Editors' Overview

The 49th issue of the *International Productivity Monitor* features six articles on a range of productivity-related topics: the potential impact of pro-competitive regulatory reforms on productivity; adult skills and productivity; labour productivity as a measure of technological change; efficiencies defenses and productivity growth; efficiency adjustments of hours worked; and the usefulness of the SNA as a measure of progress.

Canada's productivity performance has been abysmal in recent years and measures are needed to improve this performance. One policy proposal has been the deregulation of product markets. In the first article in this issue, **Gilbert Cette** from NEOMA Business School, **Jimmy Lopez** from Université de Bourgogne, **Giuseppe Nicoletti** from LUISS University and **Océane Vernerey** from Université de Bourgogne model the impact of procompetitive regulatory reforms on productivity. The model shows how reforms in upstream sectors influence productivity in downstream sectors that rely on upstream sectors output as inputs. Their model covers 15 OECD countries and uses the OECD Product Market Regulation database. They find that if Canada adopted best-practice regulations, GDP per capita could increase 6.5 to 10 per cent in the long term, mainly from gains in professional services and wholesale and retail trade.

These very large impacts suggest that procompetitive regulatory reforms may be an important contributor to the revitalization of productivity growth in Canada. This work should serve as an important contribution to the ongoing debate on the effect of regulatory reforms in Canada.

Skills have always been known to be a crucial determinant of productivity growth, but the exact relationship between skills and productivity has been poorly understood. In the second article, **Dan Andrews**, **Balázs Egert** and **Christine de La Maisoneuve** from the OECD, using the results of the 2023 Programme for the International Assessment of Adult Competencies (PIAAC). shed new light on these linkages. They find that the relationship between skill levels and productivity at the firm level is associated with R&D intensity. They conclude that work-related training is central for improving adult skills, but the effectiveness of this training requires workers to have strong foundational skills, emphasizing the importance of early education policies.

The measurement and quantification of technological change has always been challenging for economists. Total factor productivity growth is considered a superior measure of technological change compared to labour productivity as it captures the role of capital. In the third article, **Ulrich Kohli** from the University of Geneva proposes to adjust labour productivity for the use of capital in a new measure called, Total Labour Productivity (TLP). This new measure grew at a 1.3 per cent average annual rate in the US private non-farm business sector from 1990 to 2023, mid-way between the rate of growth of official BLS estimates of labour productivity (1.6 per cent) and total factor productivity (0.9 per cent).

The impact of mergers on economic activity is two-fold: it reduces competition and raises prices, but also increases productivity through economies of scale and scope. This latter effect has been called the "efficiencies defense" and has been incorporated in competition law in many countries. In the fourth article, **Robin Shaban** from 2R Strategy employs a cross-country econometric model to investigate the impact of efficiencies defenses on total factor productivity (TFP). She finds that the introduction of these defenses in mergers is associated with higher TFP growth. However, she cautions that the effectiveness of the efficiency defenses varies across countries by their design and implementation as well as by the enforcement resources at the disposal of the competition body.

In the Jorgenson production model, capital is adjusted for efficiency while labour input is not. In the fifth paper, **Barbara Fraumeni** from the University of Southern Maine proposes to adjust hours worked for efficiency so there is symmetric treatment of the two factors of production in the model. She uses the scores from the 2012 Programme for the International Assessment of Adult Competencies (PIAAC) by age group, finding that persons in the age group of 55 and over showed 95 per cent of the efficiency as those in the 25-34 age group, while those in the 45-54 range scored 96.2 per cent of the younger cohort. She then applies these numbers to hours worked in the United States and finds that the efficiency-adjusted hours worked grow 0.01 percentage points per year less than unadjusted hours worked from 1975 to 2023. In turn, this raises total factor productivity growth by 0.01 percentage points, a very small effect. The author also explores the possibility of vintage effects but finds no compelling evidence that the quality of labour input at the lowest level of detail changes over time.

The "Beyond GDP" debate is highly relevant for productivity analysis since GDP is the numerator in the productivity definition. If GDP is poorly measured, productivity estimates may also be put in question. In the final article, **Paul Schreyer**. formerly OECD Chief Statistician and now at the Economic Statistics Centre of Excellence, assesses Diane Coyle's recent book *The Measure of Progress: Counting What Really Matters*. He first identifies what he sees as the key messages of the book, namely that GDP is not a reliable measure of societal progress, that GDP falls short even by its own standards as a measure of economic activity, and that alternative frameworks for measuring progress are needed. Schreyer is overall sympathetic to what he calls a "thought-provoking critique of the SNA", but argues that GDP remains a good tool for gauging economic developments.

Table of Contents

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The Potential Impact of Pro-competitive Regulatory Reforms on Productivity and Growth in Canada

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Abstract

This article explores how regulations that restrict competition in key Canadian non-manufacturing sectors such as energy, transport, trade, and professional services have contributed to the country's long-standing productivity gap with the United States. Using international data on anticompetitive regulations and productivity from 15 countries and a large number of industries over the 1996-2021 period, the study finds that regulation in these upstream sectors, which supply essential inputs to the rest of the economy, plays a role in shaping overall productivity performance. Taking results causally, a thought experiment suggests that if Canada were to implement an ambitious reform effort aimed at adopting best international practices in regulating these four sectors, GDP per capita could rise in the long term by between 6.5 and 10 percent, depending on the range of reforms implemented. Gains would originate from procompetitive reforms in all sectors, with the largest ones coming from the professional services and retail distribution. Overall, the findings highlight the major economic benefits Canada could reap from implementing a deeper and swifter pro-competitive reform agenda than in the past.

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The Canadian economy stopped converging to US productivity levels in the mid-1970s, when its relative productivity level reached a plateau, and started diverging in the subsequent period and until recently. The average growth rate of output per hour worked fell well behind the United States during the ICT revolution of the 1990s, with the gap persisting in this century. Overall, labour productivity growth declined from an average of 2.3 per cent per year over the previous four decades to only 0.9 per cent per year in the 2000s, a rate close to that of the Euro Area (EA). Labour productivity levels, which were half way between the EA and the United States in the 1970s, aligned with those of the EA more recently, suffering a 20 per cent gap relative to the United States.

The persistent slowdown in Canadian productivity has been more pronounced than the global trend, and especially more severe than in the United States, where productivity continued to grow at roughly twice the Canadian pace, accentuating the divergence between the growth trajectories of the two closely interconnected economies. Given that productivity is the principal engine of GDP per capita growth, this deceleration has led to disappointing gains in living standards, as reflected in a widening gap in GDP per capita relative to the United States.

This divergence has attracted considerable scholarly attention, prompting investigations into its magnitude and root causes (Baldwin and Gu, 2007; Rao *et al.*, 2008; OECD, 2016; Sharpe and Uguccioni, 2017). Small average firm size (Leung *et al.*, 2008; Baldwin *et al.*, 2014), changes in industry composition (Almon and Tang, 2011; Tang, 2017) and low innovative effort (Ranasinghe, 2017) were among the structural sources of productivity weakness that were identified in past studies. However, causes that are directly related to public policy are of particular interest to decision-makers. For instance, OECD (2025) points to R&D incentives as an area for policy intervention as well as measures to ease persisting barriers to competition in Canadian markets.

Indeed, both past and recent work has related the disappointing Canadian productivity performance to weak competitive pressures and distortions due to restrictive product market policies. For instance, Conway and Nicoletti (2007) point to regulations weakening competitive pressures in the non-manufacturing industries, suggesting that these may have curbed the adoption, diffusion and efficient use of information and communication technologies. Their estimates indicate that pro-competitive reforms could have boosted productivity growth rates by between 0.5 to 1 percentage point per year, both directly in ICT-producing industries and indirectly in the rest of the economy via cheaper and better intermediate inputs. More recently, Gu and Willox (2018, 2023) have argued that limited competition in the information and cultural services sector has curbed aggregate productivity growth and Chen and Tombe (2024) have attributed about half of the widening productivity gap between Canada and the United States to rising resource misallocation due to market distortions partly reflecting policy-induced barriers to interprovincial mobility of labour and capital. Ab Iorwerth and Rosell (2018) estimated the potential long run GDP per capita gains from aligning Canadian FDI regulations on those of the United States at a maximum of over 5 per-cent.

In this context, this article examines whether weak competitive pressures in certain non-manufacturing sectors of the Canadian economy contributed to the aggregate productivity slowdown, by propagating throughout the economy and potentially hindering Canada's ability to fully benefit from the digital transition. The possibility that changes in performance in one part of the economy may have broader effects in the aggregate has been widely acknowledged in economic research.[2] An abundant literature is also devoted to the effects of market regulation on productivity and growth (for a survey, see Campos *et al.*, 2025).

This study looks at how regulations restricting competition in a subset of industries that are key providers of intermediate inputs to the rest of the economy (henceforth called "upstream sectors") can influence aggregate productivity developments.[3] Building on earlier research (Conway and Nicoletti, 2007; Bourlès *et al.*, 2013; Cette *et al.*, 2016;...), the article looks at a set of sectors that play a pivotal aggregate role because their services are widely used in all areas of economic activity. These upstream sectors include: energy, transport, communications, retail and wholesale distribution referred to as trade, and the professional services. Together, these sectors' output represents 30 per cent of the Canadian GDP and 40 per cent of intermediate inputs used in other sectors of the economy.[4] Hence, competitive conditions that affect market power in these upstream sectors quickly and extensively propagate their effects throughout the economy via input-output relationships.

To measure competitive conditions in these upstream sectors we leverage a new vintage of comparative indicators of policies and regulations that affect barriers to entry and restrictions to business conduct in regulated sectors. The policy indicators are an extension of the OECD's product market regulation indicators, which we map approximately into the upstream non-manufacturing sectors covered by our analysis. Due to significant changes in the methodology of the OECD indicators in 2018, we have revised their design and values in collaboration with the OECD to enable consistent tracking of the evolution of regulations over the period from 1995 to 2023. This required a simplification

2 For instance, Gabaix (2011), di Giovanni *et al.* (2014) and Giroud and Mueller (2019) explore the aggregate effects of changes in the performance of large firms; Barrot and Sauvagnat (2016), Caliendo *et al.* (2018) and Stumpner (2019) trace the aggregate effects of regional performances; and Jones (2011), Acemoglu *et al.* (2012) and Carvalho and Gabaix (2013) point to the aggregate effects originating from specific industries.

3 We measure this influence using direct I-O relationships to be consistent with previous research in this area. An interesting alternative would be to use Leontief inverses instead, which take into account the complete set of supply chains relationships in the economy.

4 This is computed as the ratio of the value of intermediate inputs sourced from these non-manufacturing sectors over the total value of intermediate inputs consumed by all other sectors of the economy. These figures are derived from the OECD Input-Output Tables and the StatCan Database in 2015. The precise classification of sectors is provided in Table A2 in the online appendix available at https://csls.ca/ipm/49/Comp_App.pdf

of the indicators' structure, also reducing the amount of regulatory information contained in each indicator relative to the more complete coverage of the most recent vintage of the OECD indicators.[5]

As in Cette *et al.* (2016), the analytical framework relates industry-level productivity to capital intensity and other drivers (proxied by a full set of fixed effects), including prominently the knock-on effects of regulations in upstream sectors on all other sectors of the economy. Estimates are provided for both hourly labour productivity and total factor productivity (TFP) and are based on cross-country, industry-level data covering 15 OECD countries and 19 sectors over the past 25 years. This approach allows to evaluate the potential contribution of procompetitive regulatory reforms in upstream sectors to Canada's future productivity and GDP growth.

The time-consistent OECD regulatory policy indicators reveal that, relative to peer countries, Canada has lagged in implementing ambitious pro-competitive reforms in most of the key non-manufacturing sectors covered by the analysis. While Canada's pro-competitive stance was better than average in the 1990s, subsequent reform efforts have been more limited than elsewhere especially in this century, considerably worsening Canada's relative position. The sectors currently characterized by subpar regulatory approaches account for a significant share of intermediate inputs across the economy, including in high-tech manufacturing and ICT industries that are vital to digital-era growth.

Taking our results causally, a thought experiment based on our estimates suggests that insufficient reform in these areas could explain a large part of the over 20 per cent shortfall in Canadian productivity relative to the United States currently observed, with the greatest impact arising from weak competition in network industries (communications, energy and transport) professional services and retail distribution. Simulations using our coefficient estimates suggest that instantly and simultaneously aligning Canada's non-manufacturing regulations with international best practices – which would represent an extremely ambitious reform agenda – could increase aggregate labour productivity in the very long term by a maximum of 10 per cent. Assuming that this maximum effect of reforms would fully unwind over two decades, the current Canada-US GDP per capita gap could have been reduced by more than one third if such reforms had been implemented at the beginning of this century, all else equal. Sector-specific analysis attributes shares of this potential overall gain to improvements of 1 per cent, 4.5 per cent and 4.5 per cent from reforms in network, retail distribution, and professional services, respectively.

Were Canada to align instead its regulations on those of the United States – which would represent a less ambitious reform agenda – the maximum gains would

5 For a precise definition of what is specifically captured by these regulations, a comparison to the 2023 vintage and the mapping from regulations to sectors please refer to Table A3 in the online appendix. The resulting consistent time-series for energy, transport and communication is already available on the OECD website. The corresponding series for retail distribution and professional services will also be available shortly on the OECD PMR website.

be smaller, about 5 per cent, and a sizeable gap would remain, requiring reforms elsewhere in the economy. The latter gains are comparable to those obtained by Ab Iorwerth and Rosell (2018), who performed a similar experiment focusing on the easing of FDI restrictions.

This maximum effect of reforms is partly driven by the assumption that retail regulations are representative of regulations affecting the broader "Retail, wholesale and vehicle repair" sector, a standard assumption required by data limitations.[6] Scenario analysis based on alternative estimates controlling for this approximation suggests that lower bound long-term gains from reforms (excluding retail) are still very significant. Reforms would raise Canadian GDP by 6.5 per cent, with most of the gains coming from the easing of regulations in the professional services.

If the regulations in the upstream sectors covered by the analysis are a reflection of (or related to) broader sectoral regulatory approaches, our estimates could capture the effects on productivity of these broader approaches as well. For instance, data limitations preclude coverage of changes in sectoral FDI restrictions and accurate account of sectoral barriers to internal trade, which were shown to be significant in previous research. Thus, we cannot exclude that our estimates and scenario analysis may also reflect changes in such broader regulatory settings. If so, properly accounting for such changes could reduce the impact of reforming the narrower set of regulations on which our analysis is focusing.[7]

Our results survive changes in model specification, several robustness checks and, as discussed extensively in later sections, are likely to be little affected by endogeneity bias that could occur if sectoral productivity performances were to influence regulatory policies, implying reverse causality. The main potential source of such bias is eliminated by ignoring the potential effects of sectoral regulations on the productivity of regulated sectors themselves.[8] Other possible sources of endogeneity would be either very unlikely to occur (e.g. low productivity downstream sectors lobbying for more regulation in upstream sectors) or biasing our estimates downwards (e.g. low productivity downstream sectors lobbying for upstream deregulation). Remaining endogeneity issues that could bias estimates upwards (e.g. high productivity downstream sectors lobbying for deregulation of upstream sectors) are partly accounted for by fixed effects and partly compensated by the possible downward bias induced by other omitted effects, such as the positive effects of deregulation on capital intensity (on this see Alesina *et al.*, 2005).

Still, the precision of our estimates and productivity scenarios could be affected by

6 The OECD indicators do not cover regulations in wholesale trade and vehicle repair and such sectoral detail is not available in the harmonized OECD input-output tables. Therefore, the assumption is standard in this line of research (see for instance Bourlès *et al.*, 2013 and Barone and Cingano, 2011).

7 We thank an anonymous referee for alerting us of this possibility.

8 While we ignore the own-effects of regulations in regulated sectors (e.g. the effects of retail regulation on retail productivity), we do cover the cross-effects of regulations in regulated sectors, such as the effects of regulations in retail on the productivity performance of other regulated sectors (e.g. telecoms or the professional services).

other factors. First, our within-sector analysis cannot account for the possible effects of between sector reallocation or other general equilibrium adjustments highlighted in Chen and Tombe (2024). Second, we ignore the possible productivity effects of upstream regulations in downstream sectors that are omitted from our analysis (e.g. agriculture, mining, petroleum refinery and the non-market sector). Third, due to data limitations, we ignore the possible effects of other important regulations, such as FDI and service trade restrictions and barriers to internal trade, which were shown to be important for Canada's productivity performance (Ab Iorwerth and Rosell, 2018). Extending the analysis of procompetitive reforms to include between-sector reallocation effects, spillovers on sectors not covered in this study and a broader range of regulatory barriers to competition could be fruitful avenues for future research.

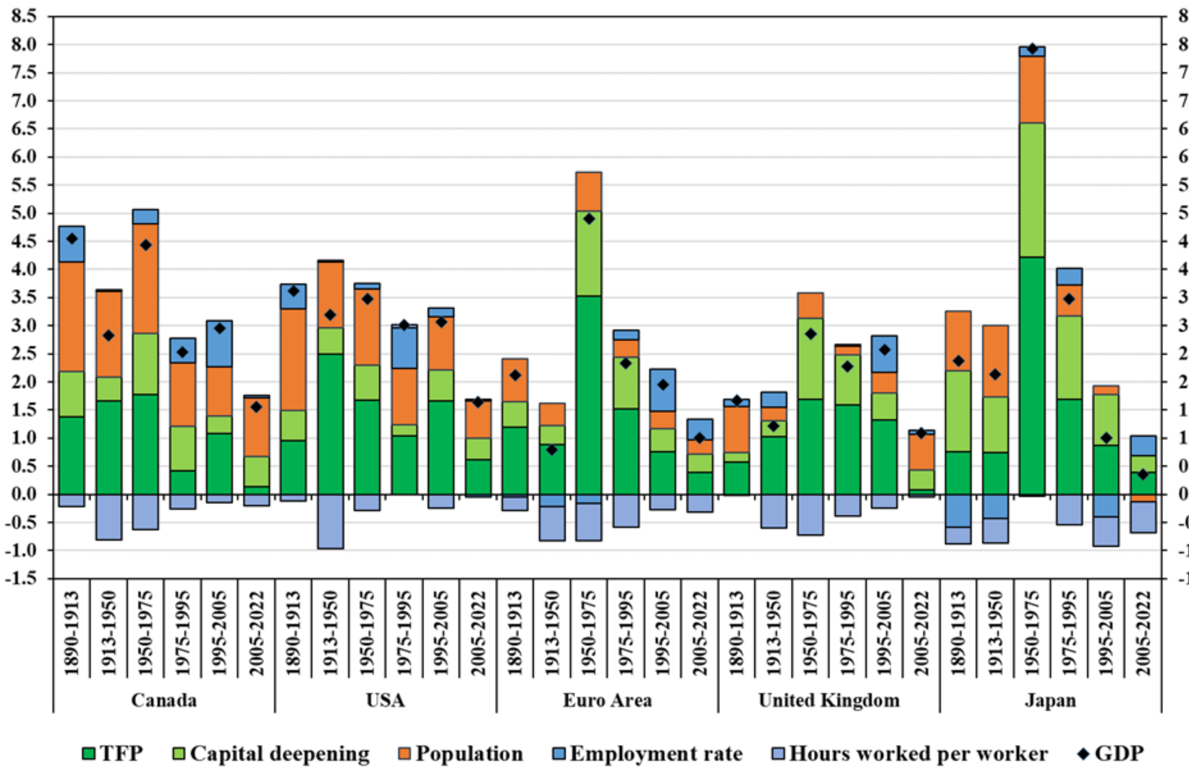
The article is structured as follows. The first section provides some background on historical developments in Canadian productivity cast against those of the United States and other major OECD countries. Section 2 then discusses the role that the persistence of anticompetitive market regulations may have played in this context, with reference to previous research linking such regulations to growth and a focus on those affecting the non-manufacturing sectors. Section 3 lays out our empirical methodology – the analytical framework and the data – and illustrates the results that provide the basis for our scenario analysis, in which we provide simulations of the potential impact of further product market reforms on Canadian aggregate productivity and GDP growth. Section 4 concludes.

Productivity and GDP growth in Canada

It is interesting to put Canadian growth performance into a historical and cross-country perspective (Chart 1). Over the very long period 1890-2022, average annual GDP growth was stronger in Canada, at around 3.4 per cent, than in the United States (3.2 per cent) and the (historically reconstituted) Euro Area (2.2 per cent), but also than in Japan (3.3 per cent) and the United Kingdom (1.9 per cent). However, this stronger performance was primarily due to faster population growth. GDP per capita growth averaged 1.8 per cent annually, below the United States (2.0 per cent) and Japan (2.4 per cent), although slightly higher than the EA (1.7 per cent) and the UK (1.5 per cent). In fact, hourly labour productivity growth averaged 2.0 per cent per year over this long period in Canada, lower than in the other advanced economic areas considered here, i.e. the United States (2.1 per cent), the EA (2.2 per cent) and Japan (2.4 per cent), with the exception of the UK (1.5 per cent), whose weak productivity growth performance can be explained by a higher starting level in 1890 than in the other economic areas.

The 1890-2022 period can be broken down into six different sub-periods: pre-World War I (1890-1913); pre-World War I to post-World War II (1913-1950); post-World War II to the first oil shock (1950-1975), this sub-period often referred to as 'the Golden Age' (or in French 'les 30 glorieuses'); from the first oil shock to the start of the productivity rebound in the United States linked to the spread of ICTs

Chart 1: Sources of GDP Growth

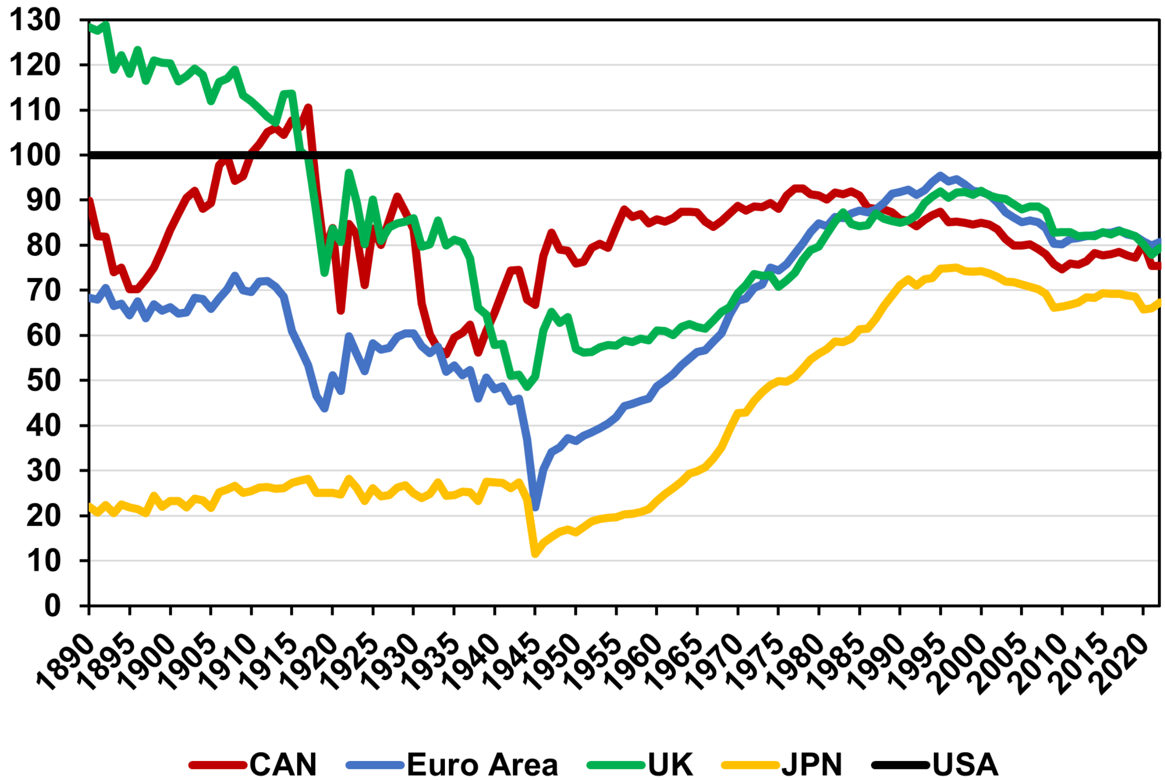


Note: The Chart shows average GDP growth rates and its components. The accounting decomposition of growth proposed in this chart assumes a Cobb-Douglas production function with two factors of production, the volume of fixed capital and the number of hours worked. The elasticity of GDP with respect to capital (labour) is assumed to be equal to 0.3 (0.7). The employment rate is the ratio of employment to total population. Hourly labour productivity growth corresponds to the sum of the growth in total factor productivity (TFP) and capital deepening (the two green bars).
Source: Bergeaud *et al.* (2016) – See: www.longtermproductivity.com.

(information and communication technologies) (1975-1995); the decade of the ICT-driven productivity rebound in the United States (1995-2005); and finally the recent years (2005-2022), characterized by major economic shocks – the Great Financial Crisis that began in 2008-2009, the COVID-related health crisis and the inflationary crisis of recent years.

Compared to the United States, Canadian annual hourly labour productivity growth had quite different profiles over these periods. It was more dynamic over the 1890-1913 sub-period (2.2 per cent vs. 1.5 per cent), reflecting a catch-up process. In fact, before World War I, this catch-up seemed achieved (Chart 2). However, over the next sub-period 1913-1950, labour productivity growth was much lower (2.1 per cent vs. 3.0 per cent), reflecting a major slowdown. A catch-up process appeared again in the third sub-period 1950-1975 (2.9 per cent vs. 2.3 per cent), but was still incomplete in 1975, at the time of the first oil shock, when hourly labour productivity in Canada was about 10 per cent lower than in the United States. A slowdown happened again in the next three sub-periods, 1975-1995 (1.1 per cent vs. 1.2 per cent), 1995-2005 (1.4 per cent vs. 2.2

Chart 2: Comparative Levels of Labour Productivity per Hour Worked, 1890-2020 (United States = 100)



Note: The Chart shows levels of labour productivity per hour worked in percentage of US levels.
Source: Bergeaud *et al.* (2016) – See: www.longtermproductivity.com.

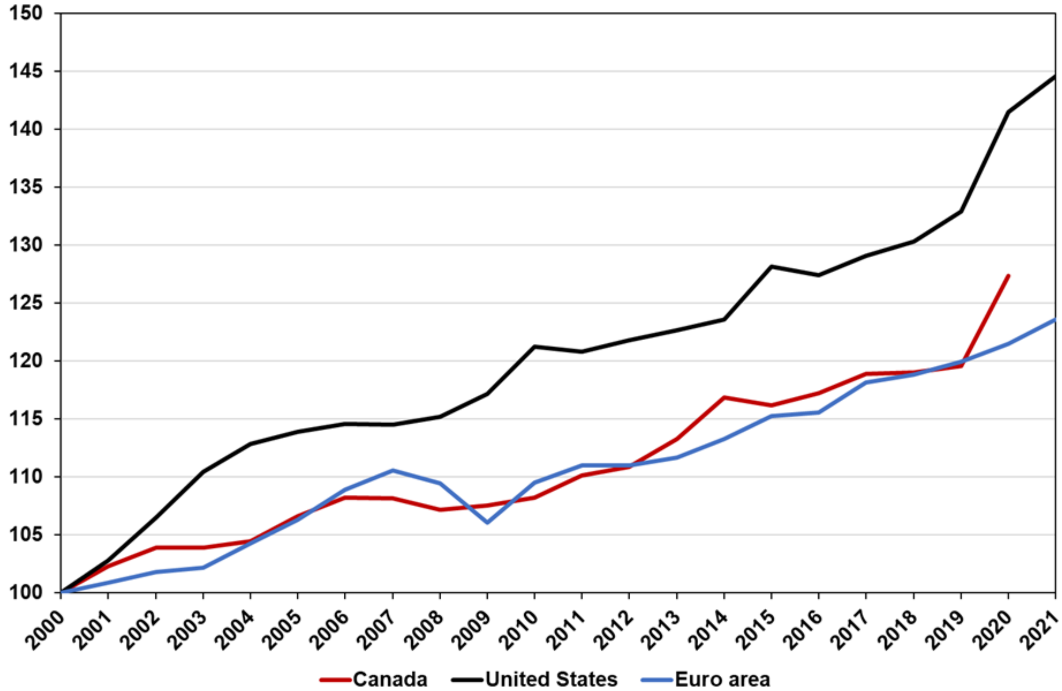
per cent) and 2005-2022 (0.7 per cent vs. 1.0 per cent).

Comparing Canadian postwar productivity trends relative to the United States with those of the EA, the UK and Japan, a major difference emerges. Whereas in the other economic areas, the process of catching up with US productivity levels lasted until the mid-1990s, in Canada it stopped two decades earlier. By 2022, at the end of these trends, hourly labour productivity levels were roughly equivalent in Canada, the EA and the UK, and around 20 per cent lower than in the United States. The case of Japan is quite specific: labour productivity trends over the post-World War II period are similar to those observed on average in the EA, but at levels around 20 per cent lower, due to economic activities in agriculture and services that are highly protected from competition (Bergeaud *et al.*, 2018).

Since 2000, hourly labour productivity trends in Canada have been fairly similar to those observed in the EA and the UK (Charts 1 and 2), with a comparable drop-off from the average productivity level observed in the United States. The same similarity in productivity trends between Canada and the EA can be broadly observed in the database that we use in our analysis (Chart 3).

As a result of these trends, in 2022 Canada's GDP per capita was nearly 25 per cent below that of the United States, a smaller gap in the EA, the UK and Japan

Chart 3: Average Labour Hourly Productivity Index (2000 = 100)



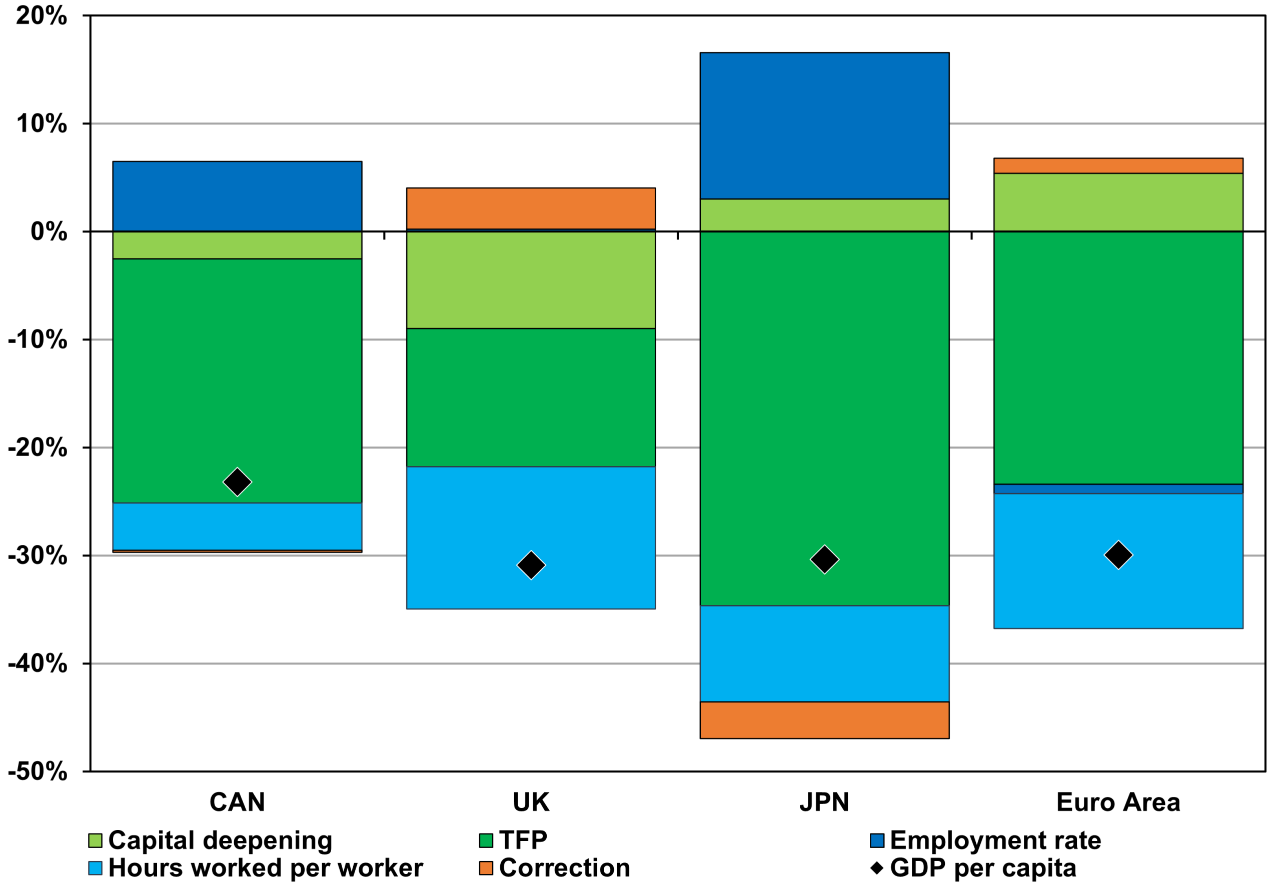
Source: Authors calculations on their database: EUKLEMS & INTANProd (Bontadini *et al.*, 2024) .

(Chart 4). In all four areas the gap was essentially due to lower hourly productivity and, to a lesser extent, shorter average working hours. Weak TFP, rather than capital deepening, is the main cause of this gap in hourly productivity. At the same time, higher employment rates partly offset weaker productivity in both Canada and Japan.

The Canadian specificity of an earlier productivity slowdown than that observed in other advanced economic areas has already been commented on in previous works, such as Conway and Nicoletti (2007),[9] and more recently Sharpe and Sargent (2023), Sargent (2024) or the Bank of Canada (Rogers, 2024). Several studies have sought the root causes of the Canadian specificity in several structural factors. These included the size distribution of Canadian businesses, skewed towards smaller sizes than in the United States (Leung *et al.*, 2008; Baldwin *et al.*, 2014); changes in Canadian industry structure, which moved faster than in the United States away from manufacturing towards less productive services (Almon and Tang, 2011; Tang, 2017); the skill composition of the Canadian workforce, with skill shortages in key areas (OECD, 2006); differential contributions of ICT-producing and ICT-using sectors, with their tim-

9 Conway and Nicoletti (2007: 5) note that "Canada is the only country with long-time series data in which labour productivity per hour has, on average, fallen behind that of the United States in both the 1980-1994 and 1995-2005 periods (in both levels and growth rates)". As far as we know, they are the first to make this point.

Chart 4: Gaps in GDP per capita relative to the United States and contributions, 2022 (PPP US$ 2010)



Note: The chart shows per cent gaps in GDP per capita relative to the United States and the percentage point contributions of its components. The accounting decomposition of the GDP per capita in this chart assumes a Cobb-Douglas production function with two factors of production, the volume of fixed capital and the number of hours worked. The elasticity of GDP with respect to capital (labour) is assumed to be equal to 0.3 (0.7). The employment rate is the ratio of employment to total population. The contribution of hourly labour productivity is the sum of the total factor productivity (TFP) and capital deepening (the two green bars). The correction term results from the cross effects of the various components.
Source: Bergeaud *et al.* (2016) – See: www.longtermproductivity.com.

ing differing across the two countries (Gu and Willox, 2018, 2023); and business dynamism, which suffers from relatively high innovation costs (Rasaninghe, 2017). Haun and Sargent (2023) also point out that productivity trends and levels in this century are fairly similar in Canada to those observed in other advanced countries.

However, a common conclusion is that Canada's relatively stringent product and service market regulations-particularly compared to the United States-played a major role (Conway and Nicoletti, 2007; Sharpe and Sargent, 2023; Sargent, 2024; Gu and Willox, 2018, 2023; Chen and Tombe, 2024; Rogers, 2024; OECD, 2025). This explanation also applies to productivity slowdowns occurring later in other countries (e.g. Nicoletti and Scarpetta, 2003; Bourlès *et al.*, 2013; OECD, 2015; Cette *et al.*, 2016). We devote the rest of this article to substantiate this claim.

The Role of Anticompetitive Regulations

Regulation and Productivity

Market regulations are pervasive in all advanced countries. Most of them are aimed at addressing public objectives that would not be achieved by the spontaneous operation of product, labour or financial markets. These include prominently safety, health and equity outcomes but also cover other domains such as environmental and consumer protection, fair competition, economic efficiency (e.g. in natural monopolies) and property rights (e.g. from new ideas) – where market failures are common. In product markets, these regulations may affect ease of entry (or exit) and growth opportunities by new firms, the behaviour and prerogatives of incumbents as well as the incentive structure of both of them.

Ultimately, product market regulations influence the degree of rivalry among firms and the competitive pressures they experience and, in turn, this affects their incentives to enhance the efficiency of production processes, the quality and variety of the product they supply and their efforts to innovate. While these linkages are complex and ambiguous, they stress the importance of competitive pressures for productivity outcomes.[10] For these reasons, assessing the need for regulations and making sure that their objectives are achieved in a way that is the least intrusive or distortionary for healthy market forces is an important objective for growth-oriented public policy. Often, both the need for regulation and their optimal design change with developments in technology and the business environment.

With this in mind, over the past few decades, numerous product market reforms have been implemented across the OECD. These reforms are expected to influence innovation and productivity throughout the economy-both in regulated and unregulated sectors-through several channels.

First, heightened competitive pressures resulting from reforms increase incentives for incumbent firms to improve efficiency and innovate, while simultaneously forcing less efficient firms out of the market. Second, reducing barriers to entry and firm growth allows new, efficient, and innovative firms to emerge and thrive. These mechanisms foster productivity gains both within firms and across sectors, by facilitating the reallocation of resources where they are most productive, while also enhancing overall business dynamism. Third, the resulting productivity improvements in key upstream sectors that supply intermediate goods and services can cascade through supply chains, amplifying the positive effects of reforms on the broader economy. Taken together, these three channels contribute to stronger aggregate productivity and GDP growth.

A large body of empirical research has documented the positive relationship be-

10 As shown by Aghion *et al.* (2002), the link between competitive pressures and efficiency enhancements can be heterogenous across firms, being stronger for firms that are close to the efficiency frontier than for firms that are far away from it, which may suffer from a "discouragement" effect. In the aggregate, this can generate a bell-shaped relationship between competition and innovation.

tween competitive pressures and productivity, via creative destruction and other channels.[11] Studies span multiple levels of analysis: at the firm level (e.g. Geroski, 1995; Nickell, 1996; Nickell *et al.*, 1997; Blundell *et al.*, 1999), the sector level (Nicoletti and Scarpetta, 2003; Griffith *et al.*, 2006; Inklaar *et al.*, 2008; Buccirossi *et al.*, 2013; Cette *et al.*, 2018), and the aggregate level, typically through panel data analyses across countries (Conway *et al.*, 2006; Aghion *et al.*, 2009).

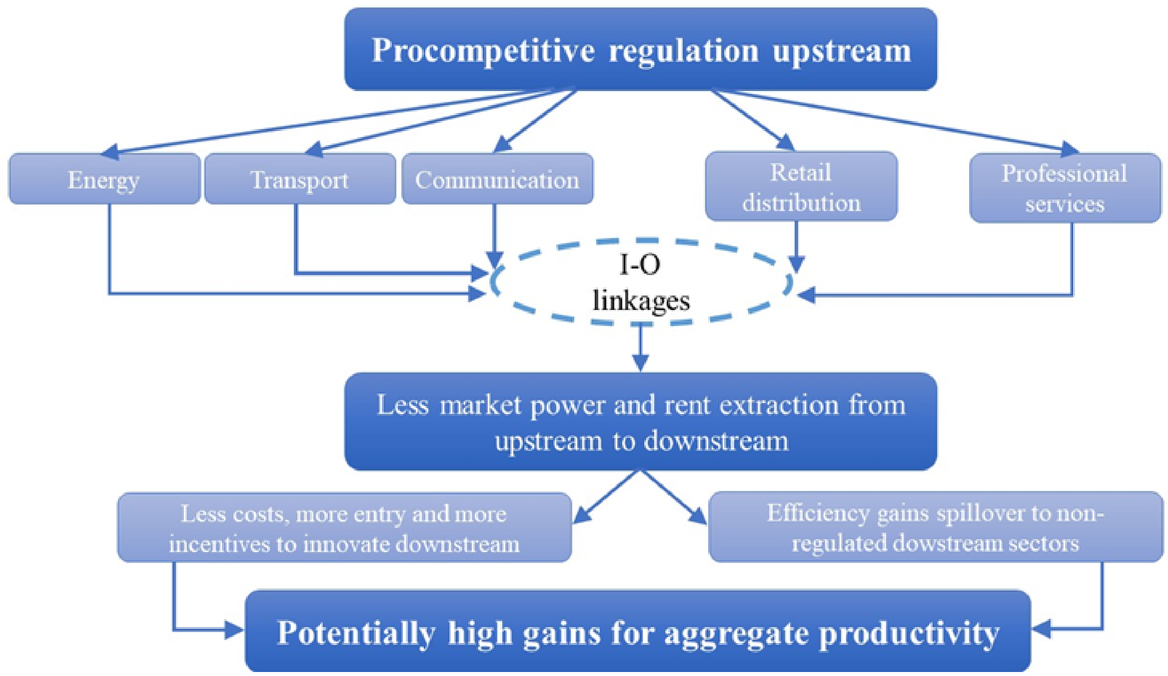
More recent studies emphasize that imperfections in goods and services markets - especially in upstream sectors that provide intermediate goods - can dampen the incentives of downstream firms that use those goods in production to improve productivity via restructuring, investment or innovation. A focus solely on intra-sectoral competition overlooks these important cross-sector linkages. This insight is important for policy-making as it suggests that the productivity-enhancing potential of reforms in downstream industries can be reduced by the lack of pro-competitive reforms in sectors that provide essential intermediate inputs. These often include key non-manufacturing industries – such as communications, transport, energy, distribution and business services - that are often sheltered from international competition and protected at home.

Anticompetitive regulations in upstream industries work their way to downstream industries by changing incentive structures (Figure 1). Regulation that unnecessarily curbs competition upstream grants market power to regulated firms, allowing them to raise prices and capture rents. While these rents could in principle be used for research and development, firms enjoying them often have little incentive to innovate, as their dominant market position reduces the need for further efficiency gains. When upstream firms gain excessive market power, they can appropriate a share of the returns from downstream innovation (e.g. by overcharging for the supply of their products), thereby discouraging entry and efficiency enhancements in downstream markets as well. Furthermore, the concentration of upstream suppliers reduces competition and limits the variety of products available for downstream firms, further undermining their ability to innovate and improve quality. With lower incentives to innovate in both upstream and downstream industries, the result is lower aggregate productivity growth.

Empirical evidence confirms that product market regulations in upstream industries negatively affect the productivity of industries that rely heavily on inputs from regulated sectors. These findings are supported by cross-country and sectoral panel analyses, including studies by Conway and Nicoletti (2007), Barone and Cingano (2011), Bourlès *et al.* (2013) and, more recently, Andrews *et al.* (2025).

11 Aghion and Griffith (2005) provide a conceptual illustration and evidence of these linkages between competition and growth. See also Aghion and Howitt (2009), Acemoglu *et al.* (2006) and Crafts (2006). Through a theoretical approach and estimates on a UK firm dataset, Aghion *et al.* (2009) show that a higher competition should encourage incumbent innovation in sectors that are initially close to the technological frontier, whereas it may discourage incumbent innovation in sectors that are initially further behind the frontier. For a survey of this literature, see Campos *et al.* (2025).

Figure 1: From Upstream Regulation to Downstream Productivity: Transmission Channels



Source: Authors of the article.

The Scope for Easing Anticompetitive Regulations in Canada

As widely discussed in both the academic and the policy arenas, Canadian product markets suffer from a lack of competitive pressures, especially in the non-manufacturing industries. Regulatory settings are still adverse to competition in some important services sectors – such as the professional services – and liberalization in some network industries has been slow and limited – such as in energy and transport. This is compounded by the persistence of differences in regulation and other hindrances to mobility across provinces that curb competitive pressures at the national level as well as by the existence of barriers to foreign direct investment and trade in services that limit competitive pressures from abroad.

Some of these regulatory settings are recorded in the OECD indicators that compare anticompetitive regulations across countries and over time.[12] For instance, the most recent OECD data (which is based on replies by the Canadian government to a questionnaire focusing on the province of Ontario and the city of Toronto) shows that regulations in trade and the professional services are slightly more restrictive of competition than in the average OECD country and by far more restrictive than in the average of the five best practice OECD coun-

12 The data and corresponding documentation are at https://www.oecd.org/en/topics/product-market-regulation.html for non-manufacturing regulations, https://www.oecd.org/en/topics/services-trade-restrictiveness-index.html for service trade restrictions, and https://www.oecd.org/en/topics/sub-issues/sustainable-investment/fdi-regulatory-restrictiveness-index.html for FDI restrictions.

tries. The comparative position of Canada is similar in the network industries, with a particularly bad comparative scoring in energy and communications.

These indicators cover a very wide range of government provisions restricting competition in these sectors, but unfortunately their time coverage is short due to a change in data collection methodology that occurred in 2018. Therefore, they can hardly be used in empirical analysis aimed at identifying the effects of reforms on productivity. To obviate this problem, we developed in full collaboration with the OECD a simplified version of the sectoral indicators of regulation that covers less ground in terms of regulatory provisions but provides a consistent historical series from 1998 to 2023. Table A3 in the online appendix shows how the most complete and the simplified versions of the sectoral indicators are related. Overall, simplified indicators cover less services, less regulatory areas and less information in each regulatory area (for more detail, see the Data section).

For coherency, in the rest of this study we use the indicators with the longest time coverage, which are used in the empirical analysis described in the next section. It is important to note that using this simplified indicator may provide an incomplete account of countries' procompetitive stance as well as affect their relative positions in the cross-country comparison. However, as explained below, the source of identification in our analysis is solely the change in the impact of upstream regulations on downstream sectors in each country. Therefore, what is relevant for the precision of the estimates is the variability of upstream regulations over time rather than the relative positions of countries in each regulatory area.

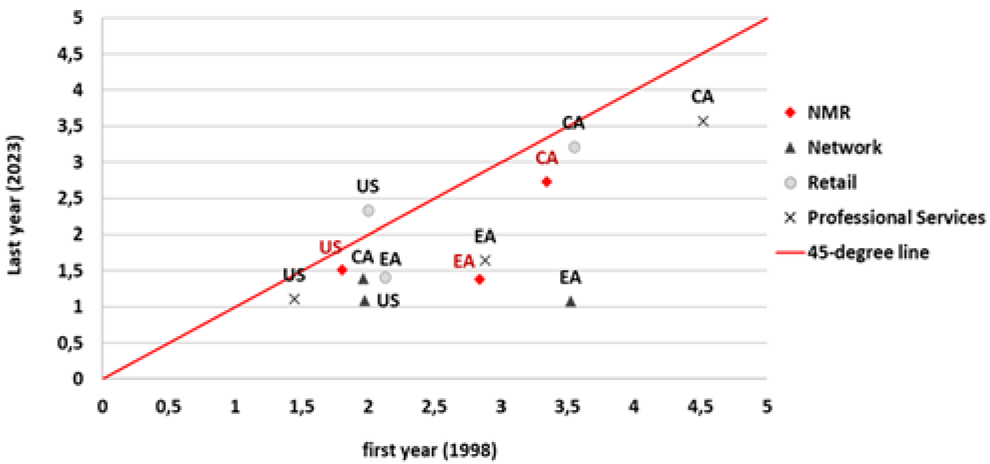
According to these simplified but time-consistent indicators most Canadian regulations have not only been persistently less procompetitive than in the United States over the past 30 years but they also were generally less procompetitive than in the Euro Area (Chart 5, Panel A). Reforms were implemented in the three economic areas over this period, although less so in the United States where deep regulatory changes had already occurred earlier. However, in Canada they were more limited in scope. As a result, in 2023 competition in Canadian non-manufacturing markets was more restricted than in the EA in both services and most network industries (Box 1). Chart 5 (Panel B) shows that delays in reforming energy and transport turned Canada from one of the least to one of the most restrictively regulated in these sectors. By contrast, the simplified indicator is unable to capture changes in regulation of the communication sector in Canada that may have occurred since 1998, when Canada was comparatively more procompetitive than other OECD countries in the areas covered by the indicator.[13]

An important element that is not covered by the OECD indicators are inter-provincial barriers to trade and mobility, especially concerning non-manufacturing

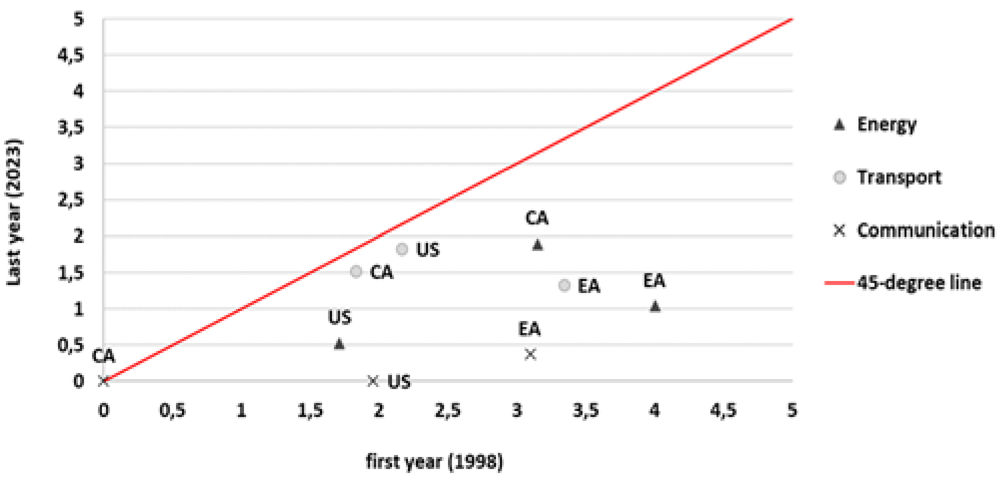
13 Incidentally, this implies that Canadian data for this sector do not contribute to the identification of the effects of network sector reforms on productivity in our sample.

Chart 5: Evolution of Anticompetitive Regulations in the Non-manufacturing Industries in the United States, Canada (CA) and the Euro Area (EA), 1998-2023 (indicators increase with restrictions to competition)

Panel A: Non-Manufacturing Regulation (NMR), Decomposed into Network, Retail Distribution and Professional Services Industries



Panel B: Decomposition of Regulation in Network Industries



Note: The first available year for the United States in the new annual version of the ETCR (Energy, Transport and Communications Regulation) indicator is 2013. Therefore, the value shown for 1998 for the United States comes from the older version of the indicator, which was originally provided at five-year intervals.
Source:Authors' calculations based on OECD data

Box 1: Restrictions to Competition in the Canadian Non-Manufacturing Sectors

Since 1998, the OECD surveys legislations and regulations potentially affecting competitive pressures in several non-manufacturing sectors of OECD countries as well as of a subset of non-OECD and emerging economies. The survey is implemented periodically in full collaboration with the governments of the covered countries and qualitative replies on details of such laws and regulations are converted into quantitative indicators – the so-called OECD PMR indicators – that allow to compare policy settings and use the indicators in empirical analysis.

While a full account of laws and regulations affecting competition in Canadian non-manufacturing markets is outside the scope of this paper, it can be useful to provide a few examples drawing from the information underlying the OECD 2023 PMR indicators to highlight areas where Canada lags behind in procompetitive reforms relative to other countries. In interpreting such examples it is important to keep in mind that some regulations vary across Canadian provinces and, in these cases, the OECD only records regulations in the Ontario province and the city of Toronto.

One such area is retail distribution, where according to the OECD data Canada always requires licensing (independent of outlet size), maintains national monopolies for certain products (such as the sale of alcohol) and price controls for other goods (such as gasoline), and regulates hours more restrictively than in other OECD countries. Another area is the professional services, which are an important component of the so-called knowledge-intensive services where digitalization and AI can be widely applied. In most of the services covered by the OECD indicators (accountants, architects, lawyers and engineers, real estate agents and notaries), Canada's regulations concerning entry requirements and business conduct are much more restrictive than in the best practice OECD countries. For instance, professionals in accounting, law, engineering and architecture retain exclusive rights in many of their activities, have to pass professional examinations and register as members of professional associations. Also, regulations restrict their the form of business (generally prohibiting limited liability or joint-stock companies), cooperate interprofessionally (e.g. between architects and engineers or lawyers and accountants), advertise their services (e.g. in accounting) or freely set their tariffs (e.g. in engineering). These restrictions stifle market access, competition and efficiency and have been lifted in many OECD countries, without negative consequences for the quality or the reliability of the services provided.

In network industries as well Canadian regulations are often more restrictive than elsewhere, thwarting competition. This is the case, for instance, in electricity transmission and distribution as well as gas distribution, storage and supply where legal or de facto local monopolies dominate markets, while rail freight is characterized by a duopoly. In some cases, vertical integration of these companies persists, with rules requiring only operational or accounting separation. In transport, public ownership of sometimes dominant companies delivering services is pervasive, with some of them (e.g. water transport) exempted from antitrust rules. In air transport, airlines covered by open-sky agreements do not enjoy all the "freedom of the air" rights and no regulatory supervision is exerted on airport charges. In telecommunications, markets for fixed line services as well as for wholesale mobile call origination/termination services are scarcely competitive.

products. Given the lack of cross-country comparative data on such internal barriers, we could not account for the effects of such barriers in our analysis. However, a multitude of studies report the existence of such internal barriers in Canada and analyse their potential for curbing competition and growth both by raising entry costs via regulatory compliance, to the advantage of local incumbents, and by preventing business dynamism via obstacles to the mobility of labour and capital (Albrecht and Tombe, 2016; Bemrose *et al.*, 2017; OECD, 2019, 2023; Manucha and Tombe, 2022; Teeter, 2024).

Indeed, despite the implementation of the Agreement on Internal Trade (AIT) in 1995 and the Canadian Free Trade Agreement (CFTA) in 2017 (along with several smaller but significant interprovincial agreements), a number of significant (especially non-tariff) barriers remain to internal trade in goods and services in Canada. These include outright prohibitions (e.g. for alcohol and tobacco) as well as technical and regulatory or administrative obstacles (such as differences in standards, processing or labeling obligations, licensing or permit requirements). In one of the rare cross-country studies on this subject, Bambalaite *et al.* (2020) find for instance that heterogeneity in occupational entry regulations across Canadian provinces is relatively high in both the personal and professional services and higher than across the United States, with mobility restrictions playing a large role in certain services (e.g. driving instructors, taxi) or professions (e.g. real estate agents).

Research has argued that these barriers are economically significant and involve high costs in a number of activities, such as for example in trucking and professional services. Such costs are especially relevant for Small and Medium-Sized Enterprises (SMEs), which constitute the backbone of the Canadian economy and whose inability to upscale has been related to weak aggregate productivity growth.

Finally, mainly due to their short time coverage, we also do not consider barriers to international services trade and investment, which are considered significant in Canada by international organizations such as the IMF and the OECD.[14] Canada was assessed to be more restrictive than the United States and the EA in both services trade and FDI, with restrictions in excess of those of the other two areas in a majority of the sectors and areas covered by the indicators. [15]

Lack of action in all these product market areas is likely to have affected aggregate productivity growth by curbing incumbents' incentives to enhance efficiency, hindering the growth potential of dynamic SMEs, limiting the entry of new startups and discouraging innovation. The result-

14 OECD data on these barriers are available only over the past decade. Services Trade Restrictions Indicators (STRI) cover construction, wholesale and retail distribution, transport, storage and postal services; FDI restrictions indicators cover almost all 2-digit NACE sectors and several policy areas, including foreign equity restrictions, screening and approval requirements and restrictions on foreign personnel.

15 Canada's FDI Regulatory Restrictiveness Index was 0.15 in 2023 compared to 0.05 for the United States and 0.02 for the Euro Area. Its total services (incl. construction) Regulatory Restrictiveness Index was estimated to be 0.20 in 2024, higher than 0.18 for the United States and 0.17 for the Euro Area.

ing low competitive pressures, especially in knowledge-intensive service sectors, such as those providing business services, may also have limited the ability of the Canadian economy to fully reap the benefits of developments in both technology (the ICT, the digital and AI revolutions) and global trade and investment. In the following analysis we are only able to capture the effects of some of these regulatory obstacles to growth to the extent that they are correlated with our (simplified) sectoral indicators of regulation. Hence, our estimates of the potential effects of product market reforms do not reflect the full impact that a wider range of procompetitive policies might have on aggregate productivity.

The Impact of Anticompetitive Non-manufacturing Regulations on Canadian Productivity

In the rest of this study we provide an assessment of the potential gains that the Canadian economy might obtain by implementing further product market reforms. The focus is on reforming Non-Manufacturing Regulation (NMR) to increase competitive pressures in energy, transport, communication and services markets. To this end, we estimate the economy-wide impact on productivity of regulations that curb competition in these non-manufacturing industries and use the estimates in a thought experiment that simulates the expected long-run effects of pro-competitive reforms in such regulations on aggregate productivity and GDP per capita. An important caveat in interpreting our results is that the regulations we cover could be related to other omitted sector-specific and time-varying regulations, which we are unable to capture with our explanatory variables. If so, both our estimates and our scenario analysis could also include the impact of changes occurring in such omitted regulations as well.

However, within the limitations inherent in the use of the relatively narrow and simplified set of regulatory indicators described in the previous section, our analysis is up to date, granular and well-focused from a policy standpoint. It takes into account the changes that regulations (in Canada and elsewhere) have undergone between 1998 and 2023 and the regulatory data is sufficiently detailed to allow breaking down the expected gains by regulated sector: energy, transport, communications, retail distribution and the professional services.

This section first describes our main approach to assess the impact of regulations on productivity. Then it describes the data used to implement this approach. Finally, it provides our main results on impact coefficients and expected effects of further reforms on the Canadian economy.

Analytical framework

In order to study the impact of product market reforms on productivity and GDP growth, we estimate an empirical productivity model at sector level, using up to date historical data for economic and policy variables. The basic data are the annual industry-level components of the OECD PMR indicators – which we have revised, made consistent over time and (approximately) mapped into the corresponding NACE sectors – and the most recent revision of the new sectoral EUKLEMS & INTANProd database (Bontadini *et al.*, 2024), which provides data up to 2021. Additional data includes input-output tables, which are used to compute the trickle-down effects of regulations and controls for other policies and structural conditions potentially affecting productivity.

The EUKLEMS & INTANProd database includes a coherent set of production accounts that include both National Accounts (NA) and non-NA intangible investments in the estimation of value added.[16] These data are supplemented with similar data for Canada provided by Statistics Canada. Our estimates of impact coefficients currently cover the period 1996-2021 for an unbalanced panel of 15 OECD countries and 19 sectors of activity.

Scenario analyses of the expected gains from further Canadian reforms take as a starting point the sectoral regulatory stance in 2023 as recorded in the simplified version of the NMR indicator. These expected gains are first calculated for the sample of sectors included in the analysis, and then extended to estimate gains for overall GDP on the basis of transparent and plausible assumptions concerning sectors of the economy not covered.

Measuring the Trickle-down Effects of Regulation

In the spirit of Conway *et al.* (2007) and Bourlès *et al.* (2013), the focus of our analysis is on the economy-wide effects of reforms in a few key non-manufacturing sectors for which we have reasonably complete and timely regulatory data. The sectors covered by our regulatory data include energy, transport, communication, retail distribution and the professional services. Hence, the first step in our analysis is to map these indicators into the corresponding NACE sectors (Table A4 in the online appendix). This mapping is necessarily approximate for three reasons. First, the OECD indicators sometimes only cover a subset of activities within each of these broad economic areas. Second, even within these areas, there is no precise correspondence between the OECD indicators and the national accounts categories. Third, cross-country time-series data are often not available at the level of detail covered by the indicators. A notable example is the distribution sector, where the OECD PMR indicator only covers laws and regulations affecting retail sales of food, clothing and pharmaceuticals, and sectoral data are not available at this level of detail.[17]

As explained in the previous section, anti-competitive regulations in the key non-manufacturing sectors covered by our analysis have trickle-down effects that in-

16 NA intangibles include investments in R&D, software &databases, mineral explorations and literary and artistic designs, but do not cover other increasingly important intangible investments (non-NA): attributed industrial designs, financial product development and, especially economic competencies such as branding, training and organizational capital (see Figure A1 in the online appendix). As the OECD indicators for trade and the professional services are only collected every five years, annual values were calculated by interpolation.

17 The implicit assumption in our analysis is therefore that the evolution of regulation recorded in the OECD indicators is representative (or at least correlated with) with regulations affecting the sector to which the indicator is mapped.

fluence the productivity of all other sectors, including the non-regulated ones, via input–output interlinkages. To account for the effects of upstream regulation on other sectors, we calculate the variable $NMR^{up}_{(c,i,t)}$ as follows:

$$NMR^{up}_{c,i,t} = \sum_j int^{USA}_{i,j} \times NMR_{c,j,t},$$
$$\text{with} \quad int_{i,j} = 0 \text{ if } i = j.$$

Where $NMR^{up}_{c,i,t}$ is our measure of the size of the pass-through effect or "regulatory burden" on the downstream sector i in country c in period t. This effect depends on $NMR_{c,j,t}$, which is the regulation specific to the regulated sector j and the intensity of use of intermediate inputs produced by the regulated sector j for the downstream sector i, $int^{USA}_{i,j}$. This variable is calculated as the ratio of consumption of intermediate inputs used by sector i, produced by sector j, to sector i's total output, based on the 2015 US Input–Output table.

We use the US table rather than country-specific ones for three reasons. First, regulations can also affect the propensity to use intermediate goods, raising a kind of endogeneity that would make the interpretation of changes in $NMR^{up}_{c,i,t}$ difficult. Second, the United States has a diversified industrial structure that guarantees that all sectors are well represented in the I–O table. Third, the United States is the country against which Canadian performance is often benchmarked. Excluding the United States from our estimating sample allows us to control to some extent for the possible endogeneity between regulation and input–output coefficients.[18] Any remaining endogeneity would only result from a correlation between the way the propensity to use intermediate goods has been affected by regulations in the United States and similar relationships in other countries, which seems unlikely given the lack of synchronization of regulatory changes in the United States with those of the other countries in our sample, highlighted in Chart A3 in the online appendix.[19]

We also include as a control labour market regulations in our estimations, focusing in particular on employment protection legislation (EPL). Unlike product market regulations, these are defined at the all industry level. To introduce a sectoral dimension in a manner that is consistent with our measure of the trickle-down effect of non-manufacturing regulation, we assume that the impact of such regulations is greater in sectors with higher labour intensity. We therefore compute the indicator $EPL^{d}_{c,i,t}$ as follows:

$$EPL^{d}_{c,i,t} = \left(\frac{LAB}{GO}\right)^{USA}_{2015,i} \times EPL_{c,t}$$

Where $EPL_{(c,t)}$ represents the value of the OECD EPL indicator, LAB is labour compensation, and GO is total output in value

18 We also exclude intra-sector intermediate consumption (i.e. $int_{ij} = 0$ if j = i). Therefore, our focus is solely on the relationship between sectors. Estimating the effects of regulation within sectors would lead to strong endogeneity issues, notably reverse causality.

19 While most regulatory reforms occurred over the 1998-2023 period in European countries, the United States experienced earlier reform waves during the 1980s.

terms (in millions of dollars) for each sector in the United States in 2015. As for the I–O coefficients, use of the US data as a benchmark, together with the exclusion of this country from regressions, limits any endogeneity between country-specific EPL and the labour intensity measure.

Modelling the Relationship Between Regulations and Productivity

Building on Cette *et al.* (2016), we estimate a reduced–form relationship between productivity and regulation for an unbalanced panel of 15 countries and 19 industrial and services sectors over the 1996–2021 period.[20] We estimate the model using an index of total factor productivity (index base 100 in 2015) and the level of labour productivity (ratio between real value added in PPP and number of hours worked).

In order to formalize the phenomenon of technological catch-up, as well as sector-specific temporal evolutions, we include in the estimates the cross fixed effects *industry × year* ($\phi_{i,t}$). We also include *country × year* ($\phi_{c,t}$) and *country × industry* ($\phi_{c,i}$) cross effects, which enable us to control for various other sources of omitted variables and unobservable variability, such as country-specific macroeconomic shocks and economy-wide public policy changes or time-invariant differences in the measurement of labour productivity.

Specifically, these fixed effects can account for changes in economy-wide product market regulations (such as barriers to entry related to domestic business creation or greenfield FDI) as well as for cross-country time-invariant differences in sector regulatory approaches (such as light-hand regulation versus interventionism). For the labour productivity equation, we also include the logarithm of capital intensity $\ln(intK)_{c,i,t}$, with or without non-NA intangible assets, depending on the definition of productivity.[21]

We therefore estimate the following equations:[22]

$$\begin{aligned}\ln(\mathrm{tfp}_{c,i,t}) = \alpha \;+\; & \beta\, NMR^{up}_{c,i,t-1} \\ & + \gamma\, EPL^{d}_{c,i,t-1} \;+\; \phi_{c,i} \;+\; \phi_{c,t} \\ & + \phi_{i,t} \;+\; u_{c,i,t}.\end{aligned} \tag{1}$$

20 Countries are Austria (AT), Belgium (BE), Canada (CA), Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Italy (IT), Netherlands (NL), Sweden (SE), Slovakia (SK), United Kingdom (UK), United States (US). In estimations, the United States is dropped from the sample to avoid endogeneity with I-O and labour intensity coefficients. The list of covered sectors can be found in the online appendix Table A2.

21 Although we control for any effect of regulation that operates through capital intensity, we do not identify to what extent the effect actually passes through changes in this variable. Therefore, to the extent that such effects exist, our estimates may under or overestimate the total impact of regulation on productivity. Underestimation is more likely given the findings of Alesina *et al.* (2005) as to the depressing effects of anticompetitive regulations on investment.

22 In the empirical analysis, the regulatory burden variable is lagged by one year because we assume that, once established, regulations can take some time to be implemented and to exert their effects. Robustness analyses using the contemporaneous variables do not alter the results.

$$\ln(\mathrm{lp}_{c,i,t}) = \alpha \;+\; \beta\, NMR^{up}_{c,i,t-1} \;+\; \gamma\, EPL^{d}_{c,i,t-1} \;+\; \lambda \,\ln(int K)_{c,i,t} \;+\; \phi_{c,i} \;+\; \phi_{c,t} \;+\; \phi_{i,t} \;+\; u_{c,i,t}. \quad (2)$$

The use of lagged regulation and the "fully saturated" fixed effects structure of the estimated models allows to control for most potential sources of endogeneity, such as omitted variables or confounding factors. Indeed, given this structure and the use of the 2015 US I-O table, the statistical identification of the effects of regulations on productivity depends only on changes occurring in such regulations in each country and sector over time.

Yet, possible estimation bias due to reverse causality deserves discussion. While we are investigating the impact of regulations on productivity, policies may also change in response to economic shocks. For example, if a sector experiences on average low or declining productivity in a certain country, firms in that sector may exert political pressure to raise anticompetitive regulations, thereby protecting the sector from competition and preserve existing rents. In this case, the direct effect of sector regulation on productivity within that sector would be overestimated. However, this bias does not affect our estimation results as we are not concerned with the effects of regulation on productivity within the regulated upstream sector but only on its effects on downstream industries.

Some residual endogeneity might remain if productivity-impaired downstream industries attempt to induce regulatory reforms in upstream industries in order to improve their business conditions (e.g. low productivity manufacturing industries lobbying to ease regulations in the professions or telecoms to obtain cheaper business or communication services). But in this case the direction of endogeneity would tend to bias our estimates downwards, implying that our estimates of the negative effects of regulation in upstream sectors on aggregate productivity would be on the conservative side. The opposite lobbying scenario, in which productivity-impaired industries would push for tighter regulations in upstream industries does not seem realistic as, by generating or inflating upstream rents, it would worsen even further the business conditions of downstream industries, running against their business interests.

Still, we cannot exclude that some endogeneity could originate from a more likely situation: lobbying by dynamic downstream sectors aimed at easing regulations in upstream sectors (i.e. energy-intensive high-tech or digital-intensive ICT sectors pressing for reforms in energy or telecoms) to protect their business interests. This would indeed tend to bias our estimates upwards implying an overevaluation of the potential gains to be obtained from reforms. However, our country-industry fixed effects partly address this risk by capturing the relative productivity characteristics of downstream sectors in each country. This issue will be discussed further in the next subsection.

Simulating the Impact of Reforms

In order to provide an economic analysis of the results, we carry out scenario analyses. The scenarios considered highlight the effects on labour productivity of aligning Canada's sectoral regulations on best OECD practices. In this respect, it is important to notice that the OECD indicators do not score as best practice (i.e. a zero score) the complete absence of regulation, but rather the alignment of regulation to the internationally recognized most pro-competitive regulatory approches that can be used to achieve public policy goals in each sector. To remain realistic, in our scenario analysis we do not assume regulatory alignment to such theoretical best practices but to the best practices actually observed across the countries in our sample (i.e. to the regulatory approaches adopted in each sector by the country whose indicator score is closest to the theoretical best practice).

As shown in Chart 6, overall the UK is the most pro-competitive country in our sample. However, for each regulated sector, the most pro-competitive country may vary. For the simulations, we use the UK as the benchmark for the energy, transport and communications sectors, the Czech Republic as the reference for retail regulations, and Sweden as the benchmark for professional services.

The effect of these reforms on labour productivity is calculated for all sectors represented in our database, then aggregated at the national level based on each sector's share of the total hours worked in the country. We assume a zero effect for sectors not covered by our estimates. These omitted sectors include the non-market sector, i.e., public administration, as well as agriculture, oil extraction, mining, and real estate activities. To the extent that reforms have cascading effects on these sectors, our cautious assumption tends to underestimate the impact of reforms.

Despite our realistic approach concerning alignment on best practices, it is important to note that implementing the wide range of reforms envisaged in this policy experiment represents an extremely ambitious policy agenda, whose effects would unfold over an extended period of time. Indeed, our model only allows to estimate its ultimate results in the very long period. Keeping this in mind is important to interpret correctly the simulation results.

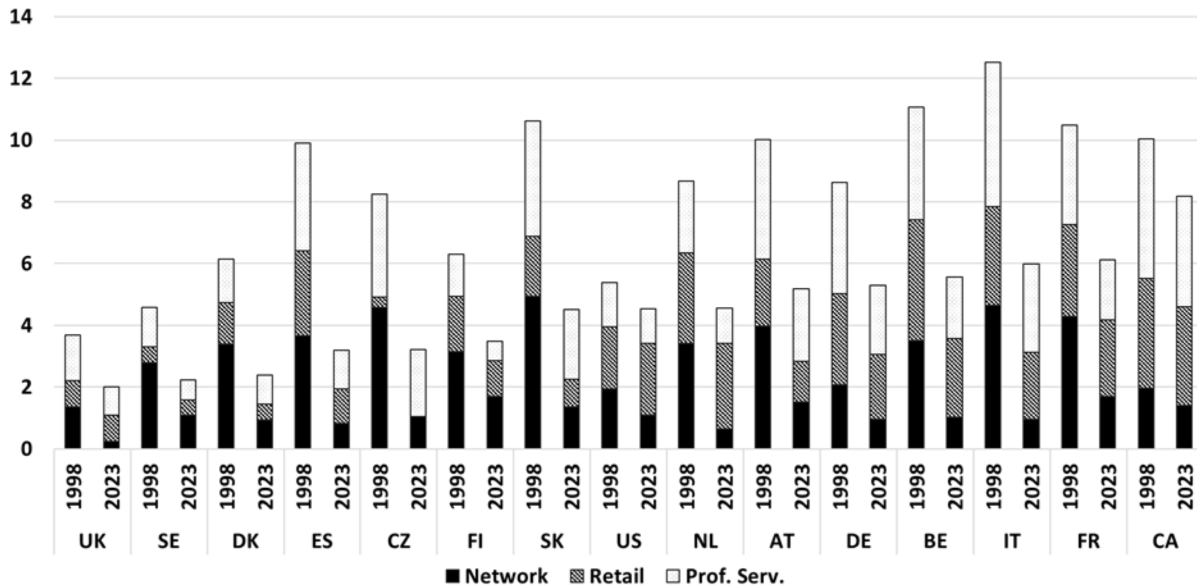
We calculate the long-run aggregate labour productivity effect of reforming regulation in sector j as follows:

$$\begin{aligned} &Aggr.LP\ gain\ from\ reform\ in\ j \\ &= \sum_i \hat{\beta} \times \left(NMR_{c,j} - NMR_{c,j}^{low} \right) \\ &\qquad \times \left(int_{i,j}^{c} \times w_{c,i} \right) \times 100 \end{aligned} \tag{3}$$

Where $NMR_{c,j}$ is our measurement of the level of sector regulation indicator j in country c, $NMR_{c,j}^{low}$ the level of the sector regulation indicator j in the most pro-competitive country, $\hat{\beta}$ the estimated coefficient of equation (2), $w_{c,i}$ the proportion of sector i in the total number of hours worked in country c in 2015, more pre-

23 In the scenario analysis we use the input-output table of Canada to measure intermediate input intensities. This ensure a better accuracy of the potential effects of reforms in Canada.

Chart 6: Evolution of Non-Manufacturing Regulations by Sector in Selected OECD Countries, 1998-2023



Note: The Chart shows the overall level of restrictions to competition in the network sectors, retail distribution and the professional services in each country as well as the contribution of regulatory restrictions in each of these sectors. For each regulated industry, these indicators score regulations over the range 0-6 from least to most restrictive of competition. The index for each industry is then stacked.
Source: Authors calculations based on the OECD indicators of non-manufacturing regulation.

cisely $w_{c,i} = \frac{EMPH_{c,i}^{2015}}{EMPH_{c,TOT}^{2015}}$, and $int_{i,j}^{c}$ the proportion of intermediate input intensity in country c in 2015.[23]

The formula (3) makes clear that, in each country, the aggregate productivity gain from reform in a specific regulated upstream sector depends crucially on three factors: (i) the distance of upstream sectoral regulations from best practice, (ii) the intensity of downstream sectors intermediate sourcing from the regulated sector and (iii) the relative importance of the downstream sectors for the aggregate economy. So, for instance, reform in a specific non-manufacturing upstream sector will have a strong (weak) aggregate productivity impact when the upstream sector supplies a large (small) amount of intermediate inputs to downstream sectors that represent a large (small) share of the economy.

Data

As briefly mentioned above, the study combines several data sources: EUKLEMS & INTANProd data; OECD cross-national data on non-manufacturing regulations revised and made consistent over time especially for this study; OECD cross-national data on employment protection legislation; 2015 OECD Input-Output tables for the United States and the other countries; and Canadian productivity, capital and input-output data provided by StatCan. After

24 Austria-AT, Belgium-BE, Canada-CA, the Czech Republic-CZ, Germany-DE, Denmark-DK, Spain-ES, Finland-FI, France-FR, Italy-IT, the Netherlands-NL, Sweden-SE, the Slovak Republic-SK, the United

cleaning, the combination of these different data sources results in a sample comprising 15 countries[24], for a set of 19 sectors over the 1996-2021 period.[25]

Productivity

The EUKLEMS & INTANProd database provides detailed data for 27 EU member states, the United States, Japan and the UK, covering 40 industries (although coverage may vary over time and across countries) and 23 industrial aggregates over the period 1995 to 2021. The database includes information on key variables for studying productivity, including output, intermediate inputs, gross value added, employment, employee compensation, as well as investment in capital stocks, for both tangible and intangible assets. The analysis in this article uses the revised version of EUKLEMS & INTANProd of 2025 (Bontadini *et al.* (2024)).

We measure TFP and labour productivity in two ways: a "traditional" one where value added is calculated considering non-NA intangible assets as intermediate consumption, and an "extended" one in which non-NA intangible assets are considered as investment.[26] Consistent with the EUKLEMS & INTANProd database, we take "extended" productivity measures as the baseline for our discussion of the results. Results based on the "traditional" measures are similar and are presented in the online appendix (Table A6 in the online appendix). Canada's productivity indicators are constructed from data provided by StatCan, which are consistent with EUKLEMS & INTANProd data.

Labour productivity is expressed as output (value added) per hour worked. In the measurement of the total factor productivity and capital intensity variables we use total tangible assets excluding residential buildings to avoid any bias due to differing housing stocks across countries. All variables are expressed in chain-linked constant PPP US $ with 2015 as the base year.

Anti-competitive Regulations

To identify the impact of competition on productivity, we use data on regulation in key non-manufacturing industries provided by the OECD. These indicators are widely recognized in the literature for their quality since: i) they are explicitly competition-oriented, ii) they record regulations at a granular level, iii) they are regularly updated, and iv) they are less exposed to various types of criticism than other competition indicators – such as for example context dependency, respondent subjectivity and endogeneity problems. In addition the underlying legislative and regulatory data has been vetted by respondent authorities in each country covered by the indicators.

Kingdom-UK, the United States-US

25 All estimates exclude from the outset sectors A, B, and the public sector. The choice of sectors is consistent with the previous study by Bourlès *et al.* (2013). We also exclude sectors C19 and L: the former shows aberrant productivity levels for several countries, and the latter is excluded because it is difficult to define productivity in real estate activities, whose value added largely depends on variations in property prices. For sector definitions see Chart 7, page 27.

26 For more details on variable calculations, see the online appendix.

The indicators cover energy (gas and electricity), transport (rail, road and air), communications, retail distribution and the professional services (accounting, legal, engineering, architecture). These indicators score regulations over the range 0-6 from least to most restrictive of competition. Historical coverage varies by sector, ranging from annually 1975 to 2023 for the network sector to every 5 years from 1998 to 2023 for the distribution and professional services sectors.[27] Since changes in the survey underlying the indicators introduced a break in 2018, this study uses a novel time-consistent indicator series of non-manufacturing regulation that was expressly constructed in collaboration with the OECD. As already mentioned, the price to pay for time consistency was to simplify the indicators reducing the amount of information included in each of them (Table A3 in the online appendix). This has resulted in changes in the ranking of countries relative to the more complete indicators that are available on the OECD website only over the 2018-2023 period. However, in most cases, the time profiles of the simplified and more complete indicators, which reflect reforms occurred over the 1998-2023 period, has remained similar.

Chart 6 shows the values of the NMR indicator (by regulated sector) in 1998 and in 2023, in order to highlight the evolution of regulations. Countries are arranged in ascending order according to the level of regulation observed in 2023.[28] While all the countries in the sample have introduced regulatory reforms, the extent of reforms in Canada was limited and the country has remained relatively regulated in the international comparison.

Labour market regulations are measured by the OECD's Employment Protection Legislation (EPL) indicator. This indicator also ranges from 0 to 6, where 0 represents hiring and firing regulations that are most favourable to labour market flexibility. We use version 1 of this indicator, which compiles data on individual and collective dismissals for both regular and temporary contracts. The indicator is available for the period 1998–2019. To ensure comparable time coverage with the PMR indicators and EUKLEMS data, we extrapolated values for the years 1996–1997 and 2020–2021. The annual evolution of this indicator is shown in Chart A9 in the online appendix, where Canada appears as having the least restrictive hiring and firing rules.

Intermediate Input Intensity

As already explained, to estimate the effect of upstream regulations on downstream sectors we use input–output data for the United States in 2015, while the scenario analysis is based on country-specific 2015 input–output tables.[29] Chart 7 illus-

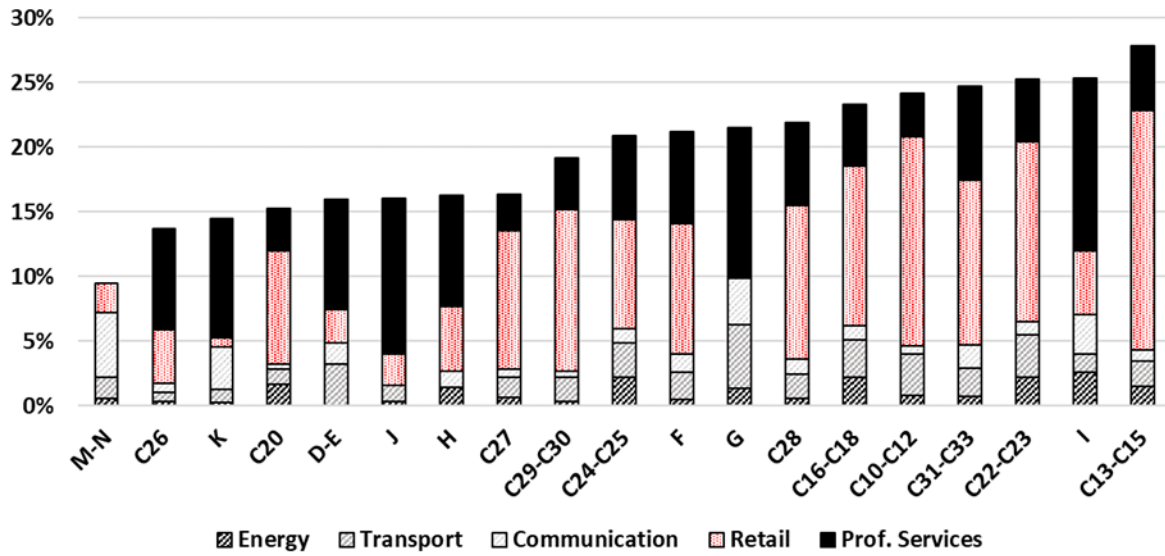
27 To obtain annual series, the values of these indicators were simply interpolated over the 5-year intervals. Sensitivity analyses using different calculation methods (back-casting, extrapolations centered on the survey dates) can be provided by the authors upon request. Overall, results are robust to such variations.

28 Charts A4-A8 in the online appendix show the annual evolution of regulation in our sample countries in each sector over the 1998-2023 period.

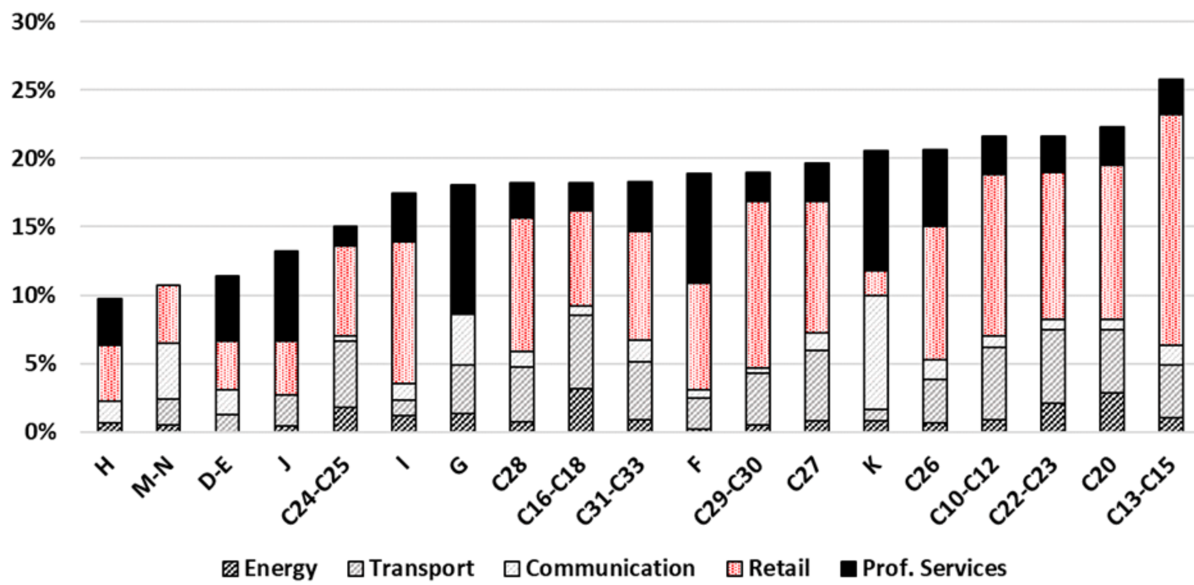
29 For comparability purposes, we use OECD Input-Output Tables for the year 2015.

Chart 7: Intermediate Input Intensity Calculated on Our Database

Panel A: United States in 2015



Panel B: Canada in 2015



Note: Each sector's intensities are computed as the ratio of the value of intermediate inputs sourced from the regulated non-manufacturing sectors over gross output of the sector. We exclude intra-sector intermediate consumption. Detail of sectors : C10–C12 (Manufacture of food products, beverages and tobacco); C13–C15 (Manufacture of textiles, wearing apparel and leather products); C16–C18 (Wood, paper, printing and reproduction); C20 (Chemical products); C22–C23 (Rubber, plastic and non-metallic mineral products); C24–C25 (Basic and fabricated metal products); C26 (Computer, electronic and optical products); C27 (Electrical equipment); C28 (Machinery and equipment n.e.c.); C29–C30 (Motor vehicles and transport equipment); C31–C33 (Furniture, jewellery, musical instruments, toys; repair and installation of machinery); D–E (Energy and utilities); F (Construction); G (Wholesale, retail and vehicle repair); H (Transport and storage); I (Accommodation and food services); J (Telecoms and postal services); K (Financial and insurance activities); M–N (Professional, scientific, technical and administrative services).
Source: OECD Input-Output Tables in 2015

trates intermediate consumption intensity (computed as the ratio of intermediate consumption to gross output) in the United States and Canada in 2015, from the regulated sectors j (energy, transport, communication, distribution and professional services) to the other sectors i of the economy (including the regulated sectors themselves, with $j \neq i$). We exclude self-consumption of intermediates in the regulated sectors.

There is a marked heterogeneity in intensities, since each downstream sector has a distinct use of intermediate inputs.[30] The majority of manufacturing sectors use considerable intermediates from the distribution sector, so the effect of regulation in this sector can be significant on productivity levels. In contrast, the catering (I), finance and insurance (K) and communications (J) sectors use more inputs from the upstream professional services sector.

We map the regulation indicators into the sectoral aggregates described in the input-output tables. The mapping can only be approximate as the tables do not provide the industry detail corresponding to the OECD indicators and the indicators do not cover all the industries aggregated in the tables' sectors: typically, regulations only cover a subset of these industries. The implicit assumption in this article (as well as in much of the empirical research using the OECD indicators of sectoral regulation) is that the subset of regulations covered by the indicators is representative of the wider regulatory stance in each sector.

All results are shown for both multifactor productivity (TFP) and hourly labour productivity (LP) using their "extended" definition that includes both NA and non-NA intangibles. However, results for the "traditional" definition including only NA intangibles are similar (Table A6 in the online appendix). All in all, the model specification is validated by the data. The capital intensity coefficient for the labour productivity estimates corresponds roughly to the average share of capital remuneration in value added, as expected.

Consistent with previous research (Conway *et al.*, 2007; Bourlès *et al.*, 2013; Cette *et al.*; 2016, Cette *et al.*, 2018), regulations in the upstream sectors have a negative impact on productivity in the downstream sectors. Estimates on a shorter period using both the previous and the current version of the regulation indicators produce very similar results (Table 1 columns 2, 3, 5 and 6). Thus, regulation-induced lack of competition in sectors that provide significant intermediate inputs to the whole economy affects the efficiency in which production inputs can be used in downstream sectors that use the regulated products. This induces widespread productivity losses that translate into lower GDP per capita.

While results are qualitatively similar across all columns, the size of the estimated negative effects of regulations on productivity is larger when the previous version of the regulation indicator is used (over the

30 These intensities of intermediate input use vary between approximately 10 per cent and 25 per cent of total production, depending on the sector. The remaining share (75 per cent to 90 per cent of total production) corresponds to the sum of the shares of value added and other intermediate consumptions, for example in industrial products, in total production.

Table 1: Estimation Results

Period	1996–2021	1996–2013	1996–2013	1996–2021	1996–2013	1996–2013
Regression	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	TFP all intangibles (log)	TFP all intangibles (log)	TFP all intangibles (log)	LP all intangibles (log)	LP all intangibles (log)	LP all intangibles (log)
Capital intensity (log-lag)				0.236***	0.237***	0.226***
				(0.014)	(0.020)	(0.020)
NMR_{up}^{new} (lag)	-0.420***	-0.411***		-0.322***	-0.433***	
	(0.096)	(0.125)		(0.093)	(0.121)	
NMR_{up} (lag)			-0.511***			-0.476***
			(0.088)			(0.086)
EPL^d (lag)	-0.334***	-0.345***	-0.281***	-0.085	-0.114	-0.049
	(0.082)	(0.094)	(0.095)	(0.080)	(0.092)	(0.092)
Constant	4.920***	4.884***	5.112***	-2.210***	-2.157***	-2.007***
	(0.086)	(0.103)	(0.102)	(0.090)	(0.111)	(0.107)
Observations	6,155	4,127	4,127	6,155	4,127	4,127
R-squared	0.773	0.863	0.864	0.997	0.998	0.998
Country × time	YES	YES	YES	YES	YES	YES
Country × industry	YES	YES	YES	YES	YES	YES
Industry × time	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

shorter period for which consistent data are available). This difference is particularly large for labour productivity, where the coefficient is almost doubled (compare columns (4) and (6)). However, this difference is due more to the change of period than to the change of regulation indicator, since the estimate on labour productivity with the new indicators but over the short period 1996-2013 also results in an estimated value of the coefficient of the regulation indicator higher than the estimate made over the whole period 1996-2021. A similar finding is obtained when the the sample is truncated just before the COVID crisis (Table A13 in the online appendix).

The decrease in the estimated value of the coefficient of the regulation indicator over the entire 1996-2021 period as compared with the shorter 1996-2013 (or 1996-2019) period may reflect inter alia three factors. First, regulations may have had a weaker impact on productivity in the recent period, due to other possible domestic policy offsets (state aid, etc.) – partly related to the pandemics – or to a diversification of sourcing (including from abroad), which might have reduced their effects for downstream industries. Second, for the same reasons, the measurement of the stringency of regulation indicators might have been less precise in the most recent years than in the past, which might bias the estimate of the regulation coefficient towards zero over the whole period. Third, variability of regulations over time and across countries has declined in the latest period, due to policy convergence, reform fatigue and other policy priorities, reducing the heuristic scope of the NMR indicators.

Labour market regulations, here summarized by the OECD employment protection legislation indicator, also have a negative impact on TFP growth, though the impact appears insignificant on labour productivity. This latter result is consistent with previous analyses, such as Cette *et al.* (2018), who show that labour market regulations have an impact on productivity of the same nature as that of a rise in labour costs: they reduce innovation efforts and the use of the most advanced technologies, which lowers TFP and labour productivity, but simultaneously they encourage substitution between production factors in favor of non-technological capital and against labour, which positively affects labour productivity. All in all, the overall impact on labour productivity resulting from these two contradictory effects is uncertain (and here insignificant), while the impact on TFP is clearly negative.

The estimation results are robust to a number of standard tests. Not only do the results not change significantly over different periods (as discussed), but they also do not change as single countries are dropped from the sample (Table A10 in the online appendix), and are broadly unchanged when specific sectors are dropped (Table A11), or certain years are omitted (Table A9). The results are also very robust to the exclusion of the labour market regulation indicator (Table A7). Finally, as already mentioned, they are robust to different ways of measuring TFP and labour productivity (Table A6) as well as to different ways to account for the break in the NMR indicator series (Table A8 and A12).

As already discussed, there are many reasons why our estimation approach helps neutralize sources of possible endogeneity between upstream regulatory policies and downstream productivity outcomes: the use of a (lagged) indicator that reflects slow-moving policy changes, the use of an input-output table from a country (the United States) excluded from estimations and the "fully saturated" fixed effects structure of the estimated model, which account for most omitted variables and confounding factors. Indeed, while filtering out fixed effects from both productivity and regulation variables leaves little variance to be explained by changes over time in the latter (Table A5 in the online appendix), visual inspection suggests that the remaining variance highlights a negative correlation between reform trends and changes in productivity (see Charts A10-A11 in the online appendix).[31]

However, we cannot exclude some residual upward endogeneity bias in the estimated coefficients in one instance of possible reverse causality: if firms in sectors in which downstream productivity has increased over the sample period were able to successfully lobby for more procompetitive regulations in upstream sectors. This seems unlikely as casual observation would suggest for instance that it was the combination of technological progress with more procompetitive policies in sectors like energy, transport and communications that supported efficiency improvements in a range of sectors (including hi-tech ones), rather than the reverse.

Other potential sources of bias in our estimates are related to measurement error,

31 These figures plot residual variance in labour productivity vs residual variance in regulations when fixed effects are filtered out of the original variables. They highlight a negative relationship between (filtered) productivity and (filtered) regulations overall and in selected country examples, even before additional controls for capital intensity and EPL are included in the regression.

which however would tend to make coefficients smaller and less significant. For instance, the choice of relying on the US 2015 input-output table to ensure exogeneity could imply two kinds of errors. First, it could provide a poor proxy for intermediate input use in other countries. Second, to the extent that such coefficients partly reflect changes in the use of intermediate inputs due to past deregulation, it could make identification of the effects of regulations on productivity more difficult (as part of these effects would already be incorporated in the input-output coefficients).

Another source of measurement error is related to the approximate mapping of industry-specific regulations into broader sector aggregates. To the extent that regulations are not representative of these sectors' market environment, their trickle down effects could be mismeasured, blurring the identification of their effects on productivity. Among all the regulated sectors covered in the analysis, the approximation is particularly rough for retail distribution because its regulatory settings are also attributed to wholesale trade and vehicle repair, which constitute the bulk of intermediate inputs flowing to other sectors (since in most countries retail distribution is mostly an intermediate input to its own output).

Given that, overall, the sector "retail and wholesale trade and vehicle repair" represents an important share of intermediate inputs in the economy (Chart 7), error in measuring regulation in this sector could bias significantly the regression results. However, excluding this sector from our summary indicator of regulation (NMR^{new}_{up}) and estimating the effects of retail regulation separately leaves regression results largely unaffected. The estimated effect of other upstream regulations on downstream productivity remains negative and significant, with even a larger impact coefficient, while the separate effect of retail regulation is not significant at conventional levels (Table A14).[32] As we shall see, error in measuring regulations in this sector (due to approximate mapping) affects the results of the scenario analysis discussed in the next section.

Finally, our relatively limited coverage of the broad set of regulations potentially affecting productivity performance could be a source of overestimation of the impact coefficients. This might be the case if regulations we do not cover are positively correlated with the ones included in the NMR. For instance, FDI and both foreign and domestic service trade restrictions were shown to be significant in Canada. These restrictions are likely to affect especially the knowledge-intensive sectors that are driving productivity in advanced economies. The NMR could capture part of these omitted effects, thereby overestimating the effects of regulations in upstream sectors on aggregate productivity.

Scenario Analysis

32 Insignificance of retail regulations when it is included separately in the same regression is consistent with mismeasurement issues.

Using the estimation results just discussed, it is possible to simulate the effects of various kinds of product market reforms on labour productivity. In this section, we focus on ambitious reforms aimed at instantaneously aligning 2023 sectoral regulations on those observed in best practice countries in the sample. Based on our NMR_{up}^{new} indicators, best regulatory practices in 2023 ($NMR_{c,j}^{low}$) are observed in the Czech Republic for retail distribution, in Sweden for professional services and in the UK for each of the three network activities (energy, transport and communications).

This reform agenda is ambitious because industry-specific regulatory gaps between countries are large and closing them at once in all sectors is difficult for both practical and political reasons. Historical experience suggests that reforms are usually legislated and implemented gradually and often meet resistance from incumbents and interest groups. Moreover, specific country conditions require the careful tailoring of reforms to match national concerns. For these reasons, the scenario proposed here should be considered only illustrative of the potential (very) long-run productivity and GDP per capita gains that could be obtained with an ambitious and forward-looking reform agenda.

For the scenario analysis we use formula (3) described above. The coefficient β used for the simulation is that corresponding to the estimation results provided in column (4) of Table 1, and we use the Canadian input–output table to better capture the trickle-down effects of reforms on downstream sectors in our country of interest. However, we use country-specific sector shares in total hours w to aggregate sector productivity gains to the national level in order to take into account cross-country differences in industry structure.

The effect of these reforms is calculated for all sectors represented in our database, and then evaluated at the national level, assuming a zero effect on sectors not covered. The omitted sectors include the non-market sector, i.e., public administration, but also agriculture, mining and oil extraction and real estate activities. If, as expected, reforms in the covered sectors also have a positive impact on productivity in these omitted sectors, our conservative assumption would tend to underestimate the simulated reform impact on aggregate productivity and GDP per capita. At the same time, as noted earlier, the possibility that our regression results also capture changes in other sector-specific regulations that are omitted from our analysis would tend to overestimate this impact.

In interpreting the simulation results, one should keep in mind that-aside from the size of the impact coefficient β-they depend on three country-specific factors: the distance of sectoral regulations from best practice, the intensity with which intermediates sourced from regulated sectors are used downstream (the input–output coefficients), and the weight of each downstream sector in the economy. Together, these factors will determine cross-country differences in the impact of the simulated reforms on aggregate productivity and GDP per capita. Given the importance of regulation gaps and input–output coefficients for the simulation outcomes, the online appendix provides some sensitivity analysis. First, we explore an alternative scenario in which regulations are aligned on those of the United States. This corresponds to a less ambitious reform agenda. Second, we perform the best practice alignment scenario using regression results that exclude retail regulation from the NMR_{up}^{new} variable. This accounts for the possibility that the simulation results are inflated by error in measurement in the approximate mapping of retail regulation to the broader "Retail, wholesale trade and vehicle repair" sector.

Chart 8 shows the main simulation results. For each country, the total height of the bars indicates the overall effect on GDP per capita of reforms aligning regulations in each regulated activity to the best practice. This overall effect is broken down by the sector of regulated activity in which the reforms are implemented, the two bars showing the effect of different reforms, taking these estimated coefficients all else equal.

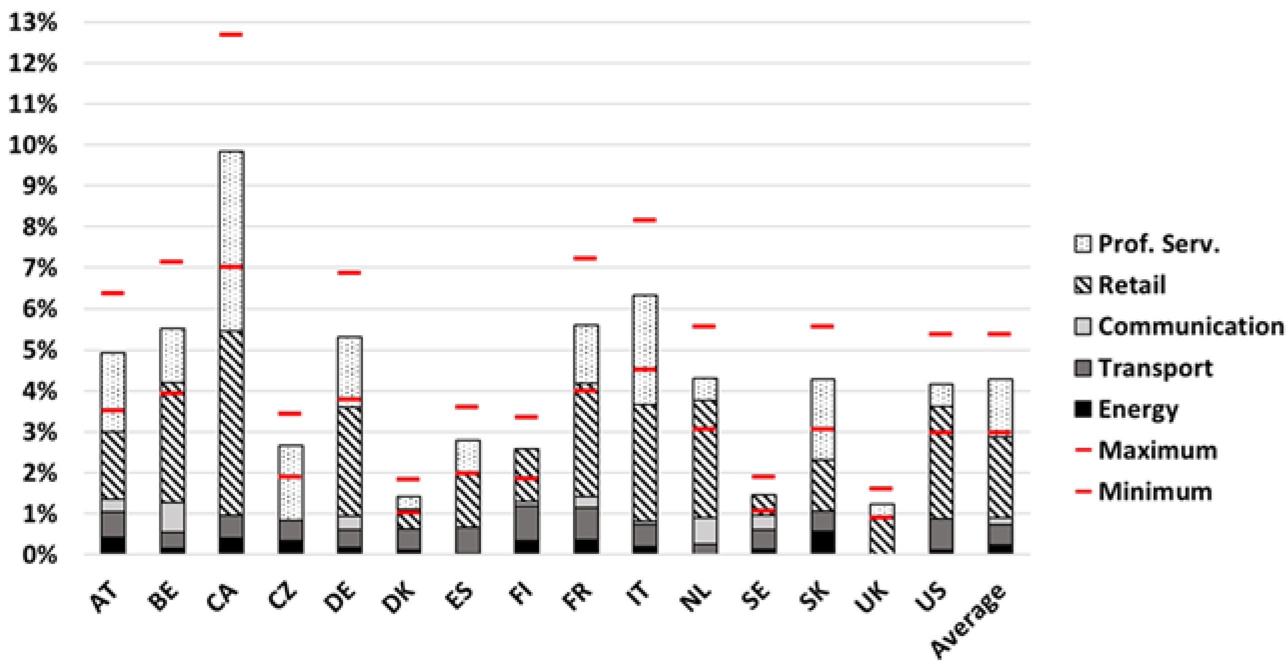
The average impact of reforms on GDP ranges from around 1.5 per cent in Denmark, Sweden and the UK, where the initial level of regulations is the closest to best practice and therefore the reforms envisaged are the smallest, to almost 10 per cent in Canada, where the initial level of some regulations is the farthest away from best practice. Behind Canada, the countries where reforms would have the most favorable impact on GDP per capita are Italy, France and Belgium (around 6.5 per cent, 5.5 per cent and 5.5 per cent respectively). On average, the effect is around 4.5 per cent for the countries in the sample. In all countries, the most significant effects come from reforms in the professional services and retail distribution.

However, further analysis suggests that the effect of retail distribution could be overstated by weighting it with the input–output coefficient corresponding to the larger aggregate that includes also wholesale trade and vehicle repair. Performing the same simulation omitting the impact of retail regulation, whose effect is scarcely significant when it is estimated separately (Table A14 in the online appendix), reduces the impact of reforms on the GDP per capita of the average country from 4.5 per cent to 3 per cent and the impact in Canada from 10 per cent to 6.5 per cent (Chart A12 in the online appendix). The impact on the Canadian economy remains the highest among the countries in our sample, followed by Italy (4.2 per cent), Austria (4 per cent), the Slovak Republic (3.8 per cent) and France (3.5 per cent).

Given the current level of Canadian GDP, the maximum impact of reform would amount to an overall \$300 billion CAD increase in GDP, equivalent to a per capita gain of about \$7,500 CAD. Assuming that the effects of reforms would be felt over a period of 5 to 10 years, this would correspond to an annual per capita gain of about \$750 to \$1,500 CAD. Moreover, the total 10 per cent gain in GDP per capita for Canada corresponds to around 50 per cent of the country's current GDP per capita gap with the United States. Excluding reforms in trade, these numbers still be significant, with 195 billion CAD increase in GDP, equivalent to \$4,875 CAD increase per capita and annual per capita gains ranging from \$488 to \$976 CAD.

The United States would benefit from a GDP per capita gain of more than 4 per cent from the implementation of the simulated reforms, as restrictions to competi-

Chart 8: Simulation of the Impact from Adopting Best Regulatory Practices (long-run per cent gains in GDP and GDP per capita)



Note: The Chart shows the point estimates of the effects of regulatory reforms that align regulations in each sector to best practices in our sample as well as their confidence interval (one standard error). The simulations are based on the coefficient of NMR in Table 1 column 4 and on country-specific intensities of intermediate inputs.
Source: Authors' calculations.

tion remain in a number of sectors. But if Canada were to undertake less ambitious reforms aimed at easing its regulations, in each regulated sector, to the level currently observed in the United States, the Canadian GDP per capita gains would be about 5 per cent (see Chart A13 in the online appendix), leaving about three quarters of Canada's productivity gap with the United States to be filled.[33] Other reforms would therefore be necessary in Canada to bring it closer to the average level of labour productivity observed in the United States, these may entail lowering interprovincial barriers to trade or barriers to FDI for example, or reforming the labour or financial markets.

The potential gains in labour productivity and GDP per capita from reforming product markets in a procompetitive sense are significant. However, they should be put into perspective. First, they result from an ambitious reform effort, as in some sectors the current regulatory gap between Canada and best practice countries is large. Second, they should be considered attainable only gradually over a long time span. Given their scope and depth, the reforms required to adopt best practices will need time to be implemented and the corresponding productivity gains will also unfold slowly. This observation raises the eternal problem of undertaking ambi-

33 This scenario assumes that the United States leaves its regulations unchanged at the 2023 level.

tious structural reforms: their political cost is immediate and can be high, as the professions and activities concerned oppose them and defend their anti-competitive rents, while the induced economic benefits only appear gradually. The gap between the immediate and delayed effects of reforms and between the beneficiaries and the losers from reforms contributes to explain why many countries, including Canada, may find it difficult to undertake such wide-ranging and swift regulatory changes.

Finally, as in all simulations based on empirical estimates, the scenario analysis assumes all else equal. It cannot account for several general equilibrium effects that can be ignited by reforms themselves. These include changes in the allocation of resources across sectors, changes in the intensity of use of intermediate inputs, changes in the allocation of hours worked across sectors and changes in the total hours worked in the economy. Also, it is assumed that benchmark countries, whose regulations are taken as representative of best practices or as a reference point (e.g. for the United States-Canada comparison) on which regulations are aligned, do not change their regulations during the experiment. The impact of these assumptions on the entity of the aggregate productivity gains spurred by reforms is difficult to assess as some of these changes may have conflicting effects on sectoral and aggregate productivity.

Conclusions

Our article estimates the effects of anticompetitive regulations in non-manufacturing sectors that provide key intermediate inputs to the economy on the hourly productivity performance of sectors downstream. Then, our simulations use the share of hours worked in each sector to provide the overall impact of reforms on aggregate productivity and GDP per capita. We estimate that, in the very long term, Canadian GDP could rise by between 6.5 and 10 per cent, depending on the range of reforms implemented. The maximum gains would correspond to roughly half the current income gap with the United States.

We consider that our estimates likely provide a lower bound on the gains that could be obtained from a wider set of reforms. First, in order to obtain unbiased estimates we ignore the gains originating from efficiency increases in the regulated upstream sectors themselves, which would also possibly contribute to boosting aggregate productivity. Second, while our sectoral analysis accounts for within-sector labour and capital reallocations ignited by reforms (e.g. from low to high productivity firms), it cannot account for the possible reallocations between sectors (e.g. from low to high-tech or low to high knowledge-intensive sectors). These reallocation effects have the potential to be relevant in Canada where, according to Chen and Tombe (2024), resource misallocation is high and rising, accounting for half of the widening productivity gap between Canada and the United States. Third, our analysis does not cover the potential gains to be obtained from lowering other types of regulations, as for instance trade and investment barriers internally (via the elimination of interprovincial barriers and harmonization of provincial regulatory policies) or internationally (via the easing of barriers to FDI and services trade), which remain relatively high in Canada.[34] While accounting for these other potential reforms in the empirical analysis could reduce the estimated impact of the set of non-manufacturing reforms that are considered in our analysis, it is reasonable to expect that their joint effects on productivity and GDP per capita would be greater than those resulting from our simulations. These further (likely positive) effects of reforms could however be mitigated by other offsetting general equilibrium adjustments. Future research could usefully investigate these additional channels in order to obtain a fuller picture of the potential growth benefits of implementing a procompetitive reform agenda in Canada.

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34 Our assessment of the effects of NMR regulations on productivity can indirectly take into account the effects of regulations on FDI if there is a correlation between these two types of regulations. However, this is not the case for the portion of FDI regulations that is not correlated with NMR regulations. This means that a reduction in FDI regulations could add to the impact on productivity that we are assessing.

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Appendix: The Potential Impact of Procompetitive Regulatory Reforms on Productivity and Growth in Canada

Details on Variable Calculations

Total Factor Productivity ($TFP_{c,i,t}$) represents the efficiency with which factors of production are combined to generate value added. The definition of the variables are based on the Jorgenson production function framework.

Total factor productivity is provided directly by EUKLEMS & INTANProd in the form of an index, base 100 in 2015, calculated as the Solow residual using the Jorgenson approach.

We use two measures of total factor productivity (TFP):

The non-extended measure, taken from the EU-KLEMS & INTANProd statistical module, which serves as a reference for national accounts variables.

The extended measure, available in the EU-KLEMS & INTANProd analytical module, uses value added consistent with the new intangible assets that are not yet accounted for in national accounts, such as design, branding, organizational capital, training, and new financial products

Labour Productivity ($LP_{c,i,t}$) is calculated as the ratio between value added (chain-linked volumes (2015), millions of national currency) and the number of hours worked by persons employed (thousand hours).

As with total factor productivity, there are two measures of labour productivity: an extended version and a non-extended version.

The Capital Intensity $(\text{int } K)_{c,i,t}$ is calculated as the ratio between total tangible (excluding residential) and intangible assets (expressed in chained volumes, base 2015, in millions of national currency) and the number of hours worked (in thousands of hours). Depending on the definition of the endogenous variable (extended or non-extended labour productivity), new intangible assets are included or excluded from the calculation.

It is important to note that, due to a lack of information, the calculation of intangible assets for Sweden does not include "Computer software and databases" among the intangible assets included in the national accounts, nor "NFP - New Financial Products" among those excluded from the national accounts.

Table A1. Country Coverage of EU-KLEMS

Code	Label	Further information
AT	Austria	1995–2021
BE	Belgium	1999–2021
CA	Canada	2000–2020
CZ	Czech Republic	2002–2021
DE	Germany	1995–2021
DK	Denmark	2000–2021
ES	Spain	1995–2021 (lack of information for sectors C20, C26 and C27)
FI	Finland	1995–2021
FR	France	1995–2021
IT	Italy	1995–2021
NL	Netherlands	1995–2021
SE	Sweden	1995–2021 (lack of information for sector C20)
SK	Slovakia	2014–2021 (lack of information for sector I)
UK	United Kingdom	1995–2020
US	United States	1995–2021 (lack of information for sector C28)

Source: Computed by the authors based on sample data.

Table A2. Sector Coverage of EU-KLEMS

Code	Label	Description
C10–C12		Manufacture of food products; beverages and tobacco products
C13–C15		Manufacture of textiles, wearing apparel, leather and related products
C16–C18		Manufacture of wood, paper, printing and reproduction
C20		Manufacture of chemicals and chemical products
C22–C23		Manufacture of rubber and plastic products and other non-metallic mineral products
C24–C25		Manufacture of basic metals and fabricated metal products, except machinery and equipment
C28		Manufacture of machinery and equipment n.e.c.
C26		Manufacture of computer, electronic and optical products
C27		Manufacture of electrical equipment
C29–C30		Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment
C31–C33		Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment
D–E		Electricity, gas, steam and air conditioning supply; Water supply; sewerage, waste management and remediation activities
F		Construction
G		Wholesale and retail distribution and repair of motor vehicles and motorcycles
I		Accommodation and food service activities
H		Land transport and transport via pipelines; Water transport; Air transport; Warehousing and support activities for transportation
J		Postal, courier activities and Telecommunication
K		Financial and insurance activities
M–N		Professional, scientific and technical activities; Administrative and support service activities

Source: Computed by the authors based on sample data.

Table A3. Non-Manufacturing Regulation: OECD PMR 2023 vs Simplified 1998–2023 OECD NMR Indicators

Panel A. Energy, Transport and Communication Regulation (ETCR) Indicators

ETCR PMR 2023									
Indicator	**Energy**		**Transport**					**Communications**	
	Electricity	Gas	Air	Rail	Road freight	Road coach	Water	Fixed	Mobile
Governance	3	3	3	3	3	3	3	3	3
Entry	8	9	6	5	8	5	5	11	10
Vertical separation	4	4	–	1	–	–	1	2	–
Price regulation	4	4	2	–	2	1	2	7	4
Other	–	New regulatory issues 4	–	–	Foreign entry 3	Foreign entry 2	Foreign entry 4	New regulatory issues 6	New regulatory issues 6
ETCR simplified 1998–2023									
Indicator	**Energy**		**Transport**					**Communications**	
	Electricity	Gas	Air	Rail	Road freight	Road coach	Water	Fixed	Mobile
Governance	1	1	1	–	–	–	–	1	1
Entry	3	2	2	2	3	–	–	2	2
Vertical separation	1	1	–	1	–	–	1	1	–

Panel B. Indicators of Regulation in Professional Services

Professions PMR 2023						
Indicator	**Lawyers**	**Notaries**	**Accountants**	**Civil engineers**	**Architects**	**Real estate agents**
Form of business/governance	6	6	6	6	6	6
Entry	6	6	6	6	6	6
Advertisement	1	1	1	1	1	1
Price regulation	2	2	2	2	2	2
Foreign entry	3	3	3	3	3	3
Professions simplified 1998–2023						
Indicator	**Lawyers**	**Notaries**	**Accountants**	**Civil engineers**	**Architects**	**Real estate agents**
Form of business/governance	2	–	2	2	2	–
Entry	3	–	3	3	3	–
Advertisement	1	–	1	1	1	–
Price regulation	2	–	2	2	2	–

Panel C. Indicators of Regulation in Retail Distribution

Retail Distribution PMR 2023			
Indicator	**Food**	**Clothes**	**Pharmaceuticals**
Entry	11	11	5
Opening hours	3	3	1
Price regulation	5	5	1
Advertisement	–	–	1
Retail Distribution simplified 1998–2023			
Indicator	**Food**	**Clothes**	**Pharmaceuticals**
Entry	4	4	–
Opening hours	3	3	–
Price regulation	5	5	–

Source: Computed by the authors using OECD PMR information.
Note: The numbers refer to the number of sub-indicators used to construct the aggregate indicator.

Table A4. Mapping of NMR Indicators to NACE Non-manufacturing Sectors

NACE code	NACE label	NMR indicator
D–E	Electricity, gas, steam and air conditioning supply ; Water supply; sewerage, waste management and remediation activities	Energy
G	Wholesale and retail distribution and repair of motor vehicles and motorcycles	Retail distribution
H	Land transport and transport via pipelines, Water transport, Air transport ; Warehousing and support activities for transportation	Transport
J	Postal, courier activities and Telecommunication	Communications
M–N	Professional, scientific and technical activities ; Administrative and support service activities	Professional services

Source: Provided by the authors of the article.

Table A5. Analysis of Variance (R^2)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	country	industry	year	Country*year	Country*industry	Industry*year	Country*industry Country*year Industry*year
TFP all intangibles (log)	0.0538	0.1782	0.0616	0.1896	0.4123	0.4890	0.7832
LP all intangibles (log)	0.1432	0.5408	0.0594	0.2383	0.7972	0.6642	0.9571
Capital intensity (all)	0.7646	0.1595	0.0146	0.7693	0.9914	0.1758	0.9970
NMR_{up}^{new} (lag)	0.4834	0.2510	0.1625	0.6650	0.8033	0.4242	0.9952
NMR_{up} (lag)	0.4033	0.2974	0.1848	0.6160	0.7611	0.5024	0.9912
EPL^d (lag)	0.4537	0.4376	0.0100	0.5047	0.9432	0.4487	0.9958

Source: Calculated by the authors based on our sample.
Example: The country*year fixed effects explain 18.96% of the variability in total factor productivity (TFP).

Table A6. Main Results with Total Factor and Labour Productivity not Extended (NA intangibles)

Period regression	1996–2021 (1)	1996–2013 (2)	1996–2013 (3)	1996–2021 (4)	1996–2013 (5)	1996–2013 (6)
VARIABLES	**tfp NA intangibles (log)**	**tfp NA intangibles (log)**	**tfp NA intangibles (log)**	**lp NA intangibles (log)**	**lp NA intangibles (log)**	**lp NA intangibles (log)**
Capital intensity (log-lag)				0.168*** (0.014)	0.162*** (0.019)	0.152*** (0.019)
NMR_{up}^{new} (lag)	−0.549*** (0.105)	−0.568*** (0.137)		−0.428*** (0.103)	−0.584*** (0.134)	
NMR_{up} (lag)			−0.585*** (0.097)			−0.568*** (0.095)
EPL^d (lag)	−0.288*** (0.090)	−0.305*** (0.104)	−0.230** (0.104)	−0.039 (0.088)	−0.090 (0.101)	−0.013 (0.102)
Constant	5.000*** (0.094)	4.978*** (0.113)	5.169*** (0.113)	−2.356*** (0.098)	−2.283*** (0.120)	−2.146*** (0.117)
Observations	6,155	4,127	4,127	6,155	4,127	4,127
R-squared	0.764	0.854	0.855	0.997	0.998	0.998
Country*time	YES	YES	YES	YES	YES	YES
Country*industry	YES	YES	YES	YES	YES	YES
Industry*time	YES	YES	YES	YES	YES	YES

Source: Estimated by the authors.

Table A7. Main Results Without Employment Protection Law (EPL)

Period regression	1996–2021 (1)	1996–2013 (2)	1996–2013 (3)	1996–2021 (4)	1996–2013 (5)	1996–2013 (6)
VARIABLES	**TFP all intangibles (log)**	**TFP all intangibles (log)**	**TFP all intangibles (log)**	**LP all intangibles (log)**	**LP all intangibles (log)**	**LP all intangibles (log)**
Capital intensity (log-lag)				0.234*** (0.014)	0.235*** (0.020)	0.225*** (0.020)
NMR_{up}^{new} (lag)	−0.400*** (0.096)	−0.400*** (0.125)		−0.317*** (0.093)	−0.429*** (0.121)	
NMR_{up} (lag)			−0.538*** (0.088)			−0.481*** (0.085)
Constant	4.838*** (0.083)	4.806*** (0.101)	5.084*** (0.102)	−2.234*** (0.088)	−2.188*** (0.108)	−2.014*** (0.106)
Observations	6,155	4,127	4,127	6,155	4,127	4,127
R-squared	0.773	0.862	0.863	0.997	0.998	0.998
Country*time	YES	YES	YES	YES	YES	YES
Country*industry	YES	YES	YES	YES	YES	YES
Industry*time	YES	YES	YES	YES	YES	YES

Source: Estimated by the authors.

Table A8. Results with Stepwise Break in NMR Indicator*

1996–2021	**(1)**	**(2)**
VARIABLES	**TFP all intangibles (log)**	**LP all intangibles (log)**
Capital intensity (log-lag)		0.232*** (0.014)
$NMR_{uprc} \times (1 - d2016)$ (lag)	−0.335*** (0.050)	−0.301*** (0.048)
$NMR_{uprc} \times d2016$ (lag)	−0.518*** (0.080)	−0.416*** (0.078)
Constant	4.983*** (0.072)	−2.088*** (0.077)
Observations	6,155	6,155
R-squared	0.775	0.997
Country*time	YES	YES
Country*industry	YES	YES
Industry*time	YES	YES

Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
*Results do not change when EPL is included.
Source: Estimated by the authors.

Table A9. Sensitivity to Year Exclusion

Panel A: Total Factor Productivity

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Exclusion of :	Y1996	Y1997	Y1998	Y1999	Y2000	Y2001	Y2002	Y2003	Y2004	Y2005	Y2006	Y2007	Y2008
VARIABLES	TFP all intangibles (log)												
NMR_{up}^{new} (lag)	-0.340***	-0.352***	-0.365***	-0.369***	-0.451***	-0.454***	-0.447***	-0.483***	-0.459***	-0.445***	-0.428***	-0.412***	-0.413***
	(0.098)	(0.097)	(0.097)	(0.098)	(0.097)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)
EPL^{d} (lag)	-0.331***	-0.336***	-0.329***	-0.339***	-0.341***	-0.341***	-0.338***	-0.313***	-0.317***	-0.320***	-0.335***	-0.331***	-0.334***
	(0.087)	(0.087)	(0.087)	(0.082)	(0.083)	(0.083)	(0.083)	(0.082)	(0.083)	(0.084)	(0.083)	(0.084)	(0.083)
Constant	4.850***	4.874***	4.881***	4.885***	4.946***	4.949***	4.942***	4.963***	4.945***	4.937***	4.927***	4.911***	4.914***
	(0.085)	(0.086)	(0.086)	(0.087)	(0.086)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)
Observations	5,969	5,969	5,969	5,950	5,931	5,931	5,931	5,912	5,912	5,912	5,912	5,912	5,912
R-squared	0.760	0.763	0.763	0.766	0.768	0.766	0.767	0.770	0.769	0.770	0.771	0.772	0.774

1996-2021	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Exclusion of :	Y2009	Y2010	Y2011	Y2012	Y2013	Y2014	Y2015	Y2016	Y2017	Y2018	Y2019	Y2020	Y2021
VARIABLES	TFP all intangibles (log)												
NMR_{up}^{new} (lag)	-0.430***	-0.420***	-0.424***	-0.429***	-0.433***	-0.428***	-0.407***	-0.404***	-0.414***	-0.428***	-0.419***	-0.446***	-0.427***
	(0.098)	(0.098)	(0.097)	(0.097)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.099)	(0.098)	(0.098)
EPL^{d} (lag)	-0.324***	-0.347***	-0.341***	-0.339***	-0.334***	-0.335***	-0.337***	-0.338***	-0.362***	-0.358***	-0.334***	-0.325***	-0.314***
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.084)	(0.085)	(0.085)	(0.084)	(0.082)	(0.082)
Constant	4.926***	4.922***	4.925***	4.925***	4.929***	4.924***	4.908***	4.907***	4.917***	4.929***	4.915***	4.932***	4.914***
	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.088)	(0.087)	(0.087)
Observations	5,912	5,912	5,912	5,912	5,893	5,893	5,893	5,893	5,893	5,893	5,893	5,912	5,942
R-squared	0.775	0.776	0.776	0.779	0.779	0.780	0.781	0.781	0.780	0.781	0.783	0.785	0.781

Panel B: Labour Productivity

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Exclusion of :	Y1996	Y1997	Y1998	Y1999	Y2000	Y2001	Y2002	Y2003	Y2004	Y2005	Y2006	Y2007	Y2008
VARIABLES	LP all intangibles (log)												
NMR_{up}^{new} (lag)	-0.230**	-0.242**	-0.265***	-0.275***	-0.352***	-0.350***	-0.342***	-0.375***	-0.357***	-0.346***	-0.330***	-0.318***	-0.317***
	(0.095)	(0.095)	(0.094)	(0.095)	(0.094)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)
EPL^{d} (lag)	-0.082	-0.081	-0.084	-0.093	-0.094	-0.091	-0.088	-0.073	-0.071	-0.072	-0.082	-0.077	-0.084
	(0.085)	(0.085)	(0.084)	(0.080)	(0.081)	(0.081)	(0.081)	(0.080)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
Constant	-2.264***	-2.247***	-2.237***	-2.234***	-2.193***	-2.187***	-2.194***	-2.187***	-2.200***	-2.205***	-2.216***	-2.230***	-2.226***
	(0.090)	(0.091)	(0.091)	(0.091)	(0.091)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)
Observations	5,969	5,969	5,969	5,950	5,931	5,931	5,931	5,912	5,912	5,912	5,912	5,912	5,912
R-squared	0.998	0.998	0.998	0.998	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997

1996-2021	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Exclusion of :	Y2009	Y2010	Y2011	Y2012	Y2013	Y2014	Y2015	Y2016	Y2017	Y2018	Y2019	Y2020	Y2021
VARIABLES	LP all intangibles (log)												
NMR_{up}^{new} (lag)	-0.334***	-0.322***	-0.324***	-0.328***	-0.332***	-0.322***	-0.306***	-0.307***	-0.320***	-0.337***	-0.334***	-0.365***	-0.343***
	(0.095)	(0.095)	(0.095)	(0.094)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.096)	(0.095)	(0.095)
EPL^{d} (lag)	-0.069	-0.095	-0.091	-0.092	-0.091	-0.087	-0.088	-0.088	-0.111	-0.106	-0.084	-0.077	-0.069
	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.082)	(0.082)	(0.082)	(0.080)	(0.080)
Constant	-2.211***	-2.208***	-2.202***	-2.187***	-2.193***	-2.207***	-2.219***	-2.221***	-2.212***	-2.208***	-2.212***	-2.179***	-2.200***
	(0.092)	(0.092)	(0.092)	(0.091)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)
Observations	5,912	5,912	5,912	5,912	5,893	5,893	5,893	5,893	5,893	5,893	5,893	5,912	5,942
R-squared	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.998	0.998

Source: Estimated by the authors.

Table A10. Sensitivity to Country Exclusion

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Exclusion of :	AT	BE	CA	CZ	DE	DK	ES	FI	FR	IT	NL	SE	SK	UK
VARIABLES							TFP all intangibles (log)							
NMR_{up}^{new} (lag)	-0.331***	-0.545***	-0.470***	-0.523***	-0.464***	-0.395***	-0.498***	-0.501***	-0.416***	-0.252**	-0.394***	-0.332***	-0.456***	-0.291***
	(0.103)	(0.102)	(0.099)	(0.096)	(0.100)	(0.099)	(0.107)	(0.100)	(0.101)	(0.101)	(0.100)	(0.101)	(0.097)	(0.091)
EPL^d (lag)	-0.327***	-0.386***	-0.345***	-0.289***	-0.301***	-0.303***	-0.284***	-0.324***	-0.372***	-0.442***	-0.288***	-0.319***	-0.331***	-0.416***
	(0.083)	(0.084)	(0.084)	(0.082)	(0.089)	(0.085)	(0.086)	(0.084)	(0.086)	(0.117)	(0.084)	(0.084)	(0.082)	(0.076)
Constant	4.542***	5.022***	4.958***	4.986***	4.938***	4.902***	4.967***	4.994***	4.916***	4.836***	4.880***	4.849***	4.945***	4.818***
	(0.054)	(0.090)	(0.088)	(0.085)	(0.090)	(0.089)	(0.093)	(0.089)	(0.090)	(0.091)	(0.089)	(0.090)	(0.086)	(0.080)
Observations	5,661	5,718	5,775	5,794	5,661	5,661	5,739	5,661	5,661	5,672	5,661	5,687	5,984	5,680
R-squared	0.779	0.779	0.780	0.782	0.767	0.774	0.775	0.780	0.768	0.780	0.780	0.764	0.779	0.762

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Exclusion of :	AT	BE	CA	CZ	DE	DK	ES	FI	FR	IT	NL	SE	SK	UK
VARIABLES							LP ext (log)							
NMR_{up}^{new} (lag)	-0.261***	-0.398***	-0.369***	-0.433***	-0.350***	-0.374***	-0.425***	-0.419***	-0.310***	-0.193**	-0.267***	-0.216**	-0.351***	-0.231***
	(0.099)	(0.099)	(0.096)	(0.093)	(0.097)	(0.097)	(0.105)	(0.097)	(0.098)	(0.109)	(0.098)	(0.098)	(0.094)	(0.088)
EPL^d (lag)	-0.066	-0.121	-0.087	-0.059	-0.039	-0.080	-0.002	-0.081	-0.091	-0.204	-0.046	-0.080	-0.087	-0.175**
	(0.081)	(0.082)	(0.081)	(0.079)	(0.087)	(0.083)	(0.084)	(0.082)	(0.084)	(0.126)	(0.082)	(0.082)	(0.080)	(0.075)
Constant	-2.603***	-2.143***	-2.233***	-2.183***	-2.217***	-2.166***	-2.134***	-2.131***	-2.196***	-2.268***	-2.294***	-2.271***	-2.187***	-2.232***
	(0.067)	(0.094)	(0.093)	(0.090)	(0.095)	(0.094)	(0.099)	(0.094)	(0.096)	(0.096)	(0.095)	(0.095)	(0.091)	(0.085)
Observations	5,661	5,718	5,775	5,794	5,661	5,661	5,739	5,661	5,661	5,672	5,661	5,687	5,984	5,680
R-squared	0.998	0.998	0.960	0.998	0.998	0.998	0.998	0.998	0.997	0.997	0.998	0.998	0.998	0.998

Source: Estimated by the authors.

Table A11. Sensitivity to Sector Exclusion

Panel A: Total Factor Productivity

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exclusion of :	C10_C12	C13_C15	C16_C18	C20	C22_C23	C24_C25	C26	C27	C28	C29_C30
VARIABLES					TFP all intangibles (log)					
NMR_{up}^{new} (lag)	-0.454***	-0.590***	-0.494***	-0.317***	-0.356***	-0.399***	-0.151*	-0.370***	-0.473***	-0.439***
	(0.100)	(0.100)	(0.099)	(0.096)	(0.100)	(0.098)	(0.089)	(0.096)	(0.097)	(0.097)
EPL^d (lag)	-0.398***	-0.368***	-0.315***	-0.215**	-0.357***	-0.366***	-0.466***	-0.331***	-0.317***	-0.366***
	(0.091)	(0.081)	(0.084)	(0.086)	(0.085)	(0.084)	(0.078)	(0.081)	(0.083)	(0.086)
Constant	4.852***	5.045***	4.970***	4.820***	4.872***	4.906***	4.722***	4.888***	4.957***	4.940***
	(0.113)	(0.088)	(0.088)	(0.086)	(0.089)	(0.087)	(0.079)	(0.086)	(0.087)	(0.087)
Observations	5,826	5,826	5,826	5,878	5,826	5,826	5,852	5,852	5,826	5,826
R-squared	0.778	0.773	0.771	0.770	0.775	0.777	0.748	0.780	0.778	0.776

1996-2021	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Exclusion of :	C31_C33	D_E	F	G	H	I	J	K	M_N
VARIABLES					TFP all intangibles (log)				
NMR_{up}^{new} (lag)	-0.366***	-0.424***	-0.427***	-0.435***	-0.465***	-0.497***	-0.403***	-0.420***	-0.537***
	(0.099)	(0.098)	(0.097)	(0.105)	(0.098)	(0.100)	(0.100)	(0.099)	(0.107)
EPL^d (lag)	-0.334***	-0.340***	-0.360***	-0.302***	-0.302***	-0.291***	-0.344***	-0.329***	-0.247***
	(0.084)	(0.084)	(0.088)	(0.083)	(0.083)	(0.084)	(0.082)	(0.081)	(0.096)
Constant	4.883***	4.930***	4.931***	4.924***	4.952***	4.968***	4.898***	4.932***	4.993***
	(0.088)	(0.087)	(0.087)	(0.092)	(0.087)	(0.089)	(0.089)	(0.087)	(0.093)
Observations	5,826	5,825	5,825	5,825	5,825	5,825	5,825	5,825	5,825
R-squared	0.776	0.767	0.774	0.777	0.779	0.776	0.766	0.785	0.773

Panel B: Labour Productivity

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exclusion of :	C10_C12	C13_C15	C16_C18	C20	C22_C23	C24_C25	C26	C27	C28	C29_C
VARIABLES					LP all intangibles (log)					
NMR_{up}^{new} (lag)	-0.341***	-0.459***	-0.390***	-0.238**	-0.268***	-0.294***	-0.037	-0.312***	-0.379***	-0.345
	(0.097)	(0.097)	(0.096)	(0.093)	(0.097)	(0.095)	(0.087)	(0.093)	(0.094)	(0.095
EPL^d (lag)	-0.101	-0.105	-0.081	0.042	-0.114	-0.121	-0.254***	-0.079	-0.065	-0.126
	(0.089)	(0.078)	(0.082)	(0.084)	(0.082)	(0.081)	(0.076)	(0.079)	(0.080)	(0.084
Constant	-2.755***	-2.123***	-2.144***	-2.309***	-2.236***	-2.231***	-2.309***	-2.236***	-2.178***	-2.178
	(0.119)	(0.092)	(0.093)	(0.091)	(0.093)	(0.092)	(0.085)	(0.090)	(0.091)	(0.092
Observations	5,826	5,826	5,826	5,878	5,826	5,826	5,852	5,852	5,826	5,826
R-squared	0.997	0.998	0.997	0.997	0.997	0.997	0.998	0.997	0.997	0.997

1996-2021	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Exclusion of :	C31_C33	D_E	F	G	H	I	J	K	M_N
VARIABLES					LP all intangibles (log)				
NMR_{up}^{new} (lag)	-0.263***	-0.371***	-0.309***	-0.325***	-0.365***	-0.444***	-0.298***	-0.297***	-0.399***
	(0.096)	(0.094)	(0.095)	(0.102)	(0.095)	(0.097)	(0.096)	(0.097)	(0.105)
EPL^d (lag)	-0.077	-0.106	-0.052	-0.055	-0.050	-0.044	-0.089	-0.098	-0.045
	(0.081)	(0.082)	(0.086)	(0.081)	(0.081)	(0.081)	(0.080)	(0.080)	(0.093)
Constant	-2.262***	-2.189***	-2.238***	-2.210***	-2.184***	-2.141***	-2.270***	-2.167***	-2.166***
	(0.093)	(0.091)	(0.093)	(0.096)	(0.092)	(0.093)	(0.093)	(0.093)	(0.098)
Observations	5,826	5,825	5,825	5,825	5,825	5,825	5,825	5,825	5,825
R-squared	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997

Source: Estimated by the authors.

Table A12. Sensitivity to Sector Exclusion Version with Break in NMR

Panel A: Total Factor Productivity

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exclusion of :	C10_C12	C13_C15	C16_C18	C20	C22_C23	C24_C25	C26	C27	C28	C29_C30
VARIABLES	TFP all intangibles (log)									
$NMR_{uprc} \times (1 - \text{d2016})$ (lag)	-0.358***	-0.291***	-0.351***	-0.293***	-0.350***	-0.327***	-0.309***	-0.343***	-0.364***	-0.380***
	(0.052)	(0.053)	(0.051)	(0.049)	(0.052)	(0.051)	(0.046)	(0.050)	(0.050)	(0.050)
$NMR_{uprc} \times (\text{d2016})$ (lag)	-0.565***	-0.431***	-0.542***	-0.538***	-0.526***	-0.501***	-0.451***	-0.517***	-0.557***	-0.528***
	(0.083)	(0.083)	(0.082)	(0.080)	(0.083)	(0.082)	(0.074)	(0.080)	(0.081)	(0.081)
Constant	4.750***	4.917***	5.004***	4.946***	4.994***	4.968***	4.916***	4.996***	5.022***	5.031***
	(0.081)	(0.074)	(0.074)	(0.072)	(0.075)	(0.074)	(0.067)	(0.072)	(0.073)	(0.073)
Observations	5,826	5,826	5,826	5,878	5,826	5,826	5,852	5,852	5,826	5,826
R-squared	0.779	0.773	0.773	0.772	0.777	0.778	0.749	0.782	0.779	0.778

1996-2021	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Exclusion of :	C31_C33	D_E	F	G	H	I	J	K	M_N
VARIABLES	TFP all intangibles (log)								
$NMR_{uprc} \times (1 - \text{d2016})$ (lag)	-0.296***	-0.325***	-0.351***	-0.290***	-0.350***	-0.347***	-0.356***	-0.319***	-0.369***
	(0.051)	(0.051)	(0.050)	(0.055)	(0.051)	(0.051)	(0.052)	(0.052)	(0.055)
$NMR_{uprc} \times (\text{d2016})$ (lag)	-0.529***	-0.503***	-0.550***	-0.529***	-0.517***	-0.610***	-0.485***	-0.483***	-0.458***
	(0.082)	(0.081)	(0.081)	(0.089)	(0.082)	(0.084)	(0.083)	(0.082)	(0.094)
Constant	4.949***	4.975***	5.006***	4.939***	5.002***	5.014***	4.985***	4.972***	5.006***
	(0.074)	(0.073)	(0.073)	(0.078)	(0.074)	(0.074)	(0.074)	(0.074)	(0.077)
Observations	5,826	5,825	5,825	5,825	5,825	5,825	5,825	5,825	5,825
R-squared	0.777	0.768	0.776	0.778	0.780	0.778	0.768	0.786	0.774

Panel B: Labour Productivity

(All fixed effects are included but not presented in the table)

1996-2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exclusion of :	C10_C12	C13_C15	C16_C18	C20	C22_C23	C24_C25	C26	C27	C28	C29_C30
VARIABLES	LP all intangibles (log)									
$NMR_{uprc} \times (1 - \text{d2016})$ (lag)	-0.313***	-0.253***	-0.314***	-0.270***	-0.310***	-0.290***	-0.255***	-0.325***	-0.332***	-0.341***
	(0.051)	(0.051)	(0.050)	(0.048)	(0.050)	(0.049)	(0.045)	(0.048)	(0.049)	(0.049)
$NMR_{uprc} \times (\text{d2016})$ (lag)	-0.455***	-0.308***	-0.437***	-0.446***	-0.431***	-0.391***	-0.332***	-0.428***	-0.454***	-0.421***
	(0.081)	(0.080)	(0.080)	(0.077)	(0.080)	(0.079)	(0.072)	(0.078)	(0.079)	(0.079)
Constant	-2.661***	-2.174***	-2.053***	-2.118***	-2.067***	-2.112***	-2.080***	-2.080***	-2.055***	-2.039***
	(0.088)	(0.079)	(0.079)	(0.077)	(0.080)	(0.078)	(0.073)	(0.077)	(0.078)	(0.079)
Observations	5,826	5,826	5,826	5,878	5,826	5,826	5,852	5,852	5,826	5,826
R-squared	0.997	0.998	0.997	0.998	0.997	0.997	0.998	0.997	0.997	0.997

1996-2021	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Exclusion of :	C31_C33	D_E	F	G	H	I	J	K	M_N
VARIABLES	LP all intangibles (log)								
$NMR_{uprc} \times (1 - \text{d2016})$ (lag)	-0.258***	-0.304***	-0.314***	-0.252***	-0.306***	-0.324***	-0.314***	-0.300***	-0.332***
	(0.050)	(0.049)	(0.049)	(0.054)	(0.049)	(0.050)	(0.050)	(0.051)	(0.053)
$NMR_{uprc} \times (\text{d2016})$ (lag)	-0.422***	-0.395***	-0.441***	-0.432***	-0.412***	-0.528***	-0.351***	-0.398***	-0.398***
	(0.080)	(0.078)	(0.079)	(0.086)	(0.079)	(0.081)	(0.080)	(0.080)	(0.091)
Constant	-2.132***	-2.109***	-2.081***	-2.127***	-2.080***	-2.052***	-2.135***	-2.037***	-2.068***
	(0.079)	(0.077)	(0.079)	(0.083)	(0.078)	(0.078)	(0.079)	(0.080)	(0.082)
Observations	5,826	5,825	5,825	5,825	5,825	5,825	5,825	5,825	5,825
R-squared	0.997	0.998	0.997	0.997	0.997	0.997	0.997	0.997	0.997

Source: Estimated by the authors.

Table A13. Results from 1996 to 2018 (avoiding the COVID-19 crisis)

1996–2018	(1)	(2)	(3)	(4)
VARIABLES	TFP all intangibles (log)	TFP NA intangibles (log)	LP all intangibles (log)	LP NA intangibles (log)
Capital Intensity (log-lag)			0.239***	0.166***
			(0.016)	(0.016)
NMR_{up}^{new} (lag)	-0.467***	-0.625***	-0.425***	-0.572***
	(0.105)	(0.116)	(0.102)	(0.113)
EPL^{d} (lag)	-0.293***	-0.243***	-0.051	-0.011
	(0.084)	(0.092)	(0.082)	(0.090)
Constant	4.931***	5.029***	-2.152***	-2.278***
	(0.091)	(0.100)	(0.096)	(0.105)
Observations	5,437	5,437	5,437	5,437
R-squared	0.805	0.793	0.998	0.997
Country*year	YES	YES	YES	YES
Country*industry	YES	YES	YES	YES
Industry*year	YES	YES	YES	YES

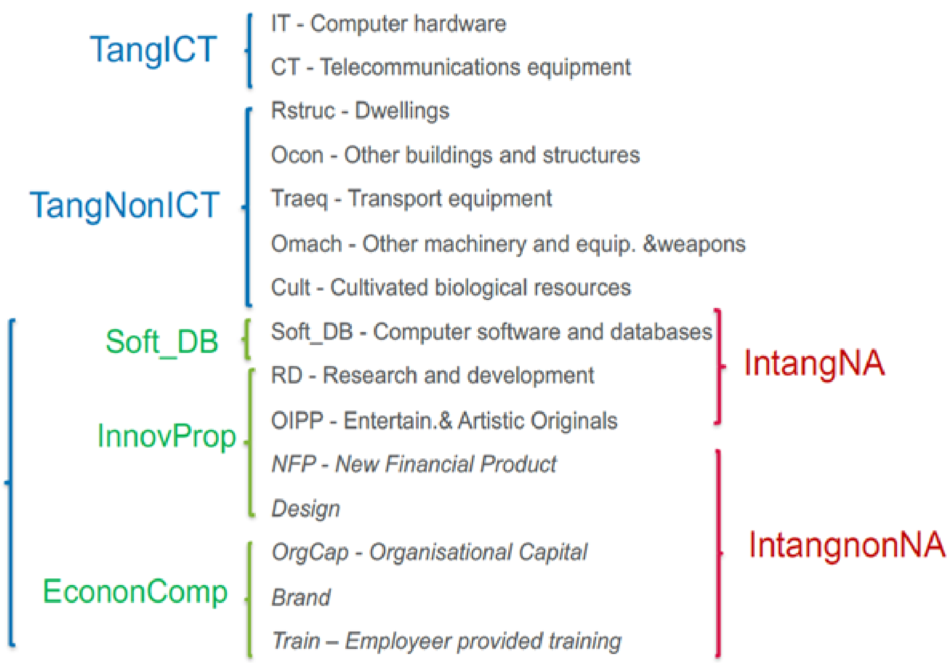
Source: Estimated by the authors.

Table A14. Regression Separating out the Effects of Retail Regulation from Those of Other Non-manufacturing Regulations

	1996–2021	1996–2021	1996–2021	1996–2021
	(1)	(2)	(3)	(4)
VARIABLES	TFP all intangibles (log)	TFP all intangibles (log)	LP all intangibles (log)	LP all intangibles (log)
Capital Intensity (log-lag)			0.237***	0.237***
			(0.014)	(0.014)
NMR_{up}^{new} (lag) excluding retail	-0.686***	-0.724***	-0.390***	-0.444***
	(0.121)	(0.125)	(0.118)	(0.121)
Retail Regulation^{new} (lag)		-0.153		-0.215*
		(0.119)		(0.116)
EPL^{d} (lag)	-0.289***	-0.300***	-0.056	-0.072
	(0.082)	(0.082)	(0.080)	(0.080)
Constant	4.851***	4.924***	-2.307***	-2.206***
	(0.064)	(0.085)	(0.072)	(0.090)
Observations	6,155	6,155	6,155	6,155
R-squared	0.774	0.774	0.997	0.997

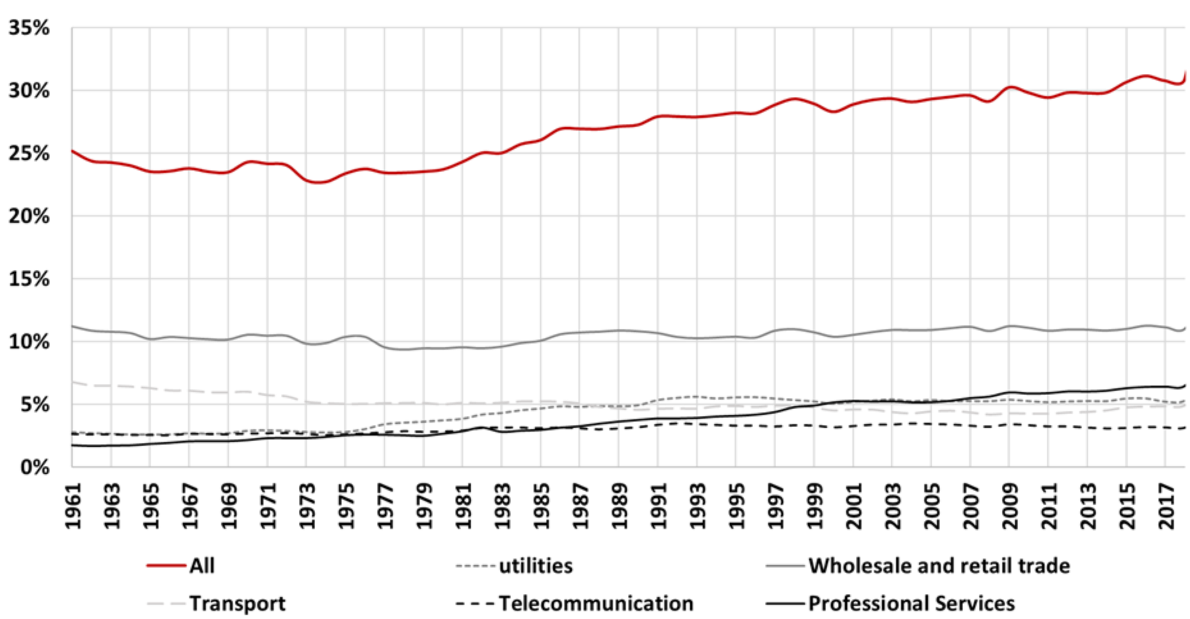
Source: Estimated by the authors.

Figure A1: Classification of Tangibles and Intangibles Assets



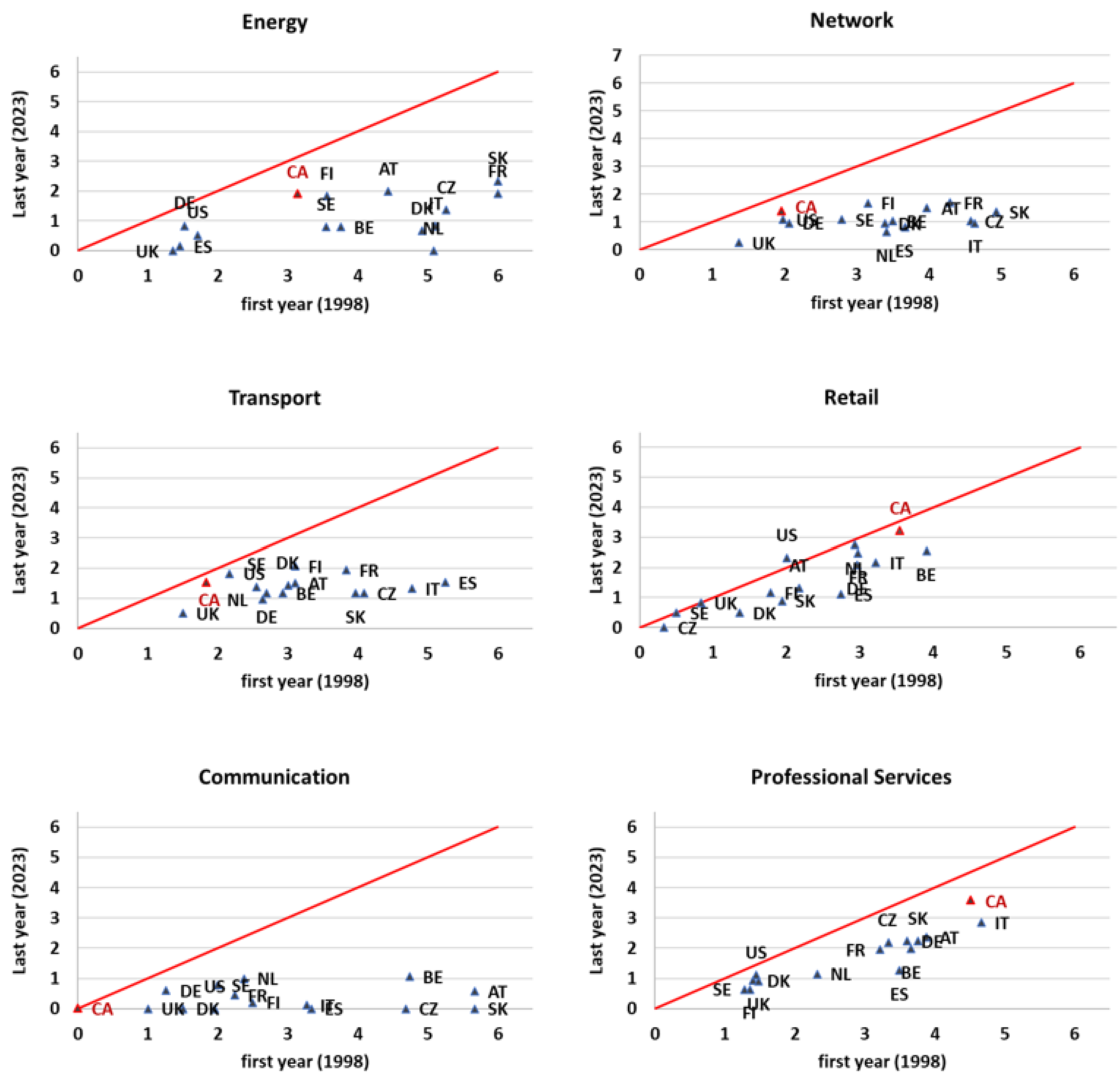
Source: EUKLEMS-IntanProd version 2025 documentation

Chart A1: Shares of Non-manufacturing Sectors Covered by the OECD NMR Indicators in Canadian GDP



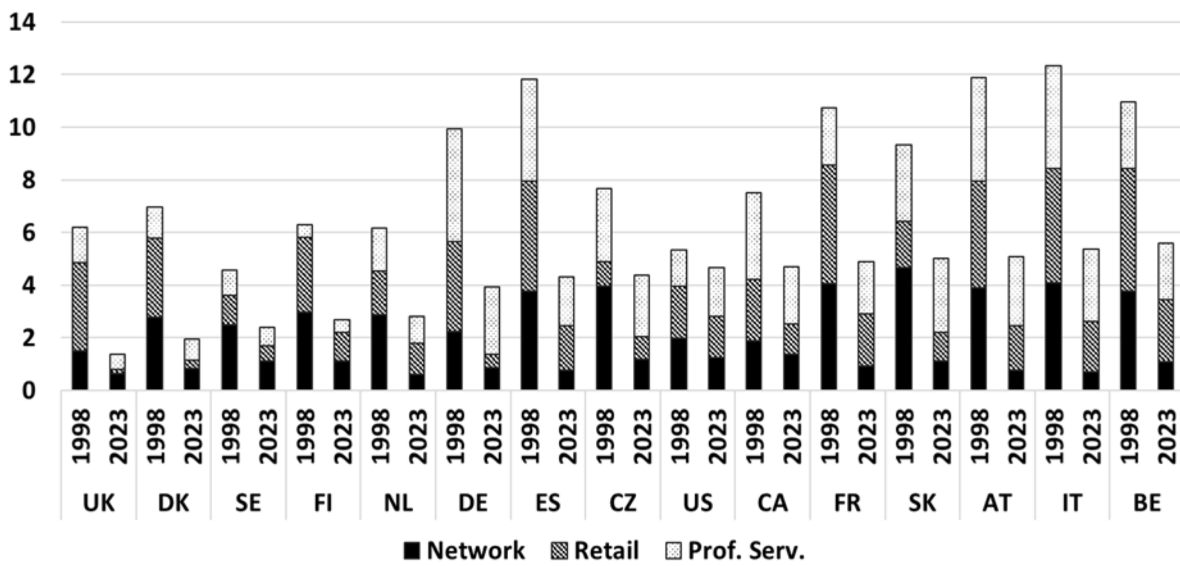
Source: calculated by the authors based on StatCan data

Chart A2: Evolution of Anticompetitive Regulations in the Non-manufacturing Industries by Country and Sector, 1998-2023



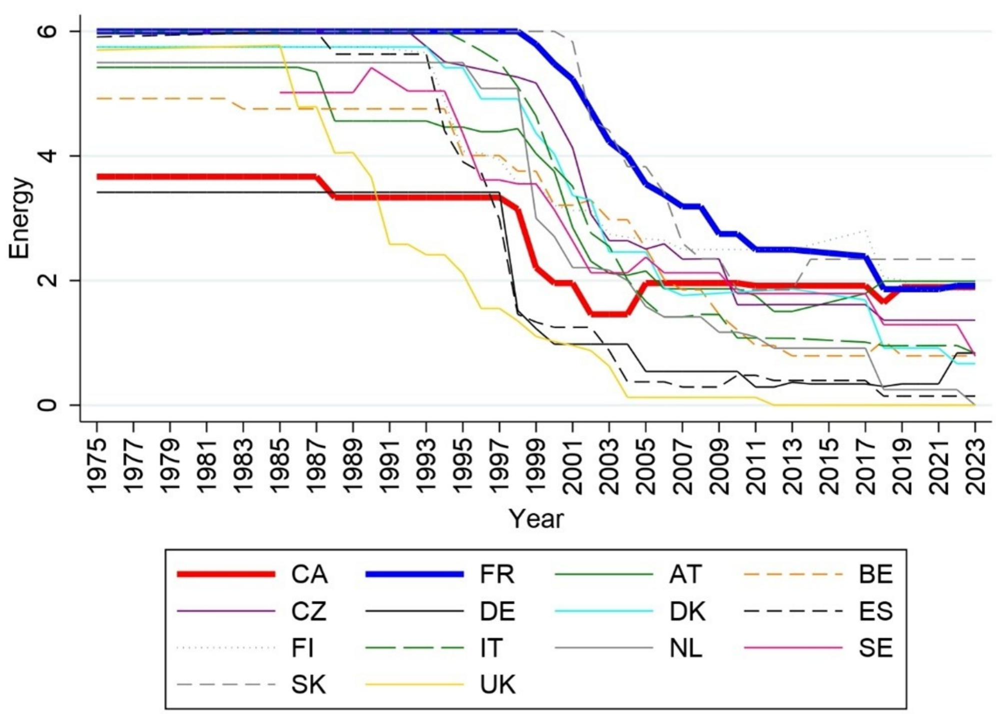
Source: Calculated by the authors based on OECD data

Chart A3: Evolution of Non-Manufacturing Regulation (Version with Break) Calculated on our Database



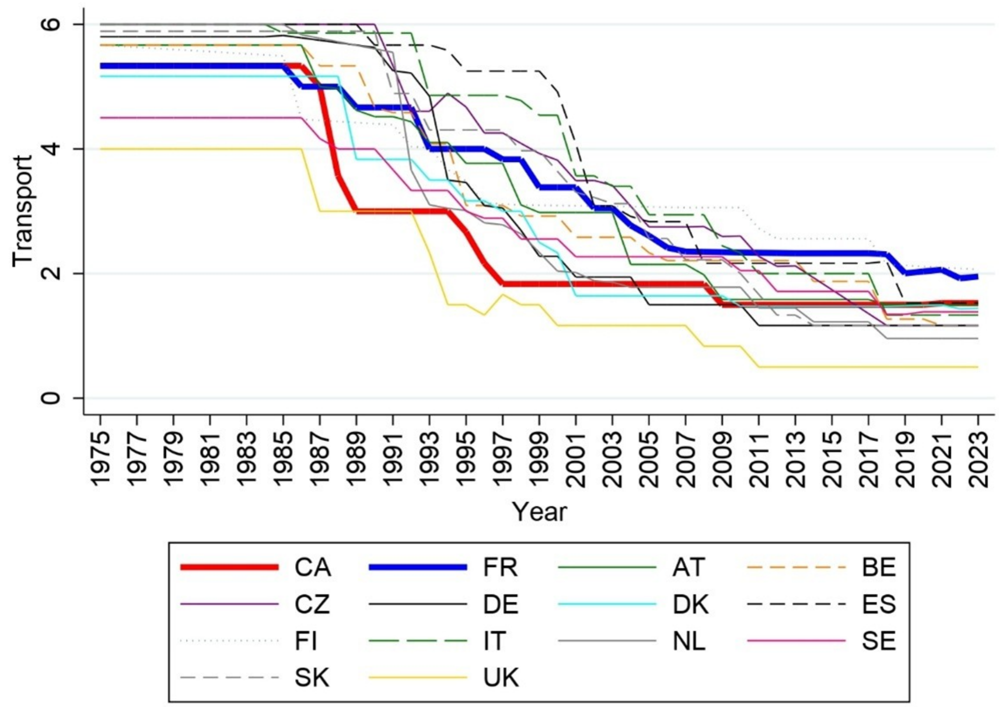
Source: OECD

Chart A4: Evolution of Energy Regulation Calculated on our Database



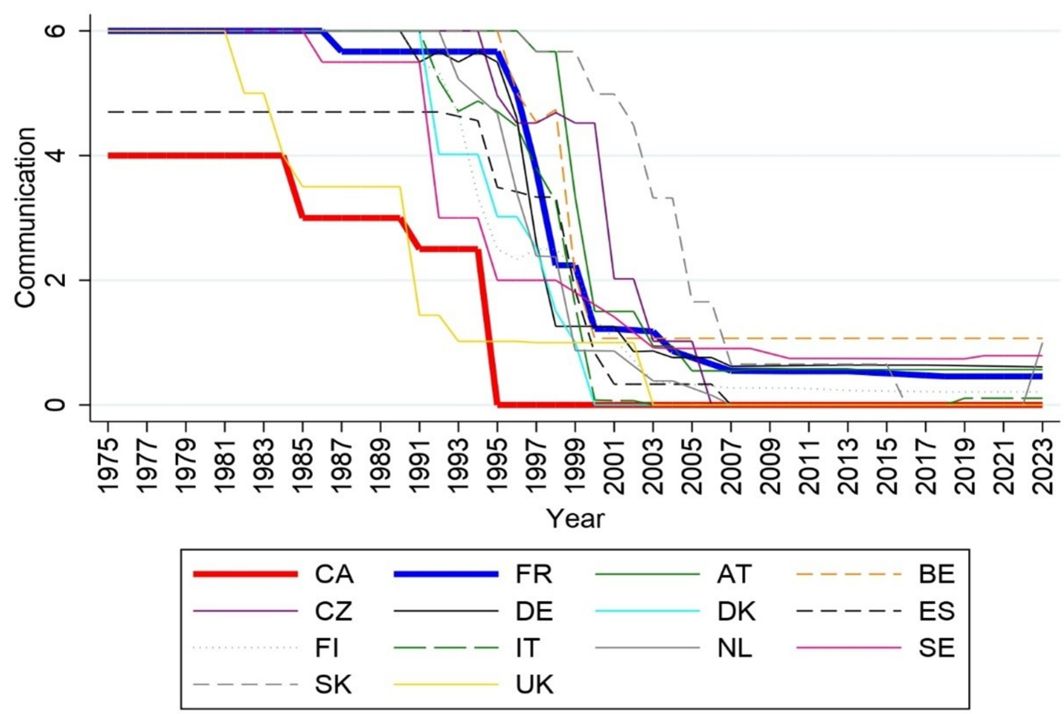
Source: OECD

Chart A5: Evolution of Transport Regulation Calculated on our Database



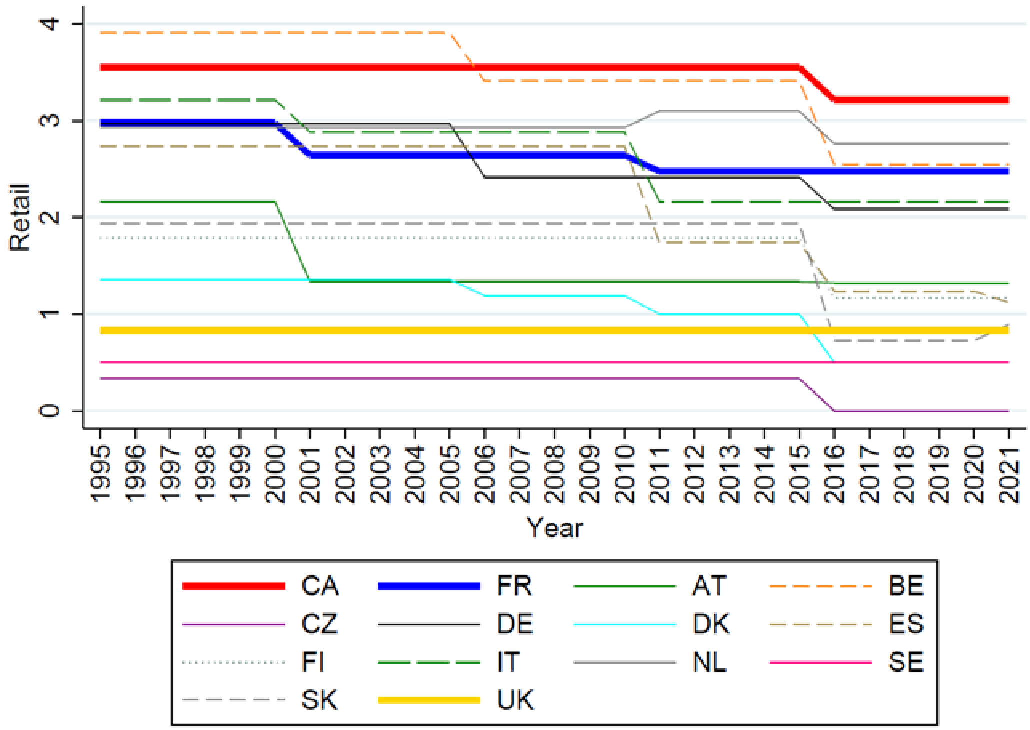
Source: OECD

Chart A6: Evolution of Communication Regulation Calculated on our Database



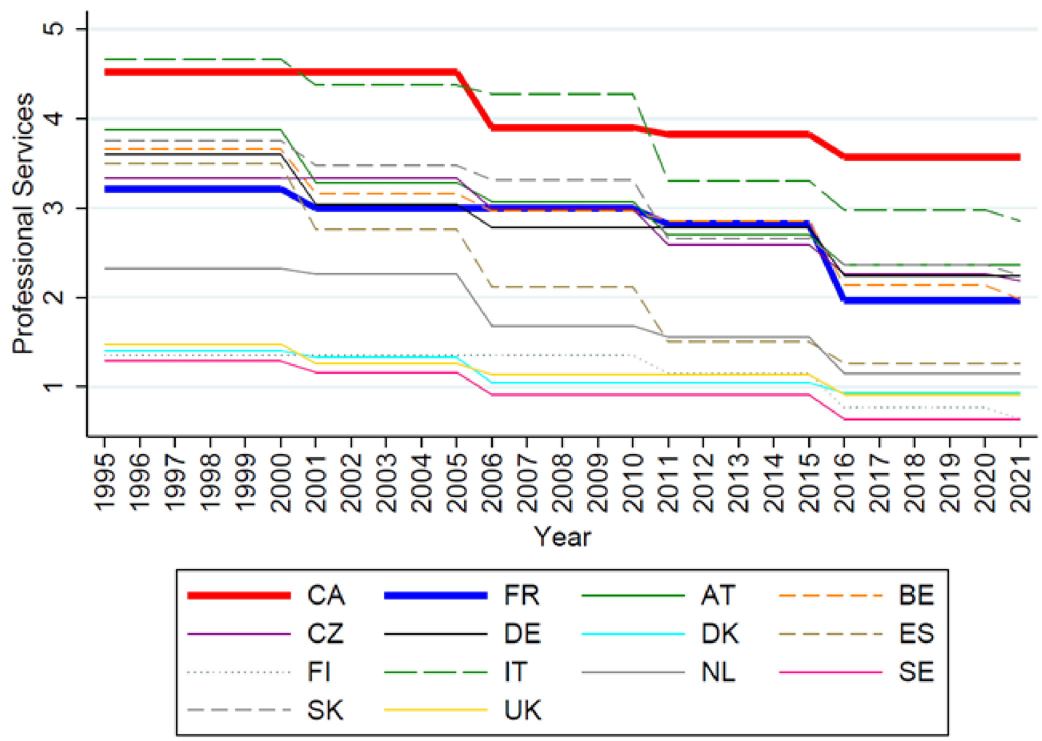
Source: OECD

Chart A7: Evolution of Retail Distribution Regulation Calculated on our Database



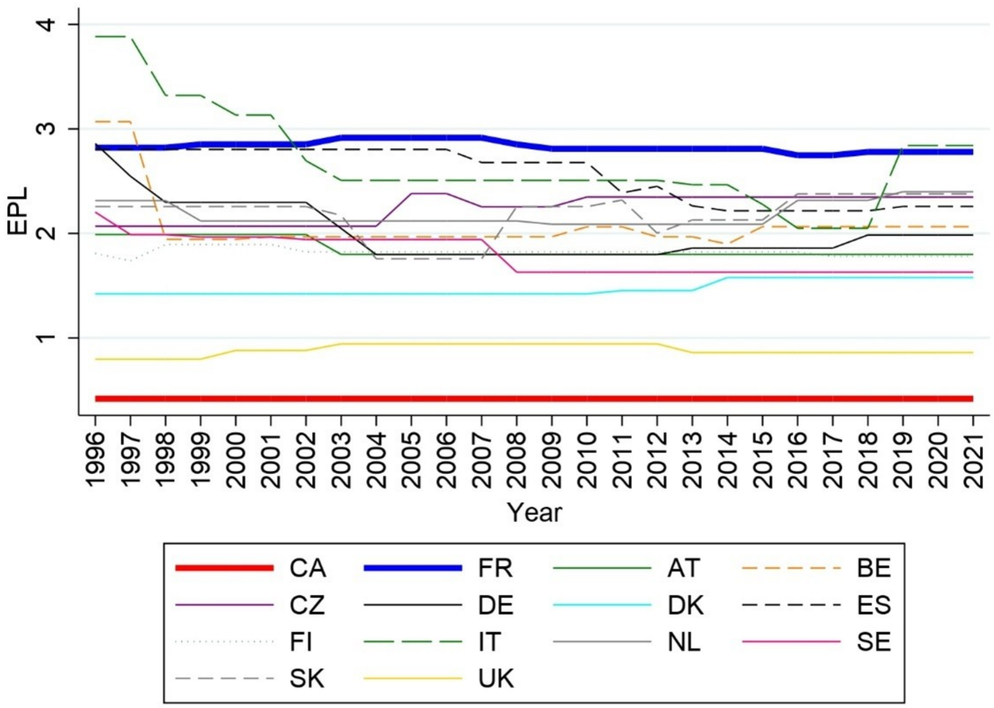
Source: OECD

Chart A8: Evolution of Pofessional Serices Regulation Calculated on our Database



Source: OECD

Chart A9: Evolution of Employment Protection Legislation (EPL) Calculated on our Database (Individual and collective dismissals and temporary contracts)



Source: OECD

Chart A10: Labour Productivity vs Non-manufacturing Regulations After Filtering out Country-time, Industry-time and Country-Industry Fixed Effects from the Original Variables

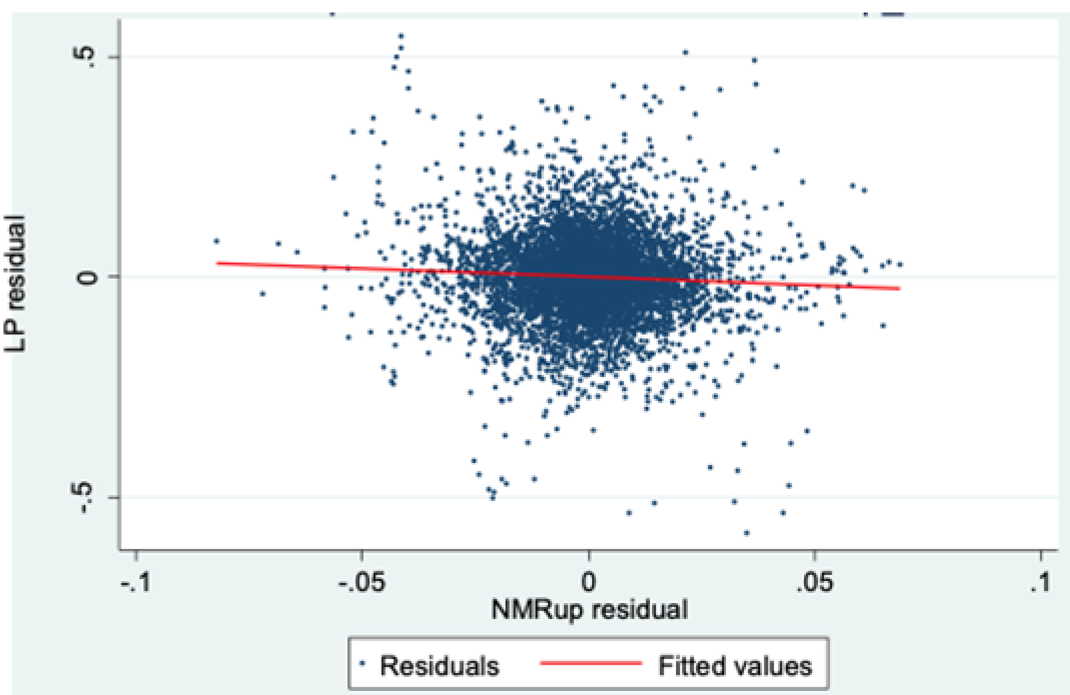


Figure A12. Labour Productivity vs Non-manufacturing Regulations After Filtering out Country-time, Industry-time and Country-Industry Fixed Effects from the Original Variables (means over sectors, selected country examples)

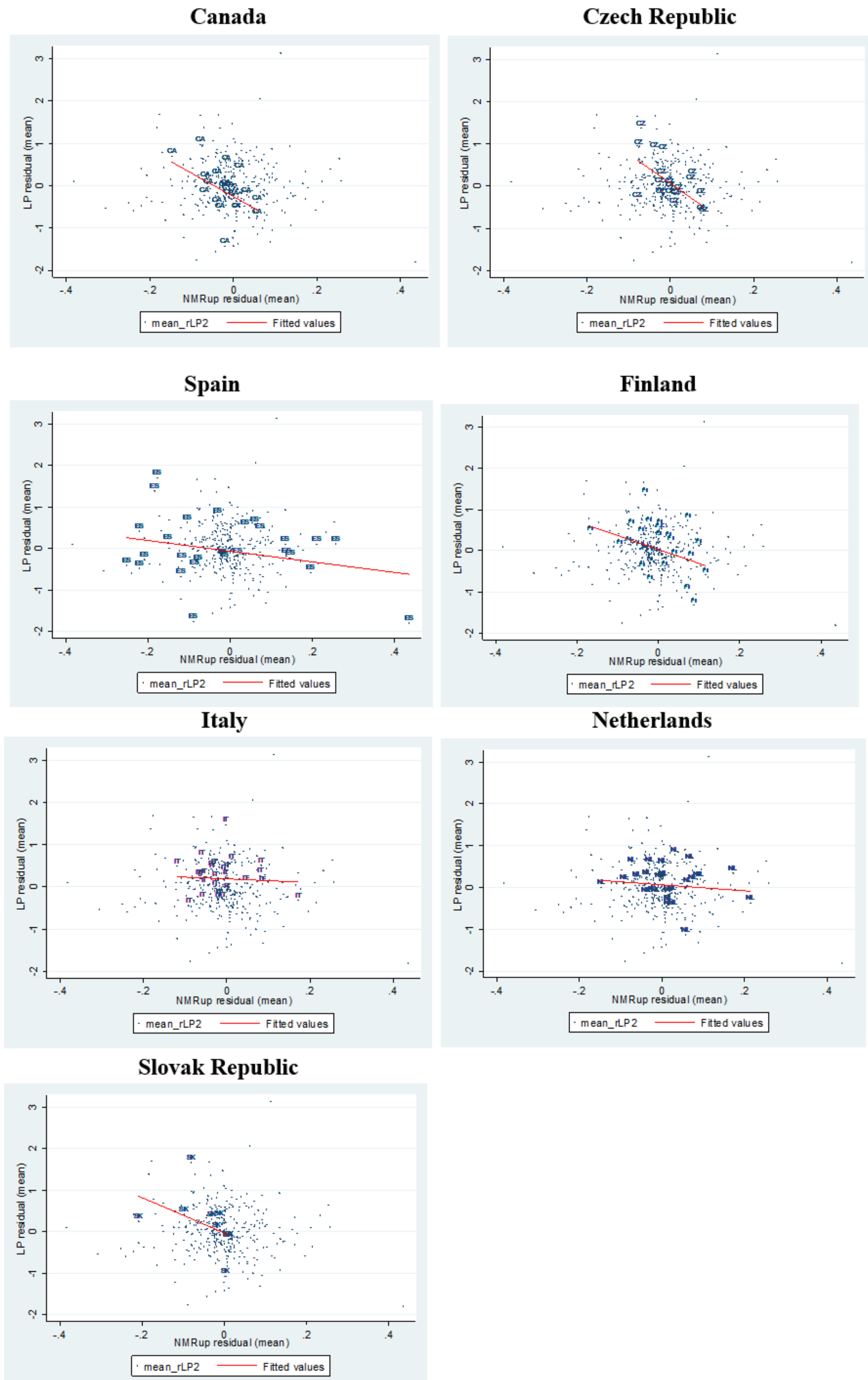


Figure A13: Simulation of the GDP per Capita Impact of Aligning 2023 Non-Manufacturing Regulations in Each Country on 2023 Best Practices, Assuming That Retail Regulation Has No Effect on Productivity

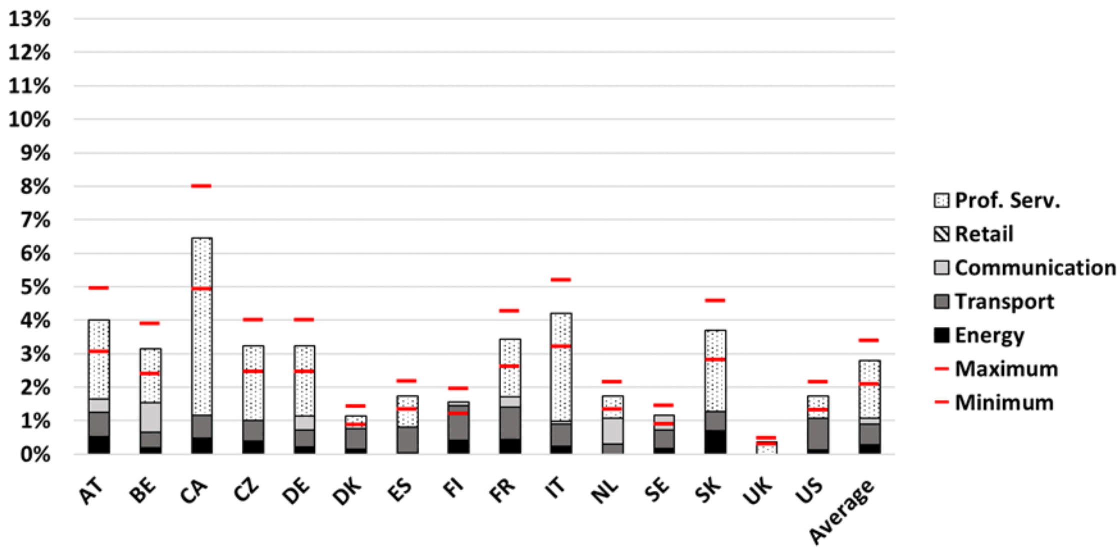
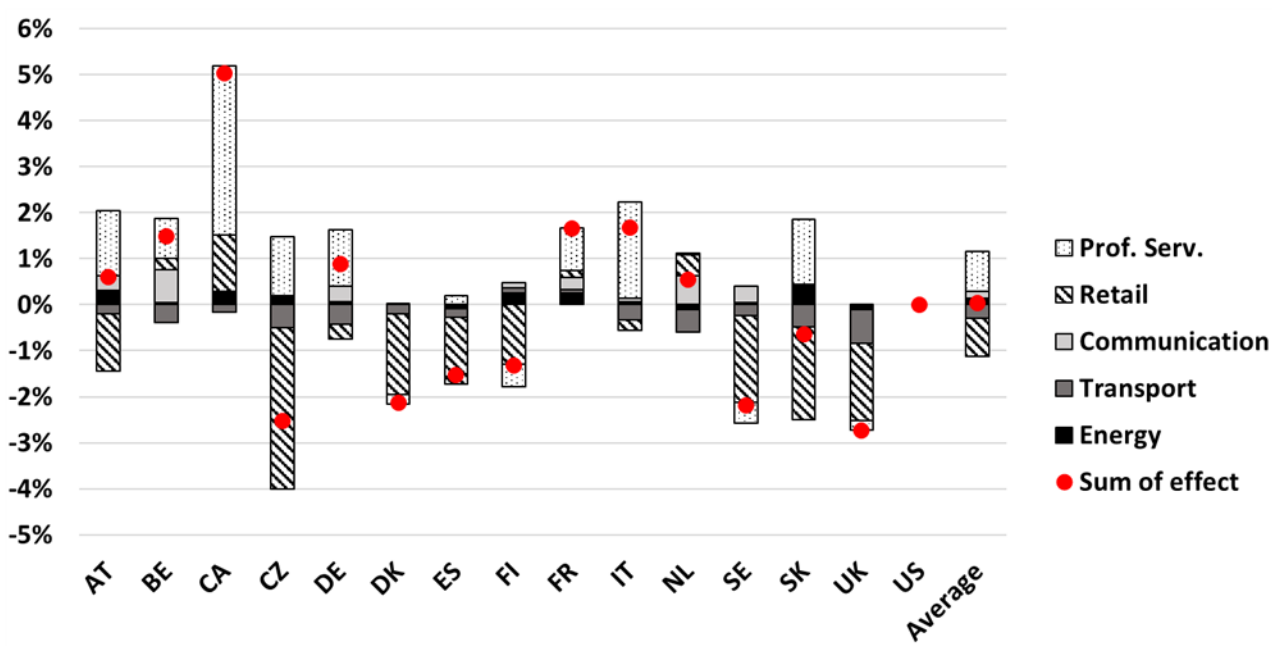


Figure A14: Simulation of the GDP per Capita Impact of Aligning Non-Manufacturing Regulation in Each Country to US 2023 Regulatory Practices



Adult Skills and Productivity: New Evidence from PIAAC 2023

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Abstract

The 2023 Programme for the International Assessment of Adult Competencies (PIAAC) reveals large cross-country differences in adult skill levels that carry important implications for productivity. Cross-country analysis shows a positive relationship between labour productivity and the average level of adult skills at the industry level. This reflect partly a positive link between adult skills and R&D intensity – which is estimated to account for one-quarter of cross-country differences in industry productivity. But the ways in which skilled workers are allocated to different job roles and firms also matters. Higher productivity is observed in industries with lower labour market mismatches and where high-skilled workers are employed in larger and more dynamic firms. Differences in these patterns of allocation can account for at least 12 per cent of the productivity gaps between countries. These findings highlight the importance of policies aimed at enhancing adult skills and structural reforms to improve labour market adaptability and reallocation.

Human capital is widely recognized as a key determinant of cross-country differences in living standards – primarily through its impact on productivity (Hall and Jones, 1999; Jones, 2016; Hanushek 2017) – and is thus a structural policy priority for many countries (OECD, 2018). Recent OECD research found that nearly one-sixth of the productivity slowdown in advanced OECD countries could be accounted for by the slowdown in the pace of human capital accumulation (Andrews *et al.*, 2024). It also suggested that OECD countries differed in their capacity to allocate human capital efficiently, although the aggregate nature of the exercise prevented deeper analysis of this phenomenon. Thus, the release in December 2024 of the

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latest Programme for the International Assessment of Adult Competencies (PIAAC) is particularly timely, as it provides a fresh opportunity to examine the channels linking the level of adult skills and their allocation across job roles and firm types to productivity.

A large body of literature, including OECD research, has investigated the skills-productivity nexus via the role of skills shortages and mismatch, managerial quality and organizational structure, and skill composition on firm-level productivity performance. For example, Adalet McGowan and Andrews (2017) used PIAAC to illustrate the relevance of skill mismatch for labour productivity via the allocative efficiency channel but focused less on how the level of skills shaped industry productivity. Other studies find that skill shortages and mismatch reduce firm productivity by increasing hiring costs, compelling firms to employ less productive workers, or limiting their ability to invest in innovation (Fox and Smeets, 2011; Ilmakunnas *et al.*, 2004; Marcolin and Quintini, 2023; OECD, 2024b). Across OECD economies, skill mismatch remains a significant issue, particularly in fast-changing high-tech and science-driven industries, where firms struggle to align skill supply with market demand (Andretta *et al.*, 2021; Bijnens and Dhyne, 2021; Criscuolo *et al.*, 2021). Well-managed firms are found to better utilise their workforce and invest in continuous training (Caroli and Van Reenen, 2001; Bender *et al.*, 2018).

Against this background, the contribution of this article is to study how the level and allocation of adult skills relate to labour productivity performance, including an assessment of the relative magnitude of these two channels. In doing so, this article leverages a novel cross-country, sector-level dataset derived from the newly published PIAAC data and examines how adult skills are intertwined with productivity through two key channels: i) the direct level of skills (PIAAC score) effect on labour productivity in non-farm business sectors; and ii) the allocation of skills to different job roles and types of firms. This latter channel reflects the capacity of economies to more efficiently allocate their existing stock of skills at any point in time – by minimizing labour market mismatches – as well as to redeploy scarce high-skilled labour over time to underwrite the expansion of dynamic firms. A further layer of analysis explores how skills shape labour productivity performance via the R&D channel. Regression analysis combined with closing-the-gap (between country-level skills and global best practice) simulations are employed to illustrate the economic significance of these channels.

The article is organized as follows. The first section highlights key insights from the 2023 PIAAC data. Section 2 introduces an analytical framework to examine the transmission channels using sector-level datasets. Section 3 then empirically evaluates the significance of these channels using cross-country sector-level regressions and conducts simulation exercises to demonstrate the economic relevance of the results. Section 4 provides a brief policy discussion in light of the empirical findings.

The Programme for the International Assessment of Adult Competencies (PIAAC)

The Programme for the International Assessment of Adult Competencies (PIAAC), also known as the Survey of Adult Skills is an OECD initiative to evaluate and analyze adult skills across various OECD countries. This comprehensive survey assesses key information-processing skills such as literacy, numeracy, and adaptative problem-solving in technology-rich environments for adults aged between 16 and 65. These skills are considered essential for individuals to effectively participate in society and for fostering economic growth. The first cycle of PIAAC was conducted over three rounds between 2011 and 2018 and involved 31 OECD and 6 non-OECD countries. The second cycle began in 2022, with participation from 29 OECD and 2 non-OECD countries. The results from the first round of this second cycle, published in December 2024, provide updated insights into the evolving skills landscape of the adult population.[2]

In 2023, PIAAC scores – whether measured by literacy, numeracy or adaptative problem-solving – varied significantly across countries, reflecting stark disparities in adult skill levels across countries (Chart 1). Based on a simple average of the three PIAAC components, the top performers include Finland, Japan and Sweden, whereas Chile, Poland and Portugal have the lowest PIAAC scores (Chart 1, Panel A). And the scale of these differences is material: average PIAAC scores in the top three performing countries are around 10 per cent higher than the OECD average and 25 per cent higher than in the bottom three performing countries.

An analysis of literacy, numeracy, and problem-solving rankings across countries reveal a degree of consistency among the top performers, suggesting well-rounded and balanced skill levels (Chart 1, Panels B to D)[3]. Yet, some countries exhibited heterogeneous performance across the domains, highlighting the nuanced challenges countries face in achieving balanced adult skills. For example, Austria performed relatively well in numeracy and problem solving but lagged in literacy. Latvia was doing much better at numeracy than at literacy and problem solving. Ireland exceeded the OECD average in literacy but fell behind in numeracy and problem solving. New Zealand and the United States also displayed strong literacy skills but lagged in numeracy and, to a lesser extent, in problem solving.

Adult Skills and Productivity: The Analytical Framework

As discussed in this section, a nuanced understanding of the latest PIAAC results requires an analysis of granular – sector-level – data to pin down the key mechanisms linking adult skills and productivity, including via the innovation and reallocation channels.

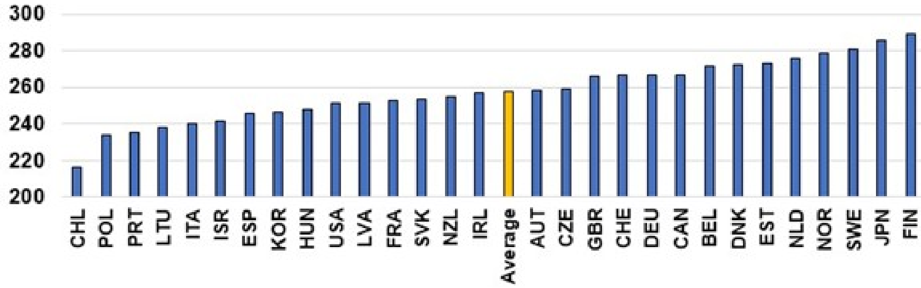
Skills and Productivity: Towards a Better Understanding of the Chan-

2 See Box 1 in Andrews *et al.* (2025) for more details on the construction of the PIAAC scores.

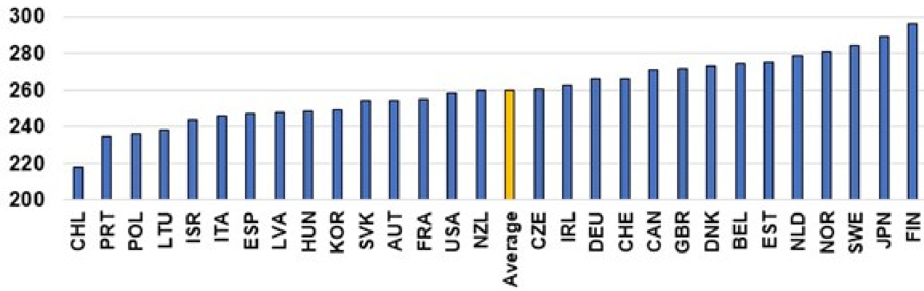
3 Finland, Japan, Sweden, Norway and the Netherlands are the top five performers across all three areas.

Chart 1: PIAAC Scores in 2023 in OECD Countries, in points

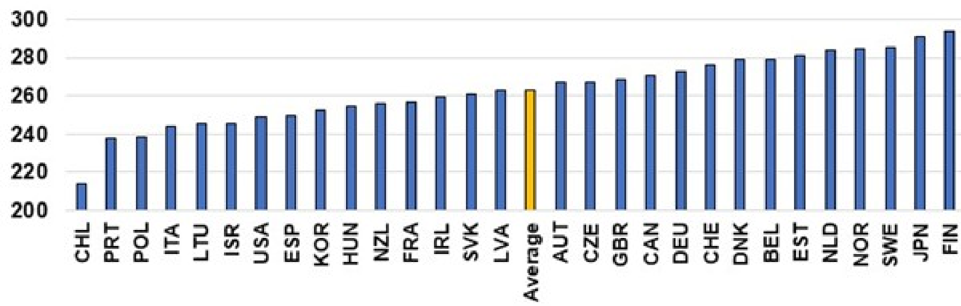
Panel A. Average PIAAC Scores



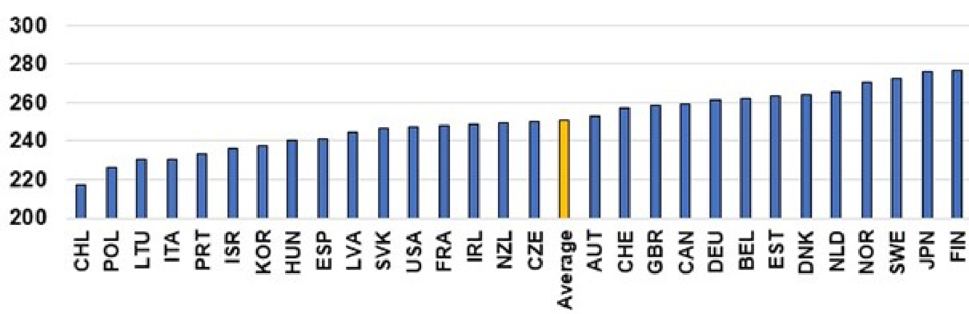
Panel B. PIAAC Literacy Scores



Panel C. PIAAC Numeracy Scores



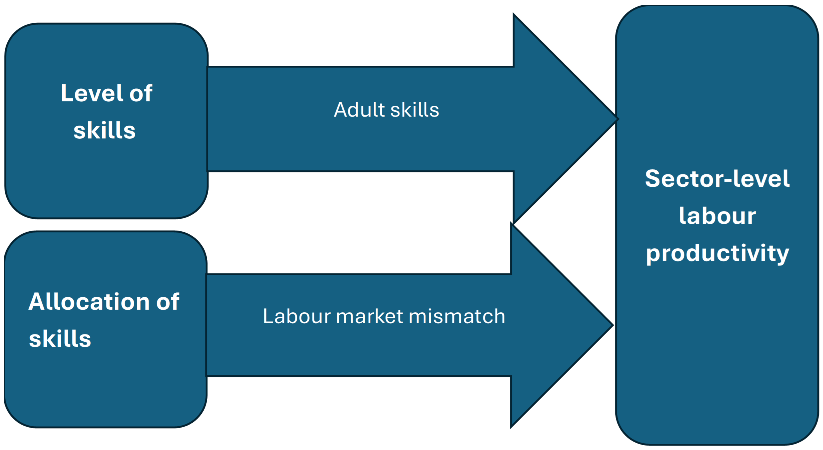
Panel D. PIAAC Problem Solving Scores



Note: Average PIAAC scores displayed in Panel A are the simple averages of the PIAAC scores on literacy, numeracy and problem solving. In this chart and in the rest of the article, Belgium (BEL) refers to the Flemish Region and the United Kingdom (GBR) refers to England. The PIAAC scores are for all adults aged 16-65 including the 20 per cent of adults who are not in the labour force.

Source: Authors' calculations.

Figure 1: PIAAC-implied Country-level Productivity Gains in the OECD



Source: Authors' calculations.

nels

A key observation is that within any given sector, a higher average level of adult skills will directly support aggregate productivity performance (Figure 1). A greater proportion of highly skilled workers – relative to lower-skilled workers – will enable both the broader diffusion of new and existing ideas and the generation of new ideas, via investments in R&D.

But adult skills will also impact productivity via indirect channels through the allocation of skills across job roles and firm types. Since the stock of adult skills is relatively fixed in the short to medium term, the extent to which skilled workers are allocated efficiently across firms will also matter for sector-level productivity (Figure 1). Earlier OECD research found that higher rates of skill mismatch within industries go hand in hand with lower labour productivity due to inefficient resource allocation (Adalet McGowan and Andrews, 2017). From the perspective of a single firm, hiring an over-skilled worker may be beneficial for productivity.[4] But over-skilling in any given firm could be harmful for aggregate productivity if there exist more productive firms that could better utilize these skills but find it difficult to expand due to a lack of suitable labour.[5] Indeed, frictions to the matching process are likely to be particularly costly to aggregate growth in R&D intensive sectors, to the extent that it impedes innovation and the scope for produc-

4 This assumes there are no adverse effects on job satisfaction and the higher wages do not more than offset any associated productivity gains. The definition of overskilled is A PIAAC score, as a proxy for technical skills, above that required for the job or a level of educational attainment greater than that required for the job based on minimum education requirements for occupations.

5 Mismatches arise from reallocation being hindered by labour market rigidities relating to insufficient short-term wage adjustments, stringent labour market regulations (including dismissal regulations and anticompetitive non-poaching clauses) and the absence of geographical mobility across regions.

6 Labour market mismatch collectively dampens innovation prospects via a few channels: i) mismatched researchers may struggle with efficiency, hinder creativity, and slow scientific breakthroughs; ii) high turnover disrupts projects and erodes institutional knowledge; iii) firms incur higher training costs, and skill mismatches create frictions that delay R&D and increase errors; and iv) skilled researchers may end up in less innovative

tivity spillovers to other sectors (Acemoglu *et al.* 2018; Adalet McGowan and Andrews, 2017; Lehr, 2024; Moretti, 2021).[6]

In an economy where firms are relatively homogenous, the potential gains to aggregate productivity from a better allocation of mismatched workers would be relatively small. In practice, however, the degree of firm heterogeneity is striking:

- First, highly productive firms co-exist with low productivity firms: even within narrowly defined industries in the United States. Firms at the 90th per centile of the total factor productivity (TFP) distribution are twice as productive as firms at the 10th per centile (Syverson, 2004).
- Second, the same is true with respect to the firm size distribution, with many small firms co-existing with a smaller number of very large firms, which are typically more productive (Bartelsman *et al.*, 2013).
- Finally, firms vary greatly in their growth potential: many firms do not grow at all, a small cadre of young firms tend to disproportionately drive net job creation, while small and old firms tend to destroy jobs on net (Haltiwanger *et al.* 2013; Criscuolo *et al.* 2014).

This widespread firm heterogeneity implies that aggregate productivity will also depend upon how skilled workers – which are currently in short supply (OECD, 2024a) – are allocated across firms and matched to various job roles. At any point in time, aggregate productivity is an increasing function of static allocative efficiency, which measures the extent to which scarce resources are allocated to their highest valued use in the form of higher quality (i.e. more productive) firms (Haltiwanger, 2011; Andrews and Hansell, 2021). Dynamic allocative efficiency captures the extent to which resources are moving towards higher quality firms over time. Achieving static allocative efficiency in one period requires sufficient dynamic allocative efficiency in preceding periods, and differences in this process is now a leading explanation for why some countries are more productive than others (Bartelsman *et al.*, 2013; Hsieh and Klenow, 2009).

Skills and Productivity: The Estimation Framework

To analyze and identify the effects of the level and the allocation of skills on productivity, this article exploits a novel cross-country sector-level database created by merging sector-level labour productivity data from the OECD National Accounts database with a range of skills indicators drawn from the 2023 PIAAC dataset. This dataset encompasses twelve one-digit industries across 25 OECD countries (listed in Chart 2).

The analysis focuses exclusively on nonfarm business sectors, excluding non-market-based sectors and sectors such as agriculture, public administration, arts, health, education and mining, mainly because of problems associated with the measurement of labour productivity in these

firms, while geographical mismatches and lack of clustering further impede innovation.

sectors. The dataset is purely cross sectional and focuses on 2023 (and nearby years). Appendix A in Andrews *et al.* (2025) provides data definitions, sources and selected descriptive statistics.

Chart 2 provides a snapshot in the cross-county variation in the level of adult skills across key industries in the non-farm business sector. On average, adult skills are higher in intangible-intensive sectors such as finance and insurance and professions, scientists and technicians than elsewhere. For example, the average level of adult skills in finance and insurance is 15 per cent higher than in administrative and support services. Nevertheless, there remains significant cross-country variation in the level of adult skills within any given industry, which we exploit for identification purposes in this article.

The different channels through which adult skills shape sector-level productivity outcomes are examined through a series of regressions. Two broad channels emerge:

- A direct channel relating labour productivity to the level of skills, reflecting the generation of new ideas (via R&D) and the diffusion of leading technologies. Raising the floor of basic skills, i.e. reducing the share of workers with low literacy and numeracy, facilitates technological diffusion and, in turn, boosts productivity growth.
- An indirect channel linking labour productivity to the allocation of skills to different jobs (i.e. labour market mismatch) and firms (according to their size and growth potential).[7]

In the baseline regression, the log of sectoral labour productivity (LABPROD, equation 1) or R&D intensity (R&D expenditure as a share of value added) (equation 2) is regressed on the log of average PIAAC scores, the mean of literacy, numeracy, and problem-solving scores, in corresponding industries (the level of skills effect):

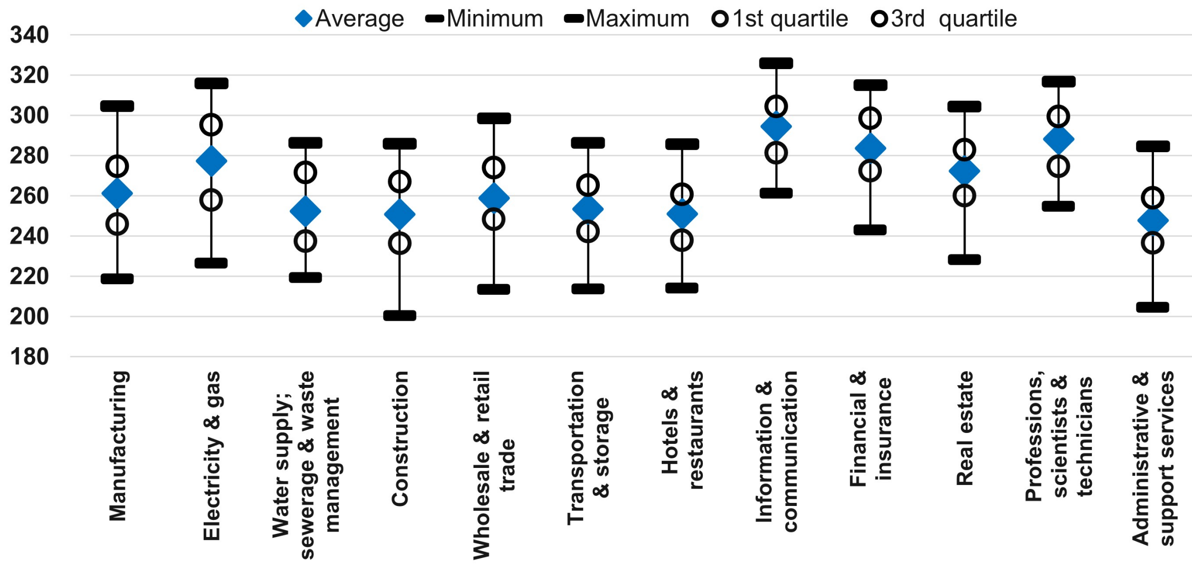
$$\log(LABPROD_{c,s}) = \alpha \cdot \log(PIAAC_{c,s}) + CFE_c + SFE_s + \varepsilon_{c,s} \quad (1)$$

$$R\&D_{c,s} = \theta \cdot \log(PIAAC_{c,s}) + CFE_c + SFE_s + \varepsilon_{c,s}. \quad (2)$$

where c and s denote countries and sectors, and CFE and SFE are country and sector fixed effects. Country fixed effects absorb country-specific factors, such as economic structure, policy and institutions. Sector fixed effects capture technological and market characteristics common across countries. By controlling for these unobserved factors, the model uses within-country and within-sector variation to isolate the impact of adult skills on productivity, mitigating endogeneity and omitted-variable bias. Fixed effects also limit reverse causality, when it operates through unobserved factors, if productive sectors systematically attract skilled workers due

7 Additional channels, not considered here explicitly, as they are largely captured by our fixed-effects structure, include ICT intensity (connected to the R&D channel), the capital-labour complementarity and age and gender composition. Managerial quality is an additional channel. Yet, in the 2023 PIAAC dataset, there are various definitions of managers and data availability differs across definitions, countries and sectors, which leads us to exclude this channel from the empirical analysis.

Chart 2: PIAAC Scores in Non-farm Business Sectors across OECD Countries, 2023



Note: Individual-level PIAAC scores are aggregated to the sectoral level and cover workers aged 16 to 65 using representative weights.

Source: Authors' calculations based on PIAAC 2023.

to inherent advantages such as advanced technologies, innovation and better managerial practices (which supply dynamic work environments and professional development opportunities).

However, fixed effects may not fully eliminate reverse causality if sector-specific factors differ across countries. If highly productive sectors invest more in training or attract skilled workers differently, the coefficient α on the $\log(PIAAC)$ in equation (1) may be upwardly biased. To reduce this risk, three additional strategies are applied:[8] *i)* controlling for the allocation of skilled workers across firms of differing growth potential and size; *ii)* adding controls for sectoral R&D intensity (equation (3)), managerial skill, and training participation; and *iii)* including capital per worker and, as a robustness check, using total factor productivity (TFP) as the dependent variable, though this results in a non-trivial reduction in sample size. R&D intensity (R&D) can be added to equation (1) to capture the effect of R&D on labour productivity:

$$\begin{aligned}\log(LABPROD_{c,s}) = \alpha \cdot \log(PIAAC_{c,s}) \\ + \beta \cdot R\&D_{c,s} \\ + CFE_c + SFE_s \\ + \varepsilon_{c,s}.\end{aligned} \tag{3}$$

To proxy the allocation of skills, equation (1) is augmented with two allocative terms: the degree of qualification and field-of-study mismatch (*labour market mismatch*) and the extent to which skilled workers are allocated to high-growth firms

8 Alternatively, an instrumental variables strategy could be employed but identifying valid instruments in a cross-country, cross-sector context for adult skills is particularly challenging.

(*skills allocation to firms*):

$$\log(LABPROD_{c,s}) = \alpha \cdot \log(PIAAC_{c,s}) + \delta \cdot mismatch_{c,s} + \gamma \cdot skills\ allocation\ to\ firms_{c,s} + CFE_c + SFE_s + \varepsilon_{c,s}. \quad (4)$$

In this article, workers are deemed mismatched if they are misaligned in terms of both their specialization (field-of-study mismatch) and their qualification (qualification mismatch).

Qualification (vertical) mismatch compares workers' highest qualification (level of education) to the qualification required for their job. Field of study (horizontal) mismatch compares workers' field of study (area of education) with the area of their current job (for more details, see Andrews *et al.* 2025). Research shows that labour market mismatch is particularly costly for individual workers but also at the aggregate level if field-of-study mismatch is associated with qualification mismatch (Montt, 2015, 2017).

Our mismatch indicator, combining qualification and field-of-study misalignment, has some potential shortcomings. First, education-based proxies may conceal large variation in actual skills: some workers may lack the competencies their jobs nominally require, while others may exceed task demands without the "correct" credential or major. Second, the indicator is static and does not account for work experience and learning (e.g. on-the-job training, informal upskilling, or micro-credentials), which can close gaps irrespective of initial education. Finally, the measure omits soft skills as well as firm- and sector-specific human capital.

In this article, the allocation of skills to firms captures: i) a snapshot of the state of allocation and is calculated as the difference in the average skills (i.e. PIAAC score) of workers in large and small firms (in terms of employment); and ii) the dynamic allocation across growing and declining firms by comparing the average skills (i.e. PIAAC score) of workers in growing firms (in terms of employment) and the average skills of workers sunk in declining firms.[9]

As an extension to the baseline results, R&D is regressed on adult skills (PIAAC) and an R&D-specific mismatch metric that combines qualification and field-of-study mismatches among engineers and scientists, who are primarily responsible for R&D activities.[10] Some caution is warranted when interpreting these results, given the significant reduction in sample size. The regression is specified as follows:

$$R\&D_{c,s} = \theta \cdot \log(PIAAC_{c,s}) + \vartheta \cdot R\&D\_specific\ mismatch_{c,s} + CFE_c + SFE_s + \varepsilon_{c,s}. \quad (5)$$

9 Some caution is needed regarding the variables using firm characteristics as PIAAC data on firms do not provide a representative sample at the firm level within a sector. Additionally, individuals are selected without ensuring they reflect the entire workforce of their respective firms.

10 This corresponds to STEM (Science, Technology, Engineering and Mathematics).

Table 1: Cross-country Sector-level Estimates of Adult Skills (PIAAC) Effects on Productivity

	Panel A: log(labour productivity)					**Panel B:** R&D expenditures as a share of value added			
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	−1.081	0.690	−1.586	−0.307	3.668	−1.582**	−1.386**	−1.623**	−1.508**
Level of skills effect									
log(average PIAAC)	2.300**				1.374**	0.291**			
log(literacy)		1.982**					0.256**		
log(numeracy)			2.377**					0.298**	
log(problem solving)				2.176**					0.278**
R&D intensity					2.922**				
R^2	0.883	0.881	0.884	0.881	0.889	0.764	0.758	0.773	0.755
No. observations	293	293	293	293	293	199	199	199	199
No. countries	25	25	25	25	25	18	18	18	18
Country fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: * and ** denote statistical significance at the 10% and 5% levels, respectively, based on robust standard errors. Average PIAAC scores are the simple average of the PIAAC scores on literacy, numeracy, and problem solving.
Countries in labour productivity specifications: Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, United Kingdom.
Countries in R&D specifications: Austria, Czech Republic, Estonia, Finland, France, Germany, Hungary, Italy, Japan, Latvia, Lithuania, Netherlands, Norway, Portugal, Slovakia, Spain, Sweden, United Kingdom.

Source: Authors' calculations.

Productivity, Adult Skills and Reallocation at the Sector Level

The Level of PIAAC Scores and Sector-level Productivity

Baseline Results

Graphical inspection of the data suggests a positive cross-country relationship, at the industry level, between average PIAAC scores and both sectoral labour productivity and R&D intensity (see Andrews *et al.*, 2025). Regression analysis formally confirms these patterns.

Regression analysis suggests that a 1 per cent increase in average PIAAC scores is associated with more than a 2 per cent gain in labour productivity (Column 1, Panel A of Table 1). To explore whether different skills have a different impact, the regression was re-run with literacy, numeracy and problem-solving scores included individually (Table 1, Columns 2 to 4). The elasticity on numeracy (2.4) exceeds those on literacy (1.9) and problem solving (2.2), but these differences are not substantial.

Turning to Column 5, controlling for R&D intensity in the labour productivity regression indicates that a sizeable part of the level of skills effect can be explained by R&D: the coefficient on average PIAAC scores drops from 2.33 (Table 1, Column 1) to 1.37 (Table 1, Column 5). One interpretation is that around 60 per cent of the direct effect of skills on productivity is general – that is, related to the adoption of existing knowledge – while 40 per cent emanates from R&D activities that are typically devoted to the generation of new knowledge. Accordingly, Panel B of Table 1 explores the link between R&D intensity and adult skills, confirming a robust positive association between R&D expenditure as a share of value added and average PIAAC scores. Similarly to the labour productivity regressions in Panel A, numeracy yields the highest coefficient estimate in the R&D regression, while literacy has the lowest, but again these differences should not be overstated.

Before proceeding, we test the robustness of the baseline results. Each test is based on fewer observations due to limited data for additional variables. First, regressions adding intangibles show that including managerial skills barely affects the PIAAC coefficient, while including adult training slightly reduces it. Second, the coefficient on adult skills remains positive and significant after controlling for capital per worker and when using total factor productivity (TFP) instead of labour productivity, despite the smaller sample (Table B1 in Appendix B, Andrews *et al.*, 2025).

Economic Significance

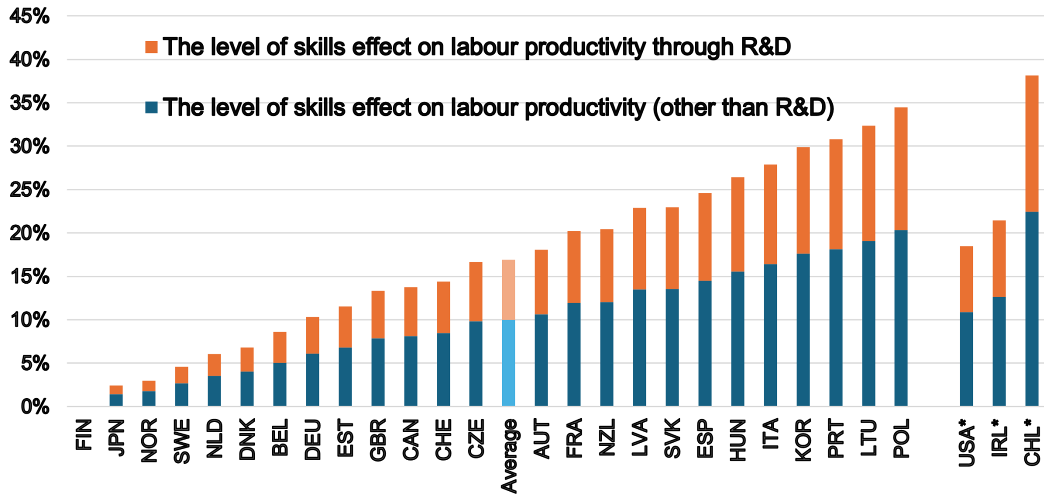
How large are the aggregate labour productivity gains from closing the sector-level adult skills gap to the top-performing countries? To answer this question, back-of-the-envelope calculations are conducted.[11] They suggest that closing the PIAAC gap would boost productivity by 17 per cent on average across OECD countries (Chart 3). However, this effect amounts to more than 30 per cent in laggard countries such as Portugal, Lithuania or Poland. Purely for illustrative purposes, Chart 3 also includes implied productivity gains for three countries which are included in PIAAC but lack adequate industry-level productivity data. These estimates should be treated with caution.

The total PIAAC effect in Chart 3 can be decomposed into two main channels: i.) the effect of the general level of skills that affects labour productivity in a broad sense, and ii.) the effect through R&D. For the average OECD country, closing the PIAAC gap with the top performers could boost labour productivity by 17 per cent, of which 10 per centage points would be accounted for by the general skill effect and 7 per centage points would reflect the R&D channel.

Thus far, the analysis shows that raising the average level of adult skills could yield material productivity gains across OECD countries. Given the large and persistent cross-country productivity differences, it is natural to ask how much of these gaps stem from adult skill disparities. To explore this, we extend the simulation exercise by comparing the implied productivity gains from raising each country's skill level to the average of the three best performers

11 First, the difference between a country-sector's PIAAC score and the mean of the average PIAAC scores of the top 3 performing OECD countries in the corresponding sector is calculated. The average performance of the top three countries is used instead of that of the single top performer, primarily to reduce the influence of any outlier country. Second, the estimated coefficient linking PIAAC to productivity (Table 1, Column 1) is applied to translate the PIAAC gap into productivity gains. Third, sector-specific weights (in terms of value added) are used to aggregate the sectoral results to the country level.

Chart 3: Country-level Labour Productivity Gains Resulting from Closing the Sector Skills Gap, 2023



Note: The total labour productivity gains arising from closing the sector-level PIAAC gaps are calculated as follows: i.) sector-level PIAAC gaps are determined relative to the 3 best performing sectors, ii.) sector-level productivity gains are calculated by multiplying the sector-level PIAAC gap by the estimated coefficient linking sector-level labour productivity to PIAAC, and iii.) sector-level productivity gains are aggregated to the country level using sectoral value added weights. The general level of skills effect (blue part) accounts for around 60 per cent of the total productivity gains. This 60 per cent is obtained as the difference between the coefficient estimate on PIAAC without and with controlling for R&D (2.300 vs. 1.374). The rest, in orange, indicates productivity gains through the R&D channel. Countries marked with an asterisk (*) lack sectoral productivity data. For these countries, sector-level productivity gains can be estimated by multiplying the sector-level PIAAC gap by the coefficient that links sector-level labour productivity to PIAAC in in-sample countries.

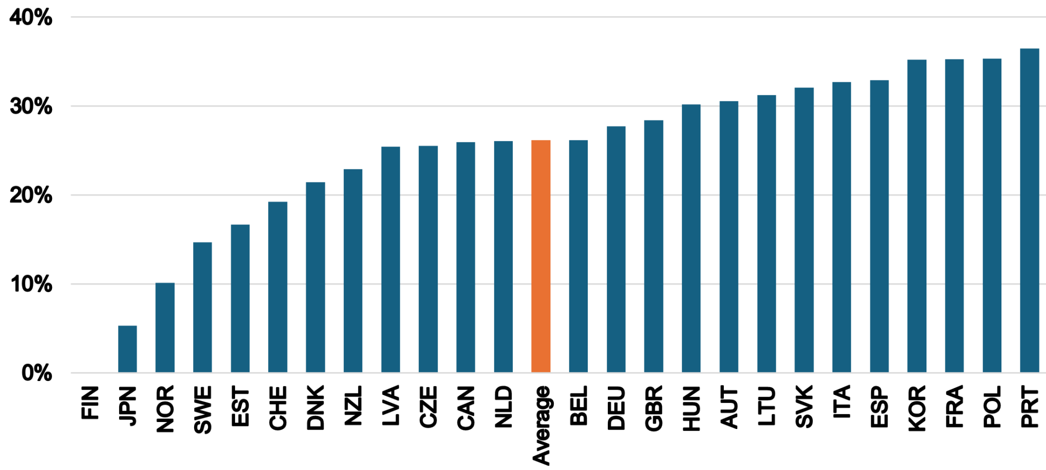
Source: Authors' calculations.

(Chart 3) with observed sector-level productivity gaps. On average, differences in adult skills can potentially account for one-quarter of cross-country productivity variation (Chart 4), and up to one-third in some Southern and Eastern European countries. These estimates leave plenty of scope for other factors to explain the productivity gap – including the efficient allocation of skills – which is explored below.

The results presented in Table 1 show the average positive relationship between labour productivity and PIAAC scores at the sector level. However, this average relationship masks significant differences across group of countries in the extent to which adult skills translate into productivity gains. Specifically, the pass-through of adult skills to productivity is considerably stronger in Nordic countries compared to other OECD economies (Table D1 in Appendix D in Andrews *et al.* (2025)). This disparity may reflect the greater efficiency of Nordic economies in allocating human capital, possibly supported by structural policy frameworks that facilitate reallocation and adaptability (Andrews *et al.*, 2024). This observed heterogeneity across countries motivates a deep dive into the link between human capital allocation and productivity in the next section.

The Allocation of Skills and Productivity Performance

Chart 4: Country-Level Productivity Gap Explained by Sector-Level PIAAC Differences, 2023



Note: Country-level productivity gap explained by sector-level PIAAC differences, compared to top 3 PIAAC performing countries. The bar for each country is a weighted (by value added share) average of the PIAAC contribution of each sector to overall productivity. The overall average is a simple average of the contributions in each country. PIAAC scores used for the calculations are the simple averages of the PIAAC scores on literacy, numeracy and problem solving.

Source: Authors' calculations.

While labour productivity is clearly connected to the average level of adult skills, so far we have been silent on how those skilled workers are allocated across firms and jobs within a given sector. To address this question, we emphasize two interrelated concepts: how efficiently skills are allocated at any point in time (i.e. static allocative efficiency) and whether skills are being allocated to better/more productive firms over time (i.e. dynamic allocative efficiency). While PIAAC does not contain data on firm productivity, it does contain information on the size of firms (measured by headcount) as well as the growth status of firms (i.e. headcount is growing, static or declining), from which we can draw inferences about firm performance. Moreover, PIAAC contains various measures of labour market mismatch, which previous OECD research has shown to have a close theoretical and empirical link with static allocative efficiency (Adalet McGowan and Andrews, 2017).

Labour Market Mismatch

Labour market mismatch arises when workers are employed in jobs that are either too demanding or not challenging enough. Qualification and field-of-study mismatches are prevalent in OECD countries. On average, nearly 35 per cent of workers in the OECD are employed in jobs that require a lower or higher qualification than their highest level of qualification. Similarly, over 35 per cent of workers holds jobs that do not align with their field of study. These mismatches differ across countries. For instance, Korea has the highest level of field of study mismatch but performs much better in terms of qualification mismatch. Conversely, Switzerland excels in minimizing qualification mismatch but faces challenges in terms of field of study mismatch.

Labour market mismatch is potentially most acute when measured by the combination of qualification and field of study mismatch – that is, when workers are mismatched both in terms of qualification and field of study. According to this metric, more than 10 per cent of workers on average across the OECD experience mismatch. The incidence of mismatch tends to be higher in industries such as transport, hospitality and administrative services and lower than average in ICT, finance and professional services.

Allocation of Skills Across Firms

The way in which skills are allocated to firms of various size is also connected to the concept of static allocative efficiency. There is evidence that larger firms are often more productive than smaller firms and can better deploy skilled workers and that better-skilled workers can perform jobs more productively in larger firms (Haltiwanger, 2011). In this regard, the new 2023 PIAAC data confirms that average worker skills are higher in larger firms on average across the OECD (Chart 5, Panel A), but the strength of this connection varies significantly across countries (Chart 5, Panel B).

The dynamic allocation of skills across firms can be measured through the skills of workers employed in growing, static and declining firms in terms of employment (Chart 6, Panel A). Improving allocative efficiency over time implies that growing firms would attract and employ more skilled workers while declining firms would be left with workers with lower skills. On average across the OECD, skills are moving in the right direction over time: growing firms employ more skilled workers than declining firms, by a margin of 4 per cent on average across OECD countries (Chart 6, Panel B). However, this is not always the case: in New Zealand and Italy, declining firms employ workers with better skills than growing and static firms (Figure 8 and Appendix E in Andrews *et al.* (2025)).

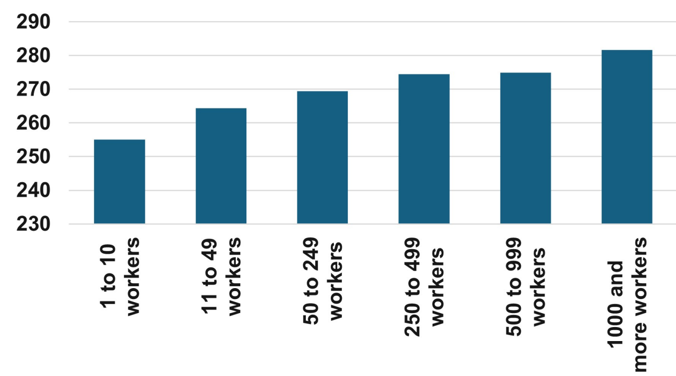
Labour Market Mismatch, Skills Allocation Across Firms and Productivity

Preliminary eyeball econometrics, based on binscatter charts, explained in Chart 7, suggest a negative relationship between overall labour market mismatch and labour productivity (Chart 7).

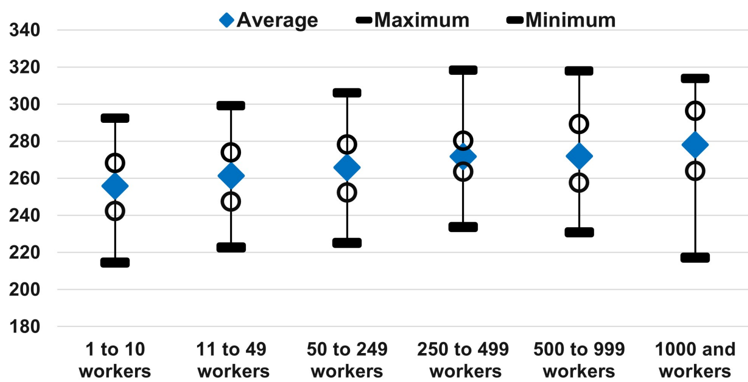
More formally, the cross-country sector-level estimation results indicate that the share of mismatched workers tends to be negatively related to sector-level productivity, particularly when field-of-study and qualification mismatches are combined (Table 2, Columns 2 to 6). Similar results are obtained for the R&D-specific labour market mismatch, which focuses on mismatch amongst engineers and scientists (see Box 3 in Andrews *et al.*, 2025). Put differently, countries and industries that achieve a more efficient matching of workers in terms of qualification and specialization are found to exhibit higher labour productivity. Interestingly, the coefficient on average PIAAC declines somewhat with the inclusion of mismatch, consistent with the negative cross-country relationship between the two variables (Figure A3 in Ap-

Chart 5: Adult Skills by Firm Size, OECD Average:

Panel A. PIAAC Scores in Points by Firm Size



Panel B. The Distribution of PIAAC Scores by Firm Size

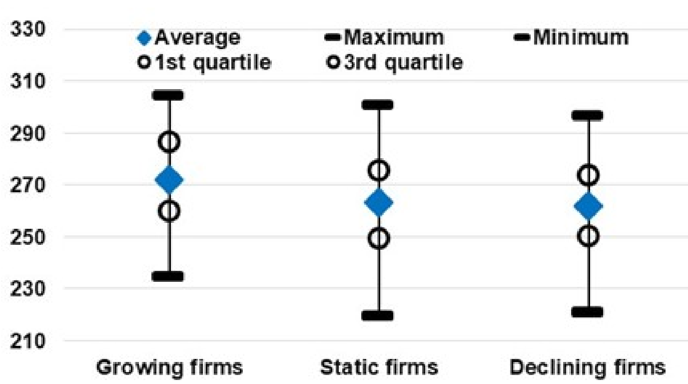


Note: PIAAC scores displayed are the simple averages of the PIAAC scores on literacy, numeracy and problem solving.

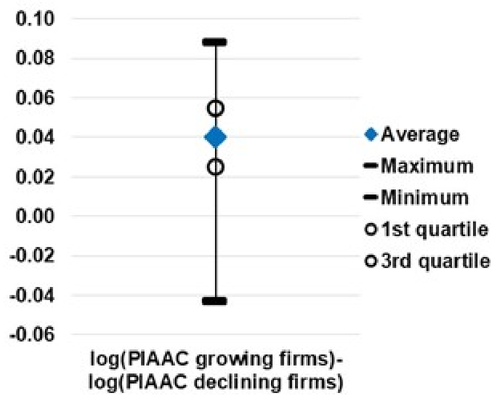
Source: Authors' calculations.

Chart 6: PIAAC Scores of Workers in Growing, Static and Declining Firms

Panel A. PIAAC scores by types of firms



Panel B. The Difference in PIAAC Scores between Growing and Declining Firms



Note: PIAAC scores displayed are the simple averages of the PIAAC scores on literacy, numeracy and problem solving. Firms are growing, declining or static in terms of headcount. Static firms refer to firms that "stayed more or less the same" in terms of headcount.

Source: Authors' calculations.

pendix A in Andrews *et al.* (2025)).

The allocation of skilled workers across firms of different sizes also plays a significant role (Table 2, Columns 3 and 4). First, productivity is higher in industries where larger firms employ a greater proportion of more skilled workers compared to smaller firms. Consistent with this is the finding, that more skilled workers in smaller firms tends to act as a drag on sectoral productivity. On the dynamic side, allocating higher-skilled workers to expanding firms at the expense of declining firms is associated with higher productivity (Table 2, Columns 5 and 6). The inverse holds true: productivity is lower when higher-skilled workers remain trapped in declining firms. Finally, additional analysis suggests that the link between labour productivity and the allocation of skills to dynamic firms remains intact after controlling for the role of financial frictions and insolvency regimes (see Box 4 in Andrews *et al.* 2025).

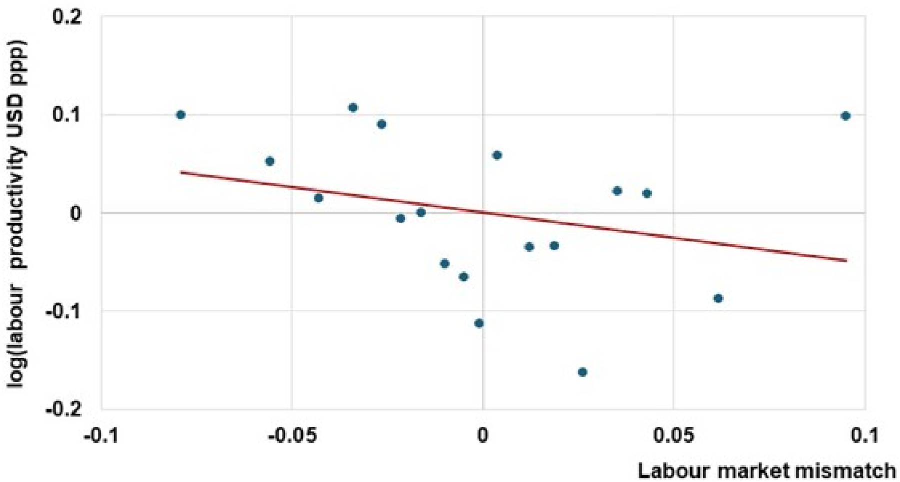
Economic Magnitudes

How large are the aggregate labour productivity gains from closing the sector-level labour market mismatch gap to the best-performing sectors/countries? This exercise is similar in spirit to the one conducted for the gaps in adult skill levels.[12] These simulations suggest that closing the mismatch gap would be associated with a productivity boost of almost 5 per cent on average across OECD countries (Chart 8). This is in the same ballpark as estimated by Adalet McGowan and Andrews (2017).

A useful comparison is between the potential productivity gains from closing adult skill gaps (Chart 3) and mismatch gaps (Chart 8). Countries such as Finland and Norway combine high skill levels with low mismatch, yielding limited poten-

12 The calculations involve deriving the sectoral mismatch gaps relative to the best 3 performing OECD countries, followed by the calculation of the sectoral productivity gains (calculated as the mismatch gap multiplied by the coefficient estimate on mismatch (Column 2 in Table 2)). Finally, the sectoral productivity gains are aggregated to the country level by using sectoral value-added.

Chart 7: Labour Productivity and Labour Market Mismatch



Note: The figure uses the STATA binscatter command: it shows logged average labour productivity for each of the 18 bins of labour market mismatches, purged of country- and sector fixed effects. Labour market mismatch is measured as the combination of qualification and field-of-study mismatch.

Source: Authors' calculations.

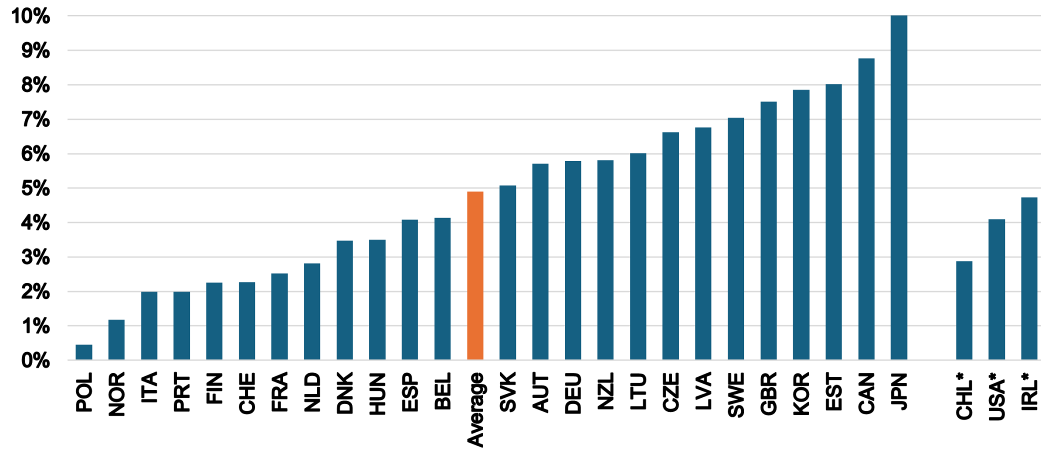
Table 2: Labour Productivity and the Allocation of Skills

	log**(labour productivity)**					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
PIAAC = average of literacy, numeracy and problem solving						
Constant	−0.508	1.035	1.489	0.099	0.161	−0.767
Adult skills effects						
log(PIAAC)	2.303**	2.044**	3.689**	2.054**	2.928**	2.219**
Allocation of skills effects						
Labour market mismatch						
Labour market mismatch (qualification and field-of-study)		−1.031**	−0.984**	−0.994**	−1.060**	−1.012**
log(PIAAC small firms)			−1.733*			
log(PIAAC large) − log(PIAAC small)				0.663*		
Allocation of skills across firms						
log(PIAAC declining firms)					−0.861**	
log(PIAAC growing) − log(PIAAC declining)						0.579**
R^2	0.880	0.885	0.887	0.886	0.887	0.887
No. observations	278	278	278	277	273	272
No. countries	25	25	25	25	25	25
Country fixed effects	YES	YES	YES	YES	YES	YES
Sector fixed effects	YES	YES	YES	YES	YES	YES

Note: * and ** denote statistical significance at the 10% and 5% levels, respectively, based on robust standard errors. Average PIAAC scores used in the regressions are the simple average of the PIAAC scores on literacy, numeracy, and problem solving.

Source: Authors' calculations.

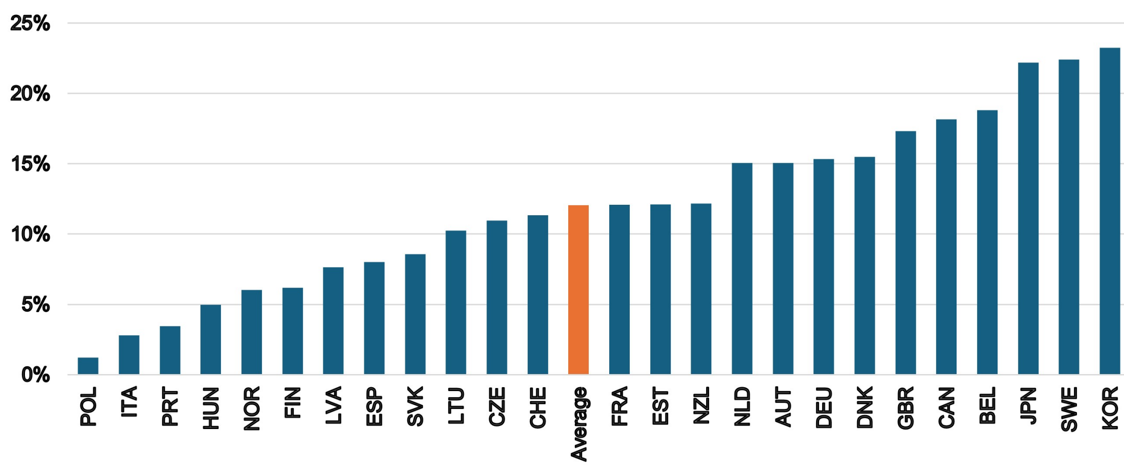
Chart 8: Country-Level Labour Productivity Gains Implied by Closing Sector-Level Labour Market Mismatches



Note: Country-level productivity gains implied by closing sector-level labour market mismatches are calculated as follows. First, the mismatch gap is determined vis-à-vis the top 3 least mismatched countries/sectors. Second, the coefficient estimate of -1.031 from Table 2 is used to calculate the implied sectoral productivity gains. Finally, sectoral value-added weights are employed to obtain country-level implied productivity gains. Countries marked with an asterisk (*) lack sectoral productivity data. For these countries, sector-level productivity gains can be calculated by multiplying the sector-level labour market mismatch gap by the estimated coefficient linking sector-level labour productivity to mismatch in in-sample countries.

Source: Authors' calculations.

Chart 9: Country-Level Productivity Gap Explained by Sector-Level Labour Market Mismatch Disparities



Note: The calculations are done as follows. First, we calculate the difference in labour market mismatch of all countries in a specific sector relative to the average of the top 3 countries with the least mismatch. Coefficient estimates from column 1 of Table 2 are used to derive the implied labour productivity gap, which is then compared to the observed productivity gap. Sectoral value-added shares are used to calculate the contribution of mismatches to the country level productivity gap. Labour market mismatch is used to proxy static allocative efficiency and the estimates are potentially conservative estimates as they do not include dynamic allocative efficiency effects.

Source: Authors' calculations.

tial gains from either channel. In contrast, Korea shows both low skills and high mismatch, implying large gains from improving both the level and allocation of skills. These patterns align with the negative correlation between adult skills and labour market mismatch across OECD industries (Chart A3 in Andrews *et al.*, 2025), though the relationship is far from perfect. Some countries that would benefit most from reducing mismatch are not those with the largest skill shortfalls. For example, Poland and Portugal exhibit low mismatch and potential productivity gains of only about 1 per cent, while Japan, with substantial mismatches, could gain up to 9 per cent, despite minimal returns from higher skill levels (Chart 3).

What proportion of the cross-country labour productivity gaps can be explained by the allocation of skills? The implied productivity gains in Chart 8 are compared with the observed overall productivity gap. For the average OECD country, differences in labour market mismatch explain around 12 per cent of cross-country productivity gaps relative to best practice (Chart 9). This is a conservative estimate because dynamic allocative efficiency effects will eventually feed into static allocative efficiency. In some countries (e.g. New Zealand, Italy, Canada), skilled workers are not strongly concentrated in expanding firms, limiting productivity growth. If these countries could match the allocation pattern observed in the average OECD economy, labour productivity could be 3 per cent higher. Similarly, moving from the bottom quartile to the OECD average in skill allocation (Chart 6, Panel B) would yield productivity gains of roughly 1 per cent. While the aggregate benefits of better skill allocation appear substantial, a more systematic quantification of dynamic allocative effects is left for future research.

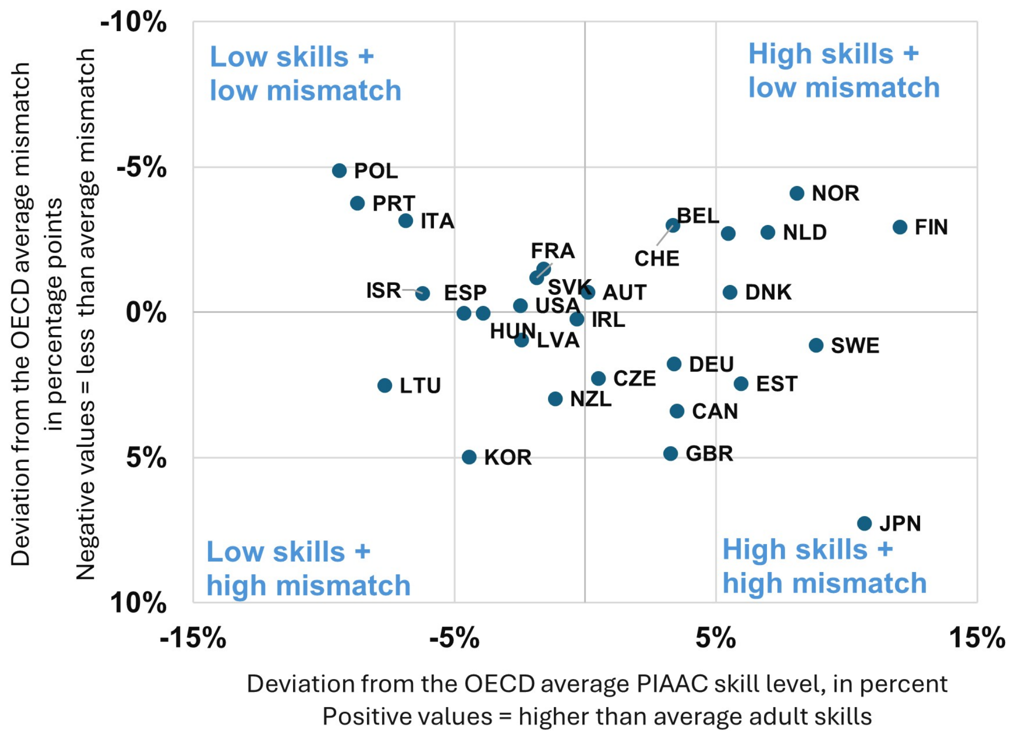
Overall, for an average OECD country, the general and R&D-specific level of skills channel accounts for almost 25 per cent of these gaps, while the allocation of skills, captured through the general labour market mismatch, explains more than 12 per cent. Collectively, differences in the level and allocation of adult skills can explain roughly 40 per cent of productivity gaps across OECD countries.

Policy Discussion

The results illustrate the importance of adult skills for productivity and raise two key policy questions for future research. First, given the strong link between sectoral productivity and worker skills, what can policy do to raise workforce skill levels? Second, how can countries better allocate existing skills, since productivity tends to be higher where labour market mismatch is lower and skilled workers are employed in more productive firms?

Before addressing these policy questions, Chart 10 summarizes country performance on two dimensions, adult skills and labour market mismatch, to sharpen the focus on productivity-enhancing reforms. The top-right quadrant includes countries such as Finland, Norway, and the Netherlands with above-average adult skills and below-average labour market mismatch and thus serve as role models. In the bottom-right quadrant, Japan and, to a lesser extent, the United Kingdom perform well on skills but face high mismatch, indicating scope to

Chart 10: OECD Countries in Terms of Adult Skills and Labour Market Mismatch



Note: The calculations are done as follows. First, we calculate the difference in labour market mismatch of all countries in a specific sector relative to the average of the top 3 countries with the least mismatch. Coefficient estimates from column 1 of Table 2 are used to derive the implied labour productivity gap, which is then compared to the observed productivity gap. Sectoral value-added shares are used to calculate the contribution of mismatches to the country level productivity gap. Labour market mismatch is used to proxy static allocative efficiency and the estimates are potentially conservative estimates as they do not include dynamic allocative efficiency effects.

Source: Authors' calculations.

improve labour market matching. Human-capital and skill-building policies remain priorities for countries on the left-hand side, especially Korea and Lithuania, which face the dual challenge of below-average skills and above-average mismatch.

The first policy question is relevant for countries needing to boost adult skills. Work-related training is crucial for improving adult skills, as it enhances adaptability and productivity and is strongly correlated with higher PIAAC scores. Yet in many OECD countries, participation in training programs remains low (OECD, 2020), especially amongst less-educated workers who stand to benefit most. This underscores the importance for early education policies that build strong foundational skills. OECD research emphasizes that participation in high-quality early-childhood education, high-quality teachers, school support for homework and regulated use of digital devices all improve student outcomes (Andrews *et al.*, 2024). These foundations make future workers more adaptable to changing job demands and technologies.

OECD research also emphasizes flexibility in adult learning, allowing individuals to choose when, where, how, and what to learn, is essential for increasing participation and inclusiveness, especially amid disruptions from digitalization and the green transition (OECD, 2023). Many OECD countries support training in green and AI-related fields, but availability varies and low-skilled workers are less likely to access such opportunities, highlighting the need for stronger incentives and outreach (OECD, 2024c).

The second policy question, improving the allocation of skills, is particularly important for countries with large labour market mismatches. Although the effect is smaller than that of improving average skills, this channel may yield quicker gains. Evidence suggests that financial frictions and rigid insolvency regimes hinder restructuring and penalize entrepreneurship, constraining productivity in dynamic sectors. Future research should explore how policies can better support the efficient reallocation of skills (see Box 4 in Andrews *et al.*, 2025).

On this front, it is significant that the share of workers in growing firms is positively associated with policy frameworks that support reallocation, measured by a composite indicator covering product market regulations, employment protection, insolvency regimes, and ALMP spending (Andrews *et al.*, 2025). Barriers such as occupational licensing, non-compete clauses, and housing constraints may also impede mobility. Overall, structural reforms that promote labour market fluidity and firm dynamism remain essential to ensure efficient skill matching, especially at a time when headwinds to human capital accumulation have never been stronger (Andrews *et al.*, 2024).

Conclusion

This article exploited the 2023 Programme for the International Assessment of Adult Competencies (PIAAC), which reveals large cross-country differences in adult skill levels. Average PIAAC scores in the top three performing countries are around 10 per cent higher than the OECD average and 25 per cent higher than in the bottom three performing countries.

Cross-country sector-level analysis suggests that the latest PIAAC outcomes have important implications for aggregate productivity in three ways. First, there is a robust positive correlation between the level of labour productivity and the average level of adult skills in the non-farm business sectors. Assuming a causal relationship, cross-country sector-level analysis implies that i.) closing the sector-level gap in PIAAC outcomes of the average OECD country to the top three performing countries could lift the average OECD labour productivity level by 17 per cent; ii.) This level of skills effect can potentially account for on average one-quarter (and up to one-third) of cross-country sector-level labour productivity gaps; and iii.) There is a positive relationship between R&D intensity and adult skills and over one-third of the impact of adult skills on labour productivity can be accounted for by the R&D channel (which supplies the generation of new ideas). This leaves plenty of scope for adult skills to impact productivity via other channels, such as the adoption of existing technologies.

Second, the mismatch of workers in terms of qualification and field of study and the effective allocation of skilled workers to different job roles and firm types varies across countries, with important implications for productivity. Labour productivity is higher in sectors where labour market mismatch is lower and where high-skilled workers are more likely to be allocated to larger – as opposed to smaller – firms. Productivity is also higher when high skilled workers are deployed to growing firms, while it tends to be lower when they are trapped in declining firms.

Finally, assuming a causal relationship, closing the labour market mismatch gap of the average OECD country to the best performing countries can potentially account for more than one-tenth of the cross-country sector-level productivity gaps to best-performing countries.

These findings suggest that high priority should be assigned to understanding the scope for policies – including adult training programmes – to raise the average level of adult skills. However, significantly improving adult skills through raising the foundational skills of younger generations is a process that spans across generations. While the aggregate productivity impact of the allocative channel is more modest, it may be more leverageable by policy in the near term, highlighting the role of structural reforms to support labour market reallocation and adaptability.

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Labour Productivity as a Measure of Technological Change

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Abstract

Average labour productivity (ALP) is today the productivity measure most used by policy makers, the media, and the general public. Economists recognize however that it is an inadequate measure of technological change. This is because ALP is a hybrid measure that captures both shifts in the production possibilities frontier and movements along the frontier itself. Thus, the flaw of ALP as a measure of technological change is not that it uses labour as a benchmark, which is a perfectly appropriate, but that, by being a partial measure of productivity, it ignores the role of capital, not just when accounting for technological change, but, even much more seriously, in production altogether. Put in other words, the numerator of the ALP ratio is not consistent with its denominator as a measure of technological change, and it is not the denominator that is at fault, but the numerator. A complete, or total measure of labour productivity (TLP) is therefore proposed and compared to the ALP and the better-known total factor productivity (TFP) measures. The relationship between the three productivity measures can also be analyzed in the dual price space. Numerical results for the U.S. private nonfarm business sector are provided as an illustration.

Output or gross domestic product (GDP) per unit of labour is today the aggregate measure of productivity most used by policy makers, the media, and the general public. Yet, average labour productivity (ALP) so defined has somewhat of a bad press among economists.[2] For a start, by crediting the totality of productivity gains to labour and thus overlooking the contribution of capital, it seems rather one-sided. Much more importantly, though, ALP is fundamentally a partial measure of productivity, to use the terminology of Domar (1962), and it is therefore not fit to measure technological change. This is why economists tend to favour the concept of

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2 The wide acceptance of this concept probably has to do in part to its early adoption by the Organisation for European Economic Co-operation (OEEC, the ancestor of the Organisation for Economic Co-operation and Development, OECD) in 1949 under the influence of Jean Fourastié; see Boulat (2006: 97).

total factor productivity (TFP) that takes into account of both labour and capital.[3]

ALP is somewhat of a hybrid measure of productivity growth. It is well known that it combines elements of technological progress – which in the context of a simple two-input, one-output production function can be thought of as an upward shift in the production function – and effects of technical change – which can be described as changes in the input mix, i.e. movements along an isoquant.[4]

Economists are mostly interested in the progression of productivity over time. What matters then, when comparing different measures, is not the size of the numerators and denominators, but the growth rates of their components. With capital services typically increasing more rapidly than employment, and indeed output, ALP growth will tend to exceed TFP growth, whereas *average capital productivity* (AKP) growth will not just fall short of TFP growth, but it will even tend to be negative. This does not make AKP a very appealing concept; hence it is its inverse – which is a measure of the capital intensity of production (KIP) and usually is increasing over time – that receives more attention.

Even though ALP is not an appropriate measure of technological progress, the focus on labour should not be rejected out of hand. This would be tantamount to throwing out the baby with the bathwater, to use a metaphor dear to economists. There might be good reasons to focus on labour. For one thing, labour is more intuitive a concept and better understood by the wide public than physical capital. Even though output per unit of labour is not the same as income per capita, labour productivity is often used as a welfare indicator or a measure of economic development.[5]

Furthermore, labour can be viewed as the only true primary factor of production – since capital has been produced by labour in previous periods – and thus it is the ultimate force behind production, technological change, and growth.

Technological change is often modelled as being disembodied and factor augmenting. It is as if an available endowment of labour and capital increased with the passage of time when measured in terms of efficiency units. If labour and capital both benefit from efficiency gains at the same rate, technological change is said to be balanced, or Hicks-neutral. If the passage of time benefits labour exclusively, technological change is said to be labour-augmenting, or Harrod-neutral, and if capital is the sole beneficiary, techno-

3 The term total factor productivity seems to have been introduced by Kendrick (1961); see Domar (1962) who prefers the name The Residual; this term is also known as multifactor productivity (MFP), and it is often referred to as the Solow (1957) residual when derived from econometric estimates.

4 Technological progress is sometimes described as increases in knowledge, whereas technical change may be thought of as changes in processes. Technical change is often incremental and internal to firms, whereas technological change is a broader process and it may imply a shift in the technological paradigm. While this distinction is fuzzy, it is convenient to distinguish the two types of changes that can occur in the context of our model. See Nelson and Winter (1982), Rosenberg (1983), and Freeman and Soete (1997) for in-depth analyses.

5 A high average labour productivity in international comparison does not necessarily mean that the country's workers are better skilled or more hard working: it might simply mean that the have more capital to work with, and this capital goes unaccounted for.

logical change is described as being capital–augmenting, or Solow-neutral. There is some evidence that technological change tends to be largely labour augmenting (i.e. coming close to being Harrod-neutral), thus yet another argument in favour of the use of labour as a yardstick.[6]

TFP, on the other hand, models technological change as if it were Hicks-neutral. In any case, one should be able to use any benchmark one pleases. Technological change can be measured from different perspectives, but it is important to be fully aware of the standpoint one takes. We will argue that labour is a perfectly appropriate reference, but that ALP is generally not an acceptable measure of technological change, not because it neglects the role of capital in that process, but, much more importantly, because it actually ignores the contribution of capital to current production altogether. The numerator and denominators of ALP are not consistent with one another for the purpose of measuring technological change, and, moreover, it is not the denominator that is at fault (if it is selected by design), but the numerator. In lieu of a partial productivity measure such as ALP, what is needed is a complete, i.e. total productivity measure, one that takes all inputs and outputs into account, even though the focus is on labour.

In order to present our argument in the simplest possible way, we will use here a very basic representation of the technology that could be thought of as being modelled by a one-output, two-input (labour and capital) aggregate production function. Our approach, however, can easily be generalized to include more inputs and/or outputs.[7]

As usual when modelling technologies at the aggregate or national level, we will assume constant returns to scale, perfect information and foresight, optimization, the absence of adjustment costs and full capacity utilization, perfect competition, the absence of measurement errors as well as of externalities such as environmental issues, but these assumptions could be relaxed if needed at the firm or industry level. We will apply measurement theory to obtain a total labour productivity (TLP) – or Harrodneutral – index of technological change and we will show how it differs from the well-known TFP index. We will further show that TLP, by netting out the contribution of capital, is better related to the evolution of real wages than is ALP. This is all the more relevant since the growth in ALP is often used as a benchmark by policy makers and employers alike when assessing the inflationary potential of nominal wage increases. TLP can be thought of as an upper bound of the growth of real wages made possible by technological progress, abstracting from the effect of changes in factor intensities. Actual measures for the United States will be reported as an illustration.

The article contains five sections and proceeds as follows. In the first section, we

6 See Kohli (1991, 2010, 2015) for some evidence for the United States, for instance, and Chambers (1988) for a good theoretical review of the different forms of technological change.

7 See Kohli (2025) for a more general model with the focus on imports.

review the relationship between ALP and TFP. In the following section, we formally define TLP, and we show how it relates to ALP and TFP. In the third section we re-examine the relationship between all three productivity measures in the dual, price space; this will also enable us to bring the marginal labour and capital productivity concepts into the analysis. This is followed by an empirical illustration, using data for the U.S. private nonfarm business sector. The last section concludes.

Average Labour and Total Factor Productivity

Consider a simple one-output, two-input technology. The quantity of output at time t, which could be thought of as real GDP, is denoted by $q_{Y,t}$, and its price by $p_{Y,t}$. We assume two factors of production, capital (K) and labour (L); the corresponding quantities at time t are denoted $x_{K,t}$ and $x_{L,t}$, with rental prices $w_{K,t}$ and $w_{L,t}$.[8]

We begin with the national accounts identity that implies the equality between the country's nominal output (Y_t) and factor payments:[9]

$$Y_t = p_{Y,t}q_{Y,t} = w_{K,t}x_{K,t} + w_{L,t}x_{L,t} \tag{1}$$

Let $Q_{Y,t,t-1}$ and $P_{Y,t,t-1}$ denote the growth factors (one plus the rate of growth between time $t-1$ and time t) of real output and its price:

$$Q_{Y,t,t-1} = \frac{q_{Y,t}}{q_{Y,t-1}}, \quad P_{Y,t,t-1} = \frac{p_{Y,t}}{p_{Y,t-1}} \tag{2}$$

Similarly, we define the growth factors of the quantities and prices of capital and labour:

$$\begin{aligned} X_{K,t,t-1} &= \frac{x_{K,t}}{x_{K,t-1}}, \qquad X_{L,t,t-1} &= \frac{x_{L,t}}{x_{L,t-1}}, \\ W_{K,t,t-1} &= \frac{w_{K,t}}{w_{K,t-1}}, \qquad W_{L,t,t-1} &= \frac{w_{L,t}}{w_{L,t-1}} \end{aligned} \tag{3}$$

The ALP, AKP and KIP indices can now be obtained as:

$$\begin{aligned} ALP_{t,t-1} &= \frac{Q_{Y,t,t-1}}{X_{L,t,t-1}}, \quad AKP_{t,t-1} = \frac{Q_{Y,t,t-1}}{X_{K,t,t-1}}, \\ KIP_{t,t-1} &= \frac{X_{K,t,t-1}}{Q_{Y,t,t-1}} \end{aligned} \tag{4}$$

Let $s_{K,t}$ and $s_{L,t}$ be the cost shares of capital and labour in production at time t:

$$s_{K,t} = \frac{w_{K,t}x_{K,t}}{p_{Y,t}q_{Y,t}}, \quad s_{L,t} = \frac{w_{L,t}x_{L,t}}{p_{Y,t}q_{Y,t}} \tag{5}$$

with $s_{K,t} + s_{L,t} = 1$, and define $\bar{s}_{K,t,t-1}$ and $\bar{s}_{L,t,t-1}$ as their averages over consecutive periods:

$$\bar{s}_{K,t,t-1} = \frac{s_{K,t} + s_{K,t-1}}{2}, \bar{s}_{L,t,t-1} = \frac{s_{L,t} + s_{L,t-1}}{2} \tag{6}$$

We next define $X_{t,t-1}$ as a Törnqvist in-

8 The return to capital is measured on an ex-post basis as it is typically done when dealing with country-wide data and while assuming perfect foresight and the absence of adjustment costs; relaxing these assumptions would undeniably impact on the actual measurement of TLP, just like it has been shown to affect measures of TFP; see Berndt and Fuss (1986), Hulten (1986), and Oulton (2007).

9 Indirect taxes and subsidies are netted out of output prices to ensure this equality.

put quantity index:[10]

$$X_{t,t-1} = X_{K,t,t-1}^{\bar{s}_{K,t,t-1}} \cdot X_{L,t,t-1}^{\bar{s}_{L,t,t-1}} \tag{7}$$

We then obtain the TFP index as:

$$TFP_{t,t-1} = \frac{Q_{Y,t,t-1}}{X_{t,t-1}} \tag{8}$$

The relationship between $ALP_{t,t-1}$ and $TFP_{t,t-1}$ can easily be derived:

$$\begin{aligned} ALP_{t,t-1} &= \frac{Q_{Y,t,t-1}}{X_{L,t,t-1}} \\ &= \frac{Q_{Y,t,t-1}}{X_{K,t,t-1}^{\bar{s}_{K,t,t-1}} X_{L,t,t-1}^{\bar{s}_{L,t,t-1}}} \cdot \frac{X_{K,t,t-1}^{\bar{s}_{K,t,t-1}} X_{L,t,t-1}^{\bar{s}_{L,t,t-1}}}{X_{L,t,t-1}} \\ &= \frac{Q_{Y,t,t-1}}{X_{t,t-1}} \cdot \left(\frac{X_{K,t,t-1}}{X_{L,t,t-1}} \right)^{\bar{s}_{K,t,t-1}} \\ &= TFP_{t,t-1} \cdot \left(\frac{X_{K,t,t-1}}{X_{L,t,t-1}} \right)^{\bar{s}_{K,t,t-1}} \end{aligned} \tag{9}$$

This result is well known: ALP growth is the resultant of TFP growth (technological change) and of the impact of increases in the capital-labour intensity ratio (technical change). Since the capital-labour ratio tends to increase over time, ALP growth will typically exceed TFP growth.

Total Labour Productivity

There is an extensive literature about measuring productivity in the presence of intermediate goods or services.[11] Most of this literature deals with sectorial or industrial analyses, where intermediate inputs might be energy, materials, and purchased services. Aggregation over sectors and industries must be carried out with special care in order to avoid any double accounting. The issue of double accounting does normally not arise at the national level since domestic intermediate goods then typically wash out.[12] Nonetheless, a complete accounting of production and productivity gains at the national level requires that all primary inputs and outputs be taken into account.

In our case of interest, the issue is not so much one of double accounting, but rather one of accounting omission. Many national statistical agencies publish ALP and TFP statistics, often at the aggregate and at the industry level. An important issue at the industry level is how is “output” measured? Is it a gross output measure, that takes all inputs into consideration, or is it a value-added measure that nets out intermediate inputs, i.e. treats them as negative outputs?[13]

In the first case, TFP will be measured relative to an aggregate or weighted growth rate of labour, capital, and intermediate goods, whereas in the latter case the de-

10 The Törnqvist index is a superlative index and it has been shown by Diewert (1974, 1976) to be exact for the Translog functional form introduced by Christensen, Jorgenson, and Lau (1973). It is typically numerically very close to another superlative index, the Fisher almost ideal index; see Diewert (1978).

11 See Kendrick (1961), Domar (1961, 1962), Binswanger (1974), Berndt and Wood (1975, 1982), Hulten (1978), Gollop (1979), Jorgenson and Fraumeni (1981), Jorgenson, Gollop, and Fraumeni (1987), Balk (2009, 2010), for instance.

12 Imported intermediate inputs are subtracted from gross output when calculating GDP.

13 The OECD offers some valuable guidelines in this respect; see OECD (2001, 2023).

nominator of TFP will be an aggregate of just labour and capital. Each approach has some advantages and some drawbacks,[14] but they both make perfect sense. It is therefore all the more surprising that the same logic is not being followed when it comes to measuring labour productivity.[15] Independently of whether intermediate inputs are included or left out, the numerator – gross output, or value added by labour and capital, as it may be – is not consistent in an accounting sense with the denominator (labour). The same is true at the aggregate level, where intermediate inputs are not an issue, but where the numerator is typically a gross output measure, whereas it should be a value-added measure after having netted out capital services.

In order to obtain an appropriate labour measure of technological change one needs a *total* measure that is compatible with accounting identity (1) above. That is, the contribution of capital to production cannot just be ignored: it must be netted out. In other words, one must treat capital services as an intermediate input, i.e. a negative output. This is not to say that we generally view labour as a fixed input and capital as a variable one, which would make little sense from a national or a firm viewpoint in the short run, but simply that the numerator should be consistent with the primary input variable that is being used as the denominator in calculating productivity.

Let us begin by rewriting accounting identity (1) as follows, thereby defining Λ_t as nominal *net output*, i.e. nominal value added by labour (equivalently, the wage bill):

$$\Lambda_t = p_{Y,t}q_{Y,t} - w_{K,t}x_{K,t} = w_{L,t}x_{L,t} \quad (10)$$

Treating capital as a negative output can be thought of as replacing the production function implicit throughout Section 2 by a real value-added function, a special case of a variable profit function (Diewert 1974, 1978). We then need a measure of net output, i.e. real value added by labour. The value shares of gross output and capital in net output are:

$$\lambda_{Y,t} = \frac{p_{Y,t}q_{Y,t}}{\Lambda_t} > 1, \quad \lambda_{K,t} = \frac{w_{K,t}x_{K,t}}{\Lambda_t} > 0 \quad (11)$$

with $\lambda_{Y,t} - \lambda_{K,t} = 1$. The Törnqvist quantity index of *net output*, i.e. real value added by labour, then is:

$$Q_{\Lambda,t,t-1} = Q_{Y,t,t-1}^{\bar{\lambda}_{Y,t,t-1}} \cdot X_{K,t,t-1}^{-\bar{\lambda}_{K,t,t-1}} \quad (12)$$

where $\bar{\lambda}_{Y,t,t-1}$ and $\bar{\lambda}_{K,t,t-1}$ are the average value shares over consecutive periods.[16]

We then can define the *total labour pro-*

14 See Schreyer (2001) for a good discussion.

15 The same is typically true when it comes to measuring capital productivity, although we are aware of two exceptions. Thus, Lawrence, Diewert, and Fox (2006) compute what they call a capital TFP measure. Similarly, Balk (2010) derives a number of capital productivity measures, treating labour as a negative output; nonetheless, he does not follow the same approach when defining labour productivity.

16 Quantity index (12) would be exact for the representation of the technology by a translog variable profit function treating capital as a negative output; see Diewert (1974, 1982, 2022).

ductivity (TLP) growth factor as:[17]

$$TLP_{t,t-1} = \frac{Q_{\Lambda,t,t-1}}{X_{L,t,t-1}} \qquad (13)$$

The difference between ALP and TLP is thus that in the latter case the real contribution of capital to production is netted out. This is as if, in the Laspeyres case, the constant dollar value of capital services were being subtracted from real gross output. The quantity of capital services generally increases more rapidly than real gross output, so that the growth in real net output will be that much reduced. Consequently, one should typically expect TLP to grow at a slower rate than ALP.

The question now obviously arises as to the relationship between the TLP and TFP measures. Note that it follows from (5) and (11) in view of (1) that:

$$\lambda_{Y,t} = \frac{1}{1-s_{K,t}} = \frac{1}{s_{L,t}}, \qquad \lambda_{K,t} = \frac{s_{K,t}}{1-s_{K,t}} = \frac{s_{K,t}}{s_{L,t}} \qquad (14)$$

In terms of averages over consecutive periods we use the following approximations:

$$\bar{\lambda}_{Y,t,t-1} = \frac{1}{2}\left(\frac{1}{s_{L,t}} + \frac{1}{s_{L,t-1}}\right) = \frac{\bar{s}_{L,t,t-1}}{s_{L,t}s_{L,t-1}} \simeq \frac{1}{\bar{s}_{L,t,t-1}} \qquad (15)$$

$$\bar{\lambda}_{K,t,t-1} = \bar{\lambda}_{Y,t,t-1} - 1 \simeq \frac{1}{\bar{s}_{L,t,t-1}} - 1 = \frac{\bar{s}_{K,t,t-1}}{\bar{s}_{L,t,t-1}} \qquad (16)$$

We thus find:[18]

$$\begin{aligned} TLP_{t,t-1} &= Q_{Y,t,t-1}^{\bar{\lambda}_{Y,t,t-1}} X_{K,t,t-1}^{-\bar{\lambda}_{K,t,t-1}} X_{L,t,t-1}^{-1} \\ &= \left[Q_{Y,t,t-1} \cdot X_{K,t,t-1}^{-\frac{\bar{\lambda}_{K,t,t-1}}{\bar{\lambda}_{Y,t,t-1}}} \cdot X_{L,t,t-1}^{-\frac{1}{\bar{\lambda}_{Y,t,t-1}}}\right]^{\bar{\lambda}_{Y,t,t-1}} \\ &\simeq \left(Q_{Y,t,t-1} X_{K,t,t-1}^{-\bar{s}_{K,t,t-1}} X_{L,t,t-1}^{-\bar{s}_{L,t,t-1}}\right)^{\bar{\lambda}_{Y,t,t-1}} \\ &= TFP_{t,t-1}^{\bar{\lambda}_{Y,t,t-1}} \end{aligned} \qquad (17)$$

Since $\bar{\lambda}_{Y,t,t-1} > 1$, TLP will tend to exceed TFP whenever technological change is positive. This is not surprising, since technological progress is fully allocated to labour by design. It is important to stress that, unlike ALP, TLP is a complete measure of technological change in that it takes the contribution of capital to production into account. Like TFP, TLP does not depend on the change in the capital-labour ratio over time. Both TFP and TLP measure the shift in the production possibilities frontier, independently of the capital-labour ratio, albeit from different perspectives.[19]

We may now examine the relationship between TLP and ALP. From (9) and (17)

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17 As suggested earlier, the adjective *total* is used to indicate that TLP is a *complete* or *comprehensive* measure of technological change, one that takes *all* inputs and outputs into account; it could also be described as a *Harrod* measure since it imputes all technological change to labour.

18 We have verified in our empirical illustration of Section 5 below that this approximation holds to at least the fourth decimal point.

19 See Kohli (2025) for further perspectives in an open economy context.

we find:

$$ALP_{t,t-1} = \frac{Q_{Y,t,t-1}}{X_{L,t,t-1}}$$

$$= \frac{Q_{Y,t,t-1}^{1+\bar{\lambda}_{K,t,t-1}} \cdot Q_{Y,t,t-1}^{-\bar{\lambda}_{K,t,t-1}}}{X_{L,t,t-1}} \cdot X_{K,t,t-1}^{-\bar{\lambda}_{K,t,t-1}} \cdot X_{K,t,t-1}^{\bar{\lambda}_{K,t,t-1}}$$

$$= \frac{Q_{\Lambda,t,t-1}}{X_{L,t,t-1}} \cdot \left(\frac{X_{K,t,t-1}}{Q_{Y,t,t-1}}\right)^{\bar{\lambda}_{K,t,t-1}}$$

$$= TLP_{t,t-1} \cdot KIP_{t,t-1}^{\bar{\lambda}_{K,t,t-1}} \tag{18}$$

where KIP is again the capital intensity of production index as defined in (4). Thus, the progression of ALP over time can be decomposed into the contribution of technological change, measured here by TLP, and a second term that captures the effect of the increasing capital-labour ratio (movement along the isoquant) that goes with the increase in KIP. In a way, this somewhat alien term stands for the lack of recognition of the role of capital in production when computing ALP: it is what it takes to convert a total productivity measure (TLP) back to a partial one (ALP). Expression (18) shows that since KIP tends to increase over time ALP will typically exceed TLP.

Our discussion could easily be replicated by focusing on capital rather than on labour. All we need to do is to interchange the subscripts K and L, and one ends up with a *total capital productivity* (TKP) measure, one that is in the spirit of Solow-neutral technological change, with the numerator being output net of the input of labour services. Thus, in analogy to (17), we would obtain:[20]

$$TKP_{t,t-1} \simeq Q_{Y,t,t-1}^{1/\bar{s}_{K,t,t-1}} X_{L,t,t-1}^{-\bar{s}_{L,t,t-1}/\bar{s}_{K,t,t-1}} X_{K,t,t-1}^{-1}$$

$$= \left(Q_{Y,t,t-1} X_{L,t,t-1}^{-\bar{s}_{L,t,t-1}} X_{K,t,t-1}^{-\bar{s}_{K,t,t-1}}\right)^{1/\bar{s}_{K,t,t-1}}$$

$$= TFP_{t,t-1}^{1/\bar{s}_{K,t,t-1}} \tag{19}$$

Given that $\bar{s}_{K,t,t-1} < \bar{s}_{L,t,t-1}$ typically, one would normally expect $TKP_{t,t-1}$ to exceed both $TLP_{t,t-1}$ and $TFP_{t,t-1}$, as long as the latter is indeed greater than one. This might come as a surprise in view of our earlier comment that AKP growth is likely to be negative since the denominator (capital) then tends to grow more rapidly than the numerator (output). The situation is different with TKP growth, though, for now it is not just the denominator that may grow rapidly, but the numerator – being magnified, so to speak – will too, and, as long as the fraction is greater than unity, the latter effect will dominate. This Solow-like index would be particularly relevant in the context of an economic model treating labour as a variable input, in the presence of unemployment for instance,[21] or if the focus is on the return to capital as in Lawrence, Diewert, and Fox (2006).

Total Labour Productivity: A Dual Approach

There is another way to conduct our analysis. Let $\Lambda_{t,t-1}$ be the growth factor

20 This TKP measure would be equivalent to what Lawrence, Diewert, and Fox (2006) label a capital TFP measure.

21 See Kohli (1983), for instance.

of the wage bill. From (10) we can write:

$$\Lambda_{t,t-1} = \frac{\Lambda_t}{\Lambda_{t-1}} = W_{L,t,t-1} \cdot X_{L,t,t-1} \quad (20)$$

We next define the *implicit* price index of net output:

$$\tilde{P}_{\Lambda,t,t-1} = \frac{\Lambda_{t,t-1}}{Q_{\Lambda,t,t-1}}, \quad (21)$$

which has the implicit (or indirect) Törnqvist form. Note that this index is not identical to the *direct* Törnqvist price index, which, in analogy to (12), would be given by:

$$P_{\Lambda,t,t-1} = P_{Y,t,t-1}^{\bar{\lambda}_{Y,t,t-1}} \cdot W_{K,t,t-1}^{-\bar{\lambda}_{K,t,t-1}} \quad (22)$$

This is due to the fact that the Törnqvist does not satisfy the factor reversal test. This is a minor flaw, for it is well known that direct and implicit Törnqvist are typically numerically very close to one another (Diewert 1976; 1978). In what follows, we will therefore use either one as a close approximation for the other.[22]

It then immediately follows from (13), (20) and (21) that TLP can be expressed in the dual price space:

$$TLP_{t,t-1} = \frac{W_{L,t,t-1}}{\tilde{P}_{\Lambda,t,t-1}} \quad (23)$$

That is, TLP can also be thought of as the increase in real wages measured in terms of net output, a finding that is not really surprising in view of a similar result of Jorgenson and Griliches (1967) with regard to TFP:

$$TFP_{t,t-1} = \frac{W_{t,t-1}}{\tilde{P}_{Y,t,t-1}} \quad (24)$$

where $\tilde{P}_{Y,t,t-1}$ is the implicit GDP price deflator. Interestingly enough, an expression somewhat similar to (23) appears in Domar's (1962) review of Kendrick (1961), but he dismisses it as "merely an index of the real wage rate".[23]

The point, though, is that $\tilde{P}_{\Lambda,t,t-1}$ — the denominator in (23) — is not the price of gross output, but the price of the value added by labour, so that the ratio (23) does indeed provide a measure of technological change.

Whereas TFP and TLP can be expressed in terms of price changes, things are not quite that obvious when it comes to ALP since, by totally excluding capital, it is a partial productivity index. Nonetheless, substituting prices for quantities and vice versa, the mirror image of ALP that emerges is the real wage rate, i.e. the *marginal labour productivity* (MLP) index; the *marginal capital productivity* (MKP) index can be similarly defined. We thus

22 Alternatively, in order not to have to make any arbitrary choices, we could use a *symmetric* Törnqvist index defined as their geometric mean:

$$\hat{P}_{\Lambda,t,t-1} = \left(P_{\Lambda,t,t-1}\,\tilde{P}_{\Lambda,t,t-1}\right)^{1/2} = \left[\left(\frac{P_{Y,t,t-1}}{Q_{Y,t,t-1}}\right)^{\bar{\lambda}_{Y,t,t-1}} \cdot \left(\frac{W_{K,t,t-1}}{X_{K,t,t-1}}\right)^{-\bar{\lambda}_{K,t,t-1}} \cdot \Lambda_{t,t-1}\right]^{1/2}$$

and similarly on the quantity side. The resulting indices then satisfy the factor reversal test. See Kohli (2025).

23 See Domar (1962: 604), expression (12).

obtain:

$$MLP_{t,t-1} = \frac{W_{L,t,t-1}}{P_{Y,t,t-1}}$$
$$MKP_{t,t-1} = \frac{W_{K,t,t-1}}{P_{Y,t,t-1}} \tag{25}$$

The links between MLP, TFP, and TLP can also be examined in the dual price space. In analogy to (9) we find:

$$\begin{aligned} MLP_{t,t-1} &= \frac{W_{L,t,t-1}}{P_{Y,t,t-1}} \\ &= \frac{W_{K,t,t-1}^{\bar{s}_{K,t,t-1}} W_{L,t,t-1}^{\bar{s}_{L,t,t-1}}}{P_{Y,t,t-1}} \cdot \left(\frac{W_{L,t,t-1}}{W_{K,t,t-1}}\right)^{\bar{s}_{K,t,t-1}} \\ &= TFP_{t,t-1} \left(\frac{W_{L,t,t-1}}{W_{K,t,t-1}}\right)^{\bar{s}_{K,t,t-1}} \end{aligned} \tag{26}$$

Thus, the growth in MLP will both reflect technological progress, as measured by the increase in TFP, and technical change, i.e. changes in the slopes of the isoquants at the production point. As for the link between TLP and TFP, following the same steps as in (17), we find:

$$\begin{aligned} TLP_{t,t-1} &= \frac{W_{L,t,t-1}}{\tilde{P}_{\Lambda,t,t-1}} \simeq \frac{W_{L,t,t-1}}{P_{\Lambda,t,t-1}} \\ &= \frac{W_{L,t,t-1}}{P_{Y,t,t-1}^{\bar{\lambda}_{Y,t,t-1}} W_{K,t,t-1}^{-\bar{\lambda}_{K,t,t-1}}} \\ &\simeq \left(W_{L,t,t-1}^{\bar{s}_{L,t,t-1}} P_{Y,t,t-1}^{-1} W_{K,t,t-1}^{\bar{s}_{K,t,t-1}}\right)^{1/\bar{s}_{L,t,t-1}} \\ &= TFP_{t,t-1}^{1/\bar{s}_{L,t,t-1}} \end{aligned} \tag{27}$$

The mirror image of (18), finally, yields the relation between MLP and TLP:

$$\begin{aligned} MLP_{t,t-1} &= \frac{W_{L,t,t-1}}{P_{Y,t,t-1}} \\ &= \frac{W_{L,t,t-1}}{P_{Y,t,t-1}^{1+\bar{\lambda}_{K,t,t-1}} P_{Y,t,t-1}^{-\bar{\lambda}_{K,t,t-1}} W_{K,t,t-1}^{-\bar{\lambda}_{K,t,t-1}} W_{K,t,t-1}^{\bar{\lambda}_{K,t,t-1}}} \\ &= \frac{W_{L,t,t-1}}{P_{\Lambda,t,t-1}} \cdot \left(\frac{W_{K,t,t-1}}{P_{Y,t,t-1}}\right)^{-\bar{\lambda}_{K,t,t-1}} \\ &= TLP_{t,t-1} \cdot MKP_{t,t-1}^{-\bar{\lambda}_{K,t,t-1}} \end{aligned} \tag{28}$$

Thus, while TLP is a complete measure of technological change from a labour perspective, MLP, which also includes the effect of technical change (resulting from the change in the capital-labour ratio), is a hybrid productivity measure that is "merely an index of the real wage rate", and thus just a *partial productivity measure* to use Domar's own terminology.

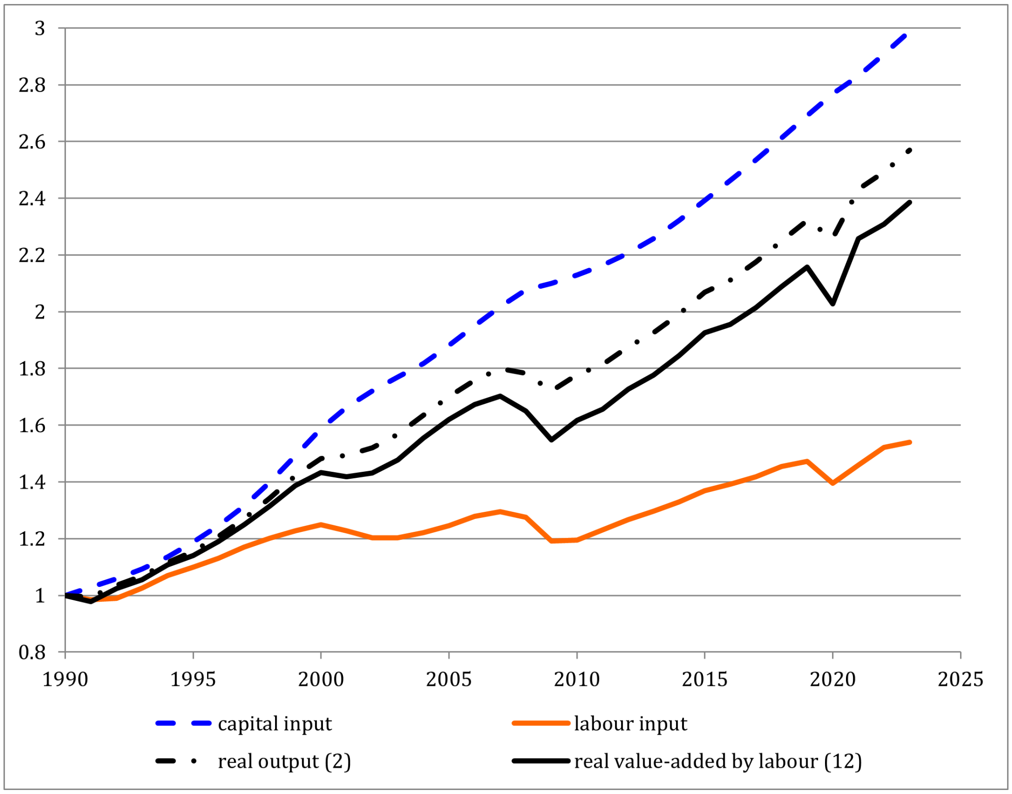
Numerical Illustration

We will take the case of the U.S. private nonfarm business sector, 1990–2023, as an illustration. The data are from the Bureau of Labor Statistics (BLS, 2017; 2024). We basically require series for real output ("real value-added output"), as well as for the capital and labour input quantities. These are readily available from the BLS in index form.[24] We further require current-value data on labour compensation and capital costs in order to be able to measure input shares; these are also available from the BLS.

Chart 1 shows the paths of the four quantity variables of interest: capital input ($x_{K,t}$), labour input ($x_{L,t}$), real out-

24 Note that there is no need to worry about intermediate inputs since domestic intermediate inputs cancel out at the aggregate level, whereas imports are already netted out from domestic output.

Chart 1: Input and Output Data U.S. Private Nonfarm Business Sector, 1990-2023



Source: Computed by the author on the basis of BLS (2024)

put ($q_{Y,t}$), and real output net of capital services ($q_{\Lambda,t}$) obtained by compounding $Q_{\Lambda,t,t-1}$ as given by (12). Real output of the U.S. private nonfarm business sector is found to have increased by 156.9 per cent over the 33-year period (corresponding to an average annual rate of about 2.9 per cent). The growth was not smooth, though: two dips in the growth path are clearly visible, in 2009 on the aftermath of the financial crisis, and in 2020 following Covid-19. Labour services increased by 54.0 per cent (a 1.3 per cent average yearly increase) over these three decades. Capital services nearly trebled over the same time, increasing by 198.8 per cent (a 3.4 per cent average yearly growth rate). As for real value-added by labour, i.e. real net output treating capital services as an intermediate input, the data reveal an increase of 138.6 per cent, which corresponds to an annual increase of 2.7 per cent.

Our first three measures of productivity are reported in Table 1, and depicted graphically in Chart 2.[25] Not surprisingly,

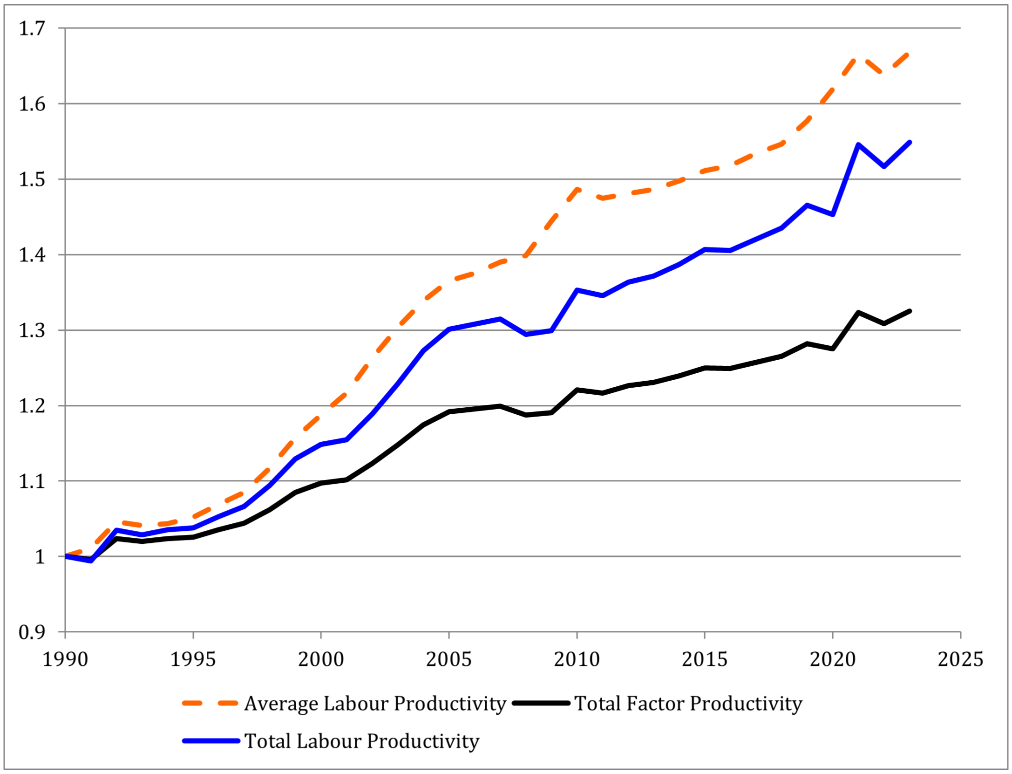
25 It must be noted that our measure of ALP differs from the "labor productivity" index published by the BLS since the BLS uses the number of hours worked—rather than its own measure of labour input—as the denominator, thereby ignoring its labour composition index; the BLS's "labor productivity" index, that records a 94.8 per cent increase over the sample period, is thus all the more a partial index. If one really wanted to focus on hours worked exclusively when assessing TLP, one should use as the numerator a measure of real value added net of the contribution of capital services and net of the contribution of the labour composition index.

Table 1: Average Labour, Average Capital, Total Factor, Total Labour, and Total Capital Productivity Measures: U.S. Private Nonfarm Business Sector, 1990–2023

	Average Labour Productivity	Average Capital Productivity	Total Factor Productivity	Total Labour Productivity	Total Capital Productivity
Year	$ALP_{t,t-1}$ (4)	$AKP_{t,t-1}$ (4)	$TFP_{t,t-1}$ (8)	$TLP_{t,t-1}$ (13)	$TKP_{t,t-1}$ (19)
1991	1.0108	0.9664	0.9962	0.9944	0.9883
1992	1.0350	1.0119	1.0277	1.0407	1.0905
1993	0.9949	0.9986	0.9961	0.9942	0.9876
1994	1.0027	1.0071	1.0042	1.0062	1.0126
1995	1.0079	0.9898	1.0017	1.0026	1.0051
1996	1.0161	0.9964	1.0093	1.0142	1.0277
1997	1.0151	0.9958	1.0085	1.0129	1.0253
1998	1.0293	0.9936	1.0173	1.0260	1.0531
1999	1.0359	0.9927	1.0215	1.0322	1.0664
2000	1.0265	0.9809	1.0113	1.0168	1.0347
2001	1.0245	0.9613	1.0038	1.0055	1.0117
2002	1.0379	0.9837	1.0198	1.0296	1.0620
2003	1.0323	1.0025	1.0221	1.0336	1.0665
2004	1.0269	1.0157	1.0230	1.0354	1.0677
2005	1.0201	1.0046	1.0146	1.0227	1.0413
2006	1.0069	0.9972	1.0034	1.0053	1.0093
2007	1.0108	0.9900	1.0032	1.0050	1.0088
2008	1.0063	0.9626	0.9900	0.9843	0.9730
2009	1.0329	0.9536	1.0026	1.0042	1.0071
2010	1.0291	1.0193	1.0253	1.0412	1.0677
2011	0.9919	1.0044	0.9967	0.9946	0.9915
2012	1.0043	1.0141	1.0081	1.0132	1.0210
2013	1.0036	1.0032	1.0035	1.0057	1.0090
2014	1.0076	1.0058	1.0069	1.0114	1.0177
2015	1.0088	1.0083	1.0086	1.0140	1.0223
2016	1.0047	0.9910	0.9994	0.9991	0.9985
2017	1.0104	1.0006	1.0066	1.0108	1.0174
2018	1.0080	1.0040	1.0064	1.0105	1.0168
2019	1.0199	1.0016	1.0128	1.0210	1.0334
2020	1.0269	0.9462	0.9947	0.9914	0.9865
2021	1.0286	1.0525	1.0380	1.0640	1.0983
2022	0.9831	0.9972	0.9888	0.9812	0.9728
2023	1.0186	1.0036	1.0124	1.0211	1.0303
1990–2023	**1.6677**	**0.8597**	**1.3248**	**1.5487**	**2.2174**
Annual mean	**1.0156**	**0.9954**	**1.0086**	**1.0133**	**1.0244**

Note: All reported numbers are growth factors.
Source: Computed by the author on the basis of BLS (2024)

Chart 2: Average Labour, Total Factor, and Total Labour Productivity Measures Cumulated values, U.S. Private Nonfarm Business Sector, 1990-2023



Source: Computed by the author on the basis of BLS (2024)

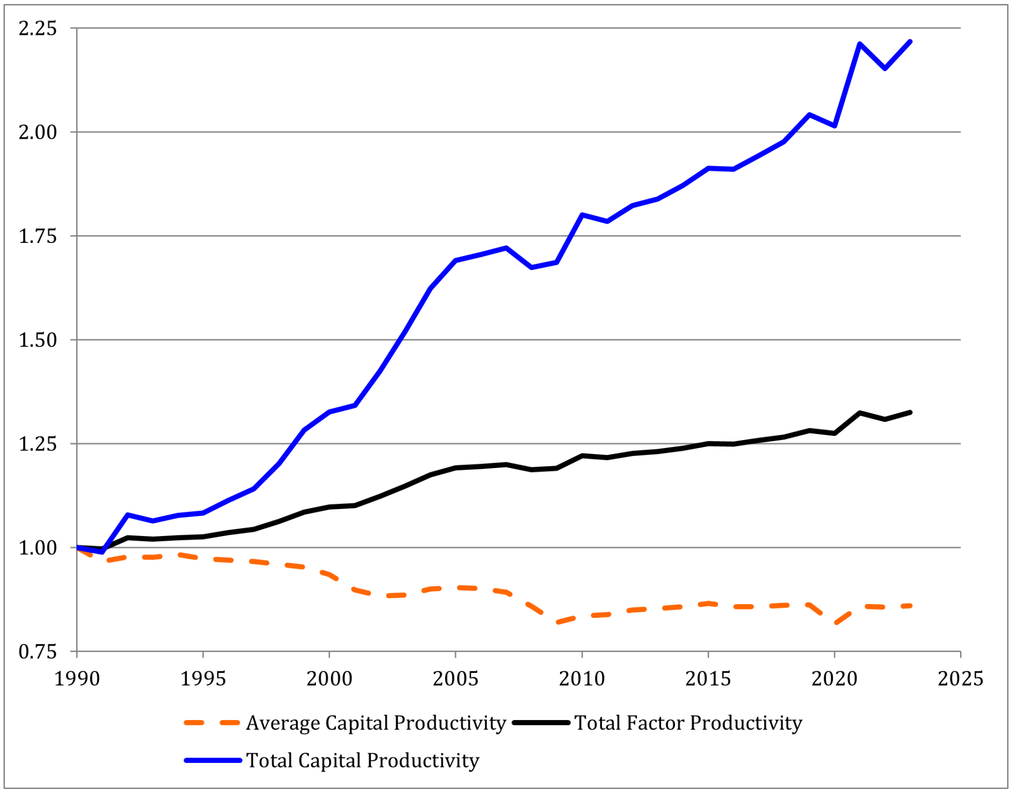
the lower growth rate of the labour input—compared to capital, and thus to output—implies a rather healthy estimate of ALP growth at about 66.8 per cent (1.6 per cent per annum) over the sample period; see Table 1, column 1. As we have come to expect, not all of this is technological progress, since the capital-labour ratio has increased substantially over the sample period, by a total of 94.0 per cent (2.0 per cent per year).[26] If the effect of the implied technical change shown by the last term on the right-hand side of expression (9) is netted out (it adds up to about 25.9 per cent, i.e. 0.7 per cent yearly), or if one simply uses expression (8) directly, then obtains a TFP increase of 32.5 per cent over the sample period, which amounts to close to 0.9 per cent annually; see Table 1, column 3.

If one wants to use labour as a benchmark, all technological progress may be allocated to it, but only after having netted out the contribution of capital to production. In that case, as shown by (17), the effect is magnified by a factor of $1/\bar{s}_L$ to yield a total TLP increase of nearly 54.9 per cent over the period, i.e. about 1.3 per cent annually as shown in Table 1, column 4.

The paths of our first three measures of productivity growth are shown in Chart 2. One can see that TLP dominates TFP,

26 For its measure of capital-labour intensity too, the BLS uses the number of hours worked as the denominator, whereas we use its labour input measure instead.

Chart 3: Average Capital, Total Factor, and Total Capital Productivity Measures Cumulated values, U.S. Private Nonfarm Business Sector, 1990-2023



Source: Computed by the author on the basis of BLS (2024)

while ALP is found to progress even more rapidly. One would normally expect capital to grow more rapidly than labour: TFP growth should therefore fall short of ALP growth. This is indeed what expression (9) predicts. Nonetheless, there are a few observations in our sample where this relationship is reversed, in particular in 2021–2022 when employment recovered strongly after a dramatic fall in 2020 as a consequence of Covid-19, thus leading to a rather exceptional reduction in the capital-labour ratio. As predicted by (17), TLP exceeds TFP whenever technological progress (i.e. Domar's Residual) is positive, which happened in the vast majority of the observations. As for the relationship between ALP and TLP, we find that the former exceeds the latter in just over half the observations. In the remaining cases, the capital intensity of production actually fell somewhat, thus reversing the inequality in accordance with (18).

For the sake of completeness, we also report values of AKP and TKP—the Solow-like index of technological progress—as given by (19). These are shown in columns 2 and 5 of Table 1. As expected, AKP is mostly falling over time, at an average rate of about 0.5 per cent for a total decline of 14.0 per cent, whereas TKP is increasing at an average yearly rate of 2.4 per cent, thus more than doubling (a 121.7 per cent rise) over the sample period. This substantial increase can be explained by the magnification effect relative to TFP due to the relatively smaller capital share as shown by (19). The paths of AKP, TFP, and TKP are shown in Chart 3. While the divergence between the partial and total productivity measures was already evident in Chart 2 for labour, the contrast is even more striking for capital, with one measure declining steadily and the other one increasing sharply. This demonstrates that productivity measures should not be defined casually, but rather with a definite framework in mind.

Concluding Comments

As stressed throughout this article, ALP is not suitable as a measure of technological change since it is a partial productivity index that totally neglects the role of capital, not so much when it comes to the shifts in the technology, but much more importantly in production altogether. This is if one considers the national income identity: any attempt to express a link between $q_{Y,t}$ and $x_{L,t}$ that excludes $x_{K,t}$, on either side of the identity, is incomplete. Given that it is perfectly appropriate to focus on labour (the denominator in that case), one must conclude that it is the numerator that is faulty. One might object that this is untrue, for, as shown by (9), ALP does take capital into account, even twice so: first explicitly in the last right-hand terms of (9), and a second time implicitly in the denominator as an element of TFP. That is exactly the point: one cancels the other one out.

It would be a simple matter for statistical agencies to publish series on TLP (and TKP) in the future: all the necessary data are readily available. Thus, computing $Q_{\Lambda,t,t-1}$ and TLP with the help of (12) and (13) is no more difficult than deriving $X_{t,t-1}$ and TFP using (7) and (8). Labour productivity measures are often used for international comparisons, not least by the International Labour Organization (2025). It would then be of advantage to compare "pure" labour productivity series, i.e. data that are not tainted by the hidden influence of capital accumulation.

One could of course also define labour productivity in terms of *net domestic product* (NDP) as opposed to GDP. The measure of ALP would be directly impacted if the numerator were real NDP rather than real GDP, but what ultimately matters is the growth in productivity rather than its level, so it is not possible to come to definite conclusions in the absence of information about the rate at which fixed capital is consumed. The measure of TLP would presumably be less affected, since only the weights $\lambda_{Y,t}$ and $\lambda_{K,t}$, as defined in (11) would be somewhat reduced.

The difference between ALP and TLP also is particularly meaningful if the country (or the firm) is heavily indebted. Although the ALP and TLP measures would not be affected if part or all of the capital income were due to foreign investors, TLP would be much more relevant than ALP from a national—as opposed to domestic—income perspective.

A further point that speaks in favour of TLP is that this measure of labour productivity is more directly related to real wages than is ALP. The passage from TLP to MLP, as it can be seen by comparing (25) with (23), is really quite simple: it is just a matter of replacing one price deflator ($P_{\Lambda,t,t-1}$) by another one ($P_{Y,t,t-1}$). This contiguity is also supported by the data. Thus, while the BLS figures indicate that real wages increased by a factor of 1.45 over the sample period, TLP increased by a factor of 1.55, whereas ALP was multiplied by 1.67 (see Table 1). The notion that ALP- and MLP-growth should be equal is inherited from the common reference to Cobb-Douglas production functions that restrict the elasticity of substitution between labour and capital to unity and thus imply constant factor shares, whereas the reality is quite different, with the U.S. capital share having tended to increase over the sample period.

Yet another area where the concept of TLP could find a useful application is when it comes to unit labour costs (ULC). Many statistical agencies, including the BLS, publish ULC measures. ULC, defined as total labour compensation divided by real output, or, equivalently, the nominal wage divided by ALP, are often used in international competitiveness comparisons (OECD, 2025). It would certainly make sense, in such studies, to substitute TLP for ALP as the denominator in order to obtain a clean ULC index, a measure of the cost of the real value added by labour without having the unaccounted-for influence of capital.

Naturally, TLP is also relevant at the sector, the industry, and even the firm level. The real value added by labour can be calculated as described above, after having netted out the contribution of capital and, if relevant, of intermediate inputs such as energy, materials, and purchased services.

To sum up, our purpose in this article is not to advocate the rejection of ALP as a measure of productivity growth. It is a descriptive – rather than analytical – statistic that is informative about the state of the economy and its historical evolution. In a way, just like it is true for capital, its inverse – in this case the labour intensity of production – is just as informative. In any case, it is important to remind users that ALP is a hybrid measure that combines the effects of shifts in the production possibilities frontier (e.g. shifts of the isoquants related to a production function) and movements along that frontier (e.g. movement along an isoquant). Expanded knowledge and improvements in the technology are not the same as plain capital accumulation.

This does not mean, however, that labour should not be used as a benchmark. Quite the contrary: we have listed in the introduction a number of reasons why a labour productivity measure is appealing. This is all the more true if technological change tends to be mostly labour augmenting: a Harrod-like measure such as TLP is therefore particularly appropriate. TFP as a measure of technological change, of course, retains all its validity and its importance, but one must realize that it implicitly describes a Hicks-neutral type of technological change.

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The Relationship between Efficiencies Defenses for Mergers and TFP Growth

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Abstract

This article investigates whether efficiencies defenses in merger control lead to greater economic efficiency, specifically by examining their impact on national total factor productivity (TFP) growth. Efficiencies defenses are provisions in competition law that allow efficiencies from mergers to be weighed against potential harms. While increasingly common—present in 40.4 per cent of countries by 2010—their effectiveness remains underexplored. To address this gap, the study adapts the econometric model from Buccirossi *et al.* (2013), using data from the Penn World Tables version 10.01 and the Comparative Competition Law Dataset (Bradford *et al.*, 2018). The analysis estimates the causal relationship between the introduction of efficiencies defenses and TFP growth. The results yield two key findings. First, introducing efficiencies defenses is generally associated with higher TFP growth, suggesting they may enhance economic performance. However, the effectiveness likely varies by the design and implementation of these provisions—an area for future research. Second, these legal reforms often coincide with increased enforcement resources. While efficiencies defenses appear to contribute to productivity gains, their impact depends heavily on the capacity of enforcement agencies. Without sufficient resources, even well-designed competition laws are unlikely to produce meaningful results.

For over a century, architects of competition law in nations across the globe have grappled with the challenge of reconciling the potential efficiency-enhancing benefits of mergers with the potential harm these transactions can impose on competition within markets. Consolidation of business can lead to greater economies of scale and other synergies, but at the cost of greater market power, resulting in deadweight loss, higher prices, and other consumer and societal harms. Some lawmakers have attempted to reconcile these two seemingly competing outcomes of mergers is by through efficiencies defenses. These provisions articulate how competition law en-

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forcers and adjudicators should consider efficiencies outcomes when evaluating mergers, including how these efficiency benefits should be weighed against harms from a merger and what kinds of efficiencies and harms should be included in their analysis.

Efficiencies defenses for mergers have become increasingly common over time. Given their prevalence, it is worth examining if they actually drive greater efficiency within national economies. However, to date there has been limited, if any, empirical research on the effectiveness of these defenses. More generally, mergers could play an important role in driving total factor productivity growth by reorganizing the ways that labour and capital are combined for production within national economies.

To illustrate, in 2023 the world's Merger and Acquisition (M&E) volume, measured as deal value, was equal to 2.5 per cent of global GDP (IMAA, n.d.; World Bank, n.d.). To be sure, M&A deal value is not a perfect measure of generated economic value, as measured by GDP. Furthermore, deal value is typically a multiple of the income or assets of a business, not the value at a given point in time. However, it does point to the potential magnitude of the impact mergers could have in shaping economic outcomes. Seeking to optimize merger control law to enhance economic well-being and standards of living is a worthwhile task for policy makers. To that end, this study fills an important gap in the literature by investigating whether legislated efficiencies defenses for mergers have an impact on the efficiency and productivity of economies.

Furthermore, Canada in particular has seen some notable reforms to its Competition Act. These changes include removing its legislated efficiencies defense, outlined in bill C-56, which received royal assent in December 2023. While Canada is not included in this empirical analysis for reasons explained later in the paper, this research could help inform Canadian policy makers as they re-evaluate the role of efficiencies considerations in mergers going forward.

For this analysis, Total Factor Productivity (TFP) is used as the measure of macroeconomic efficiency. Not only does TFP capture the types of efficiencies that could be created through mergers, but it is also an important ingredient of economic growth, particularly in developed economies. Thus, TFP and its growth are highly relevant indicators for economic policy makers.

To test whether efficiencies defenses lead to greater TFP growth, this study builds on the econometric analysis done by Buccirossi *et al.* (2013), which estimates the impact of competition laws on TFP growth for industries in 22 OECD countries. We expand on Buccirossi *et al.* (2013) in two ways. First, a similar model is estimated using global dataset not limited to OECD countries. National- rather than industry-level data from the Penn World Tables version 10.01 (PWT 10) and the Comparative Competition Law Dataset developed by Bradford and Chilton (2018) are used. Second, using these data an in-depth investigation is undertaken into the impact of efficiencies defenses on productivity growth specifically, rather than competition law and merger control more generally.

Importantly, the focus of this study is efficiencies defenses implemented by legislators and included within competition law legislation. Some jurisdictions, notably the United States, have efficiencies defenses that have been created and implemented by the enforcers of competition law, not lawmakers (US Department of Justice and Federal Trade Commission, 2010). These forms of efficiencies defense are not examined here.

The article is organized as follows. The first section provides more detailed background on efficiencies defenses. It also includes a descriptive analysis about the adoption of defenses by countries around the world and the characteristics of countries that do and do not have them. The second section begins with a brief literature review of whether efficiency defense lead to greater economic efficiency, an overview of the model and data used for the econometric analysis, and regression results. The third section provides an interpretation of the empirical results of the previous section, and the last section concludes.

What are Efficiencies Defenses?

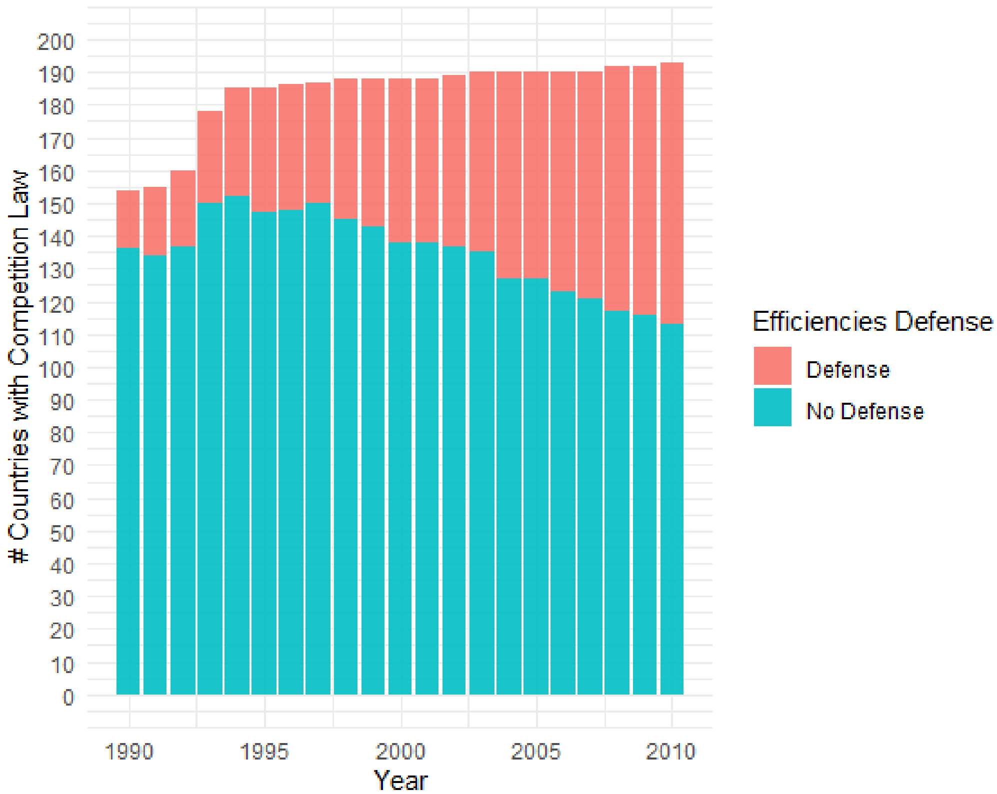
The idea of an efficiencies defense for mergers in the context of competition law was formalized by Oliver Williamson in his 1968 article "Economies as an Anti-Trust Defense: The Welfare Trade-Off". Williamson argued that the American test for assessing mergers, which asks if the merger will "substantially lessen competition, or [will] tend to create a monopoly", may lead to "serious economic loss" (Williamson, 1968:18). His point was that the rule does not consider potential efficiencies arising from mergers, namely economies of scale and scope. He posits that in merger assessment, policy makers face a tradeoff between increased market power resulting from a merger (allocative inefficiency) against the efficiencies it produces (economies of scale and scope).

Since the publication of Williamson's 1968 article, nations have adopted efficiencies defenses of various forms. These defences are provisions within competition legislation that create some type of exemption for potentially harmful mergers on the basis that they create efficiencies. Some defences more closely mirror Williamson's original model than others. Some defenses, like Canada's section 96 (1) which was recently stricken from the Competition Act, are weighted defences. They require that law enforcers and judges weigh the harms from a merger against the efficiencies it creates. Other defenses, like that articulated in the European Union's Treaty on the Functioning of the European Union, put bounds on the types of efficiencies that can be considered in this weighing exercise. In the case of the EU, efficiencies must be to the benefit of consumers and not undermine the competitive process. Some defences are very broad, providing exemptions to mergers that create efficiencies without specifying the type of magnitude of the efficiency. In some laws, efficiencies are considered as a factor among several others when evaluating mergers (Shaban, 2024).

Efficiencies defenses – a common fixture of merger control

Efficiencies defenses are identified through the Comparative Competition Law dataset (Bradford and Chilton, 2018). The dataset is a census of all competition

Chart 1: Countries with Competition Laws in Force, With and Without Efficiencies Defense, 1990 to 2010.



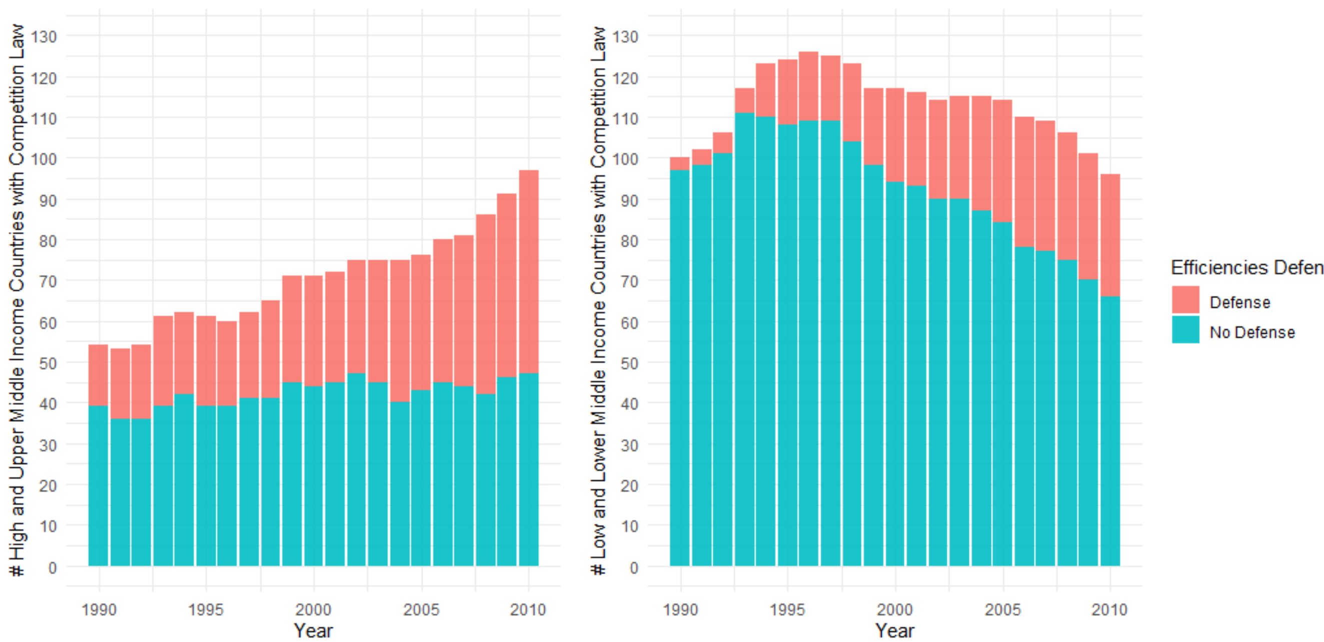
Source: Comparative Competition Law Dataset (Bradford and Chilton, 2018) and the World Bank table The World by Income and Region.

laws in force spanning the 1800s to 2010 and includes variables indicating whether a law contains an efficiencies defense for mergers. Chart 1 shows the number of countries with competition laws in force each year from 1990 to 2010, broken down by whether or not it has an efficiencies defense.

A small number of nations had efficiencies defences in the early 1990s, with defenses became more widespread beginning in late 1990s. By 2010, 41.5 percent of nations with a competition law had an efficiencies defense, based on data from the Comparative Competition Law Dataset.[2] In that year, nations in Europe and Central Asia were most likely to have a defense (45.0 per cent), followed by Sub-Saharan Africa (17.5 per cent), East Asia and Pacific (13.8 per cent), and Latin America and Caribbean (12.5 per cent). In modern times these defenses have become a common fixture of competition laws across the world.

2 Jersey Channel Islands and Faroe Islands have been removed from the data used for this chart. Furthermore the data are limited to those countries and years for which the World Bank as assigned an income category from the table The World by Income and Region. For example, the Comparative Competititon Law Dataset has entries for Kosovo begining in 2004, but the World Bank assigned Kosovo and income category only in 2010.

Chart 2: Countries With and Without Efficiencies Defense, by Income Group, 1990 to 2010



Source:

Chart 2 gives a further breakdown of countries presented in Chart 1 by income group, based on the World Bank's income classification system. The first panel shows an increasing number of high- and upper middle income countries that have adopted competition laws over time. The number of nations at this income level that do not have an efficiencies defense has been relatively stable over time, ranging from a high 47 in 2002 and 2010 to a low of 36 in 1992. In contrast, the number and proportion of nations in this income category with a defense has increased steadily, from 15 (27.8 per cent) in 1990 to 50 (51.5 per cent) in 2010. The second panel of Chart 2 presents data for low- and lower middle income countries with competition laws. The number of nations at this income level with a competition law declined from a high of 126 in 1996 to a low of 97 in 2010. The competition laws of low and lower middle income countries are more likely to have an efficiencies defense in more recent years (31.3 per cent in 2010) than in the mid-1990s (12.9 per cent in 1995). Overall, the figures highlight that high- and upper middle income nations with competition laws are more likely to have an efficiencies defense than low- and lower middle income nations. However, nations of both income levels have been increasingly adopting defenses over time.

Table 1 shows that, overall, countries with defenses are more likely to be higher income, although in more recent years a greater proportion of countries with a defense were upper-middle income. Countries that adopted defenses from 1991 to 2000 were more likely to be lower-middle income, while countries across the income categories adopted defenses from 2001 to

Table 1: Count, Incidence, and Percent of Nations by Efficiencies Defense Status and World Bank Income Category, 1997 to 2009

Income Group	Defense in Force for Entire Period	Defense Introduced	Defense Removed	No Defense in Force During Period	Total
Count					
High income	18	14	1	19	52
Upper middle income	4	11	2	23	40
Lower middle income	4	17	0	33	54
Low income	6	7	0	35	48
Total	32	49	3	110	194
Incidence (%)					
High income	34.6	26.9	1.9	36.5	100.0
Upper middle income	10.0	27.5	5.0	57.5	100.0
Lower middle income	7.4	31.5	0.0	61.1	100.0
Low income	12.5	14.6	0.0	72.9	100.0
Total	16.5	25.3	1.5	56.7	100.0
Percentage (distribution)					
High income	56.3	28.6	33.3	17.3	26.8
Upper middle income	12.5	22.4	66.7	20.9	20.6
Lower middle income	12.5	34.7	0.0	30.0	27.8
Low income	18.8	14.3	0.0	31.8	24.7
Total	100.0	100.0	100.0	100.0	100.0

Source: Comparative Competition Law Dataset (Bradford & Chilton, 2018) and the World Bank table *The World by Income and Region.*

Table 2: Percent of Countries by Efficiencies Defense Status and World Bank Region Categories, 1997 to 2009

Geography	Defense in Force for Entire Period	Defense Introduced	Defense Removed	No Defense in Force During Period
East Asia & Pacific	6.3	16.3		17.3
Europe & Central Asia	62.5	36.7	100	10.9
Latin America & Caribbean	6.3	18.4		20.0
Middle East & North Africa	6.3	10.2		12.7
North America	3.1			0.9
South Asia	6.3			6.4
Sub-Saharan Africa	9.4	18.4		31.8
Total	100	100	100	100

Source: Comparative Competition Law Dataset (Bradford & Chilton, 2018) and the World Bank table *The World by Income and Region.*

2010.

The large majority of countries with a defense are in Europe and Central Asia, as Table 2 shows. Countries from Europe and Central Asia also made up the largest segment of countries that adopted a defense during that period. The geographic distribution of countries with no defense remained very similar across the two periods presented in the table. Of countries that adopted a defense in the two periods, a relatively large proportion of them were also in Europe and Central Asia, painting a picture of efficiencies defense diffusion in that region. However, in more recent years, countries from other regions made up a larger proportion of defense adopters.

Do Efficiencies Defenses Lead to Greater Economic Efficiency?

Total Factor Productivity (TFP) is the measure of efficiency for this analysis because it is a critical driver of economic growth, making it a highly relevant policy indicator. It is also relevant for studying the impact of mergers and merger control law because it reflects the way that labour and capital are used within an economy (industry, or firm) to produce value added. Mergers can reorganize businesses and the ways they use and combine labour and capital. In this way, mergers influence the determinants of TFP and its growth. By extension, laws that impact merger activity, including efficiencies defenses, have the potential to influence TFP as well. Despite the importance of TFP as a driver of economic growth, to date there is no indication of any empirical research exploring the effectiveness of legislated efficiencies defenses, specifically.[3] This study fills an important gap in the literature by providing this empirical research.

Empirical research done by Buccirossi*et al.* (2013) provides some insight into the impact competition law can have on TFP growth. The authors examine the degree to which competition policy, including merger control, impacts the productivity of industries in 22 OECD nations from 1995 to 2005. They find that, overall, quality competition policy positively contributes to TFP growth, and this relationship is statistically significant. [4] The researchers find that the relationship between competition policy quality and TFP growth also holds when they examine competition law and enforcement targeted at mergers specifically.

The Model

The econometric model developed by Buccirossi*et al.* (2013) is the basis for the model put forward in this study. Their model is grounded in the theoretical framework put forward by Aghion and Howitt (2006) based in Schumpeterian growth theory. Using a fixed-effects approach following Nicoletti and Scarpetta (2003) and Griffith, Redding, and van Reenen (2004), Buccirossi *et al.* regress TFP growth of national industries (country-industry level) onto their own competition law index that reflects the quality of a nation's competition law.

To capture the endogenous drivers of industry TFP growth of a country, they also include variables that measure the growth of TFP at the technological frontier for a given industry and the distance of a given country-industry from that technological frontier. The authors consider industry-country and country-level factors that also contribute to TFP growth. Industry-country controls include trade openness, R&D intensity, and human capital. National-level controls include product-market regulation and various measures of the quality of a nation's institutions, particularly with respect to

3 To inform the literature serach for this section of the paper, a systematic search for "efficiencies defense mergers", "efficiency defense mergers", "efficiencies defense competition", and "efficiency defense competition" was conducted on the American Economic Association, EconLit, Hein Online, and Oxford Academic databases. Of the top 50 most relevant results from each database, papers were selected to inform this section of the paper. A search of relevant studies from the OECD competition policy collection was also undertaken.

4 Their evaluation of competition policy quality includes these factors: the degree of independence of a nation's competition authority; separation between the adjudicators and the prosecutors; whether business bvehaviours that are illegal under competition law align well with behaviours that actually lead to negative impacts on social welfare; the scope of an authority's investigative powers; the level of fines, imprisonment, or other deterrents; the "toughness" of a competition authority, reflected in its level of activity and the size of the sanctions it imposes in the event of a conviction; and the amount and the quality of the financial and human resources of a competition authority.

a nation's legal system. In addition, the authors also include variables to capture industry-country deviations in TFP growth from both linear and quadratic trendlines to account for the effect of business cycles. To address potential endogeneity issues, Buccirossi *et al.* (2013) use lagged versions of the competition policy variable and most other explanatory variables, which in effect implies one-directional causality.

Like Buccirossi *et al.*, the model developed for this study also uses a fixed-effects approach. However, a key difference with this study's model is that is uses country-level, rather than industry-level data. Using country-level data provides a novel contribution to the literature. It also allows for more countries to be included in the study since industry-level productivity data is not available for many countries outside the OECD.

The specification for this analysis is the following:

$$\begin{aligned}\Delta TFP_{i,t} = \alpha &+ \beta_1 \text{ Efficiency Defense Measure}_{i,t-1} \\ &+ \beta_2 \text{ Competition Law Intensity}_{i,t-1} \\ &+ \delta\left(\frac{\text{Frontier}_t - TFP_{i,t}}{\text{Frontier}_t}\right) + \chi Z_{i,t-1} \\ &+ \psi_i + \phi_t + u_{i,t} \qquad (1)\end{aligned}$$

Total factor productivity growth of nation i at time t is a function of a measure of the intensity of competition law and its enforcement and the presence of an efficiencies defense within a nation's competition law, both of which are lagged one year to establish causality as in Buccirossi *et al.* (2013).[5] Therefore, this model does not make use of instrumental variables. As a robustness check, this study presents regressions results estimated with variables lagged over two and three years.

In the model, TFP growth is also a function of nation i's relative distance from the TFP frontier,[6] deviations in TFP growth from both linear and quadratic trendlines to account for the effect of business cycles (included in $Z_{i,t-1}$), additional lagged country-specific controls, and country and year fixed effects (ψ_i and ϕ_t, respectively). Country-specific controls include trade openness and human capital. Trade openness facilitates TFP growth by facilitating the transfer of technology between firms across countries (Buccirossi *et al.*, 2013; Miller and Upadhyay, 2000). Following Buccirossi *et al.* (2013), measures of the quality of a country's institutions are included. In addition, based on the findings of Miller and Upadhyay (2000), the nation's deviation of its market exchange rate from purchasing power parity is included, which factors into a nation's trade posi-

5 The results in Table 3 illustrate that there may be some relationship between a government's choice to introduce an efficiencies defense and devoting greater resources to competition law enforcement. To explore whether there is any potential endogeneity between the variables capturing the intensity of competition law and the variable denoting whether a nation has an efficiencies defense, regressions presented in this article are estimated with the competitive intensity variable lagged an additional year. The results of these regressions are not materially different from the preferred specifications presented in the article.

6 Given the structure of this variable, there is the possibility that for nations that are very far or very close to the frontier, the variable may create extreme values that have an outsized impact on the estimated model. However, summary statistics for the variable that are provided in Table 5, along with further investigation by the author, find that there are no notable outlier observations.

tion and openness. Countries with "[t]rade policies that lower (raise) the real exchange rate toward or below (above) its purchaisng power parity value assocate with higher total factor productivity [levels]," which may have implicaitons for TFP growth. (Miller & Upadhyayb, 2000: 408).[7]

Unlike in Buccirossi *et al.* (2013), variable for the technology frontier is not included in this model (although a variable for distance from the frontier is included) because the technology frontier is global. Since all nations are subject to the same frontier, the variable is effectively removed from the regression under a country-level fixed-effects specification. In a similar vein, a potential problem that arises from this specification is that the key variable of interest – the binary variable for efficiencies defenses – does not vary over the time period of the study for several countries. Many countries that have defenses adopted them prior to 1997, and many countries have never adopted a defense. The lack of variance over time raises specification challenges under a fixed-effects approach. To address this issue, only countries that 1) have introduced an efficiencies defence between 1997 and 2009 or 2) have never introduced a defense, are included in the data sample used to estimate the model. Limiting the sample of countries in this way allows for within- and between- country comparisons of the impact of introducing an efficiencies defense.

Another potential issue with this model, which was flagged by Buccirossi *et al.* (2013), is the risk of omitted variables and resulting bias. Despite the various controls included in the model, there are many other factors that could also impact a nation's TFP growth. The fixed-effects method used in this study will address the impact of any omitted variable that is constant within a country or across time. To address potential heteroskedasticity resulting from other non-constant omitted variables, all fixed-effects specifications are estimated using heteroskedasticity-consistent errors clustered by country following Arellano (1987), using weighting scheme HC4 to improve performance given small sample size and influential observations (Cribari-Neto, 2004).

Data and Variables

To test the impact of efficiencies defenses for mergers on the TFP growth of a nation's economy, data drawn from the Comparative Competition Law dataset (Bradford and Chilton, 2018), the Penn World Tables 10.0, and the World Bank's Worldwide Governance Indicators are used. The data covers years 1997 to 2010 and 69 countries. The sample of countries used for these regressions includes countries that have introduced an efficiencies defense at some point between 1997 and 2010 and countries that have never introduced a de-

7 From Miller and Upadhyayb (2000: 408): "The local price deviation from purchasing power parity has a significant negative effect at the 5 per cent level. What does this imply? An increase in deviations from purchasing power parity means that the countries' currency becomes less undervalued (more overvalued). Trade policies that lower (raise) the real exchange rate toward or below (above) its purchasing power parity value associate with higher total factor productivity. In sum, real exchange rate changes that stimulate exports (and limit imports) associate with a higher total factor productivity."

fense. More details on these excluded observations are provided in the following sections. The variables used in this study and their summary statistics are provided in Appendix Table 1, and the sections that follow provide details on their source and construction.

Comparative Competition Law Dataset

The Comparative Competition Law Dataset is a census of all legislated competition laws in force up until 2010. It contains a detailed coding of several key aspects of competition laws, including provisions on merger control, abuse of dominance, and anticompetitive agreements. The dataset also contains a module – the enforcement database – that gives detailed enforcement information for several competition authorities around the world, including total enforcement budget in US dollars and total number of mergers reviewed. There are four key variables from this data source: a binary variable denoting whether a nation has an efficiencies defense for mergers in a given year, the Comparative Competition Law Index (CLI), the total budget of all enforcement agencies, and the total number of mergers reviewed by authorities.

The CLI aims to reflect the stringency or intensity of a nation's entire competition law. As the value of the index increases, the "regulatory risk" faced by firms increases (Bradford and Chilton, 2018). The CLI differs notably from the index developed and used by Buccirossi *et al.* (2013) in two respects. First, the index developed by Buccirossi *et al.* includes information on both the content of a nation's competition law and its enforcement, such as the number of staff and budget allocated to the nation's competition authority and the degree of independence of the competition authority from economic and political interests. In contrast, the CLI reflects only the content of a nation's competition law. Second, and more broadly, the Buccirossi *et al.* index is designed to reflect the degree to which a nation's competition policy system aligns with a given ideal following Becker's (1968) theory of optimal deterrence. In their index, Bradford & Chilton aim to provide a positive, descriptive measure of a nation's competition law that is not based on a normative standard as in the Buccirossi *et al.* index.

For EU nations, which are subject to both EU and national competition law, the version of the CLI used captures the characteristics of both a nation's domestic law and EU law. For this study, a new, modified version of the CLI is constructed by the author which removes the efficiencies defense from the CLI. While this change has a minimal impact on the overall value of the CLI index, it addresses potential correlation between the CLI and efficiencies defense variable when included in the same regression.

Data on a nation's total enforcement spending are also important aspects of the model given the clear relationship between enforcement resources and the presence of an efficiencies defense from the previous descriptive analysis. Enforcement spending is the total budget of competition agencies in 2017 US dollars. For this study, enforcement spending is divided by real GDP at constant 2017 national prices in thousands, US dollars (variable rgdpna in PWT 10.01 to adjust for the size of the nation's economy. Multiplying the CLI with total enforcement spending gives the new variable CLI and enforcement spending used in the regressions. This variable reflects the potential joint effect of competition law stringency and enforcement rigour and controls for other factors that within competition law and its enforcement that could impact TFP growth.

Importantly, the coverage of the enforcement variables is far more limited than the coverage of all other variables used in the regressions. Of the 69 countries included in the dataset, 58 per cent (40 countries) have data on total enforcement spending for 2010. However, enforcement spending does play a key role in making competition law an effective policy intervention, so these variables are included in the estimated regressions. Including these variables means that there are significantly fewer observations included in the regressions.

Penn World Tables

The Penn World Tables version 10.01 provide the majority of the variables used in this analysis given its broad coverage of countries over time. TFP growth, the dependent variable of this analysis, is available continuously for years 2000 onward. It is calculated using the growth rate of real GDP along with growth rates of real capital labour input data, and labour share (Feenstra *et al.*, 2015). Like the measure of TFP growth used by Buccirossi *et al.* (2013), it is represented as an index. The value of the index is normalized to 1 in 2005 for all countries.[8]

The PWT 10.01 is also the primary source of control variables. Using the level of TFP from the tables, the variable OECD frontier distance is constructed to reflect the relative distance of a nation's TFP from the technological frontier (the OECD average in TFP) for each year. Following Buccirossi *et al.* (2013), two variables are constructed that denote a nation's distance from the quadratic and linear trends in TFP growth: TFP growth trend difference (linear) and TFP growth trend difference (quadratic), respectively.

In addition, variables on the share of merchandise exports at current PPPs (national exports lagged), the price level of the US GDP (output side) normalized such that year 2017 equals 1 (national price level lagged), and the human capital index (human capital lagged) are included. Variables for national imports and national exports are used to reflect trade openness. The human capital index measure human capital per worker and has also been found to

8 As in Buccirossi *et al.* (2013), the measure of TFP (and by extension TFP growth) used in the PWT 10.01 relies on the strong assumption of perfect competition. Both Feenstra *et al.* (2015) and Buccirossi *et al.* discuss the implications of this underlying assumption. Feenstra *et al.* point to Burstein and Cravino (2015) who compare productivity measures developed under assumptions of perfect and monopolistic competition and find that these measures are comparable. Thus, Feenstra *et al.* make the assertion that "we expect that the methods used to construct [TFP][. . .], while derived from perfectly competitive behavior [. . .] may well apply more generally"(p. 3167). Using data on industry-specific markups, which are not available in the PWT 10.0, Buccirossi *et al.* make modifications to their measure of TFP to allow for imperfectly competitive markets.

be a determinant of TFP and TFP growth (Buccirossi *et al.*, 2013; Miller & Upadhyayb, 2000).[9]

More recent analysis has highlighted that there are several notable outliers in the PWT 10.01 data, particularly with respect to TFP levels. Inklaar and Woltjer (2021) note that a number of low-income countries have TFP levels that are greater than that of the United States, for example Egypt. The authors find that these anomalous results are likely the result of the underlying inputs data. They point to Lagakos *et al.* (2018), who show that human capital measures may understate human capital accumulation in lower-income countries, leading to lower variance in human capital across nations thus overstating TFP variation. Inklaar and Woltjer also refer to Freeman, Inklaar and Diewert (2021), who show that when resource rents are taken into account TFP levels for some outliers are corrected. As Inklaar and Woltjer (2021) point out, determining which observations are outliers is difficult to do with discernment. However, to help address the issue of outlier TFP levels the resource-rich countries examined by Freeman, Inklaar and Diewert are removed from the sample.

World Bank

Variables from the World Bank are R&D expenditure and the national rule of law index. R&D expenditure is an important driver of TFP growth. The data comes from the World Bank's online data collection. For several countries, there are notable data gaps. To address these gaps, values are interpolated assuming linear growth (or decline) from the years beginning and ending the data gap.[10]

The national rule of law index comes from the World Bank's Worldwide Governance Indicators, which provide national-level data on six governance topics based on data from 30 different sources including surveys of enterprises, citizens and experts. Buccirossi *et al.* (2013) use the national rule of law index of the World Bank's Worldwide Governance Indicators to capture "perceptions of the extent to which agents have confidence in and abide by the rules of society". The index is used as a measure of institutional quality and takes values from -2.5 to 2.5, with higher values indicating better outcomes.

Interpretation of Empirical Results

There are three sets of regressions presented in the tables that follow. In Table 3, the sample of countries includes only those that introduced a defense between 1997 and 2009. Table 4 expands the sample to include countries that have never implemented a defense, allowing for a between- and within-country comparison of the im-

9 The index is "based on the average years of schooling, linearly interpolated from Barro and Lee (2013), and an assumed rate of return for primary, secondary, and tertiary education, as in Caselli (2005)" (Feenstra *et al.*, 2015, p. 3172).

10 Countries for which data are interpolated are Australia, Burkina Faso, Switzerland, Costa Rica, Ethiopia, Ecuador, Chana, Iceland, Morocco, Mozambique, Malaysia, Norway, Philippines, Paraguay, Senegal, Sweden, Thailand, Uruguay, South Africa, and Zambia.

Table 3: Regression Results, Countries that Introduced a Defense between 1997 and 2009

	Dependent variable: *rtfpna*				
Variable	(1)	(2)	(3)	(4)	(5)
Efficiencies defense lagged	0.017*	0.025*	0.029		
	(0.009)	(0.013)	(0.019)		
Modified CLI lagged	-0.006				
	(0.023)				
CLI and enforcement spending lagged		0.545			
		(1.132)			
CLI and enforcement spending lagged, squared		-1.235			
		(8.331)			
CLI, enforcement spending, and efficiencies defense interaction lagged			-0.522		
			(0.627)		
CLI and enforcement spending quadratic, and efficiencies defense interaction lagged			12.524***		
			(4.829)		
OECD frontier distance lagged	-0.321***	-0.002	-0.022		
	(0.093)	(0.072)	(0.059)		
Efficiencies defense lagged two years			0.032***		
			(0.011)		
CLI and enforcement spending lagged two years			0.195		
			(0.847)		
CLI and enforcement spending lagged two years, squared			0.229		
			(5.542)		
OECD frontier distance lagged two years			-0.021		
			(0.076)		
Efficiencies defense lagged three years				0.031***	
				(0.007)	
CLI and enforcement spending lagged three years				0.213	
				(0.325)	
CLI and enforcement spending lagged three years, squared				-1.693	
				(2.567)	
OECD frontier distance lagged three years				-0.039	
				(0.051)	
TFP growth trend difference (quadratic)	-0.311*	-0.068	0.033	-0.400**	-0.459***
	(0.180)	(0.300)	(0.269)	(0.158)	(0.139)
TFP growth trend difference (linear)	0.896***	0.702*	0.647*	1.228***	1.310***
	(0.236)	(0.420)	(0.386)	(0.126)	(0.140)
Rule of law index lagged	0.066	0.075**	0.077**	0.102***	0.082***
	(0.044)	(0.032)	(0.030)	(0.020)	(0.014)
National exports lagged	-0.064	0.195**	0.162**	0.088	0.005
	(0.150)	(0.079)	(0.064)	(0.073)	(0.071)
National imports lagged	-0.200	0.035	0.006	-0.006	-0.135***
	(0.163)	(0.093)	(0.105)	(0.111)	(0.051)
Human capital lagged	0.319**	0.134	0.161	0.158	0.298***
	(0.125)	(0.108)	(0.111)	(0.192)	(0.112)
National price level lagged	-0.010	0.090	0.157***	0.072	0.070***
	(0.090)	(0.122)	(0.057)	(0.061)	(0.027)
R&D expenditure lagged	1.017	3.736	5.320***	2.729*	2.725**
	(2.486)	(2.331)	(1.881)	(1.613)	(1.363)
Observations	342	172	172	147	131
R^2	0.615	0.671	0.714	0.832	0.877
Adjusted R^2	0.544	0.550	0.609	0.765	0.821
F-Statistic	41.792***	21.240***	26.019***	43.011***	53.089***
	(df = 11; 288)	(df = 12; 125)	(df = 12; 125)	(df = 12; 104)	(df = 12; 89)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Countries included in regression (1) are Bulgaria, Costa Rica, Croatia, Cyprus, Estonia, Finland, Iceland, Jordan, Latvia, Mexico, Morocco, Norway, Panama, Romania, Serbia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Sweden, Thailand, Tunisia, Uruguay.

Table 4: Regression Results: Countries that Introduced a Defense between 1997 and 2009 and Never Had a Defense

	Dependent variable: *rtfpna*				
Variable	(1)	(2)	(3)	(4)	(5)
Efficiencies defense lagged	0.020*	0.023	0.020		
	(0.010)	(0.018)	(0.027)		
Modified CLI lagged	-0.003				
	(0.019)				
CLI and enforcement spending lagged		0.740			
		(0.494)			
CLI and enforcement spending lagged, squared		-2.785			
		(2.869)			
Enforcement rigour defense interaction lagged			0.024		
			(0.792)		
Enforcement rigour defense interaction lagged, squared			5.549		
			(6.456)		
OECD frontier distance lagged	-0.279***	-0.034	-0.053		
	(0.084)	(0.063)	(0.065)		
Efficiencies defense lagged two years			0.029***		
			(0.010)		
Efficiencies defense lagged three years				0.027***	
				(0.009)	
CLI and enforcement spending lagged two/three years				0.510	0.716**
				(0.486)	(0.346)
CLI and enforcement spending lagged two/three years, squared				-1.037	-2.277
				(2.654)	(1.636)
OECD frontier distance lagged two/three years				-0.061	-0.031
				(0.064)	(0.050)
TFP growth trend difference (quadratic)	-0.418***	-0.221	-0.217	-0.316**	-0.329**
	(0.071)	(0.162)	(0.160)	(0.146)	(0.157)
TFP growth trend difference (linear)	1.009***	0.810***	0.806***	1.022***	1.023***
	(0.088)	(0.210)	(0.196)	(0.139)	(0.148)
Rule of law index lagged	0.031	0.045**	0.046*		
	(0.026)	(0.023)	(0.025)		
National exports lagged	-0.006	0.136	0.093		
	(0.092)	(0.087)	(0.081)		
National imports lagged	-0.133	-0.006	-0.055		
	(0.102)	(0.079)	(0.083)		
Human capital lagged	0.130**	0.037	0.043		
	(0.062)	(0.107)	(0.106)		
National price level lagged	0.036	0.057	0.081*		
	(0.053)	(0.049)	(0.047)		
R&D expenditure lagged	1.399	2.924	3.426*		
	(2.084)	(1.787)	(1.900)		
Rule of law index lagged two/three years				0.043**	0.036*
				(0.021)	(0.019)
National exports lagged two/three years				0.060	-0.010
				(0.080)	(0.076)
National imports lagged two/three years				-0.071	-0.128*
				(0.085)	(0.068)
Human capital lagged two/three years				0.071	0.128
				(0.125)	(0.126)
National price level lagged two/three years				0.026	-0.012
				(0.029)	(0.034)
R&D expenditure lagged two/three years				3.851***	3.452**
				(1.388)	(1.473)
Observations	566	257	257	219	192
R^2	0.733	0.650	0.646	0.749	0.756
Adjusted R^2	0.689	0.543	0.538	0.666	0.665
F Statistic	121.194***	30.315***	29.829***	40.737***	35.875***
	(df = 11; 486)	(df = 12; 196)	(df = 12; 196)	(df = 12; 164)	(df = 12; 139)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Countries included in regression (1) are Argentina, Australia, Bulgaria, Burkina Faso, Chile, Costa Rica, Croatia, Cyprus, Egypt, Estonia, Finland, Iceland, India, Indonesia, Israel, Jamaica, Jordan, Latvia, Mexico, Morocco, Norway, Panama, Peru, Romania, Senega, Serbia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Sweden, Thailand, Tunisia, Turkey, United States, Uruguay.

pact of implementing an efficiencies defense. In Table 5, the sample used for the regressions in Table 4 are limited to only high- and upper-middle income countries, based on the World Bank's income classifications.[11]

Overall, the results from Table 3 suggest that introducing an efficiencies defense may have a positive impact on TFP growth. In specifications (1) and (2), the coefficient for the one-year lagged efficiencies defense is positive at a 10 per cent level of significance. In regression (3), variables that are made up of combinations of the modified CLI index, enforcement spending, and the efficiencies defence binary variables are included to reflect how enforcement intensity may impact the outcomes of efficiencies defenses. The results from this regression show that higher levels of enforcement intensity lead to positive impacts for efficiencies defenses, with the magnitude of these returns decreasing as intensity increases. Regressions (4) and (5) mirror regression (2) but variables are lagged by 2 and 3 years are lagged 2 and 3 years and find that efficiencies defenses are a positive and statistically significant determinant of national TFP growth. The results of regression (3) do not hold when estimated with lagged variables.

In Table 4 presents the same regressions from Table 3 but includes countries that never had a defense. For regressions (2) and (3), where the data are lagged one year, the coefficient for the efficiencies defense variable fails to be statistically significant at any relevant level of significance. However, for regressions (4) and (5), the variable of interest is statistically significant at a 1 percent level of significance. The results from regressions (4) and (5) may suggest that the impacts from implementing an efficiencies defense may not be immediately realized but may manifest in the long run.

In Table 5, the sample used in Table 7 is limited to only high and upper-middle income countries, based on the World Bank's income classification. Here, the coefficient for the efficiencies defense variable is statistically significant at a 1 per cent level of significance across nearly all the regressions, including the lagged specifications. The difference between the results of regression (3) in this table and those of Table 7, which does not limit the sample by country income level, may suggest that higher income countries are able to realize the benefits of efficiencies defenses more quickly than lower income countries.

Discussion

The results from the regressions show that implementing an efficiencies defense can have a positive impact on TFP growth, controlling for competition law enforcement intensity via spending and the stringency of a nation's competition laws. Due to data limitations, less can be said about the impacts of implementing efficiencies defenses in lower income countries.

An important factor to consider when interpreting these results is that there are

11 Canada is not included in any of these regressions because in the period examined for this study, Canada has always had a defense. The regressions only include countries that have implemented a defense at some point from 1997 and 2009, or have never implemented a defense.

Table 5: Regression Results: Countries that Introduced a Defense between 1997 and 2009 and Never Had a Defense, High- and Upper-Middle Income Countries

	Dependent variable: *rtfpna*				
Variable	(1)	(2)	(3)	(4)	(5)
Efficiencies defense lagged	0.016	0.031***	0.056***		
	(0.010)	(0.008)	(0.014)		
Modified CLI lagged	-0.003				
	(0.022)				
CLI and enforcement spending lagged		0.810			
		(0.588)			
CLI and enforcement spending lagged, squared		-3.348			
		(3.844)			
Enforcement rigour defense interaction lagged			0.013		
			(0.019)		
Enforcement rigour defense interaction lagged, squared			-0.010		
			(0.011)		
OECD frontier distance lagged	-0.125**	0.029	-0.109		
	(0.051)	(0.058)	(0.077)		
Efficiencies defense lagged two years			0.021***		
			(0.007)		
Efficiencies defense lagged three years				0.018**	
				(0.008)	
CLI and enforcement spending lagged two/three years				0.715	0.573*
				(0.619)	(0.345)
CLI and enforcement spending lagged two/three years, squared				-2.555	-3.213
				(3.234)	(2.680)
OECD frontier distance lagged two/three years				0.004	-0.003
				(0.055)	(0.044)
TFP growth trend difference (quadratic)	-0.423***	-0.245*	-0.413**	-0.223*	-0.218
	(0.123)	(0.145)	(0.193)	(0.120)	(0.163)
TFP growth trend difference (linear)	1.079***	1.001***	1.018***	0.959***	1.002***
	(0.082)	(0.139)	(0.190)	(0.116)	(0.163)
Rule of law index lagged	0.032*	0.064***	0.072***		
	(0.019)	(0.022)	(0.021)		
National exports lagged	0.094**	0.175***	0.054		
	(0.044)	(0.060)	(0.083)		
National imports lagged	-0.013	0.085	0.051		
	(0.054)	(0.054)	(0.053)		
Human capital lagged	0.115**	0.103	0.052		
	(0.047)	(0.076)	(0.082)		
National price level lagged	0.065**	0.089**	0.135***		
	(0.026)	(0.044)	(0.049)		
R&D expenditure lagged	2.938*	2.996**	2.597		
	(1.664)	(1.474)	(2.113)		
Rule of law index lagged two/three years				0.063***	0.048**
				(0.017)	(0.021)
National exports lagged two/three years				0.162**	0.061
				(0.063)	(0.067)
National imports lagged two/three years				0.030	-0.078*
				(0.060)	(0.041)
Human capital lagged two/three years				0.057	0.164
				(0.095)	(0.102)
National price level lagged two/three years				0.055	0.029
				(0.034)	(0.038)
R&D expenditure lagged two/three years				3.926***	3.492***
				(1.202)	(0.866)
Observations	339	183	119	163	145
R^2	0.853	0.735	0.742	0.752	0.818
Adjusted R^2	0.824	0.640	0.604	0.653	0.735
F Statistic	148.856***	30.908***	18.413***	29.290***	37.037***
	(df = 11; 283)	(df = 12; 134)	(df = 12; 77)	(df = 12; 116)	(df = 12; 99)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Countries included in regression (1) are Argentina, Australia, Bulgaria, Chile, Costa Rica, Croatia, Cyprus, Estonia, Finland, Iceland, Israel, Latvia, Mexico, Norway, Panama, Romania, Serbia, Singapore, Slovakia, Slovenia , South Africa, South Korea, Sweden, Turkey, United States of America, Uruguay.

a variety of different types of efficiencies defenses. Since efficiencies defenses were first formalized as a concept (in the North American context) by Williamson in 1968, legislators and policy makers have explored several different ways that competition law, competition law enforcers, and adjudicators can understand efficiencies and the ways they should be considered against merger harms. For instance, Canada's (former) efficiencies defense strongly mirrored the framework put forward by Williamson (1968), which required that adjudicators weigh the efficiencies resulting from a merger against the inefficiencies the merger created, namely through increasing deadweight loss (Ware and Winter, 2016). This approach contrasts with the EU's consumer-focused approach to its efficiencies defense.

Since 1997 about half (52 percent) of all defenses enacted by countries were weighted defenses similar to Canada's former defense. The other half included defenses that mirror that of the EU, and exemption and factor defenses discussed earlier (Shaban, 2024). While efficiencies defenses do enable law enforcement and adjudicators to accept mergers that may otherwise not be permitted on the basis of efficiencies, not all efficiencies defenses are agnostic to the types of efficiencies a merger creates or the impact of those efficiencies.

Furthermore, the relationship between enacting efficiencies defenses and increases in enforcement spending and merger reviews has an important role to play in understanding the impact of new efficiencies defenses. The results suggest that efficiencies defenses on their own could positively impact TFP growth. However, making changes to competition law without also providing competition law enforcers the resources they need to actually enforce the new law would be unlikely to yield positive results.

Additionally, across nearly all the preferred specifications applied to all the samples, rule of law remains a positive, and statistically significant determinant of TFP growth this finding points to the importance of institutional quality in fostering productivity advancements within a country's economy. Similarly, spending on research and development relative to the size of a nation's economy is also has a positive and statistically significant relationship to TFP growth, although this relationship is less pronounced than that of the rule of law variable.

Conclusion

Since the mid-1980s, efficiencies defenses for mergers have become increasingly more common. Yet, despite their growing prevalence, there has been little research into their effectiveness, particularly from a macroeconomic perspective. Mergers between companies have the capacity to drive substantial changes in how the private sector arranges and uses labour and capital for production. Mergers, and laws that regulate them, could have a meaningful impact on the TFP growth of national economies.

Using data from the Comparative Competition Law Dataset developed by Bradford & Chilton (2018), macroeconomic data from the Penn World Tables version 10.0, and the World Bank, this study undertakes both a descriptive and econometric analyses into the link between efficiencies defenses for mergers and TFP growth. The analysis finds a relationship between the introduction of an efficiencies defense and TFP growth. However, importantly, the analysis also points to a relationship between the introduction of an efficiencies defence and enforcement rigour, measured as both total competition law enforcement spending and the number of mergers reviewed by authorities (adjusting for the size of the national economy). While the econometric results find that efficiencies defenses can themselves impact TFP growth, the data also point to the reality that without resources to enforce these laws, they are unlikely to have an impact.

Given recent changes to Canada's Competition Act that saw the removal of its efficiencies defense for mergers, the findings of this study are pertinent. The results provide some evidence that removing the defense could undermine Canada's TFP growth. However, this assertion should be tempered by two considerations. First, this study examines the impact of introducing an efficiencies defense for mergers. It does not consider whether the impact of introducing a defense persists in the long-run and whether, consequently, there is an impact associated with removing these defenses. The study examined defenses introduced between 1997 and 2009, considereing one-, two-, and three-year lags specified in the regressions and in many cases these defenses were introduced in the last ten years of the period examined. Second, the study does not differentiate between different types of defenses, whether they be the "weighted" type of defense that Canada used to have or a more consumer-focused type of defense like in EU law. These different types of defenses have important welfare implications for consumers and could also create different impacts on TFP growth. More research is required to determine the optimal approach for considering efficiencies created by mergers, but this study provides a useful starting point to that research.

There are some important avenues for further research into efficiencies defences for mergers that are worth exploring. First, this area of research would benefit greatly from further data. Expanding the Comparative Competition Law dataset to cover years since 2010, including enforcement spending. This data could enable more sophisticated analysis of the impact of defenses of TFP growth by providing a greater number of observations, both in terms of years of data but also a greater number of countries with enforcement data. With more observations and more countries included in the analysis, more sophisticated econometric techniques can be used to unpack the causal relationship between efficiencies defenses and TFP growth. Another extension that would be possible with more data is exploring how different types of legislated efficiencies may be more or less effective at growing TFP. Including data from after 2010 would also allow studies to capture important technological transformations since that time which would also impact TFP growth. Including more recent years would provide more timely insights for policy makers.

This study highlights the broader economic implications of efficiencies defenses in merger policy, emphasizing both their potential impact on TFP growth and the critical role of enforcement capacity. As competition laws evolve, ensuring robust enforcement will be essential. Future research with richer datasets and advanced econometric methods can further clarify how efficiencies defenses shape economic performance and market dynamics.

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Table A1: Summary Statistics of Regression Variables

Variable	Obs.	Mean	St. Dev.	Minimum	Maximum	Descriptions
TFP growth	966	0.94	0.17	0.48	1.67	Growth of TFP, (PWT 10.01).
Efficiencies defense lagged	965	0.3	0.46	0	1	Efficiencies defense binary variable, one year lag (Bradford *et al.*, 2018).
Efficiencies defense lagged two years	964	0.27	0.45	0	1	Efficiencies defense binary variable, two-year lag (Bradford *et al.*, 2018).
Efficiencies defense lagged three years	963	0.24	0.43	0	1	Efficiencies defense binary variable, three-year lag (Bradford *et al.*, 2018).
Modified CLI lagged	965	0.43	0.32	0	0.99	Comparative Competition Law Index (CLI), one year lag, efficiencies defense removed (adjusted for EU law), (Bradford *et al.*, 2018).
CLI and enforcement spending lagged	309	0.02	0.03	0	0.17	CLI multiplied by budget of national enforcement agencies, one year lag (Bradford *et al.*, 2018).
CLI and enforcement spending lagged two years	266	0.02	0.03	0	0.17	CLI multiplied by budget of national enforcement agencies, two-year lag (Bradford *et al.*, 2018).
CLI and enforcement spending lagged three years	227	0.02	0.03	0	0.17	CLI multiplied by budget of national enforcement agencies, three-year lag (Bradford *et al.*, 2018).
CLI and enforcement spending lagged, squared	309	0	0	0	0.03	CLI multiplied by budget of national enforcement agencies squared, one year lag (Bradford *et al.*, 2018).
CLI and enforcement spending lagged two years, squared	266	0	0	0	0.03	CLI multiplied by budget of national enforcement agencies squared, two-year lag (Bradford *et al.*, 2018).
CLI and enforcement spending lagged three years, squared	227	0	0	0	0.03	CLI multiplied by budget of national enforcemenP level), (PWT 10.0).
OECD frontier distance lagged two years	964	0.31	0.27	-0.97	0.87	t agencies squared, three-year lag (Bradford *et al.*, 2018).
CLI, enforcement spending, and efficiencies defense interaction lagged	257	0.01	0.02	0	0.11	CLI, enforcement spending, and efficiencies defense interaction term lagged, (Bradford *et al.*, 2018).
CLI and enforcement spending quadratic, and efficiencies defense interaction lagged	257	0	0	0	0.01	CLI and enforcement spending quadratic, and efficiencies defense interaction term lagged, (Bradford *et al.*, 2018).
OECD frontier distance lagged one year	965	0.31	0.27	-0.97	0.87	Relative distance from technological frontier, one year lag, (Average OECD TFP level less national TF Relative distance from technological frontier, two-year lag (PWT 10.0).
OECD frontier distance lagged three years	963	0.31	0.28	-0.97	0.87	Relative distance from technological frontier, three-year lag, (PWT 10.0).
TFP growth trend difference (quadratic)	966	0	0.07	-0.33	0.32	Distance from TFP growth trend, (quadratic).
TFP growth trend difference (linear)	966	0	0.09	-0.42	0.44	Distance from TFP growth trend, (linear).
Rule of law index lagged	964	0.01	0.96	-1.85	2	National rule of law index, one year lag, (World Bank Worldwide Governance Indicators).

Variable	Obs.	Mean	St. Dev.	Minimum	Maximum	Descriptions
Rule of law index lagged two years	895	0.01	0.96	-1.82	2	National rule of law index, two-year lag, (World Bank Worldwide Governance Indicat
Rule of law index lagged three years	826	0.01	0.96	-1.82	2	National rule of law index, three-year lag, (World Bank Worldwide Governance Indicat
National exports lagged	965	0.26	0.3	0	2.46	Share of merchandise exports at current PPPs, one year lag, (PWT 10.0).
National exports lagged two years	964	0.26	0.3	0	2.82	Share of merchandise exports at current PPPs, two-year lag, (PWT 10.0).
National exports lagged three years	963	0.25	0.3	0	2.82	Share of merchandise exports at current PPPs, three-year lag, (PWT 10.0).
National imports lagged	965	-0.32	0.29	-2.83	-0.02	Share of merchandise imports at current PPPs, one year lag, (PWT 10.0).
National imports lagged two years	964	-0.31	0.3	-3.39	-0.02	Share of merchandise imports at current PPPs, two-year lag, (PWT 10.0).
National imports lagged three years	963	-0.3	0.31	-3.39	-0.02	Share of merchandise imports at current PPPs, three-year lag, (PWT 10.0).
Human capital lagged	965	2.35	0.67	1.05	3.69	Human capital index, one year lag, (PWT 10.0).
Human capital lagged two years	964	2.34	0.66	1.05	3.67	Human capital index, two-year lag, (PWT 10.0).
Human capital lagged three years	963	2.31	0.66	1.05	3.66	Human capital index, three-year lag, (PWT 10.0).
National price level lagged	965	0.44	0.22	0.12	1.64	Price level of CGDP, one year lag, (PWT 10.0).
National price level lagged two years	964	0.43	0.22	0.12	1.64	Price level of CGDP, two-year lag, (PWT 10.0).
National price level lagged three years	963	0.42	0.21	0.12	1.64	Price level of CGDP, three-year lag, (PWT 10.0).
R&D expenditure lagged	566	0.01	0.01	0	0.04	R&D expenditure (% of GDP), one-year lag, (World Bank).
R&D expenditure lagged two years	519	0.01	0.01	0	0.04	R&D expenditure (% of GDP), two-year lag, (World Bank).
R&D expenditure lagged three years	473	0.01	0.01	0	0.04	R&D expenditure (% of GDP), three-year lag, (World Bank).

Sources: PWT 10.0, Bradford *et al.* (2019), World Bank Worldwide Governance Indicators.

Efficiency Adjustment of Hours Worked: Two Possible Modifications of a Jorgensen Production Model

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Abstract

This article focuses on two features of the Jorgenson model of production, which is commonly used in productivity research. First, that capital stock is efficiency adjusted in that model, but hours are not. If hours are efficiency adjusted, as proposed in this article, the efficiency per hour of a much younger male college degree worker in a specific year, say 25 years old in 1980, may be different than that of a 50 year old college degree worker in that same year. Second, this article asks whether the assumption of no vitnage effects in the Jorgenson model is valid. In such a model, it is assumed that at the lowest level of detail, the efficiency of a particular type of worker as measured by quality, (marginal product, or labour input divided by hours worked), is constant over time. With no vintage effects, the efficiency of a 50 year old male with a college degree, is the same in 1980 and 2000. Hours are adjusted for efficiency by age using OECD's 2012 Programme for the International Assessment of Adult Competencies (PIAAC).

Estimating total factor productivity (TFP) growth is a challenge. Inputs and outputs have to be quantified over time when demographics and the nature of production processes change, leading to measurement challenges compounded by vintage effects.

In the time period considered,[2] 1975-2013, in the United States, women entered the labour force in significantly larger numbers. In addition, both men and women became more highly educated, with the increase in education levels of women clearly greater than that of men. The age and

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2 The dataset used in the article ends in 2013 and have not yet been updated. However, this has no impact on the major points made in the article.

education composition of the labour force shifted and technology impacted how production took place.

This article proposes adjusting hours worked by workers' efficiency to make it more consistent with physical capital stock and questions the assumption that the quality of an input at the most detailed level is constant over time. The Jorgenson model of production, which is frequently used in productivity research, is the basis for the analysis, a model which was adopted by the U.S. Bureau of Labor Statistics (BLS) with a minor modification.[3]

Adjusting hours worked by workers' efficiency will change the quantity of labour input and measured TFP change. Since capital stock's efficiency adjustment is an age adjustment, a labour input efficiency adjustment follows this adjustment concept. The age hours' efficiency adjustment is based on the age of workers using survey results from the Programme for the International Assessment of Adult Competencies (PIAAC). [4] No attempt is made to determine whether the PIAAC results are a true indicator of the level of efficiency or skills which impact directly on job performance. The purpose of this article is simply to argue for an hours adjustment, not to determine whether PIAAC is the optimal indicator.

One premise of the Jorgenson model of production is that quality of a factor of production at the most detailed level of data available is constant over time. To use an example from Bowlus and Robinson (2012: 4), this assumption means that the "physics task" performed by a 50 year old with a Ph.D. in physics granted to someone from the 1966 cohort compared to someone from a 1946 cohort is the same. Bowlus and Robinson say this is not true not mainly because of the quality of teaching, rather due to the quality of the Ph.D. recipient due to the advanced physics information passed on to the student in the later cohort. The challenge is to be able to test Jorgenson's assumption.

The assumption that quality of an input at the most detailed level of data available is constant over time should not be confused with an assumption that the quality of a factor of production is constant when more than one type of input is included. When more than one type of input is included, BLS calls this composition rather than quality. An input index can reflect changes in the composition of inputs, such as in an index of males and females of a particular type, as well as changes in the quality of an input at the most detailed level of data available. For example, with reference to the composition component, over time as more women are employed, the quality of an input including both males and females typically changes. However, it is not possible to identify within quality change the part that comes from possible changes in

3 The U.S. Bureau of Labor Statistics (BLS) averages the revaluation term in the nominal cost of capital services expression over several years because of this term's impact on nominal capital services. Bowlus and Robinson (2012: 22) note that their results are almost the same whether they use the Jorgenson or the BLS model of production.

4 See the OECD (undated) in the references for the PIAAC literacy, numeracy and problem solving documents.

the quality of an input at the most detailed level over time (the Ph.D. example) and the part that comes from changes in the composition of the input at a higher level of detail when the index includes more than one type of input.

This article contains six sections. The first part provides a description of the Jorgenson production model. The second section describes the Program for International Assessment of Adult Competencies (PIAAC). The third part discusses the adjustment of hours worked by age using PIAAC. The fourth section provides estimates of the impact of PIAAC-adjusted hours adjustment on the contribution of labour and total factor productivity to output growth. The fifth section discusses the existence of vintage effects for workers, that is whether it is possible to determine if the quality of labour at the most detailed level of disaggregation is constant over time. The sixth section concludes.

Jorgenson Production Model

The Jorgenson production model is frequently used to estimate production and the rate of change of TFP.[5]

The most frequently cited source for a description of the Jorgenson production model is Jorgenson, Gollop, and Fraumeni (1987). In the production model, capital and labour differ in that capital input is constructed with physical capital stocks and labour input is constructed with hours worked, a flow. In addition, capital compensation is estimated indirectly with a user cost of capital, or capital service flow, methodology, while labour compensation comes directly from wages paid for hours worked. The nominal dollar accounting identity, the sum of all nominal dollar physical capital and labour compensation, is:

$$\sum P_v V = \sum P_{Kk} K_k + \sum P_{Ll} L_l \qquad (1)$$

where P is price, V is the quantity of value added, K is the quantity of physical capital input with types k, and L is the quantity of labour input with types l. The quantity of value added is determined by a Törnqvist index of the quantity of physical capital input, labour input, and time.

The index of TFP change, $\bar{v}_T$, is a residual

$$\begin{aligned} \bar{v}_T &= \ln V(T) - \ln V(T-1) \\ &= \bar{v}_k[\ln K(T) - \ln K(T-1)] \qquad (2) \\ &- \bar{v}_L[\ln L(T) - \ln L(T-1)] \end{aligned}$$

with

$$\begin{aligned} \bar{v}_K &= \frac{1}{2}[v_K(T) + v_K(T-1)], \\ \bar{v}_L &= \frac{1}{2}[v_L(T) + v_L(T-1)], \qquad (3) \\ \bar{v}_T &= \frac{1}{2}[v_T(T) + v_T(T-1)]. \end{aligned}$$

5 The Jorgenson production model is often called KLEMS (physical capital, labour, energy, materials, and services).

$$v_K = \frac{P_K K}{\sum P_V V}, \quad v_L = \frac{P_L L}{\sum P_V V}. \tag{4}$$

The terms $\overline{v}_K[\ln K(T) - \ln K(T-1)]$ and $\overline{v}_L[\ln L(T) - \ln L(T-1)]$ are frequently called respectively the contribution of physical capital and labour input to economic growth. The quantity of physical capital and labour input are computed using a Törnqvist index.[6]

$$\begin{aligned} \ln K(T) - \ln(K(T-1)) = \\ \sum \overline{v}_{Kk}[\ln K_k(T) - \ln K_k(T-1)], \\ \ln L(T) - \ln(L(T-1)) = \\ \sum \overline{v}_{Ll}[\ln L_l(T) - \ln L_l(T-1)], \end{aligned} \tag{5}$$

where

$$\begin{aligned} \overline{v}_{Kk} &= \frac{1}{2}[v_{Kk}(T) + v_{Kk}(T-1)], \\ \overline{v}_{Ll} &= \frac{1}{2}[v_{Ll}(T) + v_{Ll}(T-1)], \\ v_{Kk} &= p_{Kk}K / \sum p_K K, \\ v_{Ll} &= p_{Ll}L / \sum p_L L. \end{aligned} \tag{6}$$

In all of the Törnqvist input indexes, once the growth rates are determined, typically the base year is set to nominal dollar physical capital input (also called capital services) or nominal labour input, then the growth rates are applied to generate a sequence of quantity estimates. As previously noted, physical capital input is derived from physical capital stock. The flow of the quantity of capital input, is assumed to be proportional to the quantity of physical capital stock, $A_k(T-1)$ Jorgenson, Gollop, and Fraumeni (1987:13):

$$K_k(T) = Q_{Kk} \cdot A_k(T-1), \tag{7}$$

where the constants of proportionality or quality variables, Q_{Kk}, transform physical capital stock to the flow of capital services. The flow of the quantity of labour input is assumed to be proportional to hours worked, $H(T)$. The constants of proportionality or quality variables, Q_{Ll}, transform hours worked to the flow of the quantity of labour input.

$$L_l(T) = Q_{Ll} \cdot H(T). \tag{8}$$

It is important to note that in equations 7 and 8, the quality or constants of proportionality variables, Q_s, do not depend on time, T. This feature of the Jorgenson production model is equivalent to assuming that no Jorgenson-defined vintage effects occur.

In practice, quality for both physical capital and labour input is determined by dividing the Törnqvist quantity of physical capital or labour input by lagged physical capital stock or hours worked, respectively. Hours worked is an unweighted summation, but the quantity of physical capital stock, A_k, is a weighted summation. Using the

6 In a Törnqvist index, the nominal dollar shares reflect the relative marginal products (and wages of or rate of return to) inputs.

perpetual inventory method, $(1-\delta_k)$ are the weights applied to the previous year's physical capital stock, with δ_k as the geometric depreciation rate.

$$A_k(T) = I_k(T) + (1-\delta_k)\cdot A_k(T-1), \quad (9)$$

where $I_k(T)$ is the quantity of physical capital investment.

The depreciation rate is an efficiency adjustment as it reduces the contribution of past investments to physical capital inputs based on the age of the physical capital stocks.

To summarize, there are two differences in the Jorgenson production model between physical capital and labour:

1) Physical capital stocks are efficiency adjusted, but hours worked are not, and

2) The quantity of physical capital input depends on a stock measure while the quantity of labour input depends on a flow measure. [7]

To allow for efficiency adjustment of hours for consistent treatment of labour and capital and the possibility that neither quality of capital or labour is constant at the lowest level of detail, the following two new equations could be added to the model of production:

$$K_k(T) = Q_{Kk}(T)\cdot A_k(T-1), \quad (10)$$

$$L_l(T) = Q_{Ll}(T)\cdot(1-\delta_h)\cdot H(T), \quad (11)$$

where $(1-\delta_h)\cdot H(T)$ is efficiency adjusted hours and $(1-\delta_h)$ is the hours adjustment factor which could vary by the age or some other characteristic of workers.

Program for the International Assessment of Adults Competencies (PIAAC)

The OECD sponsors the Program for the International Assessment of Adults Competencies (PIAAC), a survey of adult competencies, conducted in the first cycle between 2011 and 2018 in 39 countries including the United States (OECD, undated, Survey of Adult Skills (PIAAC)). The PIAAC survey measures the key cognitive and workplace skills which are thought to be needed for individuals to participate in society and for economies to prosper. Five thousand individuals per country between the age of 16 and 65 are interviewed in their home as part of the survey. In 2012, the skills measured are literacy, numeracy, and problem solving in technology-rich environments.[8]

On the PIAAC design web site, three sample questions are given for each of the skills, accessible from the web site that lists the skill definitions. The PIAAC web site states "Literacy is the ability to understand and use information from written texts in a variety of contexts to achieve

7 The stock versus flow issue is not going to be explored in this article. This stock versus flow issue could become a problem when econometric models determine the rate of change in TFP on the basis of output and hours, which are both flows, and physical capital stocks, without being aware of underlying assumptions needed to do so such as those in the Jorgenson model of production.

8 The three skill definitions are found at https://www.oecd.org/skills/piaac/.

goals and develop knowledge and potential."[9] "Numeracy is the ability to use, apply, interpret, and communicate mathematical information and ideas."[10] Referring to problem solving in technology-rich environments, the PIAAC web site states, "This refers to the ability to use technology to solve problems and accomplish complex tasks. It is not a measurement of "computer literacy", but rather of the cognitive skills required in the information age – an age in which the accessibility of boundless information has made it essential for people to be able to decide what information they need, to evaluate it critically, and to use it to solve problems.'[11]

There are two alternative sets of PIACC results, one by gender and one by qualifications. These will not be explored in this article.

Adjustment of Hours Worked by Age Using PIAAC in the United States

Hours worked are now going to be efficiency adjusted to remove the inconsistency between physical capital and hours worked. As previously noted, hours worked in a Jorgenson production model are an unweighted summation of hours worked without any efficiency adjustment, whereas the quantity of capital stock is efficiency adjusted.

PIAAC results support the notion that the efficiency of hours worked by individuals vary by age in the United States. As a starting point is this article's proposal to efficiency adjust both physical capital stocks and hours worked, the efficiency of hours worked will be allowed to vary by age based on the PIAAC survey results as the efficiency of physical capital stocks vary by age in the Jorgenson production model. In contrast to physical stocks which decline in efficiency as assets age, hours worked are allowed to increase in efficiency as younger workers age, before hours worked efficiency are allowed to decline in efficiency, at least through age group 55 and over.

Table 1 shows the PIAAC results[12] and the adjustments to hours worked equal to

9 Three sample questions start with a list of nine preschool rules. The test taker is first asked by what time children should arrive at preschool. The second and third depend on reading a chart of 13 types of physical exercise equipment classified by nine different effects. The first question using this chart asks the test taker to determine which muscles will benefit the most if you use a gym bench. The second question using this chart asks the test taker to determine which equipment listed has the most ineffective ratings.

10 The test taker is asked what the Celsius temperature would be if the temperature decreases by 30 degrees. Next, a brief set of information is given about a closed nuclear reactor and wind power stations in Sweden. The question asks the test taker to determine how many wind power stations would be needed to replace the power generated by the closed nuclear reactor. The last question relies on a graph showing births for every 10 years in the United States from 1957 to 2007. The question asks the test taker to indicate the period(s) for which there was a decline in births.

11 All three questions depend on use of websites. The test taker is asked to find which job search web sites of those shown, with live links, do not charge a fee and do not require that you register. The object is to bookmark these websites, but not until you have determined that they meet the requirements. Investigation requires one to link to connected websites to learn more before making a decision.

12 All PIAAC data and information in this article were obtained through the data base accessing site found at https://piaacdataexplorer.oecd.org/ide/idepiaac/.

13 There are three possible sources of PIAAC hours worked age adjustments. The results in this article feature that from 2012, but there is also a combined 2012/14 sample and the 2017 PIAAC. 2012 is featured in this

Table 1: **PIAAC Results by Age and Hours Worked Efficiency Age Adjustment Based on 2012 PIAAC***

	Age Groups				
Skill	16-24**	25-34	35-44	45-54	55 & over
Literacy***	272 (2.0)	275 (2.0)	273 (1.8)	266 (1.7)	263 (1.5)
Numeracy***	249 (2.2)	260 (2.2)	258 (1.9)	250 (2.1)	247 (1.8)
Problem Solving in Technology- Rich Environments***	285 (2.2)	283 (2.0)	279 (2.2)	271 (1.7)	267 (2.5)
Average Score	269	273	270	262	259
Hours Efficiency Adjustment***	.985	1.000	.990	.962	.950

*Standard errors are listed in parentheses.
**The hours worked efficiency adjustment listed in this column is applied to those aged 15-24.
***No significant differences in averages for Literacy (24 or less vs. 25-34, 24 or less vs. 35-44, 45-54 vs 55 & over); Numeracy (24 or less vs 45-54, 24 or less vs 55 & over, 25-34 vs 35-44, 45-54 vs 55 & over); Problem Solving (24 & less vs 25-34, 25-34 vs 35-44, 45-54 vs 55 & over)
Source: OECD

(1 - δ_h) that are applied in all years to all workers based on the 2012 PIAAC. [13] Note that the problem solving skill is the only one that monotonically declines by age group. In addition, across all skills, the largest falloff in scores between two age groups is between the 35-44 and 45-54 age groups (0.038). Because efficiency is set to 1.0 in the age group (25-34) with the highest average skill score, adjusted hours worked are lower than unadjusted hours worked for all other age groups. The 55 and over age group has an efficiency level 0.950 of that of the 25-34 age group, while the corresponding ratio for 45-54 age group was 0.962 per cent , 0.990 per cent for the 34-44 age group, and 0.985 per cent for the 16-24 age group.

Chart 1 shows the average percentage difference between unadjusted and adjusted hours between 1975 and 2013 where the Christian database is the source for hours (Christian, 2016).[14] The reduction drops from 2.06 per cent in 1975, to the smallest reduction of 1.75 per cent in 1987, before increasing to 2.41 per cent in 2013.[15] This reduction is driven by the change in the age distribution of the working age population. Most noticeably, the workforce has aged as the post-World War II baby-boomers aged. The boomer birth rate peaked in 1947, but individuals born between mid-1946 and mid-1964 are considered baby-boomers (Colby and Ortman, 2014:2). Over the 1975 to 2013 period, there were notable changes in the shares

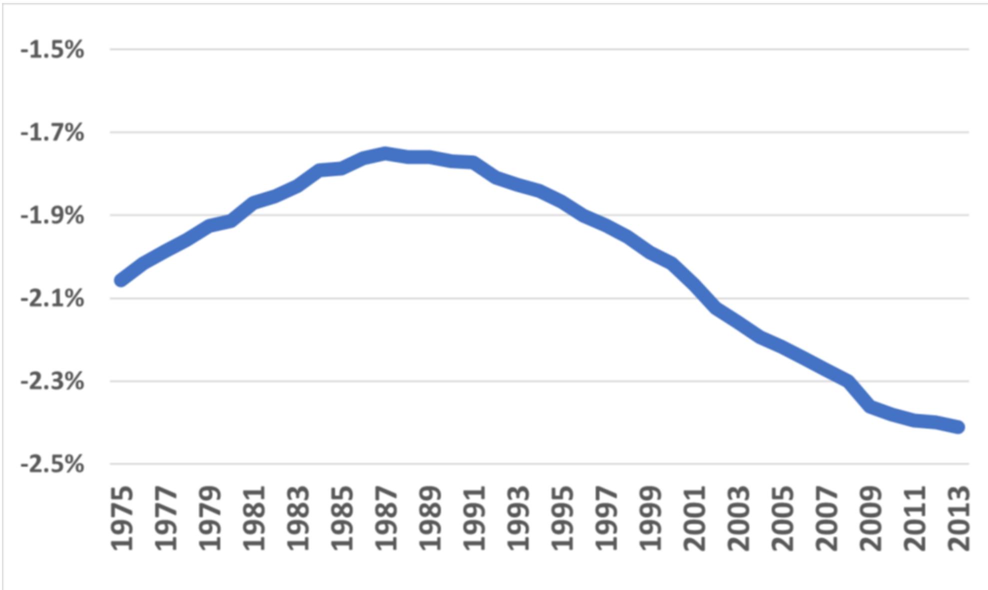
article rather than the two other possibilities for three reasons: 2017 is beyond the period covered in this article, 2012 is closer to the earlier years in the analysis than the combined 2012/14 sample, and the statistical properties, such as standard errors and P-values, could not be found online for the combined 2012/14 sample when this estimates in this article were constructed. The hours reduction is greatest in the 2012/14 sample and the smallest in 2012.

14 Christian hours are not efficiency adjusted.

15 It does not matter whether the PIAAC ratings are scaled with the lowest or the highest PIAAC rating being set to one as the logarithmic rate of change in hours from year to year would remain the same. In a Törnqvist index it is the logarithmic rate of change that matters, not the number of hours worked.

16 See Gobbi and Chabé-Ferret (2019) for a discussion of birth rates by generations. OECD, (2019: Chart 9)

Chart 1: Reduction in Hours Worked with the Age Efficiency Adjustment Based on PIAAC in the United States, 1975, 1987 and 2013 (Per cent of total)



Source: Author's compilations.

of hours worked by age categories (Chart 2).[16]

The PIAAC skill measures imperfectly capture how skills impact work performance. For example, if an individual performs unskilled labour, how important are the three skills?[17] However, the use of PIAAC skill indicators are useful as they demonstrate the concept of efficiency adjustment for hours worked.

There are other possible factors that could be used to determine worker efficiency by age. Paullin (2014) has listed a number of these as they impact on what she calls "mature" workers (Exhibit 1). Although she notes that mature workers are thought to be those generally above age 50 or 55, she also notes that age is not the only indicator of maturity.[18] There are no numerical indicators of the impact on younger and mature workers in her analysis.

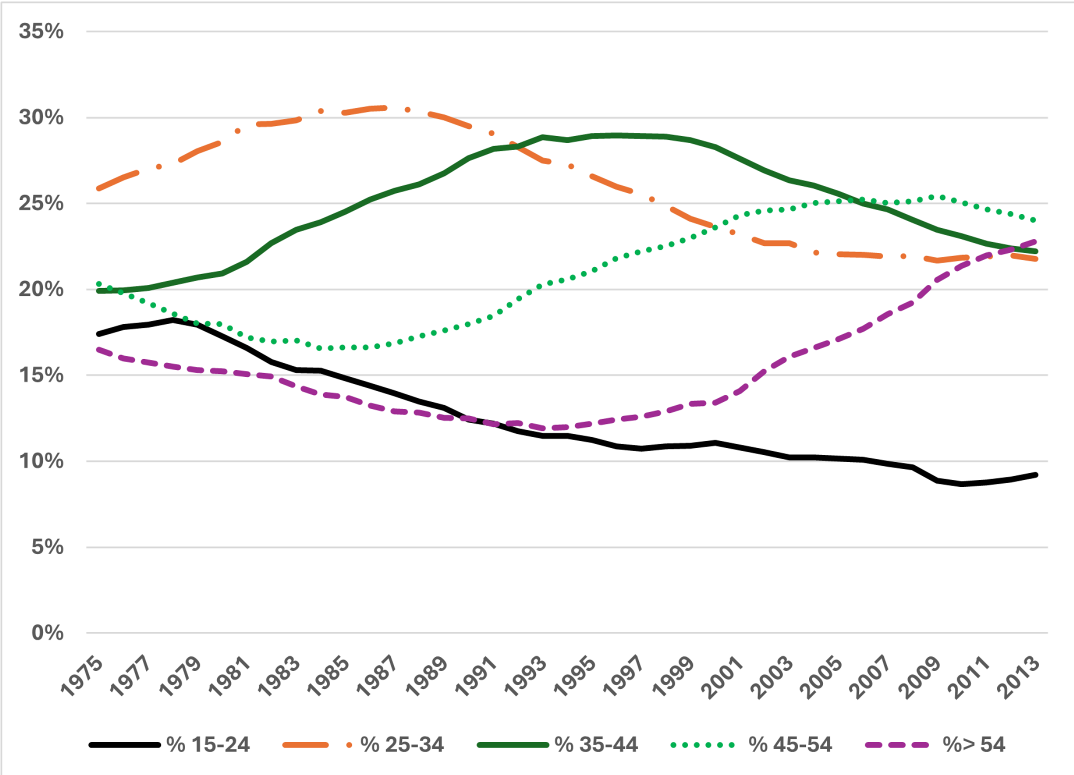
Impact of PIAAC-based hours adjustments on the contribu-

shows literacy and numeracy scores of individuals by a representative sample of age groups who participated in the Programme for the International Assessment of Adult Competencies (PIAAC) both in 2012/2014 and in 2017. This chart shows that differences occurred as individuals aged with results from participants in the 2012/14 and 2017 U.S. surveys.

17 My personal example regarding the importance of numeracy (or at least basic mathematics knowledge) for a worker performing unskilled labour is the following from a number of years ago. At my former house, a thick, large stone, New England wall was being constructed. A sub-contractor quoted the price based on surface area (length times height), instead of by cubic feet (length times height times width). The wall builder was very upset at the amount he was paid for the completed wall, but the low payment was due to the fact that the sub-contractor did not take into account the width of the wall in his quotation.

18 Paullin (2014:2) cautions that "No matter which number is chosen, chronological age is not the best way to define the mature worker. People vary in terms of when and how they experience aging and whether they perceive themselves as aging. Factors that should be taken into account in addition to chronological age include physical, mental and emotional health; career stage; job tenure; and life experiences."

Chart 2: Share of Total Hours Worked by Age Group in the United States, 1975-2013



Source: Author's compilations

Exhibit 1: Relationship Between Job Performance and Age

Factor	Relationship
Core task performance	No consistent relationship up to mid-60s
Performance quantity	May be higher for younger workers
Performance quality	May be higher for mature workers
Organizational citizenship behaviors	Higher for mature workers
Counterproductive work behaviors	Lower for mature workers
Self-reported health problems	Similar levels through middle age, then higher levels with advancing age
Clinical indicators of health	Worse for mature workers
Resistance to change	May be lower for mature workers
Innovative behaviors	No relationship
Organizational commitment	Higher for mature workers
Turnover intentions	Lower for mature workers

Source: Paullin (2014)

tion of labour and TFP to output growth

Changes in the rates of growth of contributions of labour input to growth in output are small with a PIAAC-based hours adjustment. This means the changes in the rates of growth of TFP, which is a residual (see equation 2), are also small. Using unadjusted (base case) and adjusted hours from the Christian database (Christian, 2016) and the average nominal share of labour compensation in nominal value added from Fraumeni and Christian (Fraumeni and Christian, 2019), the rates of change of hours and the contributions of labour input are estimated. In a Törnqvist index of labour input, the quantity of labour input is determined from the logarithmic rate of growth of hours weighted by the average nominal labour compensation share. Accordingly, the contribution of labour input to economic growth varies if the average labour compensation share or the rate of growth of hours changes.

The focus is on the logarithmic rate of change in hours with or without PIAAC based adjustment as all other components of TFP are the same. The logarithmic growth rates of hours worked by selected time periods decline for the no hours adjustment base case and for the hours age adjustment scenario (Table 2). If a logarithmic rate of change in hours increases in the PIAAC age adjustment case compared to the no hours adjustment base case, the rate of change of TFP decreases compared to the base case; if it decreases, the rate of change of TFP increases. Table 2, for the base case and for the hours adjustment scenario, shows all components of the rate of contributions of labour input to economic growth, for the adjusted hours labour contribution, and adjusted hours labour contribution less the base case. If the difference is positive, the rate of change of TFP is lower as a greater portion of economic growth is measured as coming from labour input; if it is negative the rate of change of TFP is higher. The results show that for the age efficiency adjustment reduced the labour input by 0.01 percentage points per year, and thereby increased TFP growth by the same amount. This is a very small effect.

Quality Constancy at the Most Vintage Detailed Level of Data Available

As previously noted earlier in the article, the Jorgenson production model assumes that the quality of inputs is constant over time at the lowest level of detail available in the data (equations 7 and 8). If the quality of labour input changes at this lowest level of detail over time, the Jorgenson model assumption is violated.

Inklaar and Papakonstantinou (2020) followed the methodology of Bowlus and Robinson (2012) to estimate vintage effects of the United States versus six European countries to determine if the Jorgenson assumption is violated and to determine the size of the vintage effect. Inklaar and Papakonstantinou find that Bowlus and Robinson defined vintage effects can occur for several reasons: The quality of students, the quality of higher education (the Ph.D. in physics example), and changes in workers' human capital production func-

Table 2: Effect of Efficiency Adjustment of Hours on Labour Input

	Average Nominal Labour Share	Logarithmic Hours Rates of Growth		Contributions of Labour Input (pp.)		Difference between Base and Adjusted Hours Contributions
Year		Base	Age Efficiency Adjusted	Base	Age Efficiency Adjusted	(Adjusted–Base)
1976–1985	0.566	0.0225	0.0228	0.0127	0.0128	0.0002
1986–1995	0.574	0.0168	0.0167	0.0096	0.0096	0.0000
1996–2005	0.576	0.0142	0.0138	0.0080	0.0078	-0.0002
2006–2013	0.551	0.0012	0.0009	0.0006	0.0005	-0.0001
1976–2013	0.568	0.0143	0.0142	0.0081	0.0080	-0.0001

Author's calculations based on OECD, PIAAC estimates for 2012 (Table 1) and hours worked constructed by Christian (Fraumeni and Christian, 2019; Christian, 2016).

tion. They note that it is possible that when more students attend higher education, the average quality of graduates given a constant quality of higher education may decline. Inklaar and Papakonstantinou also note that it is also true that the quality of higher education, through more work-relevant and better courses, or the human capital production function, through experience and on-the-job-training, may both improve, so that the net effect is uncertain.

Inklaar and Papakonstantinou conclude that Bowlus and Robinson defined vintage effects, are important in the United States looking at full-time-full-year (FTFY) non-self-employed males. Their estimates for high-skilled male workers in this category indicated that labour services per hour (quality) increased by 25 per cent between 1975 and 2015, with most of the increase (19 per cent) occurring between 1995 and 2005. For the same FTFY male category of workers, but having medium skills, labour services per hour decreased 10 per cent, with most of the decrease occurring between 1975 and 1995 and trending inconsistently subsequently. For the same FYFT male category of workers, but having low skills, labour services per hour decreased substantially during 1975-1995, with a total decline of 20 per cent for the whole period (Inklaar and Papakonstantinou, 2020:11-12).

Changes in deflated median wages over time is also an indication of Bowlus and Robinson defined vintage effects according to Inklaar and Papakonstantinou. By age groups, for U.S. high-skilled workers deflated median wages over the period 1995-2005, median wages of young workers aged 26-35 increased by 6.2 per cent, median wages of middle-aged workers aged 36-49 increased by 12.6 per cent, and median wages of old workers aged 50-59 decreased by 1.2 per cent (Inklaar and Papakonstantinou, 2020:18, Table 9).

There are two reasons to question the validity of Inklaar and Papakonstantinou's results challenging the Jorgenson model of production constancy assumption, even though it is likely that the constancy assumption is violated in at least some cases. First, the results in their paper are for labour input potentially having distinctly different characteristics within this category, e.g. FTFY non-self-employed high-skilled males.[19] Certainly in such a broad category there are composition ef-

19 High-skilled males are defined as those who have a bachelor's degree or above.

fects which can mask the extent to which the constancy assumption is violated at a more detailed level of labour input.[20] Their results are not for the individual who has a Ph.D. in physics.

Second, and most importantly, the nominal wage rates per hour worked are deflated by a U.S. consumer price index (CPI). When the CPI goes up or down, is it true that the average marginal productivity of workers has changed? If the U.S. economy was perfectly competitive, wages should instantaneously, or very quicky, adjust to inflation for those whose marginal productivity has not changed. Clearly, this is not the typical case although wages frequently adjust over time. The lack of detail on worker's characteristics, such as occupation, and a CPI to deflate nominal wages per hour worked means that Inklaar and Papakonstantinou's estimates of the extent to which quality is not constant at the detailed level cannot be accepted as valid estimates.

Conclusion

This article demonstrates that it is possible to efficiency adjust hours worked, but not possible to estimate to what extent the Jorgenson model lowest level of data detail available quality constancy assumption is violated using the approach of Inklaar and Papakonstantinou.

Efficiency adjusting hours will result in at least somewhat different measures of labour input and TFP. The impact of an hours efficiency adjustment shown in Table 2 is at most ± 0.02 percentage points. This is quite small, but other adjustment factors might result in a greater effect. Arguments advanced by both Bowlus and Robinson and Inklaar and Papakonstantinou suggest that the quality constancy is probably violated in at least some cases, but the Inklaar and Papakonstantinou estimates are not valid estimates of the size of the violation because of the highly aggregated data and the choice of a CPI as a nominal wage deflator.

Hopefully, future research will be done to develop more sophisticated hours efficiency adjustments which relate directly to skills used on the job and to produce another set of estimates of the size of possible violations of the constancy assumption.

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Is the SNA Still Useful? A Review Article on *The Measure of Progress: Counting What Really Matters*

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Abstract

Diane Coyle's *The Measure of Progress* offers a thought-provoking critique of traditional economic metrics, particularly GDP and the System of National Accounts (SNA). These metrics, she argues, are inadequate for capturing the complexities of modern economies and fail to provide a satisfactory answer to the question, "Are things getting better, and for whom?". This review article summarizes the key arguments, highlights the book's main contributions, and offers reflections on how the proposals intersect with recent advances in economic measurement.

Diane Coyle's book *The Measure of Progress: Counting What Really Matters (Princeton Universtiy Press, 2025)* offers a thought-provoking critique of traditional economic metrics, particularly GDP and the System of National Accounts (SNA). These metrics, she argues, are inadequate for capturing the complexities of modern economies and fail to provide a satisfactory answer to the question, "Are things getting better, and for whom?".

From the book, I have drawn three key messages, along with my own perspectives on them:

GDP is not a reliable measure of societal progress. I fully support this assertion. While this insight is not new, Coyle introduces many compelling arguments and examples that strengthen the case.

GDP falls short even by its own standards as a measure of economic activity. Coyle makes the case that the the underlying national accounts struggle to capture the economic structures of the 21st century. The book very well references the various challenges statisticians face when compiling GDP estimates. These challenges range from capturing intangible assets and free products to con-

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structing price indices. Although I agree with this list of issues, I diverge from Coyle's conclusion. Despite the many complexities that need resolving and the necessity for continued improvement, GDP and the underlying national accounts *do* provide a good tool for gauging economic trends, market incomes, and the key sectors driving activity.

Alternative frameworks for measuring progress are needed. This is a constructive and welcome approach. Coyle advocates for measuring *Comprehensive Wealth* — a generalized balance sheet approach — and for developing a *Time-Use Accounting Framework*. Both concepts have appeal, but I argue that many of the measurement challenges identified with GDP would not only persist but become even more pronounced when targeting *Comprehensive Wealth*. Her call for more attention to time as a metric is welcome and needed.

In her analysis, Coyle addresses both positive and negative aspects of modern life that are insufficiently gauged by our standard economic metrics. The latter include halted advances in life expectancy in some countries, inequalities in income, wealth, or health, and the effects of digitalization, where social media consumes people's attention and spreads misinformation.

The book includes many useful references and discussions on analyses of structural and secular changes in the modern economy. These largely serve as a backdrop for the measurement questions but are interesting in their own right. I will focus on the measurement aspects.

A Tour d'Horizon of Measurement Challenges

Chapters 2 to 7 deal with the complexities of modern economies and societies and the challenges they pose for measuring economic activity and societal progress.

Productivity without products. The discussion begins with a very useful primer on productivity measurement and the productivity puzzle, slower productivity growth in a period of apparent rapid technological change, offering a solid overview of the various hypotheses proposed to explain it. Coyle then focuses on two key areas. The first is the measurement of public sector productivity, where productivity improvements are often underreported. For instance, technological advancements — such as the digitization of administrative records — have clearly streamlined processes, yet productivity is still commonly measured by input metrics like hours worked by government employees. While this is a valid critique, it does little to explain the productivity slowdown in market sectors, particularly in manufacturing.

The second area, interesting and unconventional, is time. She argues that process innovations often drive productivity gains precisely because they save time: "just-in-time logistics in lean production, the time saved by keyhole surgery on outpatients rather than several days' stay in hospital".

Time also matters for consumption. Many new services are designed to save consumers time — online banking, for instance, eliminates the need to travel to and queue at a physical branch. This means that the productivity[2] of time use for consumers has increased, an effect that escapes measures of market productivity entirely (Coyle and Nakamura, 2002).

Moreover, these convenience gains are rarely reflected in quality adjustments of the output measures of market providers. Another time-related effect Coyle highlights is the shift of labour input across the production boundary as defined in the national accounts. For instance, when consumers perform online banking tasks themselves, they substitute their own time for the labour previously provided by bank employees. This raises measured productivity of the banking sector — but again it does not help explain a productivity slowdown.

Still, Coyle's central point remains compelling: if we fail to account for time in both production and consumption, we risk misunderstanding the true nature of economic transformation.

Chapter two questions the production function as the foundational concept behind productivity measurement. As Coyle notes, "This framing [of productivity measurement in a production function] has the effect of focusing attention on new inventions, machines or gadgets. Yet the giant leaps forward in productivity [...] owed much to process (rather than product) innovation [...]" (Coyle, 2025:56). She concludes that process innovation is unlikely to be well captured by a production function or by conventional growth accounting. However, this conclusion is questionable. Conceptually — and even more so in practice — traditional total factor productivity measures are designed to capture process innovation, along with other factors: successful process innovation translates into an outward shift of the production possibility frontier, signalling that more, or higher quality, output can be produced with the same resources. There appears to be no compelling reason to discard the useful framework of a production function, which links inputs, outputs, and productivity.

Dematerialization and disintermediation. Chapters 3 and 4 explore the evolving nature of products, focusing in particular on the trend towards *servitization* — the shift from physical goods to service-based solutions, such as the rapid growth of cloud computing. Coyle rightly highlights the lack of data and understanding surrounding this phenomenon. One of the key measurement challenges lies in constructing appropriate price indices: What exactly is the unit of service being delivered? How should quality changes be accounted for? These questions are central to achieving accurate deflation, a recurring and well-justified theme throughout Coyle's book (as discussed in Chapter 7 on Value).

Disintermediation — such as the rise of online shopping — is another aspect of digitalization that shifts activities across the production boundary defined in the national accounts, moving them from the

2 Most own-account household production of services falls outside the scope of GDP, as it does not involve explicit market transactions. Nevertheless, these production processes are very real—ranging from child care and booking a hotel to volunteer work. They generate service outputs and rely on inputs, typically in the form of labour or household time. Consequently, it is useful to talk about productivity of time use for consumers.

market to households. This chapter brings the discussion back to the issue of time measurement: labour in the market sector is increasingly being replaced by unmeasured household labour.

Two often-overlooked elements are highlighted here. First, there is not only time spent producing but also time required for consumption, both constrained by the 24-hour day available to consumers. Second, households are making greater use of capital services from durable goods in production. This includes the Uber driver using his own car (a market service counted in GDP), as well as the couple booking their next holiday on their private laptop (a non-market service not included in GDP). Treating household purchases of consumer durables purely as consumption expenditure fails to recognize the investment activity taking place within the household sector.

Coyle advocates for extending the production boundary to include own-account production by households. Her conjecture is that "...perhaps the long cycles observed in measured productivity growth would be partly smoothed away when work and innovation on both sides of the production boundary are accounted for" (Coyle, 2025; 125). Whether this would indeed yield a more accurate measure of productivity growth remains an open question. A major obstacle is accurately measuring quality-adjusted volumes of household production. This is almost always estimated using input volumes — namely, household time and capital — which effectively assumes zero productivity growth.

That said, Coyle's call for improved measurement of household production and innovation is both timely and important. Encouragingly, it has already been acknowledged in the updated 2025 System of National Accounts (SNA).

Free and Borders. *Free* digital services and data assets are among the most visible manifestations of the digital economy, and chapters 5 and 6 discuss their welfare effects and their immense role in businesses' competitiveness, while at the same time being "statistically invisible". The text carefully highlights the differences between market ("exchange") valuation — or its conceptual equivalent in the national accounts — and welfare valuation, which applies to free products, with the consequence that different valuations cannot simply be aggregated.

Chapter 6 on borders examines the impact of globalization on our ability to capture economic structures and activities — a challenge that becomes particularly complex when globalization intersects with digitalization, such as in the case of digital trade or cross-border data flows. Core issues — well known in the literature — include defining and measuring the volume and prices of storage and software services, as well as internationally traded data assets.

A common first step in addressing these challenges is to develop a typology to better understand business models and transaction types — an area where Coyle and Li (2021) have made a series of contributions. Further progress in defining and measuring digital trade has been achieved by the IMF, OECD, WTO, and UNCTAD, culminating in the publication of *Handbook on Measuring Digital Trade* (IMF *et al.*, 2023).

Coyle critiques the approach taken in

the handbook, for instance by writing that "the handbook makes the startling claim that 'digital trade' is for the most part included in conventional trade statistics" (Coyle, 2025: 175). However, this may stem from a confusion between what is excluded (i.e., out of scope) and what is invisible (i.e., within scope but not identifiable). The handbook suggests the latter: overall monetary flows of international trade are largely observable but insufficiently classified to identify the value of digital trade. The examples given by Coyle fall into the category of 'invisible' rather than 'excluded': e.g., statistics combine cloud services and hosting services, and do not break out prices and volumes.

At a practical level, while it is true that small-scale international trade in goods and services often escapes traditional collection methods, compilers and regulators are actively working on the issue.

Chapter 7 on value is an excellent introduction to the conceptual and practical challenges of price measurement, including the complex issue of quality adjustment when products change characteristics over time. I do not subscribe, however, to the strong criticism of chain linking and the associated non-additivity in volume levels of national accounts. The most salient analytical questions — how do material living standards evolve? what is the growth contribution of a particular industry? to name just two examples — rely on growth rates of volume measures, not on their levels. The associated weights or shares are based on current price levels that are additive.[3]

A noteworthy and important element in this chapter is Coyle's reminder that the consumer theory underlying the construction of many price indices (such as Konüs (1939) *True Cost of Living Index*) implies that GDP is, however imperfectly, designed as a measure of economic welfare. Indeed, GDP — and even more so the volume of household consumption — are distinct from, but certainly not independent of, a notion of welfare.[4]

Comprehensive Wealth and Time Use: The Way Forward

Comprehensive Wealth

The main message of the chapter 8 on wealth and Chapter 9 on a new framework is that any true measure of progress — or rather, sustainability — must be rooted in a framework of wealth. Indeed, the notion of sustainability — leaving intact the options for future generations — amounts to examining how much capital is passed on between accounting periods. This relates directly to Hick's (1946) definition of income[5] and to a whole branch of the 'green accounting' literature, for which Weitzman

3 This is not to deny that there are fundamental questions around the need for keeping reference price vectors constant, i.e., not to use chain indexes, to achieve transitivity in welfare comparisons (McKenzie (1983), Fleurbaey and Blanchet (2013)). However, these go well beyond non-additivity of national accounts in volumes.

4 On this point see also Schreyer (2016).

5 "It would seem that we ought to define a man's income as the maximum value which he can consume during a week, and still expect to be as well off at the end of the week as he was at the beginning" (Hicks, 1946: 172).

(1976) laid the foundations.

Coyle stresses the need for a comprehensive measure of wealth — well beyond produced assets — that encompasses natural capital, human capital (including health), social capital (such as trust among people), and various forms of intangible assets, such as organizational capital.

Along with a broad scope, a welfare interpretation of changes in comprehensive wealth requires valuation at shadow prices (or "accounting prices", as they are sometimes referred to; [6] Only then can real savings or comprehensive net investment be interpreted as a measure of discounted intertemporal social welfare.

It also requires introducing the notion of resource allocation mechanisms (Dasgupta (2009) and Arrow *et al.* (2003), i.e. mapping future paths of the economic–environmental–social system. Tracking changes in comprehensive wealth valued at shadow prices would thus appear to be the most important effort to pursue. However, it also turns out to be the most challenging venture, both in concept and in practice for at least three reasons.[7]

First, although "only" present changes in assets need to be observed, their valuation at shadow prices requires projections of the future evolution of the socio-economic–environmental system. For example, the measurement of human capital as people's earning potential is well established (Jorgenson and Fraumeni, 1989), but it requires projections of future income. Projections are also needed for the shadow prices of natural capital, to reflect future environmental pressures or tipping points and their consequences. Here, we enter a different world from that normally inhabited by statistical offices — a world of scenario building, horizon scanning, and comprehensive modelling and forecasting. This raises important institutional issues and questions about the political economy of official statistics.

Second, determining the exact scope of the asset base is non-trivial. For example, whether or not health ought to be recognized as a separate asset from human capital is a matter of debate and can significantly affect results,[8] to the point of potentially undermining the credibility of estimates. Many robust measures of social capital and trust are non-monetary (see, for instance, OECD (2013-2024)), and translating them into shadow prices would be a daunting task.

Finally, none of the measurement challenges that Coyle rightly highlights in relation to the SNA — deflation, free products, classifications, national boundaries, etc. — disappear when embarking on the measurement of comprehensive wealth. On the contrary, new challenges are added. This is only acknowledged in passing.

The above should in no way detract from the fact that *Comprehensive Wealth* provides an excellent reference framework for reasoning about societal progress and sustainability. However, its empirical imple-

6 See Dasgupta (2009) who capture the positive and negative externalities associated with each form of capital.

7 See Fleurbaey and Blanchet (2013) for a broader discussion of measurement and theoretical questions.

8 See for instance Arrow *et al.* (2003).

mentation with the ambition of delivering a comprehensive, single monetary indicator raises more questions than it may answer, and pragmatism is called for.[9]

There are many powerful ways to measure the evolution of assets, either in non-monetary form[10] or through the monetary valuation of a subset of assets that remains robust and reproducible.[11]

Last, but by no means least, Chapter 35 of the 2025 SNA (EC *et al.*, 2025) *Descriptions and Boundaries in Measuring Types of Capital*, now explicitly identifies natural capital, human capital, and social capital alongside economic capital. It discusses the SNA asset boundary and provides significant detail on the measurement of the various types of capital, in an effort to strengthen the analytical base for assessing sustainability and to present a broader picture of our economies and societies.

Time as a Metric

Time as a metric in an accounting framework is a recurrent topic in *The Measure of Progress*. Time is an immutable constraint, and it plays an increasingly important role in the production and consumption of — often digital — products, including those outside the SNA production boundary. Yet, time is not systematically accounted for, except in the tradition of Becker (1965), where measures of "full incomes", or the sum of utilities over time, taking into account paid work, household work, and leisure, and measuring the well-being derived from each activity, are considered.

Coyle remarks that, otherwise, economists have paid little attention to the time budget constraint and the changing allocation of time in modern economies, and she calls for "a time-use accounting framework alongside the measurement of comprehensive wealth [that] provides a holistic approach to understanding progress" (Coyle, 2025: 258).

This call for better and more systematic inclusion of time in accounting and modelling can only be supported. Indeed, there has been progress on this front: conceptually[12] as well as empirically through an expanding number of time-use surveys and by way of accounting standards. For the first time, the 2025 SNA (EC *et al.*, 2025) offers an internationally agreed accounting standard for the measurement of household non-market production, with time allocation as a major pillar.[13]

9 For a more extensive discussion, see Schreyer (2022).

10 The Dasgupta Review (Dasgupta, 2021) showcases the many empirical and theoretical aspects involved in measuring biodiversity and ecosystem services, even in physical terms. The OECD's *How's Life?* series (OECD, 2013-2024) organizes and presents available cross-country evidence on assets, offering a picture of trends in produced, human, social, and natural capital.

11 The work of the UK Office for National Statistics on Inclusive Wealth and Income (ONS, 2024) is a good example.

12 See, for instance, Coyle and Nakamura (2022) or Schreyer and Diewert (2014).

13 Paragraph 2.94 introduces this element: "Data from these [extended household] accounts can be used to derive [...] extended measures of household disposable income that reflect the implicit income derived from unpaid household service work." Chapter 34 provides detailed classifications and an extended Use Table for Unpaid Household Service Work.

Final Thoughts

In several places, Coyle portrays the existing statistical system in general and the National Accounts in particular as a "conceptual framework for classifying activities and collecting data from the 1940s". This overlooks the tremendous development that economic statistics have undergone over the decades in response to structural changes in our economies and societies. The most recent such effort dates back only a few months and has introduced salient features of digitalization, globalization, well-being, and sustainability into the SNA. In Coyle's view, these changes may be too timid and insufficient, but securing global agreement on an updated accounting framework while maintaining conceptual clarity and continuity for users, and at the same time embracing new aspects of modern economies was no small achievement. We understand the economy much better thanks to SNA. Without it we would be at a loss about what drives our economy, why some countries are rich and others are poor and how to steer macroeconomic policies.

Moreover, the statement that the "existing SNA [does not provide an accounting framework] when its components are measured in real rather than current price terms" (Coyle, 2025:253) reduces the notion of an accounting framework to the (often misunderstood) issue of the non-additivity of chain volume data in level form. It neglects the many characteristics that truly define an accounting framework, such as quadruple entry, consistency of valuation, well-defined transactions, institutional sectors, and more.

The Measure of Progress is a welcome reminder that official statistics are an under-resourced arm of public activity, and Coyle highlights this in several places. Good evidence does not come for free — not for the current frameworks, and even less so if Coyle's call for systematic coverage of new economic, environmental, and social dimensions is to be followed.

To conclude, this book is clearly worth reading. Thorough in substance, with numerous references to the academic literature and evidence to support her arguments, Coyle's style is excellent: non-technical unless truly necessary, and consistently delivering her messages with great clarity. The book offers valuable material for policymakers, researchers, and anyone interested in the future of economic statistics. One may not agree with all of Coyle's conclusions, but there is certainly more than enough food for thought.

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