Editors' Overview

The second issue of the *International Productivity Monitor* for 2022 (No. 43) includes the second part of our Symposium on Productivity and Well-Being (the first part was published in the Spring issue, No. 42). A separate introduction to the second part of the Symposium follows this overview. Below we discuss the other two articles in the issue.

Following the three articles on productivity and well-being and a reflection by John Helliwell, a well-known scholar on the study of subjective well-being and happiness, this issue includes two other major articles. The article by **Weilin Liu** and **Qian Cheng** from Nankai University, and **Robin Sickles** from Rice University focuses how an integrated production network across countries, like in the European Union, can help to optimize the allocation of resources and thus generate spatial productivity spillovers. The authors examine the impact of technology spillovers, proxied as the indirect effects of domestic and imported inputs arising from capital and intermediate goods (backward) linkages to other (neighbouring) industries, on total factor productivity (TFP) growth. They use a spatial time-varying stochastic frontier model that features technological interdependence and heterogeneous productivity growth at the industry level. To measure the effects, the authors combine data on global value chain linkages obtained from input-output tables (based on from the World Input-Output Database) with measures of total factor productivity at the industry level for 10 European Union member states and, for comparison, the United States (based on the 2017 EU KLEMS release). While there is no visible effect from the indirect use of domestic or imported capital stock along the supply chain (due to capital scarcity), the authors find substantial TFP spillover effects from the imports of intermediate inputs. On average about 27 per cent of the spillover embodied in intermediate input has transmitted across borders. Within Europe, Germany offered the most network effects, followed by the Netherlands, the Czech Republic and Sweden. Hence the authors conclude that input-output linkages constitute an important channel for the transmission of productivity spillovers.

The second article by **Bishwanath Goldar** for the Institute of Economic Growth in Delhi, India deals with a well-known conundrum about India's trade liberalization in the early 1990s. According to earlier research, this trade liberalization seems not to have led to an improvement in TFP growth in the manufacturing sector during the 1990s compared to the previous decade. Using several lines of inquiry, the author shows that the productivity growth performance of Indian manufacturing was better in the 1990s then has been assumed so far. First, the author suggests various corrections to the measurement of TFP growth measures. These adjustments include an upward revision to the growth rate of labour input in manufacturing during the 1980s, a downward revision in the labour income share during the 1990s, and correction for the underestimation of the impact of rising energy prices during the 1990s which had impacted single-deflated value added negatively. Together, these corrections significantly reduce the TFP growth gap for the 1990s compared to the 1980s. Second, the author argues that a decline in the effective protection rate following trade liberalization may have caused a downward bias in TFP because of the erosion of the rent component in value added. Third, a comparison of plant-level data for the entire manufacturing sector after 1998 confirms the view that trade liberalization raised productivity growth, though primarily in large manufacturing plans whereas smaller plants did not see such gains. Hence the author concludes that the reforms have led to an improvement in productivity growth during the 1990s.

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Introduction to the Symposium on Productivity and Well-being, Part II

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The Spring 2022 issue of *International Productivity Monitor* took an important step to begin exploring linkages between productivity and well-being with a four-article symposium. This issue includes a second part to the symposium with three articles that further explore these linkages. All seven articles were presented at an authors' virtual workshop held November 16-17, 2021. The editors are very pleased that this issue of the *International Productivity Monitor* also includes a reflection by John Helliwell who served as a discussant in the authors' workshop on measuring and improving productivity when subjective well-being is the objective. His article provides a valuable perspective on the state of the literature on the productivity-well-being linkages that are discussed in the symposium as well as direction for future research.

This introduction provides a synthesis of the contributions of the three articles included in this volume. The introduction to the Spring issue — in addition to summarizing the articles in that issue — included a discussion of the background and motivation of the symposium, organizational process, and key issues related to the productivity-well-being linkage.

Context for the Articles in this Volume

As noted in the introduction to the symposium in the spring issue of the IPM (Sharpe, Sichel and van Ark, 2022), the literature on productivity and well-being linkages both is in its infancy and highlights the two-way nature of the rela-

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tionship between productivity and well-being: higher productivity boosting well-being and higher well-being boosting productivity (perhaps through a channel of happier workers being more productive workers). The three articles in this symposium make important contributions to this literature and further highlight the two-way nature of the linkages. The article by Sarracino and O'Connor focuses on the contribution of output per person (and other factors) to well-being, and in particular the efficiency with which countries produce subjective well-being (SWB) given their inputs. The article by Peroni, Pettinger, and Sarracino examines the role played by well-being on economic productivity, while the third article by DiMaria, Peroni, and Sarracino considers linkages going in both directions. All contributors to the three research papers in the symposium are employed at STATEC Research, the research group at the National Institute of Statistics and Economic studies of Luxembourg, known as STATEC. STATEC Research has become an important centre for research on well-being measurement in general and well-being productivity linkages in particular.

A Measure of Well-being Efficiency Based on the World Happiness Report (Sarracino and O'Connor)

The first article in this symposium by **Francesco Sarracino** and **Kelsey O'Connor** both from STATEC Research in Luxembourg extends the literature that estimates and assesses the efficiency with which countries translate inputs into subjective well-being (SWB) as measured on a Cantril Ladder that collects individuals' responses to a question about their well-being. As did Legge and Smith (2022) in the spring symposium, this article valuably emphasizes that there are potential paths to boosting SWB beyond just increasing inputs. That result seems especially important for lower SWB countries with fewer available inputs, though it also applies to high SWB countries that could, in principle, boost SWB by generating it more effectively.

The key data in the article are from the 2021 edition of the World Happiness Report (Helliwell *et al.*, 2021). As noted, the measure of SWB relies on a Cantril Ladder based on questions in a Gallup World Poll. The six inputs into SWB used are real GDP per capita, healthy life expectancy, social support, freedom of choice, absence of corruption, and generosity. Efficiency measures are estimated using Data Envelopment Analysis (DEA) applied to a sample of 126 countries.

DEA is a non-parametric technique that compares a weighted average of the inputs listed above to outputs (in this case, the one output is SWB). The procedure maximizes the ratio of output to a weighted average of inputs by choosing the weights on inputs subject to appropriate constraints. The resulting efficiency measures provide a ranking of countries, indicating how effectively a country transforms inputs into SWB relative to countries at the frontier of efficiency in the sample. While this approach differs from that typically used in conventional productivity analysis, the key idea of estimating how effectively inputs are transformed into outputs is broadly analogous to estimating total factor productivity (TFP). This article also provides a useful complement to Legge and Smith (2022) who use a more conventional productivity/capital stocks approach to estimating the efficiency with which SWB is generated.

Methodologically, this article goes beyond existing literature by drawing on often-cited and publicly available data from the WHR, covering a wider set of countries, and decomposing the efficiency measure into technical and scale efficiency. Technical efficiency relates to how well a country uses a given set of inputs. Scale efficiency is about whether changing the quantity of inputs is appropriate from a well-being perspective. For example, countries facing increasing returns to scale in the production of SWB are operating below their optimal scale and would benefit from increasing inputs.

Several interesting and provocative results emerge. First, some basic numbers. The top 50 per cent of countries have efficiency scores of at least 90 per cent of frontier efficiency, while the bottom 10 per cent of countries have efficiency scores between 50 and 75 per cent. Looked at another way, of the 126 countries, 19 are at frontier efficiency. The other countries have room to improve either by boosting technical efficiency or by adjusting inputs.

Another important result is that countries with high subjective well-being rankings (such as the Nordic countries) are not always the most efficient at translating inputs into well-being (only Finland is fully efficient). Interestingly, Legge and Smith (2022) found a similar result for Nordic countries using a different methodology.

An additional result is that well-being efficiency scores are not correlated with a TFP-like measure of economic efficiency (with the latter calculated using either DEA analysis or conventional TFP estimation). This result highlights that SWB efficiency measures something different than do TFP-like measures of economic efficiency. The authors push further on this result, suggesting that "production per se does not promote well-being." This interpretation will be controversial in some quarters, given that, by construction, the estimation of SWB efficiency has already accounted for the role of GDP per person as an input. That being said, the article provides external validation of its SWB efficiency measure by demonstrating its correlation with the Happy Planet Index, a measure that is intended to capture sustainable well-being (Happy Planet Index, 2021).

In terms of policy implications, much policy advice related to SWB focuses on the quantity of inputs. This article highlights the importance of evaluating the efficiency with which a given set of inputs are utilized as well. This point is illustrated by a comparison of Costa Rica and Germany: Indeed, Costa Rica and Germany have similar levels of SWB, but Costa Rica has much fewer inputs; that is, greater well-being efficiency for Costa Rica partially offsets a lower level of inputs.

Turning to more specific policy implications, the article shows that SWB efficiency correlates positively with GDP per capita, social support, and healthy life years at birth. Of these factors, healthy life years is the most important, suggesting that investments in health are likely to boost SWB along multiple dimensions.

Productivity Gains from Worker Well-being in Europe (Peroni, Pettinger, and Sarracino

While the just-described article by Sarracino and O'Connor focuses on well-being as an output, the second article in the symposium by **Chiara Peroni, Maxime Pettinger,** and **Francesco Sarracino**, all from STATEC Research, considers the role of well-being as an input to productivity. Specifically, the authors examine the relationship between well-being in the workplace and labour productivity in 30 European countries using survey data on working conditions from 2010 and 2015. Although an extensive literature has explored these linkages, this article is the first to use relatively comprehensive data at the industry level.

The analytic framework is a Cobb-Douglas production function in which total factor productivity (TFP) depends on worker well-being (with constant returns to scale in labour and capital inputs). The production function is transformed to an equation for labour productivity, and the independent variables in the resulting relationship include a measure of worker well-being, capital deepening, and a set of other controls (average age and education of workers in the industry, proportion of large firms in the industry, the industry's labour share, and average wages by industry and country, and year, country, and sector fixed effects). The article considers the relationship in both levels and growth rates. The growth-rate specification includes two additional controls: the initial level of productivity and the change in industries' employment shares. The only deviation from conventional practice is that, because industry-level capital stock data are not available in their data set, the authors use investment per worker as a proxy for capital deepening.

Data on well-being are from the 2010 and 2015 waves of the European Working Conditions Survey, a representative survey of individuals' working conditions from which the authors construct two measures of worker well-being. The first measure is job satisfaction, constructed from responses to the question about how satisfied workers are with their jobs. This measure is somewhat higher in Western European countries than in Eastern European countries, and, within Eastern Europe, satisfaction is higher in the service sector than in construction or manufacturing.

The second measure, job quality, combines information relating to income and benefits, working time and work-life balance, social dialogue, skills development and training, safety and ethics, and stress at work. On this measure, scores are higher in Western European countries than in Eastern Europe (same pattern as the job satisfaction measure). Within Western European countries, job quality in construction is noticeably below that in manufacturing and services. Within Eastern European countries, job quality is highest in services and lowest in construction.

The remaining data are from Eurostat's Structural Business Statistics, which provides data at the two-digit industry level. The survey covers manufacturing, construction and business services, but does not include agriculture, financial services, public administration, and some other non-market activities. The authors use annual data from 2010 to 2018. In addition to estimating the levels relationship, the growth-rate specification considers the effect of working conditions in 2010 and 2015 on subsequent labour productivity growth.

Starting with the regressions in levels, the key result is that industries in which worker well-being is higher — measured either by job satisfaction or job quality — have statistically significant higher levels of labour productivity. Specifically, as job satisfaction increases by one unit — it is measured on a scale from one to four - labour productivity increases by 5 per cent. Similarly, in the growth - rate specification, higher levels of job satisfaction and quality are associated with higher levels of productivity growth during the subsequent three years (with magnitudes depending on the specification). To gauge the economic importance of these results, the authors scale their results to show that the effect of job satisfaction or quality on labour productivity is sizable relative to the effect of investment per worker (though again the magnitude of the comparison depends on the specification).

Another bonus result that will interest readers who have not delved deeply into these data is a series of bar charts plotting job satisfaction, job quality, and productivity by country and color coding to highlight differences between Western and Eastern European countries.

In terms of policy implications, this article provides industry-level evidence that workplace well-being, in addition to being intrinsically good, also contributes to labour productivity; that is, happier workers are more productive workers.

From Economic Productivity to Productive Well-being: The Role of Life satisfaction and Adjusted Net Savings (DiMaria, Peroni, Sarracino)

The third and final article in this symposium by **Charles-Henri DiMaria, Chiara Peroni** and **Francesco Sarracino**, all from STATEC Research, assesses the linkages between SWB, conventionally-measured, productivity, and sustainability for a set of European countries from 2005 to 2018. Their setup uses DEA with a ratio of a weighted average of outputs in the numerator and a weighted average of inputs in the denominator. The key innovation of the article is to allow for SWB and sustainability, as well as real GDP, to be outputs, while adding SWB to the usual set of inputs. To the extent that production processes are delivering environmentally sustainable well-being, then SWB and sustainability can plausibly be considered outputs. And, given prior literature cited by the authors providing evidence that SWB is important for productivity (see the just-described article in this symposium as well), SWB also can plausibly be considered an input.

As noted, the article uses DEA, and the estimates of weights in the numerator and denominator indicate which of SWB, sustainability, and real GDP should count as outputs and which of SWB and the usual set of inputs should count as inputs for different countries. The implementation is flexible in that different countries can have a different mix of outputs and inputs and this mix can change over time.

For experts on DEA, the authors use the "output-oriented" approach (rather than the "input-oriented" approach) on the reasonable assumption that, with SWB as an input, countries would not choose to reduce inputs including SWB. The authors also assume constant returns to scale and use a different definition of SWB to make it feasible to include SWB as both an output and an input.

For data, the article relies on real GDP as well as capital and labour measures from the Penn World Tables for 23 European countries. SWB is measured based on the Eurobarometer survey, gauging the fraction of people in each country and in each year that indicate that they are very satisfied with their lives. The article's measure of adjusted net savings is computed by the World Bank and includes "national savings minus fixed capital consumption plus educational expenditures minus depletion of natural resources and minus damages from CO2 emissions and particulate emissions."

This analysis indicates that SWB appears either as an input or an output for almost all countries in the sample, confirming the importance of considering SWB. Countries where SWB appears as an input include the Nordic countries and some western countries generally characterized by high levels of well-being (Denmark, Sweden, Finland, Luxembourg, Ireland, Netherlands, United Kingdom, Cyprus, Turkey, and Poland). The countries where SWB appears as an output are Eastern European countries and some western countries (Estonia, Hungary, Czechia, Slovakia, Lithuania, Germany, Spain, and France). Finally, SWB never appears as both an input and an output.

Adjusted net savings appears much less frequently, with Belgium and Slovenia the only countries for which this variable appears as an output most of the time.

The article does some initial investigation into what distinguishes the countries for which SWB is an input or an output. The key finding here is that countries for which SWB frequently appears as an input tend to have a large share of their population that are very satisfied with their lives. In addition, the article calculates conventional Malmquist productivity indexes (a TFP like index) and well-being adjusted Malmquist indexes for each country. Interesting results indicate that growth rates of the conventional and well-being-adjusted indexes are far from perfectly correlated, suggesting that they are conveying different information. This outcome, of course, repeats similar findings in Legge and Smith (2022) and the first article in this symposium by Sarracino and O'Connor.

Results in this article provide a provocative start to thinking about linkages between productivity and well-being and whether and why SWB appears as an input or an output. That being said, this article does not provide specific guidance to policy makers and leaves unanswered questions for future research, including further investigation into why SWB appears as an input or output in different countries.

Take-Aways and Research Directions

The introduction to the symposium in the Spring issue of the *International Productivity Monitor* included 12 take-aways that are relevant to the three articles in this symposium, and that discussion is not repeated here.

Taking a step back, the holy grail for this literature would be specific policy recommendations that countries could follow to boost well-being. Perhaps not surprisingly, the literature is not yet at that point. (Not surprising given that Development and Growth Economics often struggle with providing crisp policy recommendations for how countries can boost GDP in the long run and given the challenges of identifying the direction of causality in productivity and well-being analysis.) Such recommendations would be especially valuable given that the ultimate purpose of systems of production and distribution is to generate well-being rather than just goods and services.

The articles in the Spring symposium and the ones in this volume highlight once again that SWB matters in important ways, which are not captured by GDP. The articles also highlight some potentially implementable recommendations such as the importance of investments in health to well-being and the importance of worker well-being to boosting productivity which in turn should provide a boost to well-being. In addition, John Helliwell's closing remarks in this volume provides valuable suggestions for future research directions that could ultimately lead to more specific policy recommendations.

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A Measure of Well-being Efficiency Based on the World Happiness Report

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Abstract

We estimate a measure of well-being efficiency that assesses countries' ability to transform inputs into subjective well-being (Cantril ladder). We use the six inputs (real GDP per capita, healthy life expectancy, social support, freedom of choice, absence of corruption, and generosity) identified in the World Happiness Reports and apply Data Envelopment Analysis to a sample of 126 countries. Efficiency scores reveal that high ranking subjective well-being countries, such as the Nordic countries, are not strictly the most efficient ones. Also, the scores are uncorrelated with a traditional (total factor) measure of economic efficiency. This suggests that the implicit assumption that economic efficiency promotes well-being is not supported. Subjective well-being efficiency can be improved by changing the amount (scale) or composition of inputs and their use (technical efficiency). For instance, countries with lower unemployment, and greater healthy life expectancy and optimism are more efficient.

Traditional economic thinking elevated GDP per capita to the single-most important indicator of quality of life. However, evidence has accumulated over recent decades that demonstrates economic growth does not necessarily improve people's lives and, when prioritized and mismanaged, it may even contribute negatively (Sarracino and O'Connor, 2021 and forthcoming). This evidence invites us to expand the focus, from the singular dimension of economic output towards a more holistic concept of quality of life. Indeed, it has now been more than a decade since

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renowned scholars and international institutions have called upon us to go "beyond GDP" to conceptualize and measure well-being (e.g., Fleurbaey (2009); Stiglitz *et al.* (2009)). Which measures could support such a shift? Which output should be maximized? We use subjective well-being (SWB), a single measure summarizing the many economic and non-economic aspects of what makes a life worth living. Numerous studies make the case for SWB (e.g., Helliwell *et al.* (2013); OECD (2013)), the correlates of SWB are well known (see the World Happiness Reports (WHR)); but too little is known about how to increase well-being efficiently, that is, using the fewest resources. Efficiency analysis is important to inform decision-makers about how to use better scarce resources to increase well-being and more broadly, to steer the debate towards well-being and its inputs.

Our aim is to provide a measure of subjective well-being efficiency that goes beyond income.[2] Such a measure has significant advantages over traditional economic efficiency measures that use economic production or GDP as an output. SWB is a valid and reliable measure of well-being that reflects more than economic concerns; it captures people's assesments of their lives as a whole. SWB is also relevant for extrinsic reasons; greater SWB is associated with better outcomes of interest such as health, longevity, income, employment, social behavior, and political behaviour (De Neve *et al.*, 2013).

The idea that SWB can be produced more or less efficiently, and that this efficiency can be measured is relatively novel. We apply Data Envelopment Analysis (DEA), a technique used frequently to compute economic efficiency, to macro data from 126 countries to determine whether it is possible and meaningful to compute subjective well-being efficiency scores. The scores can inform policy-makers about how well their countries transform available resources into SWB, and could help identify sources of inefficiency. Current SWB policy advice generally discusses the quantity of inputs, not how efficiently they are used. This knowledge is necessary to inform policy makers seeking to efficiently mobilize resources to improve well-being.

The article is organized as follows. In the first section we briefly review the literature on the determinants of SWB and clarify our contribution. In section 2 we describe the data used in the analysis. In section 3, we detail the methods adopted. Section 4 reports our findings: we first describe the well-being efficiency scores, then provide initial explanations of score differences across countries, compare our scores with third-party measures of SWB and usual productivity measures, and lastly, decompose total efficiency scores into technical and scale efficiency. Section 5 summarizes three sets of robustness tests and their results. The last section summarizes our findings, discusses the limitations of present work, and offers some suggestions about the usefulness of measures of well-being productivity.

2 We use the term well-being efficiency interchangeably with subjective well-being efficiency for brevity. We always refer to subjective well-being when discussing well-being in the text

Background and Contribution

Much of the economics of happiness literature has focused on the determinants of SWB. In the series of World Happiness Reports (WHRs), six factors explain about three-quarters of the variation in SWB around the world (real GDP per capita, healthy life expectancy, having someone to count on, perceived freedom to make life choices, perceived absence of corruption, and generosity) (Helliwell *et al.*, 2013). The residual quarter is not well explained. We know certain groups of countries have higher or lower than expected SWB, given their observable characteristics – for instance, Latin America and post-communist states – but not that much is known about why. Perhaps there are important omitted variables, or perhaps Latin American countries are more efficient in transforming their inputs into well-being? For the purposes of this article, we rely upon the WHR framework, and focus on differences in well-being efficiency across countries.

We compare 126 countries based on the relative efficiency in which they turn inputs into SWB. To compute well-being efficiency, we use as inputs the six determinants of SWB identified in the WHRs, and Data Envelopment Analysis (DEA). DEA is a non-parametric frontier technique that is widely used to compute productive efficiency and total factor productivity in management and economic studies (see, for instance, Lafuente *et al.* (2016)). Relative efficiency is then measured as the "distance" in output from a best-practice frontier (or efficient frontier). This allows us to identify under-performing countries and frontier countries.

DEA allows researchers to model production activities without the need to specify the functional form of the production process; thus, allowing the data to reveal how different countries combine their inputs more or less efficiently to generate SWB. Typical regression approaches assume inputs are additively separable, and do not test for interactions or thresholds. Regression residuals, for Latin America for instance, mechanically represent an unknown input that enters additively. On the other hand, a minimum level of GDP per capita and healthy life expectancy are plausibly necessary to enjoy social relations; that is, input importance is non-linear and co-dependant (Binder and Broekel, 2012). As specifying a correct functional form is problematic, parametric methods can lead to errors including wrongly identifying countries as efficient (Ravallion, 2005).

DEA emerged as a widely used method to measure efficiency in various disciplines (Emrouznejad and Yang, 2018; Rostamzadeh *et al.*, 2021). It has been applied to study efficiency across economic sectors including, for instance, banking, health care, agriculture, transportation, education, energy, the environment, and finance (Liu *et al.*, 2013). The application of DEA in well-being research is rather new. Several studies used DEA to produce synthetic indicators of quality of life.[3] DEA also

3 See, for instance, Murias *et al.* (2006), Bernini *et al.* (2013), Guardiola and Picazo-Tadeo (2014), Mariano *et al.* (2015), and Nissi and Sarra (2018).

helped establishing whether SWB is an input or an output of economic production (DiMaria *et al.*, 2020 and 2022). The results indicate that, in most cases, SWB can be regarded as an input to production, but it is seldom an output in a sample of European countries.

Closely related to well-being efficiency, the term "happiness efficiency" was coined by Binder and Broekel (2012) in a seminal work about individuals' ability to convert resources into SWB in Britain. Cordero *et al.* (2017) also assesses individual subjective well-being efficiency in a sample of 26 OECD countries. Differences are partially explained by socio-demographic characteristics, such as gender, age, religiosity, and marital and parental status, while international differences are due more to social expenditures, unemployment rates, and institutional quality. Carboni and Russu (2015) used DEA to compute how efficiently Italian regions transform their inputs into SWB.

Three studies closely related to this article assess the cross-country differences in well-being efficiency (Debnath and Shankar, 2014; Cordero *et al.*, 2021; Nikolova and Popova, 2021). Debnath and Shankar studied how four indicators of good governance translate into happiness efficiency using DEA in a cross-sectional dataset comprised of 130 countries. Cordero *et al.* and Nikolova and Popova both studied country efficiency in transforming a set of inputs (income, education, and health) into SWB using similar but distinct approaches to DEA. Cordero *et al.* used a novel method (stochastic semi-nonparametric envelopment of data) on a sample of 82 counties over time, and found greater SWB efficiency was associated with higher social expenditures, civil liberties, and quality of government, and lower unemployment and inequalities. Nikolova and Popova used a partial frontier approach and panel data for 91 countries. Similar to Cordero *et al.*, they found greater SWB efficiency was associated with greater social support, freedom, and the rule of law and negatively associated with unemployment and involuntary part-time employment.

A limitation of these studies is the choice of SWB inputs and the contextual variables that might affect the production process. Cordero *et al.* and Nikolova and Popova use the same inputs and similar but distinct contextual variables, e.g. gender and income inequality and labour market characteristics beyond unemployment. It is not clear, however, why the contextual variables are not also inputs. Unemployment, for instance, has one of the most robust relationships with SWB (Clark, 2018). Unemployment directly affects income (one of the SWB inputs) and personality (Clark *et al.*, 2001). The aggregate variables, pertaining to inequality and governance, also directly affect SWB, for instance, through perceived fairness (Oishi *et al.*, 2011) and procedural utility (Frey and Stutzer, 2010). Indeed, Debnath and Shankar (2014) used quality of governance as an input, not as a contextual variable.

Our main contribution with respect to these works is to introduce a measure of subjective well-being efficiency that is based upon the commonly accepted and often cited WHR subjective well-being equation (Helliwell *et al.*, 2013), which uses the Cantril Ladder to measure SWB and the six inputs mentioned above. This aspect is not trivial as we need an agreed upon yardstick to select which output and inputs to consider. The WHRs provides an authoritative reference to measure well-being and select the inputs. The WHR inputs cover two (GDP and health) of the three used by Cordero *et al.* (2021) and Nikolova and Popova (2021), education is left out. Two of the other WHR inputs cover social characteristics that are often related to social capital (having someone to count on, and generosity), which is in turn strongly related to SWB (see Helliwell *et al.* (2009) for an explanation and evidence). The last two inputs pertain to important aspects of the societal and institutional context (freedom to make life choices, and absence from corruption). For an explanation of the inputs, see Layard *et al.* (2012). We also test the robustness of the WHR framework for estimating well-being efficiency and find our results are not sensitive to the exclusion or inclusion of particular well-being inputs, such as GDP, education, and unemployment.

The WHRs also make their data freely available to the public, which makes it easy for researchers to apply and expand upon the procedure developed here. Their data also cover a broader range of countries than in similar papers, except Debnath and Shankar (2014).

Another contribution of this article is to decompose efficiency scores into technical and scale efficiency (previously only conduced by Debnath and Shankar (2014)), which provides finer information about how to improve efficiency. Technical efficiency pertains to how a country uses their inputs. As an example, one can imagine a country that spends its GDP on aspects that are not strongly associated with aggregate SWB (e.g., positional consumption). Low efficiency may also occur when health is poor because poor health makes it difficult to enjoy other factors. Likewise, government programs are less efficient in the presence of corruption. On the other hand, scale efficiency pertains to the quantity of inputs. Our results indicate that most countries have too few inputs. Expanding the amount of inputs would increase SWB directly and increase the benefits derived from existing inputs.

We also assess the relationships between the inputs and well-being efficiency. It is clear that various levels of inputs affect efficiency, but it is not always clear how. The correlations we obtain between inputs and well-being efficiency can reveal likely factor complementarities or inefficient scale use due to one particular input or another. For instance, as suggested above, health and corruption are likely to affect SWB directly and also technical efficiency.

Finally, we contrast our measures of well-being efficiency with measures of economic efficiency and of sustainable well-being. It is taken for granted that promoting economic efficiency is a good thing. Seldom is it asked, to what end. The implicit assumption is that economic efficiency contributes to economic growth, thus paving the road to better lives. We test this assumption by checking whether well-being efficiency correlates with economic efficiency (calculated using GDP, capital, and labour), and find they are not correlated. Countries that are economically more efficient are not better able to convert resources into well-being. We also correlate well-being efficiency with a measure of sustainable well-being, the Happy Planet Index, to assess the validity of our measure, and find a strong positive correlation.

Illustrative findings

The ranking based on well-being efficiency scores reveals sometimes surprising success stories. The typically high ranking SWB countries, such as the Nordics, are not strictly the most efficient in transforming inputs into well-being. The most efficient countries include Finland, but also, Algeria, Belgium, Italy, Costa Rica, Slovakia, and Switzerland for a total of 19 fully efficient countries out of 126. The results also reveal the countries that could improve, such as India, Afghanistan, Tanzania and Zimbabwe. In general, well-being efficiency scores are correlated with the level of SWB – e.g. Zimbabwe experiences the lowest efficiency and SWB – but there are contrasting examples. Estonia and Hungary report a similar level of SWB, but the latter is more efficient. In general, high (or low) efficiency, does not necessarily mean high (or low) well-being. A country's inputs may be too low even when efficiently used to yield high subjective well-being. Both inputs and efficiency matter.

The input correlation analysis reveals GDP per capita, social support, and healthy life years correlate positively and significantly with well-being efficiency, in particular health, according to subsequent regression analysis. As expected, populations with better health are indeed better able to exploit their inputs. This result implies, policy makers should consider investing in health, not only for the direct benefits it brings for SWB, but also for the indirect effects that result from a more efficient use of inputs. On the other hand, perceived corruption was not correlated to well-being efficiency as expected. Among the wider list of variables, we find more optimistic and fully employed populations are more well-being efficient.

Data

Aggregate SWB data are available for approximately 150 countries in the WHRs. The particular measure of SWB is the Cantril Ladder obtained from the Gallup World Poll, which is similar to life satisfaction.[4] We use the data from the most recent report, released in 2021 (Helliwell *et al.*, 2021). The WHRs also provide data on the six inputs, which in turn originate from various sources: GDP per capita (constant 2017 international dollars, converted in logarithm) is drawn from the World Development Indicators. Healthy life expectancy at birth (HALE) is from the World Health Organization's Global Health Observatory data.

The four remaining variables are based on survey questions from the Gallup World Poll: social support (or having someone to

4 Cantril Ladder scores are determined by responses to the question: "Please imagine a ladder, with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?"

Table 1: Descriptive Statistics on the Determinants of Subjective Well-Being

Variable	mean	sd	min	max
Cantril ladder	5.56	1.13	2.38	7.78
GDP per capita PPP US$ 2011	9.42	1.15	6.97	11.65
Social support (x 10)	8.11	1.22	4.200	9.64
Healthy life expectancy at birth	64.89	6.87	48.70	77.10
Freedom of choice (x 10)	7.94	1.18	3.85	9.70
Generosity (x 10)	2.68	1.53	0.00	8.50
Absence of corruption (x 10)	2.76	1.88	0.37	9.30

Note: The number of countries is 126.
Source: Authors' compilations

count on in times of trouble) is the national share of people answering positively to the question: "if you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?"; freedom of choice is the national share of people answering positively to the question: "are you satisfied or dissatisfied with your freedom to choose what you do with your life?"; absence of corruption is the negative of the average of the national shares of people answering positively to two questions: first, "is corruption widespread throughout the government or not?", and second, "is corruption widespread within businesses or not?" Whenever data for government corruption are missing, only the perception of business corruption is used.

Finally, generosity is the residual of regressing the national average of responses to the question "have you donated money to a charity in the past month?" on GDP per capita. Therefore, it reflects people's generosity independently from the wealth of the country they reside in. Being a residual, generosity takes both positive and negative values. However, the DEA model that we use can not handle negative values. Therefore, we transformed generosity by subtracting from each score the minimum value of generosity. This transformation shifts the variable to start on zero without altering the original scale of the variable. The variables social support, freedom of choice, generosity, and absence of corruption were also multiplied by ten to produce a greater harmonization of scales across inputs.

Table 1 provides summary statistics for the variables included in the present study. Our final sample consists of 126 countries with complete information on inputs and output.

Methodology

To compute well-being efficiency, we use Data Envelopment Analysis (DEA), a technique that uses non-parametric linear programming to measure the relative performance of a group of organizational units, such as countries. Compared to other methods to compute efficiency, such as stochastic frontier analysis or ratio analysis, DEA requires no specific functional form, accommodates multiple inputs, and is not affected by problems of multicollinearity and heteroscedasticity (Tigga and Mishra, 2015). The aim of DEA models is generally to compute an envelopment, best practice, or efficient frontier such that all countries lie on or below it.[5] Countries located on the frontier receive an efficiency score equal to 1 and are regarded as efficient units. Countries located below the frontier receive a score relative to their distance from the frontier. The further they are, the lower the score, and less efficient they are considered.

Charnes *et al.* (1978) define efficiency as: "the maximum of a ratio of weighted outputs to weighted inputs subject that the similar ratios for every decision making unit be less or equal to unity". Efficiency can be described as follows:

$$TE_k = \frac{\Sigma_{r=1}^{s} u_r y_{rk}}{\Sigma_{i=1}^{m} v_i x_{ik}} \tag{1}$$

where

TE_k is the technical efficiency of country k using m inputs to produce s outputs; y_{rk} is the quantity of output r produced by country k; x_{ik} is the quantity of input i used by country k; u_r is the weight of output r; v_i is the weight of input i; n is the number of countries included in the analysis; s is the number of outputs (in present case, SWB) and m is the number of inputs.

Efficiency of country k is maximized subject to the following constraints: first, the weights applied to inputs and output of country k cannot generate an efficiency score greater than unity (see equation 2); second, the weights are strictly positive (see equation 3).

$$\frac{\Sigma_{r=1}^{s} u_r y_{rk}}{\Sigma_{i=1}^{m} v_i x_{ik}} \leq 1 \quad j = 1, ..., n \tag{2}$$

$$u_r, v_i > 0 \quad \forall r = 1, ..., s : \ i = 1, ..., m \tag{3}$$

We assume that the aim of a country is to maximize output, i.e. SWB, given the available level of inputs. Thus, we solve the linear program above using the output-orientated DEA model.

We estimate total well-being efficiency and its two components: technical and scale efficiency. Total efficiency is also known as constant returns to scale technical efficiency. A common assumption in DEA models is that decision making units operate under constant returns to scale (CRS) (Charnes *et al.*, 1978), i.e. increasing inputs yield a proportional increase in the output. As a result, differences in constant returns to scale technical efficiency can be due to differences in technical efficiency and scale. To estimate 'pure' technical efficiency we allow countries to operate under variable returns to scale (VRS) (Banker *et al.*, 1984) and various levels of scale efficiency (SE). The VRS model produces measures of TE – known as variable returns to scale technical efficiency (VRSTE) – that are not confounded by scale efficiencies (Coelli *et al.*, 2005), and estimates of scale efficiency.

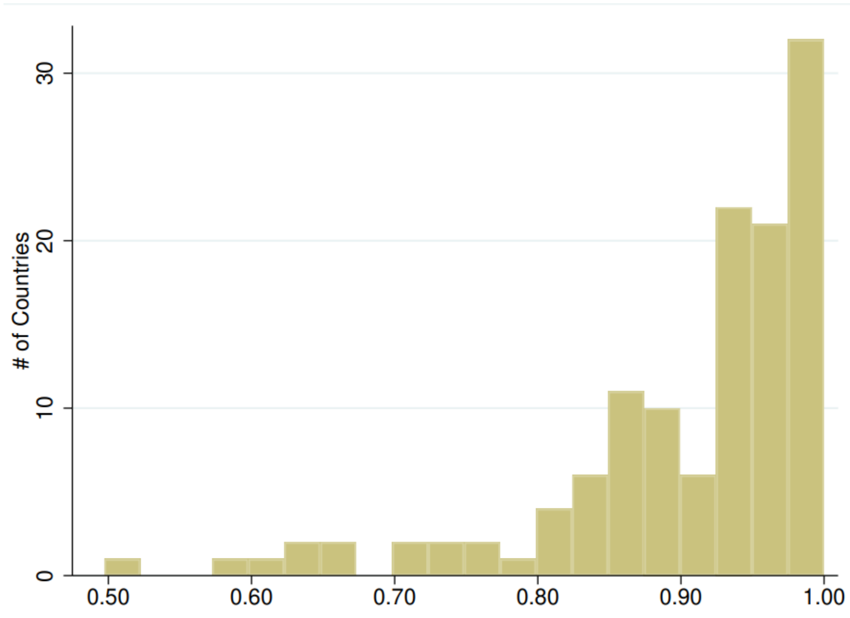
The primary equation of the output-orientated VRS model is as follows:

$$\text{minimize} \ \Sigma_{i=1}^{m} v_i x_{ik} - c_k \tag{4}$$

where c_k is a measure of returns to scale for country k.

5 The two basic models are the CCR model (Charnes *et al.*, 1978) and the BCC model (Banker *et al.*, 1984).

Chart 1: Distribution of well-being efficiency around the world



Note: The chart shows efficiency scores. Countries receive a score ranging from 0 to 1,where higher scores indicate higher efficiency.
Source: authors' own elaboration on data sourced from WHR 2021

Subject to:

$$\Sigma_{i=1}^{m} v_i x_{ij} - \Sigma_{r=1}^{s} u_r y_{rj} - c_k \geq 0 \quad j = 1, ..., n \tag{5}$$

$$\Sigma_{r=1}^{s} u_r y_{rk} = 1 \tag{6}$$

$$u_r, v_i, c_k > 0 \quad \forall r = 1, ..., s: \ i = 1, ..., m \tag{7}$$

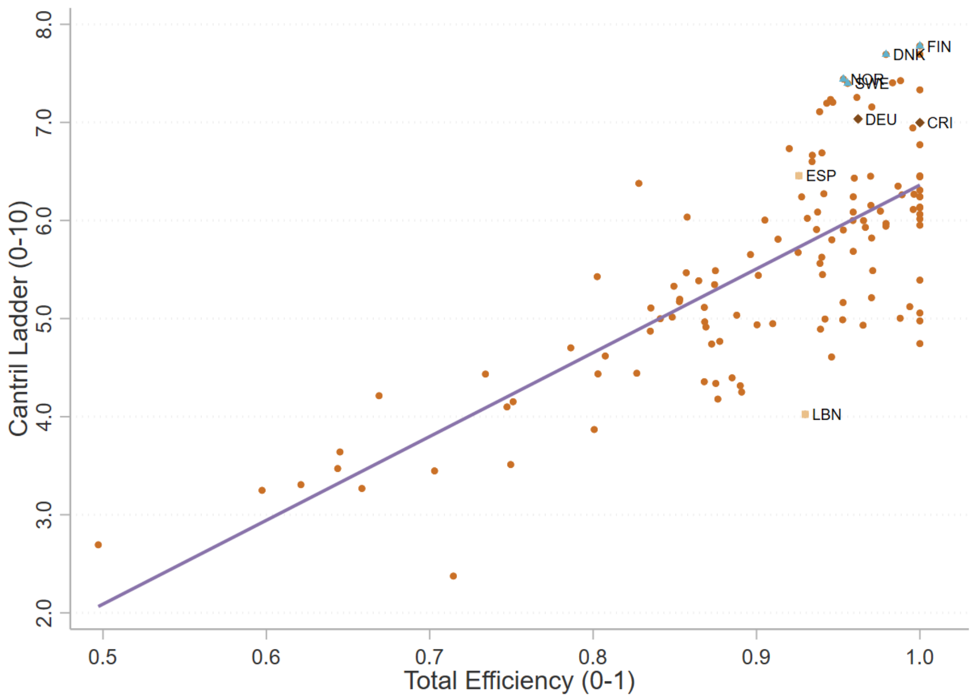
Comparing countries against a common frontier of best-practices is possible under the assumption that countries have similar "production technologies" to transform resources into SWB. It is difficult to test this assumption. Studies using various sources of data showed that happiness equations are strikingly similar across country types and country histories (Helliwell *et al.*, 2009; Powdthavee, 2010; Sarracino, 2013). This evidence lends support to the assumption that production technologies of well-being are internationally comparable. However, as the research on the comparability of reported well-being across countries is still growing, future research should assess whether differences in production technologies exist, and how important they are in determining well-being efficiency scores.

Findings

Well-being Efficiency Around the World

Efficiency scores indicate that 19 of the 126 considered countries are fully efficient; another 13 are 97.5 per cent or more efficient. The distribution of efficiency scores is presented in Chart 1, and detailed by country in the Appendix Table at the end of the article. Altogether, more than

Chart 2: Relation between Well-being Efficiency and Well-being



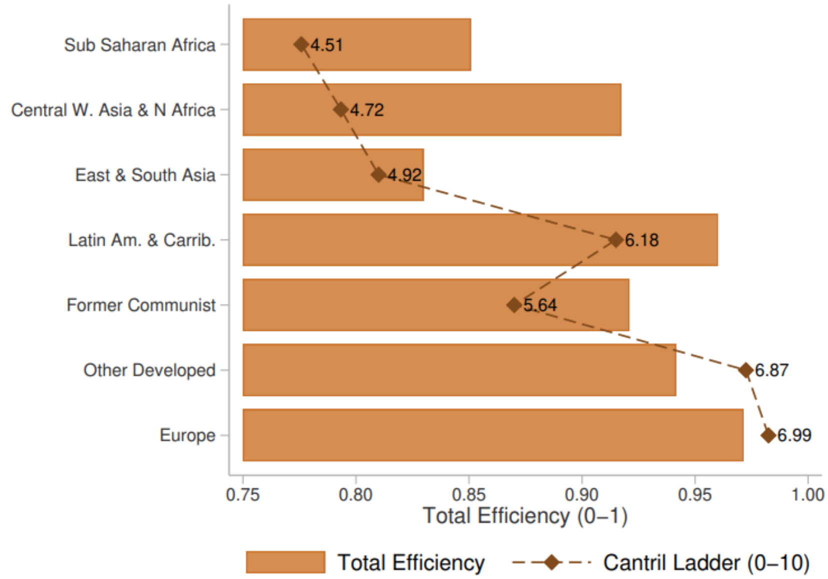
Note: The chart shows efficiency scores. Countries receive a score ranging from 0 to 1, where higher scores indicate higher efficiency. Countries are labeled with ISO3 codes, included in the Appendix Table 1.
Source: authors' own elaboration on data sourced from WHR 2021

half of the countries (81) are at least 90 per cent efficient, which might suggest we should not worry about efficiency. However, Cameroon – which is 90 per cent efficient – obtains 10 per cent less SWB from its inputs compared to a fully efficient country, and the remaining countries benefit even less. The least efficient country in our list is Zimbabwe, which is 50 per cent efficient. Increasing efficiency from 50 per cent to 75 per cent would have an effect on SWB comparable to increasing inputs by 50 per cent, ceteris paribus. Such low-efficiency countries need to critically assess how they use their inputs.

Well-being efficiency scores correlate positively with levels of well-being. However, the rankings of the two variables are distinct. Chart 2 shows that more efficient countries report higher SWB, but there are many exceptions. Lebanon (LBN) and Spain (ESP) are both 93 per cent efficient, but Spain reports nearly 2.5 more Cantril Ladder points. Efficiency matters, but Lebanon has lower inputs across the board (as shown in the Appendix Table). The Nordic countries report high Cantril Ladder scores, but they also have high inputs. They could score even higher SWB if they were more efficient. Among them, only Finland is fully efficient.

The data indicate efficiency can at least partially make up for low inputs. For instance, Germany (DEU) is only slightly happier than Costa Rica (CRI) even though Germany has a GDP per capita of more than two times that of Costa Rica's, and greater values for each of the other inputs except social support and freedom of choice.

Chart 3: Relation between Well-being Efficiency and Subjective Well-being



Note: The chart shows average efficiency scores by regions. Countries receive a score ranging from 0 to 1, where higher scores indicate higher efficiency.
Source: authors' own elaboration on data sourced from WHR 2021

Post-communist countries rank often among the least happy countries in Europe, whereas Latin American countries score frequently high in the international ranking of well-being (Helliwell *et al.*, 2021). These stylized facts are often based on regressions of life satisfaction on common macro controls and region dummies, which are negative for post-communist countries and positive for Latin American countries. Such dummy variables are analytically distinct from efficiency. Yet, they may still reflect the differences in efficiency across regions, which yields the question: are Latin American countries more efficient and post-communist countries less efficient? The results indicate that the above-mentioned stylized facts may be due in part to differences in efficiency across countries. Chart 3 indicates that Former Communist countries (identified in the Appendix Table) do indeed exhibit lower efficiency than the European, other Developed Countries, and Latin American countries. They are, however, at least as efficient as the three least happy groups. In the Latin American case, the results are consistent with expectations. They are among the most efficient, though not quite as high as European countries.

The region with the lowest average Cantril Ladder score, Sub Saharan Africa, is not the least efficient. This indicates that, as expected, this region has low inputs as well. The least efficient set of countries are in East and South Asia.[6] The range, however, is fairly broad within regions: East and South Asia include low efficiency countries such as Afghanistan and India, but also the highly efficient countries

6 The region for each country is given in the Appendix Table.

Table 2: Correlates of Total Efficiency

	Cantril Ladder	Residual	Total Efficiency	GDP per capita	Social Support	HLE	Freedom of Choice	Generosity	Corruption (absence)
Residual	0.51	1.00							
p-value	0.00								
Total Efficiency	0.75	0.80	1.00						
p-value	0.00	0.00							
GDP per capita	0.76	0.00	0.39	1.00					
p-value	0.00	1.00	0.00						
Social Support	0.75	0.00	0.41	0.78	1.00				
p-value	0.00	1.00	0.00	0.00					
HLE at Birth	0.77	0.00	0.44	0.86	0.70	1.00			
p-value	0.00	1.00	0.00	0.00	0.00				
Freedom of Choice	0.57	0.00	0.13	0.40	0.42	0.46	1.00		
p-value	0.00	1.00	0.14	0.00	0.00	0.00			
Generosity	0.00	0.00	-0.14	-0.21	-0.10	-0.16	0.16	1.00	
p-value	0.98	1.00	0.11	0.02	0.28	0.08	0.07		
Corruption (absence)	0.44	0.00	0.08	0.35	0.22	0.37	0.44	0.22	1.00
p-value	0.00	1.00	0.39	0.00	0.01	0.00	0.00	0.01	

Source: authors' own elaboration on data sourced from WHR 2021

such as Thailand and Nepal.

The Correlates of Well-being Efficiency

The previous section shows how well-being efficiency varies around the world, which countries are doing well, and which could do better, but not how to improve efficiency. If well-being is taken to be at least as important as economic production, then the well-being efficiency scores are valuable in their own right, as in the traditional productivity literature. In this section, we provide some initial exploration of the correlates of well-being efficiency. We use the same inputs to well-being as potential contextual variables that affect efficiency. This was done because we believe the variables represent inputs, as discussed in the introduction, and contextual variables. Health, for instance, will affect the efficiency in which other inputs can be used.

Simple bivariate correlations indicate GDP per capita, social support, and healthy life expectancy at birth are each correlated to well-being efficiency at about 40 per cent, as presented in Table 2. On the other hand, freedom of choice, generosity, and the absence of corruption are uncorrelated with efficiency. An additional variable, Resid, is also included, which we will address in the next section

The correlations suggest that increasing GDP per capita, social support, or healthy life expectancy would increase well-being directly (as direct inputs to well-being), but also through greater well-being efficiency. This is probably because a certain amount of economic development (GDP per capita) is necessary to enjoy other inputs, such as freedom of choice, for instance. Greater social support can also improve the effectiveness of one's inputs – having close friends and family can enhance positive activities (e.g., social) and mitigate negative ones (e.g., economic hardship). Likewise, better health improves everything from non-economic activities to productivity in wage-work (Strauss, 1986).

It is a bit surprising that the absence of corruption is not correlated with efficiency. Corruption has many pernicious effects (Bardhan, 1997), and likely reduces the effectiveness of government programs and diminishes trust at all levels in society.

Table 2 also reveals a significant amount of correlation between the inputs, especially between GDP per capita, social support, and healthy life expectancy. Many of the correlations across inputs are statistically significant and positive, except generosity. Generosity is negatively correlated with GDP per capita and healthy life expectancy; however, this is due to the method in which generosity is calculated, as discussed earlier.

Regressions are necessary to separate out the influence of one input from that of the others. In the following, we perform regressions of well-being efficiency on the inputs and additional variables that plausibly affect efficiency. The additional variables we consider include: the unemployment rate (World Development Indicators); quality of governance (Worldwide Governance Indicators); social expenditures as a percent of GDP (ILO), which serves as a proxy for the generosity of the welfare state when also including the population dependency ratio (O'Connor, 2017); the Gini coefficient (Standardized World Income Inequality Database); optimism (Gallup World Polls); and years of education (Barro *et al.*, 2021).

Unemployment affects subjective well-being directly, but can also have lasting effects on personality (Clark *et al.*, 2001). The quality of governance was found to be important for well-being (Helliwell and Huang (2008); Helliwell *et al.* (2018); Nikolova and Popova (2021)). The generosity of the welfare state covers a similar concept, but one that more immediately affects individuals' well-being (O'Connor, 2017). Income inequality, measured using the Gini coefficient, proxies for the distribution of inputs in a country, which may influence the effectiveness of outputs (e.g. through diminishing returns) and individuals' feelings of fairness and trust (Oishi *et al.*, 2011). Optimism reflects one characteristic that affects how people perceive the world and respond to different inputs. Likewise, education also affects how individuals perceive the world.

The results reveal healthy life expectancy is the most important input (as presented in Table 3). It is positively and statistically associated with total efficiency, which is consistent with the correlation analysis. The full set of inputs explains about 23 per cent of the variation in efficiency. However, only social support, healthy life expectancy, and freedom of choice are necessary to explain 22 per cent of the variation. Due to the collinearities in inputs, we sequentially dropped the variable with the lowest t-stat to arrive at the model in column 2, which maintains all variables with a t-stat above 1. Through this process, GDP per capita and the absence of corruption are dropped – two variables that intuitively support well-being efficiency. Somewhat surprisingly, only one input is correlated with efficiency when simultaneously accounting for the other variables.

Three of the added variables help to explain well-being efficiency. Countries with greater unemployment are less efficient. This is consistent with the find-

Table 3: Regressions of Total Efficiency on Well-being Inputs and Additional Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(GDPpc)	-0.014		-0.012	-0.022	-0.008	-0.015	-0.011	0.013
	(0.020)		(0.019)	(0.019)	(0.021)	(0.020)	(0.020)	(0.030)
Social Support	0.022	0.018	0.022	0.023	0.019	0.02	0.018	0.028
	(0.016)	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.017)
HLE at Birth	0.006**	0.005***	0.006**	0.006**	0.006**	0.005**	0.008***	0.009***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Freedom of Choice	-0.008	-0.01	-0.01	-0.009	-0.006	-0.004	-0.032***	-0.008
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)
Generosity	-0.004		-0.007	-0.004	-0.006	-0.005	-0.012**	-0.006
	(0.005)		(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Corruption (absence)	-0.002		-0.001	-0.003	-0.004	-0.004	-0.003	-0.004
	(0.005)		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Unempl. Rate			-0.003*		-0.002			
			(0.001)		(0.002)			
Qual. Of Gov.				0.015				
				(0.013)				
Social Exp.					0.001			
					(0.001)			
Pop. Dep. Ratio					0.003			
					(0.002)			
Gini						-0.002		
						(0.001)		
Optimism							0.004***	
							(0.001)	
Years of School								-0.020**
								(0.008)
Constant	0.531***	0.522***	0.595***	0.621***	0.386	0.681***	0.453***	0.254
	(0.107)	(0.090)	(0.123)	(0.145)	(0.247)	(0.147)	(0.103)	(0.184)
Observations	126	126	126	126	120	126	126	111
R-Squared	0.231	0.221	0.249	0.236	0.269	0.25	0.351	0.303
Adj. R-Squared	0.192	0.202	0.204	0.19	0.209	0.205	0.312	0.256

Note: robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors' own elaboration on data sourced from WHR 2021.

ings by Binder and Broekel (2012). Full employment should benefit well-being directly and also through efficiency. More optimistic populations are also more efficient. Again this result is plausible – for instance, optimistic people live longer (O'Connor and Graham, 2019) and respond to adverse shocks better (e.g. they recover from surgery quicker (Mahler and Kulik, 2000)). However, countries with more highly educated people have less well-being efficiency (controlling for the other inputs, which may act as mediators, i.e. GDP per capita and healthy life expectancy).This result is surprising. However, it is worth noting that the direct relation between education and subjective well-being when similarly accounting for mediating variables is ambiguous in the literature. The other variables are statistically insignificant. It is not too surprising that the quality of government or social expenditures are insignificant when similar inputs are already included (i.e. the absence of corruption and social support). The Gini coefficient, although not statistically significant, shows the anticipated negative sign.

The definition of well-being efficiency can lead to some counter-intuitive relations at first glance. Each of the inputs inherently have positive and negative effects on efficiency, because they affect the output and comprise the inputs. If we think of efficiency as a simple ratio, then for an input to have a positive relationship with efficiency, it needs to have a greater effect on the numerator than the denominator. This aspect may explain why two of the inputs, freedom of choice and generosity, become statistically and negatively related to efficiency when optimism is added. It is plausible that optimism, which is highly correlated with both inputs (at 60 per cent and 40 per cent respectively), picked up the positive associations between freedom of choice and generosity with the Cantril Ladder. If so, then their positive effects on the efficiency numerator are attenuated, while still affecting the denominator. Inputs that have little benefit reduce efficiency.

Altogether, the results indicate governments should invest in healthy life expectancy, reduce unemployment, and promote optimism, not only for their direct benefits on subjective well-being but also because of their effects on well-being efficiency. A healthier, more optimistic, and fully employed[7] population seemingly better mobilizes the inputs at their disposal.

Measurement and Validity of Well-being Efficiency

We investigate whether well-being efficiency correlates meaningfully with both economic efficiency and a measure of sustainable well-being, and then clarify its difference from regression residuals. These tests allow us to shed some light on the relationship between economic and well-being efficiency, and to check the validity of our measure.

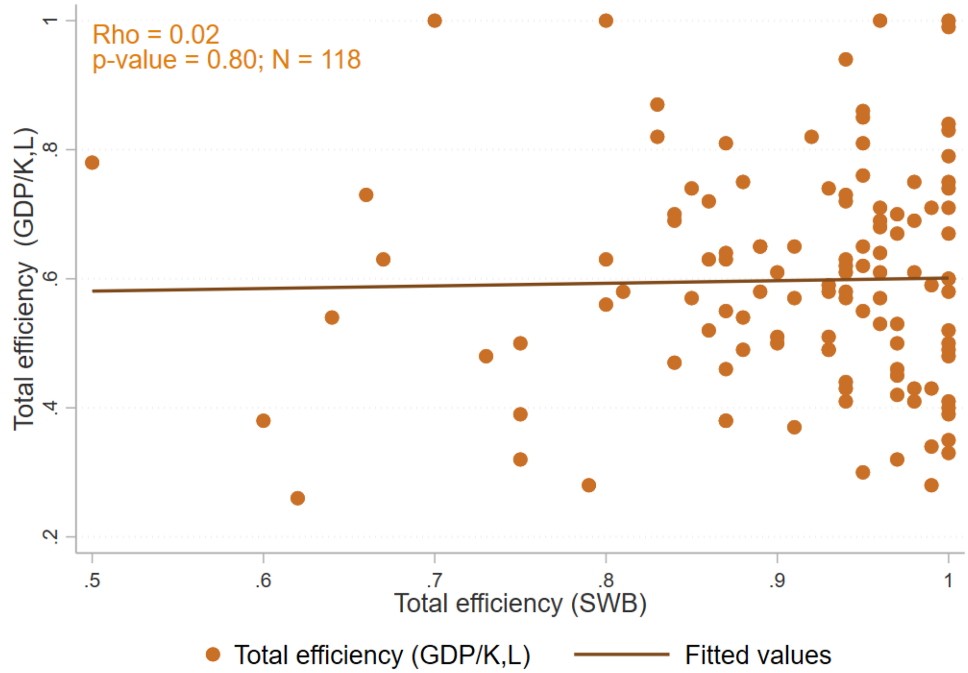
Economic efficiency attracts much attention based on the assumption that efficient economic production leads to better lives.[8] Is this actually the case? The correlation between well-being efficiency and a standard measure of economic efficiency reveals that the two measures are not statistically related. Chart 4 plots well-being efficiency (on the x axis) against economic efficiency (on the y axis). The Pearson correlation test reveals that the two measures are not correlated, yielding a correlation coefficient of 0.02, with a p-value = 0.80. Consistent with the view that the quality of growth matters for well-being (Helliwell, 2016), countries that are better equipped to transform capital and labour into GDP are not necessarily better equipped to transform their resources into well-being.

Our measure of economic efficiency was calculated by applying DEA to measures of input and output issued from the Penn World Tables v. 10 (Feenstra *et al.*, 2015). We use real GDP at constant 2017 national prices (in mil. 2017US$) as a measure of output; capital stock at constant 2017 national prices (in mil. 2017US$), and number of persons engaged in production (in millions) as measures of inputs. The present results do not change if we replace our measure of economic efficiency with total factor productivity (coeff. = 0.10, p-value = 0.34, N = 90), as computed in the

7 Among those seeking employment.

8 There is now considerable evidence that economic growth per se does not lead to lasting improvements in subjective well-being. Prominent explanations include social comparison and adaptation - income benefits are positional and short lived as people compare with others and adjust their expectations over time (Easterlin and O'Connor, 2022); others include social capital and income inequality (Mikucka *et al.*, 2017). GDP growth may erode social capital, a key ingredient to well-being (Sarracino and Mikucka, 2019).

Chart 4: Correlation between Well-being Efficiency and Economic Efficiency Scores



Note: the chart shows efficiency scores. Countries receive a score ranging from 0 to 1, where higher scores indicate higher efficiency.
Source: authors' own elaboration of data sourced from WHR 2021 and PWT v.10

Penn World Tables.[9]

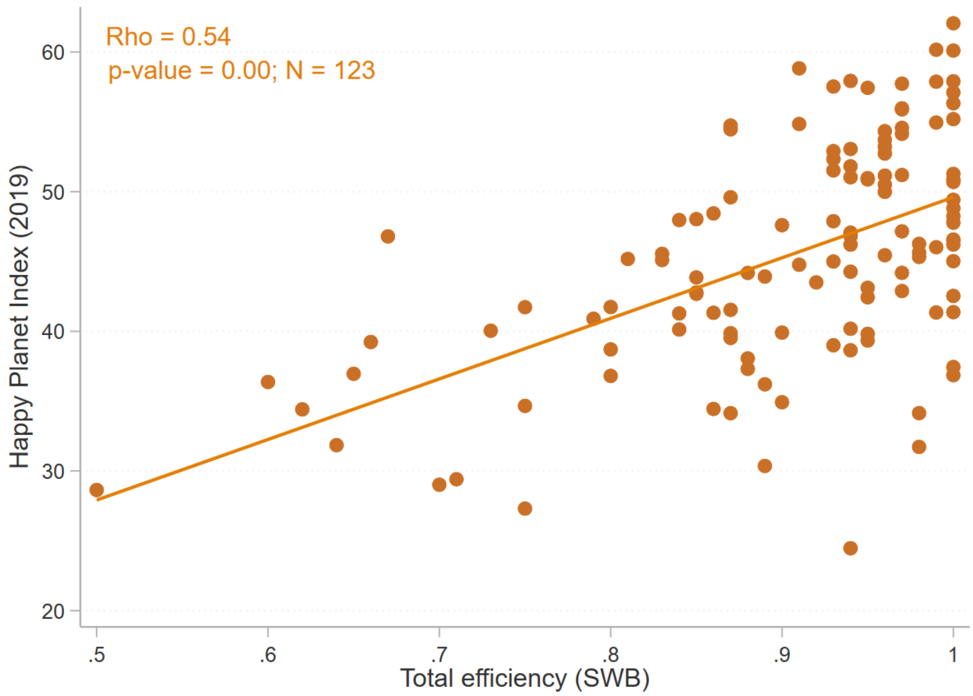
From the subjective well-being literature, there are two measures that might be considered similar to well-being efficiency: residuals from well-being equations, and the Happy Planet Index. We first address the Happy Planet Index and then residuals.

Well-being Efficiency Compared to the Happy Planet Index

The Happy Planet Index (HPI) was introduced by the New Economics Foundation (NEF) in 2006 to represent sustainable well-being or in other words, ecological efficiency at supporting well-being. It is analogous to well-being efficiency, and as such, can be contrasted with our well-being efficiency scores to assess their validity. Stated simply, the HPI is happy life years per unit of environmental input. More specifically, it can be approximated by life expectancy multiplied by the Cantril ladder, and divided by the ecological footprint (Happy Planet Index, 2021). According to the authors, the HPI can be regarded as a measure of efficiency as the numerator is an output, and the denominator includes the inputs provided by the natural environment. It thus measures efficiency as a

9 We computed our own measure of economic efficiency because TFP is available for 90 countries in our sample. Our measure of economic efficiency correlates with TFP at 20 per cent, significant at 0.027, N = 118.

Chart 5: Correlation between Well-being Efficiency and the Happy Planet Index



Note: the chart shows well-being efficiency scores and the Happy Planet Index. Countries receive an efficiency score ranging from 0 to 1, where higher scores indicate higher efficiency. The Happy Planet Index ranges from 0-100, where higher scores represent higher sustainable well-being.
Source: authors' own elaboration of data sourced from WHR 2021 and HPI 2021.

function of different inputs than those used in the present analysis, but nonetheless the concepts are similar. HPI data are freely available online and cover a broad sample of countries in recent years.[10]

Chart 5 shows the correlation between our measure of well-being efficiency (on the x axis) and the HPI (on the y axis). Higher efficiency scores correlate positively (0.54) and significantly (p-value = 0.00) with the HPI, which indicates that our measure of well-being efficiency correlates meaningfully with a third party measure of sustainable well-being. This result is only in part driven by the fact that both measures share the same output (HPI uses the Cantril Ladder from 2019 and multiplies it by life expectancy). To test the robustness of our finding, we ran a simple OLS regression of well-being efficiency on the Cantril ladder and the HPI. Results confirm the statistically significant association between our measure of efficiency and the HPI (Table 4). This finding lends some support to the hypothesis that our measure of well-being efficiency is valid.

Well-Being Efficiency Compared to Well-being Residuals

If we regress Cantril ladder over the set of inputs, residuals represent well-being

10 https://happyplanetindex.org/hpi/

Table 4: Association between the Happy Planet Index and Total Inefficiency Controlling for the Cantril Ladder

	Happy Planet Index			
	without Cantril ladder		with Cantril ladder	
well-being efficiency	0.522***	(8.46)	0.202**	(2.45)
Cantril ladder			0.421***	(4.23)
Constant	0.122	(1.64)	0.113	(1.62)
Observations	123		123	
R-squared	0.292		0.373	
Adj. R-squared	0.287		0.362	

Note: $p < 0.1$, $p < 0.05$, $p < 0.01$. The table reports the coefficients of standardized variables for ease of comparison.
Source: authors' own elaboration. Data sourced from WHR 2021 and HPI 2021

that is unexplained by a country's set of inputs. Residuals are not necessarily independent and identically distributed (iid). For instance, the average residual in Latin America is typically positive, while it is negative in post-communist countries. This is why residuals can be interpreted as region dummies to represent something more than an error term, such as the influence of culture. Mechanically, they adjust the level of subjective well-being that is predicted by the inputs, and in this way, they might be interpreted like well-being efficiency.

Residuals are distinct from efficiency for many reasons. First, by definition, residuals are unrelated to the inputs, which is not true of efficiency (due to diminishing returns or factor complementarities for instance). Empirically, the residuals obtained from the standard WHR regression, presented in column 1 of Table 5, are uncorrelated by definition with the inputs (also shown in Table 2); this is important, because it means it would not be possible to conduct the analysis in the previous sections using residuals.

Second, residuals augment the well-being function in an additively separable form, while efficiency does not: it augments the influence of the inputs. As such, efficiency corresponds more closely with regression coefficients, although the two remain distinct both in theory and in practice. In theory, coefficients cannot be interpreted like efficiency as they reflect a range of influences, including preferences for instance. In practice, estimating coefficients by country requires additional data. In contrast, DEA is used across numerous fields to estimate efficiency scores that are economically interpretable.

Moreover, the non-parametric approach of DEA is particularly useful when it is not clear what functional form should be used to estimate subjective well-being. For instance, subjective well-being is nonlinear with respect to age (Morgan and O'Connor, 2017) and relates more closely to log income than absolute income (Veenhoven, 1991; Easterlin, 2015). We also know some variables interact with each other, as either mediators or moderators. Misspecifying a regression model could lead to bias in the coefficients. In the present case, Table 2 shows our inputs are strongly correlated with each other. DEA allows us to overcome the limits of parametric methods by allowing inputs to interact with each other and to relate to the output in nonlinear ways.

To illustrate the benefits of a nonparametric approach we augment the traditional subjective well-being regression with sets of interaction terms, which allow the inputs to interact with each other in relation to subjective well-being. This adjustment increases the model's explanatory power by 6 percentage points, changes the magnitude and significance of the marginal effects, and changes the residuals.

The model in column 1 of Table 5 replicates the traditional approach found in the literature using the same data used to estimate efficiency. In contrast to the WHR, not all of the inputs are statistically significant; however, that could be due to the sample size or the level of data analysis. In the WHR 2020, the authors obtain significant relationship for each of the inputs using a larger sample that includes more countries and all of the available years (Helliwell *et al.*, 2020), and in the WHR 2021 the authors perform analysis on individual level subjective well-being (Helliwell *et al.*, 2021), not aggregate well-being. The present analysis should be expanded in future work to include more data. Nonetheless, our findings demonstrate that the inputs are related to subjective well-being in non-linear forms.

We then proceeded by allowing one input to interact with each of the others, sequentially dropping insignificant interactions with t-stats below one, and then moved to the next input. For brevity, Table 5 only presents models after dropping the pertinent interaction terms. As an example, GDP was interacted with each of the other five inputs, and of these interactions, only the ones with HLE and freedom of choice were maintained, as presented in column 2. There were three relevant interactions for social support (column 3), two for HLE (column 4), and so forth. The model in column 8 includes all of the previously significant interaction terms, while column 9 builds upon this model by dropping the low t-stat interaction between social support and freedom of choice.

The result in column 9 is a model that explains more than 80 per cent of the variation in the Cantril Ladder, 6 per cent more than the standard model without adding any inputs, just by allowing them to interact with each other. Column 10 presents the marginal effects of each input based on the model in column 9. The magnitudes of coefficients change some after allowing for interactions. Notably, the relationship for generosity increases in size and is now statistically significant.

Allowing for interactions between the inputs changes the models predictive power, input relations, and residuals. Subjective well-being is non-linear in inputs, and the specific functional form is as yet not well identified in theory or empirically. Non-parametric methods, such as DEA, allows us to overcome such challenges, and to estimate efficiency scores that are not biased by parametric choices. We emphasize that our example is data driven, thus the relevant interactions may change for different years or samples of countries. Also, we do not advocate using this ad hoc interactions approach broadly. However, it helps us to clarify the distinction between residuals and well-being efficiencies computed using DEA.

Total, Technical and Scale Efficiency

So far the analysis has focused on to-

Table 5: Regression of Cantril Ladder on Well-being Inputs and Interactions

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS	(10) Margins
ln (GDPpc)	0.125	-1.494**	0.022	-0.967	0.169	0.19	-0.301	-1.003	-1.001	0.169
	-0.121	-0.61	-0.112	-0.588	-0.124	-0.118	-0.226	-0.696	-0.669	-0.111
Social Support	0.316***	0.323***	-1.12	0.318***	-0.376	0	0.21	-1.126*	-1.130*	0.406***
	-0.094	-0.092	-0.765	-0.093	-0.3	-0.11	-0.13	-0.648	-0.615	-0.07
HLE at Birth	0.051***	-0.087	-0.101	-0.181**	0.049***	0.070***	0.114***	-0.119	-0.119	0.033*
	-0.018	-0.091	-0.089	-0.089	-0.017	-0.026	-0.032	-0.082	-0.074	-0.02
Freedom of Choice	0.164***	-0.45	0.201***	-0.553	-0.181	0.533***	0.303**	0.505	0.512***	0.174***
	-0.061	-0.466	-0.06	-0.569	-0.337	-0.123	-0.119	-0.387	-0.118	-0.053
Generos-ity	0.038	0.022	-0.312	0.028	0.849***	0.949***	-0.029	0.183	0.181	0.057*
	-0.039	-0.035	-0.346	-0.034	-0.241	-0.339	-0.059	-0.278	-0.27	-0.033
Corrupt-ion (absence)	0.073*	0.021	-0.248	0.02	0.538*	0.028	0.511	1.131**	1.129**	0.096**
	-0.04	-0.04	-0.204	-0.04	-0.283	-0.071	-0.493	-0.496	-0.473	-0.044
GDP X HLE		0.016*		0.016*				0.011	0.011	
		-0.009		-0.009				-0.01	-0.01	
GDP X Free		0.071								
		-0.049								
Ab Corr X GDP							0.153**	0.161***	0.161***	
							-0.059	-0.042	-0.04	
Support X HLE			0.020*					0.019	0.019**	
			-0.011					-0.012	-0.009	
Support X Free					0.091**			0.001		
					-0.04			-0.047		
Support X Gen			0.04			0.130***		0.108***	0.109***	
			-0.04			-0.045		-0.033	-0.033	
Support X AB Corr			0.033				0.037			
			-0.024				-0.035			
HLE X Free				0.012						
				-0.009						
HLE X Gen						-0.013				
						-0.008				
HLE X Ab Corr							-0.026**	-0.039***	-0.039***	
							-0.012	-0.01	-0.01	
Free X Gen					-0.098***	-0.148***		-0.126***	-0.126***	
					-0.029	-0.037		-0.036	-0.036	
Ab Corr X Free					-0.054		-0.06			
					-0.033		-0.038			
Ab Corr X Gen						0.02	0.022			
						-0.02	-0.021			
Constant	-3.074***	10.990**	8.606	11.907**	-1.028	-5.270***	-3.341**	10.411**	10.415**	
	-0.653	-5.276	-6.147	-5.66	-2.579	-1.196	-1.306	-4.839	-4.822	
Observat-ions	126	126	126	126	126	126	126	126	126	126
R-Squared	0.741	0.76	0.767	0.76	0.775	0.777	0.77	0.807	0.807	*na*
Adj. R-Squared	0.728	0.744	0.749	0.744	0.757	0.758	0.748	0.785	0.786	*na*

Note: robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors' own elaboration on data sourced from WHR 2021 tal well-being efficiency. However, it is possible to decompose total efficiency into technical and scale efficiency. Technical or 'pure' efficiency reflects a country's ability to transform inputs into well-being given the current set of inputs. Scale efficiency reflects whether a country is operating at the optimal scale. Countries facing constant returns to scale operate at an optimal scale; countries with increasing returns to scale have too few inputs, hence they could increase efficiency by expanding their scale; countries with decreasing returns to scale could increase their efficiency (which is similar to output per input) if they reduced their inputs. That does not necessarily mean they should reduce their inputs, however. As mentioned above, both the amount of inputs and efficiency matters for well-being.

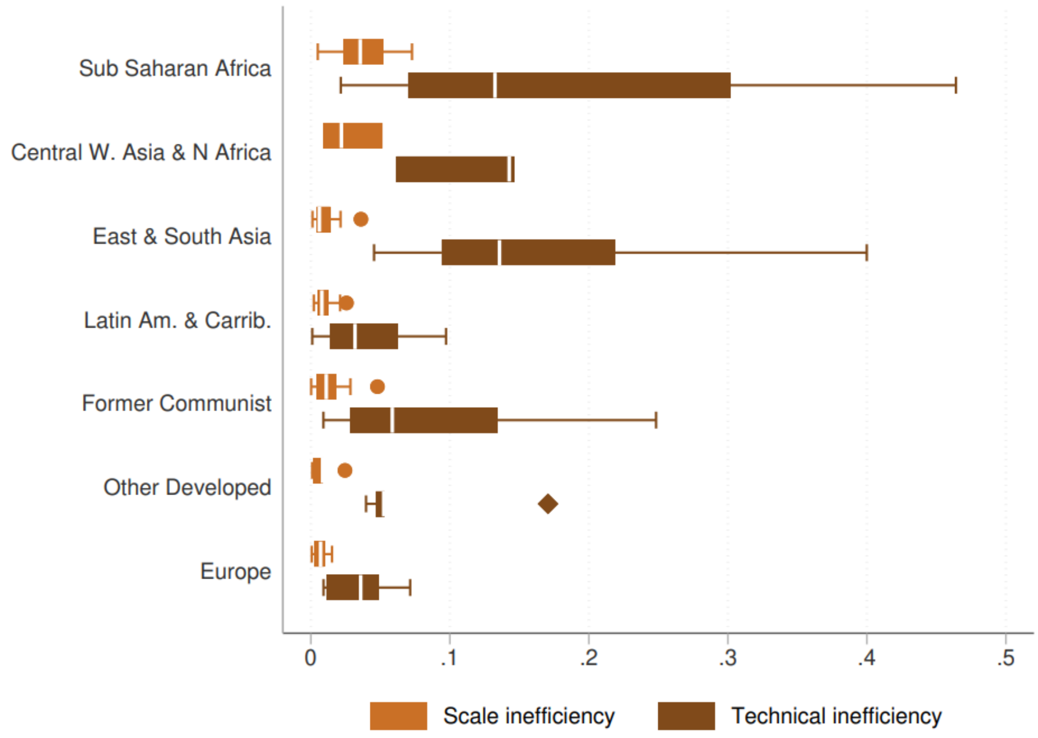
In the data, 19 countries are totally efficient, i.e. they operate at the optimal scale and utilize their inputs efficiently as shown in the Appendix Table: additional 15 countries are technically efficient, but they should adjust their scale by investing in more or less of certain inputs; another two countries are scale efficient, but technically inefficient; the remaining 90 countries are both scale and technically inefficient. In total, 105 countries are scale inefficient. Of these, 100 exhibit increasing returns to scale (IRS), and the remaining 5 exhibit decreasing returns to scale (DRS). Those experiencing increasing returns to scale are also more scale inefficient on average, at about 2.5 per cent inefficient compared to 1 per cent for the DRS. The results are intuitive, more countries suffer from too few inputs (experience IRS) than too many (DRS).

Technical inefficiencies are typically greater than scale inefficiencies. Chart 6 presents the distributions of the two types of inefficiency by region. In each group technical inefficiency is larger than scale inefficiency. However, on average, scale inefficiency is higher in Sub Saharan Africa; Central and West Asia, and North Africa; and East and South Asia, than the technical inefficiencies observed in Europe. In the latter case, technical inefficiency is below 10 per cent, and scale inefficiency is very close to zero. Averages also hide considerable heterogeneities within regions. Sub-Saharan Africa, for instance, includes countries with levels of technical efficiency comparable to European ones (this is the case in Mozambique, Uganda, Burkina Faso) as well as extreme values, such as those observed in Botswana, Zambia, and Zimbabwe. The disaggregation of total (in)efficiency into its technical and scale components reveals that more countries suffer from too few resources than too many, finding themselves on the increasing returns to scale portion of the frontier.

Robustness of Total Efficiency Scores

Our contribution depends in part on the robustness of the WHR framework. As discussed in section 2, it is difficult to determine which variables should be used as inputs. Previous authors have subjectively chosen their own sets of variables, which often overlap, but not completely. We argue that one can use the commonly accepted and often cited WHR framework to address this issue and in this section test the robustness of our results to alternative sets of inputs, first by dropping variables,

Chart 6: Technical and Scale Well-Being Inefficiency by Region



Note: The chart shows efficiency scores. Countries receive a score ranging from 0 to 1, where higher scores indicate higher efficiency.
Source: authors' own elaboration of data sourced from WHR 2021

and second by adding. We also test the robustness of our efficiency scores to outlying countries. DEA methods are sensitive to outliers. Recall that the estimated efficiency scores are relative, which means outliers could have a strong influence on the set of scores. Discussion of the robustness issues is found in the online Appendix.[11]

Conclusion

Numerous studies make the case for subjective well-being (SWB) – a single measure summarizing the many economic and non-economic aspects of what makes a life worth living – as a measure of economic and social development (Fleurbaey, 2009; OECD, 2013; Easterlin, 2019). The aim of our work is to provide a measure of subjective well-being efficiency that supplements economic efficiency. We assess countries' well-being efficiency using non-parametric techniques, the determinants identified in the series of World Happiness Reports (WHRs) as inputs, and SWB as a measure of output.

We believe that a measure of well-being efficiency has significant advantages over traditional economic efficiency for government policy. For instance, our well-being efficiency scores indicate how well countries transform their inputs into the Cantril Lad-

11 http://csls.ca/ipm/43/IPM_43_OConnor_Appendix.pdf

der. Unlike economic output, the Cantril Ladder is a valid and reliable measure of how people fare with their lives as a whole. The idea that SWB can be produced more or less efficiently – and that this efficiency can be measured – is fairly recent in the literature. Current SWB policy advice generally discusses the amount of inputs, not how well they are used. The Nordic countries generally rank among the highest SWB countries in the world, but they also have high inputs. Without well-being efficiency scores, it appears as though the only path to greater well-being is through greater inputs. Efficiency reveals an additional path. By identifying less-efficient countries and leading examples we provide insights into well-being efficiency that may help policy makers promote well-being in their country.

We utilize the WHR framework to guide our choice of inputs and output. In the WHRs, six factors (real GDP per capita, healthy life expectancy, social support, freedom of choice, absence of corruption, and generosity) explain about three-quarters of the variation in SWB around the world (Helliwell *et al.*, 2013). Historically, it has been difficult to determine which inputs to use. Various authors used different inputs and contextual variables to explain differences in efficiency, while many of the contextual variables affect SWB directly. Using the WHR framework eliminates this subjectivity, and at the same time, makes it possible for future scholars to easily expand upon our analysis. The data are freely available and cover the largest sample of countries to date, more than 150 countries (across all years, we rely on the data for 2019, but future research could use additional years). We also test the robustness of our measure of well-being efficiency to various combinations of the six considered inputs, and find our results are not sensitive to the exclusion or inclusion of additional variables.

Our findings indicate that 19 countries, out of the 126 observed in 2019, are on the efficient frontier, that is they use their inputs as effectively as the other most efficient countries and operate at an optimal scale. Efficiency is scored in relative terms; in our case, relative to the 19 countries on the frontier. The remaining 107 countries are not fully well-being efficient. The top 50 per cent of countries have efficiency scores of at least 90 per cent, and the bottom 10 per cent have scores between 50 per cent and 75 per cent. The disaggregation of total (in)efficiency into its technical and scale components reveals technical inefficiencies are larger than scale ones. Also many more countries suffer from too few resources than too many, finding themselves on the increasing returns to scale portion of the frontier.

Two aspects are worth emphasizing. The first is that countries on the efficient frontier can still improve their SWB. They can expand their inputs and or become more efficient still. The second is that high efficiency does not necessarily imply high SWB: a country characterized by high efficiency may have low levels of SWB due to low inputs. However, high efficiency can partially compensate for low inputs. For instance, Costa Rica reports nearly the same SWB as Germany, but with much lower inputs. Similarly, the Nordic countries often top the international rankings of well-being, yet only Finland is fully well-being efficient. In other words, the Nordic countries could be happier given the resources they have.

Our results also provide some insight into how countries might become more well-being efficient. For instance, countries with greater productive capacity and better health are more efficient. This finding implies policy makers might want to invest in better health not only for the direct benefits it brings for SWB, but also for the indirect effects that result from a more efficient use of inputs.

To identify the relevant factors for increasing well-being efficiency, we assessed correlations and performed regressions of the efficiency scores on the well-being inputs and an extended set of variables. Well-being efficiency correlates positively and significantly with GDP per capita, social support, and healthy life years at birth, while the regression analysis reveals that healthy life years is the single most important correlate of well-being efficiency. This result is probably because a healthy life is necessary to enjoy the other components of a happy life. Among the wider list of variables used to explain well-being efficiency, we found that more optimistic and fully employed populations are more efficient.

The correlation of well-being efficiency with third party measures of sustainable well-being, and economic efficiency provides interesting insights. We found that countries' efficiency in transforming inputs into SWB correlates positively and significantly with the Happy Planet Index. This finding supports the hypothesis that our measure of well-being efficiency is valid. In contrast, well-being and economic efficiency are not correlated. This result suggests that the countries which are more effective at turning capital and labour into GDP are not better at transforming their inputs into SWB, which contradicts the common belief that greater economic efficiency necessarily leads to better lives. We consider this result as further evidence that production and income per se does not increase well-being. The quality of economic growth matters for SWB (Helliwell, 2016).

Future analysis should expand and refine the analysis of total well-being efficiency correlates by looking, for instance, into the correlates of technical and scale efficiency separately as they are likely to differ. At the same time, it is not likely that a country will change its technical efficiency without changing the composition or amount of inputs (affecting scale efficiency); nor is a country likely to decrease its inputs, given they directly contribute positively to SWB. The determinants of total efficiency are therefore most relevant. Researchers should also assess additional data, additional variables, and apply more refined empirical techniques to identify the determinants of well-being efficiency.

Another limitation of our work has to do with causality. Although we adopted the well-established WHR framework, and tested its robustness, we can not disregard the evidence suggesting that SWB contributes to many of the variables we include among the inputs. For instance, happier people live longer and healthier lives. Another possible extension of our model could include a measure of positive affect among the inputs. Finally, we emphasize that DEA assumes substitutability of inputs, i.e. it is possible to compensate a decrease of input x by increasing input z.

This is a strong assumption considering that some of our inputs cannot be adjusted instantly. Future work could consider to use DEA with quasi-fixed inputs to address this issue.

We regard the present work as a proof-of-concept. The combined interpretation of our results provides insights about different countries' efficient or inefficient use of inputs, the correlates of efficiency, and the validity of our measure. There are, however, various methods to improve the analysis and inferences drawn from well-being efficiency scores. Nonetheless, the present work responds to the growing desire to better understand well-being and how to increase it. The result is a set of well-being efficiency scores and a framework for their estimation, both of which could be built upon and further assessed by researchers and practitioners.

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Appendix Table 1: Cantril Ladder, Efficiency Scores, and Input Values for 126 Countries (organized in descending order of total efficiency)

	Country	ISO3	Cantril Ladder	Log(GDP) p.c.)	HLE at Birth	Social Supp.	Freedom of Choice	Genero-sity	Corruption (absence)	Total Eff.	Tech. Eff.	Scale Eff.	Scale	Region
1	Finland	FIN	7.78	10.79	72.00	9.37	9.48	2.37	8.05	1.00	1.00	1.00	crs	Europe
2	Switzerland	CHE	7.69	11.14	74.40	9.49	9.13	3.25	7.06	1.00	1.00	1.00	crs	Europe
3	Israel	ISR	7.33	10.60	73.50	9.46	8.34	3.74	2.57	1.00	1.00	1.00	crs	Other Dvlp.
4	Costa Rica	CRI	7.00	9.89	71.50	9.06	9.27	1.43	1.64	1.00	1.00	1.00	crs	Latin Am. & Carrib.
5	Belgium	BEL	6.77	10.85	72.20	8.84	7.76	1.17	3.28	1.00	1.00	1.00	crs	Europe
6	El Salvador	SLV	6.45	9.08	66.40	7.64	8.77	1.80	3.18	1.00	1.00	1.00	crs	Latin Am. & Carrib.
7	Italy	ITA	6.45	10.66	73.80	8.38	7.09	2.07	1.34	1.00	1.00	1.00	crs	Europe
8	Jamaica	JAM	6.31	9.19	67.50	8.78	8.91	1.52	1.15	1.00	1.00	1.00	crs	Latin Am. & Carrib.
9	Slovakia	SVK	6.24	10.40	69.20	9.33	7.71	1.60	0.74	1.00	1.00	1.00	crs	Former Communist
10	Poland	POL	6.24	10.41	69.70	8.78	8.83	0.58	3.04	1.00	1.00	1.00	crs	Former Communist
11	Cyprus	CYP	6.14	10.59	73.90	7.76	7.40	2.81	1.35	1.00	1.00	1.00	crs	Europe
12	Romania	ROU	6.13	10.31	67.50	8.42	8.48	0.67	0.46	1.00	1.00	1.00	crs	Former Communist
13	Lithuania	LTU	6.06	10.52	67.90	9.18	7.80	0.37	2.17	1.00	1.00	1.00	crs	Former Communist
14	Bosnia and Herz.	BIH	6.02	9.61	68.10	8.73	7.22	3.68	0.37	1.00	1.00	1.00	crs	Former Communist
15	Greece	GRC	5.95	10.32	72.60	8.91	6.14	0.00	1.52	1.00	1.00	1.00	crs	Europe
16	Ivory Coast	CIV	5.39	8.56	50.10	6.79	7.36	2.71	2.01	1.00	1.00	1.00	crs	Sub Saharan Africa
17	Morocco	MAR	5.06	8.92	66.20	5.35	7.57	0.44	2.43	1.00	1.00	1.00	crs	Central W. Asia & N Africa
18	Benin	BEN	4.98	8.10	54.70	4.42	7.70	2.73	3.02	1.00	1.00	1.00	crs	Sub Saharan Africa
19	Algeria	DZA	4.74	9.34	66.10	8.03	3.85	2.94	2.59	1.00	1.00	1.00	crs	Central W. Asia & N Africa
20	Philippines	PHL	6.27	9.09	62.00	8.45	9.10	2.06	2.52	1.00	1.00	1.00	irs	East & South Asia
21	Nicaragua	NIC	6.11	8.60	67.80	8.74	8.83	3.18	3.78	1.00	1.00	1.00	irs	Latin Am. & Carrib.
22	United States	USA	6.94	11.04	68.20	9.17	8.36	4.33	2.93	1.00	1.00	1.00	drs	Other Dvlp.
23	Liberia	LBR	5.12	7.26	56.90	7.12	7.06	3.39	1.72	0.99	1.00	0.99	irs	Sub Saharan Africa
24	Guatemala	GTM	6.26	9.06	65.10	7.74	9.01	2.26	2.27	0.99	1.00	0.99	irs	Latin Am. & Carrib.
25	Netherlands	NLD	7.43	10.95	72.40	9.41	8.86	5.01	6.40	0.99	0.99	1.00	irs	Europe
26	Niger	NER	5.00	7.11	54.00	6.77	8.31	3.15	2.71	0.99	1.00	0.99	irs	Sub Saharan Africa
27	Colombia	COL	6.35	9.60	68.00	8.73	8.22	1.17	1.46	0.99	1.00	0.99	irs	Latin Am. & Carrib.
28	Luxembourg	LUX	7.40	11.65	72.60	9.12	9.30	2.44	6.10	0.98	0.99	0.99	drs	Europe
29	Latvia	LVA	5.97	10.34	67.10	9.36	6.98	0.95	2.11	0.98	0.99	0.99	irs	Former Communist
30	Denmark	DNK	7.69	10.95	72.70	9.58	9.63	3.09	8.26	0.98	0.99	0.99	irs	Europe
31	Chile	CHL	5.94	10.10	70.00	8.69	6.59	1.86	1.40	0.98	0.99	0.99	irs	Latin Am. & Carrib.
32	Portugal	PRT	6.10	10.46	72.60	8.76	8.82	0.55	0.85	0.98	0.99	0.98	irs	Europe
33	Senegal	SEN	5.49	8.13	60.00	6.88	7.59	2.70	2.04	0.97	1.00	0.97	irs	Sub Saharan Africa
34	United Kingdom	GBR	7.16	10.75	72.50	9.43	8.54	5.59	5.15	0.97	0.97	1.00	irs	Europe
35	Belarus	BLR	5.82	9.86	66.40	9.17	6.57	1.03	4.54	0.97	0.99	0.98	irs	Former Communist
36	Congo (Brazzaville)	COG	5.21	8.10	58.50	6.25	6.86	2.43	2.59	0.97	1.00	0.97	irs	Sub Saharan Africa

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	Country	ISO3	Cantril Ladder	Log(GDP) p.c.)	HLE at Birth	Social Supp.	Freedom of Choice	Genero-sity	Corruption (absence)	Total Eff.	Tech. Eff.	Scale Eff.	Scale	Region
37	Uzbekistan	UZB	6.15	8.85	65.40	9.15	9.70	5.93	4.89	0.97	0.97	1.00	irs	Former Communist
38	Brazil	BRA	6.45	9.59	66.60	8.99	8.30	2.27	2.38	0.97	0.98	0.99	irs	Latin Am. & Carrib.
39	Honduras	HND	5.93	8.65	67.40	7.97	8.46	3.51	1.85	0.97	0.97	0.99	irs	Latin Am. & Carrib.
40	Peru	PER	6.00	9.46	68.40	8.09	8.15	1.59	1.26	0.97	0.99	0.98	irs	Latin Am. & Carrib.
41	Mozambique	MOZ	4.93	7.15	55.20	7.42	8.70	3.61	3.18	0.97	0.98	0.99	irs	Sub Saharan Africa
42	Germany	DEU	7.04	10.89	72.50	8.86	8.85	3.46	5.38	0.96	0.96	1.00	irs	Europe
43	Ireland	IRL	7.25	11.37	72.40	9.44	8.92	3.62	6.27	0.96	0.96	1.00	irs	Europe
44	Mexico	MEX	6.43	9.89	68.60	8.52	9.03	1.48	1.91	0.96	0.97	0.99	irs	Latin Am. & Carrib.
45	Serbia	SRB	6.24	9.81	68.60	9.03	7.53	2.49	1.87	0.96	0.97	0.99	irs	Former Communist
46	Kyrgyzstan	KGZ	5.69	8.57	64.40	8.77	9.20	2.86	1.15	0.96	0.98	0.97	irs	Former Communist
47	Argentina	ARG	6.09	10.00	69.00	8.96	8.17	0.78	1.70	0.96	0.97	0.99	irs	Latin Am. & Carrib.
48	Hungary	HUN	6.00	10.39	68.00	9.47	7.98	0.94	1.16	0.96	0.96	1.00	irs	Former Communist
49	Sweden	SWE	7.40	10.88	72.70	9.34	9.42	3.80	7.50	0.96	0.96	1.00	irs	Europe
50	Norway	NOR	7.44	11.06	73.30	9.42	9.54	3.99	7.29	0.95	0.96	0.99	irs	Europe
51	South Korea	KOR	5.90	10.66	73.90	7.83	7.06	2.33	2.82	0.95	0.95	1.00	drs	East & South Asia
52	Gambia	GMB	5.16	7.70	55.30	6.94	6.77	6.99	2.02	0.95	1.00	0.95	irs	Sub Saharan Africa
53	Mali	MLI	4.99	7.75	52.20	7.55	6.70	2.51	1.54	0.95	1.00	0.95	irs	Sub Saharan Africa
54	New Zealand	NZL	7.21	10.67	73.40	9.39	9.12	4.45	7.66	0.95	0.95	1.00	irs	Other Dvlp.
55	Moldova	MDA	5.80	9.48	65.70	8.09	7.84	1.96	1.16	0.95	0.97	0.98	irs	Former Communist
56	Comoros	COM	4.61	8.03	57.50	6.32	5.38	3.66	2.38	0.95	1.00	0.95	irs	Sub Saharan Africa
57	Australia	AUS	7.23	10.81	73.90	9.43	9.18	4.09	5.70	0.95	0.95	0.99	irs	Other Dvlp.
58	Austria	AUT	7.20	10.94	73.30	9.64	9.03	3.48	5.43	0.94	0.95	0.99	irs	Europe
59	Albania	ALB	5.00	9.54	69.00	6.86	7.77	1.89	0.86	0.94	0.99	0.95	irs	Former Communist
60	Kazakhstan	KAZ	6.27	10.18	65.20	9.51	8.52	2.34	2.92	0.94	0.94	1.00	irs	Former Communist
61	Nepal	NPL	5.45	8.14	64.60	7.72	7.90	4.56	2.88	0.94	0.94	1.00	irs	East & South Asia
62	France	FRA	6.69	10.74	74.00	9.58	8.27	1.56	4.32	0.94	0.95	0.99	irs	Europe
63	Croatia	HRV	5.63	10.26	70.80	9.36	7.39	1.51	0.68	0.94	0.95	0.99	irs	Former Communist
64	Georgia	GEO	4.89	9.62	64.30	6.75	8.11	0.29	3.53	0.94	0.94	1.00	irs	Former Communist
65	Mongolia	MNG	5.56	9.42	62.50	9.46	7.11	4.38	1.27	0.94	0.95	0.98	irs	Former Communist
66	Canada	CAN	7.11	10.80	73.80	9.25	9.12	4.00	5.64	0.94	0.95	0.99	irs	Other Dvlp.
67	Panama	PAN	6.09	10.36	69.70	8.86	8.83	0.90	1.31	0.94	0.94	1.00	irs	Latin Am. & Carrib.
68	Japan	JPN	5.91	10.63	75.10	8.78	8.06	0.34	3.83	0.94	0.96	0.98	irs	Other Dvlp.
69	Slovenia	SVN	6.67	10.56	71.40	9.49	9.45	1.87	2.15	0.93	0.94	0.99	irs	Former Communist
70	Uruguay	URY	6.60	9.98	69.10	9.33	9.03	1.93	4.01	0.93	0.94	1.00	irs	Latin Am. & Carrib.
71	Thailand	THA	6.02	9.82	67.40	9.03	8.98	5.98	1.23	0.93	0.93	1.00	irs	East & South Asia
72	Lebanon	LBN	4.02	9.60	67.60	8.66	4.47	2.08	1.10	0.93	1.00	0.93	irs	Central W. Asia & N Africa
73	Mauritius	MUS	6.24	10.04	66.70	9.13	8.93	2.36	1.90	0.93	0.94	0.99	drs	Sub Saharan Africa

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	Country	ISO3	Cantril Ladder	Log(GDP) p.c.)	HLE at Birth	Social Supp.	Freedom of Choice	Genero-sity	Corruption (absence)	Total Eff.	Tech. Eff.	Scale Eff.	Scale	Region
74	Spain	ESP	6.46	10.62	74.70	9.49	7.78	2.40	2.70	0.93	0.93	1.00	irs	Europe
75	Bolivia	BOL	5.67	9.07	63.90	7.84	8.81	2.03	1.43	0.93	0.95	0.97	irs	Latin Am. & Carrib.
76	Malta	MLT	6.73	10.68	72.20	9.22	9.24	3.76	3.11	0.92	0.93	0.99	drs	Europe
77	Ecuador	ECU	5.81	9.34	68.80	8.08	8.30	1.74	1.61	0.91	0.93	0.98	irs	Latin Am. & Carrib.
78	Uganda	UGA	4.95	7.69	56.10	8.05	7.04	4.27	1.74	0.91	0.95	0.96	irs	Sub Saharan Africa
79	Dominican Rep.	DOM	6.00	9.82	66.10	8.84	8.77	1.66	2.54	0.91	0.91	0.99	irs	Latin Am. & Carrib.
80	Russia	RUS	5.44	10.21	64.70	9.10	7.15	1.73	1.52	0.90	0.91	0.99	irs	Former Communist
81	Cameroon	CMR	4.94	8.20	53.50	7.11	7.12	2.81	1.83	0.90	0.93	0.97	irs	Sub Saharan Africa
82	Paraguay	PRY	5.65	9.45	65.90	8.92	8.76	3.17	1.18	0.90	0.90	0.99	irs	Latin Am. & Carrib.
83	Chad	TCD	4.25	7.36	48.70	6.40	5.37	3.44	1.68	0.89	1.00	0.89	irs	Sub Saharan Africa
84	Tunisia	TUN	4.32	9.28	67.20	6.10	6.59	0.80	1.11	0.89	0.94	0.95	irs	Central W. Asia & N Africa
85	South Africa	ZAF	5.03	9.43	56.90	8.48	7.38	1.55	1.80	0.89	0.92	0.96	irs	Sub Saharan Africa
86	Swaziland	SWZ	4.40	9.07	51.27	7.59	5.97	0.98	2.76	0.89	1.00	0.89	irs	Sub Saharan Africa
87	Guinea	GIN	4.77	7.85	55.50	6.55	6.91	3.85	2.44	0.88	0.93	0.94	irs	Sub Saharan Africa
88	Togo	TGO	4.18	7.38	55.10	5.39	6.17	3.53	2.63	0.88	0.92	0.95	irs	Sub Saharan Africa
89	Madagascar	MDG	4.34	7.41	59.50	7.01	5.50	2.76	2.80	0.88	1.00	0.88	irs	Sub Saharan Africa
90	Armenia	ARM	5.49	9.52	67.20	7.82	8.44	1.16	4.17	0.87	0.89	0.98	irs	Former Communist
91	Indonesia	IDN	5.35	9.38	62.30	8.02	8.66	8.44	1.39	0.87	0.88	0.99	irs	East & South Asia
92	Burkina Faso	BFA	4.74	7.69	54.40	6.83	6.78	2.85	2.71	0.87	0.94	0.93	irs	Sub Saharan Africa
93	Gabon	GAB	4.91	9.61	60.20	7.63	7.36	0.86	1.54	0.87	0.92	0.94	irs	Sub Saharan Africa
94	Ghana	GHA	4.97	8.60	57.60	7.46	7.87	4.05	1.43	0.87	0.90	0.97	irs	Sub Saharan Africa
95	Bangladesh	BGD	5.11	8.47	64.80	6.73	9.02	2.37	3.44	0.87	0.88	0.99	irs	East & South Asia
96	Nigeria	NGA	4.36	8.54	50.10	7.34	7.29	3.21	1.27	0.87	0.87	1.00	crs	Sub Saharan Africa
97	Montenegro	MNE	5.39	9.97	68.70	8.32	6.94	1.84	1.80	0.86	0.88	0.99	irs	Former Communist
98	Estonia	EST	6.03	10.51	68.80	9.34	8.87	1.93	4.24	0.86	0.86	1.00	irs	Former Communist
99	Vietnam	VNM	5.47	8.99	68.10	8.48	9.52	1.63	2.12	0.86	0.87	0.98	irs	East & South Asia
100	Laos	LAO	5.20	8.97	59.10	7.29	9.06	3.50	3.80	0.85	0.86	0.99	irs	East & South Asia
101	Azerbaijan	AZE	5.17	9.58	65.80	8.87	8.54	0.75	5.43	0.85	0.87	0.98	irs	Former Communist
102	Libya	LBY	5.33	9.63	62.30	8.27	7.62	2.16	3.14	0.85	0.86	0.99	irs	Central W. Asia & N Africa
103	North Macedonia	MKD	5.02	9.71	65.47	8.15	7.25	3.13	0.77	0.85	0.86	0.99	irs	Former Communist
104	Cambodia	KHM	5.00	8.39	62.00	7.59	9.57	3.02	1.72	0.84	0.87	0.97	irs	Former Communist
105	Bulgaria	BGR	5.11	10.05	67.00	9.48	8.22	1.80	0.57	0.84	0.84	1.00	irs	Former Communist
106	Turkey	TUR	4.87	10.25	67.20	7.92	6.31	1.53	2.40	0.84	0.85	0.98	irs	Central W. Asia & N Africa
107	Singapore	SGP	6.38	11.49	77.10	9.25	9.38	3.16	9.30	0.83	0.83	1.00	irs	Other Dvlp.
108	Pakistan	PAK	4.44	8.45	58.90	6.17	6.85	4.12	2.24	0.83	0.86	0.96	irs	East & South Asia
109	Kenya	KEN	4.62	8.37	60.70	6.76	8.18	5.99	2.06	0.81	0.83	0.98	irs	Sub Saharan Africa
110	Namibia	NAM	4.44	9.17	56.80	8.45	7.39	1.15	1.21	0.80	0.84	0.96	irs	Sub Saharan Africa

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	Country	ISO3	Cantril Ladder	Log(GDP) p.c.)	HLE at Birth	Social Supp.	Freedom of Choice	Genero-sity	Corruption (absence)	Total Eff.	Tech. Eff.	Scale Eff.	Scale	Region
111	Malaysia	MYS	5.43	10.25	67.20	8.42	9.16	4.12	2.18	0.80	0.81	0.99	irs	East & South Asia
112	Malawi	MWI	3.87	6.97	58.30	5.49	7.65	2.92	3.20	0.80	0.83	0.96	irs	Sub Saharan Africa
113	Ukraine	UKR	4.70	9.46	64.90	8.83	7.15	2.08	1.15	0.79	0.80	0.98	irs	Former Communist
114	Mauritania	MRT	4.15	8.56	57.30	7.98	6.28	1.87	2.57	0.75	0.80	0.93	irs	Sub Saharan Africa
115	Lesotho	LSO	3.51	7.93	48.70	7.90	7.16	1.58	0.85	0.75	0.75	1.00	crs	Sub Saharan Africa
116	Ethiopia	ETH	4.10	7.71	59.00	7.48	7.54	3.41	2.68	0.75	0.75	0.99	irs	Former Communist
117	Myanmar	MMR	4.43	8.55	59.30	7.63	8.99	8.50	3.18	0.73	0.75	0.98	irs	East & South Asia
118	Afghanistan	AFG	2.38	7.70	52.40	4.20	3.94	1.80	0.76	0.71	1.00	0.71	irs	East & South Asia
119	Sierra Leone	SLE	3.45	7.45	52.40	6.11	7.18	3.63	1.26	0.70	0.73	0.97	irs	Sub Saharan Africa
120	Sri Lanka	LKA	4.21	9.48	67.40	8.15	8.24	3.40	1.37	0.67	0.67	1.00	irs	East & South Asia
121	Rwanda	RWA	3.27	7.71	61.70	4.89	8.69	3.53	8.32	0.66	0.67	0.98	irs	Sub Saharan Africa
122	Tanzania	TZA	3.64	7.89	58.00	6.87	8.50	3.89	4.11	0.65	0.66	0.97	irs	Sub Saharan Africa
123	Botswana	BWA	3.47	9.79	59.60	7.74	8.33	0.50	2.08	0.64	0.65	1.00	irs	Sub Saharan Africa
124	Zambia	ZMB	3.31	8.15	55.80	6.38	8.11	3.66	1.68	0.62	0.64	0.97	irs	Sub Saharan Africa
125	India	IND	3.25	8.82	60.50	5.61	8.76	4.00	2.48	0.60	0.60	1.00	irs	East & South Asia
126	Zimbabwe	ZWE	2.69	7.95	56.20	7.59	6.32	2.25	1.69	0.50	0.54	0.93	irs	Sub Saharan Africa
	min		2.38	6.97	48.70	4.20	3.85	0.00	0.37	0.50	0.54	0.71		
	max		7.78	11.65	77.10	9.64	9.70	8.50	9.30	1.00	1.00	1.00		
	median		5.64	9.56	66.50	8.42	8.17	2.43	2.21	0.94	0.95	0.99		
	average		5.56	9.42	64.89	8.11	7.94	2.68	2.76	0.91	0.92	0.98		

Source: Authors' compilation

On-line Appendix

Robustness of the WHR Framework for Estimating Well-being Efficiency to the Exclusion of Inputs

We start our robustness checks by dropping our current inputs one at a time from the baseline model. Our aim is to check whether models with a partial set of inputs from the WHR framework provide significantly different results.

The results indicate that our well-being efficiency scores do not depend on the inclusion of one input or another, they are remarkably robust to dropping inputs. Appendix Table 1 reports the coefficients of Spearman's rank test between the scores from the baseline model, and those from the trimmed models. The Spearman's rank test checks whether the ranking of countries resulting from two variables are statistically related. We find that in the worst case scenario, when we omit freedom of choice, the coefficient is 0.914 (significant at 1 per cent). In all other cases the coefficients range between 93 per cent and 97 per cent. We also estimated the correlations between trimmed models and found the coefficients are still above 83 per cent (this part of the correlation matrix has been omitted for brevity).

The results are similar when we use the standard Pearson's correlation test: the correlation coefficients are all above 96 per cent (significant at 1 per cent), except when we exclude freedom of choice (model CRS_TE_3) for which the correlation coefficient is 92 per cent (significant at 1 per cent). In sum, the well-being efficiency scores are stable to variations in inputs.

Additional inputs

Although the WHR framework provides empirical guidance to identify relevant variables to explain subjective well-being worldwide, the list may be incomplete: after all, 25 per cent of the variance of subjective well-being remains unexplained in the WHR regression model. Omitted variables, such as inequality, optimism, unemployment, and education, could contribute meaningfully. Education in particular was included in both Cordero *et al.* (2021) and Nikolova and Popova (2021).

To account for this possibility, we check how total well-being efficiency changes when we expand the baseline model with additional variables one at a time. The additional variables are those used in section 4 where we study the correlates of well-being efficiency.

The results indicate that adding inputs does not significantly affect our well-being efficiency ranks or scores. Appendix Table 1 reports the coefficients of Spearman's rank test and Pearson's correlation between the baseline well-being efficiency scores and new scores produced with additional inputs (listed in rows). Both tests provide fairly high coefficients. The smallest coefficient of the Spearman's rank test is 72 per cent when we include social expenditures and the population dependency ratio

Appendix Table 1: Spearman's Rank Test and Pearson's Correlations Between the Results of the Baseline Model and Trimmed Models.

Omitted inputs Observations	Correlation Coefficients	
	Spearman	Pearson
GDP per capita	0.932	0.968
Social support	0.937	0.970
Healthy life expectancy	0.970	0.980
Freedom of choice	0.914	0.921
Generosity	0.945	0.972
Absence of Corruption	0.948	0.967

Note: All coefficients are statistically significant at 1%. The number of obeservation is 126.

Source: authors' own elaboration. Data sourced from WHR 2021.

Appendix Table 2: Sensitivity of Well-Being Efficiency Scores to the Inclusion of Additional Inputs

Added Inputs	Correlation coefficients		Observations
	Spearman	Pearson	
Unemployment rate	0.89	0.96	126
Gini	0.97	0.99	126
Years of School	0.98	0.99	111
Optimism	0.99	0.99	126
Quality of Governance	0.81	0.92	126
Social Expenditures	0.72	0.9	120

Note: All coefficients are statistically significant at 1%

Source: authors' own elaboration. Data sourced from WHR 2021 and others that are documented in Section 4.

in the model. All coefficients are statistically significant at 1 per cent. The number of observations used to compute efficiency scores changes because of missing data. In those cases, we recomputed the baseline well-being efficiency scores in order to compute correlations on the same set of observations.

Excluding outliers

A potential pitfall of DEA is that extreme values in the data can have large impacts on the computed scores. To address this concern we repeat our analysis after dropping outlying values.

We analyse two cases in which we consider first the middle 98 per cent and then the middle 80 per cent of the distributions of each considered variable. In the first case, we drop all observations with values in the top or bottom 1 per cent of any of the variables. This is why the sample reduces from 126 to 115 observations. In the most conservative case, we drop all the observations with values in the top or bottom 10 per cent of any of the variables. Consequently, the sample available for the analysis drops to 39 countries. Further cuts are not possible because this would lead to samples that are too small.

The results are not sensitive to dropping outlying countries. The correlation between well-being efficiency before and after excluding outliers is remarkably high (see Appendix Table 3). In the most conser-

Appendix Table 3: Sensitivity of the Results to Outlying Values.

	Spearman's rank test		Pearson's correlation test	
	Coefficient	Obs.	Coefficient	Obs.
middle 98%	0.96	115	0.95	115
middle 80%	0.99	39	0.97	39

Note: All coefficients are statistically significant at 1%

Source: authors' own elaboration. Data sourced from WHR 2021.

vative case (dropping the top and bottom 10 per cent), the Pearson correlation coefficient is 97 per cent (significant at 1 per cent), and Spearman's correlation is 99 per cent (significant at 1 per cent). When we restrict the analysis to the middle 98 per cent, the Pearson coefficient is 95 per cent (significant at 1 per cent), and the Spearman's is 96 per cent (significant at 1 per cent).

Productivity Gains from Worker Well-Being in Europe

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Abstract

This article investigates the relationship between well-being in the workplace and labour productivity using a combined dataset covering the business economies of 30 European countries. The dataset combines information on working conditions and on the structure and performance of industries in manufacturing, construction and services. Data are sourced from representative surveys on individuals' working conditions and official structural business statistics. Regressions of labour productivity on measures of worker well-being — job satisfaction and a multidimensional index of job quality — provide evidence that a link between the two variables operates at the aggregate level: industries where worker well-being is higher have higher levels of labour productivity. This result implies that well-being in the workplace is not just desirable in itself, but it also contributes to labour productivity. This is relevant to firms, managers, unions, and policy makers as policies that foster worker well-being consequently can contribute to productivity growth.

This article investigates the relation between well-being in the workplace and labour productivity in European countries using a matched dataset which combines information on working conditions and economic performance from representative surveys.

Well-being in the workplace carries societal and economic consequences. It is increasingly recognized as being connected to health, socio-economic outcomes, and the overall well-being of the population. Worker well-being has gained further relevance due to the transformations of jobs

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(emerging of the gig economy, increase of zero-hour contracts), and, recently, the COVID-19 pandemic. These events induced dramatic changes in working conditions and practices, as well as in workers' attitudes towards their jobs, and pose major challenges to decision makers. As an example, in many countries manufacturing and service firms face dramatic labour shortages — what has been referred to as "the Great Resignation" — which impact the overall economy (Brignall, 2021). Among economic outcomes, the relationship between well-being in the workplace and productivity is not only of interest to firms, managers, and unions, but also to policy makers. This is because firm- and industry-level labour productivity are sources of aggregate productivity growth. The link between worker well-being and productivity is the focus of this article.

Throughout the article, we employ the terms worker well-being and well-being in the workplace interchangeably, to indicate the overall evaluation of one's experience in relation to one's job. In the analysis, we use two measures of worker well-being: job satisfaction, which refers to an overall evaluation of the work experience — including relations with colleagues, sense of purpose, autonomy, and economic conditions; and a job quality index, which is based on specific evaluations of several aspects of the experience on the workplace. The main difference between the two measures is that the compilation of job quality draws on a wide array of questions on various dimensions of the work experience, while job satisfaction is measured from answers to a single question. They do, however, intend to capture the same latent concept.

This article contributes to the literature on the relationship between productivity and worker well-being by providing evidence that the relationship exists at the industry level. The evidence is drawn from a matched dataset that combines well-established standard measures of labour productivity with indicators of well-being in the workplace, sourced, respectively, from official statistics and nationally representative surveys.

We use the 2010 and 2015 wave of the European Working Conditions Survey (EWCS) to build the indicators of worker well-being, namely job satisfaction and the index of job quality. The latter is based on workers' explicit evaluation of several dimensions of their job, including income, health and safety, social dialogue, mental health, and work-life balance. Data on labour productivity, employment, investment and other structural and performance indicators come from the 2010-2018 waves of the Eurostat's Structural Business Statistics (SBS). The resulting, pooled dataset, covers much of the business economies — 68 manufacturing, service, and construction industries — in 30 European countries. We use this combined dataset to estimate an empirical model of labour productivity.

Regression results show that industries with higher worker well-being display higher levels of labour productivity. Moreover, well-being in the workplace predicts productivity growth, with industries with higher satisfaction displaying higher future productivity growth. The size of the partial correlations of our measures of worker well-being is comparable in magnitude to that for investment per worker, and in some cases it is larger than the coefficients for wages. This result has policy relevance as it shows that worker well-being is not only a desirable goal *per se*, but it also contributes to productivity growth and, as a result, to economic prosperity. This suggests that a virtuous cycle of increasing well-being and growth can be established with appropriate actions.

The article consists of five main sections. Section 1 provides a literature review of the relationship between job satisfaction and productivity. Section 2 describes the data. Section 3 presents the framework. Section 4 provides the results from the analysis. Finally, section 5 discusses limitations of the data and analysis, and provides some concluding remarks.

Literature Review

The relationship between worker well-being, incentives and performance at work has been addressed by several disciplines, from psychology to organizational sciences and economics, both in theoretical and empirical settings. Many studies in the field of psychology investigate the link between well-being in the workplace — conceptualized as positive emotions, affect and engagement — and job performance from an individual perspective. These studies show that happier workers are more pragmatic, less absent, change jobs less often, make fewer mistakes in performing tasks, have less accidents, earn more money, have better relationships with colleagues and customers (Bateman and Organ, 1983; George and Brief, 1992; Pavot and Diener, 1993; Spector, 1997; Wright and Cropanzano, 2000). All these aspects are linked to productivity and profitability. Judge *et al.* (2001) provide an overview of studies in organizational psychology on the job performance – job satisfaction relationship. They conduct a meta-analysis on 312 samples and find a mean correlation of 0.3 between the two variables (job performance assessment is mainly based on supervisors' evaluation.)

Oswald *et al.* (2015) provide experimental evidence showing that positive shocks to happiness generate productivity gains. Such gains stem from increased effort rather than from higher precision in executing standardized tasks. The authors find that productivity is affected by short-run and artificially-induced increases in happiness, as well as by long-lasting shocks such as family bereavement, parental divorce and health problems.

The studies above have been conducted on individual-level data and focused on individual performances. Other studies have addressed the link between worker well-being and workplace performances. Using a meta-analysis approach, Harter *et al.* (2020) study the relationship between worker engagement and various indicators of business outcomes. The authors show that companies in which employees report higher engagement with their jobs experience less absenteeism, higher employees retention, higher customer satisfaction, fewer safety incidents, less theft, and higher product quality. What is more, engagement positively correlates with worker well-being and organizational participation, on the one hand, and broader business outcomes such as profitability and sales on the other. For the period 1984-2009, Edmans (2011) show that companies listed in the

"100 Best Companies to Work For in America" exhibit superior long-run stock market returns (compared to a benchmark), which suggests that employees' satisfaction has a significant positive impact on firm value.

All the studies above suggest the existence of a link between worker well-being and a variety of worker and firm outcomes. The evidence, however, is primarily based on small samples, case studies, or experiments, and as such is not generalizable. Studies based on representative datasets are scarce. Among the latter, two notable analyses are those of Bryson *et al.* (2017) and Bockerman and Ilmakunnas (2012): these authors study the link between job satisfaction and labour productivity for, respectively, the United Kingdom and Finland using establishment-level data. Bockerman and Ilmakunnas (2012) find a positive effect of job satisfaction on labour productivity in a sample of Finnish manufacturing plants. The study is conducted on a matched dataset which combines a measure of job satisfaction from a survey on European households to plant-level administrative data, from 1996 to 2001. The authors find that a one point increase in job satisfaction (measured on a 1 to 6 Likert scale) increases plants' labour productivity by nearly 5 percentage points. The positive significant effect of job satisfaction on labour productivity remains when applying an instrumental variable approach.

Bryson *et al.*(2017) analyse data from the Workplace Employment Relations Survey, conducted on a sample of British workplaces from 2004 to 2011. The authors measure job satisfaction by aggregating employee satisfaction scores concerning nine aspects of their working environment, and by an indicator of affect. They estimate cross-section and panel regressions (to account for unobservables), and find that job satisfaction has a positive and significant effect on the various (evaluative) measures of business performance. In contrast, job-related affect is never significant.

Another stream of literature investigates the link between productivity and intangible factors of production using firm and plant-level data. Recently, these studies have increasingly focused on the role of human factors and workplace practices, including management and HR practices, in explaining productivity patterns and variations. Overall, they find that intangible human factors impact productivity. For example, Black and Lynch (2001) address the relationship between productivity, workplace practices, human capital and the adoption of information technology by estimating a production function on data from a representative sample of US businesses. They find evidence that employee participation and profit sharing, aspects that are linked to worker satisfaction, are associated with higher productivity at the establishment level. Other contributions investigate the role of management (Bloom *et al.*, 2019), worker skills (Criscuolo *et al.*, 2021), and specific aspects of working conditions on work-life balance (Bloom and Van Reenen, 2006).

Data

The dataset used in this analysis provides information on labour productivity and factors used in production, measures of well-being in the workplace, working conditions and workforce characteristics from, respectively, Eurostat's Structural Business Statistics (SBS) and the European Working Conditions Survey (EWCS). Observations are at the industry level and cover manufacturing, construction and service industries for European countries. To the best of our knowledge, no single representative cross-country dataset is available which permits to observe both productivity and worker well-being, so we combined information from the two datasets.

The European Working Conditions Survey (EWCS) (Eurofound, 2010 and 2015) is a nationally-representative survey conducted by Eurofound every five years on random samples of workers in European countries. The latest survey interviewed about 44,000 workers in 35 countries.[2] The survey provides detailed information on respondents' working conditions, employment status, characteristics of the workplace, and selected socio-demographics. It has, however, limitations in terms of periodicity and sample sizes (Warhurst *et al.*, 2018). The survey is conducted every five years, which limits considerably the possibility to exploit the time-series dimension of the data. It is representative of workers at the country level; due to limited sample sizes, however, certain cells at the industry level may contain a small or very small number of observations. Despite these limitations, the EWCS is the only source of exhaustive information on working conditions for European countries. As such, it is the workhorse of studies on job quality for these countries (Wright *et al.*, 2017). Here, we use the 2010 and 2015 waves.[3]

The SBS is a harmonized dataset which provides information on the business economy's performance and structure, including labour productivity, turnover, value added, investments, and employment at the industry level (NACE 2-digit).[4] It is compiled from surveys conducted on firms by the EU and European Economic Area (EEA) national statistical offices, and harmonized by Eurostat. It covers manufacturing, construction, and business services, and has yearly frequency. The survey does not cover agriculture, financial services, public administrations and certain non-market activities (culture, health and personal services). We use all the waves for the period from 2010 to the latest available, 2018.

As EWCS and SBS observational units differ, we combined the two datasets using the country-NACE codes as matching variables. We proceeded by first aggregat-

2 The European Foundation for the Improvement of Living and Working Conditions (Eurofound) is a tripartite European Union Agency established in 1975 to provide research-based input for the development of social, employment and work-related policies. This survey can be accessed at https://www.eurofound.europa.eu/surveys/european-working-conditions-surveys/sixth-european-working-conditions-survey-2015. A useful summary of the survey methodological features is available at https://www.eurofound.europa.eu/sites/default/files/wpef17036.pdf.

3 We did not consider previous waves because we would have not been able to construct comparable job quality indices due to missing information. To mitigate EWCS sample size concerns, involving the number of individual observations available at the industry level, we have run the analysis on a restricted sample of industries, as well as at the NACE 1-digit level. Our results are robust to these robustness checks.

4 Industries are classified according to the classification of economic activities known as NACE rev.2. See https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF. According to NACE, SBS covers Sections B to N and Division S95 of NACE Rev.2.

ing the individual-level observations in the EWCS data, to construct industry-level indicators of well-being, working conditions and workforce characteristics. Then, we matched this dataset with the industry-level observations from the SBS, using the NACE 2-digit level and country codes available in both datasets. The matching is performed for two periods, which correspond to the 2010 and 2015 waves of the EWCS. We use SBS waves from 2010 to 2018 to compute growth rates of variables of interest.

The resulting combined dataset covers 68 manufacturing, construction and service industries for 30 countries.[5] We observe 2,040 unique industry-country pairs in two years, 2010 and 2015, which gives a total of 4,080 observations. The set of variables includes labour productivity, investment, persons employed, selected employee and business characteristics, working conditions, wages, and worker well-being. The dataset includes also the growth rates of productivity, investment and employment for the 3-periods ahead, i.e. for the periods 2011-2013 and 2016-2018.

As mentioned above, the dataset carries the drawbacks of the EWCS. In addition, its coverage is limited by the geographic and economic scope of the SBS, which excludes public services and financial industries. Despite these limitations, this dataset has the advantage of combining information on working conditions and job satisfaction with a conventional measure of productivity, which would not be available otherwise. To better gauge the information content of the dataset, we computed how much of total economy value added and employment the observed industries account for. Our sample accounts for, on average, 60 per cent of the economy total employment, and 50 per cent of total value added. The country-level employment coverage varies from a low of 48 per cent for Greece, to a high of 73 per cent for Latvia. We have also analysed patterns of missing values in the combined dataset and in the EWCS. In the combined dataset, missing values are more frequent for Eastern European countries, and for mining and quarrying activities (section B of the NACE) for the productivity variables. For job satisfaction and job quality variables, missing values are more frequent for certain service activities (sections B, J, M and N).[6] In the following section, we detail the variables used in our analysis.

Measures of worker well-being

We use two measures of worker well-being: job satisfaction and job quality. These measures are intended to capture. the same latent concept: well-being in the workplace. Job satisfaction comes from answers to the question "On the whole, are you very satisfied, satisfied, not very satisfied or not at all satisfied with working conditions in your main paid job?". Individual answers are coded on a scale rang-

5 Countries in the dataset are listed in the online Appendix D. Found at http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

6 This analysis is available from the authors upon request.

ing from 1 to 4, where higher scores indicate higher well-being. Job satisfaction is regarded as one of the satisfaction domains contributing to subjective well-being — an overall, self-reported evaluative measure of how people fare with their life as a whole. Previous studies indicate that surveys' single-item questions on job satisfaction provide valid and reliable measures of people's experience in the workplace (Van Saane *et al.*, 2003; Dolbier *et al.*, 2005). Job satisfaction is increasingly used in the economic literature to capture well-being in the workplace.

The job quality index is a composite indicator which combines several dimensions of the working experience. Specifically, it is compiled drawing on survey respondents' evaluations of the following aspects of the work experience: income and benefits, working time and work-life balance, social dialogue, skills development and training, safety and ethics, and stress at work.

The literature on the quality of work proposes a variety of indices of job quality. This reflects a lack of consensus on the definition of job quality, but also problems related to data quality and availability (Warhurst *et al.*, 2018).[7] Warhurst *et al.* (2017) recommends the following dimensions to construct job quality indicators for the UK: pay and other rewards; intrinsic characteristics of work; terms of employment; health and safety; work-life balance; and representation and voice. Bryson *et al.* (2017) use the following domains of job satisfaction: pay, sense of achievement, scope for using initiative, influence over the job, training, opportunity to develop skills, job security, involvement in decisions, and the work itself. Job quality indices based on EWCS data have been proposed by Green and Tarek (2012) and Munoz de Bustillo *et al.* (2011). The latter has been subsequently employed by Anton *et al.* (2012) to analyse the characteristics of poor quality jobs in Europe. This index includes five dimensions: pay, intrinsic characteristics of work (including autonomy, meaningfulness and skills), work-life balance, health and safety, and terms of employment. One can see that, despite the differences, there is a considerable degree of overlap across these proposals.

For the construction of our index, we followed the framework outlined in the United Nations Handbook on measuring quality of employment (UNECE, 2015), as this represents one of the two most recent contributions on the topic by an international organization concerned with the measurement of human development (OECD, 2017). We adapted it to the data at hand. Compared to the UN framework, we added a stress dimension to capture mental well-being, an aspect which is becoming increasingly relevant in the debate on working conditions. We could not account for the domains on employment-related relationships and motivation, and security of employment and protection, due to lack of available data. Another limitation of our job quality index is that it does not incorporate much information on intrinsic job characteristics, such

7 On the notion and operationalization of job quality one can see Warhurst *et al.* (2017), Green (2021), and Wright*et al.* (2017).

Table 1: Correlation Table: Selected Variables

	Labour prod.	Job quality	Job satisfaction
Labour prod.	1		
Job quality	0.1143	1	
Job satisfaction	0.1021	0.4774	1

Source: authors' calculations

as, for example, meaningfulness or sense of achievement. These aspects are the main departures of our index from the proposal by Munoz de Bustillo *et al.* (2011).

Note that the literature on job quality tends to view job quality and workplace well-being as two distinct concepts. The dimensions of job quality are rather seen as determinants of well-being (Green, 2021; Warhurst *et al.*, 2017; OECD, 2017). Here we depart from this view, and we employ a job quality index as a multi-dimensional measure of well-being in the workplace. The specific wording and methodology underlying the job quality index make it a measure of worker well-being that is complementary to job satisfaction. This allows us to ensure that the results do not depend exclusively on a single-item variable.

Note that we aggregated individual answers to obtain average measures of worker well-being at the level of the industry.[8] We also constructed a measure capturing the industries' share of satisfied and very satisfied workers.

Labour productivity is measured by gross value added per employee. An alternative indicator of labour productivity, value added per person employed, yields similar results. Thus, we omitted it from the presentation.[9] Workforce and industry characteristics are: age of employees; employees' education level; firm size (defined in terms of number of employees); industries' employment share; investment per worker; sector the industry belong to (manufacturing, construction and services). The education variable has three categories, corresponding to aggregations of the ISCED classification of educational levels. Category one, two, and three include, respectively: primary and lower secondary education; upper secondary and vocational training; tertiary, that is, graduate and post-graduates degrees. All economic variables are expressed in constant Euros, and the base year is 2015.

Table 1 presents pairwise correlations of labour quality, job satisfaction and labour productivity in the dataset. All correlations in the table are positive and significant. The correlation between the two measures of worker well-being – job quality

8 On-line Appendix A provides further details on the construction of the job quality index. http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

9 Labour productivity per person employed is an alternative, commonly used measure of labour productivity. In contrast to labour productivity per employee, which considers the number of people who are in the payroll, it takes into account the number of people involved in production. Thus, it is regarded as better suited to capture productivity performances of self-employed, family firms, and certain activities, such as professional services. In our case, difference in results are negligible. Another commonly used productivity indicator, labour productivity per hour of work, is not available in our data sources.

Table 2: Descriptive Statistics (pooled sample)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Labour productivity	3,495	69.378	213.204	-355.714	23.676	77.728	10,686.05
Labour prod (total growth)	3,368	0.019	0.293	-4.516	-0.082	0.126	5.047
Labour prod (yearly growth)	3,308	0.012	0.129	-1.501	-0.026	0.044	4.498
Investment per worker	3,389	16.903	80.657	0	2.159	10.4	3,494.00
Investment pw (total growth)	3,253	-0.008	0.639	-4.156	-0.279	0.283	4.132
Investment pw (yearly growth)	3,143	0.039	0.28	-1.322	-0.075	0.115	5.172
Employment share	3,376	0.016	0.023	0	0.003	0.019	0.22
Empl. share (change)	3,279	-0.001	0.003	-0.032	-0.001	0.0002	0.046
Job quality	3,188	6.324	1.603	0	5.333	7.308	12
Job satisfaction	3,241	3.028	0.448	1	2.833	3.25	4
Age	3,239	41.944	7.214	18	38	46	72
Education	3,185	2.117	0.483	1	1.875	2.429	3
Wage	3,051	1,557.10	1,777.73	1.194	880.968	1,754.59	37,851.14
Large firms	2,895	0.196	0.278	0	0	0.333	1

Note: Pooled sample (2010 and 2015). *Labour productivity* is gross value added per employee, in thousands of Euros (volumes, 2015); *Investment per worker* is the investment per employee, also in thousands of Euros (volumes, 2015); *Employment share* is the share of total employment accounted for by a given industry in a country; *Age* is in years; *Education* is coded from 1 to 3 (1: primary and lower secondary, 2: upper secondary and vocational, 3: tertiary education); *Large firms* is the proportion of large firms ($\geq$ 250 employees) in a given industry. *total growth* and *yearly growth* denote respectively: the variable's total, cumulated growth over a 3-years period; the variable's average yearly rate of growth computed for a 3-year period.

and job satisfaction – is about 0.5 and statistically significant.[10]

Table 2 presents descriptive statistics for the variables in the dataset. Descriptives have been calculated by pooling the observations across countries and the two years of observations, 2010 and 2015. On average, labour productivity grew by 1 per cent yearly, and by 2 per cent over a 3-years period. The "average" worker is 42 years old with a secondary degree. The proportion of large firms in a given industry is, on average, 20 per cent. The average level of reported labour satisfaction is 3 (on a scale from 1 to 4) corresponding to "satisfied" (with a standard deviation of 0.45).

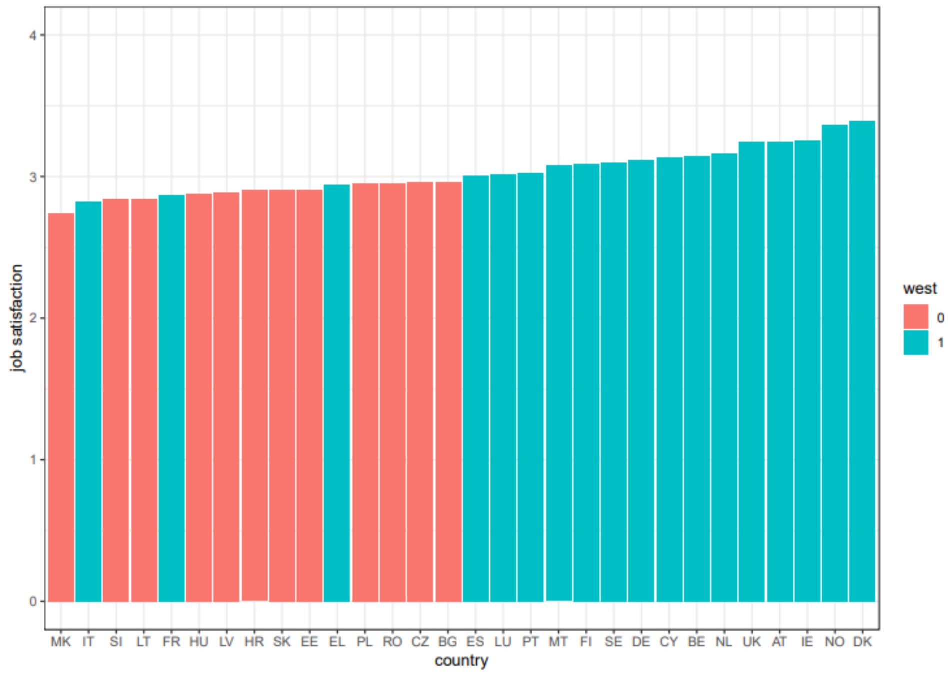
Charts 1-4 present aggregate average levels of job satisfaction and job quality by country and by groups of economic activity.[11] Job satisfaction is higher in Western European countries (denoted by blue boxes), with some notable exceptions, such as Italy, France and Greece. Job quality has its highest average levels in Scandinavian countries, and its lowest average in Greece. Across broad groups of economic activities, the data suggest that job satisfaction is about the same across sectors, whereas job quality is somewhat lower in construction — a feature that is more marked in Eastern European countries.

Chart 5 depicts average levels of labour productivity by country. Western European countries are characterized by higher levels of labour productivity compared to Eastern European countries. The lowest levels of productivity are recorded for Makedonia, followed by Bulgaria and Ro-

10 The correlation between the two measures of productivity is significant and close to 1, specifically 0.9968, so we do not report correlations for labour productivity per person employed in the table.

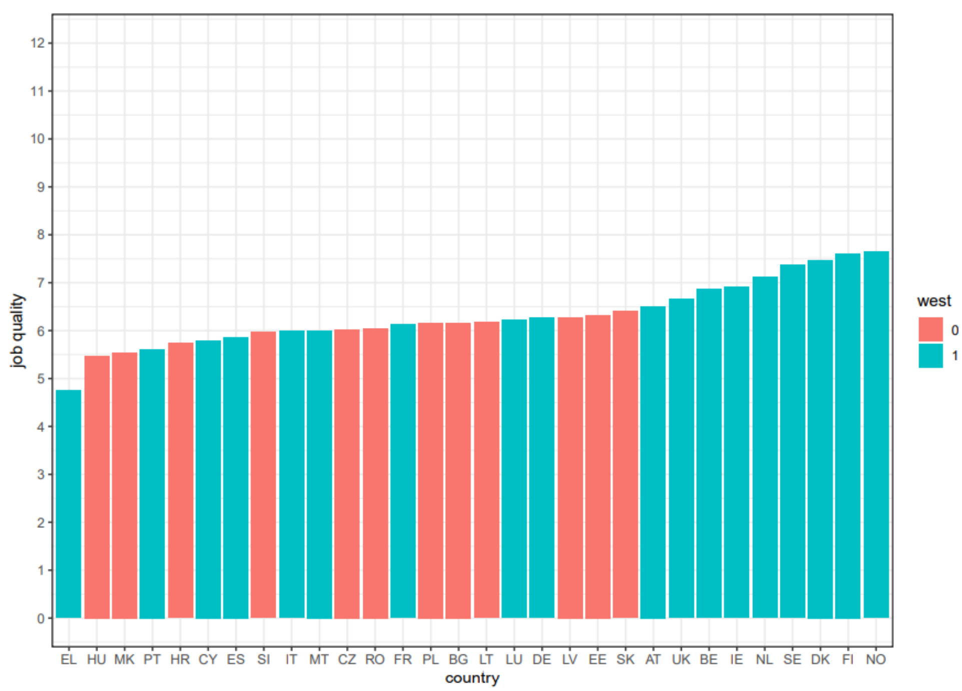
11 Country codes and corresponding country names are listed in Appendix D. http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

Chart 1: Job Satisfaction: Average by Country



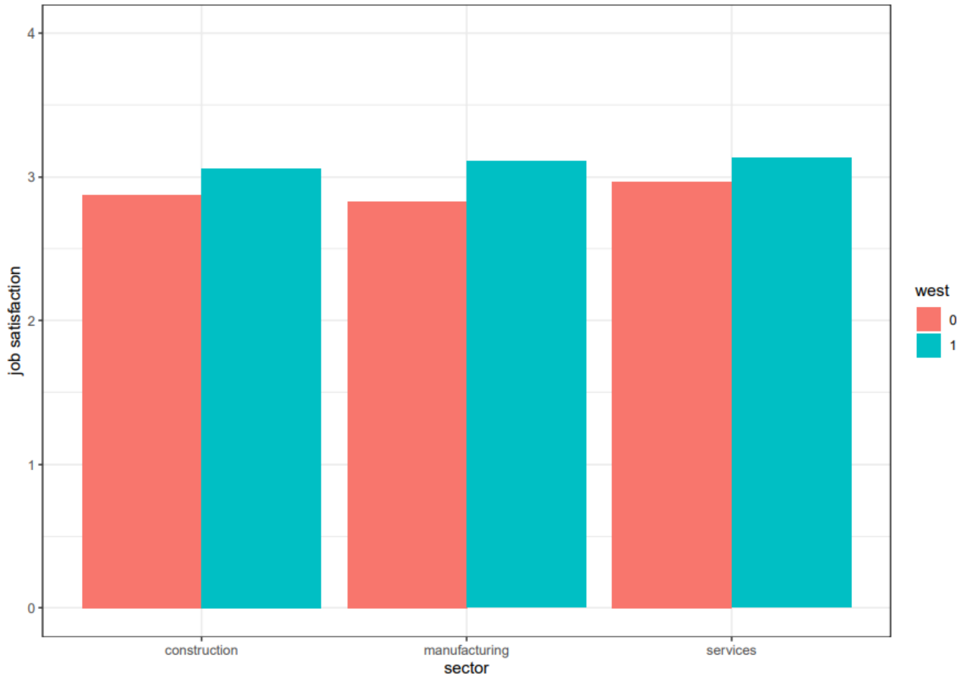
Note: Country averages of job satisfaction (pooled sample). The blue and red boxes denote, respectively, Western and Eastern European countries.
Source: EWCS.

Chart 2: Job Quality: Average by Country



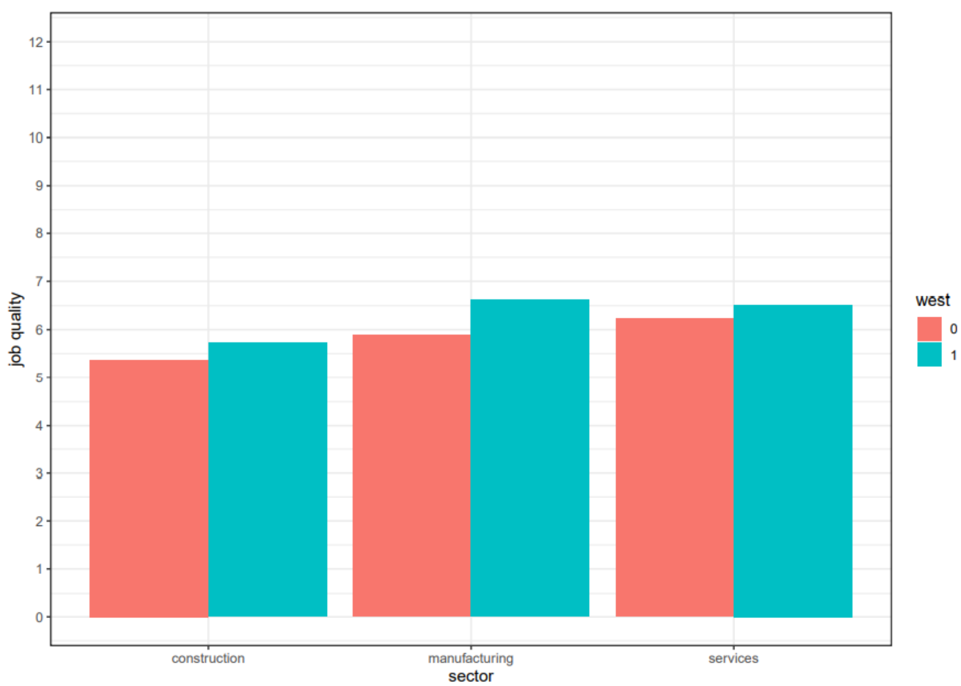
Note: Country averages of job quality (pooled sample). The blue and red boxes denote respectively, Western and Eastern European countries.
Source: EWCS.

Chart 3: Job Satisfaction: Average by Sector



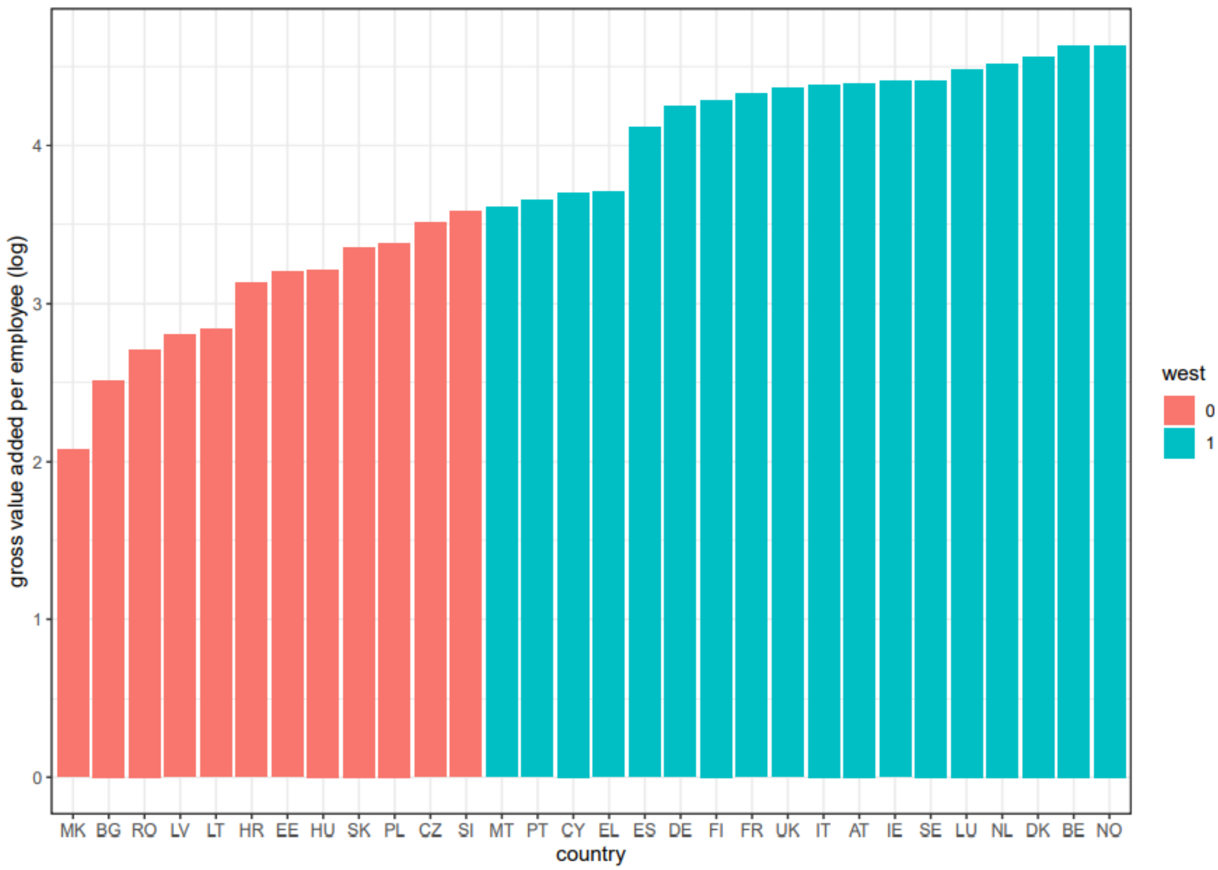
Note: Sector averages of job satisfaction (pooled sample). The blue and red boxes denote, respectively, Western and Eastern European countries.
Source: EWCS.

Chart 4: Job Quality: Average by Sector



Note: Sector averages of job quality (pooled sample). The blue and red boxes denote, respectively, Western and Eastern European countries.
Source: EWCS.

Chart 5: Labour Productivity: Average by Country



Note: (Log of) Labour productivity; the blue and red boxes denote, respectively, Western and Eastern European countries.
Source: SBS.

mania, while highest levels are those of Norway, Belgium and the Netherlands.

Method

Our empirical analysis rests on a standard model of labour productivity growth, derived from a Cobb-Douglas production function. The function links output to standard inputs to production — capital stock and labour — and to a residual, referred to as total factor productivity (TFP), which typically captures efficiency in inputs uses, technological improvements, and intangible factors of production. The term "intangibles"[12] refers to variables, or assets, such as human capital and skills, knowledge and organizational capital, management and HR practices. Intangibles are now a focus of at-

12 Increasing availability of data, and theoretical developments, have resulted in an increasing number of empirical studies on the role of intangibles assets in production and in explaining productivity patterns. Certain types of intangibles are now included in labour productivity decomposition and in datasets such as those produced by the OECD and EU-KLEMS. The set of intangible capital considered by economists has broadened over time from the initial set of human-related capital, such as personnel skills, and innovation-related variables such as R&D and software, to include aspects of the working environment, such as management and HR practices. On intangibles, one can see, for example, Corrado *et al.* (2022), and reference therein, and Bloom *et al.* (2016).

tention of productivity studies, as evidence shows they play a considerable role in explaining productivity patterns. The set of intangibles has also broadened over time, as more data sources have become available. Present analysis follows DiMaria *et al.* (2020) in considering well-being in the workplace as an intangible factor of production.

The Cobb-Douglas production function can be written as follows:

$$Y = e^{A(JS)} * K^{\alpha} * L^{(1-\alpha)} \quad (1)$$

Here, we assume constant returns to scale in labour and capital. Note that the TFP residual A captures the effect of worker well-being (denoted by JS). Thus, we regard worker well-being as an intangible factor of production.[13] Dividing by L and taking logs we obtain:

$$ln(Y/L) = A(JS) + \alpha * ln(K/L) \quad (2)$$

Based on the equation above, labour productivity growth can be expressed as the sum of (a function of) capital deepening (the change in capital per worker) and the change in the "residual" A, which depends on the intangible factors:

$$\Delta ln(Y/L) = \Delta A(JS) + \alpha \Delta ln(K/L) \quad (3)$$

The framework above lays the ground for our empirical models. The baseline model is a regression of the level of labour productivity on average job satisfaction and a set of controls:

$$ln(Y/L)_j = \alpha + \beta ln(I/L)_j + \gamma JS_j + \rho X_j + \epsilon_j, \quad (4)$$

where labour productivity depends on investment per worker (I/L), worker well-being (JS - which denotes either job satisfaction or job quality), and a vector of control variables X. The vector of controls includes workforce characteristics (age and education), the proportion of large firms in the industry j, the industries' labour shares, and average wages by industry and country. The characteristics of the workforce are known to affect economic outcomes, so it is reasonable to include them in the regression. In addition, large firms are typically characterized by higher productivity. The labour share captures the use of the labour input by industries. The dataset does not include capital stock, so we approximate capital stock by investment. The error term is ϵ. The subscript j denotes the industry.

The model also includes year, country and sector dummies. Dummies allow us to capture sector-specific effects and country-level characteristics. Country dummies capture country institutional features. The inclusion in the model of the sector dummy is motivated by the descriptives presented in the the previous section.

We also specify and estimate the model for the response variable's growth rates. We regress labour productivity growth on the levels of job satisfaction and the con-

13 One could specify the function $A(JS)$ as follows $A = \delta * JS^{\lambda}$.

trols:

$$\Delta ln(Y/L)_{j,t} = \alpha + \beta \Delta ln(I/L)_{j,t} + \gamma JS_{j,t} + \rho Z_{j,t} + \epsilon_j \quad t = 2010, 2015. \tag{5}$$

where the vector Z includes controls for industry-workforce characteristics, as for the model in levels. Additionally, we control for the "initial" level of productivity and the change in industries' employment shares. The level of productivity in the beginning of the period typically captures time persistence and, possibly, a convergence mechanisms. The changes in industries' employment shares, i.e. in the number of workers employed by each industry, possibly captures between-industries reallocation effects. We also include year, country, and sector dummies. We compute labour productivity growth in two different ways: we take the cumulated (log) change in productivity between t and $t+3$, and the yearly growth rate of labour productivity computed by averaging the labour productivity growth of the three periods ahead, $t : t+1, t+1 : t+2, t+2 : t+3$. We use two different measures of productivity growth to check the robustness of the findings

Considering the relation between job satisfaction in a given period and the *change* in labour productivity in the following periods is interesting *per se*. This amounts to check whether industries "endowed" with different amounts of job satisfaction exhibit significant differences in productivity growth. Moreover, the specifications in growth rates allow us to mitigate the possible presence of reverse causality.[14]

The models are estimated on the pooled datasets for the years 2010 and 2015 using Ordinary Least Squares (OLS) and robust standard errors clustered by year.[15]

Results

Table 3 reports results from the estimation of the regression models in levels. The coefficients of job satisfaction and job quality are small, but positive and statistically significant. The magnitude of the coefficients is, respectively, 0.047 and 0.044. This indicates that a unit increase in average job satisfaction in an industry is associated to about a 5 per cent increase in labour productivity. Note that, as job satisfaction is measured on a scale from 1 to 4, a unit increase in job satisfaction represents a sizeable increase in the variable.[16] Our baseline results are comparable with the estimate by Bockerman and Ilmakunnas (2012), which report a coefficient of job satisfaction on standard labour productiv-

14 The lack of sufficient time lags does not allow us to estimate a fixed-effect model. In other words, our dataset, which observes working conditions variables in two years only, does not permit to fully exploit the time series dimension of the data.

15 Overall, empirical results are not very sensitive to the errors' variance-covariance matrix specification for the model including job satisfaction. In contrast, results do change for the model with job quality, which now retains significance across specifications, compared to the assumption of homoskedasticity.

16 While individual responses are ordinal, we take averages at the industry level, so we can regard the well-being variables as continuous, albeit bounded.

Table 3: Regression of Labour Productivity on Job Quality and Job Satisfaction (levels)

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.044***		
	(0.000)		
job satisfaction		0.047***	
		(0.006)	
satisfied (share)			0.077 ***
			(0.005)
age	0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
education	0.241***	0.257***	0.260***
	(0.026)	(0.026)	(0.027)
large firms	0.076***	0.097***	0.096***
	(0.016)	(0.017)	(0.017)
employment share	-2.278***	-2.425***	-2.432***
	(0.075)	(0.122)	(0.123)
investment p.w.	0.327***	0.333***	0.333***
	(0.004)	(0.006)	(0.006)
wage	0.080***	0.083***	0.084***
	(0.014)	(0.003)	(0.003)
sector: construction	0.013	-0.008	-0.009
	(0.013)	(0.017)	(0.017)
sector: services	0.027***	0.035***	0.037***
	(0.010)	(0.010)	(0.011)
Country dummies	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*
Observations	2,165	2,188	2,188
R^2	0.836	0.832	0.832
Adjusted R^2	0.833	0.829	0.829

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

ity of 5 per cent in the baseline OLS regression (though job satisfaction is measured on a 1 to 6 Likert scale in their study).

Controls have the expected signs. Ceteris paribus, industries with higher proportions of large firms, more educated workers, and higher wages are characterized by higher productivity levels. Industries with higher intensity of investment (higher investment per worker) are more productive. In contrast, industries which employ larger shares of workers are less productive.

Tables 4 and 5 present estimation results for the models where the dependent variable, productivity, is specified in growth rates (respectively a three-year period growth, and average yearly growth rates). The job satisfaction coefficient is, once again, positive and significant. The job quality coefficient now appears small and only weakly significant. The coefficients on job quality and job satisfaction for the model in average yearly growth rates are positive, significant, with a magnitude of, respectively, 0.003 and 0.029 (Table 5). Controls have the expected signs.

The regression results show that a positive statistically significant association exists between well-being in the workplace and labour productivity at the aggregate, industry level. In other words, industries where workers are on average more satisfied, are also characterized by higher levels

Table 4: Regression of Labour Productivity on Job Quality and Job Satisfaction (Total Growth)

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.006*		
	(0.003)		
job satisfaction		0.059***	
		(0.002)	
satisfied (share)			0.088***
			(0.009)
labour prod. (t_0)	-0.093***	-0.095***	-0.094***
	(0.013)	(0.015)	(0.016)
age	0.000	0.001	0.001
	0.000	0.000	0.000
education	0.037***	0.032**	0.036**
	(0.012)	(0.016)	(0.017)
large firms	(0.023)	(0.016)	(0.018)
	(0.017)	(0.015)	(0.015)
empl. share	-0.537**	-0.544***	-0.550***
	(0.216)	(0.201)	(0.209)
Δ empl. share	-3.394***	-3.204***	-3.210***
	(0.381)	(0.403)	(0.325)
Δ invest. p.w.	0.067***	0.067***	0.067***
	(0.009)	(0.010)	(0.010)
wage	0.015**	0.011***	0.013***
	(0.007)	(0.004)	(0.004)
sector: construction	0.024***	0.021***	0.020***
	(0.002)	(0.001)	(0.001)
sector: services	0.035	0.031	0.033
	(0.029)	(0.029)	(0.029)
Country dummies	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	2,104	2,127	2,127
R^2	0.186	0.190	0.187
Adjusted R^2	0.170	0.174	0.172

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

of labour productivity. What is more, they are characterized by higher labour productivity growth.

The last columns in the Tables 3-5 report results for regressions where the explanatory variable of interest is the share of satisfied and highly satisfied workers within an industry. The variable retains its positive significant effect on productivity in all specifications. This shows that results are robust to an alternative specification of the variable of interest.

The tables in on-line Appendix B present regression results in detail, as controls are included in the regressions incrementally.[17] Results indicate that job satisfaction and job quality remain positive and significant following the inclusion of the controls, although the magnitude of the coefficient decreases.

We ran separate regressions replacing the country dummies with a "west" dummy (a dummy for the group of western European countries), in light of the system-

17 http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

Table 5: Regression of Labour Productivity on Job Quality and Job Satisfaction (yearly growth).

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.003**		
	(0.001)		
job satisfaction		0.029***	
		(0.003)	
satisfied (share)			0.036***
			(0.006)
labour prod. (t_0)	-0.042***	-0.042***	-0.041***
	(0.009)	(0.009)	(0.010)
age	0	0	0
	0.000	0.000	0.000
education	0.018***	0.015***	0.017***
	(0.001)	(0.004)	(0.003)
large firms	-0.001	0.002	0.001
	(0.004)	(0.004)	(0.004)
empl. share	-0.278**	-0.283**	-0.284**
	(0.124)	(0.116)	(0.119)
Δ empl. share	-3.782***	-3.488***	-3.520***
	(0.128)	(0.033)	(0.137)
Δ invest. p.w.	0.045***	0.047***	0.046***
	(0.005)	(0.004)	(0.004)
wage	0.011*	0.009*	0.010*
	(0.006)	(0.005)	(0.005)
sector: construction	0.009***	0.008***	0.007***
	(0.003)	(0.002)	(0.002)
sector: services	0.015	0.014	0.015
	(0.011)	(0.011)	(0.011)
Country dummies	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	2,035	2,056	2,056
R^2	0.154	0.161	0.155
Adjusted R^2	0.137	0.144	0.139

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

atic differences in the average value of the outcome variable between the two regions. The estimation of the models yields positive and significant coefficients for both measures of well-being.[18]

Overall, these results indicate that job satisfaction and job quality are positively and significantly associated to productivity and productivity growth, so that increases in the quality of work and worker well-being are correlated to higher productivity levels or growth rates. This association is not only statistically significant, but it is also economically meaningful.

To gauge the economic relevance of results, we have standardized the variables to obtain comparable regression coefficients. The tables in on-line Appendix C provide the corresponding results.[19] For instance, if we compare the coefficient of the share of satisfied workers (0.019 in Table 13 in Appendix C) with the size of the coefficient

18 Results not reported for reasons of space, but available from the authors.

19 http://www.csls.ca/ipm/43/IPM_43_Peroni_Appendix.pdf.

Table 6: Economic Significance of Worker Well-being. Percentages are Based on Estimates Using Standardized Variables

	Models		
	levels	total growth	yearly growth
job satisfaction	4.5%	61.6%	98.0%
job quality index	15.9%	22.6%	36.7%
share of satisfied workers	3.7%	46.6%	62.0%

Note: The coefficients of job satisfaction and job quality are expressed as a percentage of the coefficients of investment per worker. The complete set of regressions is available in online Appendix C. The model in levels (first column) refers to the coefficients from Table 13, the model using cumulative growth (second column) refers to the results from Table 14, the model with yearly growth (third column) refers to results from Table 15.

of investment per worker (the largest correlate of productivity, with a coefficient of 0.505), we see that the coefficient of job satisfaction is 4.5 per cent the size of the coefficient of investment per worker. This can be regarded as a small contribution. However, it is nearly half the size of wages (0.056). Moreover, this is the worst case we found: if we consider job quality, its coefficient (0.079) is 16 per cent the size of investment per worker (0.496). These percentages are larger when we consider the models in growth terms. For instance, the share of people satisfied with their job is 62 per cent the size of the yearly growth rate of investment per worker (see the coefficients in Table 14 in Appendix C). Such percentage jumps to 98 per cent when we consider average job satisfaction.

Table 6 shows the size of our measures of worker well-being as a share of the coefficient of investment per worker for each model considered. In sum, this evidence suggests that the size of the effect of worker well-being is comparable to one of the most important predictors of labour productivity, and in some cases it is larger than the effect of wages.

Discussion and Conclusions

The review of the literature highlighted two main obstacles to studies of the link between worker well-being and economic outcomes. First, observing jointly job satisfaction and sound measures of economic performance in representative datasets is difficult. The only study that observes both variables in a representative dataset is Bryson *et al.* (2017), at the expense, however, of having to use self-reported measures of firm performances. Second, the bulk of the evidence reports statistical correlations, rather than a "causal" effect. The relationship between worker well-being and economic outcomes, however, could suffer from an endogeneity bias stemming from reverse causality, or the presence of omitted/unobservable variables.

The only study based on data from representative surveys which addresses reverse causality is Bockerman and Ilmakunnas (2012). These authors instrument job satisfaction with satisfaction with housing, and conclude that the effect of job satisfaction on labour productivity is free from endogeneity bias. This evidence, however, is limited to one country, and is for the period 1996–2001. Here, we address the first of these issues through the use of a combined dataset.

This study provides evidence on the economic consequences of well-being in the workplace, by analysing a novel combined dataset at the industry level. To the best of our knowledge, we are the first to carry out this exercise. The dataset is built by matching two waves of the European Working Conditions Survey with information on the business economy from Eurostat's Structural Business Statistics. Among the different measures of economic outcomes considered in the literature, the use of SBS data allows us to include in the study an official measure of labour productivity, an important variable for decision makers.

The empirical results provide evidence that there is a statistically significant link between worker well-being and labour productivity in industries. We estimate regressions of labour productivity on two measures of worker well-being, namely job quality — an index summarizing various dimensions of working conditions — and job satisfaction, and various controls. The results vary depending on the measure of worker well-being employed and on model specification. For the model in levels, the effects of both measures are positive, statistically significant, and of similar magnitude. Job satisfaction also correlates significantly with future productivity growth. We also gauge the economic significance of results, by comparing the size of coefficients to those of economic variables in the dataset. Data limitations, however, do not allow us to correct for the possible presence of endogeneity bias, stemming from reverse causality or omitted variables. We mitigate this risk by estimating a model in growth rates, and by including as many controls as possible, including industry average wage levels.

The value added of this article can be summarized follows: 1) a novel matched dataset based on representative surveys; 2) a composite indicator of job quality based on the EWCS, a very rich source of information on workers' conditions; 3) evidence that job satisfaction and job quality predict productivity level, and that job satisfaction predicts productivity growth, at the aggregate-industry level.

The study has several limitations which one should keep in mind when interpreting results. There are data limitations. First, the dataset coverage is limited by the Structural Business Statistics. The SBS does not include economic activities which might account for large shares of certain economies in the sample, such as those countries that are service-intensive, or in which public administrations and non-market services are very large. The SBS, however, is the most widely used dataset in the analysis of business sector productivity performances. Indeed, the analysis of the relationship between productivity and worker well-being would be limited by the difficulties of measuring productivity for the industries excluded from the SBS. It is well known that the extension of the concept and measurement of productivity to activities such as non-market and financial services is difficult, if possible at all. Second, sample sizes for the EWCS can be severely restricted at the industry level.

A further issue concerns the measure of job quality adopted in the article. This broadly follows the relevant dimensions indicated by the UN framework, partly departing from it due to data availability issues. The literature lacks consensus on a definition of multidimensional job quality index and implementations vary. Thus, a further limitation is that it is difficult to compare results from this article to other studies in the literature, due to the varied definitions of worker well-being adopted in the literature. Limitations also include the inability to identify causal effects, as discussed above. Moreover, the issue of costs and returns on investments in worker well-being for firms would merit further investigation. To do this, however, one would have to resort to firm-level data which are currently not available.

Despite its limitations, we believe this study contributes to the literature on economic outcomes of worker well-being, and to building a body of evidence based on the relationship between well-being in the working place and economic performance. The results of this study are relevant for managers and policy makers alike as policies that foster worker well-being consequently can contribute to productivity growth. Well-being and economic efficiency (productivity) are often perceived as competing objectives. We show instead that worker well-being has positive impacts on industry-wide productivity. Economic development and well-being do not need to be alternatives; they can reinforce each other.

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A The job quality index

The job quality index used in this analysis has been compiled using data from the last two waves of the European Working Conditions Survey administered by Eurofound. The index consists of respondents' answers to questions concerning six dimensions of job quality: income and benefits, working time and work-life balance, social dialogue, skills development and training, and safety and ethics. The dimensions have been selected based on the framework outlined in UNECE (2015). Compared to the UN framework, we dropped two dimensions due to data availability, namely relationship and work motivation and security of employment. We did add a stress dimension, to capture mental well-being. Note that, while the choice of the dimension is inspired on the UN framework, the computation of individuals and aggregate indices had to be adapted to the information provided by the EWCS. Essentially, this has been done by assigning scores to mainly evaluative answers.

The index was built as follows. Firstly, we selected the questions conveying the relevant information to assess the six dimensions cited above. Then, we built individual scores, by summing the scores "earned" by respondents for each of the dimensions. The scores range from 0 to 2, from lowest satisfaction to highest satisfaction. As a result, the individual job quality index ranges between 0 and 12, where 0 indicates the lowest job quality and 12 the highest. Finally, the aggregate job quality index at industry-country level is compiled by averaging the individual scores.

What follows provide additional details on the construction of the scores for each component of the job quality index. (We refer to the questionnaire of the 2010 wave.)

- Income and benefits. This dimension provides information on overall earnings composition and satisfaction with salary/pay. Respondents indicate whether earnings from their main job include additional sources than their basic salary, and whether they are satisfied with their income by rating the statement "I am well paid for the work I do". Answers to the latter question range from 1 (strongly disagree) to 5 (strongly agree). Here, we assign a score of one to the payment of at least two types of the benefits indicated, and to a score of 5 in the question on income. Information on benefits and income are derived, respectively, from questions EF7 and 77.[16]

[16]Here, we have considered as benefits both extra payments and benefits in kind as described in the

- Working time and work-life balance. Work-life balance is evaluated based on answers to questions on whether working hours fit family and social commitments, on the presence of flexible arrangements, and on whether workers work during their free time to meet demands. For this dimension, we use questions 41, 42, 43 to assess life-work balance, and 51F and 51G to assess quality of the working time. Each earns a score of one if respondents choose the two most favourable categories. (For example, 51F produces a score of one if respondents indicate that they can take a break if they wish so at all times or most of the time.) The overall scores obtained range from 0 and 5. These are converted in the 0-2 scale by assigning values of 1 and 2 to, respectively, final scores of 3, 4 and 5.

- Safety and ethics. This dimension summarises information on the following aspects: discrimination, safety, and health and safety. the discrimination score is based on question 65. Question 70 is used to assess safety, e.g. whether the respondent has been the subject of abuse and/or threatening or humiliating behaviour. Health and safety has been assessed using question 23, which enquiries about exposures to high temperatures, fumes, dangerous or infectious substances, etc., and question 67, which asks a self-evaluation of whether work affects health.

- Social dialogue. Scores are based on questions 63 and 64.

- Skills development and training. Scores are based on answers to questions 61A and 61C.

- Stress. Questions 45A and 45B provide an objective measure of stress. Question 51N is a subjective measure.

EWCS questionnaire, rather than the sick and paid leave payments described in the UN framework, to reflect the institutional context.

B Additional regression results

Tables in this section presents results of the regressions of labour productivity (in levels and growth rates) on job quality and job satisfaction when control variables are incrementally introduced in the empirical model.

Table 7: Regression of labour productivity on job satisfaction (levels)

	Dependent variable:							
	Labour productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
job satisfaction	0.197***	0.198***	0.122***	0.131***	0.134***	0.057***	0.056***	0.053***
	(0.032)	(0.033)	(0.023)	(0.027)	(0.029)	(0.006)	(0.006)	(0.005)
age		0.003***	0.006***	0.006***	0.004***	0.001***	0.001***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education			0.345***	0.317***	0.281***	0.290***	0.287***	0.276***
			(0.032)	(0.030)	(0.026)	(0.032)	(0.032)	(0.029)
large firms				0.340***	0.293***	0.101***	0.100***	0.110***
				(0.051)	(0.053)	(0.014)	(0.014)	(0.017)
employment share					−4.300***	−2.363***	−2.356***	−2.488***
					(0.316)	(0.077)	(0.077)	(0.113)
investment p.w.						0.334***	0.334***	0.336***
						(0.007)	(0.007)	(0.006)
wage							0.000***	0.000***
							(0.000)	(0.000)
sector: construction								0.005
								(0.016)
sector: services								0.032***
								(0.009)
Country dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,188	2,188	2,188	2,188	2,188	2,188	2,188	2,188
R^2	0.576	0.577	0.600	0.609	0.624	0.830	0.830	0.831
Adjusted R^2	0.570	0.571	0.594	0.603	0.618	0.827	0.828	0.828

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

Table 8: Regression of labour productivity on job quality (levels)

	Dependent variable:							
	Labour productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
job quality	0.116^{***}	0.116^{***}	0.092^{***}	0.086^{***}	0.082^{***}	0.047^{***}	0.047^{***}	0.047^{***}
	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)
age		0.002^{***}	0.005^{***}	0.004^{***}	0.003^{***}	0.001^{***}	0.000^{***}	0.001^{***}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education			0.302^{***}	0.284^{***}	0.254^{***}	0.269^{***}	0.267^{***}	0.259^{***}
			(0.028)	(0.025)	(0.024)	(0.035)	(0.034)	(0.032)
large firms				0.291^{***}	0.248^{***}	0.079^{***}	0.078^{***}	0.087^{***}
				(0.049)	(0.050)	(0.015)	(0.015)	(0.018)
employment share					-3.994^{***}	-2.230^{***}	-2.224^{***}	-2.343^{***}
					(0.263)	(0.036)	(0.034)	(0.078)
investment p.w.						0.329^{***}	0.328^{***}	0.330^{***}
						(0.005)	(0.005)	(0.004)
wage							0.000^{***}	0.000^{***}
							(0.000)	(0.000)
sector: construction								0.027^{*}
								(0.014)
sector: services								0.025^{***}
								(0.009)
Country dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,165	2,165	2,165	2,165	2,165	2,165	2,165	2,165
R^2	0.599	0.599	0.616	0.623	0.636	0.834	0.834	0.835
Adjusted R^2	0.593	0.593	0.611	0.617	0.630	0.832	0.832	0.832

Note: *p$<$0.1; **p$<$0.05; ***p$<$0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

Table 9: Regression of labour productivity on job satisfaction (cumulative growth)

	Dependent variable:									
	Labour productivity growth									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
job satisfaction	0.051^{***}	0.070^{***}	0.070^{***}	0.062^{***}	0.061^{***}	0.061^{***}	0.062^{***}	0.062^{***}	0.061^{***}	0.059^{***}
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
labour prod. (t_0)		-0.092^{***}	-0.092^{***}	-0.099^{***}	-0.097^{***}	-0.100^{***}	-0.101^{***}	-0.096^{***}	-0.098^{***}	-0.095^{***}
		(0.018)	(0.018)	(0.017)	(0.015)	(0.015)	(0.015)	(0.017)	(0.017)	(0.015)
age			0.000	0.001^{**}	0.001^{**}	0.000^{*}	0.000	0.000^{**}	0.000^{*}	0.001
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education				0.044^{***}	0.045^{***}	0.044^{***}	0.045^{***}	0.045^{***}	0.043^{***}	0.032^{**}
				(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.016)
large firms					-0.021	-0.023	-0.024	-0.026	-0.027	-0.016
					(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.015)
empl. share						-0.246^{***}	-0.404^{***}	-0.395^{***}	-0.387^{***}	-0.544^{***}
						(0.016)	(0.059)	(0.052)	(0.045)	(0.201)
Δ empl. share							-2.835^{***}	-2.915^{***}	-2.874^{***}	-3.204^{***}
							(0.690)	(0.783)	(0.817)	(0.403)
Δ invest. p.w.								0.067^{***}	0.066^{***}	0.067^{***}
								(0.009)	(0.009)	(0.010)
wage									0.010^{***}	0.011^{***}
									(0.003)	(0.004)
sector: construction										0.021^{***}
										(0.001)
sector: services										0.031
										(0.029)
Country dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,127	2,127	2,127	2,127	2,127	2,127	2,127	2,127	2,127	2,127
R^2	0.109	0.158	0.158	0.163	0.163	0.164	0.166	0.186	0.187	0.190
Adjusted R^2	0.096	0.146	0.145	0.150	0.150	0.150	0.152	0.172	0.172	0.174

Note: *p$<$0.1; **p$<$0.05; ***p$<$0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

Table 10: Regression of labour productivity on job quality (cumulative growth)

	Dependent variable:									
	Labour productivity growth									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
job quality	-0.001	0.010^{***}	0.010^{***}	0.007^{**}	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.006^{*}
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
labour prod. (t_0)		-0.090^{***}	-0.090^{***}	-0.097^{***}	-0.095^{***}	-0.097^{***}	-0.099^{***}	-0.094^{***}	-0.096^{***}	-0.093^{***}
		(0.015)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.015)	(0.016)	(0.013)
age			-0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education				0.050^{***}	0.051^{***}	0.050^{***}	0.052^{***}	0.052^{***}	0.048^{***}	0.037^{***}
				(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.012)
large firms					-0.029	-0.031	-0.032	-0.034	-0.036	-0.023
					(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.017)
empl. share						-0.214^{***}	-0.382^{***}	-0.377^{***}	-0.364^{***}	-0.537^{**}
						(0.029)	(0.081)	(0.077)	(0.065)	(0.216)
Δ empl. share							-3.013^{***}	-3.100^{***}	-3.035^{***}	-3.394^{***}
							(0.637)	(0.725)	(0.788)	(0.381)
Δ invest. p.w.								0.067^{***}	0.066^{***}	0.067^{***}
								(0.008)	(0.008)	(0.009)
wage									0.015^{**}	0.015^{**}
									(0.006)	(0.007)
sector: construction										0.024^{***}
										(0.002)
sector: services										0.035
										(0.029)
Country dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,104	2,104	2,104	2,104	2,104	2,104	2,104	2,104	2,104	2,104
R^2	0.104	0.150	0.150	0.156	0.157	0.158	0.160	0.181	0.182	0.186
Adjusted R^2	0.092	0.138	0.137	0.143	0.144	0.144	0.146	0.167	0.167	0.170

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

Table 11: Regression of labour productivity on job satisfaction (average yearly growth)

	Dependent variable:									
	Labour productivity growth									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
job satisfaction	0.027^{***}	0.034^{***}	0.034^{***}	0.030^{***}	0.030^{***}	0.030^{***}	0.030^{***}	0.030^{***}	0.030^{***}	0.029^{***}
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)
labour prod. (t_0)		-0.037^{***}	-0.037^{***}	-0.041^{***}	-0.041^{***}	-0.043^{***}	-0.043^{***}	-0.042^{***}	-0.043^{***}	-0.042^{***}
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
age			-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education				0.022^{***}	0.022^{***}	0.021^{***}	0.022^{***}	0.022^{***}	0.020^{***}	0.015^{***}
				(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.004)
large firms					0.001	-0.001	-0.001	-0.001	-0.003	0.002
					(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.004)
empl. share						-0.194^{***}	-0.249^{***}	-0.221^{***}	-0.215^{***}	-0.283^{**}
						(0.045)	(0.069)	(0.066)	(0.059)	(0.116)
Δ empl. share							-3.087^{***}	-3.133^{***}	-3.030^{***}	-3.488^{***}
							(0.278)	(0.351)	(0.456)	(0.033)
Δ invest. p.w.								0.047^{***}	0.047^{***}	0.047^{***}
								(0.004)	(0.004)	(0.004)
wage									0.009^{**}	0.009^{*}
									(0.004)	(0.005)
sector: construction										0.008^{***}
										(0.002)
sector: services										0.014
										(0.011)
Country dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,056	2,056	2,056	2,056	2,056	2,056	2,056	2,056	2,056	2,056
R^2	0.084	0.131	0.131	0.138	0.138	0.140	0.142	0.156	0.157	0.161
Adjusted R^2	0.070	0.118	0.117	0.124	0.124	0.126	0.127	0.141	0.142	0.144

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

Table 12: Regression of labour productivity on job quality (average yearly growth)

	Dependent variable:									
	Labour productivity growth									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
job quality	0.001	0.005***	0.005***	0.003***	0.003***	0.003***	0.003***	0.004***	0.003***	0.003**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
labour prod. (t_0)		−0.037***	−0.037***	−0.041***	−0.041***	−0.042***	−0.043***	−0.042***	−0.043***	−0.042***
		(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
age			−0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
education				0.026***	0.026***	0.025***	0.026***	0.026***	0.024***	0.018***
				(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.001)
large firms					−0.003	−0.004	−0.005	−0.005	−0.007	−0.001
					(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.004)
empl. share						−0.177***	−0.236***	−0.211***	−0.203***	−0.278**
						(0.049)	(0.077)	(0.076)	(0.067)	(0.124)
Δ empl. share							−3.365***	−3.428***	−3.284***	−3.782***
							(0.143)	(0.207)	(0.360)	(0.128)
Δ invest. p.w.								0.046***	0.045***	0.045***
								(0.005)	(0.004)	(0.005)
wage									0.011*	0.011*
									(0.006)	(0.006)
sector: construction										0.009***
										(0.003)
sector: services										0.015
										(0.011)
Country dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,035	2,035	2,035	2,035	2,035	2,035	2,035	2,035	2,035	2,035
R^2	0.076	0.121	0.121	0.131	0.131	0.133	0.134	0.148	0.150	0.154
Adjusted R^2	0.063	0.108	0.107	0.117	0.116	0.118	0.119	0.132	0.134	0.137

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets.

C Regressions with standardized variables

Table 13: Regression of labour productivity on job quality and job satisfaction using standardized variables (levels).

	Dependent variable:		
	Labour productivity		
	(1)	(2)	(3)
job quality	0.079***		
	(0.000)		
job satisfaction		0.023***	
		(0.003)	
satisfied (share)			0.019***
			(0.001)
age	0.002	0.010***	0.010***
	(0.003)	(0.002)	(0.002)
education	0.129***	0.138***	0.140***
	(0.014)	(0.014)	(0.015)
large firms	0.024***	0.030***	0.030***
	(0.005)	(0.005)	(0.005)
employment share	−0.059***	−0.063***	−0.063***
	(0.002)	(0.003)	(0.003)
investment p.w.	0.496***	0.505***	0.506***
	(0.006)	(0.009)	(0.009)
wage	0.055***	0.056***	0.057***
	(0.009)	(0.002)	(0.002)
sector: construction	0.015	−0.009	−0.010
	(0.015)	(0.018)	(0.018)
sector: services	0.030***	0.039***	0.041***
	(0.011)	(0.012)	(0.012)
Country dummies	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*
Observations	2,165	2,188	2,188
R^2	0.836	0.832	0.832
Adjusted R^2	0.833	0.829	0.829

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets. Variables have been standardized for comparability of the coefficients.

Table 14: Regression of labour productivity on job quality and job satisfaction using standardized variables (cumulative growth).

	Dependent variable:		
	Labour productivity growth		
	(1)	(2)	(3)
job quality	0.033*		
	(0.019)		
job satisfaction		0.090***	
		(0.004)	
satisfied (share)			0.068***
			(0.007)
labour prod. (t_0)	−0.285***	−0.291***	−0.289***
	(0.041)	(0.045)	(0.048)
age	0.012	0.013	0.013
	(0.012)	(0.009)	(0.010)
education	0.061***	0.053**	0.059**
	(0.019)	(0.026)	(0.028)
large firms	−0.022	−0.015	−0.017
	(0.016)	(0.014)	(0.014)
empl. share	−0.043**	−0.044***	−0.044***
	(0.017)	(0.016)	(0.017)
Δ empl. share	−0.040***	−0.038***	−0.038***
	(0.005)	(0.005)	(0.004)
Δ invest. p.w.	0.146***	0.146***	0.146***
	(0.019)	(0.022)	(0.023)
wage	0.032**	0.022***	0.026***
	(0.015)	(0.008)	(0.009)
sector: construction	0.081***	0.073***	0.069***
	(0.008)	(0.003)	(0.003)
sector: services	0.118	0.107	0.113
	(0.098)	(0.100)	(0.099)
Country dummies	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	2,104	2,127	2,127
R^2	0.186	0.190	0.187
Adjusted R^2	0.170	0.174	0.172

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets. Variables have been standardized for comparability of the coefficients.

Table 15: Regression of labour productivity on job quality and job satisfaction using standardized variables (average yearly growth).

	Dependent variable:		
	Labour productivity growth		
	(1)	(2)	(3)
job quality	0.036**		
	(0.014)		
job satisfaction		0.099***	
		(0.011)	
satisfied (share)			0.062***
			(0.010)
labour prod. (t_0)	−0.291***	−0.292***	−0.288***
	(0.063)	(0.065)	(0.067)
age	0.009	0.012	0.012
	(0.017)	(0.016)	(0.017)
education	0.069***	0.057***	0.065***
	(0.004)	(0.014)	(0.013)
large firms	−0.002	0.004	0.002
	(0.009)	(0.009)	(0.009)
empl. share	−0.051**	−0.052**	−0.052**
	(0.023)	(0.021)	(0.022)
Δ empl. share	−0.034***	−0.031***	−0.032***
	(0.001)	(0.000)	(0.001)
Δ invest. p.w.	0.098***	0.101***	0.100***
	(0.010)	(0.009)	(0.009)
wage	0.054*	0.043*	0.049*
	(0.030)	(0.023)	(0.025)
sector: construction	0.070***	0.062***	0.058***
	(0.025)	(0.017)	(0.018)
sector: services	0.118	0.107	0.115
	(0.084)	(0.082)	(0.083)
Country dummies	*Yes*	*Yes*	*Yes*
Year dummy	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*
Observations	2,035	2,056	2,056
R^2	0.154	0.161	0.155
Adjusted R^2	0.137	0.144	0.139

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by year. Standard errors are reported in brackets. Variables have been standardized for comparability of the coefficients.

D Country and country codes

CODE	COUNTRY
AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
EL	Greece
ES	Spain
FI	Finland
FR	France
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxembourg
LV	Latvia
MK	FYROM-Macedonia
MT	Malta
NL	Netherlands
NO	Norway
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia
UK	United Kingdom

From Economic Productivity to Productive Well-Being: the Role of Life Satisfaction and Adjusted Net Savings

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Abstract

Productivity - a driver of economic growth - is not necessarily compatible with societal well-being, nor environmental sustainability. Various authors contributed frameworks to incorporate environmental issues in the measurement of productivity, or studied the role of subjective well-being for productivity. However, studies proposing ways to account for both subjective well-being and sustainability in productivity measurement are scarce. We examine whether and to what extent it is possible to include subjective well-being and sustainability measures among the inputs and/or outputs of a traditional productivity framework. Specifically, we adopt a data-driven approach to test whether subjective well-being and adjusted net savings meaningfully contribute to computing a productivity-like indicator. We apply Data Envelopment Analysis (DEA) to European data from 2005 to 2018. We find that including subjective well-being among the inputs and the outputs of production meaningfully contributes to the measurement of total factor productivity.

Productivity, i.e. the ratio of goods and services produced (outputs) divided by resources used in the production process (inputs), is usually considered a core indicator of economic performance, and a proxy of improving living conditions when it increases. Productivity, which in this article refers to total factor productivity, pro-

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vides a measure of how efficiently a production process uses scarce resources and develops new technologies. Enhancing productivity means making better use of available resources, and mobilizing new technological potential to provide more or better goods and services to the society. Hence, productivity is often regarded as the ultimate engine of growth, and a measure for technical progress. In fact, it is usually held that expanding the set of goods and services available for consumption allows people to satisfy a growing number of needs, thus improving their living conditions (Solow, 1956). However, the efficient mobilization of resources for economic output and technological change does not imply societal well-being, nor environmental sustainability. These aspects are important and, in case of sustainability, urgent for modern societies.

Numerous authors warned that growing productivity does not necessarily translate into improved living conditions or environmental quality. For instance, waste and pollution are two negative sides of production processes. Moreover, since the COP 21 meeting held in Paris in 2015 — where most countries commited to achieve sustainability goals — sustainability can be regarded as a desirable output of economic activity, and integrated in productivity indicators. We define sustainability as the "capacity to maintain or improve the state and availability of desirable materials or conditions over the long term", as proposed by Harrington (2016). Accordingly, many authors proposed frameworks for efficiency/productivity indicators to account, for instance, for pollution as an undesirable by-product of production (an early attempt in this regard is Pittman (1983)). Zhou *et al.* (2018) provide a survey of some frameworks used to introduce sustainability in productivity measurement. A recent example is DiMaria (2019), who included adjusted net savings (ANS), an indicator of weak sustainability and welfare, in the set of desirable outputs.[2] Conversely, studies proposing ways to account for both subjective well-being and sustainability in productivity measurement are scarce.

We contribute to this literature by applying a data-driven approach to establish whether and to what extent it is possible to extend the inputs and outputs of a traditional productivity framework to include subjective well-being and sustainability measures. We expect subjective well-being to be an input because of its positive association with productivity documented in previous literature (see, for instance, Bockerman and Ilmakunnas, 2012 and Bryson *et al.*, 2017). Additionally, we check whether subjective well-being and adjusted net savings can be outputs. If the production process delivers goods and services to satisfy people's needs, then we should expect a positive contribution of production to subjective well-being. Similarly, if the production process is environmentally sustainable, then adjusted net savings should be one of its outcomes. We posit that it is important to evaluate

2 ANS is an indicator of sustainability that translates sustainability and welfare gains into a composite indicator, as explained in Hamilton and Clemens (1999).

how well economies deliver goods and services given the resources they use. At the same time, we seek to go "beyond GDP", and to include measures of subjective well-being and environmental quality among economic indices of performance of "inclusive growth". In the framework of productivity measurement this means classifying subjective well-being either as an input, an output or both; it also implies checking whether sustainability is a desirable by-product of economic production.

This research is relevant because, if confirmed, it would suggest the existence of a virtuous cycle where investing in life satisfaction, by prioritizing social relations and environmental quality, would contribute to economic productivity (Sarracino, 2019).[3] However, the resulting economic growth would be *qualitatively* different from the traditional one, and arguably more socially and environmentally sustainable (Sarracino and O'Connor, 2021b).

The analysis builds on a procedure for optimal selection proposed by Toloo *et al.* (2021). The procedure uses linear programming to compute optimal weights for the aggregation of outputs and inputs, including subjective well-being and adjusted net savings. The test procedure allows us to tell whether a variable meaningfully contributes to a productivity indicator by checking the magnitude of weights: if a variable attracts a weight equal to zero, then it can not be considered as relevant for the productivity indicator. We find that life satisfaction should be regarded as an input for some countries, and as an output for others, whereas adjusted net savings do not appear to be a relevant output to benchmark countries. These results suggest that including life satisfaction among the inputs and the outputs of productivity could meaningfully contribute to the definition of a measure of economic performance that accounts for the quality of growth.

The article is structured as follows. The first major section summarizes the relevant literature and our contribution. Section 2 describes the method and data used in our analysis. Section 3 reports our findings: we first present the result of our optimal selection model; we then offer a classification of the considered countries based on classification tree; we finally use our results to compute a well-being adjusted Malmquist index of productivity. The last section summarizes our findings and discusses limits and advantages of the proposed measure of productivity.

Literature Review

In recent years, the subjective well-being literature shed new light on the ability of economic growth to deliver better lives (Easterlin, 2017; Helliwell and Aknin, 2018; Sarracino and O'Connor, 2021a). Empirical evidence provided a nuanced view about the role of economic growth for subjective well-being, and suggested that quality of economic growth matters (Helliwell,

3 A production process that transforms capital, labour and life satisfaction (as a multiplier of labour) in GDP per capita and life satisfaction can be regarded as socially productive, in the sense that it is well organized to deliver socially desirable outputs. This interpretation has far reaching implications that go beyond the scope of current work.

2016): if economic growth is compatible with a cohesive and inclusive society, it is reasonable to expect that well-being will improve (Easterlin, 2013; Oishi and Kesebir, 2015; Mikucka *et al.*, 2017). In contrast, if economic growth leads to loneliness and inequality, subjective well-being may arguably decline. This is consistent with the observation that the link between quality of life and affluence is, at best, weak (Lovell *et al.*, 1994; Beja, 2014).

Subjective well-being is the result of the presence of positive emotions, the absence of negative ones and satisfaction with life as a whole (Diener *et al.*, 1999). In practice, however, subjective well-being is frequently monitored through one of its components: life satisfaction, which is regarded as an evaluative and cognitive measure of subjective well-being. This individual level information is usually collected in the course of surveys, when respondents are asked questions such as: "All things considered, how satisfied are you with your life as a whole these days?" (Van Praag *et al.*, 2003). Answers usually range on a scale where low/high scores indicate total dissatisfaction. Various tests, from different disciplines, provided evidence supporting the validity and reliability of life satisfaction as a measure of how people fare with their lives (Blanchflower and Oswald, 2004; Van Reekum *et al.*, 2007; Schimmack *et al.*, 2010; Kahneman and Krueger, 2006; Layard, 2005).

The relationship between productivity and measures of well-being received particular attention in the economic literature. For instance, (Edmans, 2011) documents that companies in which employee satisfaction is higher receive higher long-run stock returns. Studies on subjective well-being on the workplace using matched employer-employee panel data report a positive association with various measures of productivity in Finland (Bockerman and Ilmakunnas, 2012), and in Great Britain (Bryson *et al.*, 2017).[4] The results hold both in levels and first differences. Furthermore, Oswald *et al.* (2015) showed that happiness increases productivity in three different experimental settings. According to the authors, productivity gains are due to the fact that satisfied people are more committed to their tasks than others.

However, few studies have tried to merge productivity and subjective well-being into one composite indicator of economic performance. For instance, DiMaria *et al.* (2020) evaluated whether life satisfaction (as an input or an output) contributed to efficiency following a procedure proposed by Pastor *et al.* (2002), using four waves of the European Social Survey (2004, 2006, 2008, and 2010). Results indicate that for some countries, mainly in Western Europe, the stock of employees satisfied with their lives should be regarded as an input, and therefore it belongs to the denominator of productivity computations. For Eastern European countries the stock of satisfied people is more likely to be an output, and therefore it belongs to the numerator of

4 Bockerman and Ilmakunnas (2012) consider the following measures of productivity: value added per hour worked, total factor productivity, and turnover per employee; Bryson *et al.* (2017) use financial performance, labour productivity, quality of product or service, and a performance scale summing up the three measures.

productivity indexes.[5]

The starting point of our analysis is the usual definition of productivity indicators as outputs divided by inputs, where outputs are GDP (to account for economic performance), life satisfaction and adjusted net saving (as an indicator of sustainability) and inputs are labour, physical capital and life satisfaction. We use data envelopment analysis (DEA), a linear programming technique, to compute optimal weights to aggregate inputs and outputs to derive productivity indicators. Since the seminal paper by Charnes *et al.* (1978), the number of publications using DEA to assess efficiency/productivity has been on the rise. Emrouznejad and Yang (2018) counted more than 10,000 publications using DEA between 1978 and 2016. Sickles and Zelenyuk (2019) provide a comprehensive treatment of both economic theory of productivity and its measurement using DEA.

The evolution of the DEA framework can be divided into two periods (Liu *et al.*, 2013). The first one, up to 1999, is mainly driven by methodological development. A notable example in this regard is the research on returns to scale (RTS) to better characterize the production process (Seiford and Zhu, 1999). A second example is the decomposition and interpretation of DEA productivity indicators in terms of efficiency change and technical change (Arcelus and Arozena, 1999). Another important contribution belonging to the early period of DEA, and related to the present work, is the introduction of undesirable output (Fare *et al.*, 1989), such as pollution, and the possibility for outputs/inputs to take negative values (see for example Cooper *et al.* (1999a)).

The second period, starting after 1999, sees a new set of methodological developments about inference for certain measures of point efficiency by using appropriate bootstrap techniques.[6] Simar and Zelenyuk (2020) provide a recent groundbreaking study on inference and DEA. This second period is in particular noticeable for the investigation of productivity in specific industries, such as banks, health care, agriculture and farm, transportation, and education.

Particularly relevant for our work is the use of DEA in sustainability studies. This line of research started to grow after 2008 thanks to methodological improvements of the early 2000s, namely the introduction of concepts such as bad output, and the possibility to deal with negative values (Zhou *et al.*, 2018). In particular, the introduction of sustainability issues in DEA empirical analysis marks an important theoretical development, as it seeks to include qualitative aspects in the computation of productivity. It is also worth noticing that — independently from the framework, hy-

5 An alternative specification of our model would be to use subjective well-being as a multiplier of labour, similarly to human capital. However, the results from the new specification would indicate whether labour or labour multiplied by subjective well-being should be regarded as input. In the present model we require labour to be always an input of productivity, and we check whether - in addition - the stock of employees satisfied with their lives contributes to the measure of productivity.

6 See Kneip *et al.* (2008), Kneip *et al.* (2011), and Simar and Wilson (2011)), or to compare groups mean (see, for instance, Kneip *et al.* (2015), Kneip *et al.* (2016), or Kneip *et al.* (2021) for Malmquist indexes

potheses, decomposition of productivity indicators, and topics under scrutiny — these studies have a point in common: the preliminary selection of inputs and outputs. In fact, the vast majority of studies adopts an a priori set of inputs and outputs based on heuristic decision-making or expert judgement. However, some authors introduced data-driven methods exploiting DEA models to select the set of relevant inputs and outputs based on optimality criteria (see, for instance, the recent works by Peyrache *et al.* (2020) and Toloo *et al.* (2021).

This research sits at the intersection of these developments. From a qualitative point of view, we investigate the suitability of accounting for life satisfaction and sustainability in the assessment of the performance of economies. From a technical point of view, we build on optimal selection methods to choose relevant inputs and outputs. In particular, we use a test procedure developed by Toloo *et al.* (2021).

Method and Data

The variable selection method

Productivity is commonly defined as the ratio of goods and services produced (output volume) by the quantity of resources used in the production processes (volume of inputs). Then,

$$\text{Productivity} = \frac{\text{output volume}}{\text{volume of inputs}} = \frac{\sum_i r_i y_i}{\sum_j w_j x_j}. \quad (1)$$

The $y_i, i = 1, ..., s$ are the outputs, in cross country analysis it is usually total GDP in constant terms, and the $x_j, j = 1, ..., m$ are inputs — at minimum physical capital K (machinery and equipments), and labour L (workers or hours worked). Productivity measures how efficiently inputs are used in the production process as well as technological developments. The ratio increases when output volume increases for a given value of inputs. Similarly, the ratio increases if the volume of inputs reduces for a given value of output volume. In our case, we add life satisfaction or Well-Being Output (WBO), and/or adjusted net savings (ANS) to the set of outputs; and life satisfaction or Well-Being Input (WBI) to the list of inputs. Our starting point is:

$$\text{Productivity} = \frac{r_{GDP}GDP + r_{WBO}WBO + r_{ANS}ANS}{w_K K + w_L L + w_{WBI}WBI}. \quad (2)$$

The problem with equation (2) is the computation of weights (r_{GDP}, r_{WBO}, r_{ANS}, w_K, w_L, w_{WBI}). One could use prices or income shares as weights (OECD, 2001), but prices/income shares for life satisfaction and adjusted net saving do not exist. This problem is not new and motivates the seminal work by Charnes *et al.* (1978). The authors overcome the issue by developing a linear program that can be solved using DEA. This technique provides optimal weights to aggregate outputs and inputs to obtain a productivity indicator.

When computing optimal weights, one of the two modelling hypotheses have to be made: either we consider that countries manage to reduce inputs to increase productivity for a given level of outputs (input approach). Or, we assume that for a given level of inputs countries try to increase the amount of outputs produced (output approach). In this article, we follow the output-oriented model. The reason is that we are interested in assessing productivity as the ability to increase outputs *given* the level of inputs used. In other words, we do not consider the hypothesis that a country is willing to decrease the use of inputs, in particular of life satisfaction, for a given level of outputs (as it is assumed in input-oriented models). This amounts to assuming that countries seek to increase sustainability and life satisfaction.

However, we recall that, by definition, inputs are resources which are under the management's control. Inputs can be increased or decreased at will: if it is easy to envisage that countries seek to increase life satisfaction, it is not as obvious to imagine a country that deliberately chooses to decrease it. In some circumstances, however, this may be the case. Think, for instance, of the famous quote by Winston Churchill during the Second World War: "I have nothing to offer but blood, toil, tears and sweat". This is an example of a country asking sacrifices to the population during adversities or economic downturns. Arguably, however, this is not often the case. Therefore, we choose the output-oriented approach and we assume that decreasing the use of inputs is not a favoured policy option. The output-oriented model is the following:

$$
\begin{aligned}
&\max_{\lambda_j} \phi_0 \\
&\sum_j \lambda_j K_j \le K_0 \\
&\sum_j \lambda_j L_j \le L_0 \\
&\sum_j \lambda_j WBI_j \le WBI_0 \\
&\sum_j \lambda_j GDP_j \ge \phi_0 GDP_0 \\
&\sum_j \lambda_j WBO_j \ge \phi_0 WBO_0 \\
&\sum_j \lambda_j ANS_j \ge \phi_0 ANS_0 \\
&\lambda_j \ge 0
\end{aligned}
\tag{3}
$$

Online Appendix A shows the steps to go from equation (2) to model (3).[7] This representation is useful to illustrate how we proceed to ascertain whether life satisfaction is an input, output or both, and adjusted net savings belongs to the set of outputs. We adopt the procedure by Toloo *et al.* (2021). Peyrache *et al.* (2020) propose a related approach. We re-write the model (3) as follows:

$$
\begin{aligned}
&\max_{\lambda_j, d_{WBI}, d_{WBO}, d_{ANS}} \phi_0 \\
&\sum_j \lambda_j K_j \le K_0 \\
&\sum_j \lambda_j L_j \le L_0 \\
&\sum_j \lambda_j WBI_j \le WBI_0 + M(1 - d_{WBI})
\end{aligned}
\tag{4}
$$

7 http://www.csls.ca/ipm/43/IPM_43_DiMaria_Appendix.pdf.

$$\sum_j \lambda_j GDP_j \geq \phi_0 GDP_0$$

$$\sum_j \lambda_j WBO_j \geq \phi_0 WBO_0 - M(1 - d_{WBO}) \tag{5}$$

$$\sum_j \lambda_j ANS_j \geq \phi_0 ANS_0 - M(1 - d_{ANS}) \tag{6}$$

$$d_{WBI} + d_{WBO} + d_{ANS} \leq k^{sup} \tag{7}$$

$$d_{WBI} + d_{WBO} + d_{ANS} \geq k_{inf} \tag{8}$$

$$\lambda_j \geq 0, \sum_j \lambda_j = 1, (d_{WBI}, d_{WBO}, d_{ANS}) \in \{0,1\}^3.$$

In this model, M is a large positive number. Assume, for example, that $d_{WBO} = 1$ then constraint (5) becomes $\sum_j \lambda_j WBO_j \geq \phi_0 WBO_0$, WBO contributes to the computation of productivity, and life satisfaction is an output. Conversely, if $d_{WBO} = 0$ the constraint becomes $\sum_j \lambda_j WBO_j \geq \phi_0 WBO_0 - M$. As M is large, then the constraint is never binding ($\phi_0 WBO_0 - M < 0, \forall \phi_0$, M large enough) and life satisfaction does not contribute to productivity assessment. The same reasoning holds for other variables. Trivially, if $d_{WBI} = d_{WBO} = d_{ANS} = 1$ the model is equivalent to model (3).

Another important aspect of the model is the introduction of constraints (7) and (8). If $k_{inf} = 1$ then we impose to select at least one of the extra variables (WBI, WBO or ANS). If $k_{inf} = 1$ and $k^{sup} = 1$ then we want to have only one extra variable selected. If $k_{inf} = 1$ and $k^{sup} = 3$ then we can have from one to three extra variables in the computation of productivity.

In this framework, the status of life satisfaction and adjusted net savings as inputs and/or outputs is country and time specific. In principle, we could impose the set of inputs and/or outputs to be the same for all countries. It would suffice to stack the model across countries and/or time. However, we chose to use a specification that allows the status of life satisfaction and adjusted net savings to change over time and across countries. In other words, our model allows life satisfaction to be an input (output) for all countries at the same time, and/or for all years. The same holds for adjusted net savings. As explained by Toloo *et al.* (2021), the input and output-oriented models can lead to the retention of different variables. Toloo *et al.* (2021) propose a model that integrates both orientations in a single model. Again, we follow the output-oriented approach as we consider the case of decreasing well-being as an input not a policy option.

A second important assumption concerns returns to scale. The model above assumes variable returns to scale, as clarified by the constraint $\sum_j \lambda_j = 1$. However, Toloo *et al.* (2021) documented that the same procedure holds also under the assumption of constant returns to scale (CRS). For our purposes, we assume CRS as it is a good benchmark to assess productivity for countries. In addition, in the case of CRS, productivity measurements yield similar results under the input and the output-oriented models.

A final important point for our work relates to the computation of Malmquist productivity index. Some authors (e.g. Kerstens and Van de Woestyne (2014)) claim that the Malmquist productivity index has no total factor productivity (TFP) interpretation in general, and argue in favor of the Hicks–Moorsteen index. An advantage of choosing CRS is that the Hicks–Moorsteen index collapses to the usual Malmquist index, thus overcoming the disputes over the most appropriate measure of TFP. At worst, CRS model is conventionally regarded as the best discriminating DEA model than a relevant benchmark (Podinovski *et al.*, 2014). Last, in this article, we have opted for DEA but it would have also been possible to use stochastic frontier analysis (SFA). In this case, the idea is to follow a model selection approach between nested models for example in the line of work of Lai and Huang (2010).

Variables used to assess productivity

We retrieve measures of output (GDP) and inputs (capital and labour) from the Penn World Tables, version 10 (Feenstra *et al.*, 2015). The sample includes 23 European countries (Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Lithuania, Luxembourg, Netherlands, Poland, Slovakia, Slovenia, Spain, Sweden, Turkey, United Kingdom).

Adjusted net savings is computed by the World Bank and is defined as the national saving minus fixed capital consumption plus education expenditure minus depletion of natural resources and minus damages from CO2 emissions and particulate emissions. Adjusted net savings is a standard indicator of (weak) sustainability.[8] Our data cover the period from 2005 to 2018 because of data availability for life satisfaction. Moreover, for the sake of simplicity, we select countries for which adjusted net saving is positive.[9]

We draw data on life satisfaction from the Eurobarometer (2005-2018). Eurobarometer is the polling instrument of the European Union, and it is used to regularly monitor the state of public opinion in Europe. It covers issues related to the European Union, as well as attitudes on subjects of a political or social nature.[10] For instance, during the interview, people are asked to reply to the following question: "On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the life you lead?". This is a typical wording used to monitor respondent's satisfaction with life. For the purposes of the present study, we use the share of people, by country and year, declaring to be very satisfied with the life they lead.

A characteristic feature of our work is the simultaneous introduction of life satisfaction in the set of inputs (WBI) and in the set of outputs (WBO) of production. If

8 https://www.un.org/esa/sustdev/natlinfo/indicators/methodology_sheets/econ_development/adjusted_net_saving.pdfpresentstheindicator. Considering ANS instead of CO2, for an analysis of a broader concept of sustainability and not just CO2 damages. In any case, it is also possible to introduce CO2 (only) as a bad output as proposed by Jeon and Sickles (2004).

9 As a remark, adjusted net savings can be negative. In this case a specific DEA model has to be used, for example Cooper *et al.* (1999b). However, the main idea behind the variable selection procedure remains the same.

10 https://europa.eu/eurobarometer/about.

WBI is measured as WBO then we would have a conflict between constraint (4) and (5). We overcome this difficulty thanks to a feature of the Eurobarometer. The survey is usually administered twice per year. For each year, we have two measurements of life satisfaction: one around August, and one in January. This gives us access to two temporally distinct measurements of life satisfaction. Specifically, we measure WBI as the share of people that are very satisfied with their life (as observed in the August surveys) multiplied by hours worked. Thus, WBI is the number of hours worked by the share of very satisfied people. Formally:

$$WBI = (\text{share of people very satisfied with their life}) \cdot \text{hours worked}_t \tag{9}$$

This amounts to treating life satisfaction as a multiplier on the work force: the higher the share of people satisfied with their lives, the larger the positive effect on labour. This modelling approach is similar to the one adopted by Barro and Lee (1994) regarding educational attainment, or by Botev *et al.* (2019) for human capital. Let δ_j be the share of people very satisfied with their life in country j, then the *total employment* input is $(1+\delta_j)\dot{hours}_j = \Omega_j \dot{hours}_j$. The effect of life satisfaction is reflected in the effective labour input as in the model by Lucas (1988). It would have been interesting to use job satisfaction instead but we are constrained by data availability.

As for WBO, we assume that governments, to a certain extent, act as social benevolent planners who foster the production of more goods and services to satisfy a growing set of needs thus, ultimately, improving people's lives. This amounts to assuming that countries seek to maximize the share of the population that is very satisfied with their life. From this point of view we are consistent with the idea of the benevolent social planner in theories of optimal growth model. WBO is based on life satisfaction measured in the month of January of each year, and it is defined as follows:

$$WBO = (\text{share of people very satisfied with their life}) \cdot \text{population}_t \tag{10}$$

we emphasize that WBI and WBO are observed at two different time periods: WBI relates to life satisfaction declared in the month of August at time t and it is multiplied by hours worked; WBO is based on the life satisfaction reported in January at time $t+1$, and it is multiplied by population.[11]

Our hypotheses are:

1. Life satisfaction in productivity measurement is
   (a) an input only: $d_{WBI} = 1$ and $d_{WBO} = 0$ and:
      i. Adjusted net saving is an output $d_{ANS} = 1$ or,

11 Many micro-econometric studies treat subjective well-being measures as cardinal, and some scholars warn that this approach may lead to biased results (Kaiser and Vendrik, 2020). However, this does not apply here. Our analysis is at the country level, and we use the proportion of respondents declaring to be very satisfied with their life by country.

Table 1: Total Factor Productivity by WBI, WBO, and ANS (per cent of times)

country	WBI	WBO	ANS	
Denmark	100	0	0	WBI only
Sweden	100	0	0	
Netherlands	100	0	0	
Ireland	100	0	0	
Poland	100	0	0	
United Kingdom	86	0	14	Mainly WBI
Finland	79	0	21	
Luxembourg	71	29	0	
Cyprus	71	7	21	
Turkey	57	7	36	
Estonia	0	100	0	WBO only
Hungary	0	100	0	
Italy	0	100	0	
France	0	93	7	Mainly WBO
Lithuania	14	86	0	
Czech Republic	0	86	14	
Slovakia	0	64	36	
Austria	0	64	36	
Spain	0	71	29	
Germany	21	43	36	
Croatia	21	36	43	Mainly ANS
Slovenia	21	7	71	
Belgium	14	7	79	

Note: authors' own computations on PWT v.10, and Eurobarometer data. WBI only: Well-being is an input all years, WBO only: Well-being is an output all years, Mainly WBI: Well-being is an input most of the years, Mainly WBO: Well-being is an output most of the years, Mainly ANS: ANS is an output most of the year. The share is computed over the pooled sample of countries-years.

ii. Adjusted net saving is not an output $d_{ANS} = 0$.

(b) an output only: $d_{WBI} = 0$ and $d_{WBO} = 1$ and:

i. Adjusted net saving is an output $d_{ANS} = 1$ or,

ii. Adjusted net saving is not an output $d_{ANS} = 0$.

(c) an input and an output: $d_{WBI} = 1$ and $d_{WBO} = 1$ and:

i. Adjusted net saving is an output $d_{ANS} = 1$ or,

ii. Adjusted net saving is not an output $d_{ANS} = 0$.

(d) not an input and not an output: $d_{WBI} = 0$ and $d_{WBO} = 0$ and:

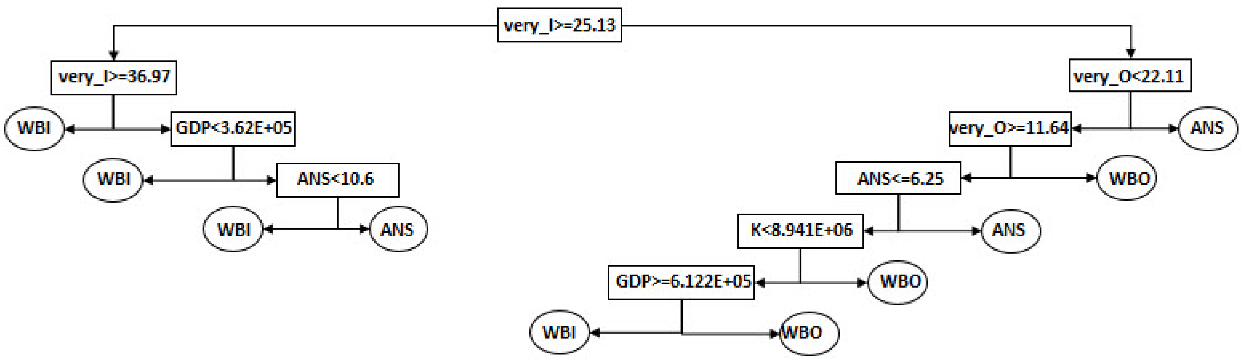
i. Adjusted net saving is an output $d_{ANS} = 1$ or,

ii. Adjusted net saving is not an output $d_{ANS} = 0$.

Results

The results of the optimal selection method indicate that life satisfaction appears either as an input or as an output for almost all countries and all years considered (see Table 1). The countries where life satisfaction is always or mainly an input are the Nordic countries: Denmark, Sweden, Finland; some western countries, such as Luxembourg, Ireland, Netherlands, United Kingdom; and Cyprus, Turkey and Poland. These countries are characterized by high levels of well-being. The countries where life satisfaction is an output are

Figure 1: Segment of a Classification Tree to Group Countries Based on Life Satisfaction (Input and Output) and Adjusted Net Savings.



Note: authors' own computations on PWT v.10, and Eurobarometer data. very_I: share of people very satisfied with their life (mid-year - input) very_O: share of people very satisfied with their life (beginning of year - output) K: capital, ANS: adjusted Net Saving, WBI well-being input, WBO well-being output. Left branch: condition is true. Right branch: condition is false.

Eastern countries, such as Estonia, Hungary, Czech Republic, Slovakia and Lithuania, and some western countries: for example, Germany, Spain and France. OECD (2020) note that these three last countries are among the economies where the majority of the headline indicators composing the OECD Better Life Index index improved. Belgium and Slovenia are the only countries where adjusted net savings appear most of the time as an output. Interestingly, life satisfaction is never at the same time an input and an output of the production process, nor are adjusted net savings and life satisfaction concurrently outputs. Each year only one extra variable is retained.

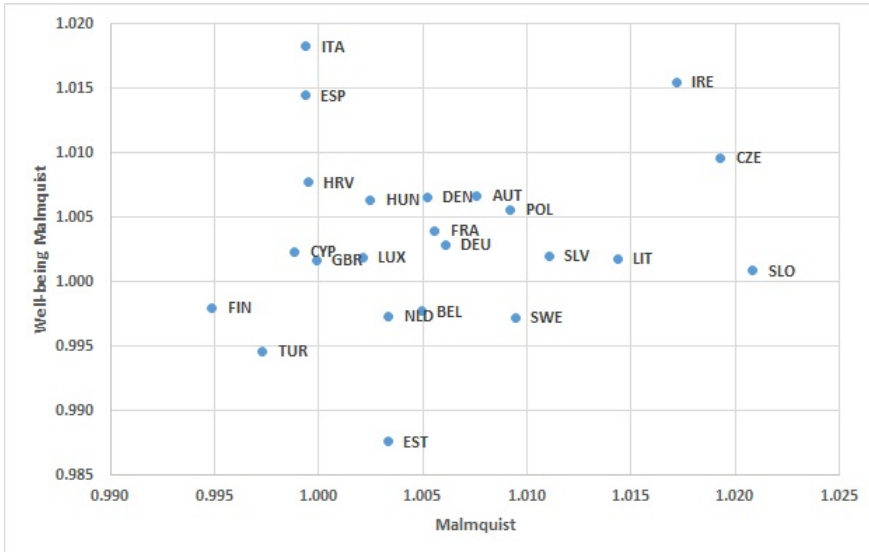
In sum, the method for optimal selection of variables indicates that it is worthwhile to correct traditional measures of productivity including life satisfaction among the inputs and outputs of production.

What makes life satisfaction an input or an output of the production process based on our data? To answer this question, we use a classification tree, a data exploration tool that allows us to group similar observations. This technique is particularly useful to investigate the features of country-years (number of observations = 23 countries * 14 years = 322) when life satisfaction is an input or life satisfaction and adjusted net savings are outputs. The classification tree selects countries into groups based on the optimal values of the dichotomous variables $d_{WBI}, d_{WBO}, d_{ANS}$.

Figure 1 shows some of the partitions generated by the algorithm. We find that a significant number of country-years for which life satisfaction is an input are characterized by a large share of their population being very satisfied with their life (over 36 per cent). This group includes countries such as: Denmark, Luxembourg, Netherlands, Sweden, United Kingdom and Poland. The latter is rather an exception. It differs from the other countries, as it exhibits a lower share of very satisfied people (between 11 per cent and 36 per cent), and a low level of physical capital compared to its GDP.

Countries listing adjusted net savings as outputs are divided into two main groups: the first one is characterized by countries

Chart 1: Correlation Between Average Malmquist (TFP) and Well-Being Adjusted Malmquist (Productivity) Indices in European Countries, 2005-2018



Note: Each indicator minus 1 is a growth rate. A value of 1 means a growth rate of 0.

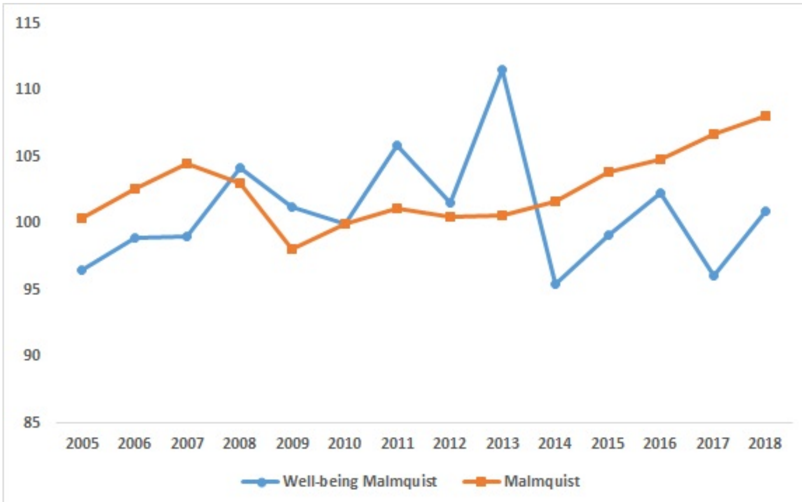
with a relatively large share of people very satisfied with their life, high GDP, and high adjusted net savings (this is the case of Belgium, for instance). The second group includes countries with an average share of people very satisfied with their life, or with a relatively high value of adjusted net savings. Slovenia and Turkey are examples of countries belonging to this group. For the remaining countries, mainly characterized by low shares of people very satisfied with their life, life satisfaction appears mainly an output of the production process.

If it is meaningful to add life satisfaction among the inputs and outputs of production, what would such well-being adjusted productivity look like? This is the last step of our analysis: we compute well-being adjusted Malmquist productivity (see the vertical axis of Chart 1), and we contrast it with traditional Malmquist productivity index (see the horizontal axis of Chart 1). By traditional Malmquist we refer to a TFP Malmquist indicator computed using solely GDP, capital and labour. Recall that well-being adjusted productivity includes life satisfaction as an input and as an output, assumes constant returns to scale, and it is based on an output-oriented method.[12]

We recall that DEA is a benchmarking exercise where countries having the best performance receive a score of 1 and are on the frontier. The lower the score is, the less efficient countries are. In our case, 4 countries are always on the frontier: Italy, Ireland, Poland, and Denmark. Laggard countries, with the lowest average performance, are Eastern European countries such as Slovenia (average score 0.75), Croatia (0.77), Czech Republic (0.77), Slovakia (0.85) or Lithuania (0.88). Luxembourg is an interesting case: it was on the frontier from 2005 to 2009 and then its score de-

12 See Grifell-Tatj and Lovell (1995) for a presentation of Malmquist TFP indexes

Chart 2: Changes Over Time of Malmquist Index and of the Well-Being Adjusted Productivity Index. (European Averages, 2010=100).



Note: authors' own computations on PWT v.10, and Eurobarometer data.

creased constantly to reach a value of 0.79 - one of the least efficient countries in 2017.

Chart 1 indicates that, in general, if a country has a positive growth rate for TFP (Malmquist over unity), it has also a positive growth rate for well-being adjusted productivity. The two measures correlate quite well for some countries, such as Luxembourg. However, the association between the two measures is not statistically significant: some countries have a significantly lower well-being Malmquist than TFP Malmquist (Slovakia is a good example), whereas other countries, such as Italy or Spain, report almost no TFP growth, but large well-being adjusted Malmquist values. In other words, when we account for life satisfaction among the inputs and outputs of production, we find that some countries appear more efficient in transforming inputs into outputs than they usually are using Malmquist index. The Spearman's rho of similarity of rankings is 0.10, not statistically significant ($Prob > |t| = 0.6472$). Thus, we conclude that the two indexes provide significantly different information from each other. The top five countries in the well-being adjusted Malmquist ranking are Italy, Ireland, Spain Czech Republic and Croatia. The bottom five are: Belgium, Netherlands, Sweden, Turkey and Estonia.

The comparison of European averages of the two indexes over time reveals that Malmquist TFP is less volatile than well-being adjusted Malmquist (Chart 2). Moreover, the trend of well-being adjusted Malmquist seems at odd with the trend of Malmquist index. We can distinguish two periods: the first one, from 2005 to 2009, is characterized by a positive trend for well-being adjusted Malmquist index, and a negative one for Malmquist index. The second period, from 2009 on-ward, is characterized by an uninterrupted growth of the Malmquist index, and flat (if not declining) well-being adjusted Malmquist index. The break in the trend of well-being adjusted Malmquist index between 2013 and 2014 appears as particularly striking (see Chart 2).

Conclusion

Is it desirable and possible to build measures of productivity that account for people's well-being? Our answer, based on data from 23 European countries monitored over 14 years, is affirmative. It is indeed desirable to build improved measures of productivity that take into account the fact that economic activity, per se, is not strictly good or bad for quality of life and for the environment. From this point of view, much of previous work focused on providing frameworks to integrate (mainly) environmental variables into traditional productivity measurements. It is also desirable because recent studies provided convincing evidence that people's well-being contributes to productivity, and that subjective well-being is not necessarily an outcome of the production process. In 1968, Kennedy stated that GDP "measures everything in short, except that which makes life worthwhile". We also show that it is possible to integrate subjective well-being measures into traditional productivity computations, thus trying to go beyond the usual economic variables. Our answers are based on a data-driven approach for optimal selection of variables (Toloo *et al.*, 2021).

Specifically, we investigate whether life satisfaction — a widely used, valid and reliable measure of subjective well-being — contributes meaningfully to productivity measures as an input and/or as an output, and that at the same time adjusted net savings — a proxy for sustainability — is an output of production. Results indicate that life satisfaction should be considered among the inputs and the outputs of production. Moreover, we found that life satisfaction is likely an input in countries where the share of people very satisfied with their life is high (above 36 per cent). Conversely, life satisfaction is likely an output in countries where the share of people very satisfied with their life is low.

We used the results of our analysis to compute well-being adjusted Malmquist productivity indexes, and we contrasted the new variable with conventional Malmquist indexes. Evidence indicates that the ranking of countries based on well-being adjusted Malmquist indexes is significantly different from the one derived from the usual Malmquist index. The correlation coefficient of the Spearman's rank test is 0.10, not statistically different from zero. Finally, the changes over time of the European averages of the two indexes indicate that well-being adjusted Malmquist indexes are more volatile than the usual indexes, and the two follow different trajectories: the first period, between 2005 and 2008, shows a positive trend which continues until 2013 when it reverts. The well-being adjusted Malmquist index indicates a remarkable break in the series between 2013 and 2014. The Malmquist index, on the contrary, follows a positive trend from 2009 onward.

Our work is not free from limitations and caveats. As we do not detect life satisfaction as an output and simultaneously as an input, we do not definitely solve the issue about what is the best indicator to compare countries. However, our results indicate that life satisfaction should be taken on board. We do so by including it among the inputs and the outputs of production. Furthermore, productivity indicators based on DEA are usually decomposed into efficiency and technical change. In our case, it is challenging to conceptualize the meaning of technical change for well-being adjusted productivity indicators. Perhaps, new wordings, such as societal progress, should be introduced to speak about technical change in relation to well-being. We also point out that high productivity growth rates can coexist with deteriorating economic and social conditions. As the efficient frontier is a relative benchmark, an inefficient country may experience productivity growth if best performers lose efficiency. Under these circumstances, productivity growth does not reflect economic and social progress.

It is also important to clarify some caveats related to the application of efficiency to subjective well-being. First, we stress that the underlying idea of efficiency indicators is that improvements can be attained when less inputs are used to produce at least the same level of output. In other words, from the efficiency point of view, if subjective well-being is an input, it may be optimal to reduce it. This option may not be socially desirable or acceptable. Thus, our productivity measure implicitly assumes that governments are benevolent and interested in expanding well-being.

Another caveat has to do with the substitutability of outputs. Assume that the computation of productivity indexes uses subjective well-being, adjusted net saving, and GDP as outputs. In this circumstances, the level of productivity could remain the same if the combination of outputs (aggregate value) remains unchanged. This is equivalent to saying that GDP, sustainability, and subjective well-being may be substitutable. This is the same critique that is often applied to indicators of sustainability drawing a distinction between weak and strong sustainability. In this case, our well-being adjusted measure of productivity is a weak-productive-well-being indicator.

With these limits and caveats in mind, we believe that our contribution provides a sensible framework to include direct measures of utility (subjective well-being) in traditional productivity computations. This framework is in its infancy and could be refined in various ways. For instance, it would be interesting to check the robustness of our findings for a longer time-series and a larger sample of countries, not just European ones. It would also be desirable to check to what extent our results are robust to the use of objective measures of well-being, such as mental health, cortisol levels and other bio-physical markers, or drug consumption. Unfortunately, to the best of our knowledge, objective measures of well-being are not widely available or comparable across countries and over time. Another interesting approach would be to consider the creation of well-being as a several step process using network DEA. In a first step, GDP and adjusted net savings result from the use of economic resources such as labour and capital. Then, as a second step, GDP and adjusted net savings generate well-being. Finally, we do not investigate, the computation of shadow prices associated to well-being variables. As explained by Forsund (2018), it would help to assess the marginal productivity of input x_j in terms of the output of type y_i

but also the marginal rate of transformation between output y_i and $y_{i'}$, and, the marginal rate of substitution between input x_j and $x_{j'}$. It would certainly offer interesting insights on the contribution of well-being to productivity.

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A Appendix

Our starting point is:

$$\text{Productivity} = \frac{r_{GDP}GDP + r_{WBO}WBO + r_{ANS}ANS}{w_K K + w_L L + w_{WBI}WBI}. \tag{11}$$

The problem with equation (11) is the computation of weights (r_{GDP}, r_{WBO}, r_{ANS}, w_K, w_L, w_{WBI}). Data Envelopment Analysis is a convenient framework to find optimal values for the weights without additional information (in particular if prices are not available). The idea is to compute optimal weights so that the ratio of equation (11), for a country labelled 0, is as large as possible, and the same ratios for all other countries are positive and below 1. As a consequence, countries with the highest ratios will have an optimal value of 1, and the closest to zero the ratio is, the lowest the efficiency is. This method allows to benchmark countries with respect to the most efficient ones. Formally, we have the following fractional program:

$$\max_{(r_{GDP},r_{WBO},r_{ANS},w_K,w_L,w_{WBI})} \frac{r_{GDP}GDP_0 + r_{WBO}WBO_0 + r_{ANS}ANS_0}{w_K K_0 + w_L L_0 + w_{WBI}WBI_0}$$

$$s.t. \frac{r_{GDP}GDP_j + r_{WBO}WBO_j + r_{ANS}ANS_j}{w_K K_j + w_L L_j + w_{WBI}WBI_j} \leq 1, j = 1, ..., N$$

$$r_{GDP}, r_{WBO}, r_{ANS}, w_K, w_L, w_{WBI} \geq 0$$

This model can be converted into a linear program model, as follows: let $t = 1/(w_K K_j + w_L L_j + w_{WBI}WBI_j)$, then the previous fractional program becomes:

$$
\begin{aligned}
&\max_{(r_{GDP},r_{WBO},r_{ANS},w_K,w_L,w_{WBI})} t(r_{GDP}GDP_0 + r_{WBO}WBO_0 + r_{ANS}ANS_0)\\
&t(w_K K_0 + w_L L_0 + w_{WBI}WBI_0) = 1\\
&s.t.\\
&t(r_{GDP}GDP_j + r_{WBO}WBO_j + r_{ANS}ANS_j)\\
&-t(w_K K_j + w_L L_j + w_{WBI}WBI_j) \leq 0, j = 1, ..., N\\
&r_{GDP}, r_{WBO}, r_{ANS}, w_K, w_L, w_{WBI} \geq 0\\
&t \geq 0
\end{aligned}
$$

Changing notation, $tr_y = u_y$ and $tw_x = v_x$ ($y \in \{GDP, WBO, ANS\}, x \in \{K, L, WBI\}$), then:

$$
\begin{aligned}
&\max_{(u_{GDP},u_{WBO},u_{ANS},v_K,v_L,v_{WBI})} u_{GDP}GDP_0 + u_{WBO}WBO_0 + u_{ANS}ANS_0\\
&v_K K_0 + v_L L_0 + v_{WBI}WBI_0 = 1\\
&s.t.\\
&(u_{GDP}GDP_j + u_{WBO}WBO_j + u_{ANS}ANS_j)\\
&-(v_K K_j + v_L L_j + v_{WBI}WBI_j) \leq 0, j = 1, ..., N\\
&u_{GDP}, u_{WBO}, u_{ANS}, v_K, v_L, v_{WBI} \geq 0
\end{aligned}
$$

Last, this linear program has a dual representation:

$$
\begin{aligned}
&\min_{\lambda_j} \theta_0 \\
&\sum_j \lambda_j K_j \leq \theta_0 K_0 \\
&\sum_j \lambda_j L_j \leq \theta_0 L_0 \\
&\sum_j \lambda_j WBI_j \leq \theta_0 WBI_0 \\
&\sum_j \lambda_j GDP_j \geq GDP_0 \\
&\sum_j \lambda_j WBO_j \geq WBO_0 \\
&\sum_j \lambda_j ANS_j \geq ANS_0 \\
&\lambda_j \geq 0
\end{aligned}
$$

In this model any improvement in productivity can only be obtained by decreasing the use of inputs. In this case, we speak of an input oriented model. Alternatively, one may be interested in assessing to what extent outputs can be increased given the use of inputs. In this case, we refer to the output oriented model:

$$
\begin{aligned}
&\max_{\lambda_j} \phi_0 \\
&\sum_j \lambda_j K_j \leq K_0 \\
&\sum_j \lambda_j L_j \leq L_0 \\
&\sum_j \lambda_j WBI_j \leq WBI_0 \\
&\sum_j \lambda_j GDP_j \geq \phi_0 GDP_0 \\
&\sum_j \lambda_j WBO_j \geq \phi_0 WBO_0 \\
&\sum_j \lambda_j ANS_j \geq \phi_0 ANS_0 \\
&\lambda_j \geq 0
\end{aligned}
$$

This model is the starting point of the procedure developed by Toloo et al. (2021) to select variables.

Reflections on Measuring and Improving Productivity When Subjective Well-being Is the Objective

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It marks an important step to expand the study of productivity to treat subjective well-being rather than GDP as the objective. At the national level, this might involve using an aggregate equation explaining national average life evaluations instead of a production function explaining GDP in terms of labour, capital and natural resources. Earlier attempts to expand GDP-based measures of productivity to something more appropriately reflecting underlying utility have involved correcting GDP in the manner suggested by Nordhaus and Tobin (1973), and also by Stiglitz *et al*. (2009) without implying any fundamental changes to how productivity analysis should be done.

A middle ground might involve moving away from the production side towards the income side, as Nick Oulton (2022) has done. This comes closer to the geographic and conceptual basis of the well-being approach by focusing on the people rather than the production process itself. That is also, on a geographic basis, likely to permit delving into narrower geographies better than does the pure capital/labour production model assumed by Agarwala *et al*, (2021).

To move the basic measure of output from produced goods and services to subjective well-being requires a much more fundamental transformation. First, it is necessary to choose a preferred measure of subjective well-being that has reasonably good claims to represent utility. The choice has generally favoured an umbrella life evaluation measure that has claims to include due account for income and health, the quality of institutions, the quality of the social context, and the variety of positive and negative emotions that affect how people feel about their lives (Helliwell, 2021). These umbrella life evaluations are typically given by answers to questions asking people to rate their current lives on a scale running from 0 at the bottom to 10 at the top. Alternative versions of this ques-

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tion ask about satisfaction with life, about happiness with life, or as a ladder that uses 10 as the top and 0 the bottom of possible lives. The levels of the answers to these alternative formulations can differ, but their estimated linkage to the various explanatory factors is remarkably similar (Helliwell, *et al.* 2017:10-12, and Helliwell, 2021), and the relative importance of the key variables is remarkably consistent around the globe (Helliwell *et al.*, 2015).

How to measure well-being productivity? The simplest first step might be to ask how well countries do at converting conventionally measured GDP into life evaluations. But if it is possible to prepare a credible list of other factors contributing to higher life evaluations, then a regression of life evaluations on these variables provides what might be thought of as a production function for well-being. What might be an appropriate measure of efficiency? It is possible to simply treat the underlying variables as inputs analogous to the capital and labour inputs appearing in a production function for GDP, and to treat the residuals as a measure of efficiency analagous to X-efficiency or some combination of Solow residuals (or Solow/Swan residuals in antipodean accounts like those of Tim Hazledine (2022), and of Jaime Legge and Conal Smith (2022)), and a time trend. But what then? If some nations are happier than others, whether because they have higher values for the variables explicitly included in the well-being equation (as explained by Sarracino and O'Connor (2022), the six variables used in the WHR modelling are GDP per capita, healthy life expectancy, someone to count on, perceived freedom to make key life choices, generosity, and trust, as measured by the absence of corruption) or because they have positive residuals for the underlying equation, how can this be used to signal where efforts could best be directed to make for happier lives? There are no easily established production models for the creation of any of the five WHR variables beyond income, and even less is known for additional factors not included in the available data and modeling.

An alternative approach is taken by Legge and Smith (2022), who add social capital and natural capital to produced capital and labour to estimate total factor productivity for well-being after using an exogenous adjustment for possible response bias based on the well-being responses of immigrants. They find, reasonably enough, that the well-being consequences of the four capitals are very different. This is not the place to comment in detail on these results, but their Figure 3 suggests strongly that their use of immigrant well-being differences to identify response biases has produced a positive response bias in the Nordic countries where straightforward analysis of residuals in global well-being equations with common global parameters would not give that result.

I suspect that if they shifted to a more global data sample, their results would be very different. Analysis of migration from very many countries to a given destination has indeed shown limited evidence that immigrants from some source countries have higher or lower life satisfaction than their locally born counterparts (Helliwell, Shiplett, and Bonikowska, 2020). But the differences are very small, and, as with Legge and Smith, are as amenable to explanation by advantages and disadvantages that migrants bring with them as by what they describe as cultural bias.

The most valuable feature of that part of their analysis is to provide a robustness check on the main features of their results. If plausible scales for differing local response styles or unmeasured cultural influences do not change the key conclusions in a material way, that increases the weight that can be attached to the results. The same applies, of course, for the use of alternative assumed functional forms for the models used by them and others to explain subjective well-being. In any event, their analysis faces a similar issue to that facing the GDP-based approaches: that there are no ways of untangling missing variables, nor of assessing the consequences for the choice of public polices, beyond the important result (in the Legge and Smith analysis) that social trust, as proxied by lack of corruption, appears to have a substantial impact on subjective well-being, as found in many other studies.

What can be done to increase the policy applicability of well-being analysis? Fortunately, subjective well-being can be measured at all geographies and for most or all population sub-groups. This means that the levels and distribution of well-being can be assessed at many interesting nodes of the economic, geographic and social fabrics, thereby locating places and situations where lives could be better, and clues to what might be done to improve them. The fact that individual life evaluations are the primary source for well-being measurement also opens the door for individual-level efficiency analysis of the sort suggested and applied by Binder and Broekel (2011).

How can well-being equations be used to create a work plan for how to use research and resources to improve well-being productivity? First, the coefficients in life satisfaction equations, to the extent they are reasonably applicable to local circumstances, can be used to attach shadow values for increases in the levels of each of the driving variables. The ratios of the coefficients can be used to estimate the improvement in well-being that would result from an increase in any of the supports for well-being. Where one of the coefficients in question is that for income, then it gives for the other variable a compensating differential of the sort used by Adam Smith centuries ago, and others more recently (e.g. Helliwell and Huang, 2010) to think about the values of non-pecuniary aspects of a job. Even more straight-forwardly, the coefficients on each variable provide an estimate of the increase in well-being that might accompany an increase in one of the supporting variables.

How then can these relative values be used to form a ranking among alternative ways to improve well-being? At the aggregate level, there are no clear production functions for the creation of health, social support, freedom and altruism, but this is where the detail and specificity of well-being analysis can help. Within health, there are many possibilities for rearranging the technology and delivery of health care in ways that improve the lives of patients and providers, curing illnesses while also building rather than just repairing physical and mental health. In education, researchers are increasingly applying the lessons of positive education, finding ways that still deliver the necessary 3 Rs monitored by the long-standing PISA studies, while also making education a positive experience for teachers, students and families, and simultaneously creating values and life skills to support happier futures. And there is growing study of how to make for happier workplaces, for happier cities, and better mental and physical health. The 2022 Global Happiness and Well-Being Policy Report presents examples from around the world of policies designed to improve well-being in all these sectors, although in most cases the attractiveness of the policies is expressed in instrumental terms, with conventional sector-specific objectives being the currency of choice (Global Happiness Council, 2022). It has been common, especially in well-being analysis of the workplace (Cotofan *et al.*, 2021) and health, and indeed more generally (de Neve *et al*, 2013), to take an instrumental approach to subjective well-being, something to be improved because it will thereby reduce quit rates, mortality (Rosella *et al.*, 2019) hospitalizations (De Prophetis *et al.*, 2020), or health care costs (Goel *et al.*, 2018). As a strategy for introducing subjective well-being into policy discussions, this has advantages, since it offers policy makers possible ways to achieve the pre-existing objectives at a lower cost and on a more sustainable basis.

Peroni, Pettinger and Sarracino (2022) in this symposium provides another useful example of an instrumental approach, showing that both job quality and job satisfaction have positive linkages to industry-level measures of output per worker.

But making subjective well-being the objective, and not just an instrument to improve other outcomes, requires a further shift in thinking and analysis. If higher life evaluations really are the objective, then that is how the analysis should be framed, with conventional inputs and outputs mainly entering via their impacts on the net resource requirements to achieve higher well-being (e.g. Frijters *et al*, 2020, Helliwell *et al*, 2020, 2021, Layard and O'Donnell, 2015, Layard, 2021). Seen in this context, happier workplaces contribute both through their direct impacts on life evaluations and through their ability, as found by Peroni *et al.*, to improve conventional productivity measures. Equally, a sense of community belonging contributes to better lives instrumentally though improved health status (Michalski *et al.* 2020), and also more directly as a driver of overall life evaluations (Helliwell *et al.* 2019).

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Productivity Growth and Spillovers across European and American Industries: A Global Value Perspective Based on EU KLEMS

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Abstract

The development of production networks has promoted knowledge flows and technology diffusion among industries over the past decades, which affects the productivity growth for countries within these networks. This article examines productivity growth in the presence of inter-sectoral linkages. We construct a spatial production model with technological spillovers and productivity growth heterogeneity at the industry-level. We use the global value chain (GVC) linkages from inter-country input-output tables to model the technological interdependence among industries, and estimate total factor productivity (TFP) growth and its spillover among European countries. We find that the spillover effects from intermediate inputs are significant. There is a network effect of TFP growth from one country to another through input-output linkages. We provide a better understanding of the impact of spillover effects on TFP growth in the context of GVCs.

The allocation of resource use within the global value chain (GVC) is one of the more important drivers of global economic growth in recent decades, connecting the industrial systems of various countries into a global production network. As goods and services production is increasingly fragmented, the growth of one coun-

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try may be more dependent on the growth of other countries than in the past. Technology improvements in one industry may be transmitted to all industries in the production network through the input-output linkages. For example, the development of new energy batteries will promote the innovation and development of the downstream automobile industry. By using diversified and advanced spare parts from upstream, the downstream manufactures can create high-quality vehicles, to achieve their own technological progress or improvement, thus boosting productivity.

The economic integration in Europe and progress in the "European Single Market" has facilitated the movement of goods, services, capital and people among member states of European Union and has enabled member states to concentrate on a specific product or even a segment or component in the supply chain. The development of production networks across countries in this region contributes to the optimization of spatial allocation of resources and thus contributes to country and to world productivity growth.

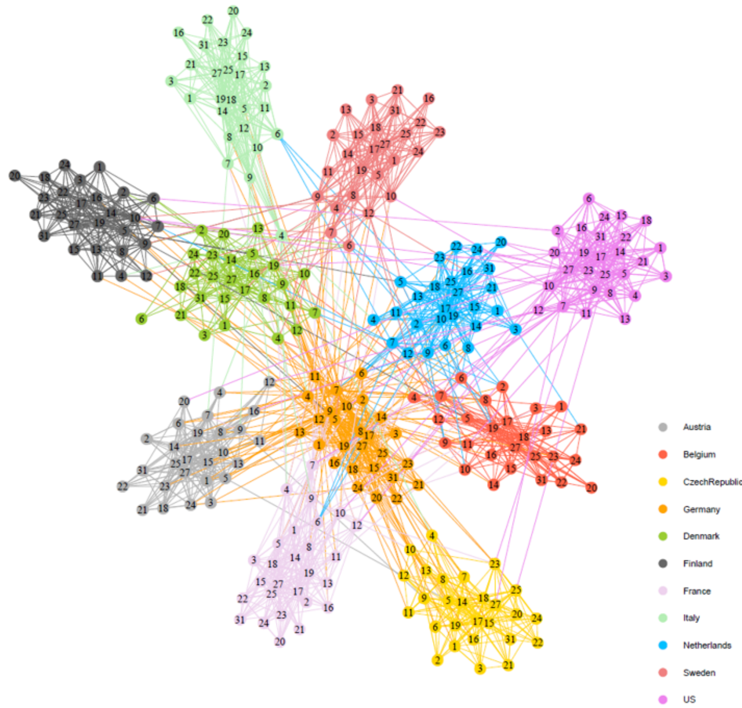
Figure 1 displays the inter-sectoral network across countries in the European area (as in Panel A and Panel C) based on the input-output linkages. Each vertex in the figures corresponds to an industry detailed product-by-product direct requirements table. For every input transaction greater than the threshold of 2.5 per cent of the total intermediates purchases for an industry, a link is drawn between this industry and its input supplier.[2] Panel B and Panel D are the inter-sectoral network diagram of the US-Asia Pacific area with the same threshold value for comparison.[3] International linkages among European countries are much denser than that among the Asian countries in our sample, which suggests that although Asia is the global manufacturing center, the production network is mainly concentrated within their national borders, whereas the European countries are more successful in the development of international value chain co-operations. Panel A and Panel C of Figure 1 suggest the different positions of European countries in the network and its evolution over time.

Germany is shown to be a regional supply hub, with the most extensive international downstream linkages to the industries in other EU countries, which suggests that it has the broadest range of customers in Europe during our sample period 2000 to 2014. Belgium had the largest number of international suppliers in Europe in 2000. However, this position was taken by Austria in 2014. The variation of relative position of countries in the network implies the changes in the pattern of supply chain across European countries. The total number of international linkages among the 297 industries of the ten European economies and the United States increased by one-

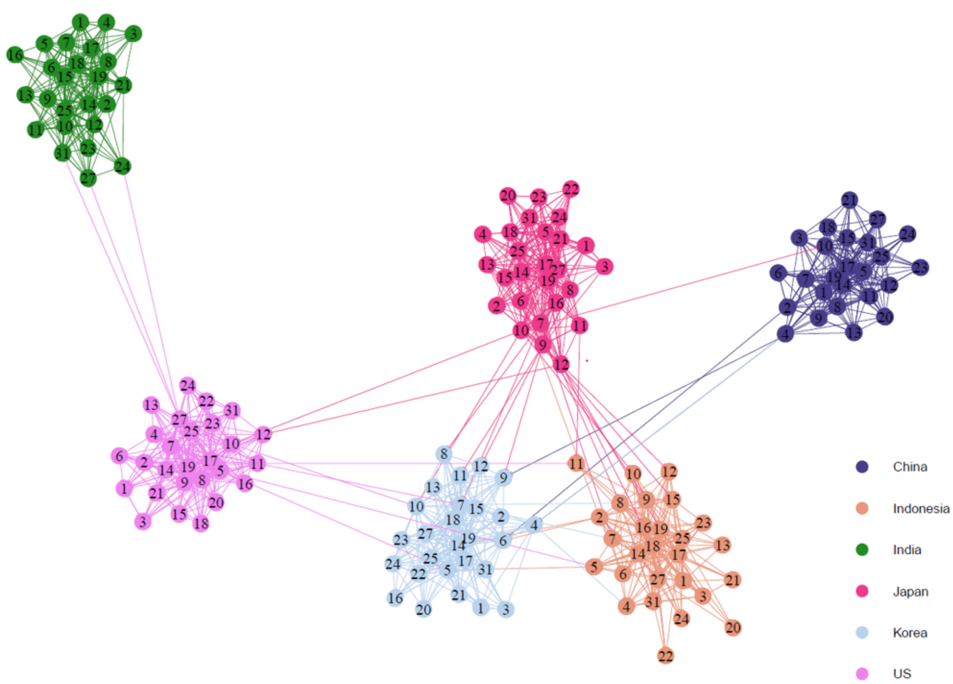
2 The European countries include Austria, Belgium, the Czech Republic, Germany, Denmark, Finland, France, Italy, the Netherlands and Sweden, which along with the United States are the foci of productivity analyses in this article.

3 The countries whose networks are displayed for the Asia Pacific area include China, Indonesia, India, Japan and Korea.

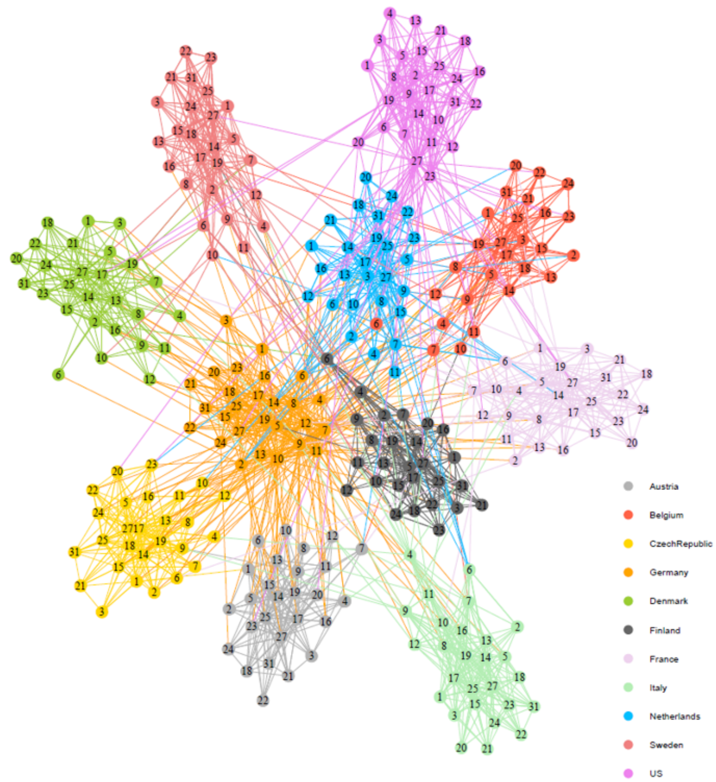
Figure 1: Intersectoral Network Corresponding to the World Input-Output Tables
Panel A: Network of EU-10 and the US in 2000



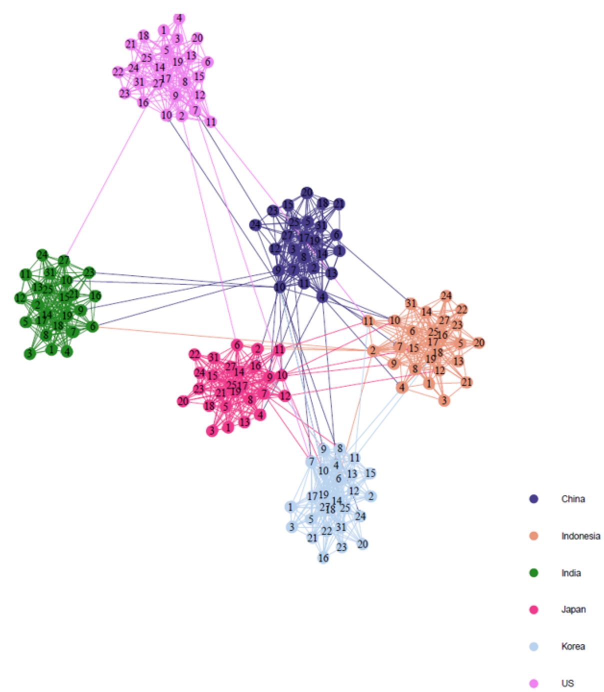
Panel B: Network of Asia-Pacific and the United States in 2000



Panel C: Network of EU-10 and the United States in 2014



Panel D: Network of Asia-Pacific and the United States in 2014



Notes: For every input transaction above 2.5% of the total input purchases of a sector, a link is drawn between that sector and the input supplier.
Source: 2016 release of the World Input-Output Database (WIOD)

third from 290 in 2000 to 384 in 2014, while the total number of domestic linkages declined by 8.3 per cent (from 2,447 in 2000 to 2,244 in 2014). This suggests that the European countries are integrating their economies and thus becoming more interdependent through the growing cross-country inter-sectoral linkages.

In contrast, the total number of international linkages among the 162 industries of the five major economies in the Asia-Pacific area as well as the United States only increased by 21.6 per cent (from 37 to 45), while the number of domestic linkages rose 1.8 per cent (from 1,422 to 1,447), as shown in Panel B and Panel D in Figure 1. The increasingly integrated European value chains offer more opportunities for these countries to appropriate advanced frontier technologies and thus promote total factor productivity (TFP) growth. Nevertheless, the spillover effects from input-output linkages are not considered in most empirical studies on productivity measurement. In this article, we explore the transmission channels of technology spillovers and empirically examine the impact of such spillovers on TFP growth, as a complement to the existing literature.

Our work is related to two strands of the literature. The first is a growing literature investigating the relationship between productivity growth and participation in the global value chain. Timmer *et al.* (2014) summarized the effects of global value chains on industry productivity growth through input-output linkages. Halpern, Koren and Szeidl (2015) used a structural model to explore the impact of imported inputs on productivity. Dhyne and Duprez (2017) examined the participation of global and local value chains and its implication for the efficiency level in Belgian firms. Lu *et al.* (2018) found that there is a positive relationship between firm foreign value-added ratio (FVAR) and productivity. Timmer and Ye (2020) used the growth accounting framework to analyze factor inputs and TFP growth in GVCs. However, most of these studies assumed that the production technology of industries or firms are independent and did not consider possible interdependencies in the production network. We differ from this literature by incorporating the spillover effect of production processes, focusing on the impact of the network effect from factor inputs and technology on TFP growth in the context of GVCs.

Our research also relates to studies that investigate the impact of technological spillovers in the form of patents as well as spillovers from product competition on productivity growth. Bloom, Schankerman and Van Reenen (2013) and Lucking, Bloom and Van Reenen (2019) discussed two types of spillovers: knowledge spillovers in the technology space and product market rivalry in the product market space. Their studies are focused on the spillovers among firms that use patenting in similar technological areas that sell products in the same market. Griliches (1979) discussed another kind of spillover that affects productivity improvement in an industry (say industry i) by purchasing intermediates from another industry, to the extent that the productivity improvements in the other industry have not been appropriated by its producers and not been incorporated in the official price indices of industry i by the relevant statistical agencies, referred to as "rent spillover."

Our study differs from Feenstra *et al.* (2013) and Feenstra, Inklaar and Timmer (2015), who measured productivity growth by the Tornqvist index using a growth accounting framework based on the residual of output growth and total input growth. We estimate TFP growth using econometric procedures which allow us to estimate sectoral productivity with flexibility in the specification of the spatial production function. The empirical specification of technology spillovers in this article differs from several previous studies. First, while Ho, Wang and Yu (2018), among others, argued that a spatial weight matrix based on international trade flows could capture multi-country technological interactions, we believe that using intermediate flows as the interaction matrix is more appropriate. The role of intermediate flows as a channel for shock propagations has been investigated in recent studies of production networks.[4] This is because, as an important vector of knowledge diffusion, intermediate flows better represent and reflect communication and cooperation in production among industries.

Second, several studies in this literature are based on the assumption of homogeneity in productivity growth across industries (Ertur and Koch, 2007; Liu and Cheng, 2021). Due to the technical and economic features of each sector, the specification of homogenous parameters when modeling economic growth may be inaccurate, as was shown by Durlauf (2001). Therefore, we use a flexible spatial Cobb-Douglas production function and a parameter identification empirical methodology based on a spatial time-varying stochastic frontier, which allows for the heterogeneous technological progress and technology spillovers at the industry level. Furthermore, unlike the imposed distribution assumptions in Glass, Kenjegalieva and Sickles (2016), we combine the spatial econometrics with the previous work of Cornwell, Schmidt and Sickles (1990) for estimation, which does not require further parametric assumptions on the distribution of the inefficiency term.

Furthermore, a few recent papers are more closely related to our work. Liu and Sickles (2021) combine the methodology of spatial econometrics model and time-varying stochastic frontier to estimate the industry-specific productivity and spillovers within the Asia-Pacific value chain. Following this method, Liu, Sickles and Zhao (2022) estimate the technology spillover between the United States and China and evaluate the impact of simulated US-Sino trade decoupling scenarios. Although the estimation technique is related to ours, both papers assume a linear technology progress and only measure the gross spillover received or offered by industry. Our analysis considers the non-linear technology progress which is more consistent with the global trend of slowdown in TFP growth and investigates the spillover from a more detailed network perspective that distinguishes the source and destination of spillover effect by countries.

4 See Acemoglu *et al.* (2012); Acemoglu, Akcigit and Kerr (2016); Autor and Salomons (2018); Carvalho and Tahbaz-Salehi (2019); Bigio and La'O (2020).

The main contribution of the article is to investigate the TFP growth and spillover in European countries with a spatial econometric model with heterogeneous technology progress. First, we extend the Cobb-Douglas production function with technology spillover incorporated, in which the parameters can be empirically estimated and used to measure industry TFP growth with interdependence. Second, we investigate the TFP growth of ten EU countries over the period 2000-2014, and find the correlations between industry TFP growth and GVC participation. Third, we estimate the network effect of TFP growth for manufacturing sectors of EU countries, based on which we further decompose the network effect into a domestic and international component.

The remainder of our article is organized as follows. In the next section we introduce our model specification and methodology for examining the spillover effect of factor inputs as well as TFP growth. Section 3 describes our data and reports descriptive statistics. Section 4 presents our empirical results with the spatial production function. Section 5 focuses on the TFP growth for European economies. Section 6 illustrates the spillover effect of TFP growth using the matrix of marginal output. Section 7 concludes.

Model

In this section, we present our spatial production model to allow interdependence in production and heterogeneity in productivity growth at the industry-level. We then derive output elasticities for the input factors using the matrix of partial derivatives of output with respect to the corresponding factor. We use these measures to examine the spillover effects of factor inputs and TFP growth.

Interdependent industrial production function

Consider the production network consisting of N industries, where each industry's production function can be represented by a Cobb–Douglas function that exhibits constant returns to scale in capital, labour and intermediate inputs. Then, for industry i at time t, we have:

$$Y_{it} = A_i(t){K_{it}}^{\alpha}{M_{it}}^{\beta}{L_{it}}^{1-\alpha-\beta}$$

$$i = 1, ..., N \qquad t = 1, ..., T$$

where Y_{it} is total output, K_{it}, M_{it} and L_{it} are the capital, intermediates, and labour used in industry i, with α, β and $1-\alpha-\beta$ as the factor output elasticity, respectively. $A_i(t)$ is the industry-level TFP and is time specific and industry specific. Therefore, output per worker can be written as:

$$y_{it} = \frac{Y_{it}}{L_{it}} = A_i(t)(\frac{K_{it}}{L_{it}})^{\alpha}(\frac{M_{it}}{L_{it}})^{\beta}(\frac{L_{it}}{L_{it}})^{1-\alpha-\beta} \tag{1}$$

$$= A_i(t)k_{it}^{\alpha}m_{it}^{\beta}$$

where y_{it}, k_{it} and m_{it} are output per worker, capital per worker and intermediate per worker, respectively. Due to technological interdependence among industries, the productivity level $A_i(t)$ is given by:

$$A_i\,(t) = \Omega_i(t) \prod_{j \neq i}^{N} A_j\,(t)^{\rho w_{ij}} \prod_{j \neq i}^{N} {k_{jt}}^{\phi w_{ij}} \prod_{j \neq i}^{N} {m_{jt}}^{\varphi w_{ij}} \tag{2}$$

In equation (2), the productivity level of industry i contains three major components. First, a proportion of technological change is exogenous and Hick-neutral, which varies both over industries and over time, given by $\Omega_i(t) = \Omega_i(0)e^{R_i(t)+v_{it}}$ where $\Omega_i(0)$ denotes the initial technology level of industry i, and $R_i(t) = \delta_{1i}t + \delta_{2i}t^2$ is a quadratic function approximating the time-varying component, v_{it} is the approximation error for the level of technology.

Second, technical progress of industry i is assumed to be affected by technological advances in neighboring industry j , and this effect depends on the strength of interdependence between industry i and industry j , which we denote as w_{ij}.

Third, following the Arrow-Romer's physical capital externalities (Arrow, 1962; Romer, 1986), capital deepening in neighboring industries may increase the total capital stock in the society, in which case the economy will accumulate knowledge and bring productivity gains to the industry in question. Similarly, according to studies on vertical specialization and offshoring (Grossman and Rossi-Hansberg, 2008; Baldwin and Robert-Nicoud, 2014), an increase in the intermediate input per worker of its upstream suppliers or downstream customers can promote productivity growth due to a deepening in the division and specialization of the production network (denoted as intermediate deepening).

We can resolve equation (2) for $A_i\,(t)$,[5] substitute $A_i\,(t)$ into the production function (1), and express the logarithm of output per worker in matrix form as:

$$\begin{aligned} lny =& \rho\,(W \otimes I_T)\,lny + \alpha lnk + \beta lnm \\ &+ \Gamma_0 + \Gamma_1 t + \Gamma_2 t^2 + v \\ &+ (\phi - \alpha\rho)\,(W \otimes I_T)\,lnk \\ &+ (\varphi - \beta\rho)\,(W \otimes I_T)\,lnm \end{aligned} \tag{3}$$

where y, k, m and v are $NT \times 1$ vectors, W is a $N \times N$ spatial weights matrix, $\Gamma_0 = ln\Omega_i(0) \otimes \iota_T$, $\Gamma_1 = \delta_{1i} \otimes \iota_T$, $\Gamma_2 = \delta_{2i} \otimes \iota_T$, ι_T is the T dimensional vector of ones. It is the Spatial Durbin Model (SDM) that we will use for our estimations.

Spillover of factor inputs

Due to the interdependence of production, the usual interpretation of α and β as output elasticities is invalid for the spillover effect of factor inputs. Taking the output elasticity of capital, for example, the variation of output is not only affected by the change in an industry's own capital input, but also by the change of neighboring industries' capital inputs. Therefore, we compute direct and indirect elasticities using the approach proposed by LeSage and

5 More details are presented in the online Appendix A found at www.csls.ca/ipm43-Sickles/appendix.

Pace (2009). Then the matrix of partial derivatives of output per worker y, with respect to per worker capital k, in industry $1 \sim N$ and in period t is written as:

$$E_k \equiv \left[\frac{\partial lny}{\partial lnk_1}, \frac{\partial lny}{\partial lnk_2}, \cdots, \frac{\partial lny}{\partial lnk_N}\right]_t \quad (4a)$$

$$= \begin{bmatrix} \frac{\partial lny_1}{\partial lnk_1} & \frac{\partial lny_1}{\partial lnk_2} & \cdots & \frac{\partial lny_1}{\partial lnk_N} \\ \frac{\partial lny_2}{\partial lnk_1} & \frac{\partial lny_2}{\partial lnk_2} & \cdots & \frac{\partial lny_2}{\partial lnk_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial lny_N}{\partial lnk_1} & \frac{\partial lny_N}{\partial lnk_2} & \cdots & \frac{\partial lny_N}{\partial lnk_N} \end{bmatrix}_t$$

$$= (I_N - \rho W_N)^{-1} \quad (4b)$$

$$\begin{bmatrix} \alpha & w_{12}(\phi-\alpha\rho) & \cdots & w_{1N}(\phi-\alpha\rho) \\ w_{21}(\phi-\alpha\rho) & \alpha & \cdots & w_{2N}(\phi-\alpha\rho) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\phi-\alpha\rho) & w_{N2}(\phi-\alpha\rho) & \cdots & \alpha \end{bmatrix}$$

Then the mean output elasticity of own capital input for all industries can be measured by the average of the diagonal elements of the matrix derived from equation (4b), representing the percentage change of an industry output per worker due to a percentage increase in its own capital per worker. Note that these own effects include the feedback effects that arise as a result of effects passing through neighboring industries and back to the industries themselves via the input-output linkages. The mean output elasticity of neighboring industries' capital input, which we denote as the network effect, is the average column sum of the off-diagonal elements in the matrix derived from equation (4b), which represents the impact of a percentage change in an industry's capital per worker on the output per worker of all other industries. The mean overall effect of capital, reflecting the average impact of changing a percentage of capital per worker to the output per worker of all industries in the production network, is measured by the sum of the own effect and the network effect. Similarly, we can derive the own, network and overall effect of intermediate inputs. In the global value chain setting, we can further decompose the network effect into a domestic network effect coming from domestic inter-industry linkages and an international network effect coming from industrial linkages across countries, based on the information provided in the world input-output tables (Liu and Cheng, 2021).

TFP growth and spillover in EU

Differentiating equation (3) with respect to the time trend in period t, we obtain the spillover effects of technical progress:

$$g_t \equiv \left[\frac{\partial lny}{\partial t}\right] \quad (4)$$

$$= (I_N - \rho W)^{-1} \begin{bmatrix} R_1(t)\prime & 0 & \cdots & 0 \\ 0 & R_2(t)\prime & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R_N(t)\prime \end{bmatrix}$$

$$= \begin{bmatrix} \widetilde{w}_{11}R_1(t)\prime & \widetilde{w}_{12}R_2(t)\prime & \cdots & \widetilde{w}_{1N}R_N(t)\prime \\ \widetilde{w}_{21}R_1(t)\prime & \widetilde{w}_{22}R_2(t)\prime & \cdots & \widetilde{w}_{2N}R_N(t)\prime \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{w}_{N1}R_1(t)\prime & \widetilde{w}_{N2}R_2(t)\prime & \cdots & \widetilde{w}_{NN}R_N(t)\prime \end{bmatrix}$$

where $R_i(t)' = \partial R_i(t)/\partial t = \delta_{1i} + 2\delta_{2i}t$ is the independent TFP growth of industry i, $\widetilde{w}_{ij}$ is the (i,j)th element of $(I_N - \rho W)^{-1}$. In the diagonal element of the matrix in equation (5) is the own effect g_t^{own}, representing the productivity change of industry itself at time t. The off-diagonal element of the matrix is the network effect $g_t^{network}$, which corresponds to the spillover effect of TFP growth from neighboring industries. For example, $\widetilde{w}_{21}R_1(t)'$ represents the productivity change attributed to the spillover that originate from industry 1 and received by industry 2. Therefore, the index of rows denotes the industry of spillover receiving and the index of columns denotes the industry of spillover offering. Furthermore, assuming there are s countries in the production network and q industries in each country, by partitioning the matrix of $g_t^{network}$ into block matrices, we can rewrite $g_t^{network}$ to decompose the spillover transmitted domestically and internationally as:

$$g_t^{network} = \begin{bmatrix} 0 & \widetilde{w}_{12}R_2(t)\prime & \cdots & \widetilde{w}_{1N}R_N(t)\prime \\ \widetilde{w}_{21}R_1(t)\prime & 0 & \cdots & \widetilde{w}_{2N}R_N(t)\prime \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{w}_{N1}R_1(t)\prime & \widetilde{w}_{N2}R_2(t)\prime & \cdots & 0 \end{bmatrix}$$

$$= \begin{bmatrix} \widetilde{g}_t^{11} & \widetilde{g}_t^{12} & \cdots & \widetilde{g}_t^{1s} \\ \widetilde{g}_t^{21} & \widetilde{g}_t^{22} & \cdots & \widetilde{g}_t^{2s} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{g}_t^{s1} & \widetilde{g}_t^{s2} & \cdots & \widetilde{g}_t^{ss} \end{bmatrix} \quad (5)$$

where $\widetilde{g}_t^{ij}$ is a $q \times q$ submatrix of $g_t^{network}$. The submatrices in main block diagonal $\widetilde{g}_t^{ii}$ denotes the spillover of productivity growth within country i. The submatrices in off-diagonal $\widetilde{g}_t^{ij}$ represents that the spillover of productivity change across borders goes from country j to country i (e.g $\widetilde{g}_t^{12}$ represents the spillover from country 2 to country 1).

Data

We draw our data from the EU KLEMS dataset. The 2017 release of EU KLEMS Growth and Productivity Accounts provides data on factor inputs and gross output for all 28 member states of the European Union and the United States. We extract a panel comprising 10 European economies (Austria, Belgium, the Czech Republic, Germany, Denmark, Finland, France, Italy, the Netherlands and Sweden) over the 2000-2014 period.[6] These 10 countries accounted for about 80 percent of European Union GDP in each year of the sample period,[7] which is representative of the complex production network among the EU countries. In addition, we include the United States in our sample for comparisons of TFP growth between the United States and Europe. Since the main purpose of our study is to investigate productivity growth and spillovers in a context of GVC, we omit the non-market economy industries of these countries.[8]

We calculate the volume indices for gross output and intermediate inputs using 2010 as the base year. Capital services and labour services volume indices are directly obtained from the growth accounting. We also use the real values of input and output

6 Although the latest EU KLEMS Growth and Productivity Accounts up to the 2019 release can be accessed, gross output and intermediate inputs related variables are missing post-2015 for some countries. In addition, WIOD database provides data of input-output linkages used in the section below covers the period of 2000-2014, therefore our sample centers on 2000-2014 when both data sources are available.

7 Data sources: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD

8 Our sample excludes the real estate activities, community social and personal services, other service activities and activities of households.

Table 1: Variable Definitions and Summary Statistics

	Variable	Obs	Mean	Std. Dev.	Min	Max
Real Variables	ln y	3,945	10.49	1.52	6.51	14.89
	ln k	3,945	10.04	1.58	5.82	14.53
	ln l	3,945	4.97	1.65	0	10
	ln m	3,945	9.93	1.53	6.04	13.95
Index Variables	y_{QI}	3,945	99.48	15.85	26.63	253.03
	k_{QI}	3,945	96.03	25.07	28.31	831.52
	l_{QI}	3,945	104	14.63	61.53	219.82
	m_{QI}	3,945	100.02	18.85	26.49	294.7

Note: Note: The gross output(y), the capital stock(k) and the intermediate input(m) are measured in prices (at million US$) of the year 2010. The unit of labor(l) is in thousands. For index variables the base year is also 2010, and the base value is 100.

Source: EU KLEMS Database 2017 and WIOD

variables to verify the robustness of empirical findings. Real gross output and real intermediate inputs are measured by the corresponding nominal values divided by the price indices which are provided by Socio Economic Accounts (SEA) from the World Input-Output Database (WIOD). The real capital stock is measured by using the nominal values provided by EU KLEMS and the capital price indices derived from the PWT version 9.1 (Feenstra *et al.*, 2015). The capital stock in the WIOD is in nominal values and we use the price index from the PWT as the deflator. However, the price index from the PWT is at the national level and thus the deflators for each industry are the same within each country. Summary statistics of these variables are reported in Table 1.

We use the flows of intermediate goods between industries provided by WIOD to construct the spatial weights matrices. In order to match the industries from EU KLEMS with the industries from WIOD, we aggregate some of them and obtain 27 industries in each country (Appendix Table A.1).[9] We extract industry international input–output linkages among these industries from the world input-output table for the period from 2000 to 2014, and use averages of the intermediate flows over this time as the weights to address potential endogeneity problems that might arise were we to use time-varying weights (Cohen and Paul, 2004; Ertur and Koch, 2011).

The spatial weight matrix W_{supply} is constructed using the transpose of the input-output matrix and the elements on main diagonal are set to zero. In order to reflect the technology spillover in the production network, W_{supply} is row normalized, so that its element w_{ij} captures the share of the upstream industry j's product in the total intermediate consumption of the downstream industry i which is consistent with the direction of technology spillovers from upstream industries to downstream industries as discussed in Acemoglu *et al.* (2012), Acemoglu, Akcigit and Kerr (2016), and Autor and Salomons (2018).

We also consider the interaction matrices W_{demand} and $W_{transaction}$ to check the robustness of our results. W_{demand} is obtained by the original input-output matrix,

9 http://www.csls.ca/ipm/43/IPM_43_Sickles_Appendix.pdf.

Table 2: Estimates SDM Production Functions

parm	Index Variables						Real Variables	
	W_supply		W_demand		W_transaction		W_supply	
	T-VFE	T-VRE	T-VFE	T-VRE	T-VFE	T-VRE	T-VFE	T-VRE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnk	0.0643***	0.0699***	0.0702***	0.0736***	0.0697***	0.0736***	0.1502***	0.1615***
	(0.0084)	(0.0073)	(0.0084)	(0.0072)	(0.0084)	(0.0073)	(0.0119)	(0.0093)
lnm	0.5540***	0.5697***	0.5510***	0.5679***	0.5500***	0.5668***	0.5742***	0.6063***
	(0.0081)	(0.0074)	(0.0081)	(0.0074)	(0.0081)	(0.0075)	(0.008)	(0.0071)
$W \bullet lnk$	-0.0384	-0.0543**	-0.0833***	-0.0770***	-0.0792**	-0.0800***	-0.1620***	-0.1640***
	(0.0259)	(0.0178)	(0.0228)	(0.0162)	(0.0256)	(0.0175)	(0.0149)	(0.0117)
$W \bullet lnm$	0.0444	0.003	0.0631	0.0707*	0.0932**	0.0820*	0.0535	0.0002
	(0.0312)	(0.0295)	(0.0323)	(0.0312)	(0.0337)	(0.0322)	(0.031)	(0.0295)
Country-dummy	no	yes	no	yes	no	yes	no	yes
Year-dummy	yes	yes	yes	yes	yes	yes	yes	yes
$W \bullet lny(\rho)$	0.2680***	0.2990***	0.2251***	0.1970***	0.2161***	0.2061***	0.3080***	0.3080***
	(0.0337)	(0.0319)	(0.0348)	(0.0339)	(0.0351)	(0.0342)	(0.0323)	(0.0318)
$\sigma v2$	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0007	0.0007
LL	9273	8886	9279	8891	9280	8892	9184	8813
R2	0.6904	0.6943	0.6919	0.6964	0.6927	0.6967	0.9091	0.9267
Adjusted R2	0.6118	0.615	0.6136	0.6177	0.6147	0.618	0.886	0.9077
Number of obs	3945	3945	3945	3945	3945	3945	3945	3945

Note: "T-VFE" is Time-varying FE and denotes spatial CSS model (Cornwell, et al., 1990) with Fixed Effect, and "T-VRE" is time-varying RE and denotes spatial CSS model with Random Effects. "LL" denotes the loglikelihood. Significant at: *5, * *1 and * * * 0.1 percent.The individual coefficients of δ_{1i} and δ_{2i} are not shown in this table due to the excessive quantities.

Source: Authors' calculations using EU KLEMS Database 201.

where its element w_{ij} represents the share of intermediate inputs from upstream industry i to downstream industry j. This channel of spillovers is consistent with the spillovers of "learning-by-doing". We add the original and transposed matrix of the input-output table together to construct the spatial weights $W_{transaction}$, where its element w_{ij} represents two-way intermediate flows between industry i and industry j.

Empirical results

Estimations of Industrial Production Functions

In Table 2 we report the estimation results of the SDM specified production functions based on Equation (3). We use both the output per capita index and real per capita output for the dependent variables. The EU KLEMS database provides both the gross output growth index (year 2010=100) and real output. We provide results for both to check for any substantive differences and to examine the robustness of our findings across these different output measures. The gross index numbers utilize gross output (Y), capital service (K), labour service (L) and intermediate input (M) from the EU KLEMS. Columns 1–6 of Table 2 report empirical results based on three weighting matrices W_{supply} , W_{demand} and $W_{transaction}$.

More specifically, columns 1, 3 and 5 are the empirical results specified by the spatial weight matrix of W_{supply}, W_{demand} and $W_{transaction}$ respectively, with the Time-varying fixed effect (T-VFE) and columns 2, 4 and 6 are the corresponding empirical results with the Time-varying random effect (T-VRE). Estimates of the coefficient ρ of the spatially lagged dependent variable range between 0.1970 and 0.2990 for these three specifications of the weighting matrix and are statistically significant at the 0.1 per cent level, suggesting positive network effects in production among the industries in our study. Given the similarity of results based on these three weighting matrix specifications, we will discuss results for the matrix W_{supply}.[10] The real value data is based on traditional input indicators, i.e., the capital stock and number of employees, which come from the WIOD database.

From Column 7-8 of Table 2 we can see that the estimation results for the real variables and volume indices reported in Columns 1–2 are quite comparable and we focus our discussion below on results based on volume indices.[11] As shown in the first two Columns of Table 2, coefficients on capital and intermediate are both significant and positive in all estimations. It is important to note that these parameters in the spatial Durbin model cannot represent the output elasticities of the factor inputs (LeSage and Pace, 2009). We should use the direct and indirect effects estimates derived from Equation (4b), which will be fully explained in the next subsection. The coefficients on $Time$ and $Time^2$ representing the average Hicks-neutral technological change of industries are positive in first order and negative in second order, which implies that technical progress is represented as an inverted-U curve. This is consistent with the trend of TFP growth slowdown in Europe as discussed in several previous studies (Feenstra *et al.*, 2015; van Ark and Jäger, 2017; Gordon and Sayed, 2019). The model specifications using Time-varying FE and Time-varying RE model are the same. The Hausman-Wu statistic for the time-varying fixed effects v. time-varying random effects specification has a p-value of 0.00 and we thus focus the remainder of our discussion of results based on the time-varying fixed effects specification.

Spillover of input factors

The first two rows of Table 3 show the estimated overall direct, indirect and total output elasticity of factor inputs. The direct elasticity is calculated by the mean of the diagonal entries of the matrix derived from Equation (4b) and the indirect elasticity is computed by the mean of the row sums of off-diagonal entries. We follow the method LeSage and Pace (2009) suggested to test the significance of these coefficients by drawing parameter estimates 1000 times from the variance-covariance matrix of the parameter estimates to generate the distribution of these effects. The direct elasticities of capital per capita and intermediates per capita are 0.064 and 0.557, and

10 We choose the result of the estimation with the spatial weight matrix of W_{supply} to disscuss in detail since a number of recent papers show that the supply-side intermediate linkage from upstream suppliers to downstream customers is a major channel of TFP spillovers (See Acemoglu *et al.* (2012); Acemoglu, Akcigit and Kerr (2016); and Autor and Salomons (2018)).

11 The reason is that the index for capital input is capital services instead of the capital stock, wherein the former considers the user cost of the asset. And the index of labour input is labour service, which takes into account the contribution of skill levels of different workers.

Table 3: Direct, Indirect, and Total Elasticity of Input Factors

		Direct		Indirect		Total	
		Elasticity	asy. t-stat	Elasticity	asy. t-stat	Elasticity	asy. t-stat
overall	K/L	0.0640***	7.77	-0.0271	-0.8	0.0369	1.1
	M/L	0.5567***	68.01	0.2622***	9.38	0.8189***	28.81
domestic	K/L	0.0640***	7.77	-0.0196	-0.8	0.0445	1.81
	M/L	0.5566***	67.98	0.1893***	9.49	0.7458***	35.7
international	K/L	0	-0.79	-0.0075	-0.8	-0.0076	-0.8
	M/L	0.0001***	6.19	0.0730***	8.76	0.0731***	8.75

Note: Empirical standard deviations of the elasticity based on a 1000 MCMC draws using the variance-covariance matrix of the parameters following the algorithms of Lesage and Pace (2009, P.150). * Indicates significance at 5%; **Indicates significance at 1%; ***Indicates significance at 0.1%.

Source: Authors' calculations.

both are strongly significant. The spillover effect of capital is negative and statistically insignificant, which indicates that the growth in capital of neighboring industries does not contribute to output growth of the industry itself. The main reason is that the increased usage of capital in the neighboring (supplier or customer) industries appear to have a negative effect on the industry itself because of the scarcity in capital. The adverse effects of this competitive relationship may counterbalance the spillover effects of the complementary relationship among industries. The indirect elasticity of intermediate deepening is 0.262 and highly significant, indicating that industry's output growth could be benefited when its neighboring industries has increased the intermediate inputs. Therefore, when the spillover effect from intermediate input is incorporated, the output elasticity of intermediate input increases from 0.557 to 0.819, which can be attributed to intermediate augmenting-type technical progress because of the improvement of vertical specialization in the production network.

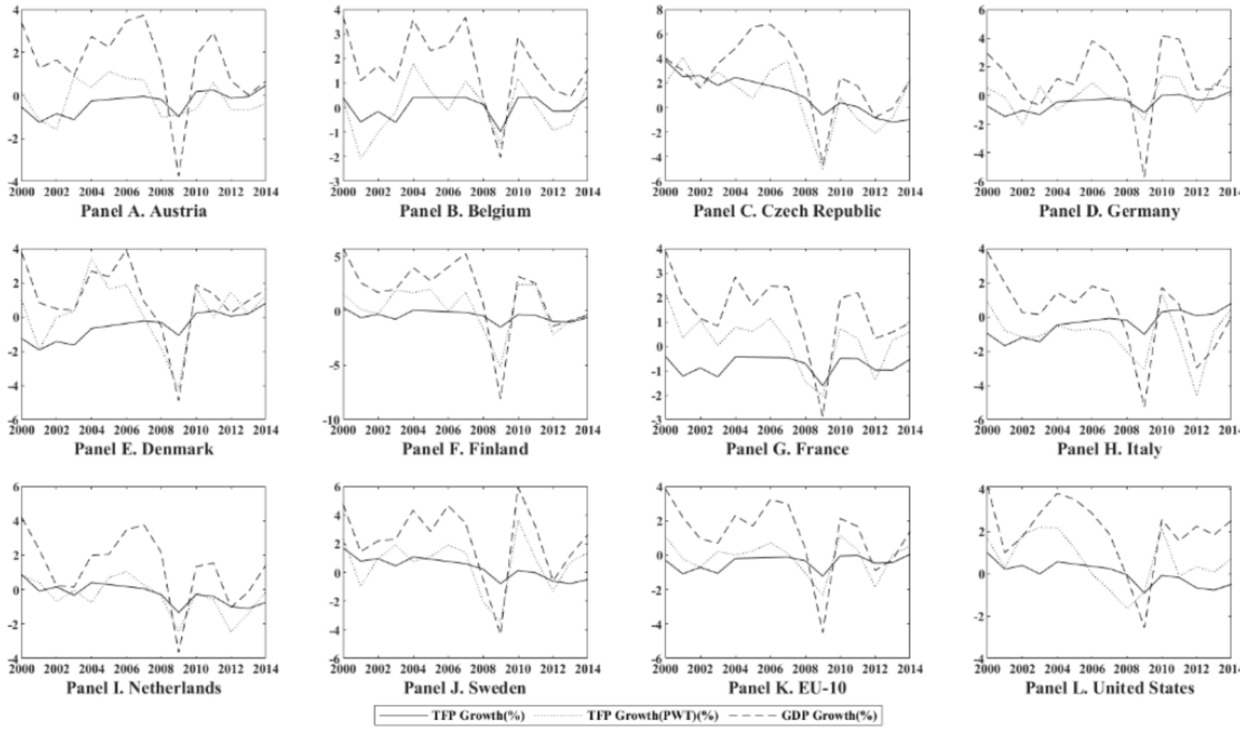
In order to distinguish the network effects that are based on domestic versus international industrial linkages, we follow Liu and Cheng (2021) and decompose the different spillover effects into domestic effects involving the domestic value chain and international effects involving the international value chain. As the last two rows of Table 3 show, the international indirect elasticity of intermediate input is 0.073 and is statistically significant, and accounts for approximately 28 per cent of the overall indirect effects of the intermediate input. This suggests that 28 per cent of the spillovers embodied in the intermediate input has transmitted across borders, which can be an important channel for production interactions among industries.

TFP Growth of EU

TFP Growth of EU economies

We also calculate the own industry TFP growth g_t^{own} by Equation (5) in Section 2 and aggregate with Domar weights at the national level. Chart 1 shows the aggregate TFP growth of the 10 European countries and the United States from 2000 to 2014. It is noticeable that TFP growth in all of the countries fell sharply in the global financial crisis, and rebounded in 2010, but fell again due to the Euro Area recession. The estimates are fairly close to the findings reported by the Penn World Table (Feenstra *et al.*, 2015). As shown in Chart 1,

Chart 1: Productivity Growth in EU Countries and the United States, 2000-2014



Source: Authors' calculations

the trend of TFP growth in these countries were basically consistent with their GDP growth during the 2000-2014 period, but exhibits a smaller fluctuation. We can see that the EU-10 (Panel K.) experienced a decrease in TFP growth from -0.29 per cent in 2000 to -1.08 per cent in 2001, gradually recovering to -0.11 per cent in 2007. During the global financial crisis, the TFP growth rates had sharply fallen because of the slowing demand, weak investment and lingering structural rigidities (van Ark, 2016; van Ark and O'Mahony, 2016; Duval *et al.*, 2020). Subsequently, TFP growth rebounded in 2010 and started to decline after the Euro Area recession.

Compared with the TFP growth performance of the United States (Panel L.), before the global financial crisis of 2008, EU-10 TFP growth was lower than the average annual TFP growth of the United States (0.38 per cent). Nevertheless, the decelerating trend of TFP growth in the United States continued during the following years and TFP growth dropped to its lowest point in 2009 (-0.90 per cent). Although TFP growth in the United States rebounded in 2010, as did other economies in the EU-10, the rebound failed to return TFP to its pre-crisis growth rate, and then it declined again in 2011- 2014. This would seem to indicate that the global financial crisis may have induced a long term TFP growth slowdown, especially in United States. One key reason for the slowdown of technological progress in United States is related to lower productivity-enhancing investment (Bianchi *et al.*, 2019; Anzoategui *et al.*, 2019) in terms of R&D expenditure (per cent of GDP) and the number of patent applications.

We can see that annual TFP growth rates in all countries except the Czech Republic range between -2 per cent and 1 per cent. Over the sample period, Denmark, Italy, Germany, and Austria showed an increase in TFP growth. More specifically, we observe that the TFP growth rates decreased initially from 2000 to 2003 and then started to increase from 2004 to 2007. During the global financial crisis of 2008-2009, the TFP growth rates fell again, which indicates that the financial crisis did decrease the TFP growth. Then the TFP growth rates in these countries rose from 2010 till 2014.

The TFP growth rate in Belgium was almost the same in 2000 and 2014, but it also showed a similar trend with the aforementioned four countries over the 14-year period. In contrast, France, Finland, the Netherlands, Sweden, and the Czech Republic and showed a decline in TFP growth, from -0.41 per cent, 0.33 per cent, 0.87 per cent, 1.71 per cent and 3.84 per cent in 2000 to -0.53 per cent, -0.59 per cent, -0.74 per cent, -0.50 per cent and -0.97 per cent in 2014, respectively. Notably, the Czech Republic saw the fastest TFP growth before the global financial crisis, which can be attributed to its industrial structure and the benefits from GVC participation (van Ark *et al.*, 2013). The Czech Republic is a small open economy with relatively large manufacturing sectors, and it is also the largest player in intra-regional trade in terms of manufacturing inputs among the European economies.[12]Participating in GVCs has stimulated the TFP growth of manufacturing sectors in Czech Republic through specialization, knowledge spillovers, and learning by doing, among other factors (Criscuolo and Timmis, 2017).

TFP Growth by Industry

In Table 4, we selected the top three industries with the fastest average TFP growth in each country from 2000 to 2014. The most prevalent industries in that list are those related to the digital economy. The electrical equipment industry in the United States, with the annualized average TFP growth of 4.80 per cent, turned out to have the most rapid TFP growth of all industries in 2000-2014. Electrical equipment industries in other countries also are high performing in terms of TFP growth, with 3.57 per cent TFP annual growth in Sweden, followed by 2.37 per cent in the Czech Republic, 1.61 per cent in France, 1.42 per cent in the Netherlands, and 1.39 per cent in Germany. The telecommunications industry also exhibited a high TFP growth in EU-10, and its average annual growth rates in Denmark, Finland, Italy, Sweden, the Netherlands, Germany, France, Belgium were 4.66 per cent, 3.53 per cent, 3.43 per cent, 3.11 per cent, 2.52 per cent, 2.50 per cent, 2.46 per cent and 1.03 per cent respectively. The rapid growth in these related industries benefitted from advances in information and communication technology

12 See Organization for Economic Co-operation and Development Bilateral Trade in Goods by Industry and End-use database, International Standard Industrial Classification, Revision 4 (2016 edition).

Table 4: Top Three Industries with the Fastest TFP Growth in EU-10 and United States (%)

Country	Industry	TFP growth	rank
Austria	Coke, Refined Petroleum	3.61	3
	Postal and Courier	1.68	17
	Financial and Insurance Activities	0.88	35
Belgium	Mining, Quarrying	1.05	30
	Telecommunications	1.03	31
	Coke, Refined Petroleum	0.78	42
Czech Republic	Machinery, Equipment	2.97	8
	Electrical Equipment	2.37	12
	Transport Equipment	2.36	13
Germany	Telecommunications	2.5	10
	Electrical Equipment	1.39	26
	IT and other information services	1.03	32
Denmark	Telecommunications	4.66	2
	Chemicals, Pharmaceuticals	1.64	19
	Publishing, Media Services	1.61	21
Finland	Telecommunications	3.53	5
	Trade & Repair of Motor Vehicles	1.41	25
	Agriculture	1.07	29
France	Telecommunications	2.46	11
	Electrical Equipment	1.61	20
	Agriculture	0.75	46
Italy	Telecommunications	3.43	6
	Financial and Insurance Activities	1.09	28
	IT and other information services	0.54	66
Netherlands	Telecommunications	2.52	9
	Electrical Equipment	1.42	24
	Financial and Insurance Activities	0.81	38
Sweden	Electrical Equipment	3.57	4
	Telecommunications	3.11	7
	IT and other information services	1.71	16
United States	Electrical Equipment	4.8	1
	Publishing, Media Services	2.07	14
	IT and other information services	1.52	22
EU-10	Telecommunications	0.02	0
	Electrical Equipment	0.01	0
	Retail Trade	0.01	0

Note: The TFP growth rates are annual compound growth rates from 2000 to 2014.

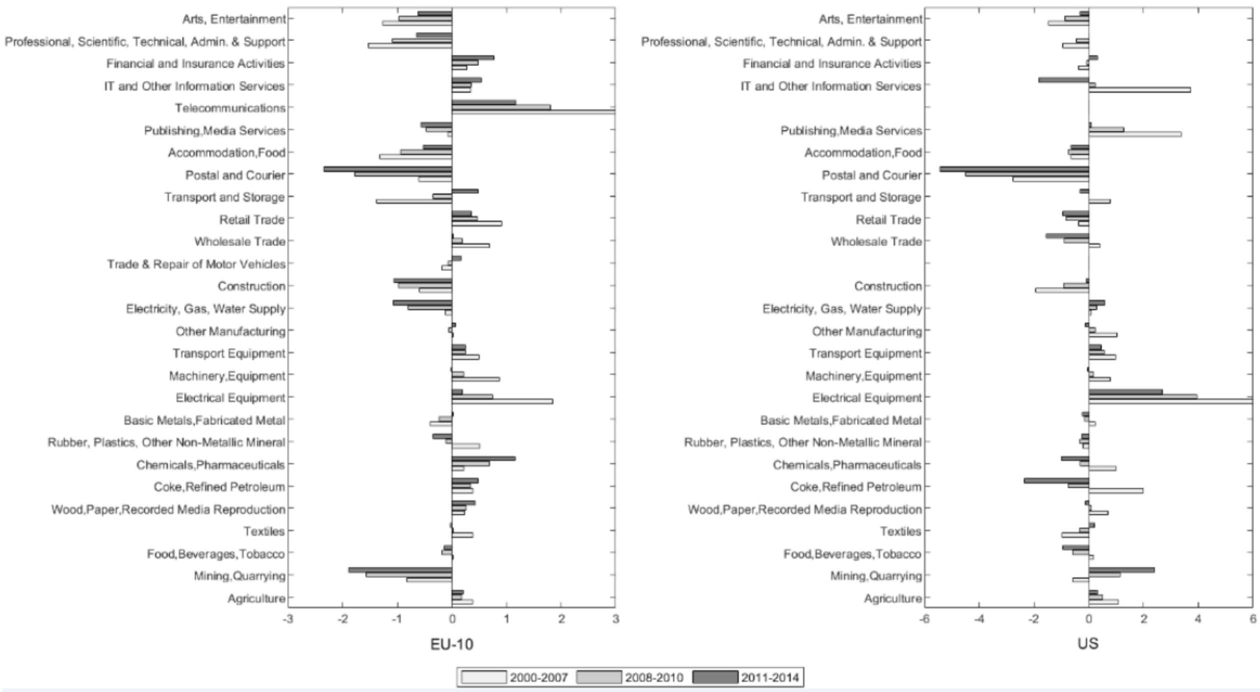
Source: Authors' calculations.

(ICT) during this period (Oulton, 2012; Bloom *et al.*, 2012). Rapid development of new products and production tools, such as robotics, artificial intelligence, and digital technologies, penetrated the economies more and more extensively through the input-output network and the momentum of these new technology spillovers may impact TFP growth in other industries to a much greater extent in the future.

In Chart 2 we report the average annual industry TFP growth rate in the EU-10 and the United States during three periods: 2000-2007, 2008-2010, and 2011-2014.[13] We can observe that the change of TFP growth showed less variations in the EU-10 average than the United States. IT and other information services, coke and refined petroleum, electrical equipment, publishing and media services had a 3 per cent

13 According to the above results, the global financial crisis has significantly damaged the TFP growth of the European countries and the United States. Therefore, we divide the sample time period into three subperiods: the pre-crisis period (2000-2007), the global financial crisis itself (2008-2010), and the post-crisis period (2011-2014).

Chart 2: Average of Industry TFP Growth in the EU Countries and the United States (average annual rate of change)



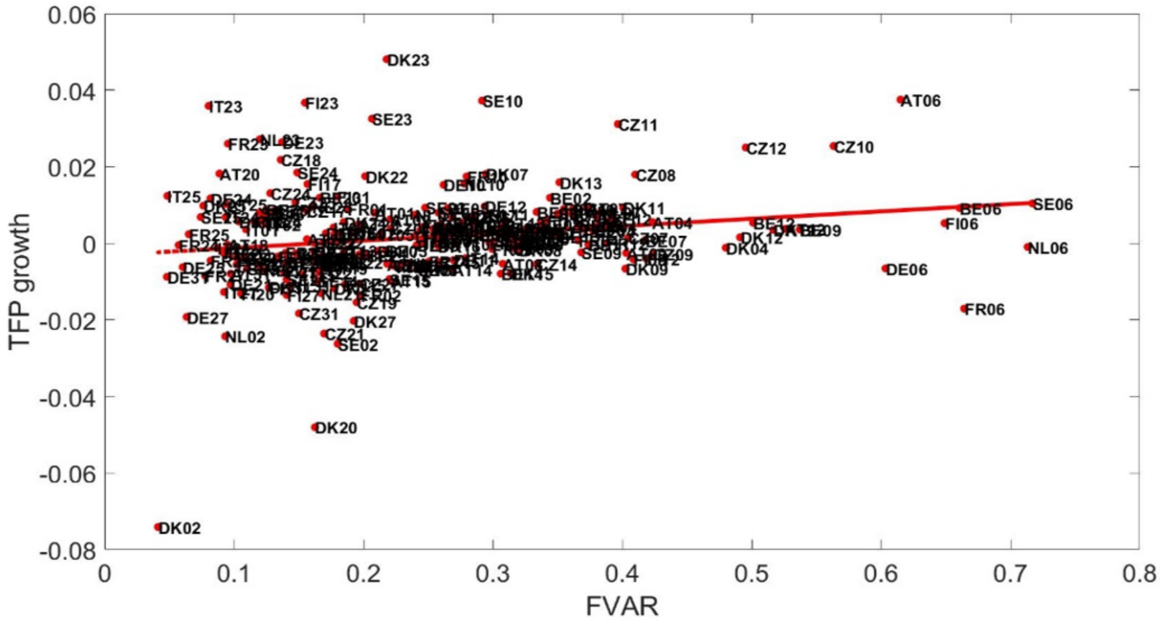
Note: EU-10 refers to the average of the 10 countries TFP growth.
Source: Authors' calculations

decline in average annual TFP growth rate for the United States in 2010-2014 compared with 2000-2007. By contrast, the industry with the most significant decline of the EU-10 average TFP growth rate was telecommunications (with 1.88 per cent decline). The average annual growth rate falls from 3.05 per cent in 2000-2007 to 1.17 per cent in 2010-2014. Focusing on the EU-10 average, the slowdown of TFP growth after the global financial crisis appears to have been widespread and easily visible in several industries. Two exceptions to these trends are the chemicals and pharmaceuticals and transport and storage industries whose TFP growth after 2008 increased. When comparing the average industry TFP growth in the EU-10, telecommunications and electrical equipment also had the fastest TFP growth over the full sample period from 2000 to 2014, as we discuss the industry-specific TFP growth above. Postal and courier and mining and quarrying experienced a dramatic decrease in TFP, with the average annual growth from -0.61 per cent and -0.82 per cent declined to -2.35 per cent and -1.88 per cent, respectively.

TFP Growth and Global Value Chain participation

In this section, we examine links between TFP growth and GVC participation in EU countries, which would help us to better understand how GVC participation could account for the change of industry TFP growth. GVC participation is represented by the foreign value-added ratio (FVAR) in our analysis, which reflects the ratio of

Chart 3: FVAR and TFP growth for European industries in 2007



Source: Authors' calculations using EU KLEMS Database and WIOD

foreign value added to gross exports and is calculated using the method developed by Wang *et al.* (2013). Chart 3 plots FVAR values against TFP growth rates for industries in 2007. To examine this correlation, we estimate the following regression model $g_{TFPi} = \gamma_0 + \gamma_1 \mathrm{FVAR}_i + \varepsilon_i$. Here, g_{TFPi} is the TFP growth rates of industry i; γ_0 is the intercept; FVAR_i is the foreign value-added ratio; ε_i is an error term representing all other influences. OLS estimated parameter for FVAR_i is 0.02 and significantly different from zero, which implies that there exists the positive relationship between industry TFP growth and FVAR for most industries in the EU-10. Increased involvement in the GVC, and the stronger production linkages with other countries this entails, may lead to a higher pace of TFP growth and may suggest that an industry generates faster TFP growth through technology spillovers of upstream and downstream industries in the global production network. FVAR is higher for coke and refined petroleum (06) than other industries in Chart 3, mainly due to the energy import dependencies of European countries. Production of coke and petroleum products relies heavily on imported intermediate inputs.

Spillover of TFP growth of EU Manufacturing sectors

The discussion above is focused on the TFP growth realized by the industry on its own. However, the rapid development of the global value chain boosted the spread of new knowledge and technology among the participating industries, especially those manufacturing industries interconnected in the production network. This means that technology progress exhibited by these industries are interdependent. The progress in an industry may provide spillovers to other industries through input-output linkages and these spillovers may propagate together to form the network effect. Our spatially specified model enables us to estimate the network effects in the global value chain setting. We will focus on the network effects between EU manufacturing sectors in this section.

Spillover of TFP growth by Economy

Chart 4 plots the aggregate own effect TFP growth superimposed with network effects offered by industries in eleven countries during 2000-2014.[14] In general, the own and network effects of TFP growth vary in the same directions. Germany offered the most, with 1.40 per cent annual average domestic and 0.19 per cent annual average international spillovers. The United States offered the second highest, with 0.62 per cent annual average domestic and 0.69 per cent annual average international spillovers, followed by the Netherlands, the Czech Republic and Sweden. The other six countries provided a negligible annual average network effect.

From 2000 through 2014, the trend of total effects in Austria, Belgium, Denmark, France, and Italy, were similar and positive. Among these five countries, as a regional hub in the Euro area, Belgium contributed relatively more network effects through knowledge spillovers than the other four countries, especially after the global financial crisis. An explanation for this is deepening participation of Belgium manufacturing industries in global and local value chains (Dhyne and Duprez, 2017).

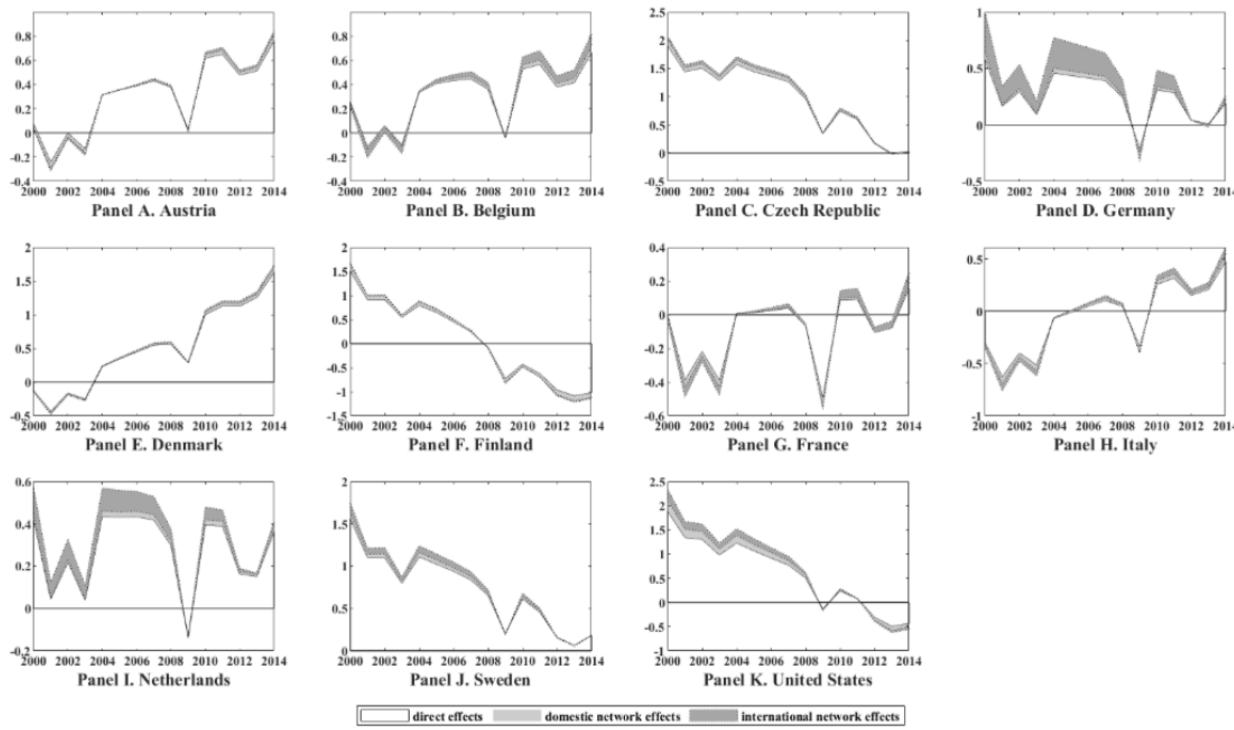
It can be seen in Chart 4 that the Czech Republic, Finland, Sweden, Germany, and the Netherlands saw declines in the overall effects of manufacturing industry's TFP growth, but the decline was more prominent in the Czech Republic, Finland and Sweden. In contrast, Germany, as the most important hub in the intra-Europe production network and with strong linkages with other countries, declined relatively less than the other economies in TFP growth and provided the most positive international spillovers to the other economies by exporting high-technology and complex intermediate goods. Netherlands was the second largest contributor in TFP growth spillovers, mainly due to its well-developed manufacturing foundation and advanced port and logistics system.

Recalling the GVC trade network in Figure 1, Netherlands provides a similar role as a transferring hub between the United States and Germany, the two large advanced economies that set the productivity frontier in many industries.[15] In addition, the Czech Republic also provides relatively high growth spillovers along with its own rapidly increasing TFP. Comparing the domestic and international configuration of network effects, we can find that there were more international spillovers in European

14 Figure A.1 in the online Appendix shows these effects from the receiving perspective. The results based on both perspectives are broadly similar, though the spillover measured by receiving is less than the spillover measured by offering. http://www.csls.ca/ipm/43/IPM_43_Sickles_Appendix.pdf.

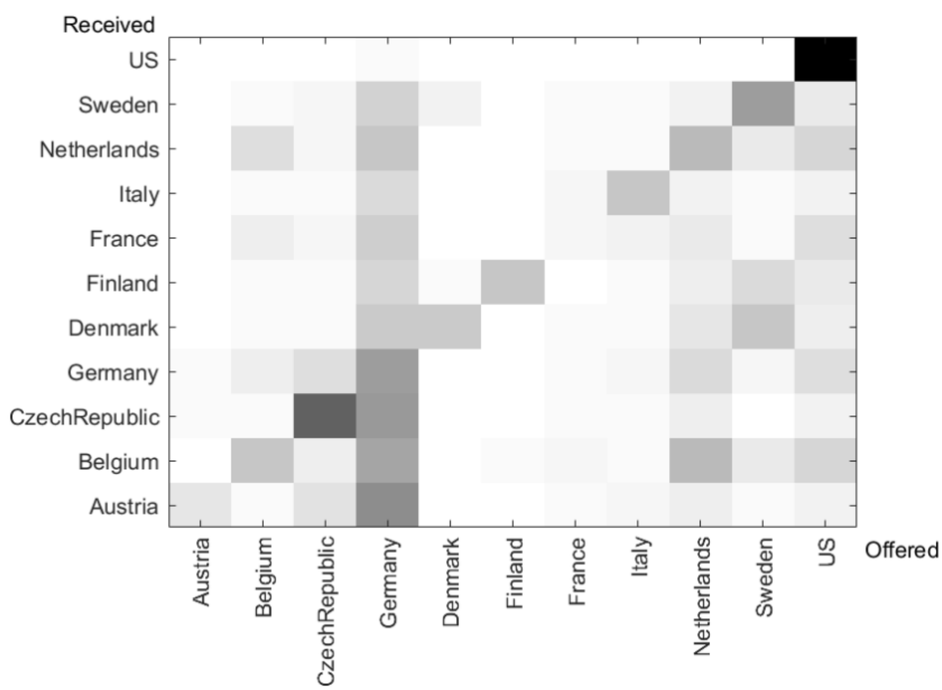
15 https://www.worldbank.org/en/topic/trade/publication/global-value-chain-development-report-2019

Chart 4: Direct and Network Effects of TFP Growth in EU Countries and the United States



Source: Authors' calculations

Chart 5: Distribution Matrix of Network Effects of TFP Growth among Countries



Note: The horizontal axis represents the offering country and the vertical axis represents the receiving country. The anti-diagonal blocs correspond to domestic spillovers and other blocs correspond to international spillovers. The darker the color of the blocs, the more spillover effect between each pair of countries.

countries and more domestic spillovers in the United States, which will be discussed in detail in the next section.

Domestic and international spillovers

Chart 5 shows the distribution of network effects of TFP growth between each pair of offering-receiving countries in 2007. From the columns which represent the network spillovers offered by countries, Germany obviously offered the most to other industries in the entire production network (2.45 per cent), followed by the United States (1.78 per cent), the Netherlands (1.10 per cent) and the Czech Republic (1.03 per cent), whereas other countries contributed only limited network effects. For almost all countries except Germany, the spillover effects in domestic production networks, which is represented in the diagonal blocks of the matrix in Chart 5, were higher than the corresponding spillover effects in the bilateral production networks with other countries. In the Czech Republic, Denmark and Finland the domestic network effects accounted for above 50 per cent of the total network effects, indicating that the TFP growth spillovers were more likely to occur through domestic input–output linkages in these countries.

In contrast, there were 50-86 per cent spillover effects across borders in the United States, Austria, Italy, Sweden, Belgium, the Netherlands, France and Germany. Germany contributed the most technology spillovers to other countries, with international network effects of 2.11 per cent. Germany offered TFP growth spillovers of 0.39 per cent, 0.35 per cent, 0.31 per cent to Austria, the Czech Republic and Belgium, respectively. The spillover the Czech Republic received from Germany is much more than other countries in our sample. This is not surprising since Germany is the biggest trading partner of the Czech Republic. Our estimates also suggest that the bilateral technology spillovers in Belgium versus the Netherlands, and Denmark versus Sweden, are relatively higher than other bilateral technology spillovers, which implies that their cooperation in value chains is more successful in promoting each other's TFP growth.

Conclusion

The increasingly close value chain cooperation in the European Union over the past several decades has become an important factor in boosting productivity growth for the countries who integrated into these production networks. The input-output linkages provide an important channel for the transmission of the technology and productivity spillovers among countries. In this article, we develop a spatial production model that features technological interdependence and heterogeneous productivity growth at the industry level. We use our spatial model to measure TFP growth and spillover in the Europe.

Our estimation results suggest that intermediate inputs have positive externalities for gross output and that about 27 per cent of the spillover embodied in intermediate input has transmitted across borders. This can be an important channel for production interactions among industries. TFP growth in our sample countries fell sharply during the global financial crisis and the Euro Area recession. Germany offered the most network effects with 1.40 per cent annual average domestic spillover and 0.19 per cent annual average international spillover. The United States offered the second highest amounts of network effects, followed by the Netherlands, the Czech Republic and Sweden. The other six countries, Austria, Belgium, Denmark, Finland, France, and Italy, provided a negligible annual average network effect.

From a more detailed network perspective that distinguishes the source and destination of spillover effect by countries, we also find that Germany, as the most important hub in intra-Europe production networks, has the most international spillovers offered to its European counterparts over the entire sample.

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Appendix A

In this section, we obtain equation (3).

Taking the logarithm of Equation (2), we have:

$$\ln A_i(t) = \rho \sum_{j \neq i}^{N} w_{ij} \ln A_j(t) + \phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt} + \ln \Omega_i(t) \qquad \text{(A1)}$$

We can rewrite equation (A1) as the following:

$$\left(1 - \rho \sum_{j=1}^{N} w_{ij}\right) \ln A_i(t) = \phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt} + \ln \Omega_i(t) \qquad \text{(A2)}$$

We can solve (A2) for $A_i(t)$, if $\rho \neq 0$ and if $1/\rho$ is not an eigenvalue of W:

$$\ln A_i(t) = \left(1 - \rho \sum_{j=1}^{N} w_{ij}\right)^{-1} \left(\phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt} + \ln \Omega_i(t)\right) \qquad \text{(A3)}$$

Replacing (A3) in the production function (1) written per worker, and then taking the logarithms, we have:

$$\ln y_{it} = \left(1 - \rho \sum_{j=1}^{N} w_{ij}\right)^{-1} \left(\phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt} + \ln \Omega_i(t)\right) + \alpha \ln k_{it} + \beta \ln m_{it} \qquad \text{(A4)}$$

Putting $\Omega_i(t)$ into (A4), rewrite function (A4) in matrix form as the following:

$$\ln \boldsymbol{y} = \rho(\boldsymbol{W} \otimes \boldsymbol{I}_T) \ln \boldsymbol{y} + \alpha \ln \boldsymbol{k} + \beta \ln \boldsymbol{m} + \boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1 t + \boldsymbol{\Gamma}_2 t^2 + \boldsymbol{v} + (\phi - \alpha\rho)(\boldsymbol{W} \otimes \boldsymbol{I}_T) \ln \boldsymbol{k} + (\varphi - \beta\rho)(\boldsymbol{W} \otimes \boldsymbol{I}_T) \ln \boldsymbol{m}$$

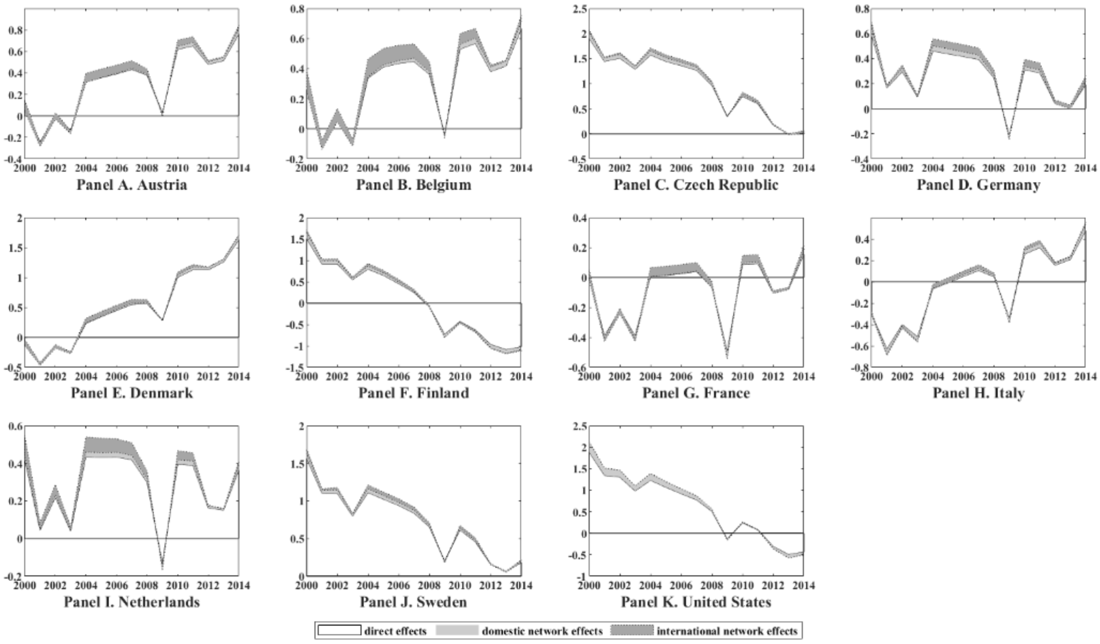
where $\boldsymbol{y}$, $\boldsymbol{k}$, $\boldsymbol{m}$ and $\boldsymbol{v}$ are $NT \times 1$ vectors, W is a $N \times N$ matrix, $\boldsymbol{\Gamma}_0 = \ln \Omega_i(0) \otimes \boldsymbol{\iota}_T$, $\boldsymbol{\Gamma}_1 = \delta_{1i} \otimes \boldsymbol{\iota}_T$, $\boldsymbol{\Gamma}_2 = \delta_{2i} \otimes \boldsymbol{\iota}_T$, $\boldsymbol{\iota}_T$ is the T dimensional vector of ones.

Table A.1 Industry Classifications and Codes

No.	Industry	ISIC Rev. 4
1	Agriculture	A
2	Mining, Quarrying	B
3	Food, Beverages, Tobacco	10-12
4	Textiles	13-15
5	Wood, Paper, Recorded Media Reproduction	16-18
6	Coke, Refined Petroleum	19
7	Chemicals, Pharmaceuticals	20-21
8	Rubber, Plastics, Other Non-Metallic Mineral	22-23
9	Basic Metals, Fabricated Metal	24-25
10	Electrical Equipment	26-27
11	Machinery, Equipment	28
12	Transport Equipment	29-30
13	Other Manufacturing	31-33
14	Electricity, Gas, Water Supply	D-E
15	Construction	F
16	Trade & Repair of Motor Vehicles	45

17	Wholesale Trade	46
18	Retail Trade	47
19	Transport and Storage	49-52
20	Postal and Courier	53
21	Accommodation, Food	I
22	Publishing, Media Services	58-60
23	Telecommunications	61
24	IT and Other Information Services	62-63
25	Financial and Insurance Activities	K
27	Professional, Scientific, Technical, Admin. & Support Service	M-N
31	Arts, Entertainment	R-S

Chart A.1. Network Effects of TFP Growth among Different Countries



Did Trade Liberalization Boost Total Factor Productivity Growth in Manufacturing in India in the 1990s?

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Abstract

India undertook substantial trade reforms from 1991 onwards, accompanied by extensive industrial reforms. Several studies undertaken to date based on growth accounting have reported that total factor productivity (TFP) growth in Indian manufacturing in the initial seven to ten years of the post-reform period was lower than that in the decade before the reforms. This finding is in sharp conflict with the sizeable econometric literature that has unambiguously established a positive effect of trade reforms on productivity, backed by strong theoretical reasons to expect such an effect. This article asserts that certain corrections are required in the computation of TFP growth in Indian manufacturing for the 1980s and 1990s for making a valid comparison and presents the corrected TFP growth rates. Further, an argument is built theoretically with some preliminary empirical support that a downward estimation bias is likely to arise when the conventional growth-accounting approach to the measurement of TFP growth is applied to a situation when major trade reforms are underway, as was the case with Indian manufacturing in the 1990s. Based on the TFP growth estimates obtained, a supportive plant-level analysis of the impact of tariff reform on productivity of Indian manufacturing plants, and the identified possible downward bias in TFP estimation, it is argued that in all probability the productivity growth performance of Indian manufacturing was better in the 1990s following the reforms than the performance in the 1980s.

There is a sizeable econometric literature on the impact of trade liberalization on productivity in manufacturing in emerging economies based on firm-level or plant-level data.[2] Being based on firm- and plant-level panel data, these studies have a clear

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2 See, for example, Pavcnik (2002); Schor (2004); Fernandes (2007); Amity and Konnigs (2007); Hu and Liu (2014); and Jongwanich and Kohpaiboon (2017).

methodological advantage in ascertaining the effect of trade liberalization on productivity (as against a simple comparison of productivity growth rates between pre- and post- reform periods based on growth accounting). The inference one may draw based on this literature is that trade liberalization significantly enhances productivity in manufacturing firms and manufacturing plants in emerging economies.

There is a similar body of literature for Indian manufacturing, dealing with the impact of trade liberalization on manufacturing sector productivity, which is the theme of this article.[3] The findings of these studies indicate that India's trade liberalization had a positive effect on productivity in Indian manufacturing. This conclusion finds additional support and strength from the findings of the econometric studies undertaken at the industry-level, also showing a positive effect.[4]

Notwithstanding the strong empirical basis that the above mentioned studies provide for expecting trade liberalization to yield substantial productivity gains for the manufacturing sector, India's experience has been quite different, at least apparently so, and this makes an interesting case to study. India is the largest emerging economy after China and had a highly restrictive trade regime by the end of the 1980s. The tariff rates in India were among the highest in the world and there were extensive quantitative restrictions on imports of varying degrees of strictness. In 1991, a process of major trade liberalization began in India. In the course of the following 10 years, substantial trade liberalization took place and manufacturing productivity growth did not move in the way expected.

To elaborate on India's economic reforms, the liberalization of its international trade regime that India made from 1991 onwards involved, the removal of quantitative restrictions (QRs) on imports and a huge reduction in tariff.[5] These developments in turn helped in removing the anti-export bias prevailing in the pre-reform period. Along with trade liberalization, extensive reforms were carried out in industrial policy and related aspects such as foreign direct investment.[6] These reforms were however not accompanied by any significant pick-up in the growth rate in total factor productivity (TFP) in manufacturing (to be more specific, organized manufacturing). Rather, there was a fall. This is the impression one would gather from the estimates of TFP growth in Indian manufacturing available for the 1980s and 1990s in

3 See Krishna and Mitra (1998), Natraj (2011), Topalova and Khandelwal (2011), Ahsan (2013), Harrison *et al.* (2013), Gupta and Veeramani (2015a), Mukherjee and Chanda (2020) and Goldar *et al.* (2020).

4 See Chand and Sen (2002), Goldar and Kumari (2003), Das (2006, 2016), Ghosh (2013), and Rijesh (2019).

5 For discussion on trade and tariff reforms, see Nouroz (2001), Goldar (2002), Das (2003a, 2003b), Panagariya (2004a), Virmani *et al.* (2004), Pursell *et al.* (2007), Banga and Das (2012), Das (2016) and Singh (2017), among others.

6 See Joshi and Little (1996), Ahluwalia (2002), Bajpai (2002), Das (2003b), and Panagariya (2004b), among others.

quite a few studies.[7] This is indeed a matter of surprise because economic reforms are expected to boost TFP growth in the industrial sector for the reasons explained below.

The domestic industrial and trade reforms are expected to lead to an increase in the rate of TFP growth in manufacturing through various channels.[8] The reforms are expected to put pressure on domestic producers to improve resource-use efficiency. The reforms are also expected to create conditions that will force the removal of the inefficient producers from among the domestic producers (or contraction in the market share of such producers) and help the efficient producers to thereby capture a larger share of the market and the average efficiency in the industry goes up.[9]

In addition to these, reforms are expected to contribute to productivity in various other ways including gains in productivity arising from increased access to imported intermediate inputs[10] and capital goods. But these arguments, though based on sound theory, did not meet the expected outcomes – this is the sense one would obtain based on the findings of most studies on TFP growth in Indian manufacturing based on growth accounting. It appears therefore that the beneficial forces unleashed by trade and industrial reforms did not materialize into an accelerated TFP growth in Indian manufacturing in the 1990s. Is this true?

Why the economic reforms failed to result in a marked increase in the TFP growth rate in Indian manufacturing in the 1990s is an intriguing question. It has received the attention of scholars writing on productivity in Indian manufacturing. One explanation is the J-curve hypothesis of productivity and growth (Virmani and Hashim, 2011). The argument is that in the initial phase of economic reforms, there was obsolescence of skill, capital and technology in some industries, sub-sectors and sectors. Thus, a portion of the employees in Indian manufacturing had to be directed to retraining and re-skilling and a part of capital assets became obsolete and had to be replaced, and it is only over time that Indian manufacturing could overcome these developments. This is the reason why there was a sharp increase in the growth rate in TFP after 2003, reflecting lagged effect of economic reforms.

At its core, this article is concerned with

7 See, for instance, Trevedi, *et al.* 2000; Goldar and Kumari, 2003; Goldar, 2006; Banga and Goldar, 2007; Virmani and Hashim, 2011; and Trevedi *et al.* 2011; for a review of studies, see Goldar, 2014; the estimates of TFP growth in these and other studies are shown later in Table 1. Bollard *et al.* (2013), however, have reported a significant increase in the growth rate of TFP in Indian manufacturing during 1993 to 2007 in comparison with the TFP growth rate during 1980 to 1992. In terms of the methodology adopted, this study was quite different from the ones listed above. Another study that reported an increase in the TFP growth rate in Indian manufacturing in the post-reform period in comparison with the pre-reform period is Unel (2003). See Goldar (2004) and Goldar (2014) in this context.

8 See Topalova and Khandelwal (2011), Rijesh (2019) and Goldar, *et al.* (2020), among others.

9 Interestingly, the estimates of Bollard *et al.* (2011) for relatively bigger plants within Indian manufacturing indicate that reallocation did not contribute more to TFP growth in the post-reform period than in the pre-reform period.

10 See Goldberg *et al.* (2010) for an analysis of how improved access to imported intermediate inputs contributed to productivity growth in Indian manufacturing in the post-reform period.

the effect of economic reforms, particularly trade reforms, on TFP growth in Indian manufacturing. An important focus is on TFP estimation methodology. The article points out certain inaccuracies in the manner TFP growth in Indian manufacturing has been commonly computed in many previous studies that have applied the growth accounting methodology based on ASI (*Annual Survey of Industries*)[11] data and made a comparison of the manufacturing sector TFP growth rate between the pre- and post-reform periods.

In addition, the article addresses the issue of an estimation bias that is inherent in the measurement of TFP growth when the conventional growth accounting methodology is applied to industries of a highly protected developing economy undergoing substantial trade liberalization. This was the situation faced by Indian manufacturing in the 1990s. An argument is advanced that due to the collective effect of the aforementioned inaccuracies in TFP measurement and the identified bias, the measured TFP growth in many of the studies undertaken in the past, may have failed to capture properly the improvements in TFP in manufacturing that took place in the first decade of the post-reform period. To correct the measurement inaccuracies and show their significance, a new set of TFP growth estimates with and without corrections are presented in the article.

As regards the bias in the TFP growth measurement noted earlier, it is difficult to provide empirical content for this line of argument. Nonetheless, an attempt is made to put forward some empirical evidence, even if sketchy, in support of the argued estimation bias in TFP growth measurement. These computations and pieces of evidence when seen along with the figures on conventionally measured TFP growth will help in making a better assessment of the impact of trade and industrial reforms on TFP growth in Indian manufacturing in the 1990s.

The main part of the analysis is based on data on the aggregate organized manufacturing sector and panel datasets at the industry level. This is supplemented by another piece of research in which econometric analysis is carried out of the impact of tariff reductions on productivity using plant-level data for Indian manufacturing for the years 1998-99 to 2010-11.[12] The aim is to gain a better understanding of the issue under investigation.

The article is organized as follows. Before going into the productivity trends, an examination of the trends in the import-penetration ratio is done in section 1. The estimates of TFP growth in Indian manufacturing (organized segment) presented in various earlier studies are taken up for discussion in section 2. Certain inaccuracies on TFP measurement are pointed out and corrections are made in this section. In section 3, an attempt is made to provide empirical content to the theoretical argument that a downward bias may arise in the mea-

11 Annual Survey of Industries, National Statistical Office, Ministry of Statistics and Programme Implementation, Government of India.

12 These are financial years, from April 1 to March 31 of the following year. Thus, 2008-09 means, April 1, 2008 to March 31, 2009, similarly for other financial years.

surement of TFP based on growth accounting in a situation of ongoing trade reforms. Section 4 is devoted to an analysis of the effect of trade liberalization on manufacturing productivity based on plant-level data. Finally, the key conclusions of the study are summed up in section 5.

Trends in Import Penetration Ratio

To begin the discussion, the following question may be asked: did trade liberalization of the 1990s (and later) lead to a substantial hike in import competition faced by domestic producers of manufactured goods in India, resulting in a marked increase in the import penetration ratio?[13] What does the available data on import penetration tell us on this point?

According to the estimates made by the present author (computation and data sources explained in Goldar, 2022), the import penetration ratio in Indian manufacturing (excluding petroleum products) was about 9 per cent in 1990-91 and it rose only by 3 percentage points between 1990-91 and 1998-99. Going by the estimates made by Das (2016: 21), the import penetration ratio in manufacturing increased from about 10 per cent in 1990-91 to about 15 per cent in 2009-10. It is, however, important to note that it was lower in 1996-97 than in 1990-91.

The quantitative restrictions (QRs) on imports of intermediate and capital goods were mostly removed in the 1990s, but the QRs on a large section of consumer goods continued during most of the 1990s and QRs were only removed in 2000 and 2001. Thus, the trends in import penetration should be seen for intermediate goods and capital goods separately from consumer goods. For intermediate goods, Das (2016: 36) finds that the import-penetration ratio rose only by a couple of percentage points between 1990-91 (when it was about 11 per cent) and 1996-97, and then it came down, with the result that the import penetration ratio for intermediate goods in 1999-2000 was almost the same as that in 1990-91. By and large, the same was the trend in import penetration ratio in capital goods – it was about 16 per cent in 1990-91, there was a slight increase till 1996-97 and then a fall – the figure for 1999-2000 was only slightly higher than that for 1990-91.

The removal of QRs on imports of manufactured products took place along with a substantial lowering of tariff rates on imports. The tariff rates in India by the end of the 1980s were very high, one of the highest in the world, and with the initiation of trade reforms coupled with industrial reforms, the tariff rates were cut substantially. According to Pursell *et al.* (2007),[14]

13 The import penetration ratio is defined as imports divided by availability, where availability is equal to domestic production plus imports minus exports (Das, 2016:19).

14 According to the data on tariff rates provided by Pursell *et al.* (2007), the collection rate of duty in 1991 was about 60 per cent of the value of imports. This probably also includes countervailing duty (equal to excise duty on domestic products) and thus the protective component of actual customs duty paid was lower than 60 per cent. Nouroz (2001) reports that in 1992-93 the average tariff rate across manufacturing industries was about 92 per cent and the collection rate was about 46 per cent. These two rates fell to 35 per cent and 28 per cent respectively by 1997-98

the average industrial tariff fell from 130 per cent in 1991 to about 40 per cent by the end of the 1990s. Somewhat similar figures on tariff rates on industrial products have been reported by Das (2016:24).[15] According to Nouroz (2001) the import-weighted average tariff for manufactured goods was 90.5 per cent in 1987 which came down to 38 per cent in 1994 and further down to 30 per cent in 1997 (also see, Mathur and Sachdeva, 2005; and Singh, 2017).

Along with the lowering of tariff rates, there was a lowering of the effective rate of protection (ERP) of Indian manufacturing industries (accorded by tariff) during the 1990s.[16] It is important to recognize, however, that before the onset of tariff reforms in the post-1991 period, there was a good deal of 'water in tariff' (also called tariff redundancy). This arises when the tariff rate is more than the difference between the domestic price and the international price of a tariff-protected good. It means that the domestic producers are charging a price less than the maximum chargeable price level beyond which the price of the imported substitute (even after paying the tariff) will become cheaper – this is often caused by intense competition among the domestic producers in the local markets. To provide some data on this aspect in the Indian context, although the average tariff rate on industrial products was more than 100 per cent in 1986, the difference in the prices of like products in India and in international markets, which is known as implicit tariff, was on an average only about 50-60 per cent. For one sizeable section of industries, comprising mostly consumer goods industries, it was less than 30 per cent (Pursell *et al.*, 2007, pp. 5, 22-24). By 1991, going by the estimates made by Pursell *et al.* (2007:5), the average implicit rate of tariff was only about 30-40 per cent. Interestingly, it touched zero by 1993, increased slightly thereafter and then came back to zero by the end of the 1990s. An additional point to be noted here is that, in the early 1990s, tariff cuts were combined with substantial depreciation in the exchange rate that neutralized the effect of tariff cuts; this would be realized by examining the trends in the real effective exchange rate during the early 1990s (Goldar, 2002; Pursell, *et al.*, 2007). The main point being made here is that in the first half of the 1990s, the tariff cuts probably did not put a large section of the domestic manufacturers at any great disadvantage vis-à-vis imports because of (a) the previously prevailing significant 'water in tariff' (i.e., tariff redundancy) and (b) the fact that effect of tariff cuts was neutralized to some extent by exchange rate depreciation.

Given the changes that took place in respect of tariff rates on industrial goods and

15 See Goldar *et al.* (1992), Goldar and Saleem (1992), Nouroz (2001), and Goldar (2002) for information on tariff rates in the pre-reform period and in the initial five to ten years of the post-reform period.

16 For an analysis of trends in the effective rate of protection (ERP) of Indian manufacturing accorded by tariff in the 1980s, 1990s and 2000s, see Goldar and Saleem (1992), Nouroz (2001), Ahluwalia (2006), and Das (2003a, 2016). There is a clear indication that the ERP accorded by tariff to Indian manufacturing fell during the 1990s following the tariff cuts. According to the estimates presented in Ahluwalia (2006), the average ERP of Indian manufacturing fell from about 166 per cent in 1988-89 to 55 per cent in 1996-97. Das (2016, Figures 4.2 and 4.4) reports that the average ERP of manufacturing was 129 per cent in 1990-91, which fell to about 40 per cent by the end of 1990s, and to 21 per cent by 2009-10.

QRs, how does one interpret the findings regarding import penetration ratio – the absence of any marked increase in import penetration? Does this mean that the QRs on intermediate and capital goods were not constraining the imports of such goods before the QRs were removed? Or is it possible that although imports were permitted and tariffs were lowered, the exchange rate depreciation made imports very costly and therefore increases in imports did not take place? Or could this be interpreted as showing that the domestic industry was able to improve its competitiveness sufficiently after the initiation of trade reforms impelled by the challenges and strengthened by improved access to imported materials, parts and components, and capital goods, so that they could squarely meet import competition? If the last one is the true explanation or a major explanation, then a follow-up question that arises is, why did this improvement in the competitiveness of domestic producers not show up in the estimates of TFP growth in growth accounting studies? Taking a cue from this question and other observations made above, the basic purpose of the article, as stated earlier, is to draw attention to the possibility that the measured TFP growth for Indian manufacturing has not properly captured the improvements that took place. This is essentially the argument made.

Corrections Needed in TFP Growth Estimates

In this section, attention is drawn to three corrections that need to be made in computing TFP growth in Indian manufacturing based on the growth accounting methodology applied to ASI data for a valid comparison between the 1980s and 1990s. To provide empirical content to the arguments, a fresh set of TFP growth estimates are presented – these are shown with the corrections and without the corrections, so that the impact of corrections may be judged. The construction of the dataset on output and inputs is similar to (but not the same as) that in earlier studies of the present author (Goldar, 2015, and Goldar, 2017) and is explained in the online Appendix. [17] The basis data source is ASI, which is the source used by most earlier studies on TFP growth in Indian manufacturing.

Before taking up the corrections needed, it is important to provide some information on the gap in TFP growth rates between the pre-reform period and post-reform period (or to be more specific the initial phase of the post-reform period) reported in various studies. Table 1 shows the total factor productivity (TFP) growth estimates for Indian manufacturing (organized segment) covering most of the studies undertaken.

For the estimates based on the value-added function, the gap in TFP growth between the pre-reform and post-reform period is about one percentage point per annum or higher (with one exception where the gap is 0.5 percentage points). In some studies, the gap is about two percentage points per annum. In the case of the TFP estimates based on gross output function,

17 http://www.csls.ca/ipm/43/IPM_43_Goldar_Appendix.pdf.

Table 1: Estimates of TFP Growth in Indian Manufacturing, Earlier Studies

Author(s)	Pre-reform Estimated TFPG (% per annum) and period in parentheses	Post-reform Estimated TFPG (% per annum) and period in parentheses
Panel A: Based on Value-Added Function		
Trivedi *et al.* (2000)	3.06 (1981-82 to 1990-91)	1.96 (1990-91 to 1997-98)
Goldar and Kumari (2003)	4.27 (1981-82 to 1990-91)	1.60 (1990-91 to 1997-98)
Goldar (2004)	2.14 (1979-80 to 1990-91)	1.57 (1991-92 to 1999-2000)
Goldar (2006)	4.52 (1981-82 to 1990-91)	1.86 (1990-91 to 1997-98)
Ahluwalia (2006)	3.8 (1980-81 to 1990-91)	-7.8 (1991-92) 3.4 (1991-92 to 1997-98)
Rajesh Raj and Mahapatra (2009)	1.40 (1980-81 to 1990-91)	(-)0.52 (1991-92 to 2002-03)
Trivedi *et al.* (2011)	2.1 (1980-81 to 1990-91)	1.0 (1991-92 to 2007-08)
Datta (2014)	2.05 (1980-81 to 1990-91)	(-)0.45 (1990-91 to 2003-04)
Rijesh (2019)	3.4 (1980-81 to 1990-91)	2.9§ (1991-92 to 2007-08) (-)3.2 (2008-09 to 2013-14)
Panel B: Based on Gross Output Function		
Trivedi et al. (2000)	1.26 (1981-82 to 1990-91)	0.63 (1990-91 to 1997-98);
Goldar and Kumari (2003)	1.89 (1981-82 to 1990-91)	0.69 (1990-91 to 1997-98)
Trivedi (2004)	1.90* (1980-81 to 1991-92)	0.70* (1992-93 to 2000-01)
Goldar (2006)	2.13 (1981-82 to 1990-91)	0.90 (1990-91 to 1997-98)
Banga and Goldar (2007)Ä	0.88 (1980-81 to 1989-90)	0.26 (1989-90 to 1999-2000)
Virmani and Hashim (2011)Ä	0.61 (1981-82 to 1990-91)	0.25 (1990-91 to 1997-98)
Das and Kalita (2011)	0.65# (1980-81 to 1989-90)	0.31# (1990-91 to 1999-2000)

Major economic reforms began in India in 1991. The estimates of TFP growth for the post-reform period shown in the table include, in most cases, one or two years of the pre-reform era. However, it is appropriate to consider the estimates shown in the last column of the table as the estimates of TFPG for the post-reform period, since post-reform years dominate. (2) Most available studies on TFPG in Indian manufacturing at the aggregate level based on growth accounting are included in the table, but not all. (3) While specifying the period for which TFP growth estimates are provided, some authors have included the first year, and some have not. The periodization as given by the author(s) has been adopted for the table without making any change. (4) If both single-deflated and double-deflated GVA (gross value added) based estimates are available, the former has been taken.

This estimate of Das and Kalita (2011) is the average of ten two-digit industry-level estimates each of which is the Domar aggregation of TFP growth in constituent three-digit industries (together accounting for about 70 percent of manufacturing GVA). Das (2003b) presented estimates of TFP growth in three broad industry groups. For capital goods industries and consumer goods industries, the average rate of TFP growth during the 1990s was found to be lower than that during the 1980s. * Trend growth rates in TFP. § Combining the estimates for 1991-92 to 2000-01 and 2001-02 to 2007-08 provided in the study. *Ä* These studies use capital, labour, energy, materials, and services (KLEMS) as five inputs.

Source: Prepared by the author

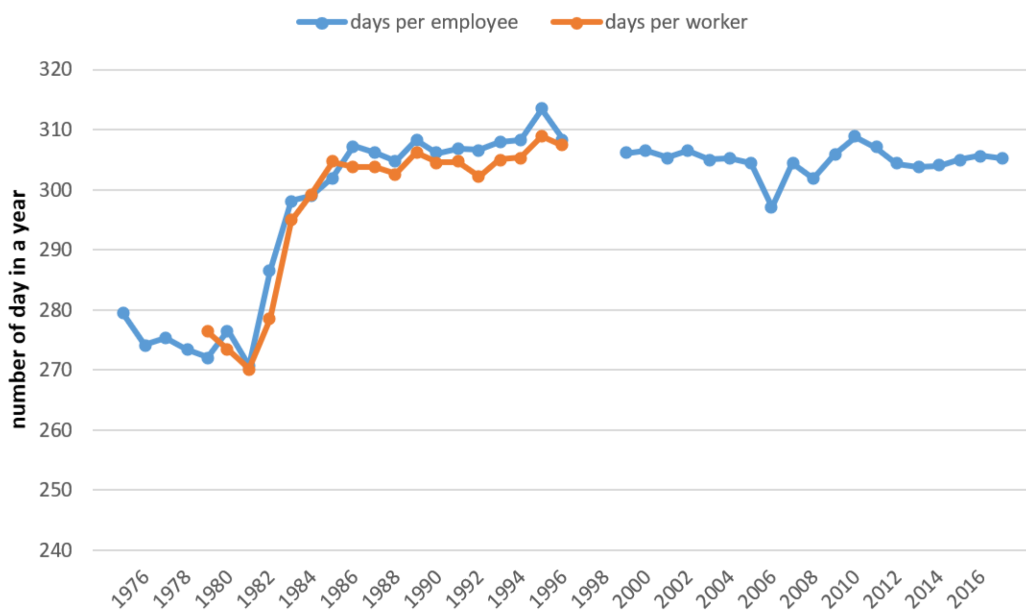
the gap is relatively smaller. But the gap in TFP rate between the post-reform period and the pre-reform period is more than one percentage point in some cases.

The shortcoming or inaccuracies in the computed TFP growth rates are taken up next. These points are relevant to the studies which are based on ASI data (applicable to most studies on TFP growth in Indian manufacturing).

Inaccuracy 1

One aspect to which attention needs to be drawn is that there was a significant increase in hours of work among workers in manufacturing in the 1980s, and this needs to be accounted for in the TFP growth estimates. This may be seen in Chart 1 which shows days worked per employee and days worked per worker during 1975-76 to 2017-18. During the 1980s there was a significant increase in days worked per employee and per worker, coming to an additional 35 days in a year. Going by headcount (number of persons employed or number of employees), the growth in labour input in manufacturing was slow in the 1980s, only 0.5 per cent per year. It is necessary to correct this by incorporating changes in days worked per

Chart 1: Days worked Per Year Per Worker and Per Employee, Indian Manufacturing, 1975-1976 to 2017-2018



Source and note: Author's computations based on EPWRF (Economic and Political Weekly Research Foundation) dataset which has been prepared using ASI data (hereafter called EPWRF dataset based on ASI). Data on days worked are not available for 1997-98 and 1998-1999.

employee. The average annual growth rate in days worked per employee was about one per cent during 1980-1990. This raises the growth rate in labour input in manufacturing during 1980-1990 from 0.5 to 1.5 per cent per annum.

In her analysis of jobless growth in Indian manufacturing in the 1980s, Bhalotra (1998a:23) has noted this phenomenon of significantly rising days worked per employee in that decade. She has provided some explanations for the observed hike in hours per employee in the 1980s: uncertainty, competition, fear,[18] and infrastructure development.[19] She has noted that the growth in hours worked per worker was one of the contributory factors to the measured TFP growth in Indian manufacturing in the 1980s.[20]

This raises a methodological question. If hours worked per worker go up in a particular period because of de-hoarding of surplus labour that existed at the beginning of the period, better infrastructure availability helping in cutting down power shortages and raw materials shortages, a changed policy environment, should this be treated as more labour input or as more productivity. Note here that in the empirical literature on productivity, labour input in manufacturing has been measured on the basis of hours worked in many studies rather

18 Falling employment and reduced support of government for workers induced fear and discipline among workers. Less time was lost because of industrial disputes.

19 Time losses on account of power shortages and materials shortfalls were avoided.

20 Bhalotra (1998b) observes that unless the recuperation of time losses are accounted for, the TFP estimates exaggerate TFP growth in Indian manufacturing in the 1980s.

than the number of persons (Kathuria *et al.* 2014:33).[21]

If one is undertaking a study on TFP growth in Indian manufacturing in the 1980s only, one may use the number of persons employed as the measure of labour input or base the measure of labour input on total days worked by all employees, and then interpret the estimates of TFP growth accordingly. But, when the estimates of TFP growth are to be compared between the 1980s and 1990s, and in one decade, days worked per employee has increased significantly and in the other decade there has been no such increase, then it seems reasonable to argue that it is essential to take into account the increases in days per employee in the 1980s as a part of increases in labour input to make the comparison meaningful. The implication is that the computed TFP growth for the 1980s will go down if this aspect is incorporated into the computation.

Inaccuracy 2

The second issue that needs attention relates to the income share of labour in gross value added. In applying the growth accounting methodology, it is assumed that factor income shares are equal to the elasticities of output with respect to the factors of production. This involves the assumptions of constant returns to scale and perfect competition in product and factor markets. Let α and β be the true elasticity of output (real gross value added) with respect to labour and capital. The rate of TFP growth (TFPG) is computed as:

$$TFPG = \hat{Y} - \alpha\hat{L} - \beta\hat{K} \qquad (1)$$

where the caret symbol denotes the growth rate, Y denotes real GVA (gross value added), L denotes labour input and K denotes capital input. Note, however, that the true elasticities are not known and in their place, the income shares are used. Let α^* be the observed income share of labour and β^* be the observed income share of capital.

The computed TFPG, denoted by TFPG′, then becomes:

$$TFPG' = \hat{Y} - \alpha^*\hat{L} - \beta^*\hat{K} \qquad (2)$$

If the observed income shares of labour and capital (α^* and β^*) deviate from the true elasticities (β and β), the measured TFP growth will differ from true TFP growth (see Box 1 in this context). The important question here is whether trade reforms had an impact on the labour income share and hence on the deviation of observed income shares from the true elasticities and did this cause an underestimation of TFP growth for the 1990s? It looks like there are reasons to believe so.

Protection from international trade results in rents which are distributed between labour and capital according to their rel-

21 This is not true for studies on India's organized manufacturing. The measure of labour input is based on headcount (e.g., total number of persons engaged) in Goldar and Kumari (2003), Unel (2003), Das (2003b), Goldar (2004b, 2006), Banga and Goldar (2007) Trevedi, *et al.* (2011), and Rijesh (2019). This is possibly true for several other such studies on manufacturing sector productivity based on ASI data.

ative bargaining power. There need not be proportional distribution of rents, proportional to non-rent factor incomes; hence α^* and β^* are expected to differ from the true elasticities. There is some literature for India and other developing countries which provides an empirical basis to argue that the removal of trade protection tends to lower the income share of labour.[22] This occurs presumably because relatively greater downward adjustments in their incomes are made by labour than capital as rents associated with protection are eroded with liberalized trade.

The average income share of labour in India's organized manufacturing (emoluments divided by GVA, both at current prices) was about 39 per cent during 1980-1990 and about 28 per cent during 1991-1999. One possible interpretation of these figures is that the labour income share in the post-reform period understates the true elasticity of GVA with respect to labour (hereafter called GVA-labour elasticity) in this period. Or one may argue that labour income share understates the elasticity in both pre-reform and post-reform periods, and the extent of deviation is greater in the post-reform period. If this is true,[23] then the conventionally measured TFP will understate TFP growth in Indian manufacturing, particularly in the 1990s.

The underestimation of TFP growth occurs because the growth rate in labour input in Indian manufacturing has been much lower than that in capital stock (which is taken as a measure of capital input). Hence, if the income share of labour is less than the GVA-labour elasticity because of the disproportionate redistribution of rents associated with trade reform, then this tends to raise the estimated growth rate in total input, and thus understates the growth rate in TFP. Possibly such a gap was there in the data for the post-reform period, causing an under-estimation of TFP growth. Or the gap might have been there in both pre- and post-reform periods but was greater in the post-reform period leading basically to the same or similar consequence.

To pursue the above line of argument further, let us consider the trends in labour income share and what adjustment is needed for a more accurate TFP growth measurement. A precise adjustment of the labour income share to reflect properly the GVA-labour elasticity is difficult to do, and thus not attempted here. Nonetheless, a rough adjustment is done based on two econometric exercises – in one exercise, a Cobb-Douglas two-input production function is estimated to derive the GVA-labour elasticity, and in the other exercise, an econometric model for explaining labour income share is estimated.

22 On this issue, especially in the Indian context, see Goldar and Agarwal (2005); Abraham and Sasikumar (2017); Gupta and Helble (2018); and Goldar (2022); among others.

23 Whether this is true or not, needs a detailed investigation. While some analysis is presented here, a complete, thorough treatment of issue is beyond the scope of the article.

Box 1: Factor Income Share and Output Elasticities

In applying the growth accounting methodology for estimating TFP growth, there is an assumption that factor income shares are equal to the elasticity of output with respect to various factors of production. In the case of a two-input production function, taking value added as output, and labour and capital as inputs, the application of growth accounting methodology assumes that the elasticity of real value added with respect to labour is equal to the income share of labour in gross value added, and the elasticity of real value added with respect to capital is equal to the income share of capital in value added. Since the income shares of labour and capital add up to one, there is an assumption of constant returns to scale. Doubts have often been expressed on the validity of these assumptions in the context of the application of the growth accounting methodology to industries in developing countries.

Unel (2003) presented estimates of TFP growth in Indian manufacturing in the pre- and post-reform periods. For one set of estimates, the elasticity of GVA with respect to labour was taken as constant at 0.6. The argument given is that labour income share in Indian manufacturing significantly understates elasticity of output with respect to labour, especially for the 1990s. He referred to the elasticities emerging from production function estimates in Ahluwalia (1991) and noted that labour's income share in manufacturing in five leading industrialized countries was in the range of 0.57 to 0.65. This issue has been examined in Goldar (2004).

In the analysis undertaken by Viramani and Hashim (2009) using an estimated CSE (constant elasticity of substitution) production function, they have found that wage rate and marginal productivity of labour in Indian manufacturing were nearly the same during 1980-91, but the wage rate was about 20 per cent lower than marginal productivity during 1992-2001. This means that labour income share was smaller than corresponding elasticity in the post-reform period. This finding has relevance to the analysis presented in this article.

Bosworth *et al.* (2007) have studied the sources of growth of the Indian economy using the growth accounting framework. Instead of using the income shares of labour and capital as elasticities for computing TFP growth for industry and services sectors, they take the output elasticity with respect to labour and capital as 0.6 and 0.4 respectively. They note that self-employed workers form a dominant part of employment in India, and there is considerable difficulty in separating labour income component and capital income component out of the mixed income of the self-employed. While there are some arguments for taking the GVA elasticity with respect to labour to be more than labour income share, a different set of arguments, for instance increasing returns to scale, embodied technological progress and externalities associated with investment, could provide a basis for taking the GVA elasticity with respect to capital as substantially above the income share of capital (Romer, 1987).

Table 2: Estimates of a Cobb-Douglas Production Function, Indian Manufacturing

Dependent variable: ln(Y/L)

Period: 1980-81 to 2017-18
(22 two-digit industries)

Explanatory variables	**Regression-1 (Fixed-effects)**	**Regression-2 (FGLS)**	**Regression-3 (difference GMM)**	**Regression-4 (system GMM)**
ln(Y/L)t-1			0.727(15.5)***	0.702(19.1)***
ln(K/L)	0.436(1.72)*	0.429(15.02)***	0.255(3.64)***	0.250(3.47)***
ln(K/L)*D1990-1999	0.030(0.72)	-0.031(-1.84)*	-0.075(-2.24)**	-0.066(-1.75)*
ln(K/L)*D2000-2007	0.166 (2.74)**	0.036(1.87)*	-0.021 (-0.62)	-0.009(-0.22)
ln(K/L)*D2008-2017	0.180(2.01)**	0.050 (2.66)***	-0.030(-0.65)	-0.016(-0.29)
D1990-1999	-0.107(-0.73)	0.116(1.74)*	0.229(1.97)**	0.187(1.44)
D2000-2007	-0.732(-3.04)***	-0.244(-2.79)***	-0.033(-0.28)	-0.082(-0.60)
D2008-2017	-0.868(-2.47)**	-0.374(-4.01)***	-0.022(-0.12)	-0.076(-0.35)
ln(man-days per employee)	0.055(0.19)	0.272(4.85)***	0.333(1.43)	0.425(1.80)*
Time (year)	0.032(2.94)***	0.037(17.69)***	0.006(1.71)*	0.007(3.05)***
Number of observations	836	836	792	814
R-squared	0.77			
F-value and prob.	73.8 (0.000)			
Wald chi-sqr and prob.		3810.0(0.000)	2795.5(0.000)	5921.0 (0.000)
Sargan test of over-identified restrictions, chi-sqr, and prob.			511.4 (0.92)	609.7(0.32)
AR(1)			-3.56(0.000)	-3.56(0.000)
AR(2)			2.15(0.031)	2.12(0.034)
No. of instruments			569	605

Source and note: Author's computation based on EPWRF dataset on ASI. In addition, data on prices have been used. Y=real gross value added; L=labour input (persons employed); K=deflated fixed capital stock. D1990-1999, D2000-2007 and D2008-2017 are dummy variable for the periods 1990-99, 2000-07 and 2008-17 respectively. Robust standard errors. t-values in parentheses. *, **, *** Statistically significant at 10 percent level, 5 percent level and one percent level respectively.

The estimation of a constant-returns-to-scale Cobb-Douglas two-input production function has been done by using panel data for 22 two-digit industries from the years 1980 to 2017. The fact that days per employee grew significantly during the 1980s has been incorporated into the analysis by taking days per employee as an additional explanatory variable.[24] A time trend variable is included to capture the impact of technical change as well as other developments in the economy. Intercept and slope dummy variables have been included in the estimated model for the periods, 1990-1999, 2000-2007, and 2008-2017. The purpose is to find out if the capital and labour elasticities in the periods 1990-99, 2000-2007 and 2008-17 were significantly different from that during 1980-89. The results are shown in Table 2. In regressions (1) and (2), the results obtained by applying the fixed-effects model and the feasible generalized least-squares (FGLS) method are presented.[25] In regressions (3) and (4), the

24 Number of persons employed and days per employee are taken as two variables instead of combining them into one variable to impart greater flexibility in modelling.

25 Tests of cross-sectional independence (Pesaran test, Friedman test, and Frees test) indicate the presence of cross-sectional dependence. This provides justification for using the FGLS method. In estimating the model, heteroskedastic and correlated error structure has been incorporated along with AR1 autocorrelation structure.

results obtained by applying the difference and system GMM (Generalized Method of Moments) estimators are presented.[26]

To take up the results in Regressions (1) and (2) first, the coefficient of the capital-labour ratio is found to be positive (as expected) and statistically significant. The numerical value of the coefficient is plausible as the elasticity of value-added with respect to capital input. The coefficient of the interaction term involving the capital-labour ratio and the dummy variables for the periods 2000-2007 and 2008-2017 are positive and statistically significant which indicates that the elasticity of real GVA with respect to capital was relatively higher (and thus the elasticity with respect to labour was relatively lower) in the periods 2000-2007 and 2008-2017 than that during 1980-1989. The interaction term involving the capital-labour ratio and the dummy variable for the period 1990-1999 is negative and statistically significant in the FGLS estimates. The hypothesis that the elasticity was the same between the two periods 1980-89 and 1990-99 is therefore rejected. This suggests that the GVA-labour elasticity during 1990-1999 was higher than that during 1980-1989 (contrary to the pattern seen in the actual income shares).

Turning next to the results in Regression (3) and (4), the coefficient of capital-labour ratio is found to be positive and statistically significant, as in Regressions (1) and (2). The interaction terms involving the capital-labour ratio and the period dummy variables for 2000-2007 and 2008-2017 are statistically insignificant. It may thus be inferred that the GVA-labour elasticities in 2000-2007 and 2008-2017 were not significantly different from that in 1980-1989. On the other hand, the interaction term involving the capital-labour ratio and the period dummy variable for 1990-1999 is negative and statistically significant, as in the FGLS estimates. This indicates that the elasticity of value added with respect to capital (hereafter GVA-capital elasticity) was lower and hence the GVA-labour elasticity was higher in 1990-1999 than that in 1980-1989. This is the opposite of what one might think based on observed trends in labour income share.

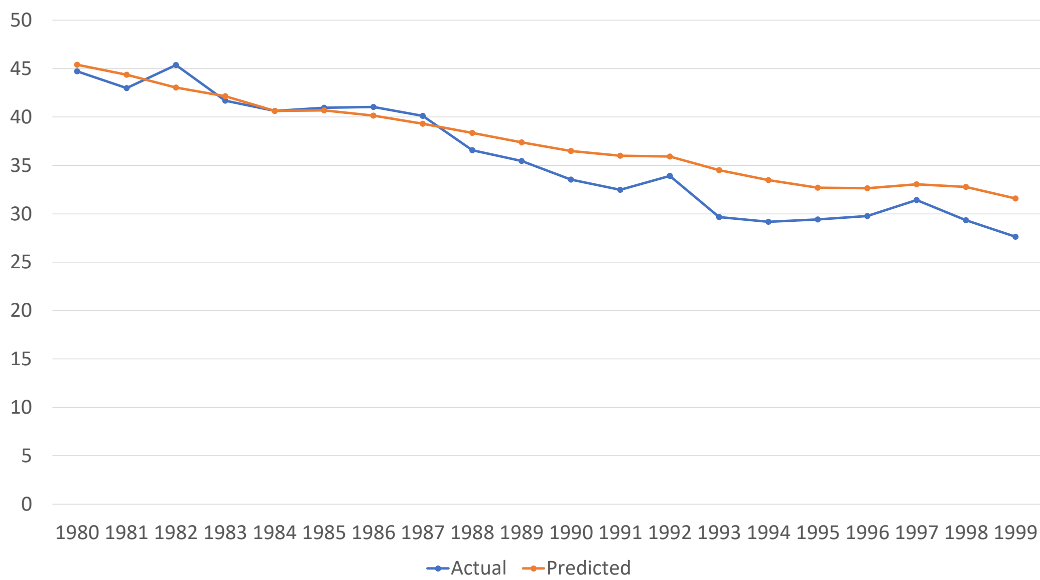
The results in Table 2 suggest that to apply the growth accounting methodology to compute TFP growth in Indian manufacturing in the post-reform period, the income share of labour for the 1990s should be adjusted upwards to the level of that in the 1980s, i.e., upward adjustment by about 11 percentage points or even higher.

In the second exercise, an analysis of inter-industry inter-temporal variation in labour income share is done by (a) estimating an econometric model to explain labour income share of various two-digit industries in the period 1980-1988, and then (b) using that model to predict labour income share for the 1990s which is then compared with actual labour income share.[27] The

26 The GMM and the FGLS methods have been used in the estimation of production based on industry-level data by Pablo-Romero *et al.* (2019).

27 Labour income share is regressed on the logarithm of capital-output (value added) ratio and time trend (see Annex-B). See Gupta and Helble (2018) who have employed a similar specification for a plant-level study with several other control variables added.

Chart 2: Labour Income Share in GVA (%), Indian Manufacturing, 1980-1999, actual and model predicted



Source and note: Author's computation based on EPWRF dataset on ASI. The estimated fixed-effects model that has been used for the prediction of labour income share (see Annex-B).

predicted (based on the fixed-effects model) and actual labour income for the period 1980 to 1999, the average across two-digit industries, are shown in Chart 2. A gap is found between the predicted labour income share and the actual labour income share for the 1990s. On this basis, it seems an upward correction of 3.3 percentage points in the average labour income share in the 1990s is needed to use the labour income share in the application of growth accounting.

Since the first exercise suggests an upward adjustment by 11 percentage points or higher and the second exercise suggests an upward adjustment by 3.3 percentage points, the middle path has been taken and thus the average of the two figures has been adopted. Accordingly, an upward adjustment by 7 percentage points has been done with the hope that with this adjustment labour income share in the 1990s will better represent the GVA-labour elasticity.

As a follow-up to the discussions on methodology above, some estimates of TFP growth in Indian manufacturing (organized) based on ASI data are presented next. Table 3 shows the growth rates in real GVA, labour inputs (persons employed) and capital input (fixed capital stock formed by perpetual inventory method) and labour income share in GVA for the periods 1980-1990, 1990-1999 and 1991-1999. Since 1991 was a year of economic crisis, it is perhaps not fair to include it in the post-reform period to evaluate the relative performance in the two periods. Hence, for the post-reform period, growth rates in the years 1990-1999 and 1991-1999 are both considered, the latter being the preferred sub-period for judging the relative performance.

It is evident that based on the conventional measure of TFP, the performance in terms of TFP growth was relatively worse in the post-reform period (see the second

Table 3: Growth Rates in Real GVA, Labour and Capital Input, and TFP, Indian Manufacturing

Period	Real GVA (% p.a.)	Labour (% p.a.)	Capital (% p.a.)	Labour income share	TFP (% p.a.)	TFP alternate (% p.a.)
1980-1990	8.1	0.46	7.18	0.39	3.5	3.4
1990-1999	7.28	1.25	8.72	0.28	0.7	1.1
1991-1999	8.85	1.3	9.05	0.28	1.9	2.5

Source and note: Author's computation based on EPWRF dataset on ASI (along with data on prices).

last column) – a gap of about three percentage points per annum. The gap reduces substantially when the period 1991-1999 is taken rather than 1990-1999, which seems to be more appropriate for comparison to evaluate the impact of reforms. In this case, the gap is 1.6 percentage points per annum.

The revised set of estimates of TFP growth that are obtained after incorporating the above-mentioned two adjustments relating to days per employee and labour income share is presented in the last column of Table 3. The gap in the growth rate of TFP between the pre- and post-reform periods comes down substantially. In this case, the gap is 0.9 percentage points per annum.

Inaccuracy 3

Attention may next be drawn to another possible source of bias in TFP estimates. This bias arises from differences in the growth rate of prices of energy input and that of manufactured products.

Energy prices grew faster than manufacturing sector output prices in the 1970s. The gap considerably narrowed in the 1980s when the growth rate in energy prices was only slightly higher than the growth rate in prices of manufactured products (6.6 as against 6.1 per cent per annum).[28] In the 1990s, again, energy prices grew faster than manufactured product prices – the trend growth rate during 1990-99 were 9.7 per cent per annum for fuel, power, light and lubricants and 6.7 per cent per annum for manufactured products. The implication is that if the single-deflated value added is used for computing TFP growth (as in Table 3), there will be a downward bias in the estimated TFP growth for the post-reform period of the 1990s.[29]

To address this issue regarding the divergence between the rate of growth in energy prices and that in manufactured product prices which tends to create a bias in the estimates of TFP growth based on the single-deflated GVA, a KLE (capital-labour-energy) production function is used. In this framework, the net output is defined

28 These comparisons are based on the official series on wholesale price indices, Office of the Economic Adviser, Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry, Government of India

29 For a discussion on the biases in TFP measurement arising from the use of single-deflated GVA, see Balakrishnan and Pushpangadan (1994 and 1998); and Rao (1996).

30 Energy cost is deflated by an energy price index to derive the series on energy input. For a discussion on econometric estimation of the KLE production function, see Brockway *et al.* (2017), among others.

Table 4: Growth Rates in Real Net Output, Labour and Capital Input, Energy Input, and TFP, Indian manufacturing (KLE production function framework)

Period	Real net output (GVA+ energy cost) (% p.a.)	Labour (% p.a.)	Capital (% p.a.)	Energy (% p.a.)	Labour income share in net output	Energy income share in net output	TFP (% p.a.)	TFP alternate (% p.a.)
1980-1990	8.2	0.46	7.18	5.52	0.3	0.24	3.32	3.02
1990-1999	7.27	1.25	8.72	3.84	0.22	0.23	1.31	1.72
1991-1999	8.55	1.3	9.05	3.77	0.21	0.23	2.38	2.8

Source and note: Author's computation based on EPWRF dataset on ASI.

as gross output minus materials and services input. There are three inputs: labour, capital and energy.[30] The growth rate of TFP is obtained as the growth rate in deflated net output minus the growth rates in labour, capital and energy inputs weighted by their respective income shares. The computed growth rates of TFP for the pre-reform and post-reform periods obtained by applying the KLE production function framework are shown in Table 4.

After energy input is incorporated into the method of computing TFP growth based on growth accounting, the rate of TFP growth for the period 1991-1999 is found to be only one percentage point lower than the growth rate in TFP for the period 1980-1990 (see second last column). In the next step, adjustments are made for the increase in days per employee in the 1980s and the dip in the income share of labour in the 1990s because of which a gap probably arose (or the existing gap got widened) between labour income share and the GVA-labour elasticity. After making these adjustments, the growth rate in TFP in manufacturing during 1980-1990 is found to be 3.0 per cent per annum and that during 1991-1999 is found to be 2.8 per cent per annum – the gap is only 0.2 percentage points.

One point that may be raised here is concerned with the computation of capital stock series, for which the rate of economic depreciation has been taken as 5 per cent. However, in the initial period after the onset of trade and other economic reforms, the rate of obsolescence of capital assets must have been relatively higher and there is justification for using a higher rate of depreciation for the first half of the 1990s. If a higher rate of deprecation is applied say 6 or 7 per cent per year, the annual average growth rate in capital stock in the 1990s will go down, and the gap in the growth rate in TFP between the 1980s and 1990s seen in Table 4 will probably disappear. The growth rate in TFP in the 1990s may even turn out to be higher than that in the 1980s if a higher rate of deprecation is applied to the 1990s on the ground that the rate of obsolescence of capital assets was much higher in the 1990s than in the 1980s.

Since the estimates of production function presented in Table 2 have played a key role in the adjustments made above, a brief discussion on the reliability of the production function approach to deriving the GVA-labour elasticity rather than base it on income share would be in order here.

It is known that due to market imperfections in emerging economies, the key assumption in the growth accounting framework that factors are paid according to marginal product is not valid and there is some advantage in carrying out productivity analysis based on an estimation of a production function. The advantage of the production function approach is that the assumption of constant returns to scale and perfect competition need not be imposed (Kathuria, *et al.*, 2014:43). The major disadvantage of the production function approach is the problem of identification of the production function because of simultaneity in the determination of inputs and output. Additionally, there are problems of autocorrelation and multi-collinearity, and biases in estimates caused by errors in the measurement of inputs, particularly capital input.

Because of the errors in the measurement of capital input, the coefficient of capital tends to be underestimated and if one imposes constant returns to scale, the coefficient of labour is over-estimated. Thus, the production function approach does not necessarily have a clear advantage over the growth accounting approach. Also, when one uses time-series data on aggregate manufacturing or industry-wise panel data for estimating a production function, one is assuming implicitly that an aggregate production function exists. The existence of an aggregate production function requires several stringent conditions including the condition that each specific type of labour and capital should receive the same price in each industry (Jorgenson *et al.* 2005:364). Thus, the competitive market assumption probably becomes necessary to ensure that the same price prevails in each industry for a specific type of labour or capital.

While the above point about the aggregation applies to the production function estimates based on industry-level data, the production function estimates based on plant-level data used in the analysis presented later in Section 4 do not involve an aggregation to the economy level. In these estimates, the GVA-labour elasticity is found to be above 0.5, supporting the estimates based on the industry-wise panel data in Table 2. A very similar estimate of the elasticity of real GVA with respect to labour (0.54 to 0.59) is reported in Gupta and Veermani (2015a, Table 4) based on plant-level data of ASI.

To sum up, in the discussion above, certain corrections that need to be made to TFP growth estimates for the 1980s and 1990s for ensuring a valid comparison were pointed out and a fresh set of estimates of TFP growth in Indian manufacturing with and without making the corrections were presented. The upshot of the above discussion is that if due corrections are made to TFP growth estimates, there is a very small difference (or no difference at all) in the estimated growth rates of TFP in Indian manufacturing between the decade preceding the economic reform and the initial phase of post-reforms. Next, the analysis is taken a step further. A theoretical analysis concerning productivity growth is presented on the basis of which a bias in TFP measurement for Indian manufacturing in the post-reform period is identified.

Providing Empirical Content to the Estimation Bias Identified

There is an extensive literature on how market imperfections can result in a downward bias in TFP measurement. The online Appendix argues that due to trade reforms a downward bias might arise in the estimates of TFP growth in Indian manufacturing in the 1990s because in this period the rent element in GVA existing earlier was significantly eroded.[31] The analysis presented in the appendix is rather simplistic as it did not taken into account the developments in the exchange rate and the relative prices between tradeable goods and non-tradeable goods and services because of the trade reforms. A full theoretical analysis has not been done here. This will be taken up in future research.

In this section, the issue is addressed empirically. To assess the impact of trade liberalization on rents, a production function is estimated in which the effective rate of protection (ERP) is introduced as an additional variable. A simple Cobb-Douglas specification is used. Real GVA is taken as output and the number of persons employed and fixed capital stock at constant prices are taken as labour and capital input. It should be noted that these data enter in the computation of TFP indices. The issue raised is, if there is an element of rent within the real GVA and it is affected by changes in ERP, then the computation of TFP will also be affected. This is subjected to empirical verification by investigating whether the element of rent in GVA is impacted by changes in ERP.

The production function (representing technology) used for empirical analysis based on panel data on industries (subscript i) over time (subscript t) may be written as:

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{3}$$

In this equation, Y denotes gross value added (real), L labour input and K capital input. The term A represents total factor productivity. GVA is the observed gross value added which has two components: the true value addition denoted by Y and the rent component proportion denoted by R such that GVA=Y(1+R). There are a set of factors (w) which influence variations in A across industries and over time. There is another set of factors (z), probably overlapping with w to some extent, which influences the rent component. The estimable equation may thus be derived as:

$$GVA_{it} = A\,(w)_{it}[1 + R(z)_{it}] L_{it}^{\alpha} K_{it}^{\beta} \tag{4}$$

This equation is estimated in log-linear form. It is assumed that ERP influences both the 'A' component and the 'R' component of the above equation. The influence of w (which includes ERP) is assumed to be picked up by a variable B along with the industry dummies and time dummies. As regards z, ERP is taken as one of the variables impacting R. The estimable equation thus becomes (allowing for some approxi-

31 http://www.csls.ca/ipm/43/IPM_43_Goldar_Appendix.pdf.

mation):

$$
\begin{aligned}
lnGVA_{it} = a_i + b_t + \theta B_{it} + \phi ERP_{it} \\
+ \alpha lnL_{it} + \beta lnK_{it} + u_{it}
\end{aligned}
\tag{5}
$$

The above model is estimated by using panel data on industries for the years 1986 to 1999 with the additional assumption of constant returns to scale. Data on ERP at the two-digit industry level have been taken from Goldar and Kumari (2003, Appendix Table 1) for the years 1983-84, 1989-90, 1992-93, 1994-95 and 1997-98. Additionally, ERP for various industries for the years 1999-2000 has been taken from Virmani *et al.* (2004), which is then matched with the estimates for earlier years. Using this information and applying interpolation, a dataset on ERP has been formed for 12 industrial groups for the years 1986-87 to 1999-2000. Accordingly, the 22 industries mentioned earlier have been mapped into 12 industry groups. Data on real GVA, labour and capital input has been taken for the corresponding 12 groups for the same years.

There is difficulty in constructing an appropriate variable B that will pick up the influence of w on TFP. Unable to find a suitable method of handling the problem, the variable is proxied by the price-based measure of TFP. This is based on the price function which is dual to the production function. If $Y = f(L, K)$ is the production function, then there exists a price function $P_Y = g(P_L, P_K)$ as its dual where P_Y, P_L and P_K are the prices of output (value added), labour input and capital input. The Divisia price index of technical change or the rate of growth in TFP may be written as (Jorgenson and Griliches, 1967):

$$
\widehat{A^p} = \alpha_L \widehat{P_L} + \alpha_K \widehat{P_K} - \widehat{P_Y} \tag{6}
$$

In this equation, the caret symbol represents the growth rate. Aiyar and Dalgaard (2005) find that the estimates of TFP growth they obtain by using the price function are different from that obtained from the primal, i.e., the production function. Thus, there is some justification for using the price-function-based estimates of TFP growth for the aforementioned 12 industry groups as a proxy for the variable B in equation (13) for its estimation.

To implement this methodology, data on P_Y, P_L and P_K have been taken. P_Y is the deflator of GVA. P_L is computed as the ratio of total emoluments to the number of persons employed, and P_K is computed by subtracting total emoluments from the current price GVA and dividing the balance by the constant price fixed capital stock. Since the production function is assumed to be of the Cobb-Douglas form, this should also apply to the price function. Thus, $ln(P_Y)$ has been regressed on $ln(P_L)$ and $ln(P_K)$ to obtain the coefficients which are treated as approximating the parameters α_L and α_K in equation (6). This provides the growth rate in A^p, i.e., the price-based measure of TFP. Applying the growth rates, an index has been formed for each industry group, taking the first-year value as 1.0. Then, the logarithm of the index is used as a variable to represent B in equation (5).

The estimated regression equations are shown in Table 5. It is assumed the production function is characterized by con-

Table 5: Estimates of Production Function with ERP as Additional Variable, Indian Manufacturing

Dependent variable: ln(real GVA/L)

Period: 1986-87 to 1999-00 (12 industry groups) – 168 observations

Explanatory variables	Fixed-effects model	Random-effects model	Pooled mean group estimator	Dynamic fixed effects model
	Regression-1	Regression-2	Regression-3	Regression-4
ln (K/L)	0.406 (5.62)***	0.466 (5.22)***	0.326 (7.05)***	0.313 (3.35)***
ERP	0.0005 (-0.86)	0.0005 (-0.67)	0.0005 (1.67)*	0.0011 (2.13)**
Price-based TFP measure	1.4 (12.72)***	1.39 (10.18)***	1.065 (10.85)***	1.333 (9.56)***
Time			0.048 (10.85)***	0.056 (7.17)***
Error correction term			-0.702 (10.85)***	-0.644 (-8.48)***
R-squared	0.53	0.59		
Wald Chi-square and prob.	12062.7 (0.000)	6.005.7 (0.000)		

Source and notes: Author's computation based on EPWRF dataset on ASI along with data on ERP. Year dummies are included in Regression-1 and Regression-2. L=labour and K=capital. t-values in parentheses. *, **, *** statistically significant at 10, 5 and 1 percent respectively. For the fixed and random-effect models, the bootstrapped standard errors are used. For the pooled mean group estimator and dynamic fixed-effects model, the long-run coefficients are shown in the table.

stant returns to scale, and accordingly, the logarithm of the real GVA to labour ratio is regressed on the logarithm of the capital-labour ratio, with ERP and the price-based TFP index (B) as additional explanatory variables. In the model, the dummy variables for years have been used to pick up the influence of year-specific factors. To begin with, the equation is estimated by the fixed-effects model and the random-effects model, the results of which are shown under Regression-1 and Regression-2 in Table 5.

From the results presented in Regression-1 and Regression-2, it is found that the coefficient of log(K/L) is positive as expected. The coefficient is found to be statistically significant. What is important to note is the positive coefficient of the ERP variable. However, in the estimates obtained by the fixed- and random-effects model, the coefficient is statistically insignificant. Thus, there is some indication of a bias, but not a strong one.

To carry out a more sophisticated econometric analysis, panel unit-root tests of the four variables ln(GVA/L), ln(K/L), ERP and the estimated price-based TFP have been done. The tests indicate that ln(GVA/L) and ln(K/L) are integrated of order zero, i.e., these are I(0). For ERP, the test results are conflicting. It seems this variable could be I(0) or I(1). In the case of the price-based TFP, it is found to be I(1). Hence, the results presented under Regression-1 and Regression-2 come into question. In such a situation, a panel ARDL (auto-regressive distributed lag) model will be more appropriate. Accordingly, the pooled mean group (PMG) estimator and the dynamic fixed-effects (DFE) models have been applied. The results are shown under Regression-3 and Regression-4 in Table 5. In these two cases, instead of using time dummies, a time trend variable has been used.

In the estimates of the pooled mean group (PMG) model and the dynamic fixed-effects (DFE) model, the coefficient of capital intensity is found to be positive, but not statistically significant. Perhaps, the use of the trend term has caused this. However, the coefficient of ERP is found to be positive and statistically significant. This could be treated as econometric evidence of a bias in the measurement of real GVA growth caused by the lowering of ERP.

Given that effective protection has fallen about 60 percentage points between the end of 1980s and the end of 1990s,[32] and the fact that the TFP growth rate in the 1990s was almost as high as that in the 1980s (after making appropriate corrections, see the last column in Table 4), it would perhaps not be wrong to claim that the TFP growth performance in Indian manufacturing was better in the 1990s.

Plant-Level Analysis of the Impact of Trade Liberalization on TFP

Existing Literature for Indian Manufacturing

Several studies have been undertaken on the impact of trade liberalization on productivity in Indian manufacturing using firm-level or plant-level data. The findings of these studies indicate that trade liberalization had a positive effect on productivity in Indian manufacturing.[33]

Most of these studies are based on data on manufacturing companies drawn from the Prowess database of the Centre for Monitoring Indian Economy (CMIE). Some studies have used ASI unit-level data.[34] In most of these studies undertaken for Indian manufacturing, the Levinsohn-Pertin (2003) methodology for measuring TFP has been used. Kealey *et al.* (2019) has raised the question of whether the method applied for the estimation of TFP at the firm/plant level makes a difference to the results of the regression analysis carried out subsequently for assessing the impact of trade liberalization on productivity. They have taken data on Columbian manufacturing plants between the years 1981 to 1991 and compared the results of estimated econometric models linking trade policy to TFP based on three alternate methods of estimation of TFP: Levinsohn and Petrin (2003), Ackerberg *et al.* (2015), and Gandhi *et al.* (2017). They find that when the productivity estimates obtained by the Levinsohn and Petrin method are used, the regression results show a positive effect of trade liberalization on productivity, but not when they use the method suggested by Gandhi, Navarro, and Rivers (2017) for productivity estimation, which is based on a more flexible form of the production function. They conclude that the nature of the relationship between trade

32 The 60 percentage points decline in ERP when coupled with the estimated regression coefficient of the DFE model implies a fall in GVA (due to erosion of rent component) by about 6 per cent in 10 years. This would mean that the measured annual TFP growth rate in Indian manufacturing in the 1990s needs to be raised by 0.6 percentage point to make valid comparison with the measured TFP growth rate for the 1980s.

33 The studies include Krishna and Mitra (1998), Topalova and Khandelwal (2011), Ahsan (2013), Harrison *et al.* (2013), Gupta and Veeramani (2015a) and Goldar *et al.* (2020).

34 The studies undertaken by Harrison *et al.* (2013) and Gupta and Veeramani (2015a) are based on the unit-level data of ASI and thus have a much bigger coverage of the factories in the organized manufacturing sector. Natraj (2011) used unit-level ASI data as well as such data for the informal sector units.

policy and TFP found in the regression analysis is not robust to the method of productivity estimation.

A Fresh Analysis of the Effect of Trade Reforms on TFP based on Plant-level Data

Since bigger industrial enterprises have higher capabilities, they are in a better position to meet the challenges of trade liberalization and gain from it. Such gains may be smaller or even absent for small-sized industrial enterprises. The observed growth in TFP following trade reforms in the data for aggregate manufacturing will be subject to the extent of differences between big and small industrial enterprises in terms of the productivity-enhancing effects of trade reforms, and the relative share of these two categories of enterprises in the aggregate GVA. To examine this aspect, an analysis of the effect of the tariff on TFP in manufacturing plants has been undertaken using the unit-level data of ASI. The coverage extends to the entire organized manufacturing sector.

Another interesting issue is the role of 'water in tariff', as discussed in Section 2. In a regression analysis, taking productivity as the dependent variable and the effective tariff rate as the explanatory variable, the estimated coefficient is likely to be affected if there is considerable 'water in tariff'.[35] An attempt made to address this issue is shown in the Table in on-line Appendix.[36]

The dataset used for the analysis is the same as used in Goldar (2020). The period covered in the dataset is 1998-99 to 2012-13. However, the estimation of TFP and the regression analysis for assessing the impact of tariff rates on TFP have been done by using data for the years 1998-99 to 2010-11.

For measuring TFP, a two-input Cobb-Douglas production function is used. Deflated GVA is taken as the measure of output. The number of persons employed is taken as the measure of labour input. Deflated value of the fixed capital stock (net closing value) is taken as the measure of capital input. Deflated value of energy cost is taken as a proxy for capturing productivity shocks. Productivity estimation has been done for only those plants which were covered in the ASI survey at least three times during the years 1998-99 to 2012-13.

NRP, ERP and the rate of input tariff are the main explanatory variables. The data on NRP (tariff) and tariff-based ERP used for the analysis is for the years 1997-98 to 2009-10.[37] Since the tariff and ERP variables are used in the econometric model with a one year lag, the productivity and other related data are taken for the years

35 This does not affect the studies that use the relative price, domesetic versus international (refecting implicit tariff) as the explanatory variable. See Chand and Sen (2002) and Rijesh (2019).

36 http://www.csls.ca/ipm/43/IPM_43_Goldar_Appendix.pdf.

37 The author is grateful to the recently deceased Professor Deb Kusum Das for kindly sharing the database on NRP and ERP he had constructed at three-digit industry level which was utilised by him for the report he prepared for the Reserve Bank of India (Das, 2016). These data were used in Goldar *et al.* (2020). Using these data on NRP along with tariff data on agricultural and mineral products, the author has constructed the input tariff rates.

1998-99 to 2010-11. For combining the data on NRP (output tariff), ERP and input tariff with the productivity estimates a mapping of industrial classifications has been done. For each plant, the industrial class (at a four-digit level of National Industrial Classification, 2004) to which it belonged during 2004-05 to 2007-08 has been considered.

Estimation of TFP at the plant level has been done by using three methods: Levinshon and Petrin (2003), Ackerberg *et al.* (2015), and Wooldridge (2009). Separate regression equations have been estimated for the plants having a fixed capital stock of Rs 20 million or more (at 2011-12 prices) and the plants with smaller capital stock.

For model estimation, the logarithm of TFP is taken as the dependent variable and the one-period lagged value of NRP, ERP or input tariff rate is taken as the explanatory variable along with year dummies. In addition, two other variables are introduced in the equation. These are the share of contract workers in total workers employed and the share of ICT (information and communication technology) assets in total fixed assets.

A panel dataset on plants is used for the regression analysis. Data on about 50,000 plants are used. The number of observations per plant is about five on average. The estimation method for the regressions is the fixed-effects model. The standard errors have been clustered at the plant level. The results are shown in Table 6.

The results indicate a positive effect of trade liberalization on TFP in Indian manufacturing plants. Interestingly, when data on all plants are taken, NRP and ERP have a significant positive coefficient for the productivity estimates based on the Levinsohn-Petrin (2003) method, not for productivity estimates based on the Ackerberg-Caves-Frazer (2015) method and the Wooldridge (2009) method. When the analysis is undertaken separately for the factories with a fixed capital stock of Rs 20 million or higher and the factories with smaller capital stock, the results for the three sets of productivity estimates are found to be similar. A positive effect of tariff reform on TFP is found for the relatively bigger plant with a capital stock of Rs 20 million or more. The effect is minimal or absent among small-sized plants (similar finding has been reported by Mukerjee and Chanda, 2020). ASI data for 2011-12 reveals that the plants with a fixed capital stock of Rs 20 million or more accounted for about a quarter of the total number of operating factories, more than 90 per cent of aggregate value-added, more than 95 per cent of aggregate fixed capital stock and about 70 per cent of aggregate employment of organized manufacturing. Thus, the trend in productivity at the aggregate level of the manufacturing sector should reflect mostly the impact of trade reforms on the relatively bigger plants.

The favourable impact of input tariff cuts on TFP is found to be bigger than the impact of output tariff cuts. This finding is consistent with the findings of several earlier studies including Schor (2004) for Brazil, Amiti and Konnings (2007) for Indonesia and Topalova and Khandelwal (2011) and Gupta and Veeramani (2015a) for India.

As regards the role of 'water in tariff' or tariff redundancy, the results in online Appendix C suggest that in industries in

Table 6: **Impact of Trade Policy on TFP, Plant-level Analysis, 1998-2010**

Explanatory variable	All Plants		Plants with Real Fixed Capital Stock of Rs 20 million or more		Plants with Real Fixed Capital Stock below Rs 20 million	
	Panel-A: TFP estimated by the Levinsohn-Petrin (2003) method					
Lagged NRP	-0.0005		-0.0011		0.0003	
	(-1.66)*		(-2.53)**		-0.61	
Lagged input tariff	-0.0021		-0.0052		-0.0008	
	(-5.05)***		(-7.37)***		(-1.44)	
Lagged ERP		-0.0003		-0.0008		0.0002
		(-1.84)*		(-2.81)***		-0.67
CW	-0.077	-0.076	-0.152	-0.145	-0.046	-0.046
	(-8.02)***	(-7.89)***	(-9.59)***	(-9.18)***	(-3.92)***	(-3.91)***
ICT	1.656	1.643	1.578	1.552	1.587	1.584
	(13.53)***	(13.42)***	(6.38)***	(6.25)***	(10.92)***	(10.90)***
F-value and prob.	128.8	133.6	72.2	72.7	55	58.1
	0	0	0	0	0	0
	Panel-B: TFP estimated by the Ackerberg-Caves-Frazer (2015) method					
Lagged NRP	-0.0004		-0.0008		0.0002	
	(-1.35)		(-1.86)*		-0.39	
Lagged input tariff	-0.0013		-0.0038		-0.0003	
	(-2.94)***		(-5.39)***		(-0.50)	
Lagged ERP		-0.0002		-0.0005		0.0002
		(-1.04)		(-1.84)*		-0.68
CW	-0.114	-0.113	-0.191	-0.186	-0.065	-0.065
	(-11.85)***	(-11.76)***	(-12.06)***	(-11.77)***	(-5.36)***	(-5.35)***
ICT	3.033	3.024	2.817	2.798	2.577	2.575
	(23.31)***	(23.25)***	(11.05)***	(10.95)***	(16.80)***	(16.79)***
F-value and prob.	98	103.1	53	54.3	50.8	54
	0	0	0	0	0	0
	Panel-C: TFP estimated by the Wooldridge (2009) method					
Lagged NRP	-0.0005		-0.001		0.0003	
	(-1.51)		(-2.39)**		-0.63	
Lagged input tariff	-0.0021		-0.0051		-0.0007	
	(-4.88)***		(-7.22)***		(-1.32)	
Lagged ERP		-0.0003		-0.0007		0.0002
		(-1.64)		(-2.68)***		-0.78
CW	-0.101	-0.1	-0.181	-0.174	-0.067	-0.067
	(-10.53)***	(-10.40)***	(-11.35)***	(-10.95)***	(-5.66)***	(-5.65)***
ICT	1.545	1.532	1.465	1.44	1.495	1.492
	(12.64)***	(12.53)***	(5.92)***	(5.79)***	(10.31)***	(10.29)***
F-value and prob.	128.7	133.9	70.9	71.6	57.3	60.5
	0	0	0	0	0	0
No. of obs.	236,524	236,524	97,041	97,041	139,483	139,483

Note: Year dummies are included. CW= share of contract workers in total workers. ICT= share of ICT assets in total assets. T-values in parentheses. *, **, *** statistically significant at 10, 5 and 1 percent respectively. Source: Author's computations from unit-level data of ASI.

which there is substantial 'water in tariff', cuts in output tariff do not have a significant impact on the TFP of manufacturing plants.[38]

Conclusion

There is a substantial body of literature on the impact of trade liberalization on productivity in manufacturing in emerging economies based on firm-level or plant-level studies including such studies for Indian manufacturing. Sufficient econometric evidence has been presented in these studies to establish that the liberalization of trade enhances the productivity of the manu-

38 http://www.csls.ca/ipm/43/IPM_43_Goldar_Appendix.pdf.

facturing sector. However, several studies on TFP growth in Indian manufacturing based on the growth accounting methodology have reported a lower estimate of the growth rate in TFP in the period after India initiated major trade reforms (in 1991) along with other complementary economic reforms than that in the earlier period. Accordingly, there is a view that TFP growth in Indian manufacturing in the 1990s following the major industrial and trade reforms undertaken in India was lower than that in the decade preceding the reforms. This article has questioned that view. Certain corrections that need to be made in the computed TFP growth rates for the 1980s and 1990s were pointed out. Also, it was argued that in a period of rapid trade reforms as was the situation faced by Indian manufacturing in the 1990s, a downward bias in TFP growth estimates may arise. Based on the estimates presented, the rate of TFP growth in Indian manufacturing was higher in the 1990s than in the 1980s.

To look into the differential impact of trade reform on big and small industrial enterprises, an analysis of the impact of trade reforms on TFP in Indian manufacturing was undertaken using plant-level data for the years 1998 to 2010. This research revealed that while the relatively bigger manufacturing plants in India with a fixed capital stock of Rs 20 million and above gained in productivity from trade liberalization, their small-sized counterparts, three times in number, did not have such gains. Also, an attempt was made to incorporate the issue of 'water in tariff' explicitly into the econometric analysis of the effect of change in nominal tariff on manufacturing plants' productivity. The results of this analysis suggest that the presence of 'water in tariff' makes a difference in the regression results obtained.

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On-line Appendix

Appendix 1: Market Imperfections and Biases in TFP Measurement

Some Existing Studies

There is extensive literature on how markups and unionization of labour result in a bias in TFP measurement - a difference arising between the Solow residual, i.e., the measured TFP growth and the true rate of technical change or TFP growth. Some of the studies have examined this issue in the context of trade reforms. The sub-section presents a very brief discussion of a few of the existing studies that have dealt with the divergence between the Solow residual and the true TFP growth in a situation characterized by markups and unionization, and then the implication of the findings of these studies for the analysis presented above is pointed out. It is useful to begin the discussion with the basic equation defining the TFP growth (equal to Solow residual under certain assumptions) which is similar to eq. (1), but is based on a three-input production function:

$$\hat{A} = \hat{Q} - \alpha\hat{L} - \beta\hat{K} - \gamma\hat{M} \qquad (1)$$

In this equation, Q, M, L and K are real output, real intermediate input, labour input and capital input, respectively. The caret symbol is for growth. The parameters α, β and γ are the true factor elasticities, and thus $\hat{A}$ denotes the true growth rate in the level of TFP. Due to markups and unionization or other such market imperfections, the equation is transformed to:

$$\hat{S} = \hat{Q} - \alpha'\hat{L} - \beta'\hat{K} - \gamma'\hat{M} \qquad (2)$$

In this equation, $\hat{S}$ is the Solow residual. The difference between equations (1) and (2), i.e. between $\hat{S}$ and $\hat{A}$ is the bias.

Dobbelaere (2005) shows that the Solow residual can be decomposed into four elements, which relate to (i) markup, (ii) a scale factor (representing returns to scale), (iii) trade union bargaining power and (iv) the rate of technical change or true TFP growth, $\hat{A}$. From the equation derived, it is seen that the impact of an increase in the markup on the bias depends on the gap between the growth rates in output and capital stock.

Harrison (1994) analyses the impact of markups on the measurement of TFP growth and shows that the nature of bias in the measurement of TFP depends on the direction of growth in L/K and M/K. If the growth rates in L/K and M/K are negative or their weighted average is negative (which will describe the situation prevailing in Indian manufacturing in the 1980s and 1990s), then markups will make $\hat{S}$ less than $\hat{A}$ in the pre-reform period, and thus a lowering of markups to zero caused by trade reforms will make $\hat{S}$ in the post-reform period equal to $\hat{A}$, thereby exaggerating the productivity gain associate with the reform.

Crouzet and Eberly (2021) argue that the mismeasurement of intangible capital and rising markups have caused a downward bias in the measurement of TFP growth in the US in the recent period. In the equation derived by them for the bias in the measured TFP growth based on a value-added function, the bias depends on the GVA-labour elasticity, the level of markup, and the difference between the growth rates in capital and labour. They observe that because of the markups, the true GVA-labour elasticity is higher than the measured labour income share, which causes a downward bias in TFP measurement, if capital is growing faster than labour.

Maiti (2013, 2019) has used a value-added function framework and derived an equation linking the Solow residual to the true TFP growth in the presence of markups, union power and non-constant returns to scale. This is similar to the equation in Dobbelaere (2005). Applying this equation econometrically to Indian manufacturing with the help of ASI data for 1998-2005, Maiti (2013) finds that the conventional measure yields a TFP growth rate in Indian manufacturing of about 1 per cent per annum, but after corrections, this is found to be only a half of that.

Going by the findings of the econometric studies undertaken on Indian manufacturing in respect of the impact of trade reforms on the level of markups and the bargaining power of labour, one may surmise that trade liberalization led to a decline in markups (see, for example, Gupta and Veeramani, 2015b; and Goldar and Agarwal, 2005) and in the bargaining power of labour (see, for example, Ahsan and Mitra, 2014; and Pal and Rathore, 2014). It may be argued accordingly that the fall in markups caused an exaggeration in TFP growth in the estimate made for the 1990s (following Harrison, 1994) and therefore the measured TFP growth for the 1990s needs to be adjusted downward to make a proper comparison with the estimate the 1980s. This will nullify the entire chain of arguments made in Section 3 above to establish that the rate of TFP growth in the post-reform period was not lower than that in the pre-reform period. As a counter to this, it should be noted that the fall in the bargaining power of labour had a counterbalancing effect, perhaps exceeding the effect of the fall in the markup rates, with the net result that it is the TFP growth rate estimated for the 1980s that need to be adjusted downward to make a proper comparison with the estimates for the 1990s.

In the next sub-section, a somewhat related issue is taken up for analysis which is strictly not connected with the discussion in this sub-section but falls under the ambit of biases in TFP growth measurement. The analysis is not based on a contrast between equations (7) and (8). Rather, this may be viewed as the bias in the measurement of real GVA growth that arises in the path of transition as an economy moves from the situation described by equation (8) to the situation described by equation (7).

Bias in Measured TFP Growth Arising from GVA Growth Mismeasurement

Consider the following simplified framework that is set out to show how trade intervention impacts <u>measured</u> TFP growth through the measurement of real GVA growth.

Let Q be output, and P_Q be the price of output. Let M_1, M_2 and M_3 be three different intermediate inputs (which could be generalized to three categories of inputs). M_1 is traded (for example, steel sheets), M_2 is imported, but is a non-competing import and its price is administered (for example, crude oil) and M_3 denotes non-traded goods/services used as intermediate inputs in the manufacturing sector. PM_1, PM_2 and PM_3 are the corresponding prices.

Let L denote labour input (e.g., number of persons employed) and K denote capital input. K is made up of past investments. Suppose Is is the real value of investment done in year s and δ is the rate of depreciation (say 5 per cent), then K_t, the capital stock in year t, may be written as

$$K_t = \int_{-\infty}^{t} I_s(1-\delta)^{t-s} \tag{3}$$

Let the elasticity of output (i.e., real value added) with respect to labour be a fixed number and the elasticity with respect to capital be β (assuming a Cobb-Douglas production (value added) function). It is assumed further that $\alpha+\beta=1$, i.e., production technology is characterized by constant returns to scale and the product and factor markets are perfectly competitive.[1]

The TFP index may be written as (the numerator is gross value added, and the denominator is a measure of total input):

$$TFP = \frac{P_Q Q - [M_1 PM_1 + M_2 PM_2 + M_3 PM_3]}{L^\alpha K^\beta} \tag{4}$$

$$TFP = P_{\frac{GVA}{L^\alpha K^\beta}} \tag{5}$$

The growth rate in TFP is:

$$\widehat{TFP} = \widehat{GVA} - \alpha\hat{L} - \beta\hat{K} \tag{6}$$

The caret symbol denotes the growth rate. Since α and β are not known, these will be represented measured by observed income shares of labour and capital in gross value added under the assumption of constant returns to scale and competitive markets.

This is the *measured* TFP growth when there is no trade intervention and the value of output, intermediate inputs, annual investments and fixed capital stock are at domestic prices which are the same as international prices. Also, when there are no distortions in labour and capital input markets, α and β will be equal to factor shares.

Let us consider next how interventions in the trade regime through the imposition of tariffs and QRs impact the above measure of TFP. In the presence of distortions due to trade barriers and imperfections in factor markets, the measured TFP growth would differ from the 'true' TFP growth.

1 This assumption is perhaps not necessary for the main points put forward in this section but is being made for simplicity of exposition.

The measured TFP level may be written as:

$$TFP' = \frac{P'_Q Q - [M_1 PM'_1 + M_2 PM'_2 + M_3 PM'_3]}{L^{\alpha *} K'^{\beta *}} \quad (7)$$

P' and PM'_1, PM'_2 and PM'_3 are prices actually prevailing, which are different from those in international markets. $P'Q$ and PM'_1 are postulated to be higher than the corresponding prices in international markets (because of tariffs and QRs). Although M_3 is non-traded, it will be using traded inputs in production and the enhanced prices of traded goods used in the production of M_3 is likely to cause its price to be higher than what it would have been in the absence of trade protection.

In the next step, let us consider the definition of effective rate of protection (ERP). ERP for a production activity (or an industry) is defined as value added at domestic prices divide by value added at international prices (or, it may be expressed as domestic value added divided by international value added). In terms of the expressions in the equations used in the discussion of the framework above, ERP may be written as:

$$ERP = \frac{P\prime_Q Q - [M_1 PM\prime_1 + M_2 PM\prime_2 + M_3 PM\prime_3]}{P_Q Q - [M_1 PM_1 + M_2 PM_2 + M_3 PM_3]}$$

$$= \frac{GVA_D}{GVA_I} \quad (8)$$

In a situation where trade reforms are bringing down the effective rate of protection of domestic industries (it has been noted above that the ERP of Indian manufacturing accorded by tariff came down substantially in the post-reform period, see footnote 16), the numerator will be reduced and move closer to the denominator. Since TFP measurement is based on the numerator (see equation 7), the downward pressure on domestic gross value added might create a downward bias in the estimates of TFP growth in the post-reform period.[2]

It should be realized that even if no substantive changes take place in the production activity in terms of the quantum of products produced, the quantum of materials, energy, etc. used and the number of workers and the plant and machinery remain the same, the lowering of tariff will cause the domestic value added to go down. Essentially, in the process of tariff reform, the rent element is eroded. The decline in value-added caused by erosion of rent is obviously not a decline in TFP. If the measure of TFP must capture prop-

2 This assertion involves a number of assumptions. In reality, the situation could be different. First, the tariff cuts would often be accompanied by exchange rate deprecation. This will raise the sales realization of exporting firms. Second, more firms may be encouraged or facilitated (because of better access to imported inputs) to enter export markets. This will result in productivity gains through the export-related learning. It is obvious that the analysis here is based on several simplifying assumptions. However, the author is hopeful that the main point made in this section regarding bias in TFP measurement will come through even if a more general framework is used for the theoretical analysis.

erly the efficiency with which production activity is turning inputs into output, the inter-temporal change in the rent element should be properly accounted for because it will otherwise introduce a bias in the measurement of TFP.

Box A: How a fall in ERP may coincide with a fall in real GVA: An Illustration

According to India's input-output table for 1993-94, total output of manufacturing was Rs 4889 billion, and gross value added was Rs 1248 billion. The intermediate input used (inter-industry flows) within the manufacturing sector was Rs 1577 billion. Inputs from agriculture and mining were Rs 437 and Rs 297 billion (total Rs 734 billion) and other inputs including electricity, construction and services (treated as non-tradeable) were Rs 1330 billion. The import weighted average tariff rates on the final products produced by the manufacturing sector in 1993-94 was on average about 53 per cent (based on tariff rates for consumer goods and capital goods), and that on manufactured intermediate goods was about 48 per cent (rates taken from Mathur and Sachdeva, 2005, Table 1B), which is treated as the rate applicable to the manufactured interemediate goods consumed by the manufacturing sector. The import weighted average tariff rates for products of agriculture and mining were about 20 per cent and 33 per cent respectively. In this situation, if the tariff rates for manufactured products are lowered by 10 percentage points, the price of consumer and capital goods will fall on average by about 6.5 per cent, and that in manufactured intermediate goods will fall by 6.8 per cent (assuming domestic price = internaitional price plus tariff). Since the tariff levels of agricultural goods and minerals do not go down, their prices will remain by and large the same. The same applies to other inputs such as services. These costs will therefore not change or change marginally. The gross value added will come down to Rs 1035 billion, i.e., a 17 per cent decline. If value added is deflated by the output price index (applying single-deflation), the deflated value added shows a fall even though no pertinent change has taken place in the production process measured in terms of volumes on input used and output produced. Prior to the change in tariff the ERP was 64 per cent (based on the simple Corden method); it declines to 51 per cent after the reduction in tariff rates.

The reason for the decline in real GVA along with a fall in ERP occurring in the above example is that (a) there is an escalated tariff structure – higher tariff at higher level of processing to encourage domestic manufacturing industry and (b) tariff reduction is accomplished by a gradual compression of top tariff rates – the peak rate is lowered in stages (Panagariya, 2004; Singh, 2017).

The fall in real GVA will not occur if the manufacturing enterprises are able to pass on the entire loss of revenue to other sectors of the economy, say the services sector. For this, the supply curve of the services sector should be inelastic. This does not seem realistic. Rather, the supply curve of the services sector is likely to be elastic. If the manufacturing firms are able to cut down their intermediate input requirements substantially post the tariff reduction, then the real GVA need not fall. It may remain at the same level. However, this means that the measured TFP growth is not picking up this improvement in efficiency, because the measured growth in real GVA is nil.

An alternate way of viewing equation (8) is to treat the denominator as the efficient processing margin in a particular product line. This is so because this is the processing margin prevailing in the international markets presumably reflecting the processing margin of efficient producers. With the imposition of high tariffs on imports, the ERP goes up and the numerator goes up. Thus, the processing margin in the country (India) becomes higher than that prevailing internationally. This is obviously not a sign of greater productivity. Now, as tariff rates come down and ERP falls, the numerator will come down to the level of the denominator. This means that the processing margin in the country will match that of the efficient international players. This should obviously not be treated as a decline in productivity. It is doubtful if the methods of measurement of output, inputs and TFP as it is practised now would be able to separate the "true" value-added change and the change in the rent element in value added (see Box A). If this cannot be done, then a downward bias in TFP measurement for the post-reform period may arise. It appears therefore that the conventional measure of TFP using the deflated value of gross value added may not be giving the correct signals about productivity growth when large reductions are made in tariff rates and non-tariff barriers in a short period. Indeed, there is a possibility that the TFP growth rate will be underestimated.[3]

Appendix 2: Data Source and Measurement of Real Value-Added, Labour Input, Capital Input and Labour Income Share

Data Source

The basic source of data for the analysis is the dataset prepared by the Economic and Political Weekly Research Foundation (EPWRF) by compiling the ASI (*Annual Survey of Industries*) data. The dataset at the two-digit industry level has been used; the period covered is 1973-74 to 2017-18. The data have been provided in the EPWRF dataset according to the two-digit industries of National Industrial Classification (NIC), 2004. The industries NIC-15 to NIC-36 have been combined to obtain the estimates for the manufacturing sector. It should be noted that ASI data relate to the organized segment of Indian manufac-

3 Ahluwalia (2006) estimated the rate of TFP growth in the Indian manufacturing at 3.8 per cent per annum during 1980-1990 and 3.4 per cent per annum during 1991-1997. In evaluating the performance, she pointed out that a limitation of the TFP measure is that it is based on the growth in value added at domestic prices and does not consider the changes in the domestic prices relative to that in international prices. She noted further that in the 1990s, the domestic prices of industrial products in India had moved much closer to the international prices with the lowering levels of protection. Accordingly, she concluded that the estimates of TFP growth for the 1990s reflect the productivity gains much better than that for the 1980s. This is in spirit what is being argued here.

turing.

Variables

Gross value added (GVA): Data on gross value added at current prices for different two-digit industries are taken from the EP-WRF dataset. There are deflated by price indices for the respective two-digit industries. The price indices are with base 2004-05=100. The deflators have been formed by using the wholesale price indices (Office of the Economic Advisor, Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry, Government of India). The indices with bases 1970-71, 1981-82, 1993-94, 2004-05 and 2011-12 have been combined (spliced) to construct price indices for different two-digit industries for the years 1980-81 to 2017-18. For each two-digit industry, a suitable price index or deflator has been formed from the item-wise and group-wise wholesale price indices from the official series. In some cases, the price index for the two-digit industry could be found in the official WPI series directly. In other cases, these were derived from item-wise wholesale price indices by taking a weighted average (weights taken from the official WPI data). After obtaining the price series, the base has been shifted to 2004-05. Having obtained real value added for each two-digit industry, these have been added to derive real value added for aggregate (organized) manufacturing.

Net output (NQ): Net output is formed by adding the cost of fuels consumed to the gross value added. This has been deflated to derive the net output at constant prices. The deflators used are the same as those used for deflating GVA. The real net output series has been formed for each industry, and then added to derive the series for the manufacturing sector.

Labour input (L): Total number of persons engaged has been used as the measure of labour input. It includes all employees and also includes working proprietors, and their family members who are actively engaged in the work of the factory even without any pay (see Annual Survey of Industry writeup for 2017-18, http://www.csoisw.gov.in/CMS/UploadedFiles/ASIWrite_Up_2017_2018.pdf). For some analyses, the changes in man-day worked per employee have been taken into account.

Labour and capital income share (SL and KL): Labour income share in GVA is obtained by dividing total emoluments by gross value added, both at current prices. Capital income share is obtained as one minus labour income share. When the KLE production function framework is used, labour income share is obtained as total emolument divided by net output (= Gross value added + fuels consumed). In this case, capital income share is obtained as one minus the labour income share and the share of energy cost in net output.

Energy input (E): Date on fuels consumed has been taken for each industry and then these have been added to derive the series for aggregate manufacturing. The series on fuel consumed has been deflated by preparing a suitable price index for energy consumption in manufacturing. For this purpose, wholesale price indices for coal, electricity and petroleum products have been taken. Also, a price series (with some interpolation) has been formed for natural gas. For the recent period, 2004-05 onward, data on the price of natural gas has been obtained from *Indian Petroleum and Natural Gas Statistics* (Ministry of Petroleum and Natural Gas, Government of India). It is difficult to get the price of natural gas from earlier years. Information for certain years in the past has been taken from the Report of the Committee on Natural Gas Pricing (Chairman: T. L. Sankar), December 1996. In addition, from the plant-level data of ASI, the average price paid for gas has been computed for the years 1999 to 2004 which has been used for interpolation. For getting the price index of energy for the manufacturing sector, the price indices of coal, electricity, petroleum products and natural gas have been combined using weights. Three sets of weights have been used for different periods. These have been taken from the input-output tables for 1993-94, 1998-99 and 2007-08. The price index formed in this manner has been converted to base 2004-05=100.

Capital stock (input) (K): Capital input is measured by the fixed capital stock. The concept used is the net fixed asset (net of depreciation). The series on the capital stock has been formed for each two-digit industry and then added to derive the series for aggregate manufacturing. For deflation, the implicit deflator of gross fixed capital formation (GFCF) in manufacturing has been derived from data on GFCF at current and constant prices available in *National Accounts Statistics* (NAS). The 2011-12 base series of NAS and its corresponding back series have been used.

The construction of fixed capital stock series involves three steps: (a) construction of benchmark estimate of fixed capital stock, (b) construction of series on real gross fixed investment, and (c) construction of fixed capital series with the help of the benchmark estimate and the gross fixed investment series. These are further explained below:

(a) Benchmark estimate. The benchmark capital stock estimate has been made for 1973-74. For this purpose, data on the net and gross fixed assets by three-digit industries for the census sector of ASI and the sample sector of ASI for the years 1964-65 and 1968-89 have been taken. A mapping of the three-digit industries as per the classification prevailing in 1964-65 and 1968-69 with the two-digit industries of the EPWRF data set has been done. Accordingly, gross investment in each two-digit industry has been computed for the years 1965-66 to 1968-69 and 1969-79 to 1973-74. The net fixed capital stock figure for 1964-65 has been multiplied by a factor of 2 to obtain an approximation to the replacement value of the fixed capital stock in that year (which has then been inflated to express it at 2004-05 prices). The gross investments during the periods 1965-66 to 1968-69 and 1969-70 to 1973-74 (with proper deflation) have then been added to the estimated fixed capital stock of 1964-65 (allowing for 5 percent deprecation every year) to obtain the estimate of fixed capital stock for 1973-74 at 2004-05 prices which is the benchmark estimate of capital stock series.

(b) Gross investment in each industry i in each year t is computed for the years 1974-75 to 2017-18. The following equation

Appendix Table 1: Impact of NRP on TFP, Regression Results, By Estimation Method and the Level of Implicit Tariff Rate in the Pre-Reform Period

Explanatory variables	TFP estimates based on Levinsohn-Pertin (2003) method		TFP estimates based on Ackerberg-Caves-Frazer (2015) method		TFP estimates based on Wooldridge (2009) method	
	Low implicit tariff in 1986	Medium and high implicit tariff in 1986	Low implicit tariff in 1986	Medium and high implicit tariff in 1986	Low implicit tariff in 1986	Medium and high implicit tariff in 1986
NRP (effective tariff rate) (t-1)	0.00004 -0.11	-0.0016 (-2.18)**	0.00038 -1.16	-0.0018 (-2.39)**	0.00009 -0.27	-0.0016 (-2.12)**
Contract worker intensity	-0.074 (-5.29)***	-0.084 (-6.22)***	-0.086 (-6.11)***	-0.143 (-10.56)***	-0.096 (-6.80)***	-0.112 (-8.25)***
ICT intensity	1.806 (7.33)***	1.643 (11.07)***	3.439 (12.87)***	2.914 (18.55)***	1.686 (6.84)***	1.533 (10.36)***
F-value and prob.	41 0	108.1 0	32.9 0	80.6 0	41.7 0	107.4 0
No. of obs.	97,855	127,683	97,855	127,683	97,855	127,683

Source: Author's computations.

Notes: (1) Pursell *et al.* (2007) have provided, for various three-digit industries, the level of implicit tariff prevailing in 1986-87. Three levels are indicated: low (below 30 percent), medium (30 percent and higher, but below 70 percent) and high (70 percent or more). The extent of 'water in tariff' was relatively high among industries put in the "low" implicit tariff rate group. This group mostly includes the manufacture of food products, beverages, tobacco products, textiles, leather and leather products and non-metallic mineral products. It contains most of the consumer goods industries. The extent of tariff redundancy was relatively low among industries grouped under "medium" and "high". By the end of the 1990s, the average effective tariff rate was reduced to about 30 percent. The average implicit tariff rate fell to almost zero (thanks mainly to the exchange rate depreciation) and thus some level of 'water in tariff' continued – probably more for the industries grouped under "low" than for the industries grouped under "medium" and "high". If there is a good deal of 'water in tariff', cuts in the effective tariff rates are unlikely to impact firms belonging to that industry. The empirical results bear this out. (2) The total number of observations used in this analysis is less by about 10,000 than that in Table 7 because for some industries, the level of implicit tariff is not provided in Pursell *et al.* (2007) **, *** Statistically significant at 5 percent level and one percent level respectively.

is used:

$$I_{it} = B_{it} - B_{i,t-1} + D_{it} \tag{9}$$

In this equation, B_t is the book value of fixed assets in year t, B_{t-1} is that in the previous year, and D_t is the depreciation (accounting depreciation, annual) of fixed assets in that year. It denotes gross investment in year t. This has been deflated by the price index mentioned earlier to obtain real gross investment. One difficulty that was encountered in applying the above procedure is that the gross investment turned out to be negative for a portion of industry-year observations. In those cases, the investment has been taken as zero, and the negative amount has been adjusted to adjacent years (commonly the next year).

(c) Having obtained the benchmark fixed capital stock for 1973-74 (year ending), and the annual gross investment in each industry, the series on fixed capital stock is formed by the perpetual inventory method: $K_t = 0.95 * K_{t-1} + [I_t/P_t]$ where K denotes fixed capital stock and P is the deflator mentioned earlier. The rate of economic depreciation has been taken as 5 percent.