investing in more IT. Our work suggests replacing either-or views of causality with a positive feedback loop conceptualization in which successful IT investments initiate a virtuous cycle of investment and gain
US-studies	(Bartel, Ichniowski and Shaw, 2007)	How Does Information Technology Affect Productivity? Plant-Level Comparisons of-Product Innovation, Process Improvement, and Worker Skills	IT equipment various measures, e.g. number of computer numerically controlled machines)	1999-2003	United States	Specific survey on valve-making plants	New IT investments improve the efficiency of all stages of the production process by reducing setup times, run times, and inspection times. Adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators, notably technical and problem-solving skills, and with the adoption of new human resource practices to support these skills.
US-studies	(Aral, Brynjolfsson and Wu, 2012)	Three-Way Complementarities:Human Resource Analytics, Performance Pay, and InformationTechnology	Enterprise Resource Planning (ERP), Customer Relationship Management Systens (CRM), Supply Chain Management Systems (SCM).	1995-2002;	United States	Firm-level data; HCM vendor data; Compustat	Human Capital Management software adoption is associated with a disproportionately large productivity premium when it is implemented as asystem of organizational incentives, but has little or no benefit when adopted in isolation
US-studies	(Acemoglu et al., 2014)	Return of the Solow Paradox? IT, Productivity, and Employment in U.S. Manufacturing	IT intensity as (1) the ratio of sector computer (IT) expenditures to total capital expenditures; and (2) usage of a set of manufacturing technologies	1977, 1982, 1987, 1992, 2002, and 2007;	United States	Plant-level data; US Census Bureau's 1988 and 1993 Survey of Manufacturing Technology (SMT)	IT has no effect on output per worker on the manufacturing sector outside the computer-producing sector.

Table C1: Literature review (continued)

Focus	Author and year	Title	Measure of ICT	Time	Country coverage	Main source of data	Main finding
US-studies	(Bloom, 2017)	What Drives Differences in Management?	IT investment (in computers) per employee	2005-2010	United States	Plant-level data; US Census Bureau's Management and Organizational Practices Survey; Business R&D and Innovation Survey	US manufacturing sector, dispersion in IT expenditures per employee explains around 8% of the productivity dispersion, while management quality explains around 17% of the spread in TFP.
US-studies	(Brynjolfsson et al., 2008)	Scale Without Mass: Business Process Replication and Sector Dynamics	IT capital comprising computer hardware software	1987-2006	United States	Sector-level (IT) and firm-level data (TFP); Bureau of Economic Analysis's (BEA) "Tangible Wealth Survey"; Compustat	Using case studies, the authors illustrate how IT has enabled firms to more rapidly replicate improved business processes throughout an organization, thereby increasing productivity, market share and market value.
US-studies	(Dinlersoz, 2018)	Automation, Labor Share, and Productivity:Plant-Level Evidence from U.S. Manufacturing	Current and future dependenceof operations on technology, as well as about past and future investment in technology.	1991	United States	Plant-level data; U.S. Census Bureau's Survey on Manufacturing Technology 1991.	More automated establishments have lower production labor share and higher capital share, and a smaller fraction of workers in production who receive higher wages. These establishments also have higher labor productivity and experience larger long-term labor share declines.
Cross-country studies	(Basu, 2003)	The Case of Missing Productivity Growth	IT capital stock (computer, software, communication equipment)	1995-2000	United States; United Kingdom	Sector-level : Bureau of Labour Statistics; Bank of England	Difference in total factor productivity (TFP) between the United States and the United Kingdom from 1995 onwards can be explained by a combination of unmeasured investments in (intangible) organisational capital and ICTs, and in particular the innovation these investments induce.
Cross-country studies	(Gust and Marquez, 2004)	International comparisons of productivity growth: the role of information technology and regulatory practices$	ratio of IT expenditures to GDP	1992 to 1999	13 industrial countries	Country-level; OECD STAN	Burdensome regulatory environments and, in particular, regulations affecting labour market practices have impeded the adoption of information technologies and have slowed productivity growth in a number of industrial countries.
Cross-country studies	(Van Ark and Inklaar, 2006)	Catching up or getting stuck? Europe's troubles to exploit ICT's productivity potential	Catching up or getting stuck? Europe's troubles to exploit ICT's productivity potential	2001-2004	France, Germany, Netherlands, United Kingdom, United States	Sector-level; pre-EU KLEMS dataset i.e.the 60 Sector Database of the Groningen Growth and Development Centre (GGDC)	The relationship between ICT investments and productivity is U-shaped, whereby the initial adoption phase is followed by a period of experimentation during which ICT and productivity are negatively related. However, complementary investments eventually lead to gains from ICT in line with its marginal costs.
Cross-country studies	(Van Ark, 2008)	The Productivity Gap between Europe and the United States: Trends and Causes	ICT capital	1995-2004	EU, United States	Country-level data: EU KLEMS database	The European productivity slowdown is attributable to the slower emergence of the knowledge economy in Europe compared with the United States, partly due to lower growth contribution from ICT investments.
Cross-country studies	(Bloom, Sadun and Van Reenen, 2012)	American do IT better: US Multinationals and the Productivity Miracle"	PC and laptop per worker	1999-2006	EU (France, Germany, Italy, Poland, Portugal, Sweden and the UK)	Firm-level data: UK Census Bureau; CEP Management Survey; Harte-HanksIT panel	US firms' IT-related productivity advantages are primarlily due to their "tougher" management practices.
Cross-country studies	(Bartelsman, 2013)	ICT, Reallocation and Productivity	N.A.	N.A.,	EU countries	N.A.	Owing to the on-going advances in ICT, much higher growth is technologically feasible, but a considerable amount of churn and reallocation across firms in the market sector is needed.

Table C1: Literature review (continued)

Focus	Author and year	Title	Measure of ICT	Time	Country coverage	Main source of data	Main finding
Cross-country studies	(Hagsten et al., 2013)	The Multifaceted Nature of ICT: Final report of the ESSNet on linking of microdata to analyse ICT impact.	Broadband-enabled employees.	2004-2009	EU countries	ESSLait Micro Moments Database	Services (resp. manufacturing) firms in ten (resp. eight) out of 14 countries exhibit a significant relationship between broadband employees and labour productivity.
Cross-country studies	(Evangelista, Guerrieri and Meliciani, 2014)	The economic impact of digital technologies in Europe	Composite ICT indicators	2004-2008	EU countries	European Digitalization Development Index	Digitalisation may drive productivity and employment growth. Inclusive policies may contribute to bridge the gap between the most favoured and the disadvantaged parts of the population
Cross-country studies	(Acharya, 2016)	ICT use and total factor productivity growth: intangible capital or productive externalities	ICT capital	1973-2004	EU and US	Sector-level data: EU KLEMS	Unmeasured intangible capital accumulation rather than productive externalities were at the core of the US (and to some extent EU) TFP growth in the mid '90s.
Cross-country studies	(Corrado, Haskel and Jona-Lasinio, 2017)	Knowledge Spillovers, ICT and Productivity Growth	ICT capital	1998-2007	EU countries	EUKLEMS	The marginal impact of ICT capital is higher when it is complemented with intangible knowledge based capital. More specifically, their study shows that ICT intensive industries have better productivity outcomes in countries that are more KBC intensive, in particular with relative higher investments in organisational capital
Cross-country studies	(Cette, Lopez and Mairesse, 2017)	Upstream Product Market Regulations, ICT, R&D and Productivity	ICT capital	1987-2007	EU and US	OECD STAN; EU-KLEMS	ICT capital increases are an important channel to increase sector level MFP when upstream sectors are deregulated.
Cross-country studies	(Bartelsman, Van Leeuwen and Polder, 2017)	CDM using a cross-country micro moments database	Enterprise Resource Planning (ERP), Customer Relationship Management Systens (CRM), Supply Chain Management Systems (SCM).	2006-2009;	EU countries	ESSLait Micro Moments Database	Innovative activity contributes to aggregate productivity even while the average effect at the firm level is insignificant. Moreover, the combined use of digital technologies leads to within-firm productivity increases.
Non-US studies	(Bugamelli and Pagano, 2004)	Barriers to investment in ICT	ICT capital stock	1995-1997	Italy	Firm-level data: 'Centraledei Bilanci' (Company Accounts Data Service, CADS); 'Indagine sulle Imprese Manifatturiere' (Survey ofManufacturing Firms, SMF) by Mediocredito Centrale	The ICT marginal product exceeds its user cost, possibly due to the lack of complementary investment in human capital and the lack of a reorganization of the workplace.
Non-US studies	(Wieder et al., 2006)	The impact of ERP systems on firm and business process performance	ERP and SCM	2001	Australia	Firm level data; Survey conducted by the Australian BusinessJournal "BRW"	Except when both technologies were combined, no significant performance differences were found between ERPS adopters and non-adopters, either at the business process level, or at the overall firm level. While it could be confirmed that the longer the experience of firms with ERP, the higher their overall performance, no evidence was found of a similar effect on business process (supply chain) performance.
Non-US studies	(Castiglione, 2012)	Technical efficiency and ICT investment in Italian manufacturing firms	ICT investments	1995-2003	Italy	Firm-level survey data from Mediocredito Centrale Capitalia	ICT investments positively and significantly affect firms' technical efficiency.

Table C1: Literature review (continued)

Focus	Author and year	Title	Measure of ICT	Time	Country coverage	Main source of data	Main finding
Non-US studies	(Engelstätter, 2009)	Enterprise systems and labor productivity: disentangling combination effects	Share of computer workers, ERP, SCM, and CRM systems	2004; 2006	Germany	Firm-level data; phone interview conducted by Centre for European Economic Research (ZEW).	Replicating Aral, Brynjolfsson and WU (2006) using similar data the authors find a positive correlation between labor productivity and various measures of IT. The authors also show evidence of the complementarity between different measures.
Non-US studies	(Hall, Lotti and Mairesse, 2012)	Evidence on the impact of R&D and ICT investment on innovation and productivity in Italian firms	ICT investment expenditure	1995-2006,	Italy	Firm-level data: Unicredit "Survey on Manufacturing Firms"	R&D and ICT are both strongly associated with innovation and productivity, with R&D being more important for innovation, and ICT investment being more important for productivity
Non-US studies	(Akerman, Gaarder and Mogstad, 2013)	The skill complementarity of broadband internet	Broadband subscription	2001-2007	Norway	Firm-level data; Annual Community Survey on ICT Usage of Firms by Statistics Norway	Broadband internet complements skilled workers in executing non-routine abstract tasks, and substitutes for unskilled workers in performing routine tasks.
Non-US studies	(Pellegrino, 2017)	Diagnosing the Italian Disease	IT capital	1984-2006	Italy	Sector-level: EU KLEMS	Italy's slowdown was likely caused by the failure of its firms to take full advantage of the ICT revolution. While many institutional features can account for this failure, a prominent one is the lack of meritocracy in the selection and rewarding of managers. Familyism and cronyism are the ultimate causes of the Italian disease.
Non-US studies	(Dhyne et al., 2018)	IT and Productivity: A firm level analysis	IT purchases by firms	2002-2013	Belgium	Firm-level data; VAT transaction data obtained from tax authorities.	Using VAT transaction data between Belgium firms, this paper looks at the various dimensions of sector and firm level heterogeneity in returns of IT capital. IT investments are found to be more productivity-enhancing in the manufacturing sector and in large firms.
Non-US studies	(Chevalier and Luciani, 2018)	Computerization, labor productivity and employment: impacts across industries vary with technological level	Office and computing machinery investment	1994-2007	France	Sector and firm-level data (BRN and DADS), manufacturing sector	For the whole IT-using manufacturing sector, computerization is associated with positive but fragile effects on labor productivity, and to unambiguous declines in employment.
Non-US studies	(DeStefano, Kneller and Timmis, 2018)	Broadband infrastructure, ICT use and firm performance: Evidence for UK firms	ADSL broadband	1999-2005	United Kingdom	Ci Technology Database (CiTDB)	ICT causally affects firm size (captured by either sales or employment) but not productivity.
Non-US studies	(Mohnen, Polder and Van Leeuwen, 2018)	R&D and Organizational Innovation: Exploring Complementarities in Investment and Production	ICT investment (hardware only)	2008-2014	Netherlands	Firm-level data, Dutch Investment Survey	Investments in ICT, R&D and organisational capital are complementary, in the sense that investing in one increases the probability of investing in another one because joint investments lead to higher TFP growth than individual investments.
Other	(Brynjolfsson and Hitt, 2000)	Beyond Computation: Information Technology, Organizational Transformation and Business Performance	N.A.	N.A.	N.A.	N.A.	Relying primarily on case studies, but also on preliminary research the authors document that computerization without changes in work practices usually fails at delivering an increase in efficiency. For example, technology aiming at facilitating the interactions between a firm and its suppliers will be efficient only if the entire supply chain is reorganised accordingly.
Other	(Dedrick, Gurbaxani and Kraemer, 2003)	Information Technology and Economic Performance: A Critical Review of the Empirical Evidence	N.A.	1987-2002	N.A.	N.A.	In a conclusive review of over 50 scholarly studies on ICT and productivity published between 1987 and 2002, the authors find that "the productivity paradox as first formulated has been effectively refuted.
Other	(Syverson, 2011)	What Determines Productivity?	N.A.	N.A.	N.A.	N.A.	Provides a literature review of IT-related productivity gains.

Does Import Competition Reduce Domestic Innovation and Productivity? Evidence from the China Shock and Firm-level Data on Canadian Manufacturing

Myeongwan Kim[1]
Centre for the Study of Living Standards

Abstract

A key economic issue in Canada is the declining business research and development and slowdown in the total factor productivity (TFP) growth in manufacturing since the early 2000s. To deepen our understanding of this phenomenon, we focus on the increasing Chinese import share in the total domestic absorption in Canadian manufacturing since the early 2000s, which appears to be driven by positive supply shocks within Chinese manufacturing. Based on firm-level data in Canadian manufacturing, we find that rising Chinese import competition led to declines in R&D expenditure and TFP growth within firms but reallocated employment towards more productive firms and induced less productive firms to exit. The negative within-effects were pronounced for firms that were initially smaller, less profitable, and less productive. At the aggregate level, the positive reallocation effects on TFP more than offset the negative within-effect. We estimate that, had there been no increase in Chinese import competition between 2005 and 2010, TFP in Canadian manufacturing would have declined by 1.26 per cent per year instead of the actual 1.09 per cent per year over this period.

A key economic issue in Canada is the declining Business Enterprise Research and Development (BERD) — a key input to innovation — since the early 2000s. Espe-

1 The author is currently a Ph.D. student in the Department of Economics at the University of Toronto. This article is an abridged version of Kim (2019), which was written when the author was an Economist at the Centre for the Study of Living Standards. An earlier version was presented at the CSLS session on "The Impact of China on the Canadian Economy" at the annual meeting of the Canadian Economic Association held in Banff, Canada, June 1, 2019. The author thanks the participants at the CEA session and Alex Murray (Finance Canada) for discussion. The author also thanks Andrew Sharpe (CSLS), Bert Waslander, Simon Lapointe (CSLS) and Jianmin Tang (ISED), and two anonymous referees for useful comments. Email: myeongwan.kim@mail.utoronto.ca.

cially, in manufacturing, BERD expenditure started to decline after 2000 both in levels and as a share of sales. Accompanying this, total factor productivity (TFP) growth in manufacturing slowed after 2000.

Since the early 2000s, advanced economies including Canada have experienced a rapid increase in imports from China. A large literature has documented that increasing trade with low-wage countries have an impact on domestic innovation although the evidence is mixed for the direction of the impact.[2] In this article, we assess whether declining R&D and productivity performance in Canadian manufacturing can be linked to rising Chinese import competition in final product markets. As the competition in the domestic product market rises, surviving firms are likely to adjust their innovative effort as their rents after innovation relative to rents before innovation are affected. Moreover, less productive firms may exit and resources could be allocated towards more productive surviving firms.

There are some close antecedents to our study but their empirical evidence is mixed. Bloom, Draca, and Van Reenen (2016) use firm-level data from European countries to estimate the effect of increasing Chinese import competition on four indicators for technical change: patents, information technology intensity, R&D investment, and TFP growth. They find empirical evidence that increasing Chinese import competition had led to an increase in all four measures of technical change within firms and also reallocated employment towards more technologically-advanced firms.[3]

Autor, Dorn, Hanson, Pisano, and Shu (2017) find conflicting evidence using firm-level data for the United States. They find that, in response to increasing Chinese competition, firms scaled back their patent activity and R&D investment. Gong and Xu (2017) also studies the effect of rising Chinese import competition on R&D expenditure of the U.S. firms but focus on the reallocation effect. They find that rising Chinese competition reallocated R&D expenditure towards more productive and profitable firms but find no evidence of an impact on R&D at the aggregate level. Using survey data,[4] Keung, Li, and Yang (2016) find that Canadian manufacturing firms scaled back their effort in process innovation relatively more than product innovation in response to rising Chinese import competition between 1999 and 2005.

Those conflicting empirical results are in line with the overall ambiguity in theoretical implications for the effect of rising competition on innovation. There are multiple theories underlying the relationship between competition and innovation. For example, "trapped inputs" for production imply that increased Chinese import competition fosters innovation as it reduces the relative profitability of low-tech products (e.g. Bloom, Romer, Terry and Van

2 See Shu and Steinwender (2018) for a comprehensive review of the studies on the impact of trade liberalization on innovation and productivity.

3 They also find that technologically-advanced firms are more likely to survive for a given increase in Chinese import competition than low-tech firms.

4 The Workplace and Employee Survey (WES) by Statistics Canada.

Reenen, 2010). Also, an increasing market size for Canadian firms due to expanding trade opportunity with China may encourage innovation as firms can spread the fixed costs of innovation over the larger market (e.g. Krugman, 1980; Acemoglu, 2008).

In contrast, in a standard oligopoly model, increased competition in product markets is likely to reduce incentives to innovate as profits decline (e.g. Dasgupta and Stiglitz, 1980). If we take into account differential degrees of competition faced by firms, the relationship between innovation and competition exhibits an inverted U-shape (e.g. Aghion *et al.*, 2005). Schmidt (1997) shows that increasing competition increases managerial effort to increase profit (so likely to increase innovation) but when competition becomes too intense, managerial effort may decline eventually.[5]

As emphasized in Melitz (2003) and Bloom *et al.* (2016), it is also important to consider an economy-wide technical change that occurs through the reallocation of resources. In theory, if we maintain the menu of products fixed in the economy, then increasing trade with low-wage countries like China would results in shrinking low-tech firms and growing high-tech firms (where Canada has comparative advantages). The opposite would occur in China.

Our study adds to the literature in two ways. First, to our knowledge, there is no empirical study that uses Canadian firm-level data to explore the impact of rising Chinese import competition on R&D which is a representative indicator of innovation activities or on the overall productivity performance in manufacturing. In this article, we carry out a comprehensive assessment of trade-induced change in R&D and TFP within manufacturing firms. Especially, our data capture a broad scope of R&D expenditure covering in-house R&D, R&D contracted out, and the use of R&D performed by third-parties on a non-exclusive basis. We also explore whether technical changes occurring *between* firms are important in Canada by analyzing the effect on employment and survival of manufacturing firms, focusing on the differential effects stemming from different initial technology levels of firms.

Second, most empirical studies focus on very large firms (e.g. public firms in Compustat) or firms with patents among those large firms. Large firms or firms with successful innovation outcomes (*i.e.*, patents) could have different initial conditions and hence, their response could be quite different than the majority of smaller firms in manufacturing or firms that perform R&D whose outcome does not necessarily get patented. In our study, we use administrative firm-level data covering all incorporated firms in Canadian manufacturing. Also, the database is linked to the tax data covering all firms that claimed R&D expenditure credits in Canada. Using this comprehensive database, we explore potential heterogeneity in firm-level responses to rising import competition, providing a better understanding of trade-induced change in

5 Also, domestic innovation could decline if domestic firms are deterred from entering export markets. For example, Baldwin, Dar-Brodeur, and Yan (2016) find that Canadian manufacturing firms that entered export markets are more likely to have invested in R&D before entry and to invest more in R&D after entry.

innovation and productivity. In particular, we assess the impact of rising import competition on R&D and TFP within firms by initial conditions of firms (e.g. initial size, profitability or mark-up, and productivity level).

We find that increasing Chinese import competition reduced R&D and TFP growth within firms but reallocated employment towards more productive firms and drove less productive firms out of the domestic market. The negative within-effects on R&D and TFP growth were pronounced in initially smaller, less profitable, and less productive firms.[6] It appears that, if survived, they scaled back their R&D investment but did not resort to other productivity-enhancing activities. Even if they did, they were not successful. R&D investment within initially larger, more profitable, and more productive firms was not affected by rising Chinese import competition. We find evidence that some larger and better-performing firms engaged in productivity-enhancing activities other than R&D when the Chinese presence increased in their product market, and hence their TFP improved. Very large firms (employees>500) do not appear to have adjusted their innovative effort to enhance their productivity.

Our results show that initially smaller and poorly-performing firms that survived experienced declining profit margins due to rising import competition while larger and their better-performing counterparts did not. A larger reduction in R&D and TFP may be explained by the shrinking room to finance R&D and other productivity-enhancing effort. Firms tend to finance innovation using internal cash flows as external financing would be costly in this case. Or in a different perspective, these firms are likely to have faced greater product market competition with technology gaps initially. So, if survived, a further increase in competition may have made additional innovation unprofitable for them. In other words, the basic Schumpeterian effect dominates for these firms, reducing more the post-innovation rents than the pre-innovation rents.

At the aggregate level, our estimates imply the increased share of imports from CHina explains about 7 per cent of the total decline of $1.36 billion (2007 CAD) in R&D expenditure in Canadian manufacturing between 2005 and 2010. Our productivity decomposition exercise indicates that had there been no increase in the share of Chinese imports in the total domestic absorption in manufacturing between 2005 and 2010, the aggregate TFP level in manufacturing would have declined by 1.26 per cent per year instead of the actual 1.09 per cent per year. This implies that the positive between- and exit-effects more than offset the negative within-effects.

The remainder of the article is organized as follows. The first section provides some motivating stylized facts about Chinese import competition, R&D expenditure, and productivity performance in Canadian manufacturing. Data sources are

6 For R&D, we also find the declines were larger within foreign-controlled firms and firms receiving regular tax credits for R&D expenditure, compared to domestically-controlled firms and firms receiving enhanced tax credits, respectively. Refer to Kim (2019) for details.

introduced in section two. Section three introduces our empirical models and identification strategy, which is followed by the results in section four and five. In section six, we contextualize our empirical findings by quantifying the role of rising Chinese import competition in driving the actual change in R&D investment and TFP growth in Canadian manufacturing. Section seven concludes.

Chinese Imports, R&D Expenditure, and TFP Growth in Canadian Manufacturing

Imports from low-wage countries have implications for technical change in developed economies.[7] During the 2000s, two of the top ten importers to Canada were low-wage countries: China and Mexico.[8] However, import penetration from China had been much more important in terms of both absolute levels and changes (Chart 1). The import penetration ratio for Mexico remained below 4.0 per cent for most of the 1990s and 2000s. It increased from 2.0 per cent in 2000 to 4.0 per cent in 2015. The import penetration ratio for China surpassed that for Mexico during the early 2000s when China joined WTO, reaching 8.9 per cent in 2015. It grew by 6.9 percentage points between 2000 and 2015.

According to the official data publicly available at Statistics Canada, between 1994 and 2000, the real BERD expenditure (covering only in-house R&D) in Canadian manufacturing increased rapidly. However, it started to decline when Chinese imports surged in the early 2000s (Chart 2). Our firm-level data on R&D only cover the 2000-2012 period, preventing us from comparing the pre- and post-take-off in Chinese imports in Canada. Nevertheless, we observe similar trends after 2000. The average annual growth rate in real R&D expenditure based on our firm-level data was -0.2 per cent in manufacturing for the 2000-2012 period.[9] The average annual growth rate was 4.1 per cent for the 2000-2005 period but fell to -3.2 per cent for the 2005-2012 period.[10] BERD expenditure fell in relative terms as well. Both the manufacturing share in total BERD expenditure in Canada and R&D intensity defined as BERD expenditure as a share of the total sales in manufacturing declined after 2000.[11]

Accompanying the declining R&D expenditure, TFP growth in manufacturing slowed after 2000. Chart 3 shows time series for TFP index based on the Canadian Productivity Account for Canadian man-

7 See, for example, Bartel *et al.* (2007); Freeman and Kleiner (2005); Bugamelli *et al.* (2008).

8 The top ten exporters to Canada were: United States, China, Mexico, Germany, Japan, South Korea, United Kingdom, Italy, France, and Taiwan.

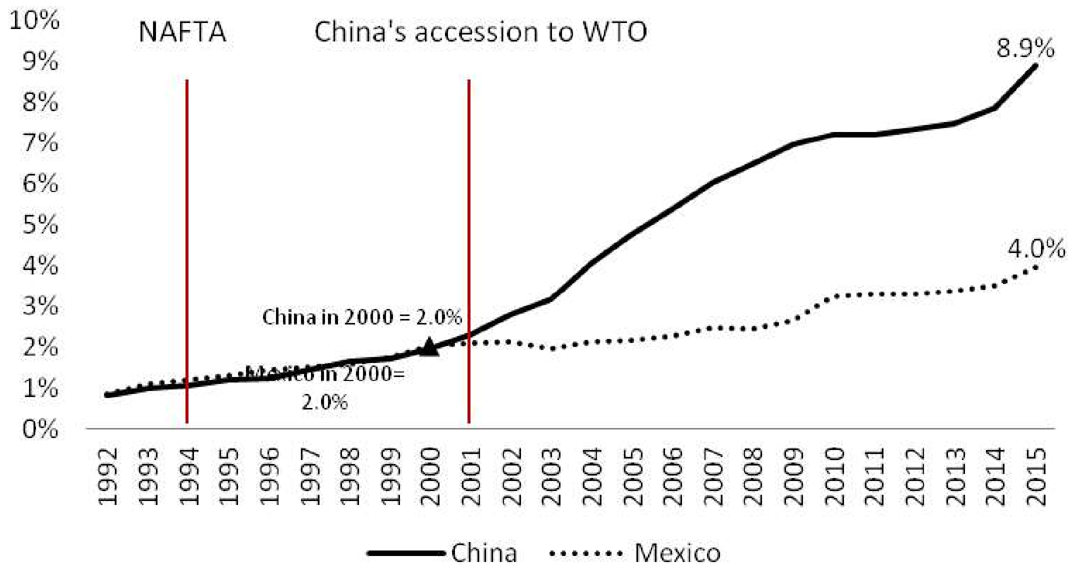
9 The average annual growth was 1.3 per cent in non-manufacturing during the same period.

10 A similar pattern is found in non-manufacturing: 5.9 per cent for the 2000-2005 period and -1.9 per cent for the 2005-2012 period.

11 See Kim, 2019:7 for details.

12 The Canadian Productivity Account data are publicly available at Statistics Canada. The CPA is constructed based on establishment-level data.

Chart 1: Import Penetration Ratio in Canada, Low-wage Countries: China and Mexico, Manufacturing, 1992-2015



Note: The import penetration ratio is defined as the ratio of imports to domestic absorption (total industry shipment less exports plus imports).
Source: Authors' calculation based on trade data base maintained by Innovation, Science, and Economic Development Canada and Statistics Canada Table 16-10-0047-01.

ufacturing.[12] TFP grew at a faster rate during the 1990s than during the 2000s. For instance, the annualized growth in TFP was 3.13 per cent over the 1992-2000 period. However, TFP declined at an annual rate of 1.09 per cent over the 2000-2009 period. After a rapid increase during the 1990s, TFP started to level off from the early 2000s. Then, it declined between 2006 and 2009 before it started to recover after 2009.[13]

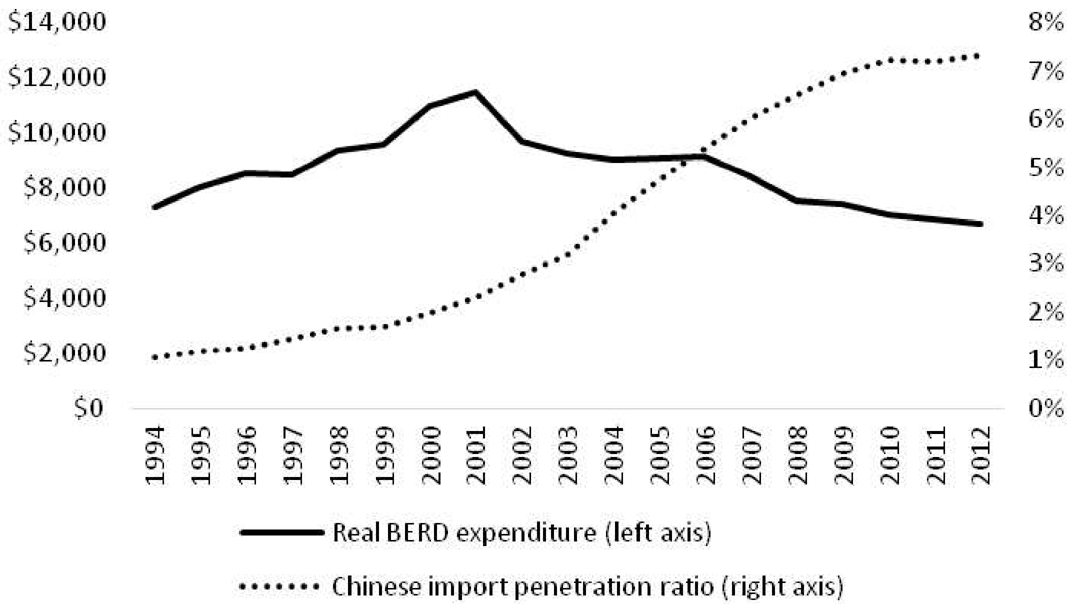
Data

The main data source for our analysis is corporate income tax (T2) files linked to Statistics Canada's Longitudinal Employment Analysis Program (LEAP) data file. The database includes information on firm-level output and conventional factors of production to estimate TFP. In order to have information on R&D expenditure for each firm, the database is linked to the Canada Revenue Agency (CRA) form T661 filed by firms to claim their tax credits for expenditure on scientific research and experimental development (SRED) — hence, T2-LEAP-SRED. We provide more detailed information on T2-LEAP-SRED in Kim (2019).

We use the Trade Data Online by Innovation, Science, and Economics Devel-

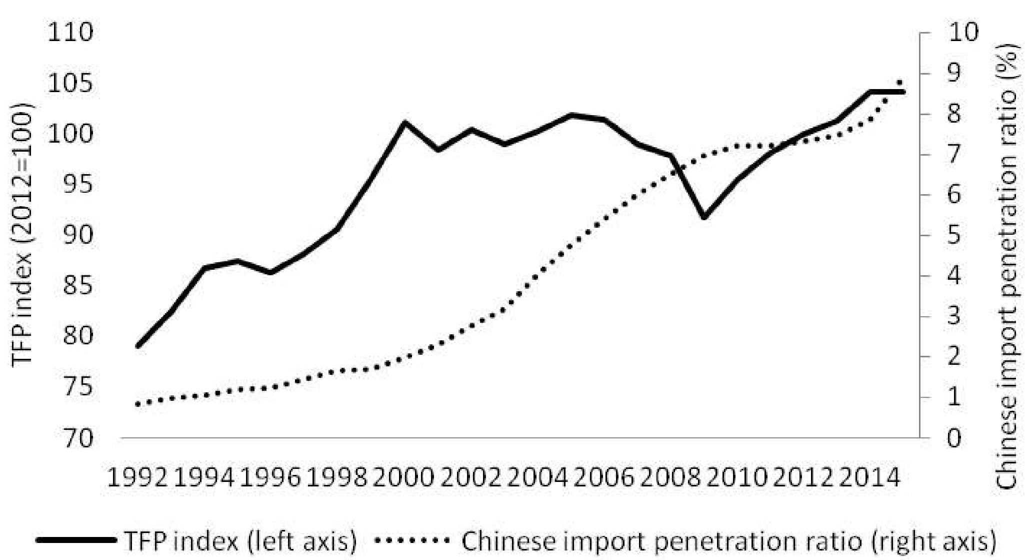
13 Again, due to the limited information in our firm-level data, we can examine TFP only for the 2000-2012 period. We observe the TFP level in manufacturing based on T2-LEAP-SRED exhibits a pattern similar to that found in the CPA data for the 2000-2012 period.

Chart 2: Real R&D Investment in Canadian Manufacturing, Millions of 2007 CAD, 1994-2012



Note: We use the GDP deflator for R&D expenditure.
Source: Author's calculations based on Statistics Canada Table 27-10-0002-01, 27-01-0273-01, 16-10-0047-01, and Trade Data Online maintained by Innovation, Science, and Economic Development Canada.

Chart 3: TFP Index (2012=100) and Chinese Import Penetration Ratio in Canadian Manufacturing, 1992-2015



Source: Authors' calculation based Statistics Canada Table 36-10-0208-01 and on trade data base maintained by Innovation, Science, and Economic Development Canada and Statistics Canada Table 16-10-0047-01.

opment Canada and the UN Comtrade database to construct our measure of Chinese import competition for Canada and other advanced economies required for our identification strategy. The UN Comtrade database follows the Harmonized Item Description and Coding System (HS). We therefore implement a mapping between HS and NAICS following the algorithm developed by Pierce and Schott (2012). Refer to Murray (2017) and Kim (2018a, b) for more detailed description of the data.

Our sample period covers 2000-2012. The sample for R&D analysis consists of firms that performed or purchased R&D at least once between 2000 and 2012. For the analysis on TFP, the sample consists of firms that have non-missing values for all the variables required to estimate firm-level TFP.

Empirical Models and Identification Strategy

Technical changes within firms

Our empirical models assess the effect of Chinese import competition on technical change within firms in manufacturing. To do so, we analyze two indicators of technical change: R&D expenditure and TFP growth. Following Bloom *et al.* (2016), we estimate the following two equations:

$$\Delta \ln(R\&D)_{i,j,\tau} = \beta^{R\&D} \Delta IP_{j,\tau} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau} \quad (1)$$

$$\Delta \ln(TFP)_{i,j,\tau} = \beta^{TFP} \Delta IP_{j,\tau} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau} \quad (2)$$

where i denotes firms and j denotes sectors in manufacturing. Δ represents the operator for long differences (e.g. 5-year long differences) for a given variable. $X_{i,j,\tau}$ includes all other controls for non-trade related factors specific to firms and to sectors in manufacturing. α_τ represents period fixed effects. $\Delta IP_{j,\tau}$ is a measure of Chinese import penetration which is constructed as follows:

$$\Delta IP_{j,\tau} \equiv \frac{\Delta M_{j,\tau}^{China}}{Y_{j,\tau_0} + M_{j,\tau_0} - E_{j,\tau_0}} \quad (3)$$

where the numerator $\Delta M_{j,\tau}^{China}$ denotes the change in import in sector j from China over period τ. The denominator $(Y_{j,\tau_0} + M_{j,\tau_0} - E_{j,\tau_0})$ represents the domestic absorption in sector j in the initial period τ_0.

Technical changes between firms: reallocation of employment and survival

To assess between-firm effects of Chinese import competition, we estimate the following equation:

$$\Delta \ln(N)_{i,j,\tau} = \beta^{N} \Delta IP_{j,\tau} + \lambda^N \left(TECH_{i,j,\tau_0} * \Delta IP_{j,\tau}\right) + \varphi TECH_{i,j,\tau_0} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau} \quad (4)$$

where N is a measure of employment. $TECH_{i,j,\tau_0}$ is a measure of technology level for firm i in sector j in the initial period τ_0.

Increasing import competition from China could affect the probability of survival. Thus, we estimate the effect of trade on survival of firms in our data as follows:

$$S_{i,j,\tau} = \beta^S \Delta IP_{j,\tau} + \lambda^S \left(TECH_{i,j,\tau_0} * \Delta IP_{j,\tau}\right) + \varphi TECH_{i,j,\tau_0} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau} \quad (5)$$

where $S_{i,j,\tau} = 1$ if firm i in sector j survives over period τ and zero otherwise. Equation (5) is estimated on a cohort of firms that exist in the sample in a given base period.[14] We follow those firms over period τ to assess their value for $S_{i,j,\tau}$.

The main parameter of interest is λ in equations 4 and 5 as it reflects whether the size of the effect of Chinese import competition on employment growth or survival varies with the initial level of technology. If low-tech firms are affected more negatively by China then we expect $\lambda > 0$. In other words, $\lambda > 0$ indicates that employment tends to shift towards high-tech firms and low-tech firms tend to exit in response to increasing Chinese import competition.

Identification strategy

To identify shocks exogenously driven by rising Chinese exporting capacity, we exploit the fact that growth in Chinese exports to developed economies like Canada since the early 2000s were mostly driven by factors internal to China (*e.g.* urbanization, opening to foreign investment, rising competitiveness in manufacturing, and accession to the WTO) rather than by positive demand shocks within developed economies.

We capture the common within-industry factors of rising Chinese exporting capacity, which stemmed from rising Chinese comparative advantage in manufacturing and lower trade costs due to factors internal to China. Thus, following Autor, Dorn, and Hanson (2013), we instrument for changes in the Chinese share of the domestic absorption in Canada using the changes in Chinese imports in the following eight advanced economies: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.[15]

The first-stage regression is the following:

$$\Delta IP_{j,\tau} = \delta \Delta IPE_{j,\tau} + \widetilde{\gamma} X_{j,\tau} + \widetilde{\alpha_\tau} + \widetilde{\eta_j} + \mu_{j,\tau} \quad (6)$$

where $\Delta IPE_{j,\tau}$ represents changes in the Chinese import penetration ratio in the eight comparison countries.

The above strategy has the following key identifying assumptions: 1.) industry-specific shocks are uncorrelated across Canada and the eight countries; and 2.) there are no strong increasing returns to scale in Chinese manufacturing such that Canadian shocks increase efficiency within relevant Chinese manufacturing industries and lead them to export more to the eight other economies. The former may be a

14 T2-LEAP-SRED is adjusted for mergers and acquisitions and legal restructuring. Therefore, we can treat disappearance of a firm as true exit.

15 We exclude the United States because its economy is highly integrated with Canada and is likely to have experienced similar demand shocks.

concern in our analysis. We are particularly concerned with the possibility of correlated shocks related to the innovation in the use of ICT technologies, which were observed in most of the advanced economies around the world, increasing demand for ICT-related goods from China.[16] The second is not of serious concern since Canada is a small open economy. Shocks within 4-digit NAICS in Canada are not likely to have a substantial impact on the efficiency within relevant Chinese industries.

It appears that the change in trade exposure to China in the eight advanced economies has good predictive power for the change in Canada. In our regression analysis, we use 5-year sub-periods covering the 2000-2012 period. R-squared varies across the 5-year sub-periods but is greater than 80 per cent in most cases — approximately 80 per cent of the variation in the import penetration ratio in Canada is presumably driven by exogenous supply shocks.

Descriptive Statistics

Summary statistics for some key variables used in our analysis by initial employment size are reported in Table A1 and A2 in the Appendix. Firms in the R&D sample (Table A1) tend to be larger in terms of employment and have a larger increase in their productivity over time, compared to the firms in the TFP sample (Table A2) which is a larger sample. Both in the R&D and the TFP sample, we find that the initial level of profitability and the initial productivity level were lower for smaller firms than for larger firms. In other words, firms with initially smaller employment are more likely to operate in more competitive markets with technology gaps in the initial period.

Both in theoretical and empirical works, it is suggested that the initial level of profitability (or product market competition) and productivity of a firm have important implications for the firm's innovative effort in response to an increase in competition.[17] It is observed that, on average, initially smaller firms experienced a larger increase in the Chinese import competition; a larger decrease in profitability; and a smaller increase in their productivity level.

Regression Results: R&D Equation

Baseline results

In Table 1, we report the regression results for estimating our R&D equation. As in Bloom *et al.* (2016), we use overlapping long-differenced samples of a 5-year period (*i.e.*, 2000-2005; 2001-2006; 2002-2007; and so on) to maximize the number of observations in our sample.[18] Using first-

16 Some robustness checks reveal that our result is not particularly sensitive to these industries. Refer to Kim (2019:18) for details.

17 See, for example, Aghion *et al.* (2005) and Autor *et al.* (2017).

18 Similar results are found when we use different lengths of overlapping sub-periods (e.g. 3-year; 6-year). We also tried using one or two long-differenced sub-periods (e.g. 2000-2007 or 2000-2005 and 2005-2010). Again, we found that the coefficients for ΔIP remain very similar to the ones reported in Table 1.

differenced samples (*i.e.*, change from one year to another) may lead to attenuation bias. It may not capture any meaningful adjustment in the innovation effort in response to increasing Chinese import competition, which is likely to occur over the medium- or long-term.

In columns 1 and 2, we estimate the same R&D equation but using different estimation methods. The OLS estimate in column 1 indicates that there is no significant effect of the China shock on the R&D expenditure growth within manufacturing firms. Using exogenously-driven variation in ΔIP, we find a negative and statistically significant effect on R&D in column 2.[19]

However, there could be unobserved industry-specific shocks that are correlated with both R&D investment and the Chinese import penetration ratio. Hence, as our first robustness check, in column 3, we report the results for controlling for industry trends in our sample. Here, we include 3-digit NAICS industry dummies.[20] We continue to obtain a negative and statistically significant coefficient on ΔIP although the coefficient is slightly smaller due potentially to attenuation bias.

In column 4, we include different firm-level controls to account for potential confounding factors. First, we include R&D intensity (R&D stock divided by value added) and tangible capital-to-value added ratio, both measured in the initial period (e.g. the 2000 value for the 2000-2005 sub-period). Second, we include the log of wage per worker averaged over our sample period.[21] Similar to Bernard *et al.* (2006) and Bloom *et al.* (2016), we use these variables as proxies for the initial technology level. Third, we include dummies for foreign-controlled firms and for the enhanced SR&ED tax credit recipients.[22] The coefficient for ΔIP remains negative and statistically significant with these control variables.

Explaining the Negative Effect

It is possible that increasing Chinese imports leads to declining R&D expenditure by creating competitive pressure on firms, reducing their expected rents after R&D relative to rents before R&D. However, with differential degrees of competition initially faced by firms, the impact of increasing competition on R&D investment may not be uniform across all firms (e.g. Aghion *et al.*, 2005).

Firms with significant market power (e.g. larger firms) may be less responsive in adjusting their R&D effort. Their rents would

19 We experiment with an alternative instrument as proposed in Bloom *et al.* (2016), which is similar in nature to the instrument adopted in Card (2001) by using as instruments the Chinese import penetration ratio measured in the initial period as instrument for its subsequent increases. We still find a negative and statistically significant coefficient. Refer to Kim (2019:17) for details.

20 We also allow the time trends to differ by 3-digit NAICS industry.

21 Wage is defined as payroll divided by average labour unit. Since the average labour unit is defined as the total payroll divided by average annual wage of a typical worker in the firm's 4-digit NAICS industry, province and firm size class, wage would be defined not at the firm-level but at the 4-digit NAICS industry x province x firm size class level.

22 We find that the control variables are jointly significant.

Table 1: R&D Equation, Manufacturing, 2000-2012

	1: OLS	2: 2SLS	3: Industry fixed effects	4: Various firm-level controls
ΔIP	-0.461	-1.027***	-0.857*	-0.805**
	(0.285)	(0.395)	0.448)	(0.398)
No. firm x period	118,427	116,683	116,683	101,485
No. firms	17,314	17,066	17,066	15,529
Estimation	OLS	2SLS	2SLS	2SLS

Note: The dependent variable is Δln(R&D expenditure). All columns include period fixed effects. Standard errors are in parenthesis. Δ denotes a 5-year difference. The number of observations is smaller for the columns based on our IV approach than column 1 since there is no HS-NAICS mapping for NAICS 3328 (see Kim (2019) for details). For column 4, some observations have missing values for some of the control variables we consider. Hence, the number of observations is slightly smaller than in the other columns. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

not be significantly affected by rising competition as it would be difficult for laggards (*i.e.*, Chinese manufacturers) to overtake leaders (*i.e.* large Canadian manufacturers) or Chinese manufacturers may operate in different product markets. On the other hand, for firms already facing a high degree of competition with technology gaps (e.g. smaller firms), increasing competition may substantially hurt their profit margins, implying less room to finance innovation[23] and/or to capture rents after R&D. As a result, if such firms survived, they might have been more responsive in reducing their expenditure on R&D as competition rises.

To empirically examine this idea, we estimate the R&D equation in which we interact ΔIP with the size indicator to examine whether the coefficient differs by size group (in terms of the initial employment size).[24] Small firms tend to be not only less profitable (or operating in more competitive markets) but also less productive in the initial period (see Table A1 in the Appendix). In column 1 in Table 2, we find negative coefficients in all three size groups but the statistical evidence for medium and large firms is weak. It appears that only small firms were negatively affected.[25]

It is likely that small firms' profit margins were negatively affected by rising import competition, leading them to reduce R&D expenditure. We estimate the impact of increasing Chinese imports on the profitability of firms performing R&D in manufacturing. Given the data availability in the T2-LEAP-SRED database, we define profitability as profit divided by sales where we use net income or loss before tax as profit.

In column 2 in Table 2, our 2SLS estimate indicates that increasing Chinese import competition indeed reduces the profitability of firms. A further analysis by size in column 3 indicates that only small firms were negatively affected by increasing import competition from China. We find

23 For example, Hall (1992) finds a positive elasticity of R&D investment with respect to cash flow controlling for other factors and that debt is not a preferred form of financing R&D. Using cash flow is likely to be the main avenue to finance R&D since external financing may be costly.

24 We define the three size groups based on the average labour unit (ALU) observed in the initial period: small ($ALU < 100$); medium ($100 \leq ALU < 500$); and large ($500 \leq$).

25 We also estimated the equation based on two size groups by aggregating medium-sized and large firms. However, we found the same qualitative results.

Table 2: R&D and Profit Equation, 2SLS, Manufacturing, 2000-2012

	Δ ln(R&Dinvestment)	ΔProfitability	
	1	2	3
ΔIP	—	-0.057***	—
		(0.018)	
$\Delta IP \times$ initially small	-1.299***	—	-0.068***
	(0.468)		(0.022)
$\Delta IP \times$ initially medium − sized	-1.056	—	-0.014
	(0.950)		(0.031)
$\Delta IP \times$ initially large	-0.991	—	-0.013
	(0.836)		(0.025)
No. observations (firm x period)	116,683	103,816	103,816
No. firms	17,066	15,956	15,956

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Initial employment size is measured as the average labour unit (ALU) observed in the initial year (*e.g.*, ALU in 2000 for the 2000-2005 sub-period). We define the three size groups based on the average labour unit (ALU) observed in the initial period: small ($ALU < 100$); medium ($100 \leq ALU < 500$); and large ($500 \leq$). Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

no evidence that the profitability of larger firms is affected by Chinese imports. This implies that rising Chinese import competition translated into increased competitive pressure (*i.e.*, decreasing mark-ups) mostly for small firms.[26]

We carry out some robustness checks. We divide observations into three groups groups by their profitability level observed in the initial year and by the initial TFP level (measured as relative to the industry average), respectively. We indeed find that a higher initial level of competition faced by firms or a lower initial level of productivity is associated with a larger negative effect of rising Chinese competition on their R&D expenditure.[27]

In summary, smaller firms or firms initially operating in more competitive markets with technology gaps appear to be the ones most directly affected by increasing Chinese import competition. Declining profit margins indicates less room to finance R&D and/or lower expected post-innovation rents implying it is optimal for them to scale down their expenditure on R&D if they survived. In contrast, profit margins of larger firms or firms initially operating in less competitive markets with relatively high levels of technology were not affected much by increasing Chinese competition, and hence, they made less or no adjustment in their R&D investment. These larger firms may have been incum-

26 These results (both R&D expenditure and profit margins by size) are not driven by very small firm or "micro-firms" in our sample. We tried dropping increasingly larger "micro-firms" (e.g. firms with ALU<2, ALU<3, ALU<4 and so on) but the significance level and the sign of the coefficients remained the same. Also, the magnitude of the coefficients did not change significantly. We also tried including industry fixed effects since small firms tend to be in industries with large increases in Chinese import penetration ratio during our sample period (see Table A1 in the Appendix). Even with the industry fixed effects, we still found that only small firms experienced declines in their R&D expenditure and profit margins due to rising Chinese import competition.

27 Refer to Kim (2019) for the results.

bents competing with each other with similar levels of technology within their product markets but faced not much competition having small or no incentives to innovate. Or if there were laggards they would quickly catch up the leaders but once they have caught up they would have been slow to innovate further given low competition. At equilibrium, there would be a larger fraction of neck-and-neck competing incumbents with not much innovation. Such initial state (or the competitiveness of the market for these firms) were not affected much when Chinese manufacturers entered the Canadian market. As a results, the incumbent firms maintained the status quo which we observe in our data: no effect on their profitability and hence, not much adjustment in their innovative effort in response to rising Chinese competition.[28]

Some firms may have undergone industry-switching or reorganization such that they shift away from the physical production of goods towards "neuro-manufacturing" where they focus more on the design, engineering, and marketing of their goods or towards producing related professional services.[29] This may have spurred additional R&D investment within these firms but this would be observed in our data only if their primary industry code did not change to non-manufacturing due to the shift of their economic activity.

Our results imply that firms accounting for a large share of the total R&D expenditure are not likely to reduce R&D in response to increasing Chinese import competition. A small number of medium-sized and large firms account for a disproportionately large share in the total R&D expenditure in Canadian manufacturing. These larger firms account for 14 per cent of the total observations but about 77 per cent of the total R&D expenditure in manufacturing.[30] Hence, the cumulative partial impact of the China shock on the aggregate R&D expenditure in manufacturing may be limited.

Regression Results: TFP, Employment, and Survival Equation

In order to assess the impact of China on the technical change in Canadian manufacturing in a broader perspective, we estimate its impact on TFP within Canadian manufacturing firms and on the employment and the survival of firms to assess potential reallocation effects. Using the estimates from these analyses, we carry out a TFP decomposition in section six to estimate the share of the aggregate TFP change in Canadian manufacturing induced

28 This is more likely to be the case for large firms or firms operating in a concentrated market. In the following section, we show medium-sized firms appear to have resorted to other types of productivity-enhancing activities while not scaling back their R&D in response to rising import competition.

29 Some U.S. examples are Apple and IBM. Apple outsources its production to China and focuses more on product development and producing related services in the United States. IBM sold their ThinkPad business line to Lenovo which produces ThinkPad laptops in China. IBM now produces professional services related to data management and system design.

30 Medium firms (large firms) account for 11 (3) per cent of the total observations but 23 (62) per cent of the total R&D expenditure in manufacturing on average over the 2000-2012 period.

by increasing Chinese import competition.

Within-effect: TFP Equation

For estimation of firm-level TFP, we experimented with OLS and GMM for a dynamic panel data model introduced in Blundell and Bond (1998) (*i.e.*, system-GMM). We estimate a firm-level Cobb-Douglas production function by three-digit NAICS industry in manufacturing and use the estimated coefficients for inputs to retrieve estimates of firm-level TFP.[31] In this section, we report the results based on OLS as we could not find a completely satisfactory specification for GMM. We carried out all our analyses using firm-level TFP estimated with system-GMM and found that the key results in the article did not change. In Kim (2019), we discuss in more detail different estimation strategies including semi-parametric approaches and our reasons for adopting OLS to estimate TFP in our study.

Table 3 reports the results from estimating the TFP equation as described in section three. As with R&D, we find that increasing Chinese import competition reduces the TFP growth within manufacturing firms as indicated by the negative coefficient in column 1. The negative effect is robust to including industry fixed effects or including the firm-level controls introduced in column 4 in Table 1 or using the alternative instrument (see footnote 23).

The negative within-effect reported in column 1 can be related to our findings for R&D: in response to rising import competition, initially smaller and poorly-performing firms experienced declining profit margins and scaled back their R&D effort. If similar firms (not necessarily R&D performers) that survived in manufacturing scaled back their expenditure on R&D (if had any) and/or did not allocate their resources to additional productivity-enhancing effort (e.g. better management or inventory controls), then their TFP growth would decline.

As is the case for the R&D sample, we find a negative effect of increasing Chinese import competition on profitability for the TFP sample (column 3 and 4). Importantly, we find that only small firms experienced a negative effect on their profitability while larger firms did not. We estimate the TFP equation by interacting ΔIP with the size indicator (defined based on ALU observed in the initial period) in column 2 in Table 3. Again, only small firms experienced a negative effect on TFP growth.[32] Medium-sized firms actually experienced productivity gain due to increasing Chinese import competition while we find no evidence that large firms' TFP growth was affected.

Medium-sized firms may have focused on other productivity-enhancing activities

31 We also estimated a production function by two- and four-digit NAICS industry and carried out all the analyses. We found that the qualitative results remained the same.

32 As is the case in our R&D analysis by size, these results are not driven by very small firm or "micro-firms". We carried out the same sensitivity test as described in fn 30. Also, small firms tend to be in industries with large increases in the Chinese import penetration ratio (see Table A2 in the Appendix). We tried including industry fixed effects and still found that only small firms' TFP growth and profit margins were negatively affected.

Table 3: TFP and Profit Equation, TFP Sample, 2SLS, Manufacturing, 2000-2012

	Δ ln(TFP)		ΔProfitability	
	1	2	3	4
ΔIP	-0.137***	—	-0.012***	—
	(0.023)		(0.004)	
ΔIP × initially small	—	-0.164***	—	-0.015***
		(0.024)		(0.004)
ΔIP × initially medium − sized	—	0.140*	—	0.018
		(0.081)		(0.018)
ΔIP × initially large	—	0.063	—	0.003
		(0.111)		(0.012)
No. observations (firm x period)	241,054	241,054	223,886	223,886
No. firms	43,331	43,331	41,984	41,984

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Initial employment size is measured as the average labour unit (ALU) observed in the initial year (*e.g.*, ALU in 2000 for the 2000-2005 sub-period). We define the three size groups based on the average labour unit (ALU) observed in the initial period: small ($ALU < 100$); medium ($100 \leq ALU < 500$); and large ($500 \leq$). Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

(e.g. better management practices or inventory controls) while not scaling back their R&D investment (if they have invested in R&D) to remain competitive in the market. In contrast, large firms' effort to enhance productivity, if any, did not seem to have much effect on its TFP growth.

We also estimate the TFP equation splitting the observations into two categories (below and above the mean) by the initial profitability and productivity level , and find that the negative effect on TFP growth is mainly on less profitable and less productive firms. Also, we find the same qualitative results for the within-effect on TFP for the R&D sample. Refer to the Kim (2019) for the discussion and the results.

Between-effect: Employment and Survival Equation

The effect of increasing Chinese imports on the overall TFP in Canadian manufacturing cannot be fully assessed with the within-effect. The aggregate TFP change also includes the change driven by the reallocation of resources. That is, increasing Chinese import competition may have reallocated employment towards more productive firms or induced less productive firms to exit. These reallocation effects could be significant in driving the aggregate change in the TFP level in manufacturing.

In this section, we report the results from estimating the effect of increasing Chinese import competition on the employment growth and the survival of firms in manufacturing, particularly focusing on differential effects stemming from different initial technology levels of firms. We would like to study whether more technologically advanced firms are less likely to reduce employment and more likely to survive in response to increasing Chinese competition in the domestic market.

In Panel A of Table 4, we estimate the effect of China on the log change in employment but allow the effect to differ by the initial technology level by interacting

Table 4: Employment and Survival equation, 2SLS, Manufacturing

TECH variable:	R&D stock		TFP	
	Panel A: Employment equation			
Dependent: $\Delta\ln(employment)$	1	2	3	4
ΔIP	-0.136*	-1.253***	-0.289***	-0.294***
	(0.068)	(0.567)	(0.045)	(0.046)
$\Delta IP \times$ Initial TECH	—	0.105***	—	0.381***
		(0.053)		(0.094)
Initial TECH	0.026***	0.022***	0.327***	0.310***
	(0.004)	(0.004)	(0.008)	(0.008)
No. observations (firm x period)	38,153	38,153	165,825	165,825
No. firms	9,628	9,628	37,042	37,042
	Panel B: Survival equation			
Dependent: S	1	2	3	4
ΔIP	-0.027***	-0.165	-0.033***	-0.032***
	(0.012)	(0.125)	(0.011)	(0.011)
$\Delta IP \times$ Initial TECH	—	0.013	—	0.068***
		(0.011)		(0.021)
Initial TECH	-0.003*	-0.004*	0.048***	0.043***
	(0.002)	(0.006)	(0.005)	(0.004)
No. firms	6,937	6,937	32,861	32,861

Note: Period fixed effects are included in all columns. Standard errors are in parentheses. Δ denotes a 5-year difference. The dependent variable in Panel A is the log change in employment. The dependent variable in Panel B is S which equals one if a given firm survived the entire 2002-2007 period and zero otherwise. We use the average R&D stock and TFP level (measured as relative to the 3-digit NAICS industry average) observed in the initial and the two years prior to the initial year to mitigate potential measurement errors (*e.g.*, average over the 2000-2002 period for the 2002-2007 period). Hence, the sample period is 2002-2012 for Panel A and 2002-2007 for Panel B. R&D stock is divided by employment. Similar results are found when we use R&D stock divided by sales. Both technology variables enter the equation in logs.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

ΔIP with the initial technology level. We use two proxies for the technology level: R&D capital stock and the TFP level (measured as relative to the 3-digit NAICS industry average). We find that increasing Chinese import competition is associated with a lower employment growth. More importantly, the negative effect of increasing Chinese import competition on the employment growth is smaller the higher the initial technology level. This is shown as the positive and statistically significant coefficients on the interaction terms (column 2 and 4). These results indicate that high tech firms may have been "shielded" from the negative effect of increasing Chinese imports on employment.

Next, we estimate the survival equation. For the survival analysis, we focus on a cohort of firms that was alive in a given initial year. We model the probability of their survival following these firms for five years. Our sample period in this analysis is 2002-2007 since we use as a measure of initial technology level the average R&D stock or the average TFP level measured based on the initial and the two years prior to the initial year to mitigate potential measurement errors. We continue to base our analysis on a 5-year sub-period to be consistent with the other analyses in the article.

The results reported in Panel B of Table 4 indicate that firms in industries with larger increases in the Chinese import penetration ratios are less likely to survive (or more likely to exit). A one-percentage-point increase in the penetration ratio is associated with a decrease in the survival probability of 0.027 to 0.033 percentage points according to column 1, 3, and 4 in Panel B.[33] Again, we find that more technologically advanced firms (as proxied by the average TFP level) are "shielded" from the negative effect of increasing Chinese imports as indicated by the positive and statistically significant coefficient on the interaction terms in column 4.[34] When R&D stock is used to proxy the initial technology level (column 2), we find the coefficient on the interaction term is insignificant but positive.

Quantifying the Role of China

Using the results from our regressions, we contextualize the findings to provide a broad picture of the role of China in driving the technical change in Canadian manufacturing. We would like to ask: *for a given period, how much of the total change in real R&D investment and the TFP level in Canadian manufacturing can be explained by increasing Chinese import competition?*

R&D Expenditure

We calculate the predicted change in the aggregate R&D expenditure driven by increasing imports from China as follows:

$$\Delta \widehat{R\&D}_{\tau}^{China} = \sum_{i} \beta^{R\&D} * \widetilde{\Delta IP}_{j,\tau} * R\&D_{i,j,0} \quad (7)$$

where $\beta^{R\&D}$ is the marginal response of R&D expenditure growth with respect to an increase in Chinese import penetration ratio and $\widetilde{\Delta IP}_{j,\tau}$ is the exogenously-driven change in the Chinese import penetration ratio for manufacturing sector j over period τ. We estimate $\widetilde{\Delta IP}_{j,\tau}$ by discounting the actual $\Delta IP_{j,\tau}$ by the R-squared from the first stage regression. $R\&D_{i,j,0}$ is the actual level of R&D expenditure for firm i in sector j at the start of period τ.

Table 5 reports the change in real R&D expenditure induced by increasing Chinese import competition for the 2000-2005 and 2005-2010 period, respectively. The estimates are based on the size-specific coefficients from column 1 in Table 2.[35]

We estimate that had there been no increase in Chinese import competition, R&D expenditure would have increased by about 8 per cent more (*i.e.*, by $1,318 million instead of $1,220 million) between 2000

33 Note that the mean exit rate of this cohort is 6.1 per cent for the 2002-2007 period. Using the mean ΔIP and initial technology level, our estimates in column 4, for example, represent roughly 1.23 percentage-point-increase in the mean exit rate.

34 Our sample and the estimates imply that increasing Chinese imports decreased the exit rate of high tech firms and increased the exit rate of low tech firms. For example, based on the estimates from column 4 and the mean ΔIP and initial TFP level observed for the 2002-2007 period, the firms in the top 30 per cent of the initial TFP level distribution have a predicted mean exit rate of 2.4 per cent which is lower than their actual mean of 3.9 per cent while the firms in the bottom 30 per cent have a predicted mean exit rate much higher than their actual mean rate (13.2 per cent vs. 9.4 per cent).

35 We carried out the same calculations assuming only small firms adjusted their R&D in response to rising Chinese import competition. We found that the role of China in explaining the total change in R&D falls roughly by a half. We also tried using the aggregate coefficient from column 2 in Table 1. With this, in an increase in the role of China by roughly 80 per cent. The former is potentially a lower bound since we assume all medium-sized and large firms did not adjust their R&D. The latter is potentially an upper bound since we impose the larger aggregate coefficient (driven mainly by small firms) on all firms in our sample.

Table 5: Change in R&D Expenditure due to China, Manufacturing, Millions of 2007 CAD, 2000-2010

	2000-2005	2005-2010
(1) R&D expenditure in Year 1 of sub-period	5,670	7,060
(2) Actual change	1,220	-1,360
(3) Actual % change	21.5%	-19.3%
(4) Induced change in R&D due to China	-98	-89
(5) Counterfactual change in R&D (2 - 4)	1,318	-1,271
(6) Counterfactual % change (5/1)	23.2%	-18.0%

Note: Estimates are computed based on the coefficients reported in column 1 in Table 2. R&D expenditure includes only domestically performed R&D in manufacturing.

and 2005. This counterfactual translates into a growth rate of 23.2 per cent between 2000 and 2005, a 1.9 percentage-point-increase from the actual growth rate of 21.5 per cent. Between 2005 and 2010, R&D expenditure in manufacturing fell by $1,360 million CAD. Our estimates imply that China can explain about 6.5 per cent of the total decline for this period. This implies that if the Chinese import penetration ratio did not change between 2005 and 2010, R&D expenditure in manufacturing would have fallen by 18.0 per cent instead of 19.3 per cent.

TFP

To assess the role of increasing Chinese imports in driving the aggregate TFP in Canadian manufacturing, we carry out a standard productivity decomposition using the estimates from Equation (1), (2), (4), and (5) following a similar decomposition methodology introduced in Bailey, Hulten, and Campbell (1992), Foster, Haltiwanger, and Krizan (2000), and Bloom *et al.* (2016):

$$\begin{aligned}\Delta \mathrm{P}_t = & \sum_{i=1}^{N} s_{i,0}\left(p_{ijt}-p_{ij0}\right) \\ & + \sum_{i=1}^{N} p_{ij0}\left(s_{it}-s_{i0}\right) \\ & + \sum_{i=1}^{N}\left(s_{it}-s_{i0}\right)\left(p_{ijt}-p_{ij0}\right) \\ & - \sum_{i\in exit} s_{i0}^{exit}\left(p_{ij0}^{exit}-\overline{p}_{j0}\right) \\ & + \sum_{i\in entrant} s_{it}^{entrant}\left(p_{ijt}^{entrant}-\overline{p}_{jt}\right)\end{aligned} \tag{8}$$

where P_t denotes the aggregate TFP level at a given point in time t. $\Delta \mathrm{P}_t$ represents the aggregate change in TFP between time 0 and t. $s_{i,t}$ denotes the employment share of firm i at time t (*i.e.*, firm employment divided by total employment in manufacturing).[36] $\overline{p}_{jt}$ is the average TFP of all firms in sector j at time t. N is the total number of firms in manufacturing.

The first term in Equation (8) is the within-firm effect which is the change in TFP level holding employment shares constant. The second term is the between ef-

36 Output shares could be used as weights in TFP decomposition. We adopt labour shares as weights in our decomposition given our econometrics framework based on Bloom *et al.* (2016).

fect, the change in TFP level due to shifting employment from less productive firms to more productive firms holding the initial productivity level constant. The third term is the cross effect which is simply the correlation between the change in TFP level and the change in employment share within firms. The second last term is the exit effect which represents the change in TFP level due to firm exits. The last term represents the entry effect. The contribution of entrants and exitors depends on entering or exiting firms' p_i relative to the average p_i of the incumbents.

We explicitly model each term in Equation (8) (except for the entry effect). Following Bloom *et al.* (2016), we can re-write Equation (8) in terms of our estimates from Equation (2), (4), and (5). Using our estimates from TFP, employment, and survival equations, we have:

$$\begin{aligned}\Delta P_t^{China} &= \sum_{i=1}^{N} s_{i,0}\left(\beta^{TFP}\Delta IP_j\right)\\ &+ \sum_{i=1}^{N} p_{ij0}\left({s_{it}}^{between} - s_{i0}\right)\\ &+ \sum_{i=1}^{N}\left({s_{it}}^{between} - s_{i0}\right)\\ &\times\left(\beta^{TFP}\Delta IP_j\right)\\ &- \sum_{i\in exit} s_{i0}^{exit}\left(p_{ij0}^{exit} - \overline{p}_{j0}\right) \qquad (9)\end{aligned}$$

where β^{TFP} is the coefficient from Equation (2). ${s_{it}}^{between}$ is the predicted share of employment for incumbent firms and s_{i0}^{exit} is the predicted share of employment in exiting firms as defined in the following.

$$\begin{aligned}&{s_{it}}^{between} =\\ &\frac{N_{i0}(1+\beta^N\Delta IP_j + \lambda^N\Delta IP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1+\beta^N\Delta IP_j + \lambda^N\Delta IP_j p_{ij0})}\end{aligned} \qquad (10)$$

where β^N and λ^N are the coefficients from Equation (4). N_{i0} is the employment level in firm i at time 0.

$$\begin{aligned}&{s_{i0}}^{exit} =\\ &\frac{N_{i0}(1-\beta^S\Delta IP_j - \lambda^S\Delta IP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1-\beta^S\Delta IP_j - \lambda^S\Delta IP_j p_{ij0})}\end{aligned} \qquad (11)$$

where β^S and λ^S are the coefficients from Equation (5).

Finally, we can compute the magnitude of each component in Equation (9) by computing the ratio $\frac{\Delta P_t^{China}}{\Delta P_t}$ where ΔP_t is the actual change in the aggregate TFP level in manufacturing over the period $0-t$.

We cannot directly quantify the entry effect at the firm-level as it is not possible to observe the technology level of a given firm before entry.[37] We can implicitly assess the magnitude of the entry effect by estimating an industry-level version of Equation (2) and compare its coefficient which presumably captures within-, between-, and entry effects with the corresponding firm-level coefficients. We estimate that the entry effect is potentially small (refer to Kim (2019:32)).

Table 6 reports the results from our productivity decomposition focusing on the

37 Note that it is not appropriate to use the technology level at the time they enter as it is likely to be endogenous.

Table 6: Change in TFP due to China, Manufacturing, 2005-2010

	As a % of the *decline* in the TFP level between 2005 and 2010
Within (-)	5.4%
Between (+)	-17.1%
Exit (+)	-3.9%
Cross (+)	0.0%
Total (+)	**-15.6%**

period 2005-2010.[38] Note that the magnitudes are presented as a share of the actual *decline* in the aggregate TFP level in manufacturing between 2005 and 2010. Hence, negative (positive) sign implies that increasing Chinese import competition has positively (negatively) affected the total change in the TFP level.

We find that the TFP level declined within manufacturing firms between 2005 and 2010, negatively affecting the aggregate TFP level in manufacturing.[39] We estimate that the within-effect driven by increasing Chinese import competition can explain roughly 5 per cent of the total decline in the TFP level in Canadian manufacturing. However, there were substantial gains in the aggregate TFP level through the reallocation of resources. In response to increasing Chinese import competition, employment shifted from less productive firms to more productive firms. Also, less productive firms exited the market although its impact on the overall TFP is relatively small. The reallocation effects (between plus exit) driven by increasing Chinese import competition more than offset the negative within-effect, resulting in a net positive effect on the aggregate TFP change between 2005 and 2010. That is, had there been no increase in Chinese import competition in Canada, the per cent change in the aggregate TFP level would have been -1.26 per cent per year instead of -1.09 per cent per year.[40] As is often the case in other empirical studies, the cross-effect is negligible.

Our estimates imply that the reallocation of resources appears to be the main channel through which rising import competition raised the overall productivity performance in Canadian manufacturing. The within effect is negative but potentially small since the effect was pronounced in

38 We also analyzed the 2000-2005 period and the qualitative results were the same — as is the case for the 2005-2010 period, the sum of the between- and exit-effect was positive and more than offset the negative within-effect. However, the impact of China was not economically significant. Also, the actual TFP growth between 2000 and 2005 was very small (e.g. 0.42 per cent based on the CPA data or 0.02 per cent based on the T2-LEAP-SRED database). Our estimates from the decomposition exercise imply that increasing Chinese import competition explains less than 2 per cent of the total increase in the TFP level in manufacturing for this period.

39 For the within-effect, we use the coefficient reported in column 1 in Table 3. If we use the size-specific coefficients reported in column 2, the within effect becomes positive (a positive contribution to the overall TFP change) but the absolute per cent level is nearly zero, increasing the total impact by about 6 percentage points. Hence, one may conclude that the within effect is either negative but relatively small or zero.

40 Or -6.82 per cent instead of -5.90 per cent (or -1.36 per cent per year instead of -1.18 per cent per year) based on the CPA data.

small firms which tend to be less productive in the initial period.

Conclusion

Utilizing as a natural experiment the rapid increase Chinese import share in the total domestic absorption in Canadian manufacturing, we find that rising Chinese import competition led to declines in R&D expenditure and TFP within firms. Especially, the declines in R&D and TFP were pronounced in smaller, less profitable, and less productive firms. The negative effect of China on R&D at the aggregate level is somewhat limited as the most-affected firms accounted for a small share of the total R&D expenditure in Canadian manufacturing. Rising import competition reallocated employment towards more productive firms and drove less productive firms out of the domestic market, more than offsetting the negative within-effects on TFP at the aggregate level.

References

Acemoglu, Daron (2008) "Equilibrium Bias of Technology," *Econometrica*, Vol. 75, No. 5, pp. 1371-1409.

Acemoglu, Daron, David H. Autor, David Dorn, Gordon H. Hanson and Brendan Price (2016) "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, Vol. 34, No. S1, Part 2, pp. S141-S198.

Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith and Peter Howitt (2005) "Competition and Innovation: An Inverted U Relationship," *Quarterly Journal of Economics*, Vol. 120, No. 2, pp. 701-728.

Autor, David H., David Dorn and Gordon H. Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, Vol. 103, No. 6, pp. 2121-2168.

Autor, David, David Dorn, Gordon Hansen, Gary Pisano and Pian Shu (2017) "Foreign Competition and Domestic Innovation: Evidence from U.S. Patents," Mimeo, December.

Baily, Martin, Charles Hulten and David Campbell (1992) "Productivity Dynamics in Manufacturing Firms," *Brookings Papers on Economic Activity: Microeconomics*, Vol. 4, pp. 187-267.

Baldwin, John R., Afshan Dar-Brodeur and Beiling Yan (2016) "Innovation and Export-market Participation in Canadian Manufacturing," Statistics Canada, Analytical Studies Branch Research Paper Series, No. 386, 11F0019M.

Bartel, Ann, Casey Ichinowski and Kathryn Shaw (2007) "How Does Information Technology Really Affect Productivity? Plant-level Comparisons of Product Innovation, Process Improvement and Worker Skills," *Quarterly Journal of Economics*, Vol. 122, No. 4, pp. 1721-1758.

Bernard, Andrew, Bradford Jensen and Peter Schott (2006) "Survival of the Best Fit: Exposure to Low-wage Countries and the (uneven) Growth of US Manufacturing Establishments," *Journal of International Economics*, Vol. 68, No. 1, pp. 219-237.

Bloom, Nicholas, Mirko Draca and John Van Reenen (2016) "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," *Review of Economic Studies*, Vol. 83, pp. 87-117.

Bloom, Nicholas, Paul Romer, Stephen Terry and John Van Reenen (2015) "A Trapped Factor Model of Innovation", LSE/Stanford mimeo.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen (2013) "Identifying Technology Spillovers and Product Market Rivalry," *Econometrica*, Vol. 81, No. 4, pp. 1347–1393.

Blundell, Richard and Stephen Bond (1998) "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, Vol. 87, No. 1, pp. 115–143.

Bugamelli, Matteo, Fabiano Schivardi and Roberto Zizza (2008) "The Euro and Firm Restructuring," NBER Working Papers, No. 14454.

Burstein, Ariel and Jonathan Vogel (2017) "International Trade, Technology, and the Skill Premium," *Journal of Political Economy*, Vol. 125, No. 5, pp. 1356-1412.

Brandt, L., J. Van Biesebroeck, L. Wang and Y. Zhang (2012) "WTO Accession and Performance of Chinese Manufacturing Firms," Centre for Economic Policy Research.

Card, David (2001) "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration," *Journal of Labor Economics*, Vol. 19, No. 1, pp. 22-64.

Dasgupta, Partha and Joseph Stiglitz (1980) "Industrial Structure and the Nature of Innovative Activity," *Economic Journal*, Vol. 90, No. 358, pp. 266-293.

Foster, Lucia, John Haltiwanger and C. J. Krizan (2000) "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," New Developments in Productivity Analysis, NBER, Chicago Press.

Freeman, Richard and Morris Kleiner (2005) "The Last American Shoe Manufacturers," *Industrial Relations*, Vol. 44, pp. 307-342.

Gong, Kaiji and Rui Xu (2017) "Does Import Competition Induce R&D Reallocation? Evidecne from the U.S.," IMP Working Paper, WP/17/253.

Hall, Bronwyn H. (1992) "Investment and Research and Development at the Firm Level: Does the Source of Financing Matter?," NBER Working Paper No. 4096.

Keung Lorenz, Nicholas Li and Mu-Jeung Yang (2016) "The Impact of Emerging Market Competition on Innovation and Business Strategy," NBER Working Paper, No. 22840.

Kim, Myeongwan (2018a) "Rising Import Competition in Canada and its Employment Effect by Skill Group: Evidence from the 'China shock'," CSLS Research Report 2018-02, August. http://www.csls.ca/reports/csls2018-02.pdf.

Kim, Myeongwan (2018b) "Rising Import Competition in Canada and its Employment Effect by Gender: Evidence from the 'China shock'," CSLS Research Report 2018-03, August. http://www.csls.ca/reports/csls2018-03.pdf.

Kim, Myeongwan (2019) "Does Import Competition Reduce Domestic Innovation? Evidence from the 'China Shock' and Firm-Level Data on Canadian Manufacturing," CSLS Research Report 2019-03, August, http://www.csls.ca/reports/csls2019-03.pdf.

Kim, Myeongwan and John Lester (2019) "R&D spillovers in Canadian Industry: Evidence from a New Micro Data," CSLS research report 2019-02, August, http://www.csls.ca/reports/csls2019-02.pdf.

Krugman, Paul (1980) "Scale Economies, Product Differentiation, and the Pattern of Trade," *American Economic Review*, Vol. 70, No. 5, pp. 950–959.

Melitz, Marc J. (2003) "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71, 6,pp. 1695–1725.

Murray, Alexander (2017) "The Effect of Import Competition on Employment in Canada: Evidence from the 'China Shock'," CSLS Research Report 2017-03, July. http://www.csls.ca/reports/csls2017-03.pdf.

Pierce, Justin R. and Peter K. Schott (2012) "A Concordance between Ten-Digit U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries," *Journal of Economic and Social Measurement*, Vol. 37, No. 1-2, pp. 61-96.

Schmidt, Klaus (1997) "Managerial Incentives and Product Market Competition," *Review of Economic Studies*, Vol. 64, No. 2, pp. 191–213.

Shu Pian and Claudia Steinwender (2018) "The Impact of Trade Liberalization on Firm Productivity and Innovation," NBER Working Paper, No. 24715.

Appendix

Table A1: Summary Statistics, R&D Sample, by Initial Employment Size, Manufacturing, 2000-2012

Employment	R&D	Initial expenditure	Initial Profitability	ΔIP Productivity	ΔIPE	Δ ln(TFP)	ΔProfitability	
<u>Total</u>								
Mean	85	430	-0.009	-0.051	0.049	0.077	0.073	-4.957
Std. Dev.	494	6,606	x	0.685	0.102	0.143	0.788	x
<u>Small</u>								
Mean	24	129	-0.016	-0.068	0.050	0.080	0.057	-5.225
Std. Dev.	32	474	x	0.675	0.099	0.141	0.772	x
<u>Medium</u>								
Mean	182	600	0.035	0.004	0.045	0.065	0.136	-3.520
Std. Dev.	134	2,025	x	0.693	0.109	0.140	0.805	x
<u>Large</u>								
Mean	1,694	9,668	0.055	0.252	0.030	0.042	0.257	-2.440
Std. Dev.	2,543	39,500	x	0.844	0.160	0.204	1.070	x

Note: The number of observations is 116,683 (small: 100,894; medium-sized: 12,740; large: 3,049). Δ denotes a 5-year difference. All the initial values are the values observed in the initial year of a given sub-period. Employment is measured as the average labour unit. We define the three size groups based on the average labour unit (ALU) observed in the initial period (*e.g.*, ALU in 2000 for the 2000-2005 sub-period): small ($ALU < 100$); medium ($100 \leq ALU < 500$); and large ($500 \leq$). R&D expenditure is in thousand 2007 constant CAD. Productivity is measured as log of deviation from the industry average. Profitability is defined as net income or loss before tax divided by sales. x indicates that the statistics is suppressed due to confidentiality requirements.

Table A2: Summary Statistics, TFP Sample, by Initial Employment Size, Manufacturing, 2000-2012

	Employment	Initial Profitability	Initial Productivity	ΔIP	ΔIPE	Δ ln(TFP)	ΔProfitability
<u>Total</u>							
Mean	41	0.048	-0.010	0.051	0.073	0.057	-0.695
Std. Dev.	291	x	0.519	0.093	0.133	0.506	x
<u>Small</u>							
Mean	16	0.048	-0.067	0.051	0.074	0.052	-0.742
Std. Dev.	23	x	0.509	0.091	0.132	0.499	x
<u>Medium</u>							
Mean	183	0.050	0.003	0.045	0.062	0.116	-0.017
Std. Dev.	127	x	0.598	0.102	0.130	0.576	x
<u>Large</u>							
Mean	1,578	0.074	0.249	0.029	0.041	0.155	0.013
Std. Dev.	2,366	x	0.765	0.169	0.207	0.672	x

Note: The number of observations is 241,054 (small: 225,697; medium-sized: 12,886; large: 2,471). Δ denotes a 5-year difference. All the initial value is the value observed in the initial year of a given sub-period. Employment is measured as the average labour unit. We define the three size groups based on the average labour unit (ALU) observed in the initial period (*e.g.* ALU in 2000 for the 2000-2005 sub-period): small ($ALU < 100$); medium ($100 \leq ALU < 500$); and large ($500 \leq$). Initial productivity is measured as log of deviation from the industry average. Profitability is defined as net income or loss before tax divided by sales. x indicates that the statistics is suppressed due to confidentiality requirements.

Frontier Firms, Productivity Dispersion and Aggregate Productivity Growth in Canada

Wulong Gu[1]
Statistics Canada

Abstract

Labour productivity growth in the business sector in Canada fell off after 2000. This article examines how innovation, innovation diffusion across firms, and business dynamism affected the productivity slowdown. The article found that both innovation and diffusion of innovation declined in Canada after 2000, contributing to the decline in labour productivity growth in that period. However, their relative contribution to the productivity slowdown is sensitive to the methods adopted. The results from a productivity decomposition into contributions of frontier firms (defined as the top 10 per cent most productive firms in an industry) and non-frontier firms show that the slowdown in the diffusion of innovation is a main source of the productivity slowdown after 2000. In contrast, the results from a stochastic frontier analysis show that the decline in innovation is the main source of the productivity slowdown after 2000. Finally, this article found that resource reallocation declined in Canadian firms after 2000, contributing to the decline in aggregate labour productivity growth.

Productivity growth has slowed in Canada and other developed countries since the early 2000s. For example, business sector labour productivity in the United States had been growing at an average rate of 2.1 per cent, year over year. Then, in 2004, the productivity growth rate began to decline, falling to an average of 1.2 per cent per year from 2004 to 2014 (Manyika *et al.*, 2017; Murray, 2018). Business sector labour productivity growth in Canada fell off after 2000, from 1.7 per cent per year in the period from 1980 to 2000 to 1.0 per cent per year in the period from 2000 to 2015 (Gu 2018).[2] This decline in productivity growth also occurred in other developed countries. Labour productivity growth after 2004 has been the weakest on record in most OECD countries since 1950 (OECD, 2015).

---

1 The author is Senior Advisor in the Economic Analysis Division at Statistics Canada. He would like to thank D. Grekou, D. Leung, H. Liu, R. Macdonald, W. Wang, A. Sharpe and three anonymous reviewers for helpful comments. An earlier version of this paper was presented at conferences organized by the International Association for Research in Income and Wealth and the Canadian Economics Association. Email: wulong.gu@canada.ca.

2 Labour productivity is defined as real value added per hour worked. The growth estimates are obtained from Statistics Canada Table 36-10-0211-01 for multifactor productivity and related variables in the aggregate business sector and major subsectors.

Previous studies have identified a number of explanations for this trend. While the slowdown in productivity growth after 2000 is partly the result of cyclical factors—such as slow output growth and the burst of the dot-com bubble in the early 2000s, and the 2008–2009 global financial crisis—a number of structural factors have also been suggested as explanations for this slowdown (Baily and Montalbano, 2016; Cette, Corde and Lecat, 2017; OECD, 2015; Murray, 2018). These structural factors include a slower pace of innovation and technological progress, a slowdown in innovation diffusion, changes in competitive intensity, a decline in business dynamism, and resource misallocation—possibly caused by the sharp decline in real interest rates.

This article examines the role of structural factors in the post-2000 productivity growth slowdown in Canada. First, this article looks at the role that innovation in frontier firms and innovation diffusion from frontier firms to non-frontier firms played in the decline in productivity growth after 2000. According to Gordon (2016), the slow pace of innovation caused the productivity slowdown in developed countries, and current technological advances such as digital technologies, robots and cloud computing are not important enough to drive strong productivity growth. He argues that historical innovations such as steam engines and electricity had far greater impacts on productivity growth than current technological developments. As an alternative explanation for the productivity slowdown, the OECD (2015) presented empirical evidence that the main cause of the productivity slowdown was not a slowing pace of innovation by frontier firms, but rather a slowing pace of innovation diffusion from frontier firms to non-frontier firms in the early 2000s (Andrews, Criscuolo and Gal, 2015; OECD, 2015).

Second, this article examines the role of changes in business dynamism and changes in resource allocation in the productivity slowdown. Previous studies for Canada, the United States and other developed countries found evidence of declining business start-ups, declining gross job creation and destruction, and rising resource misallocation in the 2000s (Decker *et al.* (2016) for the United States; Cao *et al.* (2017) and Macdonald (2014) for Canada). However, the extent to which changes in business dynamism and changes in resource allocation contributed to the productivity slowdown is not known.

To assess the relative impact of innovation and innovation diffusion on the productivity slowdown, this article divides all firms in an industry into frontier and non-frontier firms in terms of labour productivity levels, and decomposes aggregate productivity growth into contributions from frontier firms and non-frontier firms. Frontier firms are defined as the top 10 per cent most productive firms in an industry. Non-frontier firms include all other firms. Productivity growth of frontier firms is used to assess the pace of innovation over time. Productivity growth of non-frontier firms is used to assess the pace of innovation diffusion over time (Andrews, Criscuolo and Gal, 2015).

To assess the robustness of results on the roles of innovation and diffusion of innovation in the productivity slowdown from this accounting approach, a stochastic frontier production function approach was also used as an alternative. The stochastic frontier production function approach decomposes productivity growth into technical change and technical efficiency change. Technical change is calculated as the productivity growth of the most productive firms that form the production frontier, and technical efficiency change is calculated as the change in the productivity gap between non-frontier firms and the most productive firms over time. It is a measure of non-frontier firms' ability to catch up to frontier firms. For the purpose of this article, technical change is interpreted as the pace of innovation in frontier firms, and technical efficiency change represents the rate of innovation diffusion from frontier firms to non-frontier firms.

Previous studies have examined the productivity growth difference between frontier and non-frontier firms, and its implication for aggregate productivity growth. The OECD (2017) found that the dispersion in productivity growth between the best-performing and the worst-performing firms increased in a number of OECD countries, including Canada, since 2000. Andrews, Criscuolo and Gal (2015) found that the productivity growth of global frontier firms remained robust after 2004, when aggregate productivity growth in advanced economies began to slow. This was interpreted as evidence that the main source of the productivity slowdown was not a slowing pace of innovation by the most globally advanced firms, but rather a slowing pace at which innovations spread throughout the economy.

Haldane (2017) examined productivity dispersion in the United Kingdom and concluded that the decline in productivity growth in that country after the financial crisis, compared with that of the early 2000s, was the result of the poor productivity growth of non-frontier firms. The productivity growth of frontier firms in the United Kingdom was robust after the financial crisis. Cette, Corde and Lecat (2017) found that robust productivity growth of frontier firms in France increased after 2000, and that the pace of innovation did not decline in the 2000s. However, no evidence was found that innovation diffusion from frontier firms to non-frontier firms slowed after 2000 in France.

Most previous studies focused on productivity dispersion and productivity growth of frontier and non-frontier firms in the 2000s, and used this information to provide evidence on the role of innovation and diffusion in aggregate productivity growth in the 2000s. But, as Andrews, Criscuolo and Gal (2015) noted, this data limitation with short time series makes it difficult to address the issue of whether productivity growth of frontier and non-frontier firms slowed after 2000, compared with the period before 2000. Therefore, evidence for the 2000s cannot be used alone to examine the role of innovation and innovation diffusion in the post-2000 productivity slowdown. This article addresses this data limitation by using data over a longer period, including data for both before and after 2000, and constitutes the first Canadian evidence on productivity growth of frontier and non-frontier firms. This provides direct evidence on the role of innovation and innovation diffusion in aggregate productivity growth slowdown in the 2000s.

The article is organized as follows. Section one presents the data used for the analysis. Section two presents productivity dispersion of frontier and non-frontier firms, and the firms' contributions to aggregate productivity growth. Section three uses the stochastic frontier approach to decompose productivity growth into technical change (identified as innovation in frontier firms) and technical efficiency change (identified as innovation diffusion from frontier to non-frontier firms). Section four examines the effect of resource reallocation on productivity growth over time, and its contribution to the decline in aggregate productivity growth after 2000. Section five concludes.

Data Sources

The data used for this article are from Statistics Canada's T2–LEAP longitudinal firm-level database.[3] This database was created by linking two administrative databases: the Longitudinal Employment Analysis Program (LEAP) file and the Corporate Tax Statistical Universal File (T2).

The LEAP file is a database that includes all employers in Canada, both incorporated and unincorporated, that register a payroll deduction account with the Canada Revenue Agency (CRA). The LEAP file contains longitudinal firm identification numbers, which are used to examine the growth, entry and exit of firms. The firms in the LEAP file have been assigned to industries according to the North American Industry Classification System (NAICS).

The LEAP file was linked to the T2 file, which includes all incorporated firms that file a T2 tax return with the Canadian Revenus Agency. The linked T2–LEAP file provides data on total sales, payroll, net income, and assets for all incorporated firms in Canada. A derived measure of average employment, called average labour units (ALUs), is estimated and added to the file. A firm's ALUs are calculated as the ratio of the firm's total payroll to average annual worker wages in that firm's industry, size class, and province.[4]

This article focuses on incorporated businesses in Canada. Businesses in the agriculture, forestry and fishing, health, and education sectors are excluded since measures of output, inputs and productivity are less reliable for some of those sectors. The examined incorporated businesses comprise the non-farm market sector in Canada. The article examines the non-agriculture or non-farm market sector's labour productivity and multifactor productivity (MFP).[5] Labour productivity is defined as real gross output per worker. MFP is defined as gross output per unit of

3 Previous studies (e.g., Baldwin and Gu, 2011; Gu and Lafrance, 2014) have used the T2–LEAP file to study the productivity dynamics of the non-manufacturing sectors.

4 The database was cleaned for outliers, using a method based on the outliers principle developed by Tukey (1977). This method deletes values located beyond quartile 1 (and 3), which are less (and more) than three times the interquartile spread of labour productivity levels at the three-digit NAICS industry classification level in a year. About 1 per cent of the observations were classified as outliers using this method, and they were removed from the analysis in this article.

5 Because of data issues, forestry and fishing was also excluded from the non-farm market sector.

combined capital, labour and intermediate inputs. Capital input for measuring MFP is estimated as the book values of tangible assets, deflated by an industry capital stock price index. Intermediate input is measured as sales minus the sum of payroll and capital income (estimated as net income before taxes).

Labour productivity, output and employment are available for the period from 1991 to 2015. MFP and related output and input measures are available for the period from 2000 to 2015 as values of tangible assets, and intermediate inputs are available only after 2000.

Labour productivity (gross output per worker) of the non-farm market sector — derived from the T2–LEAP microdata file — shows similar trends to labour productivity (gross output per hour worked) for the business sector, derived from the Statistics Canada industry productivity database. Both estimates of aggregate labour productivity growth declined after 2000. Aggregate labour productivity of the business sector derived from the industry productivity database declined from 2.96 per cent per year for the 1991-2000 period to 0.74 per cent per year for the 2000-2015 period. Aggregate labour productivity growth of the non-farm market sector derived from the T2–LEAP file also showed a large decline after 2000—from 2.90 per cent per year to -0.07 per cent per year between the two periods.[6]

The post-2000 decline in labour productivity growth in Canada has been well documented, and numerous studies have focused on the causes of this large decline (e.g. Gu, 2018; Sharpe and Tsang, 2018). Those studies concluded that the rapid productivity growth in the 1990s can be traced to trade liberalization and the adoption of information and communications technology (ICT) in that period. The slow labour productivity growth after 2000 is related to slower growth in MFP, slower growth in demand, and a decline in the contribution of exporters and large multinational firms in the early 2000s (Baldwin, Gu and Yan, 2013; Rao and Li, 2013; Baldwin and Gu, 2004; Trefler, 2004). A decline in MFP growth in the mining sector caused by increased costs for the extraction of natural resources also contributed to the slow productivity growth in the 2000s (Gu, 2018).

Productivity Dispersion and Aggregate Productivity Growth

This section has two main objectives. First, it presents trends in the productivity growth of frontier and non-frontier firms. The productivity growth of frontier firms is commonly associated with innovation and technical progress. The productivity growth of non-frontier firms is associated with innovation diffusion from frontier firms to non-frontier firms, or catch-up of non-frontier firms to frontier firms. Second, this section decomposes aggregate productivity growth into contributions of frontier and non-frontier firms. The evidence on contributions of frontier and non-

6 After 2000, there is a large difference in growth rates in the two estimates of labour productivity growth. The sources of this difference may include the difference in industry coverage and the differences in labour unit measures.

frontier firms enables an assessment of the roles of innovation in frontier firms and innovation diffusion from frontier to non-frontier firms on aggregate productivity growth over time, and their contributions to the decline in productivity growth in Canada after 2000.

The analysis will focus on two periods: 1991–2000 and 2000–2015. Short-term changes in productivity can be caused by cyclical factors that arise from changes in the use of capital and output growth. This was the case in the early 2000s and the early 1990s (Baldwin, Gu and Yan, 2013). Focusing on these relatively long periods removes the effects of cyclical factors on productivity, and therefore allows the identification of structural factors — such as innovation and technological diffusion — on productivity growth.

Frontier firms are defined as the top 10 per cent most productive firms, in terms of labour productivity levels within the three-digit NAICS 2007 classification level. All other firms within a three-digit NAICS industry code are defined as non-frontier firms. There are a total of 87 industries in the non-farm market sector at the three-digit NAICS level of industry aggregation.

Productivity of Frontier and Non-frontier F'irms

This sub-section presents the productivity of frontier and non-frontier firms and changes in productivity dispersion in the non-farm market sector in Canada from 1991 to 2015. Both labour productivity and MFP are examined. Labour productivity is defined as gross output per worker. MFP is defined as the ratio of gross output to combined capital, labour and intermediate inputs, using the growth accounting method.

Labour productivity (gross output per worker) is presented for the 1991-2015 period. MFP (gross output per unit of combined capital, labour and intermediate inputs) is presented for the period after 2000 since the estimates of capital stock and intermediate inputs are available only after 2000.

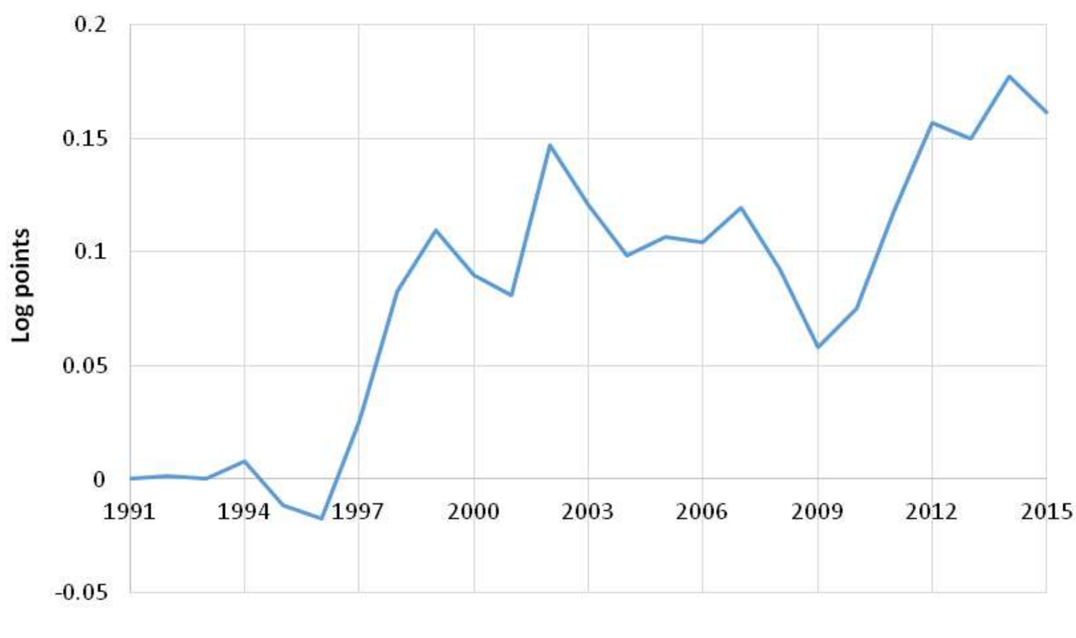
The productivity of frontier and non-frontier firms in logarithm is estimated as each group's median productivity values. The log difference in productivity between frontier and non-frontier firms is used to measure productivity dispersion. The log difference in productivity between frontier and non-frontier firms at the three-digit NAICS level is aggregated to the log productivity difference at the two-digit NAICS level and for the non-farm market sector, using a simple mean. Therefore, the log difference in productivity at the two-digit NAICS level, or for the non-farm market sector, represents the productivity dispersion in an average three-digit NAICS industry.

Panel A of Chart 1 presents the labour productivity of frontier and non-frontier firms, and aggregate labour productivity in the non-farm market sector for the 1991-2015 period. Panel B of Chart 1 presents the log difference in labour productivity levels between frontier and non-frontier firms over that period. The values are set to zero in 1991 in both charts. The values of the log productivity of frontier and non-frontier firms in a year represent the cumulative log growth in productivity of those two types of firms since 1991.

Chart 1: Labour Productivity, Frontier and Non-Frontier Firms in Canada, 1991-2015

Panel A: Labour Productivity of Frontier and Non-frontier Firms, 1991–2015, in logarithm, 1991 = 0

Panel B: Relative Labour Productivity of Frontier and Non-frontier Firms, 1991–2015, in logarithm, 1991 = 0



Note: Labour productivity is defined as real gross output per unit of labour.
Source: Statistics Canada, author's calculation from T2-LEAP file.

Table 1: Labour Productivity Growth in Canada (average annual rate of change)

	1991-2000	2000-2015	Change between periods (points)
Non-farm aggregate	2.90	-0.07	-2.97
Frontier firms	3.43	0.82	-2.62
Non-frontier firms	2.44	0.33	-2.10
CPA business sector	2.96	0.74	-2.22

Note: Productivity for frontier and non-frontier firms is defined as the median productivity for each group, not average productivity.
Source: T2-LEAP database for the first three roles, Canadian Productivity Accounts database for the fourth row.

Over the 1991-2015 period, the labour productivity of frontier firms increased faster than that of non-frontier firms in average Canadian industries. The labour productivity of frontier firms increased by a cumulative 0.43 log points, or 54 per cent, over the period from 1991 to 2015.[7] The labour productivity of non-frontier firms increased by 0.27 log points, or 31 per cent, in the same period.[8]

The increase in the relative productivity of frontier firms compared with that of non-frontier firms occurred in the second half of the 1990s and in the period after 2009, as shown in Panel B of Chart 1. The productivity dispersion did not change much in the early 1990s and the early 2000s. The pause in the overall trend toward productivity divergence between frontier and non-frontier firms in the first half of the 1990s and the first half of the 2000s was caused by the cyclical factors that arose from slow demand growth and a decline in capacity utilization. This affected exporters and multinationals more than other firms, at least in the manufacturing sector (Baldwin, Gu and Yan, 2013). The subsequent increase in the productivity growth gap between frontier and non-frontier firms in the second half of the 1990s and after 2009 was partially caused by increases in capacity utilization in the manufacturing industry, and likely also in other industries (Gu, 2018).

To remove the effects of those cyclical factors and focus on the effects of structural factors—such as innovation and innovation diffusion—on productivity growth, this article focuses on productivity growth for two relatively long periods: 1991–2000 and 2000–2015. The year 2000 corresponds to the turning point when productivity growth in Canada began to decline.

Annual average labour productivity growth of frontier and non-frontier firms for 1991 to 2000 and 2000 to 2015 can be calculated using the data in Panel A of Chart 1, as shown in Table 1. Labour productivity growth of frontier firms was higher than that of non-frontier firms in both periods. Labour productivity growth of both frontier and non-frontier firms declined after 2000. The decline was similar for

7 The change in log points can be converted to a percentage change by taking its natural exponent.

8 A productivity growth divergence in frontier and non-frontier firms was also found in Canadian manufacturing plants for the period from 1973 to 2015 (Gu, Yan and Ratté, 2018).

both groups. Labour productivity growth for both groups experienced approximately more than a 2-percentage-point decline between 1991–2000 and 2000–2015. Labour productivity growth of frontier firms declined from 3.43 per cent per year in 1991–2000 to 0.82 per cent per year in 2000–2015. Labour productivity growth of non-frontier firms declined from 2.44 per cent per year to 0.33 per cent per year between the two periods.

Before 2000, productivity growth in Canada was rapid. The rapid progress in ICT and the adoption of ICT and associated changes in workplace organization were the main force behind this rapid productivity growth (Gu and Willox, 2018; Ho, Rao and Tang, 2004). The implementation of the Canada–U.S. Free Trade Agreement and the North American Free Trade Agreement also contributed to productivity growth (Trefler, 2004, Baldwin and Gu, 2004). As a result, productivity growth of frontier and non-frontier firms was strong for the period from 1991 to 2000.

Productivity growth declined after 2000 for frontier and non-frontier firms. To the extent that productivity growth of frontier firms captures innovation and productivity, growth of non-frontier firms captures innovation diffusion. Evidence suggests that the pace of innovation and the pace of innovation diffusion from frontier to non-frontier firms both declined in Canada after 2000.

Chart 2 shows the capital/labour ratio, intermediate input/labour ratio, and MFP of frontier and non-frontier firms from 2000 to 2015.

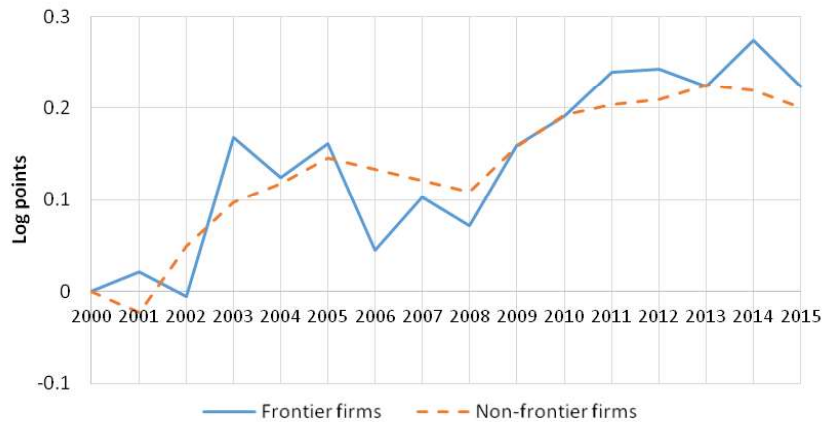
Panel A of Chart 2 shows that the capital/labour ratio increased by a similar amount for both frontier and non-frontier firms. Panel B shows that the intermediate input/labour ratio experienced little change for both frontier and non-frontier firms. Because of similar changes in capital and intermediate input intensities in frontier and non-frontier firms, most of the divergence in labour productivity between frontier and non-frontier firms for the 2000-2015 period was because of divergence in MFP growth, as shown in Panel C.

Table 2 presents labour productivity growth of frontier and non-frontier firms at the two-digit NAICS level for the 1991–2015 period, and for the 1991–2000 and 2000–2015 sub-periods. For 1991 to 2015, labour productivity growth of frontier firms was higher than that of non-frontier firms in all industries except in arts, entertainment and recreation, accommodation and food services, and other services. The biggest productivity growth difference between frontier and non-frontier firms was in utilities, mining and oil and gas extraction, broadcasting and telecommunications, finance, insurance and real estate, and wholesale and retail trade.

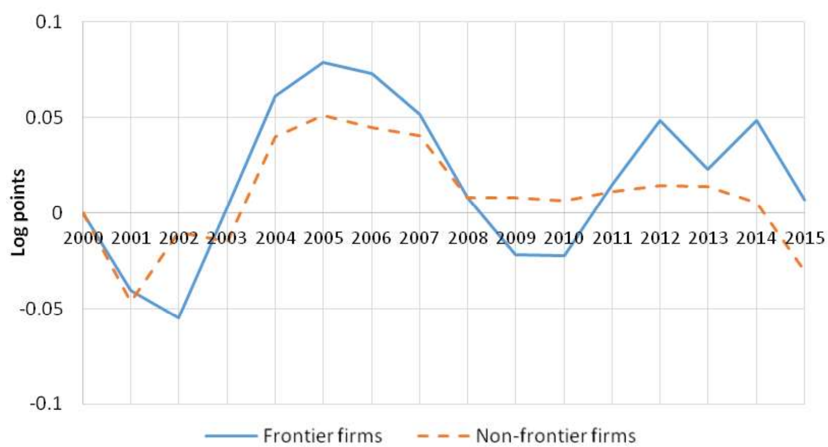
This labour productivity divergence occurred in both sub-periods (1991-2000 and 2000-2015), as shown in Panels B and C of Table 2. The productivity growth gap between frontier and non-frontier firms in the two periods was not correlated across industries. This suggests that different forces shaped the productivity divergence in those two periods. For example, the productivity divergence in the late 1990s could have been caused by the adoption of ICT and trade liberalization, while the productivity divergence in the late 2000s could have

Chart 2: Capital/Labour Ratio, Intermediate Input/Labour Ratio and Multifactor Productivity in Frontier and Non-frontier Firms in Canada, 2000-2015

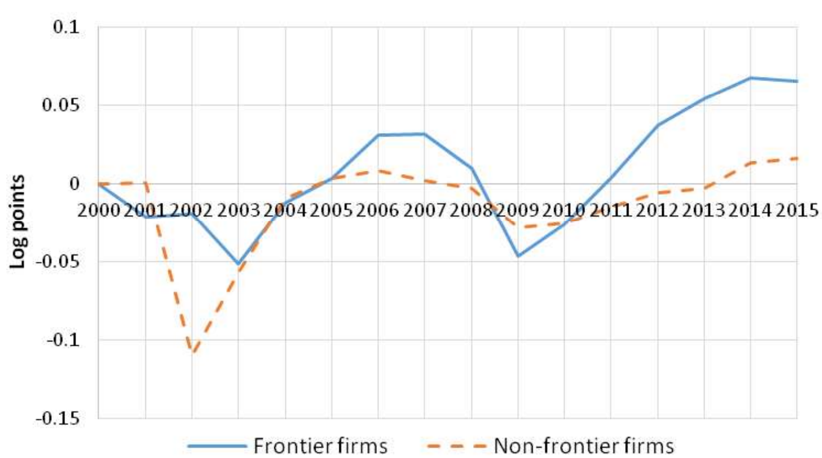
Panel A: Capital/labour Ratio of Frontier and Non-frontier Firms, 2000–2015, in logarithm, 2000 = 0



Panel B: Intermediate Input/Labour Ratio of Frontier and Non-frontier Firms, 2000–2015, in logarithm, 2000 = 0



Panel C: Multifactor Productivity of Frontier and Non-frontier Firms, 2000–2015, in logarithm, 2000 = 0



Source: Statistics Canada, author's calculation from T2-LEAP file.

Table 2: Average Labour Productivity Growth of Frontier and Non-frontier Firms by Industry, 1991–2015 (per cent per year)

Industry	Frontier Firms	Non-frontier Firms	Frontier Firms less Non-Frontier Firms
		Panel A: 1991 to 2015	
Mining and oil and gas extraction	2.16	-0.28	2.44
Utilities	7.76	4.17	3.59
Construction	1.68	0.43	1.25
Manufacturing	1.41	1.40	0.01
Wholesale and retail trrade	2.40	1.46	0.94
Transportation and warehousing	1.79	1.25	0.54
Information and culture	1.74	1.01	0.73
Broadcasting and telecommunications	2.05	0.49	1.55
Finance, insurance and real estate	1.48	0.34	1.14
Arts, entertainment and recreation	0.56	0.76	-0.20
Accommodation and food services	0.29	0.53	-0.24
Other services	0.65	0.98	-0.33
All industries	1.80	1.12	0.67
		Panel B: 1991 to 2000	
Mining and oil and gas extraction	5.24	2.25	3.00
Utilities	17.69	6.45	11.24
Construction	4.03	2.69	1.34
Manufacturing	2.41	1.91	0.50
Wholesale and retail trade	4.54	3.27	1.28
Transportation and warehousing	3.75	3.39	0.36
Information and culture	1.61	1.61	0.01
Broadcasting and telecommunications	4.57	1.35	3.23
Finance, insurance and real estate	1.46	1.41	0.05
Arts, entertainment and recreation	1.16	2.47	-1.31
Accommodation and food services	2.10	1.31	0.79
Other services	1.80	1.88	-0.08
All industries	3.43	2.44	1.00
		Panel C: 2000 to 2015	
Mining and oil and gas extraction	0.83	-1.57	2.40
Utilities	3.31	2.58	0.72
Construction	0.85	-0.70	1.55
Manufacturing	0.73	0.81	-0.08
Wholesale and retail trade	1.17	0.40	0.77
Transportation and warehousing	0.65	-0.02	0.67
Information and culture	0.89	0.68	0.20
Broadcasting and telecommunications	2.99	2.23	0.76
Finance, insurance and real estate	1.98	0.12	1.86
Arts, entertainment and recreation	0.30	-0.66	0.96
Accommodation and food services	-0.36	0.24	-0.60
Other services	0.70	0.54	0.16
All industries	1.05	0.51	0.54

Note: Frontier firms are defined as the top 10 per cent most productive firms in a three- digit NAICS industry and in a year.
Source: Statistics Canada, author's calculation from T2-LEAP file.

been caused by the use of digital technologies and the increased competition from emerging economies.

Contribution of frontier and non-frontier firms to aggregate productivity growth

This sub-section decomposes aggregate productivity growth into contributions of frontier and non-frontier firms. The aggregate labour productivity growth in an industry can be decomposed into three components: contribution from frontier firms, contribution from non-frontier firms, and contribution from share changes of frontier and non-frontier firms.

Specifically, aggregate labour productivity in year t (p^t) is equal to a weighted average of labour productivity of frontier and non-frontier firms:

$$p^t = s_1^t p_1^t + s_0^t p_0^1, \tag{1}$$

where s_1^t is the share of frontier firms in employment in year t, s_0^t is the share of non-frontier firms in total employment in year t, p_1^t is the labour productivity of frontier firms in year t, and p_0^t is the labour productivity of non-frontier firms in year t.

The change in aggregate labour productivity between year $t-1$ and year t can be written as:

$$p^t - p^{t-1} = \bar{s}_1(p_1^t - p_1^{t-1}) + \bar{s}_0(p_0^t - p_0^{t-1}) + (\sum_{i=0,1} s_i^t - s_i^{t-1})\bar{p}_i, \tag{2}$$

where a bar over a variable presents the average values of the variable in years $t-1$ and t. The first term on the right is the contribution of frontier firms to aggregate labour productivity growth, which is estimated as the change in labour productivity of the frontier firms between two years, multiplied by the shares of frontier firms in total employment averaged over two years. The second term is the contribution of non-frontier firms to aggregate labour productivity growth, which is equal to the change in labour productivity of the non-frontier firms multiplied by the share of non-frontier firms in total employment. The third term is the contribution of the employment share changes of frontier and non-frontier firms. This contribution is positive when there is a shift in the shares of employment toward frontier firms, which are more productive.

The decomposition is expressed in labour productivity levels. To implement the decomposition, labour productivity will be expressed in logarithms to reduce the impact of extreme values on the estimates, a practice that is commonly used in labour productivity decomposition (e.g. Foster, Haltiwanger and Krizan, 2001; Baldwin and Gu, 2006; OECD, 2017).

To ensure that the sum of the three components in the decomposition is equal to aggregate labour productivity growth, the labour productivity of frontier and non-frontier firms is calculated as a weighted average of labour productivity in that group of firms, using employment as weights. This differs from the earlier analysis of productivity dispersion of frontier and non-frontier firms, where the productivity of a group of firms was estimated as the median value of that group.

Table 3: **Average Share of Frontier Firms in Total Employment and Gross Output in Per Cent, 1991–2015**

	Share of Employment	Share of Output
Mining and oil and gas extraction	16.54	43.67
Utilities	8.95	47.56
Construction	4.33	20.18
Manufacturing	17.21	48.11
Wholesale and retail trade	7.27	29.16
Transportation and warehousing	5.31	31.46
Information and culture	6.46	25.29
Broadcasting and telecommunications	12.70	36.86
Finance, insurance and real estate	3.81	27.22
Arts, entertainment and recreation	5.27	37.11
Accommodation and food services	2.23	7.68
Other services	4.59	21.23
All industries	7.89	31.29

Note: Frontier firms are defined as the top 10 per cent most productive firms in a three- digit NAICS industry and in a year.
Source: Statistics Canada, author's calculation from T2-LEAP file.

The decomposition of aggregate labour productivity into the contributions of frontier and non-frontier firms is done at the three-digit NAICS level. The results are then aggregated to the two-digit NAICS level and to the non-farm market sector, using industry employment as weights.

Table 3 presents average shares of frontier and non-frontier firms in employment, and average output by industry. Frontier firms accounted for 8 per cent of total employment and about 30 per cent of gross output in Canadian industries in 1991-2015.

The share of total employment accounted for by frontier firms declined from 10 per cent in 1991 to 6 per cent in 2015. The fact that the share of frontier firms in total employment was the same as their share in the number of the most productive firms (at 10 per cent) in 1991 suggests that frontier firms were similar in size to non-frontier firms in terms of employment. However, by 2015, the share of frontier firms in total employment was smaller than their share in the number of firms. This suggests that average employment size in frontier firms was smaller than non-frontier firms in 2015.

The share of total employment accounted for by frontier firms differed across industries, as shown in Table 3. The frontier firms were smaller than the non-frontier firms in terms of employment in most industries, except mining and oil and gas extraction, manufacturing, and broadcasting and telecommunications.

The share of gross output accounted for by frontier firms averaged about 30 per cent in the 1991-2015 period, and was virtually unchanged over that period. When size is measured by gross output, frontier firms were larger than non-frontier firms in all industries except accommodation and food services. In this industry, frontier firms were smaller than non-frontier firms in terms of gross output.

Table 4 presents a decomposition of aggregate labour productivity growth in the non-farm market sector into the contributions of frontier and non-frontier firms. Frontier firms accounted for 11 per cent

Table 4: Contributions of Frontier and Non-frontier Firms to Aggregate Labour Productivity Growth (per cent per year), 1991–2000 and 2000–2015

	1991-2000	2000-2015	2000-2015 less 1991 to 2000
Non-farm Market Labour Productivity Growth	3.55	0.34	-3.21
Contributions of			
Frontier Firms	0.39	0.03	-0.36
Non-frontier Firms	3.30	0.35	-2.95
Share Changes	-0.14	-0.04	0.10
Addendum			
Labour Productivity Growth of			
Frontier Firms	3.43	1.51	-1.92
Non-frontier Firms	2.44	0.51	-1.93
Share of Frontier Firms in Employment (per cent)	8.74	7.06	

Note: Frontier firms are defined as the top 10 per cent most productive firms in a three- digit NAICS industry and in a year. The labour productivity of frontier and non-frontier firms is estimated as a weighted average of each group's productivity values.
Source: Statistics Canada, author's calculation from T2-LEAP file.

of aggregate labour productivity growth in the 1991-2000 period (0.39/3.55), and 9 per cent of aggregate labour productivity growth in the 2000-2015 period. The contributions of frontier firms to aggregate labour productivity were higher than their shares in employment because of the relatively high productivity growth of the frontier firms compared with that of non-frontier firms.

The contributions of frontier and non-frontier firms to aggregate labour productivity growth declined after 2000. This suggests that the contributions of innovation and innovation diffusion to aggregate labour productivity growth both declined. The decline in innovation in frontier firms and the decline in innovation diffusion from frontier firms to non-frontier firms both contributed to the productivity slowdown after 2000 in Canada.

Most of the decline in labour productivity growth is from the decline in the contribution of non-frontier firms. The decline in innovation diffusion had more of an impact on the post-2000 productivity slowdown in Canada than the decline in innovation. The decline in labour productivity growth of non-frontier firms after 2000 accounted for 2.95 percentage points, or 90 per cent, of a 3.21 percentage-point decline in aggregate labour productivity growth in that period. The decline in labour productivity growth of frontier firms contributed about 10 per cent of aggregate labour productivity growth after 2000.

Table 5 presents the decomposition of aggregate labour productivity growth into the contributions of frontier and non-frontier firms at the two-digit NAICS industry level for the 1991–2000 and 2000–2015 periods, and the contributions of frontier and non-frontier firms to the decline in labour productivity growth between the two periods.

Labour productivity growth declined after 2000 in all industries except utilities. Both frontier and non-frontier firms contributed to this decline in labour productivity since the productivity growth of both groups of firms declined after 2000 in all industries, except for non-frontier firms in

Table 5: **Contributions of Frontier and Non-frontier Firms to Labour Productivity Growth by Industry (per cent per year), 1991–2000 and 2000–2015**

	Labour Productivity Growth	Contributions from: Frontier Firms	Non-frontier Firms	Share Changes
		1991–2000		
Mining and oil and gas extraction	3.74	0.95	3.41	-0.62
Utilities	-9.62	1.79	-5.84	-5.57
Construction	2.24	0.18	2.16	-0.10
Manufacturing	4.15	0.38	3.10	0.67
Wholesale and retail trade	5.03	0.55	4.98	-0.49
Transportation and warehousing	4.14	0.44	3.42	0.28
Information and culture	5.74	0.40	5.58	-0.25
Broadcasting and telecommunications	2.35	0.53	2.75	-0.92
Finance, insurance and real estate	2.09	0.07	1.99	0.02
Arts, entertainment and recreation	1.61	0.41	0.94	0.26
Accommodation and food services	1.85	0.08	1.84	-0.08
Other services	4.07	0.18	4.05	-0.16
All industries	3.55	0.39	3.30	-0.14
		2000–2015		
Mining and oil and gas extraction	-3.63	0.29	-3.00	-0.92
Utilities	12.21	-0.04	12.73	-0.48
Construction	-0.43	-0.03	-0.32	-0.08
Manufacturing	1.82	0.32	1.53	-0.04
Wholesale and retail trade	-0.19	-0.17	-0.36	0.33
Transportation and warehousing	0.30	-0.19	0.42	0.07
Information and culture	-0.26	0.16	-0.46	0.05
Broadcasting and telecommunications	0.21	0.13	0.72	-0.64
Finance, insurance and real estate	0.02	0.05	0.08	-0.11
Arts, entertainment and recreation	0.25	-0.02	0.32	-0.05
Accommodation and food services	-0.18	-0.02	-0.15	0.00
Other services	0.70	0.10	0.95	-0.36
All industries	0.34	0.03	0.35	-0.04

	Labour Productivity Growth, 2000–2015 less 1991–2000	Contributions from: Frontier Firms	Non-frontier Firms	Share Changes
Mining and oil and gas extraction	-7.37	-0.66	-6.41	-0.30
Utilities	21.83	-1.84	18.58	5.08
Construction	-2.67	-0.21	-2.48	0.02
Manufacturing	-2.33	-0.06	-1.57	-0.70
Wholesale and retail trade	-5.23	-0.72	-5.34	0.83
Transportation and warehousing	-3.84	-0.63	-3.00	-0.20
Information and culture	-5.99	-0.25	-6.04	0.30
Broadcasting and telecommunications	-2.14	-0.39	-2.03	0.28
Finance, insurance and real estate	-2.07	-0.02	-1.92	-0.13
Arts, entertainment and recreation	-1.36	-0.43	-0.62	-0.31
Accommodation and food services	-2.03	-0.11	-1.99	0.07
Other services	-3.38	-0.08	-3.10	-0.20
All industries	-3.21	-0.36	-2.95	0.10

Note: Frontier firms are defined as the top 10 per cent of the most productive firms in a three- digit NAICS industry and in a year.
Source: Statistics Canada, author's calculation from T2-LEAP file.

utilities. This suggests that innovation and innovation diffusion both declined, contributing to the decline in productivity growth after 2000 in almost all industries in Canada.

Although the relative importance of innovation and innovation diffusion for productivity growth is sensitive to the definition of frontier and non-frontier firms, the overall conclusion that declines in innovation and in innovation diffusion contributed to the post-2000 decline in productivity growth is not. The same results hold when frontier firms are defined as the top 5 per cent, top 15 per cent or top 20 per cent of firms in terms of productivity levels.

To further assess the robustness of the results, an alternative approach — stochastic frontier analysis — will be used in the next section to examine the contribution to aggregate labour productivity growth of innovation in frontier firms and the catch-up of non-frontier firms to frontier firms.

Technical Progress of Frontier Firms and Catch-up of Non-Frontier Firms

This section uses the stochastic frontier approach of Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977) to decompose aggregate productivity growth into technical change and technical efficiency change. In this approach, technical change can be defined as the innovation and productivity growth of the most efficient firms, and technical efficiency change can be defined as the catch-up of non-frontier firms to frontier firms, or technical diffusion from frontier to non-frontier firms.[9] The stochastic frontier approach provides an alternative decomposition of productivity growth into the contributions of innovation in frontier firms and innovation diffusion from frontier to non-frontier firms.

The stochastic frontier production function establishes a statistical relationship between inputs and outputs for the most efficient, or frontier, firms. A shift in the frontier production function represents the productivity growth of the frontier firms. The residuals in the stochastic frontier production function measure the productivity of non-frontier firms, relative to the frontier firms.

Specifically, the stochastic frontier production function can be written as:

$$\begin{aligned} y_{it} = \alpha_o + \alpha_1 x_{it} + \sum_{t=1991}^{2015} \alpha_t dyear_t \\ + \sum_{n=1}^{N} \beta_n dind_n \\ + \sum_{t=1991}^{2015} \sum_{n=1}^{N} \gamma_{t,n} dyear_t * dind_n + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\varepsilon_{it} = v_{it} - u_{it}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim N^+(0, \sigma_u^2)$$

9 Rada and Valdes (2012) adopted this approach to decompose the productivity growth of Brazilian agriculture into contributions from technical change and technical efficiency change.

where y_{it} represents the logarithm of gross output of firm i in year t; x_{it} is a vector of inputs in logarithm; $dyear_t$ is a full set of year dummies; $dind_n$ is a full set of industry dummies; and α, β, γ are the parameters to be estimated. The composite error term ε_{it} is a sum of two components: a normally distributed error term v_{it} that represents measurement and specification errors, and a one-sided normally distributed disturbance u_{it} that represents inefficiency.

In previous studies on productivity dispersion and productivity growth dynamics, the residual $\hat{\varepsilon}_{it}$ is interpreted as the productivity of non-frontier firms relative to frontier firms (Bartelsman and Wolf, 2017; Foster *et al.*, 2016). This differs from the interpretation in the stochastic frontier analysis. In the stochastic frontier analysis, the residual $\hat{\varepsilon}_{it}$ consists of two components: $\hat{\varepsilon}_{it} = \hat{v}_{it} - \hat{u}_{it}$. Only one component, $\hat{u}_{it}$, measures the productivity of a firm relative to that of a frontier firm. The other component, $\hat{v}_{it}$, represents measurement or specification errors. This article will adopt the interpretation from studies on productivity dispersion and productivity growth dynamics. The composite residual $\hat{\varepsilon}_{it}$ is used to measure the productivity of a firm relative to frontier firms.

The frontier production function is estimated using a cross-sectional stochastic model. The dependent variable is labour productivity (gross output per worker) in logarithm. The independent variables include labour in logarithm, a full set of years, a full set of industry dummies for two-digit NAICS industries, and interaction of year and industry dummies.[10]

The estimated stochastic frontier model can be used to decompose aggregate labour productivity into two components: technical progress that represents the shifts in the frontier production function, and technical efficiency change that represents the catch-up of average firms to the production frontiers. The coefficient estimates on the full set of year dummies and industry dummies, and the interaction of year and industry dummies, provide an estimate of shifts in the frontier production function or technical progress of the most productive firms in each year. Technical progress is allowed to differ across industries in the specification. The estimated residuals are aggregated to an industry, using employment as weights, to derive a measure of technical efficiency change. The sum of technical change and technical efficiency change is equal to aggregate labour productivity growth.

The results are presented in Table 6. Labour productivity growth declined in the non-farm market sector after 2000. The decline was caused by a decline in technical change and technical efficiency change. This can be seen as evidence that the pace of innovation in frontier firms and the rate of innovation diffusion from frontier firms to non-frontier firms both declined after 2000, contributing to the decline in aggregate labour productivity growth.

The stochastic frontier analysis and the productivity decomposition into contribu-

10 When industry dummies are defined at the three-digit NAICS level, estimating the stochastic frontier model takes longer, but the results are similar. To provide a decomposition of MFP, the independent variables would include capital, labour and intermediate inputs in logarithms.

Table 6: **Technical Changes, Technical Efficiency Changes and Labour Productivity Growth in the Non-Farm Market Sector (per cent per year), 1991–2000 and 2000–2015**

	1991-2000	2000-2015	2000 to 2015 less 1991 to 2000
Aggregate labour productivity growth	3.55	0.34	-3.21
Contributions of			
Frontier technical changes	2.44	0.11	-2.33
Non-Frontier technical efficiency changes	1.09	0.26	-0.83
Residual	0.02	-0.03	-0.05

Source: Statistics Canada, author's calculation from the T2-LEAP file.

tions of frontier and non-frontier firms both show that innovation and diffusion of innovation declined in Canada after 2000. However, the two methods differ on the relative contribution of innovation and innovation diffusion to the productivity slowdown. The results from a productivity decomposition into contributions of frontier firms show that the slowdown in the diffusion of innovation is a main source of the productivity slowdown after 2000. That is because the decline in labour productivity growth of non-frontier firms after 2000 is found to account for 2.95 percentage points, or 90 per cent, of a 3.21 percentage-point decline in aggregate labour productivity growth between the periods of 1991 to 2000 and 2000 to 2015. In contrast, the results from a stochastic frontier analysis show that the decline in innovation is the main source of the productivity slowdown after 2000. That is the case as a decline in technical change and innovation by frontier firms accounted for 2.33 percentage points, or 73 per cent, of a 3.21 percentage-point decline in aggregate labour productivity growth, and a decline in catch-up of non-frontier firms to frontier firms accounted for the remainder of the slowdown.

While data on tangible assets are available only after 2000, data on total assets are available for the entire 1991–2015 period. Total assets were found to be highly correlated with tangible assets across firms, and were used as measures of capital stock when estimating the stochastic frontier production function on gross output, which includes labour and capital as inputs for the period of 1991 to 2015. The productivity estimate from this expanded stochastic frontier model provides a measure of a partial MFP that includes capital and labour as inputs, but excludes intermediate inputs. The results from this expanded stochastic frontier model are similar to the results that include only labour as an input. Both technical change and technical efficiency change measured on partial MFP declined after 2000. This decline contributed to a decline in MFP growth after 2000.

Resource Reallocation and Aggregate Labour Productivity Growth

Aggregate productivity growth can increase when productivity increases within firms, or when the share of employment and output increases in more productive firms and falls in less productive firms. Decker *et al.* (2016) found that this reallocation happened to a lesser extent in the post-2000 period, particularly in the high-tech sector, with implications for overall productivity growth.

This section uses the Olley and Pakes (OP) decomposition to decompose aggregate labour productivity growth into the contribution from productivity growth within firms and the contribution from the reallocation of employment between firms (Olley and Pakes, 1996).

Aggregate labour productivity in an industry is equal to the sum of an unweighted average of firm-level productivities and a covariance term that represents reallocation (also called the OP gap). The latter is a measure of allocative efficiency, since it increases if more productive firms increase their share of resources in the sector:

$$p^t = \frac{1}{N}\sum_{i=1}^{N} p_{it} + \sum_{i=1}^{N}(s_{it} - \bar{s}_t)\left(p_{it} - \bar{p}_t\right), \tag{4}$$

$$p^t = \sum_{i=1}^{N} s_{it}p_{it}, \tag{5}$$

where p_t is the aggregate labour productivity level in year t, which is equal to a weighted sum of labour productivity across firms using employment as weights; p_{it} is the labour productivity level of firm i in year t; and s_{it} is the share of firm i in total employment in year t. A bar over a period is the simple unweighted mean of that variable in that industry. While labour productivity is measured in levels in this OP decomposition, it will be measured in log terms in its implementation to alleviate the effect of extreme values.

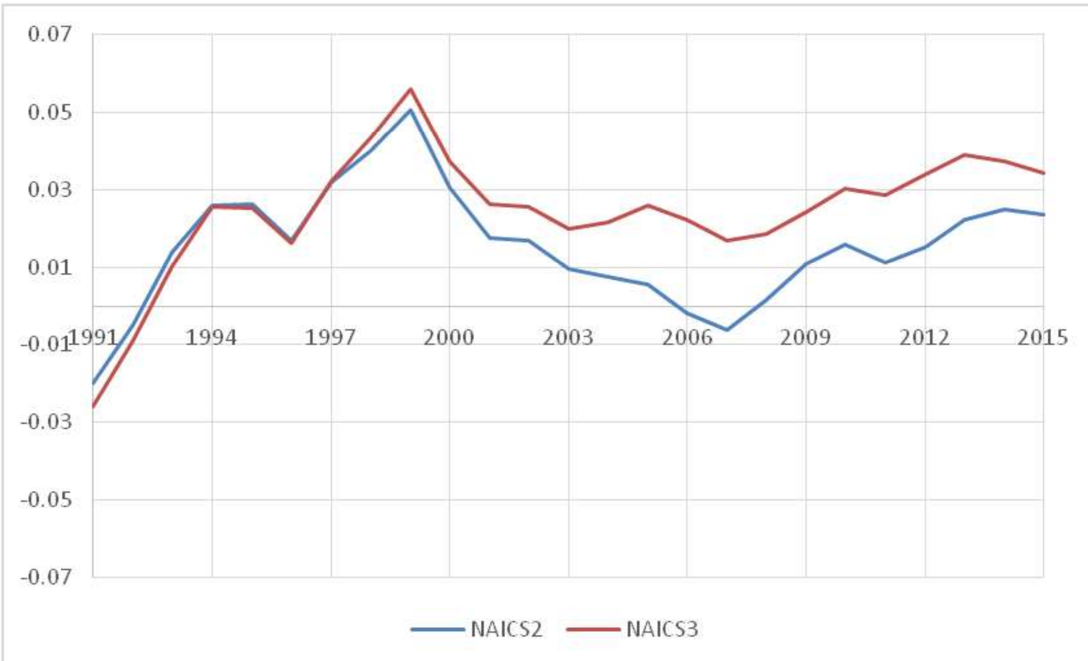
When labour productivity is measured in log terms, the log changes in aggregate labour productivity are the sum of log changes in unweighted labour productivity and the log changes in the OP covariance term. The log changes in the unweighted mean of labour productivity over a period measure the contribution of productivity growth within firms to aggregate labour productivity growth. The log changes in the OP gap measure the contribution of reallocation to aggregate labour productivity growth.

Chart 3 presents the trend in the OP covariance term. As labour productivity is measured in logs, the changes in OP covariance measure the gains in labour productivity from reallocation. The chart presents two measures of the OP covariance term. The first measure is calculated at the two-digit NAICS level and then aggregated to the total non-farm market sector using employment as weights. The second measure is calculated at the three-digit NAICS level and then aggregated to the total non-farm market sector. Both measures show similar trends.

There was an increase in the index of reallocation in the 1990s as labour was reallocated to firms with relatively higher labour productivity levels. The reallocation occurred as employment shifted from growing incumbents and entrants with relatively higher productivity levels to declining incumbents and exitors with relatively lower productivity levels. The effect of reallocation declined in the early 2000s as a result of slow growth and the tech bubble bursting in that period. After the financial crisis, there was an increase in the effect of reallocation on labour productivity growth.

The recession in the early 1990s in

Chart 3: Index of Between-Firm Reallocation in Canadian Industries, 1991–2015



Note: The index of between-firm reallocation is calculated as a 3-year moving average of the Olley-Pakes covariance term.
Source: Statistics Canada, author's calculation from T2-LEAP file.

Canada is associated with an increase in the effect of reallocation on productivity growth, possibly because the recession drove out the least efficient firms. The slow growth of the early 2000s is associated with a decline in the effect of reallocation, possibly because of distortions to reallocation dynamics. This evidence for Canada is broadly consistent with the evidence of Foster, Grim and Haltiwanger (2016) for the United States.

Overall, the improved reallocation at the three-digit NAICS level contributed 0.70 per cent per year to aggregate labour productivity growth for the 1991–2000 period (Table 7). The improved reallocation at the two-digit NAICS level contributed 0.6 per cent per year to aggregate labour productivity growth. The effect of reallocation on aggregate productivity growth was essentially zero over the period of 2000 to 2015. An increasing reallocation effect in the late 2000s was more than offset by the declining reallocation effect before the 2008–2009 financial crisis.

This suggests that the decline in aggregate labour productivity growth after 2000 was partly due to a decline in the contribution of resource reallocation in that period. The decline in the effect of resource reallocation is consistent with the evidence on the decline in business start-ups and business dynamism in Canada over time, which contributed to the decline in aggregate labour productivity growth after 2000.

Table 7: **Contributions of Reallocation and Within-firm Growth to Aggregate Labour Productivity Growth (per cent per year), 1991 to 2000 and 2000 to 2015**

	1991 to 2000	2000 to 2015	2000 to 2015 less 1991 to 2000
Aggregate labour productivity growth	3.55	0.34	-3.21
Contributions of			
Reallocation	0.70	-0.02	-0.72
Within-firm productivity growth	2.85	0.36	-2.49

Note: The effect of reallocation is calculated as the changes in the Olley-Pakes co-variance term at the three digit level of North American Industry Classification System.
Source: Statistics Canada, author's calculation from the T2-LEAP file.

Conclusion

Productivity growth has slowed in Canada since the 2000s. This article examined the causes of the productivity slowdown in Canada. It found that labour productivity growth of frontier firms was higher than that of non-frontier firms. However, labour productivity growth declined for both frontier and non-frontier firms after 2000. This suggests that the pace of innovation and the pace of innovation diffusion from frontier to non-frontier firms both declined in Canada after 2000.

A stochastic frontier analysis that decomposed labour productivity growth into contributions from technical change and technical efficiency change confirmed the decomposition results from the classification of firms into frontier and non-frontier firms: the decline in aggregate labour productivity was caused by the post-2000 declines in technical change and technical efficiency change. This can be interpreted as evidence that the pace of innovation in frontier firms and the rate of innovation diffusion from frontier firms to non-frontier firms both declined after 2000, contributing to aggregate labour productivity slowdown after 2000.

While both innovation and diffusion of innovation declined in Canada after 2000, the relative contribution of innovation and diffusion of innovation to the productivity slowdown is sensitive to the methods adopted. The results from a productivity decomposition into contributions of frontier firms and non-frontier firms show that the slowdown in the diffusion of innovation is a main source of the productivity slowdown after 2000, as the decline in labour productivity growth of non-frontier firms after 2000 accounted for 2.95 percentage points, or 90 per cent, of a 3.21-percentage-point decline in aggregate labour productivity growth between the periods of 1991 to 2000 and 2000 to 2015.

In contrast, the results from a stochastic frontier analysis show that the decline in innovation is the main source of the productivity slowdown after 2000. That is the case because a decline in technical change and innovation by frontier firms from the stochastic frontier analysis accounted for 2.33-percentage points, or 73 per cent, of a 3.21-percentage-point decline in aggregate labour productivity growth, and a decline in catch-up of non-frontier firms to frontier firms accounted for the remainder of the slowdown

Improved resource reallocation contributed significantly to aggregate labour productivity growth in the 1991–2000 period, but the effect of reallocation was essentially zero over the period from 2000 to 2015. The decline in aggregate labour productivity growth after 2000 was thus partly caused by the decline in the contribution of resource reallocation, which is consistent with previous evidence on declining business start-ups in Canada. Business start-ups and business dynamism appear to decline in Canada over time, and this contributed to the decline in aggregate labour productivity growth after 2000.

In summary, the decline in aggregate labour productivity growth in Canada after 2000 was found to be caused by a decline in innovation in frontier firms, a decline in innovation diffusion from frontier firms to non-frontier firms, and a decline in the effect of resource reallocation and business dynamism on productivity growth.

While innovation in frontier firms declined after 2000, the exact causes of this decline are not known. This could support the findings of Gordon (2016), which state that current technological advances such as mobile technology, the internet and cloud computing are not great enough to drive strong productivity growth. Or, the new digital economy has yet to generate gains in productivity (van Ark, 2016). Lastly, frontier firms were defined as the most productive firms in Canada. It is possible that frontier firms in Canada are less productive than global frontier firms. Therefore, the slower productivity growth of frontier firms may reflect a lack of innovation diffusion from global frontier firms to firms operating in Canada.

The diffusion of innovation from frontier to non-frontier firms also declined after 2000. This occurred in a period marked by digitalization, the increasing complexity of technologies, and the rising importance of tacit knowledge. That digitalization has enabled the development of a winner-take-all dynamic where technology leaders can capture most of the market share because they can replicate their provision of information goods and business processes at a low cost in a country and around the globe.

References

Aigner, D., C. Lovell and P. Schmidt (1977) "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics*, Vol. 6, No. 1, pp. 21–37.

Andrews, D., C. Criscuolo and P.N. Gal (2015) "Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries", OECD Productivity Working Papers, No. 2 (Paris, France: Organisation for Economic Co-operation and Development).

Baily, M.N. and N. Montalbano (2016) "Why is US Productivity Growth so Slow? Possible Explanations and Policy Responses," Hutchins Center Working Paper no. 22 (Washington, D.C.: Brookings Institution).

Baldwin, J.R. and W. Gu (2004) "Trade Liberalization: Export-Market Participation, Productivity Growth, and Innovation," *Oxford Review of Economic Policy,* Vol. 20, No. 3, pp. 372–392.

Baldwin, J.R. and W. Gu (2006) "Plant Turnover and Productivity Growth in Canadian Manufacturing," *Industrial and Corporate Change*, Vol. 15, No. 3, pp. 417–465.

Baldwin, J.R. and W. Gu (2011) "Firm Dynamics and Productivity Growth: A Comparison of the Retail Trade and Manufacturing Sectors," *Industrial and Corporate Change*, Vol. 20, No. 2, pp. 367–395.

Baldwin, J.R., W. Gu and B. Yan (2013) "Export Growth, Capacity Utilization and Productivity Growth: Evidence for Canadian Manufacturing Plants," *Review of Income and Wealth*, Vol. 59, pp. 665–688.

Bartelsman, E. and Z. Wolf (2017) "Measuring Productivity Dispersion," Tinbergen Institute Discussion Paper no. 2017-033 (Amsterdam, Netherlands: Tinbergen Institute).

Cao, S., M. Salameh, M. Seki, and P. St-Amant (2017) "Trends in Firm Entry and New Entrepreneurship in Canada," *Canadian Public Policy*, Vol. 43, No. 3, pp. 1–19.

Cette, G., S. Corde and R. Lecat (2017) "Stagnation of Productivity in France: A Legacy of the Crisis or a Structural Slowdown?," *Economics and Statistics*, No. 494-495-496, pp. 11–38.

Decker, R.A., J. Haltiwanger, R.S. Jarmin and J. Miranda (2016) "Declining Business Dynamism: Implications for Productivity?" Hutchins Center Working Paper No. 23 (Washington, D.C.: Brookings Institution).

Foster, L., C. Grim and J. Haltiwanger (2016) "Reallocation in the Great Recession: Cleansing or Not?" *Journal of Labour Economics,* Vol. 34, No. S1, pp. 293–331.

Foster, L., C. Grim, J. Haltiwanger and Z. Wolf (2016) "Firm-Level Dispersion in Productivity: Is the Devil in the Details?" *American Economic Review*, Vol. 106, No. 5, pp. 95–98.

Foster, L., J. Haltiwanger and C.J. Krizan (2001) "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," In *New Developments in Productivity Analysis*, (eds.) C.R. Hulten, E.R. Dean, and M.J. Harper, NBER Book Series Studies in Income and Wealth, pp. 307–372.

Gordon, R. (2016) *The Rise and Fall of American Growth: The U.S. Standard of Living Since the Civil War* (Princeton, New Jersey University Press).

Gu, W. (2018) "Accounting for Slower Productivity Growth in the Canadian Business Sector After 2000: The Role of Capital Measurement Issues," *International Productivity Monitor*, No. 34, Spring, pp. 21–39, http://www.csls.ca/ipm/34/Gu.pdf.

Gu, W. and A. Lafrance (2014) "Productivity Growth in the Canadian Broadcasting and Telecommunications Industry: Evidence from Micro Data," Economic Analysis Research Paper Series, No. 89. Statistics Canada Catalogue No. 11F0027M (Ottawa: Statistics Canada).

Gu, W. and M. Willox (2018) "Productivity Growth in Canada and the United States: Recent Trends and Potential Explanations," *International Productivity Monitor* No. 35, Fall, pp. 73–94, http://www.csls.ca/ipm/35/Gu-Willox.pdf.

Gu, W., B. Yan and S. Ratté (2018) "Long-run Productivity Dispersion in Canadian Manufacturing," Economic Insights, No. 84, Statistics Canada Catalogue no. 11-626-X (Ottawa: Statistics Canada).

Haldane, A.G. (2017) "Productivity Puzzles," London School of Economics, Speech.

Ho, M.H., S. Rao and J. Tang (2004) "Sources of Output Growth in Canadian and U.S. Industries in the Information Age," In *Economic Growth in Canada and the United States in the Information Age*, (eds.) D.W. Jorgenson, (Ottawa: Industry Canada Research Publications Program,) pp. 83–99.

Macdonald, R. (2014) "Business Entry and Exit Rates in Canada: A 30-year Perspective," Economic Insights, No. 38. Statistics Canada Catalogue no. 11-626-X (Ottawa: Statistics Canada).

Manyika, J., J. Remes, J. Mischke and M. Krishnan (2017) "The Productivity Puzzle: A Closer Look at the United States," Discussion Paper (New York: McKinsey Global Institute).

Meeusen, W. and J. van den Broeck (1977) "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error," *International Economic Review*, Vol. 18, No. 2, pp. 435–444.

Murray, A. (2018) "What Explains the Post-2004 U.S. Productivity Slowdown?," *International Productivity Monitor*, No. 34, Spring, pp. 81–109. http://www.csls.ca/ipm/34/murray.pdf.

Organisation for Economic Co-operation and Development (2015) *The Future of Productivity* (Paris, France: OECD Publishing).

Organisation for Economic Co-operation and Development (2017) *The Multiproduct Project: A Comprehensive Review.*

Olley, G.S. and A. Pakes (1996) "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, Vol. 64, No. 6, pp. 1263–1297.

Rada, N. and C. Valdes (2012) "Policy, Technology, and Efficiency of Brazilian Agriculture," Economic Research Report, No. 137., U.S. Department of Agriculture.

Rao, S. and J. Li (2013) "Explaining Slower Productivity Growth: The Role of Weak Demand Growth," *International Productivity Monitor*, No. 26, pp. 3–13, http://www.csls.ca/ipm/26/IPM-26-Rao-Li.pdf.

Sharpe, A. and W.K. Tsang (2018) "The Stylized Facts About Slower Productivity Growth in Canada," *International Productivity Monitor*, No. 35, Fall, pp. 52–72, http://www.csls.ca/ipm/35/IPM-35-Sharpe-Tsang.pdf.

Trefler, D. (2004) "The Long and Short of the Canada-US Free Trade Agreement," *American Economic Review*, Vol. 94, No. 4, pp. 870–895.

Tukey, J.W. (1977) *Exploratory Data Analysis*, (Reading, Massachusetts: Addison-Wesley Publishing Company).

van Ark, B. (2016) "The Productivity Paradox of the New Digital Economy," *International Productivity Monitor*, No. 31, pp. 3–18, http://www.csls.ca/ipm/31/vanark.pdf.

Is R&D Enough to Improve Firm Productivity?

Jianmin Tang
Innovation, Science, and Economic Development Canada
Weimin Wang
Statistics Canada[1]

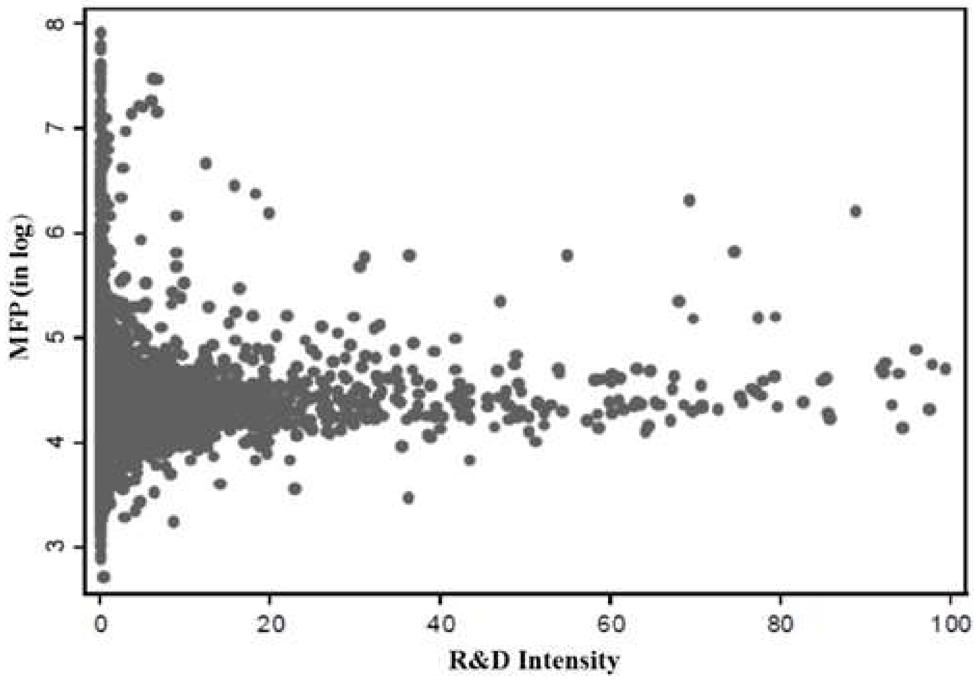
Abstract

Research and development (R&D) is critical to innovation that enhances productivity. Going beyond a simple relationship between R&D and firm productivity performance, this article investigates what co-investments and other business operating conditions facilitate R&D in improving productivity. Using a rich micro database for Canada, we show that the actual effect of R&D on productivity depends on a number of factors that play important roles in determining R&D efficiency in improving productivity. These factors include adopting certain management practices, making investments in ICT, and maintaining a skilled workforce. In addition, the article shows that firm size, foreign ownership and market power are important positive forces in improving R&D efficiency. The findings highlight the complexity of R&D in improving productivity.

Innovation generally refers to a firm's effort in the deliberate application of new ideas and information in the production of goods or services. Research and development (R&D) has long been believed to be the critical factor that drives firms to innovate (Romer, 1990; Aghion and Howitt, 1992). It enhances productivity directly by improving firms' technological capacity of applying new ideas and initiatives in production, and indirectly by nurturing internal expertise and developing in-house absorptive capacity. The built-up capacity enables firms to adopt more complex external production technologies and also to internalize external knowledge and information. Empirical literature shows that investments in R&D contribute to productivity performance (Griliches, 1979, 1986; Wakelin, 2001; Griffith et al., 2004; Hall *et al.*, 2010), although the evidence for Canada is weak (Mohnen 1992, Gu and

1 Jianmin Tang is Chief, Productivity and Competitiveness Analysis in the Strategy, Research and Results Branch at Innovation, Science and Economic Development Canada. Weiming Wang is Senior Reseaarch Economist in the Economic Analysis Division at Statistics Canada. The authors would like to thank Louise Earl, Richard Harris, Danny Leung, Luciana Marins, Larry Shute and three anonymous reviewers for insightful comments and suggestions. Views in the article are our own and do not represent, in any way, views of Innovation, Science, and Economic Development Canada, Statistics Canada, or the Government of Canada. Email: jianmin.tang@canada.ca; weimin.wang@canada.ca

Chart 1: Multifactor Productivity and R&D intensity in Canadian Manufacturing



Source: Authors' compilation based on micro data from Statistics Canada.

Tang 2004).

Chart 1 presents multifactor productivity (MFP) against R&D intensity for Canadian manufacturing firms.[2] R&D intensity is defined as the ratio of R&D stock to total physical capital stock.[3] We observe that firms vary significantly in both MFP and R&D intensity. Importantly, the relationship between MFP and R&D is not obvious. Higher R&D effort does not necessarily mean higher MFP. The natural questions are: why does R&D improve productivity for some firms relatively more than for others and what factors determine R&D efficiency?

The relationship between productivity and R&D has commonly been evaluated in isolation from the business environment where a firm operates. This may not be appropriate as the relationship is likely affected by both internal and external factors associated with the firm. Internal factors are firm specific e.g. firm size and ownership, investments in technologies, management practices, and business strategies. The external factors consist of a variety of influences that are beyond the firm's control, which include institutions (e.g. legal framework and intellectual property regimes), financial conditions, economic conditions, and public infrastructure (e.g. Coe et al, 2009). In other words, the pro-

2 Productivity (or MFP) is commonly measured as a residual of gross output net the contribution from labour, capital and intermediate inputs

3 When R&D intensity is defined as the ratio of R&D stocks to gross output, similar results are obtained.

ductivity dividend yield from R&D investments depends on those internal and external factors. If a firm has no much control over the external factors, which are generally macro conditions and are the same to all firms operating in the environment, it can certainly maneuver internal factors to strive for a better productivity dividend yield. Governments may also design industry policies to encourage the firm to invest in business activities that support R&D. Internal factors may be at the core of the difference in R&D efficiency between firms.

Thus, without considering other factors that influence productivity, the evaluation of R&D effects by simply linking only actual productivity to R&D may be misleading. The objective of this article is to examine which internal factors facilitate R&D in improving productivity in the Canadian manufacturing sector.[4] we focus on MFP (thereafter productivity). The dataset used for the purpose has rich information on production, R&D investments, business operating environment, ownership, investments in technologies, management practices, and business strategies.

A stochastic frontier model is used for studying the impact of R&D on technological frontier and for identifying factors that facilitate R&D in improving productivity. It is a significant departure from the empirical literature that focuses on the actual effect and commonly ignores the fact that how R&D influences productivity depends on the business operating environment and co-investments. The stochastic frontier analysis is able to provide us with a more sophisticated understanding of the role of R&D in productivity improvements. In particular, it is able to distinguish between the potential (or maximum) productivity effect of R&D (or the frontier) and the inefficiency of R&D in improving productivity (or the distance from the frontier), with the latter being modelled as a function of certain internal factors.[5] The specification is desirable as it allows us to explain the differences in R&D efficiency among firms.

The specification and the identification of the factors that play important roles in affecting the effectiveness of R&D in improving productivity performance should be of considerable interest to both academics and policy makers. It helps elucidate which factors enhance R&D effectiveness in improving productivity performance. In addition, it can facilitate the diffusion of best practices and help firms improve R&D efficiency. Furthermore, it provides policy makers with the evidence to design more sophisticated and effective programs to promote and support innovation activities.

The article is organized as follows. In the first main section, we set up the stochastic frontier model that is tailored to our research objective. In section two, we describe the micro data and provide some de-

4 The manufacturing sector is focused due to data limitation.

5 Multiple regression models with interaction terms between R&D and other variables can be used to test the complementarity between R&D and other variables, but those models treat R&D the same as other variables and could not identify the maximum potential of R&D in improving productivity, and they also could not approach the linkage from an efficiency perspective.

scriptive statistics on how R&D firms perform compared to non-R&D firms. In section three, we discuss the results of our stochastic frontier analysis. In section four, the final section, we conclude.

Methodology: The Stochastic Frontier Model

Productivity measures how efficiently a firm can convert inputs into output. It is often considered as technological progress. In practice, however, it reflects a firm's technological development and efficiency improvement, and is determined broadly by the firm's efforts in innovation and in investing in efficiency-enhancing activities.

In this article, we assume that a firm's productivity is mainly driven by its innovation capacity associated with technological progress, which is supported by investments in efficiency-enhancing activities. The assumption is consistent with the fact that innovation capacity determines the firm's success in the deliberate application of new ideas and information in the production of goods or services, which is the core of business operation. Following the literature (e.g. Aghion and Howitt, 1992), we indicate the firm's innovation capacity by its past and current activities in R&D.

Other investments, such as investments in ICT, are mainly used to support and facilitate the core of business operation and are considered efficiency-enhancing investments. The rationale for treating those investments as efficiency-enhancing activities will be discussed in some detail towards the end of this section.

To empirically estimate the R&D potential (or interchangeably technological frontier) and the efficiency-enhancing activities in improving productivity, a stochastic frontier analysis is conducted.[6] Let A_i^* be the R&D potential for firm i and assume it is a function of variables that related to R&D intensity (R_i) and a set of controlling variables including foreign-control, year and industry dummies (Z_i):[7]

$$A_i^* = f(R_i, Z_i)\exp(v_i) \tag{1}$$

The random error terms (v_i) are independently and identically distributed as $N(0, \sigma_v^2)$, reflecting the stochastic nature of the frontier as the frontier of the firm is not entirely under the control of the firm and is affected by random factors.

As discussed earlier, R&D is a process of applying new ideas and initiatives that requires a certain length of time to generate innovative products and production methods.[8] Thus, R&D is in stock. In addition, the square of the R&D intensity is included to capture a potential non-linear relationship between R&D and productivity. A number of empirical studies show

6 The stochastic frontier model was pioneered by Aigner *et al.*, (1977). Kumbhakar and Lovell (2000) provided an excellent introduction to stochastic frontier analysis.

7 Most R&D expenditures are on labour and materials. To avoid double accounting (with labour and intermediate inputs for production), R&D variables are entered the equation as R&D intensity, measured as the ratio of R&D stock to physical capital stock.

8 Lagged R&D variable is suggested in the literature, for example in Goto and Suzuki (1989) and Wang (2007), to reflect the delayed effect of R&D investment. Either one or two-year lagged R&D intensity are not sig-

that for certain industries, R&D investments are subject to diminishing returns (Zenger 1994, Faff *et al.*, 2013).

We control for foreign ownership as it is well known that R&D activities of foreign affiliates are subject to the headquarter effect, that is, foreign affiliates tend to do less R&D as R&D activities tend to be with their parent companies. In addition, it has been generally found that foreign-controlled firms in Canada are significantly more productive than Canadian-controlled firms. The foreign ownership productivity advantage is real and significant. It is believed that the advantage arises because foreign-controlled in Canada have the access to advanced technologies from their parents (Rao *et al.*, 2010; Tang and Rao, 2003).[9]

Year and industry dummies are introduced to capture business cycle effects and industry specific effects as technological opportunities and appropriability conditions appear quite different from one industry to another (e.g. Griliches and Mairesse, 1982; Pavitt, 1984).

Equation (1) is the technological frontier, representing the potential impact of R&D on productivity. However, not all firms are able to exploit R&D efficiently in improving productivity and the actual impact may be less than the potential. We assume that the efficiency of R&D in improving productivity depends on the firm's capacity in exploitation of the investments, which is influenced by a number of co-investments and other internal factors associated with firms' operations. Firm size, workforce skills, business operating environment, investments in technologies (including ICT), management practices, business outward orientation, and business strategies are included as the internal factors associated with firms' operations. Although the inclusion of the factors is largely driven by data availability, the coverage is comprehensive. In general, these factors may affect the efficiency of R&D in improving productivity because they influence firms' capacity, management, the economies scale and scope in exploitation of R&D. Thus, a firm's actual productivity (A_i) becomes

$$A_i = \underbrace{f\left(R_i, Z_i\right)\exp(v_i)}_{\text{Technological Frontier}}\ \underbrace{\theta(X_i)}_{\text{Efficiency}} = A_i^*\theta(X_i) \tag{2}$$

Where $A_i \leq A_i^*$ and $\theta(X_i) \in (0,1)$ represents R&D efficiency that is a function of a set of X variables influencing business efficient execution, including technology adoption, skills, better management, learning by doing, and capacity utilization. These X variables are commonly called the determinants of efficiency.

Equation (2) demonstrates the actual impact of R&D on productivity depends

nificant. This may be because R&D stock captures the effects from both current and past R&D investments. R&D investments (both in-house and purchased) are derived using data collected for the program supporting corporate's scientific research and experimental development (SRED). They are then used to build up R&D capital stock using Perpetual Inventory Method (PIM) at firm level with the depreciation rate being 15 per cent. Details are in Appendix B.

9 Note that similar results are obtained when we alternatively put the foreign ownership variable in the efficiency function.

on the efficiency-enhance X variables. The higher is the efficiency term, the closer to the potential impact is the actual impact of R&D on productivity.

Now we provide some rationale and theoretical discussion for the inclusion of the X variables. Firm size may impact on R&D efficiency. Larger-sized firms are able to benefit more from R&D than their small-sized counterparts as larger-sized firms can access lower-cost capital resources and in-house expertise/skills in commercializing successful R&D investments. They can also magnify the benefit of R&D from their larger scale and scope of production.

Skills have long been recognized as a crucial factor for R&D activities to be successful. They are essential elements for undertaking certain complex R&D investments, carrying out R&D activities efficiently, and internalizing the outcome by introducing new products and/or processes. There has been well documented evidence for the strong link between R&D and skilled labor (Morck and Yeung, 2000; Bernstein, 2002). Findings in Foley *et al.*, (1993) suggest that the lack of certain skills can act as a barrier to pursue certain business activities. Using firm-level data from the United Kingdom, Bosworth and Wilson (1993) show that there is a strong relationship between the deployment of highly qualified employees, their role in the strategic management of companies and firm dynamic economic performance.

A competitive business environment is generally considered to be positive for undertaking R&D activities. As competition threatens the viability of businesses, it reduces managerial slack and generates incentives to improve firm performance through product, process or organizational innovation (Nickell, 1996, Tang and Wang, 2005, and Tang, 2006). However, for a given R&D activity, the return on R&D investment may depend on the firm's ability or market power in commercializing R&D products (Demsetz, 1973; Peltzman, 1977).

Investments in ICT and other technologies are also efficiency-enhancing since technologies streamline R&D operations, minimize redundancies, and increase accuracy and reduce errors. In a broad context, ICT are believed to be enablers of product, process and organizational innovation (Teece 1986; Bresnahan and Trajtenberg, 1995). They also play a substantive role in the generation, storage and transmission of information and in the reduction of market failures (Biagi, 2013). The increased use of ICT has been credited with the strong resurgence of productivity growth in the United States and many other OECD countries (Jorgenson, 2001; Stiroh, 2002; Timmer and van Ark, 2005; and van Reenen *et al.*, 2010).

Management may also matter for the productivity impact of R&D because it is empowered for the strategic planning, priority setting, development and coordination of R&D programs. It also oversees day-to-day R&D operations and facilitates the absorption, implementation and commercialization of new know-how and technology from R&D. There is empirical evidence showing a robust and causal impact of managerial quality/practices on firm performance (Nelson, 1991; Bloom and Van Reenen, 2010; Bloom *et al.*, 2013b). Bloom *et al.*, (2012) attributed at least one-half of the difference in productivity growth between the United States and some European countries in 1995-2004 to superior management practices in the United States.

Like management, business strategies (e.g. product positioning against cost leadership, outward orientation) may matter for R&D efficiency. It has been suggested that to be successful in the current global economy with increased competition and ever changing markets, firms need to focus more on product positioning by exploring new ideas and designing new products to develop new markets than on cost-cutting to maintain cost leadership in old markets (Su and Tang, 2016). This is because product innovation allows firms to develop and maintain a lasting, sustainable competitive advantage (Brown and Eisenhardt, 1995; Porter, 1985). In addition, it has been suggested that outward-oriented business strategy (exporting, offshoring, and undertaking outward foreign direct investments) is also important for firm performance (Trefler, 2004; Baldwin and Gu, 2004; Tang and Van Assche, 2017). In the context of this article, outward-orientation strategies may increase R&D efficiency as they effectively increase the market available in which firms can spread the fixed costs associated with R&D investments. They also allow for better access to production resources, advanced technologies and products, and better management practices.

With this formulation, the actual productivity is specified as two components: the "technological frontier" and the "efficiency". Regardless of the terminologies, the first term is driven by the R variables while the second one is driving by the X variables. They complement each other to improve productivity. The separation is to estimate the maximum potential of R&D in affecting productivity. Thus, the frontier here should be interpreted as the technological potential and is the maximum influence of R&D on actual productivity.

For our empirical analysis, we assume that $\ln\{f(R_i, Z_i)\}$ is linear in its R&D and controlling variables. Also, following the tradition under the stochastic production frontier framework, we define $u_i = -\ln\theta_i$. This yields the following stochastic frontier regression model:

$$\ln(A_i) = \beta_0 + \beta_1 R_i + \beta_2 R_i^2 + \sum_{j=3}^{s} \beta_j Z_{i,j} + v_i - u_i\ , \quad (3)$$

where $u_i \geq 0$ is an additional error term, which a measure of inefficiency or shortfall of R&D in improving productivity to the maximum.[10]

Following Stevenson (1980), we specify u_i as a one-sided error term, independently and normally distributed with nonzero mean and truncation point at 0, $N^+(\mu_i,\ \sigma_u^2)$.[11] We hypothesize that the mean of the distribution of inefficiency is heterogeneous across firms, depending on a set of the factors that may influence R&D efficiency in improving productivity. We formulate the mean of the truncated-normal distribution for firm i as a linear

10 Note that $u_i = -\ln(\theta_i) \approx 1 - \theta_i$.

11 The superscript "+" refers to truncation on the left at zero.

function of those covariates:

$$\mu_i = \gamma_0 + \sum_{h=1}^{m} \gamma_h X_{i,h} \qquad (4)$$

where X_i is a vector of the covariates that may affect R&D in improving productivity.[12]

Data

To estimate the stochastic frontier regression model, we construct a firm-level dataset by linking four micro-data files compiled by Statistics Canada.[13] We list the variables extracted and derived from each micro database in the Appendix at the end of this article. Here we provide a brief description of each of those four micro-data files.

Micro-data Files

The first micro data file is General Index of Financial Information (GIFI). The administrative micro data file collects financial statement and balance sheet information from each firm when it files a T2 Corporation Income Tax Return. We extract information from this dataset and derive a firm's gross output, physical capital stock, and intermediate inputs. In addition, we obtain data on R&D stock and ICT stock, which are also derived from information from the tax files. The definition of some variables will be discussed in the next section.

The GIFI data is then supplemented by payroll and employment information for each employer business in Canada from The National Accounts Longitudinal Microdata File (NALMF). The data in NALMF come from various sources, mainly administrative data from statement of remuneration paid (T4), statement of account for current source deductions (PD7), corporate income tax return (T2) and goods and services tax (GST) files. Firm characteristics such as industry and ownership for example come from Statistics Canada's Business Register. For this study, we select Individual Labour Unit (ILU) as a firm's employment. This measure is closer to a head count — every individual who received at least one T4 slip in a given year. If individuals worked for different firms during the year, their 1.0 ILU is split proportionately across firms according to the share of their total annual payroll earned in each.[14]

12 With this model, we do not deal with the endogeneity issue associated with productivity and its explanatory variables. Given that R&D and ICT variables are measured as stock (mainly depending on past investments) and other variables are mostly perception-based, we do not expect this is a significant problem.

13 These micro files can be accessed for empirical analysis at Statistics Canada. Researchers wishing to access these and other micro files must submit a research proposal to the Canadian Centre for Data Development and Economic Research (CDER) at Statistics Canada.

14 Another employment measure, the Average Labour Unit (ALU), is also available if it is requested. ALU is derived by dividing the business's annual payroll (from T4) by the corresponding industry/province/size class average annual earnings per employee (from the Survey of Employment Payroll and Hours). Because the imputation is based on average payroll, it will overestimate employment of productive firms and underestimate employment of less productive firms since high productive firms in general pay high wages. Note, however, that ILU also has its own shortcomings. It overestimates employment of firms with part-time workers. The problem may be minimized by the introduction of industry dummies in the analysis.

In addition, the GIFI data is supplemented with data on foreign ownership from the Business Register (BR) through NALMF. BR is the central repository of information on businesses in Canada. Used as the principal frame for the economic statistics program at Statistics Canada, it maintains a complete, up-to-date and unduplicated list on all active businesses in Canada that have a corporate income tax (T2) account, are an employer or have a goods and services tax account.

These three databases are administrative microdata, covering all industries and for 2000-2014. The linkage of these three databases provides necessary data for our analysis, including output, inputs (labour, capital and intermediate inputs), R&D, investments in ICT (computers, communication equipment and software), and certain information on firm characteristics such as foreign ownership.[15]

Missing from these administrative micro databases are firms' business environment, business strategy, and management practices, which play very important roles in influencing the effectiveness of R&D in improving productivity. We are able to obtain these data from the Survey of Innovation and Business Strategy (SIBS) (2009 and 2012). SIBS is a sample-based survey that provides qualitative information about a firm's strategic decisions and operational tactics. The targeted population consists of firms in Canada with more than 20 employees and revenues of at least $250,000 in 14 sectors at the two-digit industry level from 11 to 56 based on the North American Industrial Classification System. SIBS surveyed 4,228 firms in 2009 and 4,467 firms in 2012, with 1,279 firms being in both time periods.

To ensure comparison over time, it is necessary to deflate the nominal variables associated with the production function. Deflators at the firm level are not available so detailed industry deflators based on the KLEMS database are used.[16] In particular, total sales, physical capital assets, payroll per employee, and the derived intermediate inputs at the firm level are deflated by gross output, capital stock, value added and intermediate input deflators at a detailed industry level.

For this research, our analysis focuses on Canadian manufacturing firms. There are three main reasons. First, the linked micro database is limited to only sample firms in SIBS. Manufacturing firms account for about 70 per cent of the sample firms. Second, relative to service industries, output and inputs for manufacturing are less likely subject to measurement errors. Finally, the link between R&D and productivity is not that straightforward for some service industries as the major business activities for some service firms are pure R&D in nature, with little application of R&D or production activities.

After linking to the sample-based surveys to the three administrative micro databases and limiting to only manufacturing firms, we end up with 2,537 and 2,356 observations in 2009 and 2012, re-

15 Gross output and inputs (labour, capital and intermediate inputs) are used to derive productivity estimates.

16 For a description of the KLEMS database for Canada, see Baldwin *et al.* (2007).

spectively. The final observations and the distribution by industry are reported in Table 1. On average, more than half of them were R&D performers, although there was a great variation across manufacturing industries.

Some Descriptive Results

Industries vary significantly in R&D intensity (Table 2). On average, the most R&D intensive industry was computer and electronics, followed at distance by electrical products and appliances and machinery. In contrast, the least R&D intensive industries were wood, beverage and tobacco, and non-metallic mineral.

In terms of the standard deviation, there was a significant variation in R&D intensity across firms within an industry. On average, the standard deviation is about 7 times the mean.

In general, R&D performers were larger than non-R&D firms in both output and employment (Table 3). In addition, they were more productive, paid higher wage rates, and were more physical capital intensive.[17]

The comparison in economic performance between R&D performers and non-R&D firms is a good starting point, but to understand the difference, we need a more rigorous analysis on the factors underlying these disparities. We focus on productivity.

Stochastic Frontier Analysis

In this section, we empirically estimate the effect of R&D on productivity and see how the actual impact of R&D is influenced by firm specifics (e.g. firm size and ownership), workforce skills, business operating environment, investments in technologies (including ICT), management practices, business outward orientation, and business strategies.

Variable Definition and Measurement

Before discussing the empirical results, we first briefly describe the definition of some key variables in the empirical analysis. The definitions and measurements of all variables are found in Table A2 in the Appendix.

For the regression model, equation (3), the actual multifactor productivity for firm i, $\ln(A_i)$, is estimated as the Solow residual, that is, real gross output minus the contributions from inputs (labour, real physical capital, and real intermediate inputs), with parameters being obtained by estimating each industry production function, controlling for year-specific effects.[18]

The physical capital stock here consists of assets associated with machinery, equipment, and building structures, excluding R&D.

The technological frontier is a function of R&D, controlling for foreign ownership,

17 The differences between R&D firms and non-R&D firms for all variables except capital intensity are statistically significant.

18 The actual multifactor productivity for firm i in an industry is calculated as $\ln(A_i) = \ln(Y_i) - \hat{\alpha}_L \ln(L_i) - \hat{\alpha}_K \ln(K_i) - \hat{\alpha}_M \ln(M_i)$, with the estimated parameters being industry-specific.

Table 1: Number of R&D and non-R&D performers by Manufacturing Industry, 2009 and 2012

Industries	2009			2012		
	No-RD	RD	Total	No-RD	RD	Total
Food	128	109	237	141	65	206
Beverage and tobacco	X	X	X	X	X	X
Textile mills and textile	37	58	95	44	38	82
Clothing and leather	58	39	97	50	32	82
Wood	83	55	138	89	44	133
Paper	48	50	98	37	41	78
Printing and support	51	44	95	63	35	98
Petroleum and coal	X	X	X	X	X	X
Chemical	52	113	165	54	93	147
Plastics and rubber	71	103	174	84	80	164
Non-metallic mineral	58	40	98	65	28	93
Primary metal	35	66	101	49	42	91
Fabricated metal	132	107	239	123	98	221
Machinery	75	145	220	70	126	196
Computer and electronic	27	116	143	34	109	143
Electrical, appliance and components	38	75	113	45	69	114
Transportation equipment	109	165	274	108	137	245
Furniture and related product	67	42	109	84	27	111
Miscellaneous manufacturing	42	53	95	68	43	111
Total manufacturing	1,136	1,401	2,537	1,237	1,119	2,356

Note: X denotes numbers being suppressed for confidentiality.
Source: Authors' tabulation based on micro data from Statistics Canada.

Table 2: R&D Intensity and Variation by Manufacturing Industry, 2009 and 2012

Industries	2009		2012	
	Mean	St. D.	Mean	St. D.
Food	0.33	3.89	0.14	0.53
Beverage and tobacco	X	X	X	X
Textile mills and textile	0.49	2.05	1.36	8.09
Clothing and leather	0.71	3.80	0.37	0.80
Wood	0.03	0.09	0.06	0.22
Paper	0.14	0.42	0.23	1.13
Printing and support	0.19	0.80	0.18	1.14
Petroleum and coal	X	X	X	X
Chemical	1.24	5.91	0.61	1.86
Plastics and rubber	0.30	0.75	0.16	0.43
Non-metallic mineral	0.07	0.17	0.09	0.28
Primary metal	0.35	2.04	0.32	1.93
Fabricated metal	0.64	6.10	1.47	16.88
Machinery	0.76	1.90	1.62	6.47
Computer and electronic	9.12	29.32	5.86	11.52
Electrical, appliance and components	1.47	4.27	1.08	3.17
Transportation equipment	1.00	5.88	0.91	4.95
Furniture and related product	0.11	0.43	0.13	0.65
Miscellaneous manufacturing	0.72	2.00	0.62	2.06
Total manufacturing	1.06	8.08	0.97	6.78

Notes: X denotes cell being depressed for confidentiality. R&D intensity is defined as the ratio of R&D stock to physical capital stock
Source: Authors' tabulation based on micro data from Statistics Canada.

Table 3: R&D Performers and Economic Performance, Total Manufacturing

	2009		2012	
	R&D Firms	Non-R&D Firms	R&D Firms	Non-R&D Firms
Average firm real gross output, million$	108.9	29.6	138.2	28.1
Average firm employment	286.5	132.8	269.2	105.6
Average firm real wage rate, 000$	42.2	38.3	44.9	40.1
Average firm capital intensity,000$	139.3	124.0	116.2	113.5
Average firm labour productivity, 000$	216.0	204.3	239.6	206.8
Average fir MFP level (non-R&D firms = 100)	101.3	100.0	101.8	100.0

Notes: Real wage rate, capital intensity, and labour productivity are defined as real labour compensation per employee, physical capital stock per employee, and real gross output per employee, respectively. MFP is calculated as residual of real gross output minus contributions from labour, physical capital and intermediated inputs with parameters being estimated through regressions.
Source: Authors' tabulation based on micro data from Statistics Canada.

business cycles and industry-specifics. The set of R&D variables consists of R&D intensity and its square. To capture a firm's R&D investment in the current and the past years, R&D intensity in this paper is measured as the ratio of R&D stock to physical capital stock.[19] R&D stock for each firm is estimated from real R&D investment using the perpetual inventory method, assuming a capital depreciation rate of 15 per cent.[20] Foreign ownership is a dummy variable with one being foreign-controlled and zero otherwise.

In the X variables for efficiency, firm size is a continuous variable measured by employment. Workforce skills are approximated by the percentage of employees with university education. Business competitive environment is indicated by the firm's market share and the firm's perception of its market power (in terms of market share, number of competing products or number of competitors) in its main market. As shown by Tang (2006), the advantage of the perception-based competition indicators comparing to industrial statistics is that (a) they are able to capture firm-specific competition as firms may face different competition even within a narrowly defined industry and (b) they reflect not only competition from domestic markets but also competition from foreign markets. As shown in Table A3 of the Appendix, the index is valued between 0 and 1. The higher is the index value, the larger market power the firm has.

For investments in technologies, we include two indicators. One is the investment in ICT. To indicate the effort in investment in ICT, we use ICT intensity and define it as the ratio of ICT stock to physical capital stock. The other is an index for adopting any non-computerized advanced technologies associated with automated material handling, information integration and control, biotechnologies and bio-products, nanotechnologies, green technologies, and other type of advanced technology. Those technologies may take the form of equipment, materials, processes, blue prints and

19 We use physical capital stock to scale down R&D stock instead of output as we also use physical capital stock to scale down ICT stocks. Results will be similar when output is used as a scale down variable.

20 See Appendix for a discussion on how R&D investment and R&D capital stock are derived.

knowledge. There are in total six non-computerized advanced technology indicators. Each indicator is a binary variable, with one for being adopted and zero otherwise. The index is a simple average of the six binary variables.

For management practices, following Brouillette and Ershov (2014), we construct an index based on a framework developed by Bloom and Van Reenen (2007). Basically, the index is a simple average of 19 indicators. The indicators, which are listed in Table A3 in the Appendix, are normalized between 0 and 1, reflecting firm production performance and human resource management practices from various aspects. The index is valued between 0 and 1. Based on Bloom *et al.*, (2013a), the higher the index value, the more structured are the management practices.

Business outward orientation refers to a firm's outward orientated strategy in terms of taking advantage of international markets for cheap inputs and for selling outputs, which may increase the returns to R&D investments. The index for business outward orientation is built based on two indicators. The first indicator is business activities outside of Canada, including business operations in foreign countries. If a firm has any business activities outside of Canada, then the indicator is one and zero otherwise. The second indicator is exporting. The indicator equals one if a firm exports or attempts to export and zero otherwise. The index for business outward orientation is a simple average of the two indicators.

The final variable being considered is forward-looking business strategy. It is defined as a strategy related to product positioning, which includes product leadership, market segmentation, product diversification and improving quality. If a firm has its long term strategies mostly focusing on product positioning, then it is equal to one; zero otherwise.

Discussion of Empirical Results

The stochastic frontier regression model is estimated using the linked micro database.

Estimation results

The estimation results for R&D performers are reported in Table 4.[21] Several interesting results emerge. For the R&D potential or technological frontier, it is found that the R&D intensity variable was positive and highly significant and its square was negative and highly significant. Thus, the estimation shows that R&D investments are highly significant in raising productivity, but they are subject to diminishing return as R&D investments increase. [22] As expected, the coefficient on the foreign ownership dummy is positive and significant, suggesting that, ceteris paribus, foreign controlled firms' technological frontier are about 12 per cent more shifted outward than domestic controlled firms' in our sample.

For the inefficiency function, all vari-

21 The stochastic frontier model is estimated in two stages. For a discussion, see Kumbhakar *et al.*, (2015).

22 Main results are similar when R&D intensity is defined as R&D stock per worker.

Table 4: Stochastic Frontier Estimation, R&D Performers in Canadian Manufacturing

Dependent variable: log of MFP	Parameter	p-value
Technological frontier		
Constant	4.4696	0.64
R&D intensity	0.6828***	0.00
Square of R&D intensity	-0.1927***	0.00
Foreign owner ship dummy	0.1177***	0.00
Year dummies	Yes	
Industry dummies	Yes	
Inefficiency		
Management practice index	-0.0723***	0.00
ICT capital intensity ratio	-0.2135***	0.00
University Education (in log)	-0.0318***	0.00
Employment (in log)	-0.0095***	0.01
Firm market power	-0.0815***	0.00
Non-computerized technology adoption index	-0.0146	0.44
Outward orientated business strategy index	0.0038	0.71
Product positioning business strategy dummy	-0.0204*	0.10
Constant	0.5972	0.95
Number of observations	2520	

Note: R&D intensity for the regressions is scaled down by 100 to ensure the coefficients associated with R&D variables are not zero in 4-digit decimal numbers. "**" and "***" stand for significance at 5 per cent and 1 per cent level, respectively.
Source: Authors' tabulation based on micro data from Statistics Canada.

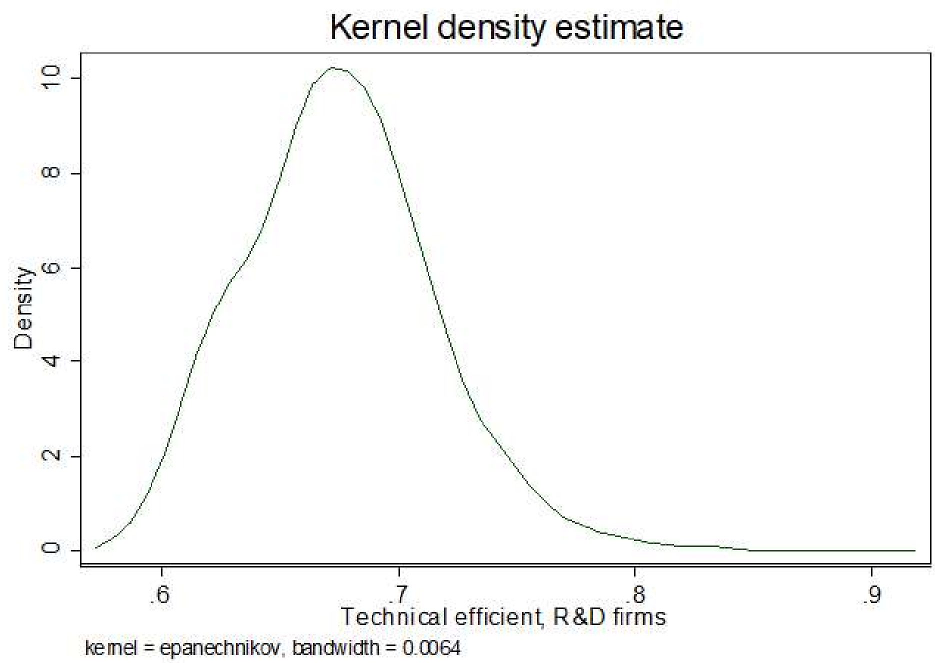
ables except non-computerized technology adoption and outward orientated business strategy are found to be statistically highly significant. Inefficiency measures the distance of actual multifactor productivity from the technological frontier. Negative for inefficiency means positive for efficiency. Thus, firms that pursued sound management practices, invested in ICT, had skilled workforce, were larger, and adopted the product positioning business strategy tend to be closer to the frontier. In addition, the estimated coefficient associated with a firm's market power is also negative and significant, which suggests that market power or share is important for the return to R&D investments.[23]

The statistical insignificance of non-computerized technology adoption or outward orientation is surprising as they increase the capacity or market to better exploit R&D investments. The lack of significance is not because those factors are correlated with those significant factors in the inefficiency function. For instance, dropping ICT intensity from the regression will not make non-computerized technology adoption significant. Similarly, the exclusion of employment and foreign-control dummy from the regression does not change the sign and the significance of the coefficient associated with outward orientated business strategy.

In sum, the estimation shows that for R&D to generate its potential productivity dividend, it is important to have co-

23 The result is consistent with the positive relationship between efficiency and market share or markups (Demsetz, 1973 and Peltzman 1977).

Chart 2: R&D Efficiency Distribution for R&D Firms



Source: Authors' tabulation based on micro data from Statistics Canada.

investments in ICT, pursue certain management practices, maintain skilled workforce, achieve a certain scale, retain a certain level of market share, and adopt the product positioning business strategy. The lack of these efforts and conditions undermine the R&D efficiency in improving productivity.

Chart 2 is the R&D efficiency distribution for R&D performing firms.[24] Most of the firms had inefficiency between 20 and 40 per centt. Thus, besides encouraging firms to undertake R&D activities, effort to enhance business conditions to improve R&D efficiency is also equally important to improve firms' productivity and competitiveness.

Elasticity of Productivity with Respect to R&D and Efficiency-enhancing Co-variates

How is productivity sensitive to R&D and efficiency-enhancing factors? In this sub-section, we estimate the elasticity of multifactor productivity with respect to each of those factors. According to equation (4), actual MFP is a function of both deterministic components and random components. This means that the actual MFP is also random. To be meaningful, we avoid the randomness and calculate

24 R&D efficiency for firm i at time t is estimated as $TE = \exp(-\hat{u}_{i,t})$.

the elasticity of productivity with respect to a factor based on the mean of actual MFP, that is,

$$E\left[\ln\left(A_i\right)\right]=E\left[\ln\left(A_i^*\right)\right]+E\left[\ln\theta\left(X_i\right)\right] \quad , \tag{5}$$

Based on equation (3), the marginal effect of the R&D on the frontier for firm i is $(\hat{\beta}_1+2\hat{\beta}_2\bar{R})\bar{R}$, with $\hat{\beta}_1$ and$\hat{\beta}_2$ being the estimated coefficients associated with the R&D variable and its square, respectively. $\bar{R}$ is the average of the current R&D variable across firms in the group. The marginal effect of foreign ownership dummy is $\hat{\beta}_3$, the estimated coefficient associated with the foreign ownership dummy.

According to Wang (2002), the marginal effect of $X_{i,h}$ on the mean of efficiency is as follows:

$$\begin{aligned}\frac{\partial E\left[\ln\left(A_i\right)\right]}{\partial X_{i,h}} &= \frac{\partial E\left[\ln\theta\left(X_i\right)\right]}{\partial X_{i,h}} \\ &= -\frac{\partial E\left(u_i\right)}{\partial X_{i,h}} \\ &= -\gamma_h\left\{1-\Lambda_i\left[\frac{\phi\left(\Lambda_i\right)}{\Phi\left(\Lambda_i\right)}\right]\right. \\ &\quad \left.-\left[\frac{\phi\left(\Lambda_i\right)}{\Phi\left(\Lambda_i\right)}\right]^2\right\} \quad ,\end{aligned} \tag{6}$$

where $\Lambda_i=\mu_i/\sigma_u$, and ϕ_i and Φ_i are the probability density and cumulative distribution functions of a standard normal distribution, respectively.

With the marginal effects, we can now estimate the elasticity of MFP (either the frontier or efficiency) with respect to each of those variables in the analysis. We separate factors that are continuous from those that are binary. Also for simplicity, we treat all variables other than those binary variables as being continuous. Furthermore, we only consider factors that are statistically significant. Finally, all elasticities are evaluated at the mean of corresponding variables across the group of sample firms.

For variables associated with the efficiency function, the impact of their changes on R&D efficiency and thus MFP depends on how they enter into the equation. For continuous variables in log, which are university education and employment, the elasticity of MFP with respect to a variable is the estimated marginal effect. For any other continuous variable, the corresponding elasticity is the product of the marginal effect of the variable and the average of the variable across firms in the group. For a binary variable, when the binary variable switches from 0 to 1, the productivity elasticity equals the estimated marginal effect times 100.

The average elasticities of MFP with respect to R&D variables by industry based on R&D performers and all firms are reported in Table 5. We calculate elasticities based on the estimated coefficients from R&D performers. According to elasticities on the basis of R&D performers, doubling the R&D intensity level from 1.8 (which was the actual average of R&D intensities of all R&D performers) to 3.6 will lead to a 1.2 per cent increase in MFP for the manufacturing as whole. The responses vary significantly across industries as industries vary in R&D intensity. The MFP increase from a doubling od the R&D intensity will be 5.9 per cent for computer and electronics, followed by 1.5 per cent for fabricated metal, 1.3 per cent for electrical, appliance and components. The smallest response is from wood, food and beverage and tobacco, less than 0.1 per cent.

Table 5: Average Elasticity of R&D in Improving Multifactor Productivity by Industry in Manufacturing

Industries	R&D firms
Wood	0.0005
Food	0.0012
Beverage and tobacco	0.0012
Non-metallic mineral	0.0013
Petroleum and coal	0.0014
Paper	0.0015
Furniture and related product	0.0023
Plastics and rubber	0.0028
Printing and support	0.0030
Primary metal	0.0039
Chemical	0.0084
Clothing and leather	0.0089
Textile mills and textile	0.0093
Transportation equipment	0.0094
Miscellaneous manufacturing	0.0094
Machinery	0.0110
Electrical, appliance and components	0.0128
Fabricated metal	0.0152
Computer and electronic	0.0590
Total manufacturing	0.0122

Source: Authors' tabulation based on micro data from Statistics Canada.

Table 6: Average Elasticity of Multifactor Productivity With Respect to Variables in Improving R&D Efficiency, Total Manufacturing

Factors	The Mean Value of Factors	Elasticities
Employment	278.81	0.0095
ICT capital intensity	0.06	0.0131
University education	16.35	0.0318
Firm's market power	0.40	0.0325
Management practice index	0.56	0.0405

Source: Authors' tabulation based on micro data from Statistics Canada.

In Table 6, we also report average elasticity of MFP with respect to other factors in equation (6) for total manufacturing on the basis of estimation for R&D performers. The impacts of those factors affect R&D efficiency and thus MFP depend on the changes in those factors?

To illustrate, here we provide an example for each factor. If management practice is more structured with a 25 per cent increase in the average index from 0.56 to 0.70, then MFP or R&D efficiency will increase 1.01 per cent. Similarly, if ICT capital intensity, the share of university education in workforce, employment, and firm's market power are doubled from 0.06 to 0.12, 16.35 per cent to 32.70 per cent, 279 employees to 558 employees, and 0.40 to 0.80, then R&D efficiency or productivity will increase by 1.31 per cent, 3.18 per cent, 0.95 per cent, and 3.25 per cent, respectively.

Finally, firms with product positioning business strategy dummy are 2.04 per cent more efficient than other firms (see Table 4).

Conclusion

Why do some manufacturers obtain a larger productivity dividend from their R&D investments than others? By estimating a stochastic frontier model based on a rich micro database for Canadian manufacturing firms, this article shows that R&D does improve productivity; however the actual impact of R&D depends largely on R&D efficiency in improving productivity. Empirical evidence indicates that there is a set of internal factors that work together in influencing R&D efficiency. These factors include management practices, investment in ICT, skilled workforce, firm size, firm's market power, and product positioning business strategy.

The findings highlight the complexity of R&D in improving productivity. They suggest that, to strive for a high productivity dividend yield from R&D investments, firms need to invest in other business activities that support R&D and its commercialization. They may also suggest that other industrial programs may be required to ensure R&D programs (R&D grants and R&D tax measures) to be more effective.

References

Acemoglu, D. and J. Lin (2004) "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry," *Quarterly Journal of Economics*, Vol. 119, No. 3, pp. 1049–1090.

Aghion, P. and P. Howitt (1992) "A Model of Growth through Creative Destruction," *Econometrica,* Vol. 60, pp. 323–351.

Aigner, D.J., C.A.K. Lovell and P. Schmidt (1977) "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics,* Vol. 6, pp. 21-37.

Andrews, D. and B. Westmore (2014) "Managerial Capital and Business R&D as Enablers of Productivity Convergence," OECD Economics Department Working Papers No. 1137, ECO/WKP(2014)33.

Baldwin, J. R. and W. Gu (2004) "Trade Liberalization: Export-Market Participation, Productivity Growth and Innovation," *Oxford Review of Economic Policy*, Vol. 20, No. 3, pp. 372-92.

Baldwin, J.R., W. Gu and B. Yan (2007) "User Guide for Statistics Canada's Annual Multifactor Productivity Program," Statistics Canada Research Paper, Catalogue no. 15-206-XIE — No. 14.

Bernstein, J.I. (2002) "A Tour of Innovation and Productivity: Measurement, Determinants and Policy," In Someshwar, Rao and Andrew Sharpe, (eds.) *Productivity Issues in Canada*, (Calgary: University of Calgary Press).

Biagi, F. (2013) "ICT and Productivity: A Review of the Literature," European Commission, Joint Research Centre technical Reports, Institute for Prospective Technological Studies, Digital Economy Working Paper 2013/09.

Bloom, N. and J. Van Reenen (2007) "Measuring and Explaining Management Practices Across Firms and Countries," *Quarterly Journal of Economics*, Vol. 122, No. 4, pp. 1351–1408.

Bloom, N. and J. Van Reenen (2010) "Why Do Management Practices Differ across Firms and Countries?" *Journal of Economic Perspectives*, Vol. 24, No. 1, pp. 203–224.

Bloom, N., R. Sadun and J. Van Reenen (2012) "Americans Do IT Better: US Multinationals and the Productivity Miracle," *American Economic Review,* Vol. 102, No. 1, pp. 167–201.

Bloom, N., E. Brynjolfsson, L. Foster, R. Jarmin, I. S. Eksten and J. Van Reenen (2013a) "Management in America," Paper Presented at the American Economic Association Meeting.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie and J. Roberts (2013b) "Does Management Matter: Evidence from India," *Quarterly Journal of Economics*, Vol. 128, No. 1, pp. 1–51.

Bosworth, Derek and Rob Wilson (1993) "Qualified Scientists and Engineers and Economic Performance," In Peter Swann (ed.) *New Technologies and the Firm: Innovation and Competition,* pp. 153-174, ed. Peter Swan, (London and New York : Routeledge).

Bresnahan T.F. and J.E. Trajtenberg (1995) "General Purpose Technologies: Engines of Growth?," Journal of Econometrics, Vol. 65, Special Issue, January, pp. 83-108.

Brown, S.L. and K.M. Eisenhardt (1995) "Product Development: Past Research, Present Findings, and Future Directions," *Academy of Management Review*, Vol. 20, No. 2, pp. 343-378.

Brouillette, D. and D. Ershov (2014) "Management Practices, Competition, Innovation and the Performance of Enterprises," Industry Canada Working Paper 2014-02.

Coe, D. T., E. Helpman and A. Hoffmaister (2009) "International R&D Spillovers and Institutions," *European Economic Review*, Vol. 53, pp. 723–741.

Demsetz, H. (1973) "Industry Structure, Market Rivalry and Public Policy," *Journal of Law and Economics*, Vol. 16, pp. 1-10

Faff, R., Y. Ho, W. Lin and C. Yap (2013) "Diminishing Marginal Returns from R&D Investment: Evidence from Manufacturing Firms," *Applied Economics*, Vol. 45, pp. 611-622.

Foley, P.D.,H.D. Watts and B. Wilson (1993) "New Technologies, Skills Shortages and Training Strategies," In Peter Swann (ed.) *New Technologies and the Firm: Innovation and Competition*, (London and New York: Routledge).

Goto, A. and K. Suzuki (1989) "R&D Capital, Rate of Return on R&D Investment and Spillover of R&D in Japanese Manufacturing Industries," *Review of Economics and Statistics*, Vol. 71, pp. 555-564.

Griffith, R., S. Redding and J. Van Reenen (2004) "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries," *Review of Economics and Statistics*, Vol. 86, No. 4, pp. 883-895.

Griliches, Z. (1979) "Issues in Assessing the Contribution of Research and Development to Productivity Growth," *Bell Journal of Economics*, Vol. 10, pp. 92–116.

Griliches, Z. (1986) "Productivity, R&D and Basic Research at the Firm Level in the 1970s," *American Economic Review*, Vol. 76, pp. 141–154.

Griliches Z. and J. Mairesse (1982) "Comparing Productivity Growth: An Exploration of French and US Industrial and Firm Data," NBER Working Paper No. 961, National Bureau of Economic Research, Cambridge.

Gu, W. and J. Tang (2004) "Link Between Innovation adn Productivity in Canadian Manufacturing Industries," *Economics of Innovation and New Technology,* Vol. 13, No. 7, pp. 671-686.

Hall, B., J. Mairesse and P. Mohnen (2010) "Measuring the Returns to R&D," in *Elsevier Handbook of the Economics of Innovation*, B.H. Hall and N. Rosenberg (eds.) Burlington Academic Press.

Jorgenson, D.W. (2001) "Information Technology and the U.S. Economy," *American Economic Review*, Vol. 91, pp. 1-32

Kohli, U. (1982) "Production Theory, Technological Change, and the Demand for Imports: Switzerland 1948-1976," *European Economic Review*, Vol. 18, pp. 369-86.

Kumbhakar, S.C. and C.A.K. Lovell (2000) *Stochastic Frontier Analysis*, (Cambridge: Cambridge University Press).

Kumbhakar, S.C., H. Wang and A.P. Horncastle (2015) *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*, (Cambridge: Cambridge University Press).

Lester, J, R. Macdonald, J. Sadeghzadeh and W. Wang (2017) "Firm-level R&D Impact on Productivity in Canadian Industries," *mimeo*, Statistics Canada.

Mohnen, P. (1992) "The Relationship between R&D and Productivity Growth in Canada."

Morck, R. and B. Yeung (2000) "The Economic Determinants of Innovation," Ottawa: Industry Canada. Occasional Paper 25.

Nelson, R. (1991) "Why Do Firms Differ, and How Does It Matter?," *Strategic Management Journal*, Vol. 12, pp. 61-74.

Nickell, S.J. (1996) "Competition and Corporate Performance," *Journal of Political Economy*, Vol. 104, pp. 725 - 46.

Pavitt K. (1984) "Sectoral Patterns of Technical Change: Towards A Taxonomy and a Theory," *Res Policy*, Vol. 13, pp. 343–373.

Peltzman, S. (1977) "The Gains and Losses from Industrial Concentration," *Journal of Law and Economics*, Vol. 20, pp. 229-263.

Porter, M.E. (1985) *Competitive Advantage: Creating and Sustaining Superior Performance*, (New York: The Free Press).

Rao, S., J. Tang and W. Wang (2010) "ICT Capital and MFP Growth: Evidence from Canadian and U.S. Industries," *Transnational Corporations Review*, Vol. 2, No. 3, pp. 59-71.

Su, Z. and J. Tang (2016) "Product Innovation, Cost-cutting and Firm Economic Performance in the Post-crisis Context: Canadian Microevidence," *Journal of Centrum Cathedra*, Vol. 9, No. 1.

Romer, P. (1990) "Endogenous Technological Change," *Journal of Political Economy*, Vol. 98, pp. 71–102.

Stevenson, R. (1980) "Likelihood Functions for Generalized Stochastic Frontier Estimation," *Journal of Econometrics*, Vol. 13, pp. 58–66.

Stiroh, Kevin J. (2002) "Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say?," *American Economic Review*, Vol. 92, No. 5, pp. 1559-76.

Tang, J. (2006) "Competition and Innovation Behaviour," *Research Policy*, Vol. 35, No. 1, pp. 68-82.

Tang, J. and S. Rao (2003) "Are Foreign-controlled Manufacturing Firms Less R&D-intensive than Canadian-controlled Firms?" *Canadian Public Policy*, Vol. 29, No. 1, pp. 111-117.

Tang, J. and A. Van Assche (2017) "Multinationals and Offshoring: Firm-Level Evidence from Canada," *Canadian Public Policy*, forthcoming

Tang, J. and W. Wang (2005) "Product Market Competition, Skill Shortages and Productivity: Evidence from Canadian Manufacturing Firms," *Journal of Productivity Analysis*, Vol. 23. No. 3, pp. 317-339.

Teece, D.J. (1986) "Profiting from Technological Innovation: Implications from Integration, Collaboration, Licensing and Public Policy," *Research Policy*, Vol. 15, pp. 285-306.

Timmer, M. P. and B. van Ark (2005) "IT in the European Union: A Driver of Productivity Divergence?" *Oxford Economic Papers*, Vol. 51, No. 3.

Trefler, D. (2004) "The Long and Short of the Canada-US Free Trade Agreement," *American Economic Review*, Vol. 94, No. 4, pp. 870-895.

Van Reenen J., Bloom N., Draca M. , Kretschmer T., Sadun R., Overman H. and Schankerman M. (2010) "The Economic Impact of ICT," Final Report for the European Commission.

Wakelin, K. (2001) "Productivity Growth and R&D Expenditure in UK Manufacturing Firms," *Research Policy*, Vol. 30, pp. 1079–1090.

Wang, E.C. (2007) "R&D Efficiency and Economic Performance: A Cross-country Analysis Using the Stochastic Frontier Approach," *Journal of Policy Modeling*, Vol. 29, pp. 345-360.

Zenger, T. R. (1994) "Explaining Organizational Diseconomies of Scale in R&D: Agency Problems and the Allocation of Engineering Talent, Ideas, and Effort by Firm Size," *Management Science*, Vol. 40, pp. 708-29.

Data Appendix

For productivity analysis outputs and inputs need to be properly measured to reflect production over a certain period. General Index of Financial Information (GIFI) provides firms' income statements and balance sheets. The income statement of a firm records incomes received and expenses incurred in both of its production and non-production activities. For using the information for productivity analysis, only production-related items should be included in the calculation of firms' outputs and inputs.

Table A1 presents the algorithm used to derive firm-level gross output, capital and labour income and intermediate input.

R&D expenditures are derived using data collected for the program supporting corporate's scientific research and experimental development (SRED). SRED program provides tax incentive in support of R&D activities of Canadian firms.

Firms' current and capital expenditures are reported in the tax form T661 that reports both allowable and qualified R&D expenses.[25] R&D investment can be measured as R&D investment = in-house R&D + purchased R&D (contract-out R&D or third-party R&D) - contract-in R&D (R&D performed for others).

Nominal R&D investment is then deflated using the implicit price index for R&D investment of all industries that is derived from CANSIM table 031-0007. The deflated or real R&D investment is then used to build up R&D capital stock using Perpetual Inventory Method (PIM) at firm level. Specifically, the current R&D capital stock (RDK_t) is equal to the previous R&D capital stock (RDK_{t-1}) net of depreciation at the rate of δplus current R&D investment (RDI_t), i.e.

$$RDK_t = (1-\delta)RDK_{t-1} + RDI_t$$

for $t = 2001$ to 2014.

The PIM calculation of capital stock requires a time series for investment data, information on the initial capital stock at the time and information on the depreciation rate. A constant geometric depreciation rate ($\delta = 15\%$) is used. Following Kohli (1982), the initial capital stock is calculated as

$$RDK_0 = \begin{cases} \frac{\overline{RDI}}{g_I+\delta} & \text{for firms born before 1985} \\ \frac{(\text{firm age})\times \bar{I}^{RD}}{g_I+\delta} & \text{for firms born after 1985 and before 2000} \\ 0 & \text{for firms born after 2000} \end{cases}$$

where $\overline{RDI}$ is the average R&D investment over the sample period, g_I the average annual growth rate of R&D investment over the sample period, and $\bar{I}^{RD}$ is the average R&D expenditure in 1985-2000.

Note that for young firms (less than 15-year old), their initial R&D capital stock at the year of 2000 is adjusted by the ratio of their age to 15.

25 See Lester *et. al.*, (2017) for a detailed discussion on how R&D expenditure can be measured.

Table A1: Algorithm for Deriving Nominal Output and Input Costs

	Gross Output (raw)
	Total sales of goods and services
+	Interest income for financial institutions
+	Commissions
+	Rental income
+	Fishing revenue
+	Management and Admin fees
+	Telecommunications revenue
+	Consulting fees
+	Sales of by-products
+	Deposit, Credit and Card services
	Total Cost
	Cost of sales
+	Operating expenses
	Profit
	Profit = gross output (raw) − total cost
	Labour Income
	Direct wages in cost of sales
+	Benefits on direct wages in cost of sales
+	Trades and sub-contracts in cost of sales
+	Employee benefits
+	Life insurance on executives
+	Salaries and wages
+	Sub contracts
	Capital Income
	Profit (if positive)
+	Gross overriding royalty
+	Freehold royalty
+	Other lease rentals
+	Exploration and development
+	Crown charges
+	Royalty costs
+	Freight-in and duty
+	Direct cost amortization of tangible assets
+	Direct cost amortization of resource assets
+	Donations
+	Amortization of intangible assets
+	Goodwill impairment loss
+	Bad debt expense
+	Loan losses
+	Amortization of resource assets
+	Amortization of tangible assets
+	Interest expense
+	Business taxes, licences and memberships
+	Government fee
+	Nova Scotia tax on large corporations
+	Property taxes
+	Royalty expenses
+	Research and development
+	Withholding taxes
+	Interfund transfer
	Intermediate input
	Intermediate input = gross output − labour income − capital income

The algorithm is for all industries including non-manufacturing. For companies with negative profit, gross output is measured by the shadow values of their business activities to ensure that capital cost/income is non-negative.

Table A2: Variable Definition, Measurement and Data Sources

Symbol	Name	Data sources	Measurement description
Y	Nominal gross output	GIFI	Total sales of goods and services plus other incomes such as commissions, management and admin fees, and consulting fees
L	Labour	NALMF	Individual Labour Unit (ILU)
K	Capital Stock	GIFI	Total tangible capital assets
k	Capital intensity	derived	The ratio of capital (K) to employment (L)
C^L	Labour compensation	NALMF	Wage and Salaries
C^K	Capital compensation	GIFI	All costs associated with the use of capital services
M	Nominal intermediate inputs	derived	Gross output minus labour costs (C^L) and capital cost (C^K).
LP	Labour productivity	Derived	Real gross output divided by employment
MFP	Multifactor productivity	Derived	Calculated as $\ln(A_i) = \ln(Y_i) - \hat{\alpha}_j^L \ln(L_i) - \hat{\alpha}_j^K \ln(K_i) - \hat{\alpha}_j^M \ln(M_i)$ with the parameters for industry j being estimated through the estimation of the production function
W	Wage rate	derived	Labour compensation (C^L) divided by employment (L)
R	R&D stock	GIFI	Derived using PIM model with 15% depreciation rate. For a more detail, see Appendix B.
R^{INT}	R&D intensity	derived	Ratio of R&D stock (R) to capital stock (K)
K^{ICT}	ICT capital stock	GIFI	Including computer equipment/software and radio and communication equipment.
k^{ICT}	ICT intensity	derived	The ratio of ICT capital stock (K^{ICT}) to capital stock (K)
D^F	Foreign ownership dummy	BR	1 for foreign controlled and 0 for Canadian-controlled
D^I	Outward-orientated business dummy	SIBS	1 for taking any business activities outside of Canada or for exporting or attempting to exporting; 0 otherwise
T	Adoption of technology	SIBS	An index that equals the simple average of six non-computerized advanced technology adoption indicators related to automated material handling, information integration and control, biotechnologies or bio-products, nanotechnologies, and green technologies
D^{BS}	Product positioning strategy	SIBS	1 for focusing on product positioning (e.g. product leadership, market segmentation, product diversification, improving quality) being the most important long term strategies; 0 for focusing on low-price and cost leadership (e.g., mass market) being the most important long term strategies
M	Management practices	SIBS	An index that equals the simple average of 19 normalized management practices indicators associated with production performance and human resources; more details are provided in Table A3 in Appendix A.
U	Education of workforce	SIBS	Percentage of employees having a university degree
C	Competition	SIBS	An index that equals the simple average of three normalized indicators that are associated with the market power that are against a firm in its main market. The first indicator is one minus the market share of a firm in its main market. The second and the third are normalized indicators on the number of competitors and competing products in the firm's main market such that 1/7 for 1, 2/7 for 2, 3/7 for 3, 4/7 for 4-5, 5/7 for 6-10, 6/7 for 11-20, and 1 for more than 20.
Ps	Deflators	KLEMS National Accounts	For gross output, capital, value added, intermediate inputs, and R&D spending.

Table A3: Management Indicators from SIBS

Indicators	Normalized value
Production Performance Management Practices	
Systematic procedure to resolve production problems	0 for no, and 1 for yes
Number of key production performance indicators	0 for none, and 1 for at least one
The frequency that the key production performance indicators are shown to managers	0 for never or don't know, and 1 for any frequency
The frequency that the key production performance indicators are shown to workers	0 for never or don't know, and 1 for any frequency
The frequency that the key production performance indicators are shown to executives	0 for don't know, 1/3 for rarely, 2/3 for periodically, and 1 for continually
The time frame for performance targets	0 for no target, 1/3 for short term (less than one year), 2/3 for long term, and 1 for both
Rewards for production performance targets	0 for none, $\frac{1}{2}$ for manager only, and 1 for all staff
Human Resource Management Practices	
Employee promotion practices	0 for based on tenure, $\frac{1}{2}$ for based on effort and tenure, 1 is for based on only effort
Policy dealing with underperforming employees	0 for inaction, 1/3 for warning, 2/3 for warning and training, 1 for immediate removal from positions
Employees involved in making decisions	0 for no, and 1 for yes
Certain methods are used to select candidates	0 for no, and 1 for yes
Training programs for new hires	0 for no, and 1 for yes
Career development programs for employees	0 for no, and 1 for yes
Formal performance agreements at least annually	0 for no, and 1 for yes
Formal appraisals for non-managerial staff at least annually	0 for no, and 1 for yes
Formal appraisals for managerial staff at least annually	0 for no, and 1 for yes
Incentive programs (stock ownership, profit-sharing, gain-sharing, merit bonus) for non-managerial staff	0 for no, and 1 for yes
Incentive programs (stock ownership, profit-sharing, gain-sharing, merit bonus) for managerial staff	0 for no, and 1 for yes
Incentive programs (stock ownership, profit-sharing, gain-sharing, merit bonus) for all staff	0 for no, and 1 for yes

Consistency Issues in the Construction of Annual and Quarterly Productivity Indices

Bert M. Balk[1]
Erasmus University

Abstract

Productivity change is generally measured in index form as ratio of output quantity index over input quantity index. Several statistical agencies publish quarterly as well as annual productivity indices, constructed from what appear to be basically the same sources. This raises the question whether, apart from measurement errors, consistency between quarterly and annual indices can be expected. This article explores, from a theoretical perspective, the options for obtaining consistency between annual and quarterly (or more general: between period and sub-period) measures of productivity change.

Productivity change is generally measured in index form as the ratio of an output quantity index over an input quantity index. The presentation is usually in the form of a percentage change (aka growth rate). Specific measures materialize by selecting the output concept to be used (such as gross output or value added) and the number of inputs to be considered (resulting in single, multiple, or total factor productivity indices) (OECD, 2001; Balk, 2018).

The frequency with which such indices are compiled varies. The 2018 edition of the *OECD Compendium of Productivity Indicators* lists annual data for 44 countries. However, a number of official statistical agencies, as well as some international organisations, publish also quarterly data (Haine and Kanutin, 2008). A well-known example is the US Bureau of Labor Statistics where such data have been published since 1967 (Eldridge, Manser, and Otto, 2008). In most cases it appears that annual and quarterly data are constructed independently from basically the same source materials. This raises the issue of consistency between annual and sub-annual index numbers. However, even when annual and quarterly index numbers are by construction not independent, there are issues for concern.

An interesting example is provided by the quarterly labour productivity series published by the UK Office for National Statistics. The basic building block ap-

1 The author is Professor Emeritus at the Rotterdam School of Management at Erasmus University. He thanks four anonymous referees for useful comments. Email: bbalk@rsm.nl.

pears to be a quarter-of-current-year-relative-to-previous-quarter productivity index, and quarterly productivity change is this index turned into a percentage. The productivity index for a quarter of the current year relative to some reference year (which is currently 2016) is obtained by chaining the quarter-of-current-year-relative-to-previous-quarter productivity indices (and normalizing to get 2016=100). The productivity index for the current year is then defined as the unweighted arithmetic mean of the productivity indices for its four quarters, after seasonal adjustment of the time series. Annual productivity change is obtained by dividing the productivity index for the current year by the same index for the previous year, and turning this ratio into a percentage.

Though in this setup quarterly productivity change has a definite meaning, the situation is less clear for the concept of annual change. In any case, the functional forms of the annual and quarterly productivity indices are grossly different, and likely to coincide only in exceptional circumstances.

Consistency as discussed in this article is a step beyond the consistency concept that figures in the National Accounts literature. There one is concerned with the requirement that annual (real) GDP must be equal to the sum of quarterly (real) GDP, and annual hours worked must be equal to quarterly hours worked, the realisation of which usually invokes some smoothing algorithm. However, as will be shown in more detail in this article, this kind of consistency does not necessarily imply that annual productivity (change) is equal to a simple mean of quarterly productivity (change). The situation is much more complex.

We are touching here a sort of "open nerve". Though users of productivity statistics are well aware of the fact that, due to the complexity of all the survey and compilation processes, one can hardly expect that an independently compiled annual measure of productivity change is equal to a simple or less simple mean of sub-annual measures, the question of what conceptually is at stake here seems to have been avoided. Though Diewert (2008), in his retrospective survey of the two OECD workshops held in 2005-2006, lists the lack of consistency between quarterly estimates of productivity growth and annual estimates as one of the 12 measurement problems where further research is required, as yet no one has taken up this challenge.

This article explores, from a theoretical perspective, the options for obtaining consistency between annual and quarterly (or more general: between period and subperiod) measures of productivity change. It is thereby assumed that all the necessary data are given, without statistical error. We are thus not talking about approximation errors. The article is necessarily a bit more technical than most articles in this journal. This is a simple consequence of the fact that the use of conventional language tends to obscure important conceptual differences. As the UK example demonstrates, the same term "productivity change" is used for quarterly and annual measures which are functionally completely different.

The article unfolds as follows. The first section considers the simple case of a single-input single-output production unit. In this case one can talk about productivity (level) as output quantity divided by input quantity. Annual output or input quantity is the simple sum of sub-annual quantities. Annual productivity then appears to be a weighted mean of sub-annual productivities. Annual productivity change is simply defined as the ratio of two annual productivities. For the definition of sub-annual productivity change there are several options: 1) compare adjacent sub-periods; 2) compare corresponding sub-periods of adjacent years; 3) compare a sub-period to an earlier year. It will appear that, whatever choice is being made, the relation between annual and sub-annual indices is anything but simple.

Section two generalizes this to a multiple-input multiple-output situation, where input and output prices are fixed. Section three considers the general case. The question is, if it be assumed that price, quantity, and productivity indices satisfy some very fundamental axioms, will it then be possible to obtain consistency between annual and sub-annual indices? The answer appears to be negative. Section four considers the use of sub-period productivity indices as approximations to or forecasts of period indices. Section five concludes.

A Simple Case

Let us for a start consider a single-input single-output production unit through two adjacent periods, called 0 and 1 respectively, of equal length. Each period consists of Q sub-periods, also of equal length. The quantity of output produced during sub-period q of period t will be denoted by y^{tq} $(t = 0, 1; q = 1, ..., Q)$. Likewise, the quantity of input used during sub-period q of period t will be denoted by x^{tq} $(t = 0, 1; q = 1, ..., Q)$. All these quantities are assumed to be strictly positive.

The quantity of output produced during the entire period t is evidently measured as the sum of the sub-period quantities,

$$y^t \equiv \sum_{q=1}^{Q} y^{tq} \quad (t = 0, 1). \tag{1}$$

Likewise, the quantity of input used during the entire period t is evidently measured by

$$x^t \equiv \sum_{q=1}^{Q} x^{tq} \quad (t = 0, 1). \tag{2}$$

These two relations are basic for what follows.

Productivity

In the case of a single-input single-output unit one can unambiguously talk about productivity as the quantity of output per unit of input. Hence, the productivity in sub-period q of period t is measured by

$$PROD(tq) \equiv y^{tq}/x^{tq} \quad (t = 0, 1; q = 1, ..., Q), \tag{3}$$

and the productivity in the entire period t by

$$PROD(t) \equiv y^t/x^t \quad (t = 0, 1). \tag{4}$$

It is straightforward to check, using expressions (1) and (3), that the productivity of any period can be expressed as a weighted arithmetic average of its sub-period productivities,

$$PROD(t) = \sum_{q=1}^{Q} (x^{tq}/x^t) PROD(tq), \quad (5)$$

the weights being input quantity shares. Alternatively, by expressions (2) and (3) the productivity of any period can be expressed as a weighted harmonic average of its sub-period productivities,

$$PROD(t) = \left(\sum_{q=1}^{Q} (y^{tq}/y^t)(PROD(tq))^{-1} \right)^{-1}, \quad (6)$$

the weights now being output quantity shares.

It is tempting to ask whether $PROD(t)$ can also be expressed as a geometric mean of the sub-period productivities $PROD(tq)$ $(q = 1, ..., Q)$. The answer appears to be negative. Employing the logarithmic mean[2] one obtains

$$\ln PROD(t) = \sum_{q=1}^{Q} \frac{LM(x^{tq}, y^{tq})}{LM(x^t, y^t)} * \ln PROD(tq), \quad (7)$$

or

$$PROD(t) = \prod_{q=1}^{Q} PROD(tq)^{\phi^{tq}}, \quad (8)$$

where $\phi^{tq} \equiv LM(x^{tq}, y^{tq})/LM(x^t, y^t)$ $(q = 1, ..., Q)$. Put otherwise, the temporal aggregate productivity $PROD(t)$ is a weighted product of the sub-period productivities $PROD(tq)$ $(q = 1, ..., Q)$, where the weights are symmetric in input and output quantities. Note however that, due to the concavity of the function $LM(a, 1)$, the sum of these weights is less than or equal to 1, though the difference is usually small. Thus expression (8) is not a geometric mean.

Productivity change

Productivity change between two (sub-) periods, as measured in ratio form, is naturally defined as the ratio of the productivities of the two (sub-) periods considered. In this way the productivity change between periods 0 and 1 is measured by

$$IPROD(1, 0) \equiv \frac{PROD(1)}{PROD(0)} = \frac{y^1/x^1}{y^0/x^0}. \quad (9)$$

When considering sub-periods, there are a number of possibilities. In line with the previous definition one could consider the productivity change between two adjacent sub-periods $q-1$ and q of period t; that is,

$$IPROD(tq, t\,q-1) \equiv \frac{PROD(tq)}{PROD(t\,q-1)} = \frac{y^{tq}/x^{tq}}{y^{t\,q-1}/x^{t\,q-1}} \quad (t = 0, 1; q = 1, ..., Q), \quad (10)$$

where we will use the convention that sub-period 0 of period t is the same as sub-period Q of period $t-1$.

A second possibility is to compare the

2 For any two strictly positive real numbers a and b their logarithmic mean is defined by $LM(a, b) \equiv (a-b)/\ln(a/b)$ when $a \neq b$, and $LM(a, a) \equiv a$. It has the following properties: (1) $\min(a, b) \leq LM(a, b) \leq \max(a, b)$; (2) $LM(a, b)$ is continuous; (3) $LM(\lambda a, \lambda b) = \lambda LM(a, b)$ $(\lambda > 0)$; (4) $LM(a, b) = LM(b, a)$; (5) $(ab)^{1/2} \leq LM(a, b) \leq (a+b)/2$; (6) $LM(a, 1)$ is concave. See Balk (2008, 134-136) for details.

productivity of a certain sub-period to the productivity of the corresponding previous sub-period; that is,

$$IPROD(1q,0q) \equiv \frac{PROD(1q)}{PROD(0q)} = \frac{y^{1q}/x^{1q}}{y^{0q}/x^{0q}} \; (q=1,...,Q). \tag{11}$$

A third possibility is to compare the productivity of a certain sub-period to the productivity of the entire previous period; that is,

$$IPROD(1q,0) \equiv \frac{PROD(1q)}{PROD(0)} = \frac{y^{1q}/x^{1q}}{y^{0}/x^{0}} \; (q=1,...,Q). \tag{12}$$

These three are the most usual modes of comparison.

Relations

The interesting question now is: which relations exist between sub-period productivity indices, of whatever type, and period indices?

Let us first look at the sub-period-to-period type indices. By setting $t=1$ in expression (5) and dividing both sides by $PROD(0)$, we obtain

$$IPROD(1,0) = \sum_{q=1}^{Q}(x^{1q}/x^{1})IPROD(1q,0); \tag{13}$$

that is, $IPROD(1,0)$ can be written as a weighted mean of $IPROD(1q,0)$ $(q=1,...,Q)$. The weights are the sub-period input quantity shares of period 1, x^{1q}/x^{1} $(q=1,...,Q)$. What error do we make by replacing these weights by $1/Q$?

Consider the following modification of the last expression:

$$IPROD(1,0) = \sum_{q=1}^{Q}(1/Q)IPROD(1q,0) + \sum_{q=1}^{Q}(x^{1q}/x^{1}-1/Q)IPROD(1q,0). \tag{14}$$

The second factor at the right-hand side of this expression can be conceived as the covariance of the input quantity shares x^{1q}/x^{1} and the sub-period productivity indices $IPROD(1q,0)$. If this covariance happens to be equal to 0, then $IPROD(1,0)$ is equal to the unweighted arithmetic mean of $IPROD(1q,0)$ $(q=1,...,Q)$. This assumption, however, is rather strong and, moreover, concerns the comparison period 1, which is unfortunate from the viewpoint of computation in real time.

Similarly, based on expression (6) we obtain

$$IPROD(1,0) = \left(\sum_{q=1}^{Q}(y^{1q}/y^{1})IPROD(1q,0)^{-1}\right)^{-1} = \left(\sum_{q=1}^{Q}(1/Q)IPROD(1q,0)^{-1} + \sum_{q=1}^{Q}(y^{1q}/y^{1}-1/Q)IPROD(1q,0)^{-1}\right)^{-1}. \tag{15}$$

The second factor at the right-hand side of this expression can be conceived as the covariance of the output quantity shares y^{1q}/y^{1} and the inverse sub-period productivity indices $1/IPROD(1q, 0)$. If this covariance happens to be equal to 0, then $IPROD(1, 0)$ is equal to the unweighted harmonic mean of $IPROD(1q, 0)$ $(q = 1, ..., Q)$. This is also a strong assumption.

Finally, based on expression (8) we obtain

$$IPROD(1,0) = \prod_{q=1}^{Q} IPROD(1q,0)^{1/Q} \times \prod_{q=1}^{Q} PROD(1q)^{\phi^{1q}-1/Q}. \tag{16}$$

The first factor at the right-hand side is an unweighted geometric mean. The second factor is not necessarily equal to 1.

The relation between $IPROD(1, 0)$ and the sub-period-to-corresponding-subperiod indices $IPROD(1q, 0q)$ $(q = 1, ..., Q)$ is less simple. Again, from expression (5) it appears that

$$IPROD(1,0) = \sum_{q=1}^{Q} \frac{x^{1q} PROD(0q)}{x^{1} PROD(0)} \quad IPROD(1q,0q); \tag{17}$$

that is, $IPROD(1, 0)$ can be written as a linear combination of the indices $IPROD(1q, 0q)$ $(q = 1, ..., Q)$. One verifies immediately that the weights $x^{1q}PROD(0q)/x^{1}PROD(0)$ do not add up to 1. Sufficient conditions for these weights to be equal to $1/Q$ are that the sub-period input quantity shares are invariant through time, $x^{1q}/x^{1} = x^{0q}/x^{0}$ $(q = 1, ..., Q)$, and that all the output quantity shares of period 0 are the same, $y^{0q}/y^{0} = 1/Q$ $(q = 1, ..., Q)$. From a practical point of view, such conditions are difficult to justify.

Alternatively, from expression (6), it appears that we can write

$$IPROD(1,0) = \left(\sum_{q=1}^{Q} \frac{y^{1q} PROD(0)}{y^{1} PROD(0q)} IPROD(1q,0q)^{-1} \right)^{-1}. \tag{18}$$

Thus, $IPROD(1, 0)$ can be written as an harmonic combination of the sub-period indices $IPROD(1q, 0q)$ $(q = 1, ..., Q)$. But note that the weights $y^{1q}PROD(0)/y^{1}PROD(0q)$ also do not add up to 1.

Finally, using expression (8), we obtain

$$IPROD(1,0) = \prod_{q=1}^{Q} \frac{PROD(1q)^{\phi^{1q}}}{PROD(0q)^{\phi^{0q}}}. \tag{19}$$

This expression can be decomposed in a number of ways. Using the period 0 viewpoint, we obtain

$$IPROD(1,0) = \prod_{q=1}^{Q} IPROD(1q,0q)^{\phi^{0q}} \times \prod_{q=1}^{Q} PROD(1q)^{\phi^{1q}-\phi^{0q}}. \tag{20}$$

Using the period 1 viewpoint, we obtain

$$IPROD(1,0) = \prod_{q=1}^{Q} IPROD(1q,0q)^{\phi^{1q}} \times \prod_{q=1}^{Q} PROD(0q)^{\phi^{1q}-\phi^{0q}}. \tag{21}$$

Using the "mean" viewpoint, we obtain

$$IPROD(1,0) = \prod_{q=1}^{Q} IPROD(1q,0q)^{(\phi^{0q}+\phi^{1q})/2} \times \prod_{q=1}^{Q} (PROD(0q)PROD(1q))^{(\phi^{1q}-\phi^{0q})/2} \quad (22)$$

It may be clear that the right-most factors of these three expressions are not necessarily equal to 1.

The adjacent sub-period indices $IPROD(tq, t\, q-1)(t = 0,1; q = 1,...,Q)$ can be related to the sub-period-to-corresponding-sub-period indices by chaining,

$$IPROD(1q,0q) = \prod_{\mu=1}^{q} IPROD(1\mu, 1\, \mu-1) \times \prod_{\mu=q+1}^{12} IPROD(0\mu, 0\, \mu-1)\ (q = 1,...,Q). \quad (23)$$

The right-hand side of expression (23) can then be inserted into expression (17), (18), (20), (21), or (22) to obtain a relation between the period 0 to period 1 productivity index $IPROD(1,0)$ and the adjacent sub-period indices. But this relation does not have a simple form.

The conclusion is that already in the extremely simple case of a single-input single-output unit temporal aggregation of productivity indices proves difficult. It is possible to relate sub-period and period productivity indices to each other, but the resulting expressions are not simple.

A More Realistic Case

Let us now consider a production unit that produces M outputs and uses N inputs. The quantity of output m produced during sub-period q of period t will be denoted by y_m^{tq} $(m = 1,...,M; t = 0,1; q = 1,...,Q)$. Likewise, the quantity of input n used during sub-period m of period t will be denoted by x_n^{tq} $(n = 1,...,N; t = 0,1; q = 1,...,Q)$. It is assumed that in each sub-period at least one input quantity and one output quantity is strictly positive.

The quantity of output m produced during the entire period t is evidently measured by

$$y_m^t \equiv \sum_{q=1}^{Q} y_m^{tq}\ (m = 1,...,M; t = 0,1). \quad (24)$$

Likewise, the quantity of input n used during the entire period t is evidently measured by

$$x_n^t \equiv \sum_{q=1}^{Q} x_n^{tq}\ (n = 1,...,N; t = 0,1). \quad (25)$$

When there are multiple inputs and multiple outputs the concept of productivity (level) is no longer unambiguous. Prices are necessary to aggregate quantities. Thus, suppose we have a set of fixed (strictly positive) output prices $p \equiv (p_1,...,p_M)$ and (strictly positive) input prices $w \equiv (w_1,...,w_N)$. The aggregate output quantity produced during sub-period q of period t is then given by

$$p \cdot y^{tq} = \sum_{m=1}^{M} p_m y_m^{tq} \quad (t = 0, 1; q = 1, ..., Q), \quad (26)$$

where vector notation is used to simplify notation and highlight the analogies to the expressions in the previous section. One could also say that $p \cdot y^{tq}$ is the sub-period tq output value expressed in *constant prices*. The aggregate output quantity produced during the entire period t is naturally given by

$$p \cdot y^{t} = \sum_{m=1}^{M} p_m y_m^{t} = \sum_{q=1}^{Q} p \cdot y^{tq} \; (t = 0, 1). \quad (27)$$

Likewise, the aggregate input quantity used during sub-period m of period t is given by

$$w \cdot x^{tq} = \sum_{n=1}^{N} w_n x_n^{tq} \quad (t = 0, 1; q = 1, ..., Q). \quad (28)$$

This is the sub-period tq input value expressed in constant prices. The aggregate input quantity used during the entire period t is also naturally given by

$$w \cdot x^{t} = \sum_{n=1}^{N} w_n x_n^{t} = \sum_{q=1}^{Q} w \cdot x^{tq} \quad (t = 0, 1). \quad (29)$$

Recall that it is assumed that all these values are given, without statistical error.

Conditional on input prices w and output prices p, the productivity (level) in sub-period m of period t is measured by

$$PROD(tq) \equiv p \cdot y^{tq} / w \cdot x^{tq} \quad (t = 0, 1; q = 1, ..., Q), \quad (30)$$

and the productivity (level) in the entire period t by

$$PROD(t) \equiv p \cdot y^{t} / w \cdot x^{t} \; (t = 0, 1). \quad (31)$$

This can be expressed in terms of sub-period productivity levels in three ways, namely

$$PROD(t) = \sum_{q=1}^{Q} (w \cdot x^{tq} / w \cdot x^{t}) PROD(tq), \quad (32)$$

$$PROD(t) = \left(\sum_{q=1}^{Q} (p \cdot y^{tq} / p \cdot y^{t}) (PROD(tq))^{-1} \right)^{-1}, \quad (33)$$

and

$$\ln PROD(t) = \sum_{q=1}^{Q} \frac{LM(w \cdot x^{tq}, p \cdot y^{tq})}{LM(w \cdot x^{t}, p \cdot y^{t})} \ln PROD(tq). \quad (34)$$

The definitions of productivity change between two periods, between two sub-periods, and between a sub-period and a period are straightforward. For instance, productivity change between periods 0 and 1 is measured by

$$IPROD(1, 0) \equiv \frac{PROD(1)}{PROD(0)} = \frac{p \cdot y^{1} / w \cdot x^{1}}{p \cdot y^{0} / w \cdot x^{0}}. \quad (35)$$

It is simple to check that the following relations hold:

$$IPROD(1,0) = \sum_{q=1}^{Q}(w \cdot x^{1q}/w \cdot x^1) IPROD(1q,0), \quad (36)$$

which generalizes expression (13), and

$$IPROD(1,0) = \sum_{q=1}^{Q} \frac{w \cdot x^{1q}}{w \cdot x^1} \frac{PROD(0q)}{PROD(0)} IPROD(1q,0q), \quad (37)$$

which generalizes expression (17). Similarly, generalizations of expressions (15), (16), (18), (20), (21), and (22) can be obtained. Moreover, analogous to the way it was done in the previous section, any sub-period-to-corresponding-sub-period productivity index $IPROD(1q,0q)$ can be written as a chain of adjacent sub-period indices.

Summarizing, by using a set of fixed input and output prices, any multiple-input multiple-output situation can effectively be reduced to a single-input single-output situation.

The System View

It is clear that the productivity index $IPROD(1,0)$, as defined by expression (35), can be re-expressed as

$$IPROD(1,0) = \frac{p \cdot y^1/p \cdot y^0}{w \cdot x^1/w \cdot x^0}; \quad (38)$$

that is, as the ratio of an output quantity index and an input quantity index. The same holds for the other productivity indices considered in the previous section.

These quantity indices have a specific functional form; they are so-called Lowe indices (Balk, 2008:68). An important disadvantage of a Lowe quantity index is that its dual price index violates a rather fundamental axiom. Consider for instance the output quantity index $p \cdot y^1/p \cdot y^0$. The dual price index is obtained by dividing the quantity index into the value ratio $p^1 \cdot y^1/p^0 \cdot y^0$, where p^t $(t = 0, 1)$ denotes the vector of period t output prices. The result is

$$\frac{p^1 \cdot y^1/p \cdot y^1}{p^0 \cdot y^0/p \cdot y^0}. \quad (39)$$

It is clear that this price index violates the identity axiom, which requires a price index to deliver the outcome 1 whenever the price vectors of the two periods compared are equal, $p^1 = p^0$. Such a violation is generally considered to be undesirable.

An integrated system of price, quantity, and productivity statistics requires functional forms $P_o(.), P_i(.), Q_o(.), Q_i(.)$, such that

$$p^1 \cdot y^1/p^0 \cdot y^0 = P_o(p^1, y^1, p^0, y^0) \times Q_o(p^1, y^1, p^0, y^0) \quad (40)$$

$$w^1 \cdot x^1/w^0 \cdot x^0 = P_i(w^1, x^1, w^0, x^0) \times Q_i(w^1, x^1, w^0, x^0), \quad (41)$$

and a reasonable number of fundamental axioms (or regularity conditions) for price and quantity indices are satisfied (Balk, 2008 and 2018). Here p^t, w^t $(t = 0, 1)$ denote the vectors of period t output and input prices respectively. Notice that the functional forms used at the output side may or may not be the same as those used at the input side (apart from the dimension of the price and quantity vectors involved).

Given these functional forms the productivity index for period 1 relative to period 0 is defined as

$$IPROD(1,0) \equiv \frac{Q_o(p^1, y^1, p^0, y^0)}{Q_i(w^1, x^1, w^0, x^0)}; \quad (42)$$

that is, output quantity index divided by input quantity index.

Consider now the sub-periods. The relation between period and sub-period quantities was presented in expressions (24) and (25). Let p^{tq} and w^{tq} $(t = 0, 1; q = 1, ..., Q)$ denote the vectors of sub-period output and input prices respectively. The relation between period and sub-period prices is, rather naturally, given by

$$p^t_m \equiv \sum_{q=1}^{Q} p^{tq}_m y^{tq}_m / y^t_m \quad (43)$$
$$(m = 1, ..., M; t = 0, 1)$$
$$w^t_n \equiv \sum_{q=1}^{Q} w^{tq}_n x^{tq}_n / x^t_n \quad (44)$$
$$(n = 1, ..., N; t = 0, 1),$$

and the relation between period and sub-period output and input values is similarly given by

$$p^t \cdot y^t = \sum_{q=1}^{Q} p^{tq} \cdot y^{tq} \; (t = 0, 1) \quad (45)$$

$$w^t \cdot x^t = \sum_{q=1}^{Q} w^{tq} \cdot x^{tq} \; (t = 0, 1). \quad (46)$$

Thus, whereas period quantities are simple sums of sub-period quantities, and the same holds for values, period prices are defined as unit values (given sub-period prices).

Corresponding to expression (42), the productivity index for sub-period $1q$ relative to period 0 is then defined as

$$IPROD(1q, 0) \equiv \frac{Q_o(p^{1q}, y^{1q}, p^0, y^0)}{Q_i(w^{1q}, x^{1q}, w^0, x^0)}$$
$$(q = 1, ..., Q). \quad (47)$$

Can these sub-period indices be related to the period index? The answer is obtained by looking at the so-called *profitability* ratio for period 1 relative to period 0, where profitability is defined as the ratio of output value over input value. On the one hand the profitability ratio can be decomposed as

$$\frac{p^1 \cdot y^1 / p^0 \cdot y^0}{w^1 \cdot x^1 / w^0 \cdot x^0} = \frac{P_o(p^1, y^1, p^0, y^0)}{P_i(w^1, x^1, w^0, x^0)} \frac{Q_o(p^1, y^1, p^0, y^0)}{Q_i(w^1, x^1, w^0, x^0)}. \quad (48)$$

But on the other hand, by temporal disaggregation, one obtains

$$\frac{p^1 \cdot y^1 / p^0 \cdot y^0}{w^1 \cdot x^1 / w^0 \cdot x^0} = \sum_{q=1}^{Q} \frac{w^{1q} \cdot x^{1q}}{w^1 \cdot x^1} \cdot \frac{p^{1q} \cdot y^{1q} / p^0 \cdot y^0}{w^{1q} \cdot x^{1q} / w^0 \cdot x^0}$$
$$= \sum_{q=1}^{Q} \left(\frac{w^{1q} \cdot x^{1q}}{w^1 \cdot x^1} \times \frac{P_o(p^{1q}, y^{1q}, p^0, y^0)}{P_i(w^{1q}, x^{1q}, w^0, x^0)} \frac{Q_o(p^{1q}, y^{1q}, p^0, y^0)}{Q_i(w^{1q}, x^{1q}, w^0, x^0)} \right). \quad (49)$$

By combining the last two expressions, using the definitions in expressions (42) and (47), one obtains

$$IPROD(1,0) = \sum_{q=1}^{Q}\left(\frac{w^{1q}\cdot x^{1q}}{w^{1}\cdot x^{1}}\times \frac{P_o(p^{1q},y^{1q},p^0,y^0)/P_o(p^1,y^1,p^0,y^0)}{P_i(w^{1q},x^{1q},w^0,x^0)/P_i(w^1,x^1,w^0,x^0)}\times IPROD(1q,0)\right). \quad (50)$$

This relation between period-to-period and sub-period-to-period productivity indices is not particularly simple. More importantly, since the productivity index at the left-hand side, $IPROD(1,0)$, is based on the same functional form(s) for the quantity indices as the productivity indices at the right-hand side, $IPROD(1q,0)$, the relation generates restrictions on those functional forms. It turns out that these restrictions are impossible to satisfy, except when $Q_o(.)$ and $Q_i(.)$ exhibit the Lowe functional form; that is, $Q_o(.) = p\cdot y^1/p\cdot y^0$ and $Q_i(.) = w\cdot x^1/w\cdot x^0$ where p and w are fixed output and input prices, respectively. But then the dual $P_o(.)$ and $P_i(.)$ violate the fundamental identity axiom.

Sub-period Productivity Indices as Approximations

Given that a consistent system encompassing period and sub-period productivity indices is impossible, can the latter be used as approximations or forecasts of the former? Can, for instance, the sub-period indices $IPROD(1q,0q)$ for $q = 1,...,Q$ be used as approximations or forecasts of the period index $IPROD(1,0)$?

Consider again the period-to-period profitability ratio; that is, the left-hand side of expression (48). Notice that this ratio can be expressed as

$$\frac{(1/Q)p^1\cdot y^1/p^0\cdot y^0}{(1/Q)w^1\cdot x^1/w^0\cdot x^0}. \quad (51)$$

Let δ^{tq} and ϵ^{tq} $(t = 0,1; q = 1,...,Q)$ be defined by

$$\delta^{tq} \equiv w^{tq}\cdot x^{tq} - w^t\cdot x^t/Q \quad (52)$$

$$\epsilon^{tq} \equiv p^{tq}\cdot y^{tq} - p^t\cdot y^t/Q; \quad (53)$$

that is, δ^{tq} and ϵ^{tq} are deviations of actual sub-period values from average sub-period values.

A first-order Taylor series expansion then delivers

$$\frac{p^{1q}\cdot y^{1q}/p^0\cdot y^0}{w^{1q}\cdot x^{1q}/w^0\cdot x^0} = \frac{(1/Q)p^1\cdot y^1/p^0\cdot y^0}{(1/Q)w^1\cdot x^1/w^0\cdot x^0} + R(\delta^{1q},\epsilon^{1q})\ (q = 1,...,Q), \quad (54)$$

where the remainder term $R(.)$ tends to zero when its arguments tend to zero. Thus, if δ^{1q} and ϵ^{1q} are small random fluctuations around 0, then the sub-period-to-period profitability ratios can be seen as approximations to the period-to-period profitability ratio.

By decomposing both sides of expression (54) and rearranging we obtain

$$IPROD(1q,0) = \left(\frac{P_i(w^{1q},x^{1q},w^0,x^0)}{P_o(p^{1q},y^{1q},p^0,y^0)}\frac{P_o(p^1,y^1,p^0,y^0)}{P_i(w^1,x^1,w^0,x^0)}\times IPROD(1,0)\right) + \frac{P_i(w^{1q},x^{1q},w^0,x^0)}{P_o(p^{1q},y^{1q},p^0,y^0)}R(\delta^{1q},\epsilon^{1q}) \quad (55)$$

$(q = 1,...,Q)$.

The factor in front of $IPROD(1,0)$ can be rewritten as

$$\frac{P_i(w^{1q}, x^{1q}, w^0, x^0)/P_i(w^1, x^1, w^0, x^0)}{P_o(p^{1q}, y^{1q}, p^0, y^0)/P_o(p^1, y^1, p^0, y^0)}. \tag{56}$$

The numerator is an index comparing sub-period input prices w^{1q} to period input prices w^1, and the denominator is an index comparing sub-period output prices p^{1q} to period output prices p^1. Thus, somewhat loosely stated, if the seasonality of input and output prices is the same, than any sub-period index $IPROD(1q, 0)$ is an unbiased forecaster of $IPROD(1, 0)$.

Conclusion

It appears that the goal of full consistency between period and sub-period price, quantity and productivity indices is unattainable. Moreover, as argued in section three, this conclusion is independent of the specific functional forms used for the various indices. This impossibility theorem implies that choices must be made.

The first choice concerns what is to be seen as the most natural accounting period for the production unit considered. In most, if not all, cases this will be a year. Annual price, quantity, and productivity comparisons can be based on indices that satisfy the basic axioms (or regularity conditions) and together form a consistent system.

Given the need for sub-annual productivity information, the second choice concerns the type of index to use. As shown, every choice entails at best an approximate relationship between sub-annual and annual indices. The nature of this approximation should be clearly communicated to the public.

References

Balk, B. M. (2008) *Price and Quantity Index Numbers: Models for Measuring Aggregate Change and Difference* (New York: Cambridge University Press).

Balk, B. M. (2018) "Empirical Productivity Indices and Indicators," in *The Oxford Handbook of Productivity Analysis*, edited by E. Grifell-Tatjé, C. A. K. Lovell and R. C. Sickles (New York: Oxford University Press).

Diewert, W. E. (2008) "OECD Workshops on Productivity Analysis and Measurement: Conclusions and Future Directions," in *Productivity Measurement and Analysis: Proceedings from OECD Workshops* (Paris/Neuchâtel: OECD/Swiss Federal Statistical Office).

Eldridge, L. P., M. E. Manser and P. F. Otto (2008) "U. S. Quarterly Productivity Measures: Uses and Methods," in *Productivity Measurement and Analysis: Proceedings from OECD Workshops* (Paris/Neuchâtel: OECD/Swiss Federal Statistical Office).

Haine, W. and A. Kanutin (2008) "Main Sources of Quarterly Labour Productivity Data for the Euro Area," in *Productivity Measurement and Analysis: Proceedings from OECD Workshops* (Paris/Neuchâtel: OECD/Swiss Federal Statistical Office).

OECD (2001) *Measuring Productivity: Measurement of Aggregate and Industry-level Productivity Growth* (Paris: OECD Publishing).

The State of Productivity Research: *The Oxford Handbook of Productivity Analysis*: A Review Article

Marshall Reinsdorf[1]
International Monetary Fund

As a key concern both for policymakers and businesses, productivity is the focus of a large body of academic and statistical agency research. The range of measurement approaches and analytical findings is so wide that keeping up with the field is a real challenge.

Help with this problem has arrived with the publication in 2018 of the *Oxford Handbook of Productivity Analysis*, by Oxford University Press edited by Emili Grifell-Tatjé from Universitat Autònoma de Barcelona, C. A. Knox Lovell from University of Queensland and Robin C. Sickles from Rice University. The *Handbook* provides a broad overview of productivity measurement and analysis followed by in-depth explanations of many productivity techniques and findings. In addition, the *Handbook* addresses topics of interest to users and compilers of national accounts and price statistics, such as hard-to-measure services of businesses and the public sector, and branches out into emerging areas of indicators of well-being.

This review article begins with a discussion of the Editors' Introduction in Part I of the *Handbook*, which provides overviews of both the general field of productivity analysis and of the chapters in the volume. It next summarizes the areas of inquiry and key findings of the 23 topical chapters of Parts II, III and IV. It concludes with some reflections on the strengths and weaknesses of the *Handbook* and on the general state of the field.

Editors' Introduction: Overview of Productivity Analysis: History, Issues and Perspectives

Coming in at 73 pages, the editors' introduction integrates highlights of each of the *Handbook*'s chapters with an impressive general review of the field of productivity analysis that considers productivity's significance, measurement, dispersion, and drivers. The significance of productivity includes microeconomic aspects such as businesses' financial performance,

1 The author is Senior Economist in the Statistics Department of the International Monetary Fund. The views expressed are those of the author and should not be attributed to the IMF, its Executive Board, or its management. I am grateful to Andrew Sharpe for helpful comments. Email: MReinsdorf@imf.org.

macroeconomic aspects such as the time required to implement major innovations across the economy, and well-being aspects. Regarding well-being, the faster growth of the standard of living than real GDP implied by Gordon's (2016) history of the US standard of living since the Civil War suggests that measured output growth (which the productivity statistics reflect) has often understated the welfare gains from new and improved goods. But recent headwinds such as rising inequality suggest a measurement gap in the opposite direction. Inequality and environmental impacts are critical aspects of well-being for understanding the significance of measured productivity growth. The Stiglitz-Sen-Fitoussi (2009) report has highlighted their importance and is part of the backdrop of the chapters that cover dimensions of well-being.

The editors' overview of productivity measurement includes dynamic productivity measures, in which intermediate inputs are produced for use in a later period. It also reviews index number and estimation-based approaches, efficiency (distance from the frontier) and knowledge spillovers in models of endogenous growth, issues in empirical estimation by statistical agencies and others such inputs of varying quality and hard-to-measure outputs, and methods to distinguish efficiency from technology. Inefficiency and slow diffusion of best practices are taken up again in the discussion of productivity dispersion, which is often found to be large. Distance-to-the-frontier scores also find a role in analysis of drivers of productivity performance as part of the calculation of the World Bank's *Ease of Doing Business* index.

The Topical Chapters

The depth and breadth of coverage of the field of productivity research and analysis in the topical chapters is indicated by the heft of this book, which contains 843 pages. Part II contains seven chapters on foundations, Part III contains eight chapters on microeconomic analysis of productivity drivers and effects, and Part IV contains eight chapters on macroeconomic analysis. The large number of distinguished productivity researchers who contributed chapters adds to the interest of the book.

Chapters in the foundations section explain productivity growth indexes and productivity level change indicators, distance function techniques for analysis of production processes with multiple outputs, and estimation of dynamic efficiency and technical change using data envelope analysis (DEA) techniques. The chapter on the labour and multifactor productivity indexes produced by the U.S. Bureau of Labor Statistics explains the details of their construction, including questions such as why the productive capital stock is not the same as the wealth capital stock. Other chapters in this section consider the measurement challenges presented by the high-tech, financial and health care industries and the unpriced services of the public sector. The section concludes with a chapter on productivity and the environment that considers materials balance models of joint production of goods and environmental "bads," and static and dynamic models of productivity effects of environmental regulations.

The microeconomic section of the *Handbook* opens with several chapters on analytical links between productivity and financial performance of firms. Analyses of productivity and the socioeconomics of family-owned firms have found that family ownership tends to be associated with higher productivity when the firm is relatively small, but lower productivity when the firm is large as the effects of prioritizing the preservation of family socioeconomic wealth and jobs for family members became more prevalent. An examination of innovation, management practices and productivity finds that reliable progress in the short run may come at the cost of sacrificing large but riskier advances in the long run, as good management practices for fostering incremental improvements may be bad for fostering truly novel innovations. Here, Amos Tversky's observation about wasting years by not being able to waste hours seems apropos.

Other chapters in this section examine the effects of international trade on innovation and productivity at the firm level. Mark-ups reflecting market power can distort standard techniques for estimating the productivity effects of trade and trade liberalizations, as well as firm-level productivity effects in other contexts. The chapter on this problem also reviews techniques for estimating mark-ups and the presence of market power, a much-discussed concern in the present era of increasing industry concentration.

The microeconomic section concludes with chapters on measuring efficiency and productivity in regulated industries. The explanations of strategies for handling noisy and incomplete information and multiproduct firms, and of DEA approaches to regulatory benchmarking are particularly useful.

In its macroeconomic section, the *Handbook* returns to the topic of the public sector, reviewing the productivity analysis literature on education and health care. A chapter on productivity and welfare performance of the public sector uses several approaches to subsume multiple dimensions of well-being (in this case, poverty, inequality, unemployment, life expectancy and education) in an overall welfare index. The results illustrate one of the drawbacks of this type of welfare index. An approach similar to that of the UN's *Human Development Index* ranks Spain last among 28 EU countries, while another welfare index based on unconstrained DEA scores has Spain tied for *first* place. The sensitivity of Spain's rank to the way the index is constructed (whose origins can be traced to the weights on unemployment and life expectancy) shows that caution is necessary when using welfare indexes. These indexes have become popular for summarizing multiple dimensions of well-being in a single number, but dashboards appear to be a safer alternative.

The macroeconomic section also contains a helpful discussion of methods for defining and measuring productivity dispersion— differences in productivity levels across establishments—and of its significance. It is followed by a chapter presenting a decomposition of value-added change into the five sources of efficiency: output prices, input prices, primary inputs, technical progress, and returns to scale. A chapter by Dale Jorgenson on the World KLEMS initiative and its findings includes a novel comparison of productivity in the United States and Japan based on industry-level purchasing power parities (PPPs).

Standard KLEMS analyses have been complicated by the fragmentation of the production process into many steps done in different countries. A chapter on global value chains decomposes these value chains[2] using tools originally developed for input-output analysis. Global value chains have raised the share of the income from production going to capital, which includes the returns to intangible capital. Shares received by highly skilled labour have also risen, leaving less for low skilled labour, and capital is found to be complementary to high skilled labour.

Industry-level productivity analysis is taken up next, in a chapter that analyses sources of differences in productivity levels and growth, finding evidence of convergence. The chapter on "Productivity and Economic Development" looks beyond growth to focus on inequality and inclusive growth as key aspects of development success, noting that productivity growth is necessary but not sufficient for achieving shared prosperity. The article also highlights the key role of education in the development of the Asian "tigers," noting the human capital accumulation needs to be biased towards higher skills to have a large pay-off.

The volume closes with a very useful review of techniques and some new findings on the labour productivity growth of nations. Human capital is among the factors included in the analysis of the drivers of labour productivity. Human capital deepening has an important effect, and omitting this variable causes the contribution of physical capital deepening to be overestimated.

Comments and Items for a Future Work

The *Oxford Handbook of Productivity Analysis* is not the first handbook on productivity; handbooks already exist that focus on productivity measurement for purposes such as official statistics or industrial management. However, this handbook fills a need for an academic reference that covers the wide range of research techniques and findings on productivity analysis and identifies emerging areas.

Some minor weaknesses of the book are that its review of the literature mentions some papers of dubious quality, and in the topical chapters a few rambling discussions could be sharpened. Also, it is unfortunate that space could not be found in this already-lengthy volume for some important and emerging topics in productivity research. Decompositions showing the industry contributions to aggregate productivity change, inputs of natural resources and the environment, and the measurement of human capital receive little attention. Issues related to globalization, such as effects on productivity measurement of profit-shifting by multinational enterprises are not mentioned. And notwithstanding the commendable attention to well-being

2 The inclusion of the value added attributable to the intangible capital such as R&D, brand equity and logistics systems distinguishes "value chains" from "supply chains".

in the introduction on the significance of productivity, the coverage of inequality and other aspects of well-being in the chapters is rather sparse. In light of the growing emphasis on well-being and sustainability, how indicators of these dimensions can help to inform our interpretation of the productivity statistics and give a more nuanced picture of economic performance would be worth exploring in greater depth in a future volume.

Finally, the productivity slowdowns that started in 1973 and in the mid-2000s also receive no attention despite the large literatures that they have inspired. The most recent slowdown has generated findings and raised questions that would be worth exploring in a future reference on productivity analysis. Some findings that might be covered are that financial frictions exacerbated by the financial crisis depressed productivity growth, and that the slowing diffusion of best practices has expanded the productivity distance between the average firm and the firms at the frontier.

A debate over measurement of the digital economy sparked by the productivity slowdown also raises questions worth considering. Tight links between prices and marginal costs (which underlie many productivity estimation techniques) have become an increasingly untenable assumption as free and nearly-free services from digital platforms have proliferated, and network externalities help small numbers of winners to control nearly the entire market. The suppliers of the free services generally enjoy ample profits, reflecting the fact that the free items help them sell other marked-up items. Using shadow prices that undo the cross-subsidization may change the picture of productivity growth. For example, when Aizcorbe, Byrne and Sichel (2019) correct the weights on the nearly-free cell phones and adjust the cell-phone index for quality change, they find that these corrections add 4 percentage points to the estimated growth rate of the index for the bundled phones and telecom services. Furthermore, new kinds of data assets have enabled innovation and product differentiation that are rewarded through higher mark-ups.

Of course, a single book-length reference cannot be expected to cover everything in such a multi-faceted field as productivity analysis. All-in-all, the *Oxford Handbook of Productivity Analysis* is an extremely valuable reference, either for a general introduction and overview of the field of productivity analysis or as a reference for looking up in-depth explanations, findings and examples. In view of the Handbook's importance, its pricing at a level that will impede its accessibility to many researchers is unfortunate. The price of the hard copy is $125 US. Access for many will only be through libraries that have purchased a hard copy or have access to the on-line version, and in an area of tight library budgets, their number may be limited. Let us hope that a reasonably priced paperback version of the Handbook will appear soon, so that the many excellent papers in this important volume will have the attention they greatly deserve.

References

Aizcorbe, Ana, David Byrne and Daniel Sichel (2019) "Getting Smart about Phones: New Price Indexes and the Allocation of Spending between Devices and Services Plans in Personal Consumption Expenditures," NBER Working Paper 25645.

Gordon, Robert J. (2016) *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*, (Princeton: Princeton University Press).

Stiglitz, Joseph, Amartya Sen and Jean-Paul Fitoussi (2009) *Report by the Commission on the Measurement of Economic Performance and Social Progress.*