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Multifactor productivity growth enhancers across industries and countries: Firm-level evidence

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Abstract

Multifactor productivity (MFP) growth is an imperative economic engine. MFP dynamism across five advanced and seven developing countries from 1996 to 2015 is analyzed, elucidating its association with financing and intangible assets. Debt is manifested by its inverted U-shaped nonlinear relationship with MFP advancement, while corporate cash holdings are negatively (positively) associated with MFP development in five (three) countries. The heterogeneous relationships between intangible assets and MFP growth are identified across industries, countries, and time; intangible assets are requisite MFP growth enhancers for manufacturing in developing countries, for service businesses in advanced countries, and for the period after the global financial crisis. The greater the productivity effect of intangible assets is, the higher a country's per-capita income and/or governance quality becomes. Additionally, the results evince the catching-up of MFP to the technological frontier. Moreover, older firms exhibit slower MFP growth than their peers, whilst the positive effects of firm size on MFP growth are larger in high-tech and knowledge-intensive industries.

Keywords: Industrial Analysis; Multifactor Productivity Growth; Cash Holding; Debt Financing; Knowledge and Technology Intensive Sectors; Intangible Assets

JEL Classification Codes: D24; D22; D25; O34; O57; G32; L6; L8; L25; M21

I. INTRODUCTION

Multifactor productivity (MFP) growth is an important engine of economic growth, and MFP differences create income differences across countries/regions (Hashmi 2013). For example, Konya (2023) argued that increasing productivity and eliminating capital market distortions should be priorities for economic policy in the medium to long run to increase income per capita. Yet MFP changes have often been empirically treated as unexpected exogenous shocks, and MFP has been theoretically modeled as a Solow residual in the production function (Solow 1957).

What are productivity enhancers across countries and industries? This paper focuses on several key MFP growth enhancers. A common driver of MFP growth at the firm level is MFP convergence toward the technological frontier through the adoption of extant technologies from the frontier (Aghion and Howitt 2008). Developing countries can particularly enhance productivity through the catch-up process (Madden and Savage 1999). Moreover, firms can enlarge the frontier by technological innovation through research and development (R&D) (Kumbhakar et al. 2012). In fact, Bartelsman et al. (2019) found that firm productivity is significantly related to product innovation. Mattsson and Reshid (2023) found that productivity divergence occurs for sectors characterized by high digital and intangible asset intensity.

Productivity growth across the globe has reaped the benefits from new technologies, including automation, mechanization, digitalization, e-commerce, robotization, and information technology, such as software and computerized information (Liu et al. 2013; Staccioli and Virgillito 2021; Alguacil et al. 2022; Zhang and Dong 2023; Nucci et al. 2023; Duan et al. 2023). The fourth industrial revolution has brought about digitalization and automation of the economy (Braña 2019). For instance, digitalization improves MFP by reducing transaction costs, facilitating servitization, and stimulating innovation investment (Wen et al. 2022). Additionally, an upswing in artificial intelligence (AI) and robotics patenting activities has exerted a positive effect on the economy through productivity improvement (Damioli et al. 2021; Zhai and

Liu 2023; Czarnitzki et al. 2023; Yang 2023). Consequently, intangible capital has accumulated and played a more prominent role in enhancing MFP growth in the modern knowledge economy. Intangible assets lack physical substance but produce commercial gains. Examples of intangible assets include R&D, goodwill, brand equity, patents, copyrights, software, licenses, AI, and big data. Antonelli et al. (2023) argue that the recent direction of technological development has been increasingly knowledge intensive and tangible-capital saving, and the output elasticity of tangible capital has constantly decreased in the consumer and high-tech sectors over time.

This paper also focuses on financing as another essential MFP growth enabler. Corporate leverage decisions were studied by Modigliani and Miller (1958), who showed that the effects of debt on firm performance can be characterized by a nonlinear quadratic function. Their trade-off theory of optimal capital structure predicts that net benefits to debt financing arise for firms with low debt levels but decrease as debt reaches high levels. Inspired by this theory, Coricelli et al. (2012) empirically analyzed the hump-shaped relationship between leverage and productivity growth using firm-level data. Bonanno et al. (2023) found that financial constraints influence firms' efficiency.

We use firm-level data compiled in the Orbis database¹ from 1996 through 2015 to analyze MFP dynamics across twelve advanced and developing countries so that we can understand universal MFP growth enhancers in an era of knowledge-based economy. In doing so, we particularly focus on the roles of

¹ There are a few studies that used Orbis data for a particular country to analyze firm-level productivity or performance (e.g., Gopinath et al. 2017; Nakatani 2019a). For instance, Gopinath et al. (2017) used the same Orbis database to analyze manufacturing firms in Spain, although their focus was resource allocation, which differs from our focus. In our analysis, the empirical analysis is done at the firm level, so the panel regression would not be contaminated by resource allocation effects (Castiglionesi and Ornaghi 2013).

intangible assets, financing (debt and cash), and technological convergence, controlling for firm characteristics such as firm size and age, which is common in the empirical literature.

This paper contributes to the literature in two ways. First, we conduct an industrial comparison to study how the knowledge- and technology-intensive sectors differ from other manufacturing and service sectors. To do this, we use firm-level data on twelve countries in different regions (Asia, Europe, the Middle East, and Latin America) with different types of economies (both advanced and developing countries) to derive robust results.² This approach is particularly important for analyzing the effects of intangible assets on MFP in the knowledge economy.³ Second, we compare the periods before the global financial crisis and after the crisis. This is motivated by the fact that economic/financial crises often trigger restructuring of the economic structure; hence, we expect that the role of intangible assets became more prominent after the crisis as knowledge-intensive technological progress advances.

Our findings are summarized as follows. In the baseline estimation, we find a nonlinear relationship between debt financing and MFP growth. Regarding internal financing through corporate cash holdings, firms with high levels of cash holdings are found to be associated with lower MFP growth rates. We also find heterogeneous relationships between intangible assets and MFP dynamics. In most countries, relationships with intangible assets are positive, although the sizes of these relationships differ.

Furthermore, all the countries show that the MFP catches up to the technology frontier. Finally, we find that larger and/or younger firms tend to have more MFP growth than their peers.

² Although Şeker and Saliola (2018) estimated the MFP in developing countries using business surveys, they did not conduct an econometric analysis to study the drivers of firm-level MFP growth.

³ Nakatani (2021a, 2023a, 2024) studied the productivity drivers of specific industries (the information and communication technology sector, the infrastructure sector, and the food sector, respectively), but the author did not study more broad categories of industries. Therefore, in this paper, we study all industries, including manufacturing, service, and the knowledge and technology intensive sectors.

At the industrial level, we find that the impact of firm size on MFP growth in the service industry is greater than that in manufacturing, implying that economies of scale have stronger effects in the service industry. An economic intuition is that large service firms with a larger capital base can compete better than small firms in retail markets, as they can increase their profits by selling more goods if they face price pressure from the competition. We also find that intangible assets are more important in the manufacturing sector in emerging markets. In contrast, in countries where financial services are highly developed—the United Kingdom—the positive relationship between intangible assets and MFP growth in the service industry is greater than that in manufacturing. In knowledge- and technology-intensive industries, the relationship between intangible assets and MFP growth is strong, and firm size is also an important productivity enhancer.

Finally, our results for the period after the global financial crisis reveal that the impact and importance of intangible assets have recently increased in many countries. Our results show the time-varying heterogeneous relationship between intangible assets and MFP growth across countries.

The rest of the paper is organized as follows. We first explain the methodology and data. Then, we show our baseline empirical results, followed by robustness checks. In the subsequent section, we conduct an industry-level analysis and estimations based on the period before and after the global financial crisis. Finally, we conclude.

II. LITERATURE REVIEW

The literature has identified several factors that contribute to MFP growth.⁴ In this section, we review the state-of-the-art literature that studies the firm-level factors that enhance MFP growth.

⁴ In economics, MFP has been traditionally treated as a residual of production function (i.e., what we call Solow residual) and a shock to the economy and financial markets (e.g., Nakatani 2014, 2017a, 2019b).

Firm-level MFP growth is often driven by the adoption of new technology from the technology frontier (i.e., technological acquisition) (Conte and Vivarelli 2014). Acemoglu et al. (2006) proposed a model in which the productivity of firms catches up with the world technology frontier as they copy/adopt cutting-edge technology and innovate. The implication of their theoretical model is that the distance to the technology frontier matters for productivity growth. In search of factors influencing the distance of laggard firms to the frontier at the firm level, Añón Higón et al. (2022) empirically found that larger, older, and more capital-intensive European firms are closer to the productivity frontier. In contrast, firms closer to the technological frontier are more likely to engage in formal R&D activities (Malva and Santarelli 2016).

Innovation via R&D has been thought to be a main engine of MFP growth (Aghion and Howitt 1996). Calcagnini et al. (2021) found that trend innovation explains a significant portion of the MFP variance in major advanced economies. Process innovation increases productivity because new processes are often introduced to reduce production costs by saving costly inputs (Mohnen and Hall 2013). The Schumpeterian endogenous growth theory postulates that technological change is an endogenous process that could be affected by changes in the reward to innovation through R&D (Ha and Howitt 2007; Alcouffe and Kuhn 2004). R&D contributes to MFP growth through investment-specific technical change (Samaniego 2007). Hall et al. (1986) found that R&D, which is a type of intangible asset, has a significant effect on patenting. According to common knowledge in the literature, the impact of R&D investment on productivity growth is greater in high-tech industries than in low-tech industries (Los and Verspagen 2000; Montresor and Vezzani 2015; Verspagen 1995). van Ark et al. (2008) insisted that the contributions from the knowledge economy explain the productivity gap between the U.S. and Europe. Castellani et al. (2019) found that both a quantity effect (relatively low level of R&D spending) and a quality effect (lower ability to transform R&D spending into productivity gains) were the main causes of low productivity in the EU relative to the U.S. The problem of using R&D spending in productivity analysis is that R&D projects

typically take a long time to complete and even completed projects may affect productivity with a lag, as firms convert R&D knowledge into new products and services (Ugur et al. 2016). Thus, contemporaneous estimations of rates of return from R&D may be biased downward (Añón Higón 2007; Doraszelski and Jaumandreu 2013).

As a result of R&D and other investments, intangible assets have accumulated notably on the corporate balance sheet due to the current digital economy. In fact, it would be more sensible to use intangible assets as a variable representing an MFP enhancer rather than R&D expenses since R&D investment does not necessarily succeed in commercial gains, while intangible assets are the assets—such as intellectual property rights—that produce value added. In fact, Corrado et al. (2017) found that the R&D stock is only one-third of the total stock of intangible assets, leading to the high elasticity of non-R&D intangible assets with respect to output. Thus, not only the R&D component of intangible assets but also non-R&D intangible assets could significantly affect economic growth by changing the MFP. Thus, we analyze the effects of (broad) intangible assets (beyond R&D) on MFP growth using cross-country firm-level data. We use the ratio of intangible assets to total assets to measure the intangibility of assets. This captures the stock of intangible capital, and the stock variable is preferable for our analysis because Ortega-Argilés et al. (2015) found that the knowledge stock has a significant positive impact on firm productivity. Kancs and Siliverstovs (2016) also found that productivity growth becomes significantly positive only after a certain critical mass of knowledge stock is accumulated. Demmou et al. (2019) found that financial frictions in intangible sectors have been a barrier to productivity growth in less financially developed countries.

Indeed, financing is also a crucial MFP determinant. The theoretical underpinnings of the inverted U-shaped relationship between credit and productivity growth were studied by Aghion et al. (2019). Better access to credit makes it easier for firms to innovate and allows low-productivity incumbent firms to remain in the market longer. They showed evidence of an inverted U-shaped association between credit

constraints and MFP growth by aggregating the data at the sectoral level, although they studied only French manufacturing. Ferragina et al. (2016) found that financial constraints have a significant and negative impact on small- and medium-sized firms. Levine and Warusawitharana (2021) found that financial frictions increase the sensitivity of MFP growth to the use of external financing. Recent studies by Nakatani (2023bc) have shown that the maturity of debt influences MFP. From the econometric viewpoint in relation to asset intangibility, Bartoloni (2013) found evidence that intangible asset intensity has a significant effect on the leverage behavior of firms. Ahamed et al. (2023) found that firms with better financing access achieve higher productivity via their own R&D stock and knowledge pools.

We analyze not only debt financing but also internal financing in the robustness check section of our paper. This is because the pecking order theory of corporate finance states that firms prioritize their sources of financing from internal financing to external financing (Myers and Majluf 1984). Put differently, internal funds such as cash are used first, and when they are depleted, debt is issued (and equity financing is used as a last resort). This theory postulates that the cost of financing increases with asymmetric information. In our paper, we study the effects of cash holdings and debt financing on MFP growth. Chang and Tang (2021) recently found that firms with higher cash holdings can enhance MFP levels, but they did not study the effects on MFP growth.

Firm characteristics must inevitably be controlled for when firm-level MFP dynamics are investigated. The literature on productivity science has demonstrated that young firms are important for productivity growth. The life-cycle theory of firm dynamics predicts that new entrants or young firms increase their MFP faster than old ones through learning by doing in new markets (Bahk and Gort 1993). Similarly, Nakatani (2024) found that technological convergence is the main productivity enhancer of start-up firms. Ghak et al. (2021) asserted that policies facilitating innovative start-ups are an important tool for enhancing knowledge diffusion and stimulating MFP growth. Moncada-Paternò-Castello (2022) indicated

the key role of entrepreneurship, creativity, and the flexibility of new and young firms to compete and grow in new knowledge-intensive sectors. Firm age also affects R&D activity. For instance, Veugelers et al. (2019) found that young leading innovators, particularly in high-tech sectors, play a pivotal role in countries' R&D performance. Pellegrino and Piva (2020) found that R&D investment growth is associated with smaller and newer companies, as an increase in R&D investment causes higher profit returns than incumbents.

Not to mention, another crucial firm characteristic is firm size. Generally, there is a positive link between MFP and firm size because larger firms are better placed to optimally utilize scale economies (Sharma 2018). Put differently, since smaller firms often face larger financial friction due to limited collateral and cash flows (Magri 2009), it is difficult to allocate resources in an efficient manner. In fact, Pagano and Schivardi (2003) found a positive link between MFP growth and firm size in Europe, indicating that the larger size of firms fosters MFP growth, as it allows these firms to take advantage of all the increasing returns associated with R&D. Despite this general tendency, Koutroumpis et al. (2020) surprisingly found that smaller and older ICT firms benefit the most from R&D. Firm size also matters for the relationship between intangible assets and productivity because Dinlersoz and Wolf (2023) found that automation is concentrated in larger plants with higher MFP. Furthermore, Ibhagui and Olokoyo (2018) found that the negative effect of leverage on firm performance is most prominent for small firms and that this effect diminishes as a firm grows. Moreover, firm size and age are consistently shown to be the most important determinants of firms' financial constraints (Hadlock and Pierce 2010), which could affect a firm's productivity or capacity to innovate (Gorodnichenko and Schnitzer 2013; Kogan et al. 2017). For these reasons, it is essential to control for firm characteristics such as age and size when analyzing the pure effects of leverage on MFP. In our paper, firm size is measured as the amount of total assets rather than the number of employees due to data limitations.

III. METHODOLOGY AND DATA

Our firm-level data are retrieved from the Orbis database published by Bureau van Dijk. The Orbis database is a cross-country longitudinal dataset of unlisted and listed firms with income statements and balance sheets. The Orbis data for all countries are reported in U.S. dollars, making our empirical results comparable across countries. We use the NACE (and ISIC) four-digit industry classifications so that we can control for industry-specific time-variant fixed effects, such as changes in product market regulations.⁵ To avoid small sample bias, countries that have at least the sum of 10,000 observations for all industries and time spans are included in our analysis.⁶ This process resulted in the inclusion of twelve countries: China, Colombia, Hungary, Italy, Japan, Poland, Romania, South Korea, Spain, Thailand, Turkey, and the United Kingdom. Among these countries, Italy, Japan, South Korea, Spain, and the United Kingdom are developed countries, while China, Colombia, Hungary, Poland, Romania, Thailand, and Turkey are developing countries (see Figure 1 for their diverse levels of GDP per capita). Note that some relevant countries, such as the United States, are missing from our sampled countries because there is no duty to make balance sheets publicly available. The timeframe of the data (i.e., sample period), descriptive statistics, and the numbers of firms and industries for each country are summarized in Table 1. Note that zero values of the natural logarithm of firm age mean that the firms are one-year-old start-up companies, and they tend to have zero values of intangible assets. Most sampled countries have larger numbers of service firms than manufacturing ones, with the exceptions of China and South Korea, where the numbers

⁵ Anderton et al. (2014) found that competition-enhancing product market regulation is associated with a higher rate of firm churning, which in turn is positively related to higher MFP. See also Polemis (2020) for the relationship between product market competition and productivity.

⁶ Since we do not have information about the status of entry and exit of firms in the markets, it might be possible that there is a potential sample selection bias. For example, when firms exit from the markets due to a failure of business, their data might disappear from the Orbis database. In that sense, only successful firms tend to be included in the data sample.

of manufacturing firms are larger than those of service firms. The number of industries varies across countries from 373 for Turkey to 737 for Italy, with an average of approximately 500 industries. The correlation matrix in Table A1 in the Appendix shows that the correlation between firm age and firm size is between 0.2 and 0.4 because firm size usually increases as firms age.

To construct our cross-country firm-level database, we use the methods proposed by Kalemli-Özcan et al. (2015), Gopinath et al. (2017), and Gal (2013). Our database is different from theirs in five aspects. First, we have more cross-sectional data than the older data used in their papers. In particular, public and private insurance companies have recently been included in the Orbis database. Second, our data cover a longer period of time, up to 2015. In contrast, Gal's (2013) data sample period ended in 2009. Third, our data cover not only advanced economies but also developing economies. Fourth, we study firms from different continents. For instance, Kalemli-Özcan et al. (2015) analyzed only European firms; rather, we studied firms in Asia, Europe, the Middle East, and Latin America. Fifth, we have wider industrial coverage of the firm data than they did. For example, Gopinath et al. (2017) focused specifically on manufacturing industries in Spain, while our research covers all industries for all sampled countries to illustrate industrial differences.

We cleaned our database as follows. First, we dropped observations involving apparent reporting mistakes. For example, we dropped firms with negative values for total, tangible, or intangible assets; sales; or the number of employees in any year. We also eliminated observations for which the costs of materials or employees were missing or had nonpositive values. Firms that lacked NACE codes were also dropped because we cannot create industry-specific fixed effects. Observations with a negative firm age or liability were also dropped. Moreover, if the ratio of liability or intangible assets to total assets exceeded unity, we dropped the observations. Another major issue in dealing with the Orbis database is the removal of duplicate data. When we found duplicate accounts, we dropped the accounts that were not used for annual reporting.

The MFP is calculated by the method developed by Gandhi et al. (2020), who proposed the nonparametric identification method to estimate gross output production functions that require flexible inputs (e.g., intermediate inputs) to be employed as a proxy variable (see the detailed explanation of their MFP estimation method in the Appendix). Their method is superior to Levinsohn and Petrin's (2003) method with Akerberg et al.'s (2015) correction because their dependent variable is the log of revenue minus material expenditure, which is referred to as a restricted profit production function that has problems since it is justified as a local approximation and because the variation in production data is large. Their key assumptions are as follows: (1) the production function is concave and differentiable for all inputs; (2) the Hicks neutral stochastic technology shock involves the Markovian process; (3) the intermediate input demand is strictly monotonic for a single instance of unobservability; (4) the firms are price takers for the intermediate input and output markets; and (5) we can independently vary the predetermined inputs conditional on the lagged input and output values. We use the method they proposed because they showed that structural estimation methods suffer from a fundamental identification problem when the production function contains flexible inputs, i.e., inputs that are variable in each period and have no dynamic implications. These scholars also showed that information in the first-order condition can be used in a completely nonparametric way. The output of the production function is value added, calculated as turnover revenue minus materials or the cost of goods sold, while the labor input is the cost of employees and the capital input is tangible fixed assets. According to the Orbis database, tangible fixed assets are all tangible assets such as buildings and machinery. Note that we do not include intangible fixed assets in the estimation of MFP because we treat intangible assets as one of the determinants of MFP dynamics in our regression equation (1). In other words, if we include intangible assets as capital inputs in the estimation of MFP, then the relationship between intangible assets and MFP would be

decided in the estimation of MFP⁷, which is inconsistent with the empirical strategy used in this paper. Like Gandhi et al. (2020), here, flexible inputs are measured in terms of prices. We use the industry-level producer price index to deflate the nominal variables. This usage of prices as flexible inputs is supported by a theoretical model by Clarke and Johri (2009), who showed that firms optimally vary their prices to control the amount of learning, which in turn influences future productivity. Following the advice of Bontempi and Mairesse (2015), we use accounting information on intangible assets (rather than expense information). Intangible fixed assets are calculated as the value of all intangible assets originating from formation expenses, R&D expenses⁸, and all other expenses with a long-term effect recorded on each firm's balance sheet. The definition of intangible assets is the same for all countries in the Orbis database, which is an advantage of our analysis in terms of the comparisons that are made.

The fixed-effects model used to identify the firm-level MFP growth enhancers is defined as follows:

$$\begin{aligned} \Delta \ln(MFP_{i,j,t}) = & \beta_1 + \beta_2 \ln(MFP_{i,j,t-1}) + \beta_3 Debt_{i,j,t-1} + \beta_4 (Debt_{i,j,t-1})^2 + \beta_5 \ln(Size_{i,j,t}) + \beta_6 \ln(Age_{i,j,t}) \\ & + \beta_7 Intangible\ Assets_{i,j,t-1} + \mu_{j,t} + v_i + \varepsilon_{i,j,t} \end{aligned} \quad (1)$$

where the subscripts i , j , and t represent the firm, industry, and time period, respectively; $\ln(MFP_{it})$ is the natural logarithm of MFP; β_1 is a constant term; β_2 captures convergence to the productivity frontier;

⁷ See Schankerman (1981) for discussions on the double-counting issues (or omission bias) regarding the inclusion of R&D or intangible assets in the estimation of MFP.

⁸ International Financial Reporting Standards says "The costs of generating other internally generated intangible assets are classified into whether they arise in a research phase or a development phase. Research expenditure is recognized as an expense. Development expenditure that meets specified criteria is recognized as the cost of an intangible asset. Intangible assets are measured initially at cost. After initial recognition, an entity usually measures an intangible asset at cost less accumulated amortization."

$Debt_{i,t}$ is debts divided by total assets; $\ln(Size_{i,t})$ is the natural logarithm of total assets⁹; $\ln(Age_{i,t})$ is the natural logarithm of firm age; $Intangible\ Assets_{i,t}$ is intangible fixed assets divided by total assets; $\mu_{j,t}$ represents industry-specific time fixed effects; v_i represents firm fixed effects; and $\varepsilon_{i,j,t}$ is an error term. Estimation model (1) is a reduced-form approach, and avoiding the omission of relevant variables is not evident, given the substantial arbitrariness in the choice of any explanatory variables in model (1). As such, any finding is surrounded by high uncertainty regarding what estimates represent.¹⁰ To avoid endogeneity problems arising from simultaneous decisions made by firms, the relevant explanatory variables (i.e., debt and intangible assets) are lagged.¹¹ The lagged variables are commonly used in the literature. Including the firm fundamentals (i.e., firm age and firm size) in the estimation is an attempt to control for these well-documented effects in the prior literature. The effects of financial crises are controlled by time fixed effects.

We compare our panel regression results across countries, although we do not conduct a pooled estimation across countries. With regard to country-level factors, this paper analyses how country-level

⁹ Some empirical studies use total number of employees as a proxy for firm size. However, in the Orbis database, the data on the number of employees are missing for some countries, and therefore, we are not able to explore this method.

¹⁰ We believe that potential omitted variable bias is not a serious problem despite the following missing factors: trade (Newman et al. 2023), foreign investment (Belderbos et al. 2021), market regulations (Anderton et al. 2014), corporate tax (Bournakis and Mallick 2021; Liu et al. 2022), corruption (Lambdsdorff 2003), staff training (Yang et al. 2010), and managerial ownership (Palia and Lichtenberg 1999). Unfortunately, there is no information on these factors in our database, so we cannot include them. Nevertheless, these omitted variables are controlled by the industry-specific time-varying and firm-specific fixed effects, $\mu_{j,t}$ and v_i , respectively. For instance, omitted variables common for the same industry, such as market regulations and corporate tax rates, are controlled by the industry-specific time-varying fixed effects, while others such as trade/foreign investment/training/managerial ownership are broadly captured by the firm fixed effects.

¹¹ For example, an adverse MFP shock can increase credit constraints of firms and banks (Nakatani 2016, 2017b).

institutional factors such as per capita income level, corruption, regulatory quality, and rule of law influence the effects of intangible assets on productivity growth later in Figures 2-5 instead of analyzing the direct effects of institutional variables on MFP, which have already been studied by many researchers. Please note that it is not simple to merge all country data for a pooled estimation because some companies are multinational corporations. A multinational corporation is headquartered in one country and has subsidiaries in other countries, indicating that they are not independent observations, especially because they often share the same intangible assets (including patents, brand equity, software, and organizational capital) and sell the same products.¹² Multinational corporations often engage in transfer pricing and intrafirm financing for global tax planning purposes, both of which further make it difficult to capture their real economic activities if their data are merged across borders.

IV. BASELINE RESULTS

Table 2 shows our baseline estimation results. Although the data period in the baseline estimation differs across countries due to the availability of data, the main findings remain unchanged when the same timeframe is used for all countries, as we will show later. Thus, the following findings about the baseline results are robust to using data for different time frames.

The MFP tends to reach its productivity frontier in all countries. The highly statistically significant negative coefficients of lagged MFP variables in all countries imply that firms with low MFP experience higher MFP growth rates, corroborating the findings of Bessonova and Tsvetkova (2022). This is consistent with the idea that MFP tends to catch up to the technology frontier, as low-productivity firms (productivity

¹² Tajika and Nakatani (2008) provided evidence of the repatriation of royalties from foreign affiliates to parent companies of Japanese multinational corporations that share the same intellectual property.

laggards) can increase their MFP through the acquisition of technology that raises MFP.¹³ In contrast, high-productivity firms have less room for MFP improvement since they need innovation to increase MFP further. New technology is usually costly, and it is highly uncertain whether such an investment results in business success.

An inverted U-shaped nonlinear relationship between leverage and MFP growth is also observed, especially in highly leveraged advanced economies. As we discussed in the literature review section, debt is envisaged to have a nonlinear relationship with MFP growth. The results for debt have the expected signs for all countries, and the estimated coefficients are statistically significant for most countries. Likewise, the literature on the debt-growth nexus has shown that leverage has a positive relationship with MFP because firms utilize their financial resources for innovative investments, but this relationship could be offset by the need to deleverage if the firms are highly leveraged.¹⁴ Our baseline results confirm this hypothesis. Namely, the linear term for debt is statistically significant at the one percent level, with a positive coefficient for all countries. The quadratic term for debt has a negative sign and is statistically significant at the ten percent level for seven out of twelve countries, especially for advanced economies. Countries that have negative signs for the quadratic leverage term without statistical significance are emerging market countries such as Thailand that have relatively low debt levels. Since these countries are still in the process of undergoing an economic transition from middle income to high income, they have limited samples of highly leveraged firms. This is why our results show statistical significance for only the

¹³ One caveat is that the negative correlation between lagged MFP level and MFP growth might just capture the mean-reversion behavior of firm-level productivity. That is, a high current productivity is followed by a lower productivity tomorrow, which could easily generate a negative correlation between lagged MFP level and future MFP growth.

¹⁴ This resembles the inverted U-shaped relationship between public debt and fiscal balance (Nakatani2021b). The idea is that net benefits to debt financing arise for countries with low debt levels but decrease as leverage reaches high levels.

positive linear leverage term in these emerging market economies. For Turkey and Spain, the quadratic terms are positive and statistically significant. In other words, in these countries, our sample shows that increasing debt has had mostly a positive relationship with MFP growth thus far.

In addition, the highly statistically significant positive coefficients of firm size in all countries indicate that larger firms experience faster MFP growth than smaller ones (i.e., economies of scale). This is because larger firms have more resources to invest in innovative activities to increase MFP. Put another way, smaller firms exhibit slower MFP growth rates than their peers.

Moreover, older firms are found to have slower MFP growth rates than younger firms. Firm age is statistically significant at the one percent level for all. With the exception of China and Turkey, firm age has negative coefficients, indicating that firms typically tend to experience lower levels of MFP growth as they become older. This finding is consistent with the life-cycle hypothesis of MFP dynamics (Huergo and Jaumandreu 2004). In China, firm age is positively associated with MFP growth, implying that younger firms exhibit slower MFP growth, which may be attributed to the fact that, in China, there are many new firms that enter the market but exit quickly because they do not necessarily succeed in business. In the case of Turkey, our result is consistent with that of Akcigit et al. (2020), who found that the economic activities of young firms have recently decreased and that market concentration has increased.

Interestingly, the results for intangible assets are heterogeneous. Among our sample of twelve countries, ten have positive coefficients for intangible assets, implying that intangible assets are positively associated with MFP growth. Among these ten countries, for six countries, the coefficients are statistically significant at the five percent level. These six countries are mostly advanced economies. Specifically, the positive coefficient of intangible assets is the largest in the United Kingdom and Japan, both of which are technology frontiers in global markets. In contrast, the positive coefficients of intangible assets are small for South Korea and Spain. Interestingly, the sign of the coefficient of intangible assets is negative in

China and Hungary. In China, the negative effects of intangible assets are highly statistically significant. This result provides evidence of the reality that the number of patents skyrocketed in China recently, but quality of these patents are not necessarily high enough to increase productivity (Hu et al. 2017). Santacreu and Zhu (2018) found that the largest increase in the number of Chinese patents occurred in the utility category, followed by the design patents (not invention patents), and stated that the technological progress in China is nonsignificant when compared with its skyrocketing number of patents. Long and Wang (2019) found that Chinese patent promotion policies have prompted a quantitative increase in patents but had negative effects on average patent quality, which explains our results about the negative coefficient of intangible assets in China. As we will show later, if we exclude the period of the skyrocketing number of patents by restricting the data for China to that before the global financial crisis, the coefficient for intangible assets becomes positively statistically significant. Finally, we analyze how income level and institutional factors influence the benefits of intangible assets for MFP growth. We find that the estimated coefficients of intangible assets are larger for countries with higher per-capita incomes, as shown in Figure 2. The positive association between income per capita and the effects of intangible assets could be a reflection of other institutional factors. Thus, we also depict the relationship between the coefficients of intangible assets and corruption in Figure 3. The figure clearly demonstrates that the productivity-enhancing effects of intangible assets are greater in countries with fewer perceptions of corruption (i.e., a higher score on the corruption perception index means a less corrupt government). We also look at how regulatory quality and rule of law are related to the productivity effects of intangible assets in Figure 4 and Figure 5, respectively. Both figures reveal that the benefits of intangible assets for MFP growth are greater for countries with better quality regulations and stronger rule of law.¹⁵ Thus, our

¹⁵ This finding is consistent with the recent findings by Nakatani et al. (2023, 2024), who found that quality of governance, including rule of law and regulatory quality, matters for efficiency of public health and education services, which are one of the large main sectors of knowledge-intensive industries in many countries, including developing economies.

research demonstrates that better quality institutions are necessary to bring productivity gains from intangible assets in the modern knowledge economy.

V. ROBUSTNESS CHECK

We next examine a different specification of regressions by including cash holdings as an additional financing instrument for firms in Table 3 for a robustness check. In Table 3, we include the ratio of cash and cash equivalent to total assets instead of the quadratic debt variable.¹⁶ This is motivated by the famous pecking order theory of corporate finance, as discussed in the literature review section:

Companies can finance expenses through the order of cash, debt, and equity because of the cost arising from information asymmetry. Since there are three financing tools and including all of them could cause a multicollinearity problem, we only focus on cash holdings and debt financing in our study. The results in Table 3 show that the effects of cash holdings on MFP growth are heterogeneous. In five countries, the coefficients of cash are negative and statistically significant, while in three countries, they are positive and statistically significant. The negative coefficients can be explained by the fact that firms with high cash holdings may not utilize their available financial resources enough for productivity-enhancing investment. Alternatively, the positive relationship could be explained by the tendency for firms that succeed in terms of the efficiency of business to earn more cash than their peers. Please note that the cash variable in our regressions is lagged to avoid reverse causality.

Furthermore, to examine the potential multicollinearity arising from the strong correlation between firm age and firm size (younger firms tend to be smaller), we excluded either firm age or firm size from the regressions in Table 4 and Table 5, respectively. The results of the estimated coefficients did not differ

¹⁶ Our variable focuses on the amount of cash held by a firm, and it is not the same as the one often used by pecking order models such as cashflow (i.e., net income plus depreciation) (López-Gracia and Sogorb-Mira 2008).

much from the baseline, except that the number of countries that have positive and statistically significant coefficients of intangible assets increased by one compared to the baseline estimation results.

Finally, we conduct robustness checks for the relationship between intangible assets and MFP growth. Obtaining precise MFP estimates does not eliminate the endogeneity concerns that arise from regressing MFP on intangible assets. There is a potential issue of simultaneity such that intangible assets are more likely to be acquired by more productive firms. Lagged explanatory variables can solve endogeneity stemming from simultaneity when there are no dynamics among unobservable variables, which is a strong, not testable, assumption (Bellemare et al. 2017). To address this concern, we conduct robustness checks by examining cases that include two- or three-year lagged intangible asset variables in regression equation (1). The results for the two-year lags are presented in Table A2, and those for the three-year lags are shown in Table A3.

Our robustness checks that employ longer lags for intangible assets have the following implications. The size of the coefficients of intangible assets on MFP growth decreases as the length of the time lag increases. This is intuitive, as the effects of intangible assets on MFP growth tend to weaken over time as intangible assets become older. This result is consistent with the reality that in industries that rely on digital innovations, the productivity-enhancing impacts of new intangible assets are short-lived (e.g., it is said that new technology is relevant for at most three years in the information technology sector). Per accounting standards, for example, the lifespan of software is assumed to be three years. Thus, it is not surprising to see that the impact of current intangible assets on MFP improvement decreases within two or three years.

We also employed the fixed-effect instrumental variable method (two-stage least squares estimator) by using lagged intangible assets as an instrument for an additional robustness check, and we obtained estimation results very similar to those of the baseline. However, those results are not presented in this

paper because the F statistic for the significance of the instrument did not exceed the desired value of 10 (Staiger and Stock 1997), although the coefficient for the instrument in the first-stage regression was statistically significant at the one percent level.

VI. ANALYSES FOR SPECIFIC INDUSTRIES AND TIME FRAMES

The baseline results presented in the section above might be a reflection of different industrial compositions across countries. Therefore, in this section, we restrict the data sample to include the same industry in each country. Specifically, we analyze the effects of the explanatory variables on MFP growth in manufacturing, service, and knowledge-intensive high-technology industries. Additionally, the different results across countries may be driven by the use of different data periods. For this reason, we also analyze the same regression but focus on the same sample period after (and before) the global financial crisis.

The industry results are similar to the baseline results, demonstrating the robustness of our results. There are several noteworthy findings for each type of industry. The impact of firm size on MFP growth is found to be larger in the service industry than in manufacturing, implying that economies of scale have larger effects on MFP improvement in the service industry. This finding is consistent with the previous finding that entry costs into the service industry are higher; therefore, firm size is more important in this industry than it is in manufacturing (Baldwin and Gu 2011). We also find that intangible assets are more important in the manufacturing sector, especially for emerging markets. In contrast, in countries where financial services are highly developed (the United Kingdom), the positive relationship between intangible assets and MFP growth is stronger in the service industry than in manufacturing. In knowledge- and technology-intensive industries, the relationship between intangible assets and MFP growth is strong, as expected, and firm size is also important. Interestingly, in knowledge-intensive high-tech sectors, the nonlinear relationship between leverage and MFP growth can be concave or convex (see a detailed discussion later).

Our results regarding the recent MFP dynamics that occurred after the global financial crisis reveal the increasing impact and importance of the intangibility of assets in many countries. We discuss the details of the industry and time-frame analyses below.

Manufacturing

There is not much difference in the lagged MFP term when the sample is restricted to the manufacturing industry, as shown in Table 6. In all the countries, the negative coefficients for lagged MFP are statistically significant at the one percent level, and the size is similar to that of the baseline results, which provides evidence that MFP is catching up to the technology frontier.

For debt, in our manufacturing samples, the linear term is positive and statistically significant at the five percent level for all countries, similar to the baseline results, while the quadratic term is negative and statistically significant at the five percent level for eight countries. For the manufacturing sector, the nonlinear relationship (captured in the quadratic term) between debt and MFP growth is statistically significant for China, Hungary, South Korea, and Romania. This is also true for Italy, Poland, and the United Kingdom, for which the results were already negative and statistically significant at the one percent level in the baseline results. This result shows that for manufacturing firms in the first four emerging countries, there is a nonlinear inverse U-shaped relationship between debt and MFP growth, which we did not observe when we used the samples of all industries.

One interesting finding regarding firm size for manufacturing is that the size of the coefficient is always smaller than that of the baseline results. This result implies that the marginal benefits of firm size on MFP growth for manufacturing are smaller than those for other industries. This may be attributed to the fact that economies of scale are more relevant in the service industry than in manufacturing because, for example, large enterprises that have a larger capital base prefer competition in retail markets, as they can increase their profits by selling more goods if they face price pressure from the competition.

The signs, sizes, and statistical significance of the coefficients of firm age for manufacturing are not very different from those in the baseline estimation. One exception is South Korea, for which manufacturing has an effect that is more than three times stronger and more negative than that in all industries. This result may be related to the special South Korean business culture. It is known that business groups, chaebols, are prevalently used in the South Korean manufacturing industry, and this might help firms survive even though they do not have high MFP growth.¹⁷

Regarding the effects of intangible assets, the estimated coefficients are positively statistically significant at the five percent level for eight countries. In addition to the five countries (Italy, Japan, South Korea, Turkey and the United Kingdom) that have positive and statistically significant coefficients for intangible assets at the one percent level in the baseline regressions, Colombia, Hungary, and Thailand also have positive and statistically significant coefficients for manufacturing. This result implies that although intangible assets do not seem to be an important contributor to MFP growth when we look at all industries, the intangibility of assets matters for manufacturing in these developing countries as well. This finding is consistent with the empirical findings of Dalgıç and Fazlıoğlu (2021), who found that manufacturing firms are influenced more by R&D (which is a major component of intangible assets) than service firms. Additionally, the relationship between intangible assets and MFP growth in Hungary is quite strong. This is not surprising because many German multinational firms, which are technology frontiers in the industry, have manufacturing plants in Hungary. Similarly, the size of the coefficient of intangible assets in Thailand is similar to that in Japan, as many Japanese manufacturing multinationals in Thailand have industry clusters. Thailand is famous for being a regional production hub for global supply chains in the automobile industry. Furthermore, the coefficients of intangible assets for manufacturing are larger

¹⁷ Almeida et al. (2015) documented how the institutional features of Chaebols helped them survive the Asian financial crisis.

than those for the overall industry in South Korea and Italy, which have relatively competitive manufacturing companies in certain industries.

Service

The convergence speed of MFP in the service sector is not very different from the results for all industries or for manufacturing. Namely, the lagged MFP coefficients are statistically significant at the one percent level, and the sign is negative for all the countries in Table 7. In some countries, such as Hungary, Romania, the United Kingdom, and Spain, the size of the coefficients for the service industry is notably larger than that for manufacturing, whereas the opposite is true for other countries, such as China.

The debt term is statistically significant at the five percent level and theoretically consistent for both the linear and quadratic terms for approximately one-half of the country samples. When the sample size is very small for the service industry (e.g., for China), the coefficients of the debt variables tend to be statistically insignificant.

Firm size is found to be quite important for MFP growth in the service industry. The coefficients of firm size are positive and statistically significant at the one percent level for all countries. The size of the estimated coefficients for firm size is much larger in the service sector than in the manufacturing sector for all samples of countries. This result implies that economies of scale are more prevalent in the service sector than in manufacturing, which is consistent with the recent finding of Nakatani (2021a), and this finding is robust in the sense that it is supported by the results of all countries.

The coefficients of firm age are negative and statistically significant at the one percent level for the service industry in ten countries. If the data sample is restricted to the service sector, we find that firm age has negative effects on MFP growth in China, similar to that in other countries.

We are interested in the relationship between intangible assets and MFP dynamics. In the service sector, the intangibility of assets is statistically significantly associated with MFP growth in Italy, Japan, South Korea, and the United Kingdom. Except for South Korea, in all the other countries, intangible assets are positively correlated with MFP growth. The positive correlation with intangible assets is the strongest in the United Kingdom, followed by Japan. In the United Kingdom, the correlation with intangible assets in the service industry is higher than that in manufacturing firms. Interestingly, intangible capital is statistically significantly and negatively associated with MFP growth in the service industry in South Korea. This is in stark contrast to the effects in the South Korean manufacturing industry. We do not find any statistically significant results for the service sectors in developing countries, except for China.

Knowledge and Technology-Intensive Industries

In our antepenultimate analysis, we focus on knowledge- and technology-intensive industries because intangible assets are deemed to have a more important influence in these industries than in other industries. Here, knowledge and technology-intensive industries include high-tech manufacturing¹⁸ and knowledge-intensive service¹⁹ industries, as defined by the Statistical Office of the European Union (Eurostat). Only notable findings are summarized below.

The results for debt in the knowledge and technology-intensive industries in Table 8 are interesting. In five countries (Italy, Japan, South Korea, Poland, and the United Kingdom), both the linear and quadratic terms of debt are statistically significant at the five percent level, with the expected signs: the coefficient for the linear term is positive, and the coefficient for the quadratic term is negative, implying an inverse U-

¹⁸ https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries

¹⁹ [https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Knowledge-intensive_services_\(KIS\)](https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Knowledge-intensive_services_(KIS))

shaped nonlinear relationship of the debt–productivity nexus. In contrast, in four countries (Columbia, Hungary, Spain, and Turkey), either the linear term or quadratic term is positive and statistically significant at the five percent level. This result might reflect the fact that in knowledge-intensive industries that require firms to make massive investments to become competitive in the market and become a productivity frontier, leveraging financial resources can be key for firm performance. It is true that, for example, in the high-technology semiconductor industry, borrowing money to make large investments and continuing to become a productivity frontier are crucial for survival and success in the rapidly growing industry. The positive and statistically significant relationship between debt and MFP growth may reflect such a practice in high-technology industries. For the remaining two countries (Romania and Thailand), the results for debt are not statistically significant.

Broadly speaking, the effects of firm size on MFP growth are greater in the knowledge- and technology-intensive sectors than in the average of all industries. Namely, for most countries, the coefficients of firm size shown in Table 8 are larger than those of the average of all industries in Table 2. This result implies the importance of firm size in high-technology and knowledge-intensive industries. As we discussed, knowledge-intensive sectors sometimes require a large amount of financing; hence, large corporations have comparative advantages because they can make productivity-enhancing investments or enjoy cost savings due to economies of scale.

The effects of firm age on MFP growth in knowledge and technology-intensive industries are statistically significant at the five percent level for half of the country samples. This result implies that innovative young firms in knowledge-intensive or high-technology industries have a tendency to show higher levels of MFP growth. However, firm age is no longer statistically significant for a couple of countries, such as Hungary, Poland, Romania, and Turkey, all of which had statistically significant coefficients for this variable

in Tables 2, 6, and 7. This is an interesting finding, indicating that firm age is not an important determinant of MFP growth in knowledge- and technology-intensive sectors.

The results for intangible assets shown in Table 8 are also interesting. The countries that have positive and statistically significant (at the one percent level) coefficients for intangible assets are Italy, Japan, the United Kingdom, and South Korea. In these countries, the relationships between intangible assets and MFP growth are stronger than those reported in Tables 2, 6, and 7 for Italy, Japan, and the United Kingdom. This underscores the importance of intangible assets in a knowledge-intensive economy, as we expected. Our result supports the findings reported by Chen et al. (2016), who provided evidence that the impact of intangible capital on output elasticity is greater in information- and technology-intensive sectors.

Before and After the Global Financial Crisis

In our antepenultimate analysis, we use the same sample period for all countries. We are particularly interested in recent MFP development occurring after the global financial crisis of 2008-09. Table 9 provides the results for the period after 2010.

We discuss the impact of intangible assets since they are the main focus of this research. First, we find that the estimated coefficients of intangible assets are positive and statistically significant at the five percent level for most countries after the global financial crisis. For example, in the baseline results presented in Table 2, Hungary and Poland did not show statistically significant results for intangible assets; however, the results are statistically significant at the five percent level for both countries when the sample period is restricted to the period after the global financial crisis. Second, in some countries, the size of the

estimated coefficients is larger in Table 9 than in Table 2.²⁰ This is the case for Spain, South Korea, and the United Kingdom, while the relationships with intangible assets are slightly smaller for Italy, Japan, and Turkey. This shows the time-varying heterogeneous relationships between intangible assets and MFP growth across countries. Third, if we exclude an outlier (China, which shows that intangible capital has negative effects), a ten-percentage-point increase in the share of intangible assets in total assets is associated with an approximate increase of between 0.1 percentage points (for Italy) and 0.9 percentage points (for the United Kingdom) in MFP growth.

In our penultimate analysis, we conduct a regression analysis for the sample period before the global financial crisis in Table 10. Again, below, we focus on the estimated coefficients of intangible assets. We find two main results. First, the estimated coefficient of intangible assets for China turns out to be positive and statistically significant at the one percent level for the period before the global financial crisis, as we already mentioned. This result means that if we exclude the period of skyrocketing patents in China, a higher ratio of intangible assets to total assets is positively associated with greater MFP growth, as we observe in other countries. Again, this result underscores the importance of the quality of intangible assets, although we are not able to control for its quality in our analysis due to the lack of data.

Another finding shown in Table 10 is that the relationships between intangible assets and MFP growth change differently across countries before and after the global financial crisis. For instance, if we look at countries that have statistically significant coefficients (in the United Kingdom and Spain), the positive relationship between intangible assets and MFP growth increases significantly after the crisis, while the opposite occurs in Italy and Turkey. In Japan, the positive relationship between intangible assets and MFP

²⁰ This result is in line with findings by Bloch et al. (2023), who found that the MFP effects of broad R&D increased slightly in the period after the crisis in two Nordic countries (Denmark and Finland).

growth remained almost the same before and after the global financial crisis. Therefore, our final analysis confirms the heterogeneous time-varying relationship between intangible assets and MFP dynamics.

In summary, our findings provide evidence of the heterogeneous associations between intangible assets and MFP over time and across countries and industries. Figure 6 compares the impact of a ten-percent increase in the ratio of intangible assets to total assets on MFP growth. We plot all the coefficients estimated with the same regression specifications in Tables 2 and 6-10. The relationships between the intangibility of assets and MFP growth are mostly positive, but the magnitude of the relationship differs across countries, industries, and time periods. Generally, the relationship between intangible assets and MFP growth is stronger in productivity frontier advanced countries such as the United Kingdom and Japan than in other countries. This finding is robust in the sense that the results are the same for the service industry, the knowledge and technology-intensive industries, and the period after the global financial crisis. In contrast, in the manufacturing industry, relationships with intangible assets can be strong in developing countries where there are many multinational manufacturing plants originating from technology frontier countries. This is the case for Hungary and Thailand. Additionally, we find that in developing countries, the relationship between intangible assets and MFP growth is greater in the manufacturing industry than in the service industry. In China, intangible assets are negatively correlated with MFP growth except during the period before the global financial crisis, as a skyrocketing number of recent unproductive patents does not necessarily indicate innovation. This finding underscores the importance of considering the quality of intangible assets when policymakers formulate industrial policy.

As an alternative way to detect a structural break after the global financial crisis with respect to the role of intangible assets, we included the cross-term of intangible assets and a dummy variable that takes the value of one after the crisis in Table 11. However, our final results in Table 11 did not show any clear pattern and demonstrated mixed results. For example, the productivity-enhancing role of intangible assets

became positive (i.e., the positive coefficients of cross-terms) in Japan, Spain, South Korea, Thailand, and the United Kingdom, while it was negative in some countries (China, Italy, Poland, and Turkey). Thus, the results before and after the crisis should be interpreted with some caveats.

VII. CONCLUSION

MFP growth is an imperative driver of economic growth. Understanding the productivity drivers is the most important research front in the economic growth literature. In our digital and knowledge economy, intangible assets can be critical for MFP advancement. Although prior studies have analyzed the effects of intangible capital on economic growth using macro-level data or sectoral data across countries, few scholars have studied its cross-industry effect at the firm level. Thus, this paper studies the relationship between MFP growth and intangible assets at the firm level across industries and countries.

We find that intangible assets have heterogeneous relationships with MFP growth across countries. The relationships are positive and stronger in technological frontier countries such as the United Kingdom and Japan. Note that the estimated coefficient is small for South Korea because only a very small number of large electronic companies are technology frontier firms. This finding is in stark contrast to the coefficient for Japan, where not only large companies but also many small- and medium-sized Japanese companies are global technological frontier firms. The relationships between intangible assets and MFP growth also differ across industries. In developing countries, relationships with intangible assets are stronger in the manufacturing sector than in the service industry, while we find the opposite in technology frontier advanced countries. Furthermore, in some countries, the relationship between intangible assets and MFP growth became stronger in the period after the global financial crisis. We also find that the productivity effects of intangible assets are greater for countries with higher levels of income per capita, lower degrees of corruption, better quality of regulation, and/or stronger rule of law. These results prove the

heterogeneous relationships between MFP growth and intangible assets across countries and industries, depending on timeframes and institutions.

We also find that debt has nonlinear impacts on MFP growth. We find an inverse U-shaped relationship between debt and MFP growth, as the debt-growth nexus predicts. Regarding an alternative financing tool for cash, firms with higher levels of cash holdings tend to experience slower MFP growth than their peers. In addition, we find that firm size and age are important for MFP development. Namely, firms tend to increase their MFP less if the firm is smaller and/or older. Finally, our results substantiate the catching-up theory of MFP; firms with low MFP experience faster MFP growth through the acquisition of extant technology from the technological frontier.

Disclosure Statement

The views expressed here are those of the author and do not reflect those of the institution to which the author belongs.

References

- Acemoglu, D., Aghion, P., & Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic Association*, 4(1), 37-74.
- Akerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6), 2411-2451.
- Aghion, P., Bergeaud, A., Cetto, G., Lecat, R., & Maghin, H. (2019). Coase lecture – The inverted-U relationship between credit access and productivity growth. *Economica*, 86(341), 1-31.
- Aghion, P., & Howitt, P. (1996). Research and development in the growth process. *Journal of Economic Growth* 1: 49-73.
- Aghion, P., & Howitt, P. W. (2008). *The economics of growth*. The MIT Press.
- Ahamed, M. M., Luintel, K. B., & Mallick, S. K. (2023). Does local knowledge spillover matter for firm productivity? The role of financial access and corporate governance. *Research Policy*, 52(8), 104837.
- Akcigit, U., Akgunduz, Y. E., Cilasun, S. M., Ozcan-Tok, E., & Yilmaz, F. (2020). Facts on business dynamism in Turkey. *European Economic Review*, 128, 103490.
- Alcouffe, A., & Kuhn, T. (2004). Schumpeterian endogenous growth theory and evolutionary economics. *Journal of Evolutionary Economics*, 14, 223-236.
- Alguacil, M., Lu Turco, A., and Martínez-Zarzoso. (2022). Robot adoption and export performance: Firm-level evidence from Spain. *Economic Modelling*, 114, 105912.
- Almeida, H., Kim, C., & Kim, H. B. (2015). Internal capital markets in business groups: Evidence from the Asian financial crisis. *The Journal of Finance*, 70(6), 2539-2586.
- Anderton, R., Di Lupidio, B., & Jarmulska, B. (2020). The impact of product market regulation on productivity through firm churning: Evidence from European countries. *Economic Modelling*, 91, 487-501.
- Añón Higón, D. (2007). The impact of R&D spillovers on UK manufacturing MFP: A dynamic panel approach. *Research Policy*, 36(7), 964-979.
- Añón Higón, D., Máñez, J.A., Rochina-Barrachina, M. E., Sanchis, A., & Sanchis, J. A. (2022). Firms' distance to the European productivity frontier. *Eurasian Business Review*, 12, 197-228.
- Antonelli, C., Orsatti, G., & Pialli, G. (2023). The knowledge-intensive direction of technological change. *Eurasian Business Review*, 13, 1-27.
- Bahk, B., & Gort, M. (1993). Decomposing learning by doing in new plants. *Journal of Political Economy*, 101(4), 561-583.

- Baldwin, J. R., & Gu, W. (2011). Firm dynamics and productivity growth: A comparison of the retail trade and manufacturing sectors. *Industrial and Corporate Change*, 20(2), 367-395.
- Bartelsman, E., Falk, M., Hagsten, E., & Polder, M. (2019). Productivity, technological innovations and broadband connectivity: Firm-level evidence from ten European countries. *Eurasian Business Review*, 9, 25-48.
- Bartoloni, E. (2013). Capital structure and innovation: Causality and determinants. *Empirica*, 40, 111-151.
- Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *The Journal of Politics*, 79(3), 949-963.
- Belderbos, R., Van Roy, V., & Sleuwaegen, L. (2021). Does trade participation limit domestic firms' productivity gains from inward foreign direct investment? *Eurasian Business Review*, 11, 83-109.
- Bessonova, E., & Tsvetkova, A. (2022). Do productivity laggards ever catch up with leaders? *Review of Income and Wealth*, 68(S1), S71-S107.
- Bloch, C., Eklund, C., & Piekkola, H. (2023). Innovative competences, the financial crisis and firm-level productivity in Denmark and Finland. *Economics of Innovation and New Technology*, 32(2), 198-212.
- Bonanno, G., Ferrando, A., & Rossi, S. P. S. (2023). Do innovation and financial constraints affect the profit efficiency of European enterprises? *Eurasian Business Review*, 13, 57-86.
- Bontempi, M. E., & Mairesse, J. (2015). Intangible capital and productivity at the firm level: A panel data assessment. *Economics of Innovation and New Technology*, 24(1-2), 22-51.
- Bournakis, I., & Mallick, S. (2021). Do corporate taxes harm economic performance? Explaining distortions in R&D- and export intensive UK firms. *Macroeconomic Dynamics*, 25(1), 5-27.
- Braña, F. J. 2019. A fourth industrial revolution? Digital transformation, labor and work organization: A view from Spain. *Journal of Industrial and Business Economics*, 46, 415-430.
- Calcagnini, G., Giombini, G., & Travaglini, G. (2021). The productivity gap among major European countries, USA and Japan. *Italian Economic Journal*, 7, 59-78.
- Castellani, D., Piva, M., Schubert, T., & Vivarelli, M. (2019). R&D and productivity in the US and the EU: Sectoral specificities and differences in the crisis. *Technological Forecasting and Social Change*, 138, 279-291.
- Castiglionesi, F., & Ornaghi, C. (2013). On the determinants of total factor productivity growth: Evidence from Spanish manufacturing firms. *Macroeconomic Dynamics*, 17(3), 501-530.
- Chang, C., & Tang, H. (2021). Corporate cash holdings and total factor productivity - A global analysis. *The North American Journal of Economics and Finance*, 55, 101316.

- Chen, W., Niebel, T., & Saam, M. (2016). Are intangibles more productive in ICT-intensive industries? Evidence from EU countries. *Telecommunications Policy*, 40(5), 471-484.
- Clarke, A. J., & Johri, A. (2009). Procyclical Solow residuals without technology shocks. *Macroeconomic Dynamics*, 13(3), 366-389.
- Conte, A., & Vivarelli, M. (2014). Succeeding in innovation: Key insights on the role of R&D and technological acquisition drawn from company data. *Empirical Economics*, 47, 1317-1340.
- Coricelli, F., Driffield, N., Pal, S., & Roland, I. (2012). When does leverage hurt productivity growth? A firm-level analysis. *Journal of International Money and Finance*, 31(6), 1674-1694.
- Corrado, C., Haskel, J., & Jona-Lasinio, C. (2017). Knowledge spillovers, ICT and productivity growth. *Oxford Bulletin of Economics and Statistics*, 79(4), 592-618.
- Czarnitzki, D., Fernández, g., & Rammer, C. (2023). Artificial Intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, 211, 188-205.
- Dalgıç, B., & Fazlıoğlu, B. (2021). Innovation and firm growth: Turkish manufacturing and services SMEs. *Eurasian Business Review*, 11, 395-419.
- Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, 11, 1-25.
- Demmou, L., Stefanescu, I., & Arquie, A. (2019). Productivity growth and finance: The role of intangible assets – A sector level analysis. *OECD Economics Department Working Papers* 1547.
- Dinlersoz, E., & Wolf, Z. (2023). Automation, labor share, and productivity: Plant-level evidence from U.S. manufacturing. *Economics of Innovation and New Technology*. Advance online publication. <https://doi.org/10.1080/10438599.2023.2233081>
- Doraszelski, U., & Jaumandreu, J. (2013). R&D and productivity: Estimating endogenous productivity. *The Review of Economic Studies*, 80(4), 1338-1383.
- Duan, D., Chen, S., Feng, Z., & Li, J. (2023). Industrial robots and firm productivity. *Structural Change and Economic Dynamics*, 67, 388-406.
- Ferragina, A. M., Mazzotta, F. & Sekkat, K. (2016). Financial constraints and productivity growth across the size spectrum: Microeconomic evidence from Morocco. *Eurasian Business Review*, 6, 361-381.
- Gal, P. N. (2013). Measuring total factor productivity at the firm level using OECD-ORBIS. *OECD Economics Department Working Papers* 1049.
- Gandhi, A., Navarro, S., & Rivers, D. A. (2020). On the identification of gross output production. *Journal of Political Economy*, 128(8), 2973-3016.

- Ghak, T., Gdairia, A., & Abassi, B. (2021). High-tech entrepreneurship and total factor productivity: The case of innovation-driven economies. *Journal of the Knowledge Economy*, 12, 1152-1186.
- Gopinath, G., Kalemli-Özcan, Ş. Karabarbounis, L., & Villegas-Sanchez, C. (2017). Capital allocation and productivity in south Europe. *The Quarterly Journal of Economics*, 132(4), 1915-1967.
- Gorodnichenko, Y., & Schnitzer, M. (2013). Financial constraints and innovation: Why poor countries don't catch up. *Journal of the European Economic Association*, 11(5), 1115-1152.
- Ha, J., & Howitt, P. (2007). Accounting for trends in productivity and R&D: A Schumpeterian critique of semi-endogenous growth theory. *Journal of Money, Credit and Banking*, 39(4), 733-774.
- Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5), 1909-1940.
- Hall, B. H., Griliches, Z., & Hausman, J. A. (1986). Patents and R and D: Is there a lag? *International Economic Review*, 27(2), 265-283.
- Hashmi, A. R. (2013). Intangible capital and international income differences. *Macroeconomic Dynamics*, 17(3), 621-645.
- Hu, A. G. Z., Zhang, P., & Zhao, L. (2017). China as number one? Evidence from China's most recent patenting surge. *Journal of Development Economics*, 124, 107-119.
- Huergo, E., & Jaumandreu, J. (2004). Firms' age, process innovation and productivity growth. *International Journal of Industrial Organization*, 22(4), 541-559.
- Ibhagui, O. W., & Olokoyo, F. O. (2018). Leverage and firm performance: New evidence on the role of firm size. *The North American Journal of Economics and Finance*, 45, 57-82.
- Kalemli-Özcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., & Yesiltas, S. (2015). How to construct nationally representative firm level data from the Orbis global database: New facts and aggregate implications. *NBER Working Paper* 21558.
- Kancs, d., & Siliverstovs, B. (2016). R&D and non-linear productivity growth. *Research Policy*, 45(3), 634-646.
- Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.
- Konya, I. (2023). Catching up or getting stuck: Convergence in eastern European economies. *Eurasian Economic Review*, 13, 237-258.
- Koutroumpis, P., Leiponen, A., & Thomas, L. D. W. (2020). Small is big in ICT: The impact of R&D on productivity. *Telecommunications Policy*, 44, 101833.

- Kumbhakar, S., Ortega-Argilés, R., Potters, L., Vivarelli, M., & Voigt, P. (2012). Corporate R&D and firm efficiency: Evidence from Europe's top R&D investors. *Journal of Productivity Analysis*, 37, 125-140.
- Lambsdorff, J. G. (2003). How corruption affects productivity? *Kyklos*, 56(4), 457-474.
- Levine, O., & Warusawitharana, M. (2021). Finance and productivity growth: Firm-level evidence. *Journal of Monetary Economics*, 117, 91-107.
- Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2), 317-341.
- Liu, T., Chen, J., Huang, C. C. J., & Yang, C. (2013). E-commerce, R&D, and productivity: Firm-level evidence from Taiwan. *Information Economics and Policy*, 25(4), 272-283.
- Liu, X., Liu, J., Wu, H., & Hao, Y. (2022). Do tax reductions stimulate firm productivity? A quasi-natural experiment from China. *Economic Systems*, 46(4), 101024.
- Long, C. X., & Wang, Jun. (2019). China's patent promotion policies and its quality implications. *Science and Public Policy*, 46(1), 91-104.
- López-Gracia, J., & Sogorb-Mira, F. (2008). Testing trade-off and pecking order theories financing SMEs. *Small Business Economics* 31, 117-136.
- Los, B., & Verspagen, B. (2000). R&D spillovers and productivity: Evidence from US manufacturing microdata. *Empirical Economics*, 25, 127-148.
- Madden, G., & Savage, S. J. (1999). Telecommunications productivity, catch-up, and innovation. *Telecommunications Policy*, 23, 65-81.
- Magri, S. (2009). The financing of small innovative firms: The Italian case. *Economics of Innovation and New Technology*, 18(2), 181-204.
- Malva, A. D., & Santarelli, E. (2016). Intellectual property rights, distance to the frontier, and R&D: Evidence from microdata. *Eurasian Business Review*, 6, 1-24.
- Mattsson, P., & Reshid, A. (2023). Productivity divergence and the role of digitalization. *Economic Analysis and Policy*, 79, 942-966.
- Modigliania, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, 48(3), 261-297.
- Mohnen, P., & Hall, B. H. (2013). Innovation and productivity: An update. *Eurasian Business Review*, 3, 47-65.
- Moncada-Paternò-Castello, P. (2022). Top R&D investors, structural change and the R&D growth performance of young and old Firms. *Eurasian Business Review*, 12, 1-33.

Montresor, S., & Vezzani, A. (2015). The production function of top R&D investors: Accounting for size and sector heterogeneity with quantile estimations. *Research Policy*, 44(2), 381-393.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187-221.

Nakatani, R. (2014). The effects of financial and real shocks, structural vulnerability and monetary policy on exchange rates from the perspective of currency crises models," UTokyo Price Project Working Paper 61, Graduate School of Economics, University of Tokyo.

Nakatani, R. (2016). Twin banking and currency crises and monetary policy. *Open Economies Review*, 27(4), 747-767.

Nakatai, R. (2017a). The effects of productivity shocks, financial shocks and monetary policy on exchange rates: An application of the currency crisis model and implications for emerging market crises. *Emerging Markets Finance and Trade*, 53(11), 2545-2561.

Nakatani, R. (2017b). Structural vulnerability and resilience to currency crisis: Foreign currency debt versus export. *The North American Journal of Economics and Finance*, 42, 132-143.

Nakatani, R. (2019a). Firm performance and corporate finance in New Zealand. *Applied Economics Letters*, 26(13), 1118-1124.

Nakatani, R. (2019b). Output costs of currency crisis and banking crisis: Shocks, policies and cycles. *Comparative Economic Studies*, 61(1), 83-102.

Nakatani, R. (2021a). Total factor productivity enablers in the ICT industry: A cross-country firm-level analysis. *Telecommunications Policy*, 45(9), 102188.

Nakatani, R. (2021b). Fiscal rules for natural disaster- and climate change-prone small states. *Sustainability*, 13(6), 3135.

Nakatani, R. (2023a). Productivity drivers of infrastructure companies: Network industries utilizing economies of scale in the digital era. *Annals of Public and Cooperative Economics*, 94(4), 1273-1298.

Nakatani, R. (2023b). Debt maturity and firm productivity—The role of intangibles. *Research in Economics*, 77(1), 116-121.

Nakatani, R. (2023c). Does debt maturity influence productivity? *Economics Bulletin*, forthcoming.

Nakatani, R. (2024). Food companies' productivity dynamics: Exploring the role of intangible assets. *Agribusiness*, 40(1), 185-226.

Nakatani, R., Zhang, Q., Garcia Valdes, I. (2023). Fiscal decentralization improves social outcomes when countries have good governance. *IMF Working Paper* 22/111.

- Nakatani, R., Zhang, Q., Garcia Valdes, I. (2024). Health expenditure decentralization and health outcomes: The importance of governance. *Publius: The Journal of Federalism*, 54(1), 59-87.
- Newman, C., Rand, J., & Tarp, F. (2023). Imports, supply chains and firm productivity. *World Development*, 172, 106371.
- Nucci, F., Puccioni, C., & Ricchi, O. (2023). Digital technologies and productivity: A firm-level investigation. *Economic Modelling*, 128, 106524.
- Ortega-Argilés, R., Piva, M., & Vivarelli, M. (2015). The productivity impact of R&D investment: Are high-tech sectors still ahead? *Economics of Innovation and New Technology*, 24(3), 204-222.
- Pagano, P., & Schivardi, F. (2003). Firm size distribution and growth. *The Scandinavian Journal of Economics*, 105(2), 255-274.
- Palia, D., & Lichtenberg, F. (1999). Managerial ownership and firm performance: A re-examination using productivity measurement. *Journal of Corporate Finance*, 5(4), 323-339.
- Pellegrino, G., & Piva, M. (2020). Innovation, industry and firm age: Are there new knowledge production functions? *Eurasian Business Review*, 10, 65-95.
- Polemis, M. L. (2020). A note on the estimation of competition-productivity nexus: A panel quantile approach. *Journal of Industrial and Business Economics*, 47, 663-676.
- Samaniego, R. M. (2007). R&D and growth: The missing link? *Macroeconomic Dynamics*, 11(5), 691-714.
- Santacreu, A. M., & Zhu, H. (2018). What does China's rise in patent means? A look at quality vs. quantity. *Federal Reserve Bank of St. Louis Economic Synopses*, 14.
- Schankerman, M. (1981). The effects of double-counting and expensing on the measured returns to R&D. *The Review of Economics and Statistics*, 63(3), 454-458.
- Şeker, M., & Saliola, F. (2018). A cross-country analysis of total factor productivity using micro-level data. *Central Bank Review*, 18(1), 13-27.
- Sharma, C. (2018). Productivity and size of firms: Evidence from Indian manufacturing. *Economics Bulletin*, 38(2), 791-798.
- Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3), 312-320.
- Staccioli, J., & Virgillito, M. E. (2021). Back to the past: The historical roots of labor-saving automation. *Eurasian Business Review*, 11, 27-57.
- Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3), 557-586.

- Tajika, E., & Nakatani, R. (2008). Welcome home to Japan: Repatriation of foreign profits by Japanese multinationals. *Discussion Papers 2008-04*, Graduate School of Economics, Hitotsubashi University.
- Ugur M., Trushin, E., Solomon, E., & Guidi, F. (2016). R&D and productivity in OECD firms and industries: A hierarchical meta-regression analysis. *Research Policy*, 45(10), 2069-2086.
- van Ark, B., O'Mahony, M., & Timmer, M. P. (2008). The productivity gap between Europe and the United States: Trends and causes. *Journal of Economic Perspectives*, 22(1), 25-44.
- Verspagen, B. (1995). R&D and productivity: A broad cross-section cross-country look. *Journal of Productivity Analysis*, 6(2), 117-135.
- Veugelers, R., Ferrando, A., Lekpek, S., & Weiss, C. T. (2019). Young SMEs as a motor of Europe's innovation machine. *Intereconomics*, 54, 369-377.
- Wen, H., Wen, C., & Lee, C. (2022). Impact of digitalization and environmental regulation on total factor productivity. *Information Economics and Policy*, 61, 101007.
- Yang, C. (2023). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy*, 51(6), 104536.
- Yang, C., Lin, C., & Ma, D. (2010). R&D, human capital investment and productivity: Firm-level evidence from China's electronics industry. *China & World Economy*, 18(5), 72-89.
- Zhai, S., & Liu, Z. (2023). Artificial intelligence technology innovation and firm productivity: Evidence from China. *Finance Research Letters*, 58(B), 104437.
- Zhang, H., & Dong, S. (2023). Digital transformation and firms' total factor productivity: The role of internal control quality. *Finance Research Letters*, 57, 104231.

Figure 1: GDP per capita in 2015 (U.S. dollars)

Note: Advanced countries in blue; Developing countries in red
 Source: IMF World Economic Outlook Database April 2023

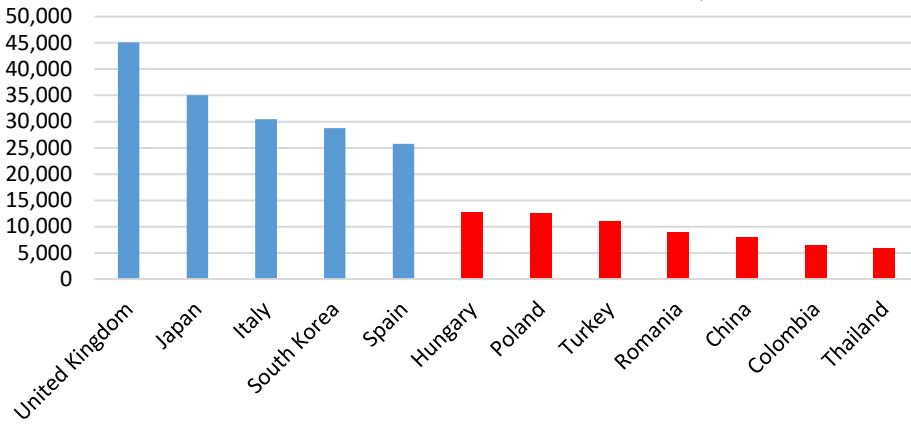
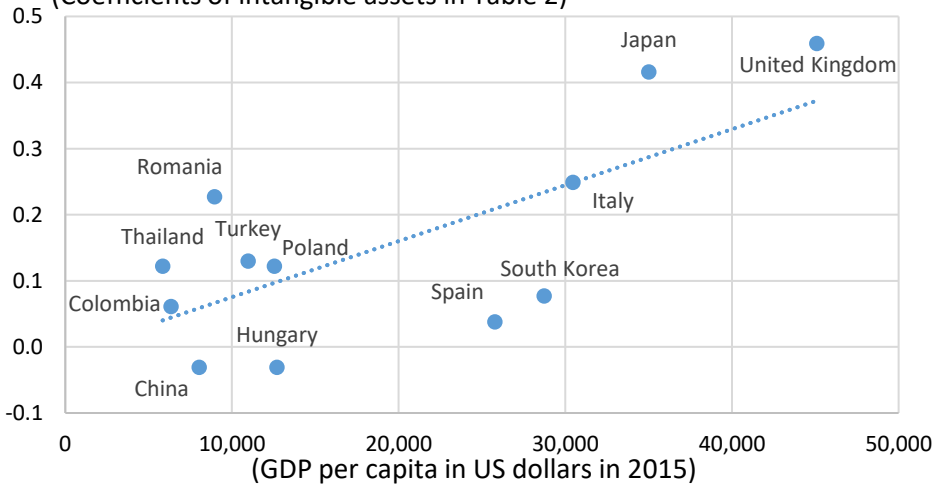
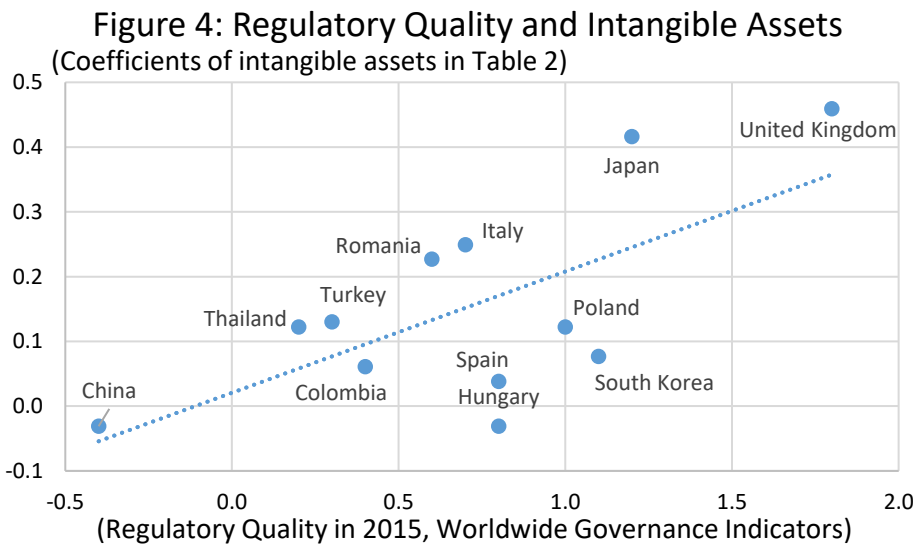
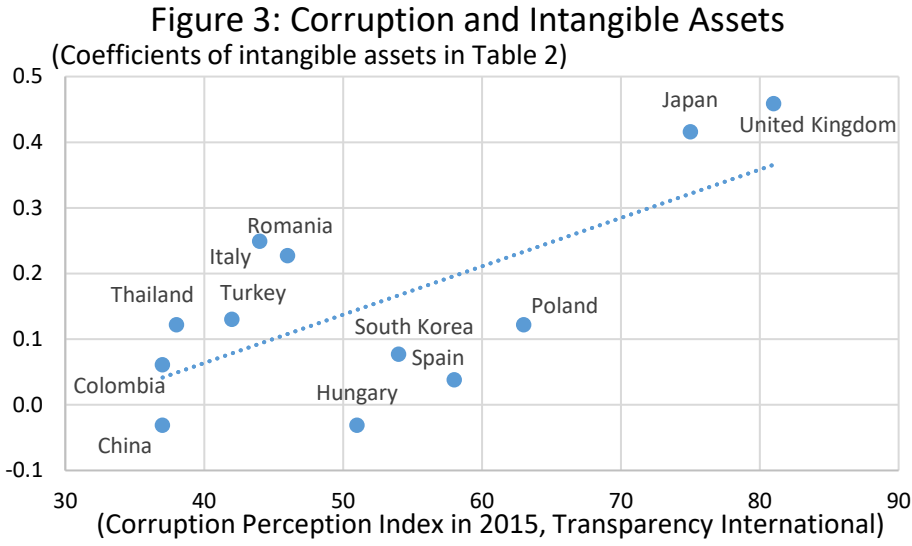


Figure 2: Income Level and Intangible Assets

(Coefficients of intangible assets in Table 2)





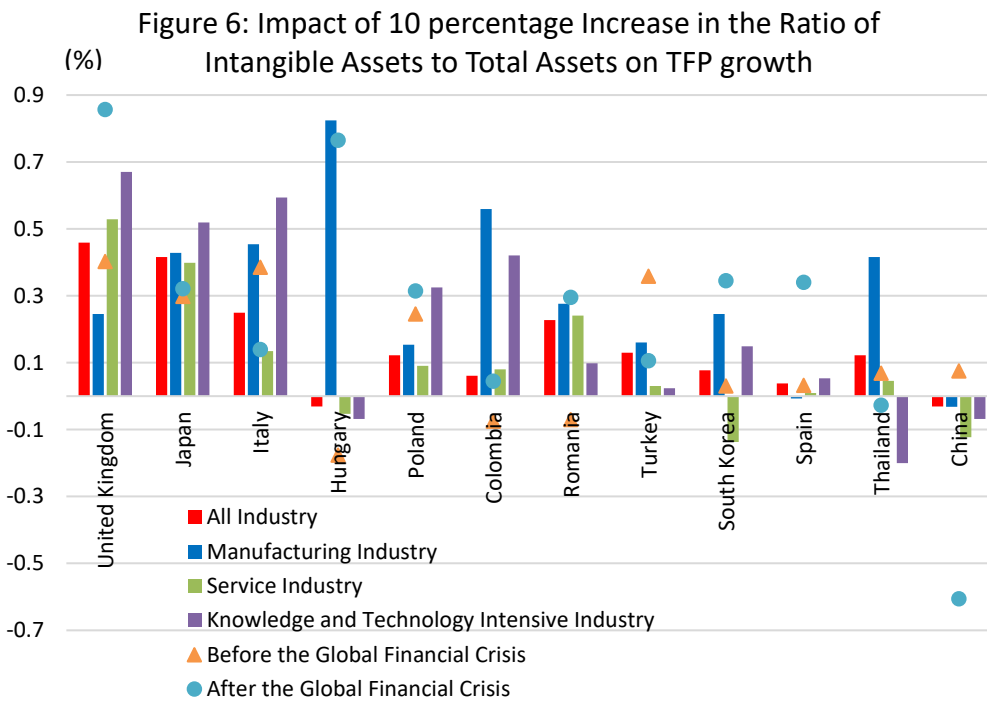
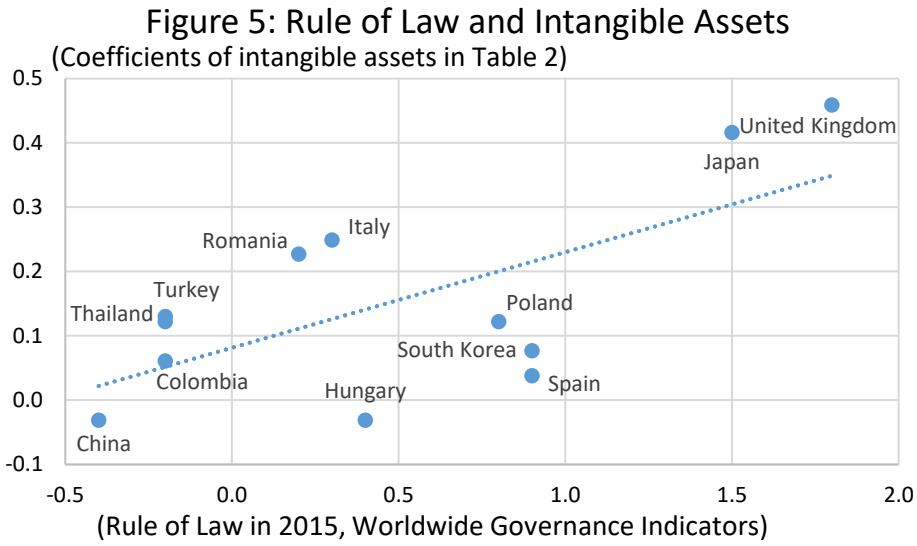


Table 1: Summary Statistics

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Type of Country	Developing	Developing	Developing	Advanced	Advanced	Developing	Developing	Advanced	Advanced	Developing	Developing	Advanced
MFP												
Mean	2.5591	5.0341	2.0830	3.6245	3.9103	2.1969	3.2766	2.0246	2.3145	3.7085	2.3001	5.8694
Standard Deviation	1.2755	1.5020	1.4794	1.5555	1.6447	1.6998	1.9551	1.2590	1.5611	1.2287	0.6998	1.9151
between	1.2780	1.5049	1.5583	1.5799	1.7461	1.7659	1.9332	1.3466	1.4897	1.2351	0.6804	1.8897
within	0.0544	0.2314	0.2583	0.3944	1.1126	0.2261	0.3803	0.2743	0.1486	0.1279	0.0705	0.2135
Min	0.1372	0.0246	0.0002	0.0000	0.0104	0.0001	0.0011	0.0000	0.0005	0.6656	0.1386	0.0923
Max	10.9965	15.4008	12.7839	15.6647	21.2192	14.2052	13.5124	16.6738	13.1447	9.7338	11.9944	16.6661
Debt												
Mean	0.5601	0.5356	0.5369	0.7706	0.6365	0.5022	0.5758	0.6667	0.5632	0.5120	0.6205	0.6414
Standard Deviation	0.2311	0.2203	0.2415	0.1954	0.2423	0.2542	0.2878	0.2348	0.2245	0.2459	0.2283	0.2372
between	0.2362	0.2162	0.2400	0.1833	0.2376	0.2490	0.2806	0.2236	0.2236	0.2471	0.2186	0.2271
within	0.0549	0.0823	0.0955	0.0831	0.0824	0.0981	0.1238	0.1026	0.0927	0.0909	0.0875	0.0988
Min	0.0007	0	0	0	0.0127	0	0.0016	0.0013	0	0.0002	0.0026	0.0009
Max	0.9964	0.9940	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9958	0.9959	0.9999
Cash												
Mean	0.1304	0.0638	0.1160	0.0988	0.2362	0.1177	0.1667	0.1288	0.0859	0.1248	0.1048	0.1376
Standard Deviation	0.1390	0.0889	0.1514	0.1375	0.1770	0.1498	0.2087	0.1509	0.1189	0.1563	0.1321	0.1687
between	0.1420	0.0854	0.1571	0.1365	0.1676	0.1503	0.2139	0.1466	0.1139	0.1529	0.1195	0.1611
within	0.0415	0.0457	0.0702	0.0823	0.0817	0.0687	0.0881	0.0839	0.0687	0.0673	0.0720	0.0721
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	0.9965	0.9565	0.9958	0.9995	0.9964	0.9945	0.9988	0.9987	0.9723	0.9612	0.9482	0.9956
Size												
Mean	17.1788	15.1597	14.9638	14.2469	15.0876	15.0693	12.4920	13.7997	14.9669	16.5269	15.3982	15.2503
Standard Deviation	2.0666	1.6946	1.6248	1.4830	1.6156	1.5736	1.9185	2.5705	1.4284	1.9237	1.6967	2.6378
between	2.0029	1.6169	1.8104	1.4310	1.6203	1.5644	1.8037	1.4622	1.3575	2.0385	1.6348	2.5982
within	0.2343	0.2946	0.2664	0.3322	0.2599	0.3191	0.4184	0.4321	0.3668	0.2912	0.2829	0.2707
Min	9.1568	7.9452	6.2442	6.1463	9.4152	8.0768	4.9053	7.7956	8.9990	8.0943	9.0867	7.1724
Max	27.0344	24.8062	23.3753	25.3817	25.7328	23.2732	21.7949	24.0672	24.9735	23.8282	23.7080	26.0382
Age												
Mean	2.3591	2.8334	2.5377	2.4857	3.4210	2.5650	2.0966	2.4321	2.2631	2.9083	2.6133	2.4566
Standard Deviation	0.5252	0.6798	0.5319	0.8138	0.5460	0.6859	0.7001	0.7176	0.6725	0.5747	0.6879	0.8935
between	0.5244	0.7089	0.5749	0.8190	0.6056	0.6808	0.7141	0.6995	0.6770	0.6116	0.7175	0.8777
within	0.1187	0.1379	0.1955	0.2638	0.1353	0.2068	0.2573	0.3035	0.2608	0.1441	0.1307	0.2181
Min	0	0	0	0	0	0	0	0	0	0	0	0
Max	4.5747	6.1633	4.9416	6.8319	5.6733	6.4800	3.2581	4.9836	4.8520	4.9416	4.9836	5.1874
Intangible Assets												
Mean	0.1553	0.1727	0.0655	0.2047	0.0293	0.0797	0.0534	0.1910	0.1250	0.0773	0.1190	0.3876
Standard Deviation	0.2040	0.2403	0.1557	0.2486	0.0812	0.1785	0.1291	0.2499	0.2113	0.1667	0.1735	0.3424
between	0.2242	0.2343	0.1567	0.2436	0.0938	0.1913	0.1271	0.2402	0.2043	0.1719	0.1680	0.3411
within	0.0408	0.1063	0.0683	0.1192	0.0376	0.0704	0.0580	0.1389	0.0789	0.0620	0.0814	0.0944
Min	0.0000	0	0	0.0000	0.0000	0.0000	0.0000	0	0.0000	0.0000	0	0.0000
Max	0.9999	0.9999	0.9962	0.9999	0.9996	0.9997	0.9998	0.9999	0.9998	0.9999	0.9999	0.9999
Number of Firms	14535	37273	14227	513433	271868	48896	147385	528,832	168,303	48,017	22,850	154,923
Number of Industries	395	431	510	737	427	574	538	610	388	455	373	604
Year												
Min	2005	2006	2005	1998	2002	2001	2001	1996	2003	2003	2005	1997
Max	2014	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
Share of Industries (%)												
Manufacturing	92.0	20.4	24.1	29.1	19.0	23.6	19.6	22.2	45.3	38.4	38.2	19.4
Services	2.3	62.7	61.7	55.0	40.8	62.9	62.7	58.4	33.8	53.9	54.5	62.6

Table 2: Baseline Estimation Results

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6654*** (0.0016)	-0.7367*** (0.0024)	-0.6892*** (0.0039)	-0.6577*** (0.0005)	-0.5754*** (0.0007)	-0.5969*** (0.0020)	-0.6872*** (0.0013)	-0.6484*** (0.0005)	-0.6626*** (0.0011)	-0.5449*** (0.0016)	-0.8457*** (0.0040)	-0.6498*** (0.0012)
Debt	0.0061** (0.0027)	0.1687*** (0.0091)	0.2404*** (0.0383)	0.2856*** (0.0118)	0.1295*** (0.0029)	0.2188*** (0.0149)	0.0960*** (0.0139)	0.1201*** (0.0062)	0.0449*** (0.0045)	0.0576*** (0.0069)	0.0234** (0.0099)	0.3417*** (0.0113)
Debt × Debt	-0.0048* (0.0026)	-0.0096** (0.0048)	-0.1046 (0.0359)	-0.1190*** (0.0089)	-0.0428*** (0.0024)	-0.0970*** (0.0141)	-0.0118 (0.0125)	0.0236*** (0.0053)	-0.0073* (0.0043)	-0.0065 (0.0070)	0.0512*** (0.0088)	-0.1810*** (0.0095)
Size	0.0091*** (0.0003)	0.1486*** (0.0025)	0.0823*** (0.0047)	0.1477*** (0.0009)	0.0842*** (0.0003)	0.0713*** (0.0018)	0.0817*** (0.0015)	0.0730*** (0.0006)	0.0499*** (0.0005)	0.0783*** (0.0009)	0.0458*** (0.0011)	0.1418*** (0.0011)
Age	0.0216*** (0.0011)	-0.0312*** (0.0075)	-0.0429*** (0.0132)	-0.0153*** (0.0017)	-0.0330*** (0.0009)	-0.0282*** (0.0051)	-0.0277*** (0.0046)	-0.0288*** (0.0013)	-0.0320*** (0.0011)	-0.0462*** (0.0025)	0.0132*** (0.0037)	-0.0275*** (0.0029)
Intangible Assets	-0.0031** (0.0015)	0.0061 (0.0086)	-0.0031 (0.0074)	0.0249*** (0.0015)	0.0416*** (0.0019)	0.0122 (0.0086)	0.0227 (0.0149)	0.0038** (0.0016)	0.0077*** (0.0027)	0.0122 (0.0094)	0.0130*** (0.0036)	0.0459*** (0.0049)
Constant	1.1759*** (0.0057)	1.4908*** (0.0381)	0.1132 (0.0730)	0.1196*** (0.0132)	1.0214*** (0.0053)	0.1498*** (0.0269)	1.1122*** (0.0199)	0.1988*** (0.0089)	0.7299*** (0.0076)	0.1988*** (0.0088)	1.1738*** (0.0179)	1.5907*** (0.0182)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	556,441	194,125	73,711	3,438,980	1,832,014	255,739	717,643	3,621,240	823,759	357,593	78,321	789,968
R-squared	0.549	0.513	0.516	0.437	0.449	0.469	0.499	0.426	0.480	0.384	0.644	0.468

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 3: Inclusion of Additional Financing Tool: Cash Holding

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6486*** (0.0065)	-0.6054*** (0.0028)	-0.6896*** (0.0039)	-0.6575*** (0.0005)	-0.5732*** (0.0007)	-0.5976*** (0.0020)	-0.6875*** (0.0013)	-0.6454*** (0.0005)	-0.6619*** (0.0011)	-0.5903*** (0.0025)	-0.8471*** (0.0040)	-0.6512*** (0.0012)
Debt	0.0482*** (0.0065)	0.1581*** (0.0077)	0.1342*** (0.0123)	0.1383*** (0.0029)	0.0768*** (0.0009)	0.1220*** (0.0049)	0.0896*** (0.0042)	0.1429*** (0.0019)	0.0368*** (0.0015)	0.0746*** (0.0036)	0.0770*** (0.0030)	0.1268*** (0.0033)
Cash	-0.0100 (0.0082)	0.0340*** (0.0122)	-0.0006 (0.0155)	0.0426*** (0.0031)	-0.0269*** (0.0009)	0.0000 (0.0000)	0.0451*** (0.0055)	-0.0271*** (0.0021)	-0.0155*** (0.0018)	-0.0042 (0.0047)	-0.0133*** (0.0037)	-0.0606*** (0.0036)
Size	0.0546*** (0.0021)	0.1335*** (0.0026)	0.0816*** (0.0047)	0.1471*** (0.0009)	0.0842*** (0.0003)	0.0711*** (0.0018)	0.0821*** (0.0015)	0.0743*** (0.0007)	0.0501*** (0.0006)	0.0839*** (0.0013)	0.0458*** (0.0011)	0.1430*** (0.0012)
Age	-0.0232*** (0.0071)	-0.0434*** (0.0082)	-0.0392*** (0.0132)	-0.0123*** (0.0017)	-0.0331*** (0.0009)	-0.0267*** (0.0052)	-0.0262*** (0.0046)	-0.0305*** (0.0014)	-0.0326*** (0.0011)	-0.0488*** (0.0036)	0.0121*** (0.0037)	-0.0257*** (0.0030)
Intangible Assets	-0.0229** (0.0095)	-0.0232*** (0.0081)	-0.0034 (0.0074)	0.0249*** (0.0015)	0.0427*** (0.0019)	0.0109 (0.0088)	0.0194 (0.0149)	0.0035** (0.0016)	0.0074*** (0.0027)	0.0228** (0.0099)	0.0127*** (0.0036)	0.0430*** (0.0050)
Constant	0.7156*** (0.0384)	1.1209*** (0.0425)	0.1341* (0.0731)	0.1532*** (0.0128)	1.0326*** (0.0052)	0.1643*** (0.0273)	1.0966*** (0.0200)	0.1817*** (0.0090)	0.7300*** (0.0076)	0.9269*** (0.0193)	1.1704*** (0.0179)	1.6489*** (0.0189)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	37,766	148,781	73,547	3,424,910	1,829,679	245,785	715,549	3,414,742	815,386	175,192	78,207	728,613
R-squared	0.618	0.429	0.517	0.437	0.449	0.471	0.499	0.429	0.480	0.479	0.644	0.473

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 4: Exclusion of Age Variable

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6680*** (0.0015)	-0.7297*** (0.0023)	-0.6848*** (0.0038)	-0.6579*** (0.0005)	-0.5771*** (0.0007)	-0.5969*** (0.0020)	-0.6875*** (0.0013)	-0.6484*** (0.0005)	-0.6657*** (0.0011)	-0.5481*** (0.0016)	-0.8438*** (0.0040)	-0.6505*** (0.0012)
Debt	0.0083*** (0.0026)	0.1659*** (0.0090)	0.2336*** (0.0380)	0.2778*** (0.0118)	0.1285*** (0.0029)	0.2168*** (0.0149)	0.0918*** (0.0139)	0.1067*** (0.0061)	0.0317*** (0.0045)	0.0592*** (0.0069)	0.0247** (0.0099)	0.3388*** (0.0113)
Debt × Debt	-0.0067*** (0.0025)	-0.0090* (0.0048)	-0.0982*** (0.0356)	-0.1121*** (0.0089)	-0.0412*** (0.0024)	-0.0929*** (0.0141)	-0.0068 (0.0125)	0.0394*** (0.0052)	0.0078* (0.0042)	-0.0065 (0.0070)	0.0493*** (0.0088)	-0.1752*** (0.0095)
Size	0.0089*** (0.0003)	0.1439*** (0.0024)	0.0814*** (0.0047)	0.1466*** (0.0009)	0.0814*** (0.0003)	0.0699*** (0.0018)	0.0804*** (0.0015)	0.0704*** (0.0006)	0.0457*** (0.0005)	0.0757*** (0.0009)	0.0468*** (0.0011)	0.1413*** (0.0011)
Intangible Assets	-0.0023 (0.0015)	0.0061 (0.0086)	-0.0026 (0.0074)	0.0256*** (0.0015)	0.0437*** (0.0019)	0.0144* (0.0086)	0.0284* (0.0149)	0.0051*** (0.0016)	0.0051* (0.0026)	0.0145 (0.0094)	0.0128*** (0.0036)	0.0496*** (0.0049)
Constant	1.2304*** (0.0053)	1.4493*** (0.0342)	0.0071 (0.0679)	0.0980*** (0.0130)	0.9602*** (0.0050)	0.0971*** (0.0251)	1.0674*** (0.0185)	0.1638*** (0.0086)	0.7295*** (0.0075)	0.7912*** (0.0124)	1.1894*** (0.0173)	1.5281*** (0.0169)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	597,339	204,301	75,152	3,441,511	1,832,019	255,793	718,149	3,622,732	832,115	359,670	78,353	790,004
R-squared	0.548	0.511	0.514	0.437	0.449	0.469	0.499	0.426	0.481	0.383	0.643	0.468

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 5: Exclusion of Size Variable

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6599*** (0.0016)	-0.7187*** (0.0023)	-0.6857*** (0.0039)	-0.6500*** (0.0005)	-0.5394*** (0.0007)	-0.591*** (0.0020)	-0.6813*** (0.0013)	-0.6448*** (0.0005)	-0.6488*** (0.0011)	-0.5193*** (0.0016)	-0.8241*** (0.0040)	-0.6308*** (0.0012)
Debt	0.0050* (0.0027)	0.2035*** (0.0092)	0.2397*** (0.0384)	0.1978*** (0.0119)	0.1336*** (0.0029)	0.2281*** (0.0150)	0.0895*** (0.0139)	0.1133*** (0.0062)	0.0519*** (0.0046)	0.0751*** (0.0070)	0.0230** (0.0101)	0.3309*** (0.0114)
Debt × Debt	-0.0034 (0.0026)	-0.0104** (0.0048)	-0.0991*** (0.0360)	-0.0430*** (0.0090)	-0.0291*** (0.0025)	-0.0968*** (0.0142)	-0.0022 (0.0125)	0.0519*** (0.0053)	0.0001 (0.0043)	0.0099 (0.0071)	0.0603*** (0.0090)	-0.1743*** (0.0096)
Age	0.0237*** (0.0011)	0.0268*** (0.0075)	-0.0165 (0.0132)	0.0264*** (0.0017)	0.0207*** (0.0009)	0.0017 (0.0051)	0.0044 (0.0045)	-0.0002 (0.0013)	-0.0034*** (0.0011)	-0.0151*** (0.0025)	0.0478*** (0.0036)	-0.0111*** (0.0029)
Intangible Assets	-0.0027* (0.0015)	0.0271*** (0.0087)	-0.0030 (0.0074)	0.0239*** (0.0015)	0.0247*** (0.0020)	0.0140 (0.0087)	0.0135 (0.0150)	0.0072*** (0.0016)	0.0042 (0.0027)	0.0211** (0.0096)	0.0100*** (0.0037)	0.0668*** (0.0050)
Constant	1.2977*** (0.0037)	3.3189*** (0.0229)	1.2292*** (0.0351)	2.0991*** (0.0059)	1.9463*** (0.0038)	1.0737*** (0.0141)	1.9885*** (0.0112)	1.0908*** (0.0038)	1.3535*** (0.0033)	1.7430*** (0.0079)	1.7229*** (0.0121)	3.4654*** (0.0103)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	556,441	194,125	73,711	3,438,980	1,832,014	255,739	717,643	3,621,240	823,759	357,593	78,321	789,968
R-squared	0.548	0.502	0.514	0.431	0.427	0.465	0.497	0.423	0.473	0.370	0.633	0.454

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 6: Estimation Results for Manufacturing Industry

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6608*** (0.0017)	-0.7453*** (0.0052)	-0.5591*** (0.008)	-0.5853*** (0.0010)	-0.5433*** (0.0016)	-0.5487*** (0.0039)	-0.5776*** (0.0028)	-0.5433*** (0.0011)	-0.6724*** (0.0016)	-0.5181*** (0.0026)	-0.7978*** (0.0064)	-0.5295*** (0.0026)
Debt	0.0068*** (0.0026)	0.1153*** (0.0410)	0.2461*** (0.0512)	0.2740*** (0.0139)	0.0813*** (0.0051)	0.2055*** (0.0227)	0.1366*** (0.0222)	0.1298*** (0.0089)	0.0496*** (0.0046)	0.0560*** (0.0087)	0.0307** (0.0147)	0.1943*** (0.0132)
Debt × Debt	-0.0070*** (0.0024)	-0.0350 (0.0394)	-0.1342*** (0.0483)	-0.0950*** (0.0104)	0.0010 (0.0041)	-0.1029*** (0.0212)	-0.0459** (0.0196)	0.0072 (0.0076)	-0.0114*** (0.0040)	-0.0142* (0.0086)	0.0272** (0.0131)	-0.0851*** (0.0112)
Size	0.0080*** (0.0003)	0.0544*** (0.0046)	0.0379*** (0.0066)	0.1184*** (0.0011)	0.0393*** (0.0005)	0.0487*** (0.0027)	0.0512*** (0.0024)	0.0508*** (0.0009)	0.0205*** (0.0005)	0.0563*** (0.0012)	0.0260*** (0.0017)	0.0753*** (0.0014)
Age	0.0237*** (0.0010)	0.0021 (0.0129)	-0.0356** (0.0180)	-0.0158*** (0.0019)	-0.0345*** (0.0015)	-0.0329*** (0.0073)	-0.0391*** (0.0064)	-0.0256*** (0.0018)	-0.1418*** (0.0010)	-0.0264*** (0.0029)	0.0112** (0.0052)	-0.0104*** (0.0031)
Intangible Assets	-0.0032** (0.0014)	0.0559*** (0.0162)	0.0824** (0.0331)	0.0454*** (0.0025)	0.0428*** (0.0038)	0.0154 (0.0158)	0.0276 (0.0300)	-0.0007 (0.0021)	0.0246*** (0.0023)	0.0416*** (0.0146)	0.0160*** (0.0051)	0.0246*** (0.0056)
Constant	1.1033*** (0.0053)	1.9928*** (0.0694)	0.0478 (0.1059)	-0.3371*** (0.0164)	0.9665*** (0.0092)	0.1457*** (0.0413)	0.5713*** (0.0314)	0.0557*** (0.0126)	0.9348*** (0.0067)	0.6875*** (0.0164)	1.1539*** (0.0277)	1.0027*** (0.0231)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing	Manufacturing
Observations	512,091	39,666	17,758	1,000,178	348,348	60,465	140,820	803,427	373,194	137,453	29,942	153,362
R-squared	0.535	0.528	0.462	0.410	0.421	0.468	0.425	0.372	0.479	0.373	0.647	0.420

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 7: Estimation Results for Service Industry

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.5798*** (0.0104)	-0.7266*** (0.0030)	-0.6946*** (0.0049)	-0.6459*** (0.0007)	-0.5470*** (0.0010)	-0.5930*** (0.0025)	-0.6975*** (0.0017)	-0.6402*** (0.0007)	-0.6403*** (0.0019)	-0.5462*** (0.0022)	-0.8189*** (0.0052)	-0.6445*** (0.0015)
Debt	-0.0153 (0.0512)	0.1506*** (0.0117)	0.2935*** (0.0546)	0.2970*** (0.0177)	0.1581*** (0.0054)	0.2544*** (0.0203)	0.0861*** (0.0190)	0.1141*** (0.0085)	0.0543*** (0.0114)	0.0609*** (0.0106)	0.0321** (0.0125)	0.3526*** (0.0158)
Debt × Debt	0.0604 (0.0468)	-0.0109** (0.0052)	-0.1344*** (0.0506)	-0.1305*** (0.0134)	-0.0768*** (0.0047)	-0.1162*** (0.0191)	-0.0129 (0.0173)	-0.0103 (0.0073)	-0.0094 (0.0105)	-0.0065 (0.0107)	0.0295*** (0.0111)	-0.1977*** (0.0133)
Size	0.0604*** (0.0052)	0.1768*** (0.0034)	0.0849*** (0.0066)	0.1263*** (0.0014)	0.1061*** (0.0007)	0.0682*** (0.0024)	0.0818*** (0.0022)	0.0648*** (0.0009)	0.0803*** (0.0013)	0.0906*** (0.0014)	0.0625*** (0.0014)	0.1446*** (0.0016)
Age	-0.0584*** (0.0183)	-0.0485*** (0.0100)	-0.0361* (0.0188)	-0.0108*** (0.0026)	-0.0393*** (0.0017)	-0.0242*** (0.0070)	-0.0177*** (0.0066)	-0.0386*** (0.0019)	-0.0559*** (0.0029)	-0.0604*** (0.0039)	0.0082* (0.0047)	-0.0230*** (0.0042)
Intangible Assets	-0.0123 (0.0210)	0.0080 (0.0109)	-0.0053 (0.0085)	0.0135*** (0.0019)	0.0399*** (0.0032)	0.0091 (0.0104)	0.0241 (0.0188)	0.0009 (0.0022)	-0.0137** (0.0062)	0.0046 (0.0128)	0.0030 (0.0046)	0.0529*** (0.0065)
Constant	1.0980*** (0.0913)	1.5064*** (0.0507)	0.2623*** (0.0995)	0.6688*** (0.0199)	0.9795*** (0.0100)	0.2145*** (0.0361)	1.4383*** (0.0280)	0.4837*** (0.0124)	0.8070*** (0.0185)	1.0525*** (0.0198)	1.0820*** (0.0224)	1.8201*** (0.0254)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	Service	Service	Service	Service	Service	Service	Service	Service	Service	Service	Service	Service
Observations	12,540	121,730	45,471	1,890,954	747,983	160,854	450,082	2,114,206	278,097	192,779	42,706	494,235
R-squared	0.600	0.515	0.519	0.433	0.451	0.468	0.510	0.427	0.481	0.386	0.651	0.465

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 8: Estimation Results for Knowledge and Technology Intensive Industry

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6581*** (0.0028)	-0.7586*** (0.0055)	-0.7383*** (0.0085)	-0.6705*** (0.0012)	-0.5610*** (0.0015)	-0.6401*** (0.0046)	-0.7968*** (0.0028)	-0.7185*** (0.0015)	-0.6464*** (0.0021)	-0.5718*** (0.0033)	-0.8560*** (0.0098)	-0.6508*** (0.0023)
Debt	0.0120** (0.0053)	0.2727*** (0.0719)	0.2705** (0.1061)	0.2761*** (0.0335)	-0.1397*** (0.0077)	0.2748*** (0.0470)	-0.0520 (0.0347)	0.1358*** (0.0252)	0.0803*** (0.0137)	0.0108 (0.0168)	0.0254 (0.0331)	0.2843*** (0.0270)
Debt × Debt	-0.0087* (0.0050)	-0.0861 (0.0688)	-0.0882 (0.1024)	-0.1036*** (0.0257)	-0.0457*** (0.0070)	-0.1070** (0.0458)	0.0467 (0.0335)	-0.0031 (0.0223)	-0.0267** (0.0123)	0.0224 (0.0173)	0.0965*** (0.0300)	-0.1413*** al
Size	0.0143*** (0.0006)	0.2158*** (0.0076)	0.0783*** (0.0129)	0.1529*** (0.0026)	0.0961*** (0.0010)	0.0903*** (0.0055)	0.0763*** (0.0044)	0.1209*** (0.0029)	0.0487*** (0.0014)	0.1036*** (0.0023)	0.0544*** (0.0038)	0.1545*** (0.0027)
Age	0.0221*** (0.0021)	-0.0348 (0.0238)	-0.0171 (0.0383)	-0.0116** (0.0055)	-0.0351*** (0.0030)	0.0062 (0.0175)	-0.0038 (0.0145)	-0.0579*** (0.0066)	-0.0363*** (0.0031)	-0.0564*** (0.0061)	0.0134 (0.0124)	-0.0408*** (0.0077)
Intangible Assets	-0.0068*** (0.0025)	0.0421 (0.0255)	-0.0068 (0.0109)	0.0594*** (0.0053)	0.0519*** (0.0050)	0.0325 (0.0208)	0.0098 (0.0293)	0.0053 (0.0075)	0.0149*** (0.0051)	-0.0200 (0.0247)	0.0024 (0.0115)	0.0670*** (0.0101)
Constant	1.0864*** (0.0106)	1.2932*** (0.1176)	0.7968*** (0.1988)	0.4212*** (0.0388)	0.9674*** (0.0163)	0.6653*** (0.0846)	3.0436*** (0.0567)	0.6593*** (0.0397)	0.9433*** (0.0199)	0.8535*** (0.0311)	1.4231*** (0.0605)	1.9623*** (0.0442)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech	High-Tech
Observations	186,006	36,930	15,990	696,083	382,695	52,027	165,145	509,232	220,885	92,117	11,903	213,686
R-squared	0.537	0.527	0.546	0.439	0.440	0.485	0.552	0.461	0.469	0.388	0.675	0.474

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 9: Estimation Results for the Period after the Global Financial Crisis

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.8589*** (0.0066)	-0.8266*** (0.0034)	-0.8354*** (0.0052)	-0.8704*** (0.0009)	-0.8423*** (0.0011)	-0.7708*** (0.0030)	-0.8629*** (0.0019)	-0.8734*** (0.0010)	-0.8325*** (0.0017)	-0.7819*** (0.0029)	-0.9021*** (0.0046)	-0.8059*** (0.0023)
Debt	0.0086 (0.0136)	0.1550*** (0.0310)	0.1137** (0.0558)	0.1353*** (0.0213)	0.1552*** (0.0045)	0.2028*** (0.0226)	-0.0287 (0.0210)	0.1216*** (0.0132)	0.0696*** (0.0068)	0.0902*** (0.0127)	0.0071 (0.0114)	0.2845*** (0.0217)
Debt × Debt	0.0044 (0.0131)	0.0284 (0.0296)	0.0094 (0.0527)	-0.0251 (0.0163)	-0.0146*** (0.0039)	-0.1014*** (0.0215)	0.0905*** (0.0199)	0.0129 (0.0115)	-0.0032 (0.0065)	-0.0125 (0.0132)	0.0668*** (0.0101)	-0.1356*** (0.01837)
Size	0.0246*** (0.0014)	0.1409*** (0.0036)	0.1099*** (0.0074)	0.2065*** (0.0018)	0.0955*** (0.0006)	0.0834*** (0.0030)	0.0930*** (0.0030)	0.1194*** (0.0018)	0.0570*** (0.0009)	0.0830*** (0.0020)	0.0427*** (0.0013)	0.1484*** (0.0024)
Age	0.0625*** (0.0079)	-0.0279** (0.0129)	-0.0318 (0.0223)	-0.0170*** (0.0037)	-0.0106*** (0.0021)	-0.0151 (0.0104)	-0.0726*** (0.0095)	-0.0478*** (0.0044)	-0.0186*** (0.0022)	-0.0149** (0.0073)	0.0215*** (0.0047)	0.0283*** (0.0078)
Intangible Assets	-0.0606*** (0.0105)	0.0045 (0.0103)	0.0765*** (0.0284)	0.0139*** (0.0019)	0.0321*** (0.0030)	0.0314** (0.0123)	0.0295 (0.0208)	0.0340*** (0.0080)	0.0345*** (0.0043)	-0.0027 (0.0154)	0.0106** (0.0043)	0.0857*** (0.0085)
Constant	1.3696*** (0.0303)	2.0257*** (0.0598)	0.0336 (0.1163)	0.1638*** (0.0265)	1.8072*** (0.0101)	0.3342*** (0.0482)	1.7036*** (0.0390)	0.1455*** (0.0252)	0.9597*** (0.0130)	1.4832*** (0.0334)	1.3261*** (0.0216)	2.3851*** (0.0435)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	45,837	115,546	44,620	1,675,716	965,079	145,850	460,751	1,339,347	434,782	152,497	62,765	253,068
R-squared	0.685	0.553	0.582	0.552	0.586	0.556	0.565	0.542	0.570	0.518	0.662	0.551

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 10: Estimation Results for the Period before the Global Financial Crisis

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.8275*** (0.0019)	-0.9999*** (0.0042)	-0.8855*** (0.0076)	-0.745*** (0.0008)	-0.7098*** (0.0011)	-0.7314*** (0.0037)	-0.8560*** (0.0023)	-0.7048*** (0.0007)	-0.8000*** (0.0018)	-0.6837*** (0.0024)	-1.0562*** (0.0123)	-0.7385*** (0.0015)
Debt	0.0047 (0.0029)	0.1799*** (0.0451)	0.2876*** (0.0629)	0.3542*** (0.0185)	0.1536*** (0.0049)	0.1869*** (0.0271)	0.0080 (0.0207)	0.0838*** (0.0084)	0.0513*** (0.0074)	0.0504*** (0.0099)	0.0550* (0.0289)	0.3660*** (0.0147)
Debt × Debt	-0.0044 (0.0028)	0.0086 (0.0417)	-0.1834*** (0.0587)	-0.1392*** (0.0136)	-0.0398*** (0.0042)	-0.0342 (0.0250)	0.0552** (0.0175)	0.0816*** (0.0070)	-0.0170** (0.0068)	0.0153 (0.0099)	0.0334 (0.0259)	-0.1885*** (0.0122)
Size	0.0040*** (0.0004)	0.1580*** (0.0051)	0.0772*** (0.0084)	0.1662*** (0.0012)	0.0861*** (0.0006)	0.0937*** (0.0033)	0.0729*** (0.0022)	0.0767*** (0.0008)	0.0565*** (0.0009)	0.1009*** (0.0014)	0.0520*** (0.0036)	0.1526*** (0.0015)
Age	0.0359*** (0.0013)	-0.0002 (0.0186)	-0.1055*** (0.0278)	-0.0369*** (0.0029)	-0.0230*** (0.0019)	-0.0633*** (0.0101)	-0.0365*** (0.0090)	-0.0366*** (0.0017)	-0.0264*** (0.0021)	-0.0496*** (0.0039)	0.0648*** (0.0149)	-0.0119*** (0.0042)
Intangible Assets	0.0075*** (0.0015)	-0.0075 (0.0215)	-0.0176** (0.0070)	0.0385*** (0.0030)	0.0298*** (0.0030)	0.0246 (0.0160)	-0.0070 (0.0032)	0.0032** (0.0016)	0.0030 (0.0045)	0.0069 (0.0137)	0.0358*** (0.0110)	0.0402*** (0.0071)
Constant	1.5396*** (0.0066)	2.5540*** (0.0834)	0.5984*** (0.1345)	0.1290*** (0.0195)	1.4320*** (0.0096)	0.1031** (0.0516)	1.6794*** (0.0309)	0.2159*** (0.0105)	0.8911*** (0.0129)	1.0517*** (0.0195)	1.4378*** (0.0660)	1.8191*** (0.0237)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	460,746	69,180	26,427	1,693,767	820,104	97,000	241,084	2,201,040	362,883	198,444	11,621	518,147
R-squared	0.595	0.685	0.630	0.497	0.524	0.557	0.595	0.478	0.562	0.487	0.760	0.519

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 11: Estimation Results for the Dummy Variable of the Global Financial Crisis (GFC)

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.6658*** (0.0016)	-0.737*** (0.0024)	-0.6893*** (0.0039)	-0.658*** (0.0005)	-0.5755*** (0.0007)	-0.5969*** (0.0020)	-0.6872*** (0.0013)	-0.6484*** (0.0005)	-0.6628*** (0.0011)	-0.5450*** (0.0016)	-0.8457*** (0.0040)	-0.6498*** (0.0012)
Debt	0.0063** (0.0027)	0.1688*** (0.0091)	0.2395*** (0.0383)	0.2865*** (0.0118)	0.1294*** (0.0029)	0.2190*** (0.0149)	0.0960*** (0.0139)	0.1190*** (0.0062)	0.0445*** (0.0045)	0.0574*** (0.0069)	0.0236** (0.0099)	0.3411*** (0.0113)
Debt × Debt	-0.0049* (0.0026)	-0.0096** (0.0048)	-0.1039*** (0.0359)	-0.1195*** (0.0089)	-0.0427*** (0.0024)	-0.0970*** (0.0141)	-0.0117 (0.0125)	0.0245*** (0.0053)	-0.0071* (0.0043)	-0.0063 (0.0070)	0.0510*** (0.0088)	-0.1803*** (0.0095)
Size	0.0092*** (0.0003)	0.1486*** (0.0025)	0.0822*** (0.0047)	0.1477*** (0.0009)	0.0842*** (0.0003)	0.0713*** (0.0018)	0.0817*** (0.0015)	0.0729*** (0.0006)	0.0500*** (0.0054)	0.0783*** (0.0009)	0.0459*** (0.0011)	0.1420*** (0.0011)
Age	0.0214*** (0.0011)	-0.0312*** (0.0075)	-0.0433*** (0.0132)	-0.0146*** (0.0017)	-0.0334*** (0.0009)	-0.0274*** (0.0051)	-0.0277*** (0.0046)	-0.0289*** (0.0013)	-0.0321*** (0.0011)	-0.0460*** (0.0025)	0.0133*** (0.0036)	-0.0299*** (0.0029)
Intangible Assets	0.0011 (0.0016)	0.0152 (0.0156)	-0.0060 (0.0077)	0.0308*** (0.0024)	0.0318*** (0.0024)	0.0273** (0.0108)	0.0207 (0.0252)	0.0001 (0.0016)	-0.0115*** (0.0033)	-0.0067 (0.0114)	0.0318*** (0.0061)	0.0324*** (0.0053)
Intangible Assets x GFC Dummy	-0.0542*** (0.0051)	-0.0114 (0.0163)	0.0283 (0.0213)	-0.0081*** (0.0026)	0.0174*** (0.0027)	-0.0278** (0.0121)	0.0030 (0.0300)	0.0506*** (0.0047)	0.0345*** (0.0035)	0.0453*** (0.0154)	-0.0246*** (0.0064)	0.0340*** (0.0053)
Constant	1.1769*** (0.0057)	1.4906*** (0.0381)	0.1143 (0.0730)	0.1175*** (0.0132)	1.0228*** (0.0063)	0.1476*** (0.0269)	1.1123*** (0.0199)	0.1994*** (0.0089)	0.7297*** (0.0076)	0.8661*** (0.0130)	1.1730*** (0.0179)	1.5948*** (0.0182)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	556,441	194,125	73,711	3,438,980	1,832,014	255,739	717,643	3,621,240	823,759	357,593	78,321	789,968
R-squared	0.549	0.513	0.516	0.437	0.449	0.469	0.499	0.426	0.480	0.384	0.644	0.468

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Appendix: Technical Explanation of MFP Estimation

Gandhi et al. (2020) developed a nonparametric identification method for gross output production functions when additional sources of variation in the demand for flexible inputs are unavailable. Their identification method regresses revenue shares on inputs to identify flexible input elasticity, solves the partial differential equation, and integrates this into the dynamic panel/proxy variable structure to identify the remainder of the production function. The output function for firm j in year t is

$$Y_{jt} = F(k_{jt}, l_{jt}, m_{jt})e^{v_{jt}}$$

where Y_{jt} is the output, k_{jt} is the log value of capital input, l_{jt} is the log value of labor input, m_{jt} is the log value of intermediate input, and v_{jt} is the Hicks neutral productivity shock ($v_{jt} = \omega_{jt} + \varepsilon_{jt}$), which is decomposed into the Markovian component ω_{jt} and ex-post productivity shock ε_{jt} . The production function is differentiable for all inputs and strictly concave for intermediate inputs. The intermediate-input demand $m_{jt} = M_t(k_{jt}, l_{jt}, m_{jt})$ is assumed to be strictly monotone in a single unobservable ω_{jt} . Firms are price takers in the output/intermediate input markets. The authors demonstrated that the first-order condition of a firm's problem is used to solve the demand for intermediate inputs, which can also be inverted to solve for productivity:

$$\omega_{jt} = M^{-1}(k_{jt}, l_{jt}, m_{jt}) + d_t$$

where $d_t \equiv \ln(\rho_t/P_t) - \ln\varepsilon$ is defined by the common intermediate-input price ρ_t and the common output price facing all firms P_t . In the proxy variable framework, they note that appropriately lagged input decisions can be used as instruments. By replacing productivity in the intermediate-input demand equation, the only sources of variation left in m_{jt} are unobservable and d_t . Identification of the production function by instrumental variables is based on projecting output onto the exogenous variables. They showed that the restrictions implied by the firm's optimizing behavior, integrated with

the idea of using lagged inputs as instruments employed by the dynamic panel and proxy variable literature, are sufficient to nonparametrically identify the production function and MFP, even when additional sources of exogenous variation in flexible inputs are absent. This is because input demand is implicitly defined by the production function through the firm's first-order condition. Under these assumptions, the share regression equation nonparametrically identifies flexible input elasticity. Then, we use the information from the share regression to recover the rest of the production function nonparametrically. Combining these two steps, the estimating equation is written with a complete polynomial degree r as follows.

$$\hat{y}_{jt} = - \sum_{0 < r_k + r_l \leq r} \alpha_{r_k, r_l} k_{jt}^{r_k} l_{jt}^{r_l} + \sum_{0 \leq a \leq r} \delta_a \left(\hat{y}_{jt-1} + \sum_{0 < r_k + r_l \leq r} \alpha_{r_k, r_l} k_{jt-1}^{r_k} l_{jt-1}^{r_l} \right)^a + \eta_{jt}$$

We estimate a gross output production function using a complete polynomial series of degree two and a polynomial of degree three for the Markovian process.

Table A1: Correlation Matrix

China	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	-0.0672	1.0000				
Cash	0.2318	-0.1568	1.0000			
Size	0.1506	0.0856	0.0016	1.0000		
Age	0.0735	-0.0353	0.0602	0.2278	1.0000	
Intangibility	0.0851	-0.1104	0.0280	-0.2964	-0.0594	1.0000

Colombia	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.1645	1.0000				
Cash	0.1564	0.9676	1.0000			
Size	0.2358	0.0846	0.0752	1.0000		
Age	0.0410	-0.2050	0.2270	0.3560	1.0000	
Intangibility	0.0965	0.1389	0.1330	0.1436	0.0048	1.0000

Hungary	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0760	1.0000				
Cash	0.1391	-0.1620	1.0000			
Size	-0.0564	0.0449	-0.2598	1.0000		
Age	-0.0847	-0.1621	-0.0706	0.2384	1.0000	
Intangibility	0.1791	0.0782	0.1114	-0.0941	-0.1339	1.0000

Italy	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0832	1.0000				
Cash	0.0742	-0.2354	1.0000			
Size	-0.0620	-0.0611	-0.2510	1.0000		
Age	0.0066	-0.1521	-0.0202	0.3212	1.0000	
Intangibility	0.1675	0.0803	0.0705	-0.2062	-0.1513	1.0000

Japan	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0231	1.0000				
Cash	0.0093	-0.3965	1.0000			
Size	0.1653	0.0177	-0.2261	1.0000		
Age	-0.1197	-0.1748	-0.0818	0.3906	1.0000	
Intangibility	0.1476	0.0051	0.0987	-0.1068	-0.2077	1.0000

Poland	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0299	1.0000				
Cash	0.2279	-0.2554	1.0000			
Size	-0.1542	-0.0554	-0.2177	1.0000		
Age	-0.1036	-0.2062	-0.0259	0.2737	1.0000	
Intangibility	0.1819	0.0096	0.1222	-0.2606	-0.2251	1.0000

Romania	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	-0.1419	1.0000				
Cash	0.2527	-0.3523	1.0000			
Size	-0.2058	0.0268	-0.3045	1.0000		
Age	-0.0570	-0.1736	-0.1480	0.3618	1.0000	
Intangibility	0.1379	-0.0239	0.1626	-0.1772	-0.0983	1.0000

Spain	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	-0.0028	1.0000				
Cash	0.1026	-0.2453	1.0000			
Size	-0.0264	-0.1285	-0.2040	1.0000		
Age	-0.0471	-0.3418	-0.0776	0.4702	1.0000	
Intangibility	0.0007	0.1529	0.0387	-0.1691	-0.1658	1.0000

South Korea	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0144	1.0000				
Cash	0.0473	-0.3226	1.0000			
Size	0.0241	0.0764	-0.1358	1.0000		
Age	-0.0127	-0.1710	-0.0871	0.4721	1.0000	
Intangibility	0.2629	0.0370	-0.0040	-0.1800	-0.1295	1.0000

Thailand	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0524	1.0000				
Cash	0.1112	-0.3402	1.0000			
Size	0.0732	-0.0272	-0.1014	1.0000		
Age	0.0553	-0.0840	-0.0966	0.2233	1.0000	
Intangibility	0.1013	0.0446	0.0358	0.1558	0.0325	1.0000

Turkey	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	-0.0034	1.0000				
Cash	0.0944	-0.2070	1.0000			
Size	0.1401	-0.0099	-0.0875	1.0000		
Age	0.0234	-0.2102	-0.0377	0.4186	1.0000	
Intangibility	0.0492	0.0449	0.0455	-0.1234	-0.0796	1.0000

United Kingdom	MFP	Debt	Cash	Size	Age	Intangibility
MFP	1.0000					
Debt	0.0255	1.0000				
Cash	0.0579	-0.2095	1.0000			
Size	0.2536	-0.0694	-0.2548	1.0000		
Age	0.0286	-0.2615	-0.0971	0.4258	1.0000	
Intangibility	0.1041	0.0939	0.1348	-0.3194	-0.4136	1.0000

Table A2: Two-Year Lags for Intangible Assets

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.7587*** (0.0019)	-0.7184*** (0.0028)	-0.7310*** (0.0045)	-0.6604*** (0.0006)	-0.5812*** (0.0008)	-0.6158*** (0.0023)	-0.6897*** (0.0015)	-0.6516*** (0.0006)	-0.6625*** (0.0013)	-0.5525*** (0.0019)	-0.8340*** (0.0056)	-0.6469*** (0.0014)
Debt	0.0126*** (0.0030)	0.1849*** (0.0263)	0.2420*** (0.0410)	0.3260*** (0.0127)	0.1364*** (0.0031)	0.2620*** (0.0167)	0.1260*** (0.0156)	0.1426*** (0.0066)	0.0561*** (0.0054)	0.0674*** (0.0077)	0.0183 (0.0129)	0.3512*** (0.0128)
Debt × Debt	-0.0086*** (0.0028)	-0.0250 (0.0251)	-0.0876** (0.0388)	-0.1381*** (0.0096)	-0.0435*** (0.0027)	-0.1379*** (0.0162)	-0.0379*** (0.0142)	0.0046 (0.0057)	-0.0158*** (0.0052)	-0.0125 (0.0080)	0.0546*** (0.0115)	-0.1964*** (0.0110)
Size	0.0118*** (0.0004)	0.1473*** (0.0029)	0.0930*** (0.0052)	0.1483*** (0.0010)	0.0838*** (0.0004)	0.0740*** (0.0020)	0.0791*** (0.0018)	0.0769*** (0.0007)	0.0505*** (0.0007)	0.0799*** (0.0011)	0.0392*** (0.0015)	0.1409*** (0.0013)
Age	0.0355*** (0.0016)	-0.0291*** (0.0105)	-0.0453** (0.0185)	-0.0052** (0.0023)	-0.0214*** (0.0012)	-0.0317*** (0.0070)	-0.0109 (0.0070)	-0.0391*** (0.0017)	-0.0301*** (0.0016)	-0.0119*** (0.0034)	0.0239*** (0.0058)	-0.0086** (0.0039)
Intangible Assets_t-2	0.0012 (0.0014)	-0.0322*** (0.0093)	-0.0009 (0.0065)	0.0136*** (0.0015)	0.0243*** (0.0021)	-0.0089 (0.0089)	0.0165* (0.0086)	-0.0001 (0.0015)	0.0030 (0.0030)	0.0011 (0.0099)	0.0009 (0.0043)	0.0265*** (0.0054)
Constant	1.2786*** (0.0069)	1.4137*** (0.0487)	0.0113 (0.0877)	0.0471*** (0.0152)	0.9885*** (0.0063)	0.1259*** (0.0330)	1.0876*** (0.0258)	0.1635*** (0.0101)	0.7140*** (0.0095)	0.7770*** (0.0160)	1.2274*** (0.0264)	1.5250*** (0.0223)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	45,483	150,108	57,834	2,808,666	1,458,307	198,269	577,197	3,010,031	622,044	302,643	45,779	613,953
R-squared	0.540	0.485	0.538	0.425	0.438	0.476	0.491	0.419	0.464	0.377	0.615	0.451

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.

Table A3: Three-Year Lags for Intangible Assets

Country	China	Colombia	Hungary	Italy	Japan	Poland	Romania	Spain	South Korea	Thailand	Turkey	United Kingdom
Lagged MFP	-0.7361*** (0.0023)	-0.7187*** (0.0032)	-0.6611*** (0.0050)	-0.6515*** (0.0006)	-0.5892*** (0.0009)	-0.6107*** (0.0026)	-0.6772*** (0.0017)	-0.6438*** (0.0006)	-0.6682*** (0.0015)	-0.5673*** (0.0020)	-0.7869*** (0.0072)	-0.6394*** (0.0016)
Debt	0.0060* (0.0035)	0.1758*** (0.0297)	0.1833*** (0.0442)	0.3350*** (0.0134)	0.1376*** (0.0033)	0.2548*** (0.0183)	0.1424*** (0.0167)	0.1542*** (0.0070)	0.0657*** (0.0063)	0.0722*** (0.0085)	0.0399** (0.0159)	0.3378*** (0.0143)
Debt × Debt	-0.0035*** (0.0034)	-0.0133 (0.0284)	-0.0563 (0.0419)	-0.1428*** (0.0102)	-0.0434*** (0.0029)	-0.1396*** (0.0178)	-0.0502*** (0.0153)	-0.0056 (0.0061)	-0.0221*** (0.0059)	-0.0160* (0.0088)	0.0338** (0.0142)	-0.1875*** (0.0123)
Size	0.0140*** (0.0004)	0.1454*** (0.0033)	0.0844*** (0.0057)	0.1476*** (0.0011)	0.0845*** (0.0004)	0.0738*** (0.0023)	0.0783*** (0.0019)	0.0796*** (0.0008)	0.0515*** (0.0008)	0.0827*** (0.0012)	0.0359*** (0.0019)	0.1403*** (0.0015)
Age	0.0334*** (0.0024)	-0.0392*** (0.0140)	-0.0460* (0.0249)	-0.0022*** (0.0029)	-0.0239*** (0.0015)	-0.0535*** (0.0091)	-0.0042 (0.0096)	-0.0426*** (0.0022)	-0.0328*** (0.0023)	-0.0114** (0.0045)	0.0055 (0.0087)	-0.0156*** (0.0051)
Intangible Assets_t-3	-0.0041** (0.0017)	-0.0319*** (0.0105)	-0.0010 (0.0065)	0.0023 (0.0015)	0.0110*** (0.0022)	-0.0197** (0.0097)	0.0209** (0.0088)	-0.0051*** (0.0015)	0.0084** (0.0033)	0.0185* (0.0105)	-0.0020 (0.0051)	0.0171*** (0.0060)
Constant	1.2026*** (0.0087)	1.4794*** (0.0601)	0.0168 (0.1050)	-0.0094 (0.0173)	1.0021*** (0.0022)	0.1650*** (0.0397)	1.0230 (0.0318)	0.1127*** (0.0116)	0.7137*** (0.0117)	0.7848*** (0.0193)	1.2324*** (0.0369)	1.5152*** (0.0269)
4 Digit Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Coverage	All	All	All	All	All	All	All	All	All	All	All	All
Observations	346,072	122,657	48,738	2,380,727	1,240,540	162,647	501,056	2,628,086	475,537	261,349	27,712	490,343
R-squared	0.534	0.489	0.494	0.426	0.446	0.476	0.489	0.420	0.466	0.388	0.6021	0.451

Dependent variables are MFP growth calculated by Gandhi, Navarro and Rivers (2020)'s method. *significant at 10%, **significant at 5%, ***significant at 1%.