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# Chasing the Dream: Industry-Level Productivity Developments in Europe

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**Chasing the Dream: Industry-Level Productivity Developments in Europe**

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**Abstract**

European countries are lagging behind in productivity growth, with significant productivity gaps across industries. In this study, we use comparable industry-level data to explore the patterns and sources of total factor productivity (TFP) growth across 28 countries in Europe over the period 1995–2020. Our empirical results highlight four main points: (i) TFP growth is driven largely by the extent to which countries are involved in scientific and technological innovation as the leader country or benefiting from stronger knowledge spillovers; (ii) the technological gap is associated with TFP growth as countries move towards the technological frontier by adopting new innovations and technologies; (iii) increased investment in information and communications technology (ICT) capital and research and development (R&D) contributes significantly to higher TFP growth; and (iv) the impact of human capital tends to be stronger when a country is closer to the technological frontier. The core findings of this study call for policy measures and structural reforms to promote innovation and facilitate the diffusion of new and existing technologies across Europe.



| | |
|---|---|
| JEL Classification Numbers: | H32; H40; L50; L60; L80; O30; O40; O52 |
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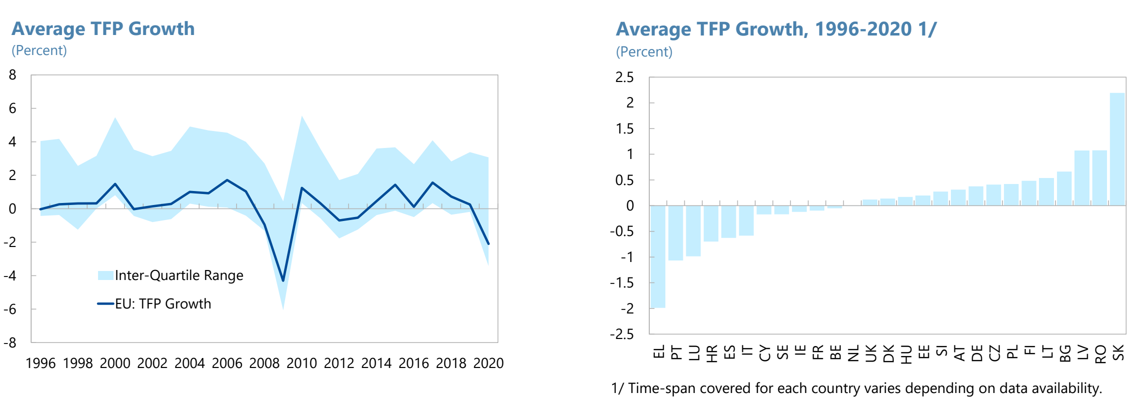
*Productivity isn't everything, but, in the long run, it is almost everything.*
—Paul Krugman

## I. Introduction

Following an extended period of economic tranquility and rapid income convergence, Europe has experienced a barrage of large shocks in recent years that resulted in diverging trends in productivity growth, which is key to raising material living standards, expanding the economy's growth potential, and strengthening international competitiveness. Understanding the drivers of total factor productivity (TFP) growth—a measure of technological advancements and the efficiency in utilizing factors of production—is therefore necessary to develop policies that can help strengthen growth prospects. We observe that aggregate TFP growth in the European Union (EU) declined from an average of 0.7 percent between 1996 and 2007 to 0.1 percent over the period 2009–2019 and -2 percent in 2020 during the COVID-19 pandemic (Figure 1). We also detect significant variation in average TFP growth rates across the EU over the period 1996–2020, with a minimum of -2 percent in Greece to a maximum of 2 percent in Slovakia. These productivity developments at the aggregate level, however, can reflect significant structural differences in human and physical capital accumulation and technological progress at the industry level. Accordingly, to provide a granular empirical assessment, this paper focuses on industry-level productivity developments that determine the aggregate.

The productivity gap between the EU and the US has widened after the global financial crisis (GFC) in 2008, with EU countries lagging behind in productivity growth (Cette, Fernald, and Mojon, 2016; Fernald and Inklaar, 2020). Furthermore, there are significant productivity gaps across EU countries and industries, which have become more prominent after the GFC. In this study, we look beyond the broad contours of productivity growth and use comparable industry-level data—drawn from the EU-KLEMS dataset—to explore the patterns and sources of TFP growth across 28 European countries over the period 1995–2020. We contribute to the literature by using the latest and most comprehensive industry-level dataset including the pandemic period and developing a granular analysis of tradable and non-tradable sectors of the

**Figure 1. Total Factor Productivity (TFP) Growth**



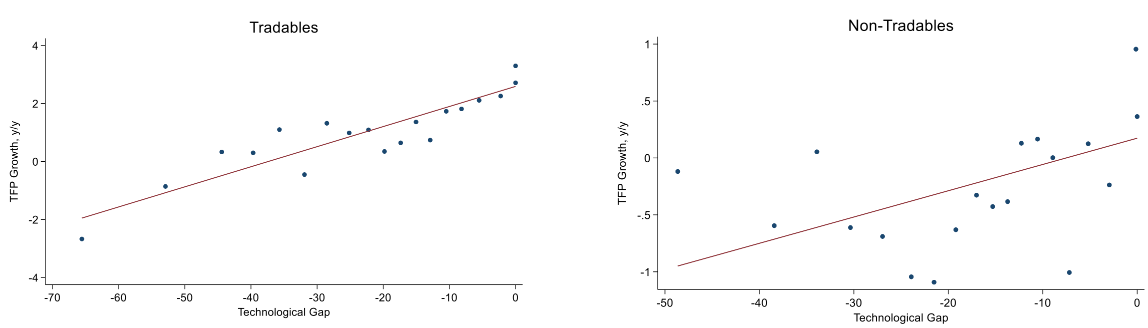

Sources: EU KLEMS; authors' calculations.

economy. This rich sectoral dataset covering a large number of economies over an extended period before and after the GFC allows us to analyze the heterogeneity of tradable and non-tradable sectors within and across countries, as well as within-sector and between-sector developments that are sensitive to aggregation bias (de Vries *et al.*, 2012; Üngör, 2017).

Our empirical results, in line with previous studies, highlight four main points.[2] First, TFP growth is driven largely by the extent to which countries are involved in scientific and technological innovation as the leader country or benefiting from stronger knowledge spillovers. Second, the technological gap—measured by a country's TFP distance to the frontier—is associated with TFP growth as countries move towards the technological frontier by adopting new innovations and technologies, as shown in Figure 2. Third, increased investment in information and communications technology (ICT) capital and research and development (R&D) contributes significantly to higher TFP growth across all EU countries. Fourth, human capital as measured by the intensity of high-skilled labor at the industry level does not appear to have a statistically significant impact on TFP growth, but there is some evidence that this effect is stronger when a country is closer to the technological frontier and human capital matters more in non-tradables than tradable sectors of the economy. For a more granular assessment, we also explore the interaction of industry-level factors with the technological gap and find that both ICT and non-ICT capital expenditures tend to moderate the negative effect of the technological gap on TFP growth. Lastly, we estimate the model for subsamples and show that the technological gap is an important driver of the TFP slowdown in post-GFC period.

TFP growth in the EU stagnated after the GFC and turned negative with the COVID-19 pandemic, with sizable productivity gaps between different industries and across countries. Reversing the downward trend and boosting productivity growth are key to raising living standards amid adverse demographic transitions and global economic realignments. As our industry-level

**Figure 2. TFP Growth and Technological Gap**




Note: These charts show a binned scatter plot of 9,151 observations.
Sources: EU KLEMS; authors' calculations.

[2] The industry-level analysis presented in this paper is broadly consistent with firm-level estimations for Europe, which also highlight the importance of R&D investment to boost productivity growth (IMF, 2024a).

empirical analysis indicates, revamping tangible and intangible capital investment in new technologies can generate higher TFP growth directly and indirectly by closing the technological gap vis-à-vis the frontier. We also find some evidence that human capital matters more when a country is closer to the technological frontier, especially in non-tradable sectors. Based on these findings, the priority should be to create a conducive environment to raise business investment and improve capital allocation by providing incentives for capital investment and R&D and strengthening human capital accumulation through education and healthcare, which can in turn promote innovation and facilitate the diffusion of new and existing technologies to countries below the technology frontier, with positive spillovers across industries (Akcigit, Baslandze, and Stantcheva, 2016; Akcigit, Hanley, and Serrano-Velarde, 2021; IMF, 2024b).

The empirical analysis presented in this paper suggests an important role for policies in reducing the technological gap among countries in Europe. Narrowing innovation and technology gaps vis-à-vis the frontier and expanding the frontier are key to advancing productivity growth on a sustainable basis. This requires (i) revamping tangible and intangible capital investment in new technologies and (ii) strengthening human capital for rapid progress in science and technology. The priority should therefore be given to creating a conducive environment for higher business investment and better capital allocation by providing incentives for capital investment and R&D and strengthening human capital accumulation through education and healthcare, which can in turn promote innovation and facilitate the diffusion of new and existing technologies to countries below the technology frontier, with positive spillovers across industries.

The remainder of this study is organized as follows. Section II provides a brief overview of the related literature. Section III describes the data used in the analysis. Section IV introduces the salient features of our econometric strategy. Section V presents the empirical results, including a series of robustness checks. Finally, Section VI summarizes and provides concluding remarks with policy implications.

## II. LITERATURE REVIEW

The conceptual framework for the analysis presented in this paper is based on the standard model of conditional convergence. This implies that countries can catch up to the technological frontier. However, differences in steady-state levels of productivity depend on structural features of the economy, such as labor and product market regulations, quality of institutional and physical infrastructure, sociodemographic factors, technology innovation and adoption, among others. There is a rich literature aiming to explain cross-country differentials in productivity and income growth patterns (Solow, 1956, 1957; Swan, 1956; Bartelsman, Haltiwanger, and Scarpetta, 2013; Crafts and O'Rourke, 2013; Cette, Fernald, and Mojon, 2016; Égert, 2016; Crafts, 2018).

For labor productivity, studies find that physical and human capital accumulation are the main determinants of labor productivity growth and key contributors of the divergence across countries (Lucas, 1988; Wolff, 1991; Benhabib and Spiegel, 1994; Maudos, Pastor, and Serrano, 2000; Barro, 2001; Kumar and Russell, 2002; Henderson and Russell, 2005; Färe, Grosskopf, and Margaritis, 2006; Enflo and Hjertstrand, 2009; Hanushek and Woessmann, 2015; Égert, de la

Maisonneuve, and Turner, 2023). These findings suggest that increasing productivity requires economic policies designed to reduce barriers to capital deepening and improve the education and health of the workforce.

Another important factor in cross-country differences in productivity growth is scientific progress and technological change (Nelson and Phelps, 1966; Romer, 1987, 1990; Grosman and Helpman, 1991; Aghion and Howitt, 1992; Greenwood, Hercowitz, and Krusell, 1997; Arcelus and Arozena, 1999; Hulten, 2001; Krüger, 2003; Guellec and van Pottelsberghe de la Potterie, 2004; Margaritis, Färe, and Grosskopf, 2007; van Ark, O'Mahony, and Timmer, 2008; Badunenko, Henderson, and Zelenyuk, 2008; Syverson, 2011; Araujo, Vostroknutova, and Wacker, 2017). Griffith, Redding, and Van Reenen (2004), Inklaar and Timmer (2007), Jorgenson, Ho, and Stiroh (2008) and Schiersch, Belitz, and Gornig (2015) develop a more granular approach to analyze TFP growth and obtain similar evidence at the industry level. These findings indicate that economic policy should also aim at fostering R&D and the diffusion of new technologies to boost productivity.

Public infrastructure is critical for effective and efficient economic activity and thereby TFP growth by enabling firms to invest in more productive machinery, preventing delays in production, and contributing to education and healthcare of the workforce (Aschauer, 1989; Munnell, 1992; Hulten 1996; Straub, 2011; Deng, 2013; Calderon and Serven, 2014; Égert, 2016). The quality of institutional infrastructure is no less important for political and socioeconomic stability and economic development by safeguarding civil and property rights and providing a safe living and working environment (North, 1990; Knack and Keefer, 1995; Easterly and Levine, 2003; Acemoglu, Johnson, and Robinson, 2004; Rodrik, Subramanian, and Trebbi, 2004; Chanda and Dalgaard, 2008). Physical infrastructure and institutions also play an important role in trade openness, financial development and the efficient allocation of resources, which in turn determine productivity growth across firms and industries (Grossman and Helpman, 1991; Edwards, 1998; Beck, Levine, and Loayza, 2000; Miller and Upadhay, 2000; Foster, Haltiwanger, and Krizan, 2001; Alcalá and Ciccone, 2004; Hiseh and Klenow, 2009; Restuccia and Rogerson, 2017; Cevik and Miryugin, 2018).

## III. Data Overview

The empirical analysis presented in this paper is based on an unbalanced panel of annual observations on 26 industries in 28 EU countries during the period 1995–2020.[3] The primary dataset for industry-level data is obtained from the EU-KLEMS database, which provides high-quality measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all EU member states.[4] In particular, it makes data available on different types of capital and skills-differentiated categories of labor. Gross output is decomposed into the contributions of intermediate inputs (i.e., energy, materials, and services) as

[3] Industries are grouped according to the statistical classification of economic activities based on the *Nomenclature des Activités Économiques dans la Communauté Européenne* (NACE).

[4] The latest release of the dataset is publicly available at https://euklems-intanprod-llee.luiss.it/ (Bontadini *et al*., 2023). O'Mahony and Timmer (2009) provide a detailed description of the contents and construction of the EU-KLEMS database.

well as value-added, which in turn is decomposed to the contributions from different types of capital and labor.

Data are available for seven different types of capital, which are aggregated based on the user cost of capital to produce capital service flows that take into account the different marginal productivities of the different components of a country's capital accumulation. In addition to aggregate measures, the EU-KLEMS database also makes available the breakdown for ICT and non-ICT physical capital spending as a share of gross fixed investment.[5] We also obtain industry-level data on intangible capital accumulation as measured by R&D expenditure as a share of gross fixed investment.

Labor inputs are differentiated with respect to skill levels as measured by educational attainment (primary, secondary, and tertiary), age, and gender. In this paper, we use the share of total working hours provided by workers with tertiary education to measure the share of high-skilled labor in a given industry. Comparable cross-country data at the industry level are available for three different skill levels, with labor inputs aggregated based on marginal productivities. These granular data series allow the assessment of TFP developments excluding the impact of changes in the composition and quality of both capital and labor inputs.

The dependent variable in this study is industry-level TFP growth, which is commonly measured as a residual after accounting for physical capital deepening and human capital accumulation. The EU-KLEMS database provides a decomposition of GDP growth into its main determinants based on a production function which includes productive capital and employment levels adjusted for hours worked, age, and for skill composition. Accordingly, TFP growth is defined as a residual term:

$$\Delta y_{ijt} = \Delta V_{ijt} - \omega_{ijt}^{K} V_{ijt} - \omega_{ijt}^{K} \Delta K_{ijt} - \omega_{ijt}^{L} \Delta L_{ijt}$$

where $\Delta y_{ijt}$ is TFP growth in country *i* and industry *j* at time *t* and *V*, *K*, and *L* denote value-added, capital, and labor, respectively. The coefficients $\omega_{ijt}^{K}$ and $\omega_{ijt}^{L}$ are the average share of capital and labor inputs, respectively. To mitigate the effects of extreme outliers, we winsorize industry-level variables at the 5$^{th}$ and 95$^{th}$ percentiles.

The main explanatory variables of interest at the industry level are the TFP growth frontier as measured by the highest level of TFP growth in a given industry and year and the technological gap as measured by the distance to frontier defined as the level of TFP of a country in a given industry and year relative to the highest level of TFP in that industry in the EU. This relative distance to the frontier represents the potential for increasing TFP by adopting new productivity-enhancing knowledge and technologies. In addition, we include a range of macroeconomic and institutional factors at the country level, such as real GDP per capita, consumer price inflation, trade openness, domestic credit to the private sector (i.e. financial development), population, and bureaucratic quality as control variables, which are drawn from the IMF's World Economic

[5] ICT assets include computers, software and telecommunication equipment, while non-ICT assets are proxied by transportation equipment.

Outlook (WEO), the World Bank's World Development Indicators (WDI), and the International Country Risk Guide (ICRG) databases.

Summary statistics for the variables used in the analysis are presented in Table 1. We observe significant heterogeneity in aggregate and industry-level productivity growth between 28 EU countries, across 26 sectors, and over the period 1995–2020. Aggregate TFP growth was 0.7 percent per year on average in the EU between 1996 and 2007 but decelerated to 0.1 percent after the GFC. As a result, over the entire sample period from 1996 to 2020, average TFP growth stood at 0.5 percent, with 11 out of 28 EU countries presenting a negative TFP growth. We also observe that TFP growth in accommodation and food services—the lowest productivity sector—was 1.6 percentage points lower than the average TFP growth across all sectors during the sample period, while TFP growth in agriculture—the highest productivity sector—was 1.4 percentage points higher than the average TFP growth. There is also significant heterogeneity in the technological gap. With an average of -19.2 percent, it varies from -67.7 percent to 0 percent.

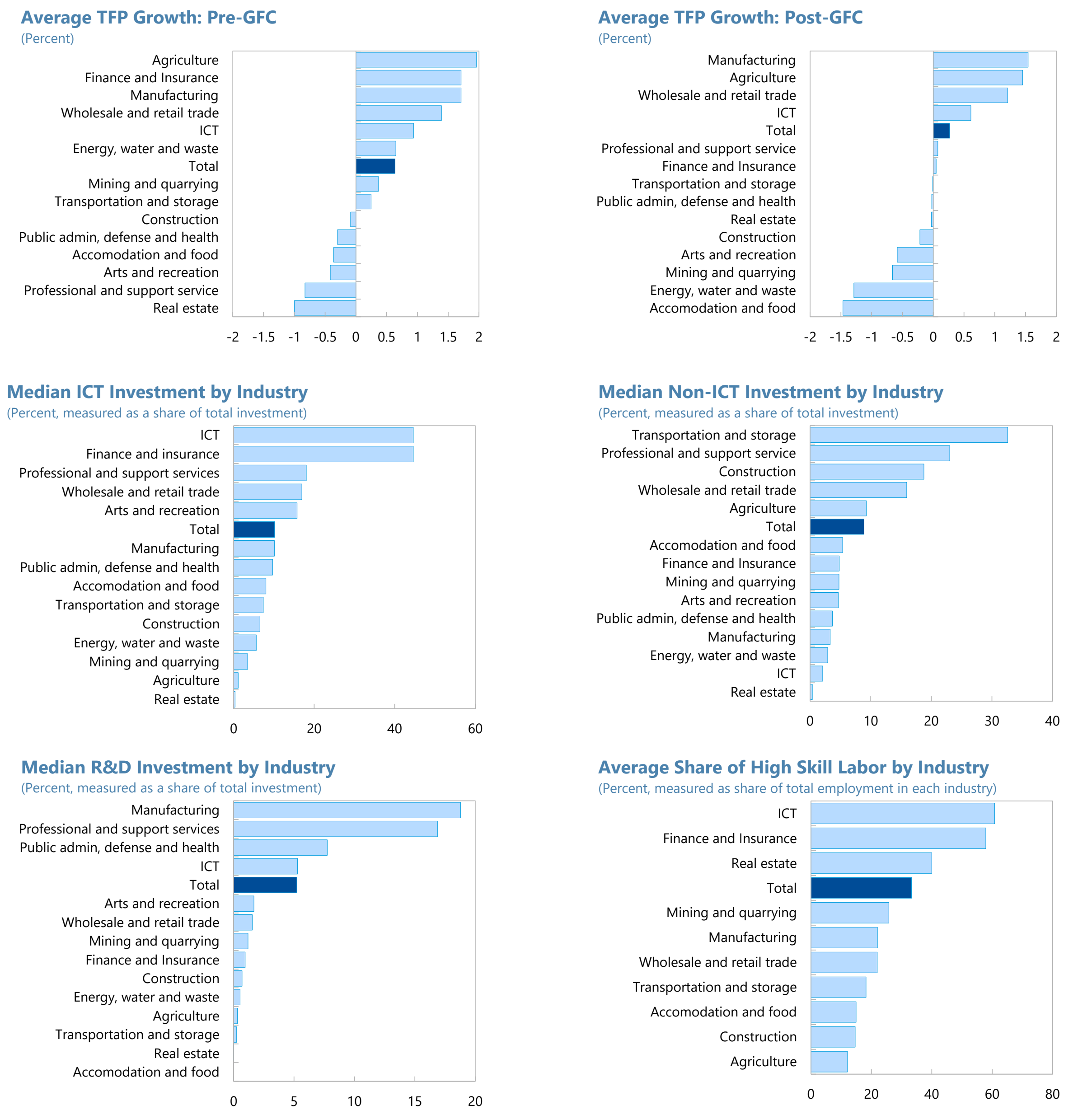
With regards to industry-level factors, we observe similarly large variation across sectors (Figure 3). ICT capital spending averaged 12.6 percent of gross fixed investment, with a minimum of 0 percent and a maximum of 44.6 percent, while non-ICT capital spending varied from a minimum of 0.3 percent of gross fixed investment to a maximum of 32.6 percent, with an average of 8.3 percent. Likewise, R&D expenditure as a share of gross fixed investment amounted to an average of 9.5 percent, with a minimum of 0 percent and a maximum of 47.8 percent.

**Table 1. Descriptive Statistics**

| Variable | Obs | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|
| **Industry-level** | | | | | |
| TFP growth | 8,438 | 0.5 | 7.0 | -50.0 | 100.0 |
| Technological gap | 9,151 | -19.2 | 16.8 | -67.7 | 0.0 |
| ICT capital spending | 11,879 | 0.1 | 0.1 | 0.0 | 0.4 |
| Non-ICT capital spending | 14,612 | 0.1 | 0.1 | 0.0 | 0.3 |
| R&D spending | 12,315 | 0.1 | 0.1 | 0.0 | 0.5 |
| **Country-level** | | | | | |
| Real GDP per capita | 18,021 | 37873.8 | 18718.5 | 9544.1 | 122170.6 |
| Inflation | 17,969 | 5.3 | 41.3 | -1.7 | 1061.2 |
| Financial development | 14,369 | 98.5 | 81.8 | 0.2 | 524.6 |
| Trade openness | 18,021 | 1.1 | 1.0 | 0.0 | 14.0 |
| Bureaucratic quality | 17,633 | 3.3 | 0.8 | 1.0 | 4.0 |
| Population | 18,021 | 18.1 | 22.8 | 0.4 | 83.2 |

Source: EU-KLEMS; IMF; World Bank; ICRG; and authors' calculations.

Figure 3. Industry-Level Developments




Sources: EU KLEMS; and authors' calculations.

## IV. Econometric Methodology

Beyond global shocks, there is a myriad of factors contributing to the productivity slowdown and cross-country productivity differentials. In this paper, we develop a granular analysis by using comparable industry-level data—drawn from the EU-KLEMS dataset—and explore the patterns and sources of TFP growth across the 28 EU countries. Following Scarpetta and Tressel (2002), Nicoletti and Scarpetta (2003), Griffith, Redding, and Van Reenen (2004), Acemoglu, Zilibotti, and Aghion (2006), Aghion and Howitt (2006), McMorrow, Werner, and Turrini (2010) and Dabla-

Norris *et al*. (2015), we model industry-level TFP growth using the following baseline specification:

$$\Delta y_{ijt} = \beta_0 + \beta_1 \Delta y_{Ljt} + \beta_2 (y_{ijt-1} - y_{Ljt-1}) + \beta_k \sum_k X_{ijt-1}^k + \beta_l \sum_k X_{ijt-1}^l (y_{ijt-1} - y_{Ljt-1}) + \eta_i + \gamma_j + \mu_t + \varepsilon_{ijt}$$

in which $\Delta y_{ijt}$ is TFP growth in country *i* and industry *j* at time *t*. $\Delta y_{Ljt}$ denotes the TFP growth frontier in the EU, which is measured by the highest level of TFP growth in industry *j* at time *t*. The TFP growth frontier captures the extent to which countries are involved in comparable scientific and technological innovation as the leader country or benefiting from knowledge spillovers. $(y_{ijt-1} - y_{Ljt-1})$ is the technological gap defined as the TFP difference in country *i* and industry *j* at time *t* with respect to the EU frontier (highest level of TFP) in industry *j* at time *t*. This relative distance to the frontier represents the potential for increasing TFP by adopting new productivity-enhancing technologies. $X_{ijt-1}^k$ is a vector of industry-level and country-level variables. Industry-level variables include ICT capital spending, non-ICT capital spending, R&D spending, and the share of high-skilled labor, while country-level variables include real GDP per capita, consumer price inflation, trade openness, domestic credit to the private sector, population, and bureaucratic quality.

We also explore how industry-level factors (ICT and non-ICT capital expenditures, R&D spending and the share of high-skilled labor) interact with the technological gap. These interaction terms are designated by $X_{ijt-1}^l (y_{ijt-1} - y_{Ljt-1})$ in country i and industry *j* at time *t*. The coefficients $\eta_i$, $\gamma_j$ and $\mu_t$ denote the time-invariant industry-specific effects and the time effects controlling for common shocks that may affect TFP growth across all industries at time *t*, respectively.[6] The inclusion of fixed effects also helps address endogeneity concerns arising from omitted variable bias. $\varepsilon_{ijt}$ is the idiosyncratic error term. Robust standard errors are clustered at the industry level.

## V. EMPIRICAL EVIDENCE

Our baseline results, presented in Table 2, provide a consistent assessment of industry-level TFP growth in 28 EU countries over the period 1995–2020. We display the specification with country fixed effects in column [1] for the whole sample of industries, in column [2] for tradable sectors, and in column [3] for non-tradable sectors.[7] We replace country fixed effects with a range of country-level control variables and present these estimations in column [4] for the whole sample of industries, in column [5] for tradable sectors, and in column [6] for non-tradable sectors. Because data on the share of high-skilled labor are available only from 2008, we present that

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[6] Country fixed effects are not included when the model incorporates country-level control variables. The results are not sensitive to replacing country fixed effects with country-level variables, which provide additional information. We also obtain broadly similar results with the inclusion of country-year and country-industry fixed effects.

[7] Tradable sectors include agriculture, forestry, fishing, mining, quarrying, and manufacturing; while non-tradable sectors include construction, wholesale and retail trade, transportation, storage, accommodation, food service, ICT, finance, insurance, real estate, professional services, public sector, education, human health, social work, arts, entertainment, and recreation.

model separately in Table 3, with the same set of specifications. In Table 4, we exhibit the results of the extended model including interaction terms for ICT and non-ICT capital expenditures, R&D spending, and the share of high-skilled labor with the technological gap.

We present standardized coefficients that allow us to compare the relative magnitude of the effects of different explanatory variables. The TFP growth at the frontier is positive and statistically significant across all specifications of the model, indicating that industry-level TFP growth is higher in all countries when there is stronger TFP growth in the frontier country. In the specification for the full sample of industries with control variables presented in column [4] of Table 2, the estimated coefficient on TFP growth at frontier is 0.25 and statistically significant at the 1 percent level, implying that a one-standard deviation increase in TFP growth at frontier is associated with, on average, an increase of about 0.25 standard deviation in TFP growth. This is

**Table 2. Industry-Level TFP Growth Estimations: Baseline**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: TFP growth | All | Tradables | Non-tradables | All | Tradables | Non-tradables |
| **Industry-Level Variables** | | | | | | |
| TFP growth at frontier | 0.271*** | 0.277*** | 0.207*** | 0.247*** | 0.265*** | 0.144** |
| | (5.783) | (4.659) | (4.071) | (5.225) | (4.581) | (2.395) |
| Technological gap | -0.310*** | -0.340*** | -0.260*** | -0.357*** | -0.403*** | -0.271*** |
| | (-9.342) | (-7.910) | (-5.556) | (-8.264) | (-6.974) | (-5.345) |
| ICT capital | 0.096*** | 0.053 | 0.150*** | 0.102** | 0.090 | 0.133** |
| | (2.837) | (1.140) | (3.634) | (2.627) | (1.522) | (2.494) |
| Non-ICT capital | -0.012 | -0.114 | 0.033 | -0.014 | -0.134 | 0.044 |
| | (-0.319) | (-1.257) | (0.846) | (-0.345) | (-1.544) | (1.118) |
| R&D spending | 0.143** | 0.126* | 0.162 | 0.148** | 0.157* | 0.112 |
| | (2.579) | (1.791) | (1.606) | (2.577) | (1.890) | (1.546) |
| **Country-Level Variables** | | | | | | |
| Real GDP per capita | | | | 0.264* | 0.407 | 0.096 |
| | | | | (1.781) | (1.339) | (0.686) |
| Inflation | | | | -0.684 | -1.551 | 0.207 |
| | | | | (-1.407) | (-1.554) | (0.525) |
| Financial development | | | | -0.072 | -0.043 | -0.118 |
| | | | | (-1.392) | (-0.521) | (-1.478) |
| Trade openness | | | | 0.111 | 0.418 | -0.120 |
| | | | | (0.680) | (1.625) | (-0.460) |
| Bureaucratic quality | | | | 0.165** | 0.138 | 0.219** |
| | | | | (2.616) | (1.256) | (2.274) |
| Population | | | | 0.635 | 1.512 | 1.515 |
| | | | | (0.533) | (0.457) | (1.315) |
| Number of observations | 8,615 | 4,153 | 3,644 | 7,505 | 3,584 | 3,200 |
| $R^2$ | 0.159 | 0.174 | 0.144 | 0.162 | 0.186 | 0.138 |
| Country fixed effects | Yes | Yes | Yes | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |

Robust t-statistics in parentheses; a constant is included in all specifications but not shown. The coefficients are standardized.
*** p<0.01, ** p<0.05, * p<0.1

an important contribution considering that the sample mean of TFP growth is 0.5 percent, confirming that there are significant cross-border innovation and technology spillovers from the frontier to the rest.[8] The estimated impact of TFP growth at frontier on TFP growth is even greater in tradable sectors (0.27 percent) than non-tradables (0.14 percent).

The technological gap, measured by a country's TFP distance to the frontier, also has a statistically significant association with TFP growth as countries move towards the technology frontier by adopting new knowledge and technologies. The economic magnitude of the technological gap is greater than any other factor in explaining productivity growth dynamics. The estimated coefficient of the technological gap is -0.36 and statistically significant at the 1 percent level for the full sample of industries in the specification including control variables presented in column [4] of Table 2, indicating that a one-standard deviation widening in the technological gap is associated with an average decline of about 0.36 standard deviation in TFP growth. The magnitude of this effect is again larger in tradable sectors of the economy than non-tradables (-0.40 percent *vs*. -0.27 percent).[9]

These findings are consistent with the view that productivity enhancements are increasingly being driven by innovation, with convergence associated with the adaptation of new and transformative technologies and knowledge spillovers. In other words, closing the technological gap would raise TFP growth, on average, by 2.3 percent across the whole sample of industries—and 2.8 percent for tradables and 3.8 percent for non-tradables. These results hold under different specifications, but we also observe the estimated coefficients on TFP growth at the frontier and technological gap are greater in magnitude for tradable sectors compared to non-tradables (services). To supplement the estimation results presented in Table 2, we visualize the complexity of underlying relationships in Figure 4, which shows a strong positive correlation between TFP growth and TFP growth at frontier and the technological gap. The higher the TFP growth at frontier and narrower the technological gap vis-à-vis the frontier, the higher the rate of TFP growth.

We also find a consistent set of results with regards to the effects of industry-level investment spending. First, ICT capital spending as a share of gross fixed investment is associated with higher TFP growth and the magnitude and statistical significance of this effect is greater for non-tradables. The estimated coefficient of ICT capital spending is 0.10 and statistically significant at the 5 percent level for the full sample of industries in the specification including control variables

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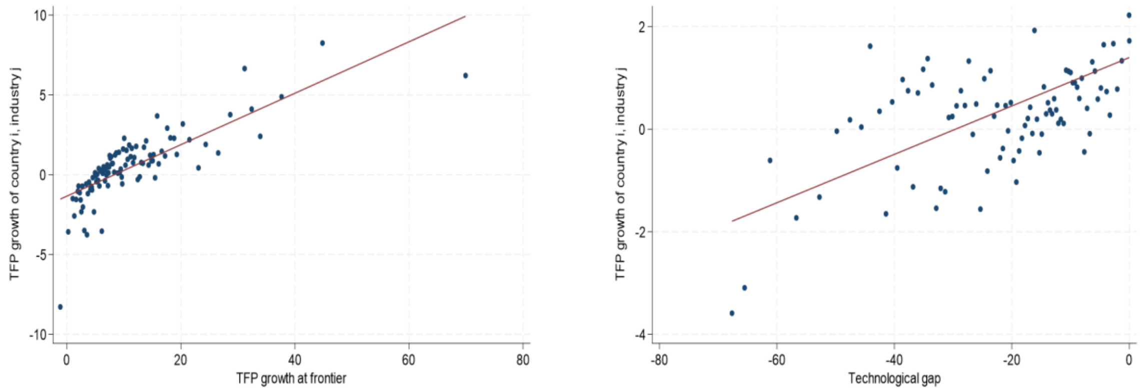
[8] The coefficient on TFP growth at the frontier requires cautious interpretation because when country *i* becomes the frontier, the explanatory variable is identical to the dependent variable. Although this is an econometric challenge, the measurement error bias associated with this issue mainly concerns the level of the coefficient, rather than the comparison of this coefficient across alternative specifications, which we focus on in this analysis.

[9] We also estimate these models with the interaction of TFP growth at frontier with the technological gap and obtain a statistically significant negative coefficient, indicating that the technological gap has a dampening effect on the impact of cross-border innovation and technology spillovers from the frontier to the rest. In other words, as expected and shown in Figure 2, the positive effect of TFP growth at frontier on TFP growth is lower in a country with a larger technological gap.

**Figure 4. TFP Growth Dynamics**




Note: These charts show a binned scatter plot of 9,151 observations.

Sources: EU KLEMS; authors' calculations.

presented in column [4] of Table 2. The positive coefficient on ICT capital spending indicates that a 1 standard deviation increase in ICT investment generates higher TFP growth by about 0.1 standard deviation in addition to directly raising output. We reason that the ICT effect is not statistically significant for tradables mainly because most manufacturing industries are not ICT-intense in capital spending. Second, non-ICT capital spending (proxied by transportation equipment) as a share of gross fixed investment does not appear to matter for TFP growth. Third, R&D spending as a share of gross fixed investment has a positive and statistically significant effect on TFP growth across all industries and tradables. The estimated coefficient on R&D spending is 0.15 and statistically significant for the full sample of industries and tradables in the specification including control variables presented in columns [4] and [5] of Table 2. This finding, consistent with the impact of ICT capital spending, confirms that an increase in intangible capital is associated with higher TFP growth. Beyond the direct contribution to productivity growth, the intensity of ICT capital and R&D spending also create positive externalities throughout the economy by accelerating the introduction and adoption of new technologies.

Turning to country-level control variables, real GDP per capita has a positive effect on TFP growth, but this is merely significant. Inflation appears to have a mixed and statistically insignificant effects on TFP growth—negative for all industries and among tradable sectors but positive on services. Financial development, as measured by domestic credit to the private sector, appears to have a negative effect on TFP growth across all specifications, but it is insignificant. Trade openness has a positive impact on TFP growth across all industries and especially in the case of tradable industries; but this effect is not significant. We also introduce the institutional dimension with the bureaucratic quality index and find that it has a positive effect on TFP growth, which is statistically significant—at the 5 percent level—for the full sample of industries and non-tradables. Finally, population has a positive coefficient across all specification of the model, but it is statistically insignificant.

In Table 3, we present results for the model including the intensity of high-skilled labor in 28 EU countries over the period 2008–2020. The findings show that human capital as measured by the intensity of high-skilled labor at the industry level does not appear to have a statistically significant effect on TFP growth at conventional levels, which is consistent with mixed results in previous studies such as McMorrow, Werner, and Turrini (2010).[10] But we obtain some evidence that this effect is stronger when a country is closer to the technological frontier and that human capital matters more in non-tradables than tradable sectors of the economy, after controlling for other factors.

**Table 3. Industry-Level TFP Growth Estimations: Baseline with High-Skilled Workers**

| Dependent Variable: TFP growth | (1) All | (2) Tradables | (3) Non-tradables | (4) All | (5) Tradables | (6) Non-tradables |
|---|---|---|---|---|---|---|
| **Industry-Level Variables** | | | | | | |
| TFP growth at frontier | 0.298*** | 0.281*** | 0.296*** | 0.292*** | 0.281*** | 0.254*** |
| | (4.415) | (4.028) | (6.454) | (4.393) | (4.033) | (5.368) |
| Technological gap | -0.589*** | -0.693*** | -0.378*** | -0.601*** | -0.695*** | -0.384*** |
| | (-7.822) | (-8.359) | (-4.606) | (-7.962) | (-8.137) | (-4.230) |
| ICT capital | 0.120 | 0.117 | 0.185* | 0.113 | 0.132 | 0.124 |
| | (1.571) | (0.933) | (1.955) | (1.557) | (1.071) | (1.646) |
| Non-ICT capital | -0.036 | -0.296* | 0.050 | -0.070 | -0.302* | 0.011 |
| | (-0.520) | (-2.006) | (1.067) | (-1.040) | (-2.090) | (0.199) |
| R&D spending | 0.106 | 0.143 | -0.001 | 0.092 | 0.134 | -0.014 |
| | (0.887) | (0.875) | (-0.029) | (0.742) | (0.793) | (-0.363) |
| Share of high-skilled labor | -0.055 | -0.156 | 0.0311 | 0.003 | -0.066 | 0.045 |
| | (-0.530) | (-1.624) | (0.269) | (0.033) | (-0.683) | (0.351) |
| **Country-Level Variables** | | | | | | |
| Real GDP per capita | | | | 0.644*** | 0.698 | 0.428 |
| | | | | (2.854) | (1.456) | (1.863) |
| Inflation | | | | -1.590 | -3.529 | -0.030 |
| | | | | (-1.308) | (-1.541) | (-0.033) |
| Financial development | | | | -0.016 | 0.074 | -0.046 |
| | | | | (-0.193) | (0.503) | (-0.489) |
| Trade openness | | | | 0.244 | 0.702 | -0.091 |
| | | | | (1.003) | (1.664) | (-0.236) |
| Bureaucratic quality | | | | 0.351* | -0.141 | 0.597** |
| | | | | (1.771) | (-0.288) | (2.800) |
| Population | | | | -0.009 | 1.598 | 1.131 |
| | | | | (-0.004) | (0.273) | (0.523) |
| Number of observations | 4,275 | 2,196 | 1,547 | 4,245 | 2,194 | 1,535 |
| $R^2$ | 0.217 | 0.233 | 0.214 | 0.215 | 0.235 | 0.203 |
| Country fixed effects | Yes | Yes | Yes | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |

Robust t-statistics in parentheses; a constant is included in all specifications but not shown. The coefficients are standardized.
*** p<0.01, ** p<0.05, * p<0.1

[10] It should be noted that human capital is key for labor productivity improvements, which are excluded from the TFP measure in the EU KLEMS database.

For a more granular assessment, we also explore the interaction of industry-level factors (ICT and non-ICT capital expenditures, R&D spending and the share of high-skilled labor) with the technological gap. These interaction results, presented in Table 4, reveal a number of interesting insights. First, ICT capital spending moderates the negative effect of the technological gap on TFP growth for the whole sample of industries and especially in the case of tradables. Even though non-ICT capital spending is not found to be a significant factor in determining industry-level TFP growth in our baseline estimations, it turns out to have a moderating effect on the technological gap. This effect, however, is only statistically significant for the full sample of industries, not for the breakdown of tradable and non-tradable sectors. The interaction of R&D spending with the technological gap only has a weak significant and negative effect across all specification, except for all industries when country level variables are included. Lastly, the interaction of high-skilled labor with the technological gap only has a statistically significant effect on the tradable sector.[11]

We subject our baseline findings to several robustness checks. First, we estimate the model for subsample periods: (i) the pre-GFC period (1995–2007); (ii) the post-GFC period (2010–2020); and the period excluding the COVID-19 pandemic (1995–2019), which might have had distortionary effects across different sectors of the economy. These results, presented in Table 5, show that the TFP growth at frontier remains a positive and significant determinant of TFP growth across almost all specifications of the model, but its impact becomes even greater after the GFC for the full sample of industries and tradables. The coefficient on ICT capital spending remains positive but only statistically significant in the period excluding the pandemic. On the other hand, we obtain mixed results for non-ICT capital spending, which is positive and significant for the pre-GFC period across all industries and the non-tradable sector, but turns negative in the post-GFC and period excluding the pandemic across all industries and the tradable sector. Finally, R&D spending as a share of gross fixed investment has a positive and statistically significant effect on TFP growth across all industries in the pre-GFC period and the period excluding the COVID-19 pandemic, but not in the post-GFC. In our view, the behavior of industry-level tangible and intangible investment variables indicate the impact of financial imbalances and resource misallocation prior to the GFC.

Second, a potential source of bias and inconsistency in estimations is the existence of systemic feedback effects between productivity and factors of production. The exogeneity assumption might not hold if higher TFP growth influences industry's future demand of inputs. To address this concern, we implement a dynamic modeling estimated via the system GMM approach (Arellano and Bover, 1995; Blundell and Bond, 1998). Although this allows for the inclusion of the lagged dependent variable as a regressor, dynamic estimations are not implemented to establish causality in this context.

[11] We also interact industry-level factors with the TFP growth at the frontier and obtain broadly similar results, which are available upon request.

## Table 4. Industry-Level TFP Growth Estimations: Interaction Terms

| Dependent Variable: TFP growth | (1)<br>All | (2)<br>Tradables | (3)<br>Non-tradables | (4)<br>All | (5)<br>Tradables | (6)<br>Non-tradables |
|---|---|---|---|---|---|---|
| **Industry-Level Variables** | | | | | | |
| TFP growth at frontier | 0.304*** | 0.287*** | 0.302*** | 0.299*** | 0.287*** | 0.265*** |
| | (4.489) | (4.094) | (6.323) | (4.459) | (4.099) | (4.944) |
| Technological gap | -0.790*** | -1.069*** | -0.410* | -0.797*** | -1.104*** | -0.372 |
| | (-6.295) | (-6.043) | (-2.000) | (-6.168) | (-6.193) | (-1.469) |
| ICT capital | 0.204** | 0.270** | 0.271** | 0.194** | 0.282** | 0.224** |
| | (2.770) | (2.552) | (2.735) | (2.764) | (2.868) | (2.550) |
| Non-ICT capital | -0.013 | -0.210 | 0.046 | -0.055 | -0.219 | -0.010 |
| | (-0.201) | (-1.173) | (0.793) | (-0.929) | (-1.269) | (-0.160) |
| R&D spending | 0.042 | 0.025 | -0.081 | 0.032 | 0.025 | -0.111** |
| | (0.352) | (0.177) | (-1.865) | (0.259) | (0.166) | (-3.095) |
| Share of high-skilled labor | -0.047 | 0.109 | -0.063 | -0.003 | 0.251 | -0.068 |
| | (-0.535) | (0.740) | (-0.548) | (-0.038) | (1.225) | (-0.516) |
| **Interactions** | | | | | | |
| Technological gap * ICT capital | 0.158** | 0.309** | 0.171** | 0.159** | 0.298** | 0.205** |
| | (2.229) | (2.759) | (3.359) | (2.233) | (2.648) | (2.561) |
| Technological gap * non_ICT capital | 0.078** | 0.032 | -0.003 | 0.059* | 0.027 | -0.036 |
| | (2.417) | (0.269) | (-0.055) | (1.892) | (0.225) | (-0.612) |
| Technological gap * R&D | -0.109* | -0.176* | -0.339* | -0.100 | -0.165* | -0.414* |
| | (-1.872) | (-1.928) | (-1.895) | (-1.680) | (-1.818) | (-1.973) |
| Technological gap * High skilled labor | 0.129 | 0.381** | -0.071 | 0.131 | 0.417** | -0.101 |
| | (1.381) | (2.516) | (-1.118) | (1.357) | (2.892) | (-1.172) |
| **Country-Level Variables** | | | | | | |
| Real GDP per capita | | | | 0.575** | 0.860 | 0.420 |
| | | | | (2.449) | (1.699) | (1.807) |
| Inflation | | | | -1.535 | -3.925 | -0.162 |
| | | | | (-1.276) | (-1.728) | (-0.171) |
| Financial development | | | | -0.014 | 0.130 | -0.103 |
| | | | | (-0.179) | (0.889) | (-0.980) |
| Trade openness | | | | 0.264 | 0.762* | -0.132 |
| | | | | (1.073) | (1.932) | (-0.343) |
| Bureaucratic quality | | | | 0.333 | -0.072 | 0.674** |
| | | | | (1.701) | (-0.138) | (3.167) |
| Population | | | | 0.258 | 1.418 | 1.341 |
| | | | | (0.128) | (0.254) | (0.578) |
| Number of observations | 4,275 | 2,196 | 1,547 | 4,245 | 2,194 | 1,535 |
| $R^2$ | 0.225 | 0.244 | 0.219 | 0.223 | 0.246 | 0.211 |
| Country fixed effects | Yes | Yes | Yes | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |

Robust t-statistics in parentheses; a constant is included in all specifications but not shown. The coefficients are standardized.
*** p<0.01, ** p<0.05, * p<0.1

The system GMM method involves constructing two sets of equations, one with first differences of the endogenous and pre-determined variables instrumented by suitable lags of their own levels, and one with the levels of the endogenous and pre-determined variables instrumented with suitable lags of their own first differences. We apply the one-step version of the system GMM estimator to ensure the robustness of the results, as the standard errors from the two-step variant of the system GMM method is shown to have a downward bias in the panels with small number of time-series observations. The use of all available lagged levels of the variables in the system GMM estimation leads to a proliferation in the number of instruments, which reduces the efficiency of the estimator in finite samples, and potentially leads to over-fitting. A further issue is that the use of a large number of instruments weakens the Hansen *J*-test of over-identifying restrictions, and so the detection of over-identification is hardest when it is most needed. Conversely, however, restricting the instrument set too much results in a loss of information that leads to imprecisely estimated coefficients. Estimation of such models therefore involves a delicate balance between maximizing the information extracted from the data on the one hand and guarding against over-identification on the other. We follow the strategy suggested by Roodman (2009) to deal with the problem of weak and excessively numerous instruments.

The system GMM identification assumptions are also validated by applying a second-order serial correlation test for the residuals and the Hansen *J*-test for the overidentifying restrictions. The values reported for AR(1) and AR(2) are the *p*-values for first- and second-order autocorrelated disturbances in the first-differenced equation. As expected, we find that there is high first-order

**Table 5. Industry-Level TFP Growth Estimations: Subsamples**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: TFP growth | All | Tradables | Non-tradables | All | Tradables | Non-tradables | All | Tradables | Non-tradables |
| | Pre-GFC | | | Post-GFC | | | Excluding Covid | | |
| **Industry-Level Variables** | | | | | | | | | |
| TFP growth at frontier | 0.158** | 0.271*** | 0.001 | 0.273*** | 0.266*** | 0.257*** | 0.239*** | 0.257*** | 0.116* |
| | (2.501) | (5.637) | (0.024) | (4.870) | (4.350) | (5.852) | (4.942) | (4.515) | (2.005) |
| Technological gap | -0.424*** | -0.465*** | -0.445*** | -0.652*** | -0.792*** | -0.411*** | -0.373*** | -0.421*** | -0.278*** |
| | (-10.190) | (-8.387) | (-6.355) | (-7.627) | (-8.287) | (-4.476) | (-8.253) | (-7.117) | (-5.496) |
| ICT capital | 0.051 | 0.014 | 0.147 | 0.083 | 0.139 | 0.094 | 0.129*** | 0.119* | 0.155** |
| | (0.605) | (0.108) | (1.325) | (1.084) | (1.048) | (1.241) | (3.243) | (1.941) | (2.843) |
| Non-ICT capital | 0.168** | 0.207 | 0.181* | -0.018 | -0.263 | 0.038 | -0.019 | -0.126 | 0.032 |
| | (2.163) | (1.512) | (2.034) | (-0.245) | (-1.659) | (0.722) | (-0.458) | (-1.334) | (0.938) |
| R&D spending | 0.207** | 0.146 | 0.205 | -0.009 | 0.041 | -0.048 | 0.174** | 0.200* | 0.105 |
| | (2.449) | (1.342) | (1.607) | (-0.061) | (0.206) | (-0.739) | (2.535) | (2.088) | (1.277) |
| **Country-Level Variables** | | | | | | | | | |
| Real GDP per capita | 1.160*** | 1.674** | 0.513 | 0.768*** | 0.898 | 0.684* | 0.254 | 0.489 | -0.017 |
| | (3.156) | (2.757) | (1.219) | (2.866) | (1.180) | (2.193) | (1.447) | (1.349) | (-0.121) |
| Inflation | -0.223 | -0.437 | 0.575 | -1.264 | -4.424 | 0.260 | -0.689 | -1.452 | 0.169 |
| | (-0.367) | (-0.445) | (0.650) | (-1.130) | (-1.571) | (0.313) | (-1.431) | (-1.445) | (0.441) |
| Financial development | -0.011 | 0.037 | -0.053 | -0.225 | -0.378 | -0.073 | -0.060 | 0.014 | -0.156* |
| | (-0.112) | (0.223) | (-0.398) | (-1.669) | (-1.229) | (-0.678) | (-1.053) | (0.147) | (-1.987) |
| Trade openness | 0.686** | 1.029** | 0.285 | 0.437 | 1.288*** | -0.033 | 0.086 | 0.373 | -0.158 |
| | (2.741) | (2.456) | (0.903) | (1.685) | (3.143) | (-0.102) | (0.517) | (1.320) | (-0.636) |
| Bureaucratic quality | 0.107* | 0.129 | 0.106 | 0.232 | 0.024 | 0.304 | 0.183*** | 0.146 | 0.235** |
| | (1.823) | (1.548) | (1.005) | (1.344) | (0.045) | (1.736) | (3.149) | (1.524) | (2.588) |
| Population | -2.056 | -2.219 | -1.025 | 1.522 | 3.113 | 3.084 | -0.091 | -0.222 | 1.183 |
| | (-0.723) | (-0.412) | (-0.337) | (0.670) | (0.462) | (1.266) | (-0.077) | (-0.071) | (0.981) |
| No of Observations | 2,673 | 1,390 | 1,078 | 4,151 | 1,858 | 1,840 | 7,155 | 3,429 | 3,043 |
| $R^2$ | 0.129 | 0.168 | 0.151 | 0.189 | 0.217 | 0.169 | 0.158 | 0.184 | 0.125 |

Robust t-statistics in parentheses; a constant is included in all specifications but not shown. The coefficients are standardized.

*** p<0.01, ** p<0.05, * p<0.1

autocorrelation, but no evidence for significant second-order autocorrelation. Similarly, the Hansen *J*-test result indicate the validity of internal instruments used in the dynamic model estimated via the system GMM approach.[12]

Similar to the baseline results, we find that TFP growth at the frontier has a direct (positive) impact on industry-level TFP growth in both specifications. The technological gap is negative and statistically significant in both specifications of the dynamic model, indicating that the pace of convergence in "follower" industries increases with the distance to the technological frontier as

**Table 6. Industry-Level TFP Growth Estimations: Dynamic Model**

| | (1) | (2) |
|---|---|---|
| Dependent Variable: TFP growth | All | All |
| **Industry-Level Variables** | | |
| TFP growth at frontier | 0.341*** | 0.335*** |
| | (3.239) | (2.929) |
| Technological gap | -0.321*** | -0.371*** |
| | (-2.981) | (-3.511) |
| ICT capital | 0.006 | 0.050 |
| | (0.118) | (0.580) |
| Non-ICT capital | 0.357** | 0.284* |
| | (2.431) | (1.904) |
| R&D spending | 0.085 | 0.030 |
| | (1.533) | (0.391) |
| **Country-Level Variables** | | |
| Real GDP per capita | | -0.018 |
| | | (-0.041) |
| Inflation | | -1.677 |
| | | (-0.656) |
| Financial development | | -0.162 |
| | | (-0.935) |
| Trade openness | | -0.224 |
| | | (-1.619) |
| Bureaucratic quality | | 0.024 |
| | | (0.062) |
| Population | | -0.118 |
| | | (-0.662) |
| Number of observations | 8,215 | 7,154 |
| Specification tests (p-values) | | |
| AR(1) | 0.000 | 0.000 |
| AR(2) | 0.404 | 0.284 |
| Hansen J-test | 0.037 | 0.029 |

Robust t-statistics in parentheses; a constant is included in all specifications but not shown. The coefficients are standardized.
*** p<0.01, ** p<0.05, * p<0.1

[12] The lagged dependent variable, asset tangibility, innovative property, and training are specified as instruments.

measured by the negative coefficient of the TFP gap. The coefficients on ICT capital and R&D spending as a share of gross fixed investment are positive but statistically insignificant, whereas non-ICT capital is found to be positive and significant, albeit with variation in magnitude and statistical significance.

## VI. CONCLUSION

Productivity growth in the EU stagnated after the GFC and turned negative with the COVID-19 pandemic, with sizable productivity gaps between different industries and across countries. This study uses rich industry-level data to explore the patterns and sources of TFP growth across 26 industries in 28 European countries over the period 1995–2020.

Our empirical results, in line with other studies, highlight four main points. First, TFP growth is driven largely by the extent to which countries are involved in scientific and technological innovation as the leader country or benefiting from knowledge spillovers. Second, the technological gap—measured by a country's TFP distance to the frontier—is associated with TFP growth as countries move towards the technological frontier by adopting new innovations and technologies. Third, increased investment in ICT capital and R&D contributes significantly to higher TFP growth across all EU countries. Fourth, human capital does not appear to have a statistically significant impact on TFP growth, but there is some evidence that this effect is stronger when a country moves closer to the technological frontier and human capital matters more in non-tradables than tradable sectors of the economy. For a more granular assessment, we also explore the interaction of industry-level factors with the technological gap and find that both ICT and non-capital expenditures tend to moderate the negative effect of the technological gap on TFP growth. Lastly, we estimate the model for subsamples and show that the technological gap is an important driver of the TFP slowdown in post-GFC period.[13]

Reversing the downward trend in productivity growth in Europe is key to raising living standards amid adverse demographic transitions and global economic realignments. First, revamping tangible and intangible capital investment in new technologies can generate higher productivity growth directly and indirectly by closing the technological gap vis-à-vis the frontier. Second, human capital remains critical for rapid progress in science and technology and thereby expanding economic growth potential. Based on these findings, the priority should therefore be given to creating a conducive environment for higher business investment and better capital allocation by providing incentives for capital investment and R&D and strengthening human capital accumulation through education and healthcare, which can in turn promote innovation and facilitate the diffusion of new and existing technologies to countries below the technology frontier, with positive spillovers across industries.

[13] We also take a closer look at the pattern and sources of TFP growth in the Baltics (Latvia and Lithuania) relative to the rest of the EU. These estimations, albeit subject to greater uncertainty due to the limited number of observations, remain broadly in line with the baseline estimations and indicate that the slowdown in TFP growth in the Baltics is largely driven by the widening of the technological gap and the decline in ICT capital spending relative to the EU average, with R&D spending making a greater contribution to TFP growth in the Baltics.

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