Food Companies' Productivity Dynamics: Exploring the Role of Intangible Assets

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8 July 2023

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Abstract

Food insecurity has risen amid economic recovery from the COVID-19 pandemic. Food companies' productivity dynamics can be driven by intangible assets, financing, economies of scale, lifecycle, and technological convergence. We confront this by studying productivity drivers for detailed food manufacturing industries using cross-country firm-level panel data. The results show that intangible assets nonlinearly and heterogeneously affect productivity growth, and countries with fewer product market regulations demonstrate higher productivity benefits from asset intangibility. Intangible assets do not play a major role for start-up companies, while technological convergence drives productivity growth as they learn new technology in the food markets. Regarding the industrial differences, the bakery sector benefits the most from asset intangibility because of its brand images. Financing is particularly important for the meat/fish and dairy sectors, where capital equipment is necessary, and leverage effects are larger for countries with more access to financial institutions. Economies of scale are a vital productivity enhancer in the grain and starch sector for lowering fixed costs. Industrial policies to (i) raise the quality of intangible assets, (ii) promote financial access, and (iii) utilize scale economies are critical for improving the productivity of food manufacturers.

Keywords: productivity growth; food manufacturing; asset intangibility; start-up; technological convergence; financing; scale economies; agri-food; product market regulations: financial development; grain and starch sector; meat and fish sector; dairy sector; fruit and vegetable sector; bakery sector

JEL Classification Codes: D24; G32; L66; O34

1. Introduction

The food manufacturing sector is essential in providing daily foods for citizens by turning agricultural crops into edible foods for humans. From the supply side, the food industry is one of the important production sectors in the economy because it is the largest economic sector within manufacturing in many countries, including countries in the European Union (Hirsch and Gschwandtner, 2013). In addition, from the demand side, food spending often accounts for a significant portion of household budgets all over the world, particularly for low-income households. Furthermore, during the COVID-19 lockdown and amid economic recovery from the pandemic, food insecurity has risen in many countries, including advanced economies such as the United States (Tian et al., 2022). Therefore, it has become increasingly important to improve productivity of food production for the well-being of human beings, as recent research has found positive associations between productivity and food security (Chavas et al., 2022; Villacis et al., 2022) and between food security and human well-being (Kornher and Sakketa, 2021).

However, productivity has been considered a somewhat puzzling factor in economics.[1] Like other industries, as evidenced by what we call the Solow residual (Solow, 1957), total factor productivity (TFP) has traditionally been treated as residual in agricultural/food production functions after capital and labor inputs are taken into consideration (Schultz, 1956).[2] Additionally, food production is closely associated with agricultural products, and there are controversial arguments about the drivers of productivity advancement. For example, there has been intensive debate about how long it takes for research and development (R&D) to materialize in agricultural productivity development (Alston and Pardey, 2001; Alston et al., 2009; Baldos et al., 2019; Fuglie, 2018; Huffman and Evenson, 1993; Pardey and Craig, 1989; Sumner et al., 2010).

Then, the question that arises is "What are drivers of productivity of food companies across sectors and countries?" We answer this question empirically, using firm-level panel data across ten countries that have good quality of regulations and sufficiently developed financial markets. Specifically, we use the Orbis database from 1996 to 2015 to analyze productivity dynamics in the detailed subcategories of the food manufacturing sector in Asia and Europe.

Prior works have identified that several factors, such as technical progress, information and communication technology (ICT), credit, and firm age, are crucial determinants of the productivity

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[1] For example, changes in productivity are often modelled as exogenous shocks that change the market equilibrium in economic theories and empirical studies (e.g., Nakatani, 2014, 2016, 2017ab). Further, productivity was found to change dramatically during financial crises (Meza and Quintin, 2007; Nakatani, 2018, 2019a), but the theoretical mechanism to explain such phenomena has yet to be well-established.

[2] Traditional engines for agricultural productivity growth have been innovation via R&D and resource allocation (Alston, 2018; Hertel et al., 2020). Farmers and agricultural firms adopt new technology by innovation through the learning process with uncertainty (Chavas and Nauges, 2020). The ICT revolution in the mid-1990s increased the intangibility of capital and aided TFP (Guevara-Rosero, 2021).

dynamics of food manufacturing companies (Chang et al., 2019; Náglová and Pechrová, 2021; Guevara-Rosero, 2021; Blažková et al., 2020). However, the existing literature is incomplete or deficient in the sense that it does not reflect the recent development of digitalization in the agrifood sector.[3] For example, despite the rapidly growing role of digital technology and intellectual property in the food industry, little literature has studied the productivity drivers of detailed food industries in relation to intangible assets. In addition, the effects of intangible assets on productivity growth could be nonlinear, and the effects of intangible assets on productivity growth for start-up (food) companies have rarely been explored.

We focus on intangible assets instead of R&D as a productivity driver for the following reasons. First, we were able to overcome a problem that the empirical literature on agriculture and food sectors has often faced, namely, we do not need to consider the lengthy lag between R&D and TFP growth (Alston et al., 2009; Alston and Pardey, 2001; Baldos et al., 2019). Instead, we study the effects of realized knowledge capital measured by intangible assets on the TFP of food manufacturers. This means that we employ the stock of intangible assets as one of the TFP enhancers in our empirical investigation. Therefore, the impacts of past investments in intangible capital, including the outcomes of successful R&D investments, have been fully captured. In other words, the effects of current intangible investment and the lagged effects of past intangible investment with depreciation are fully included in our estimations. It is better to use intangible assets as a variable representing a productivity enabler rather than R&D expenses because intangible assets (e.g., intellectual property rights) are the actual assets that actuate value-addition. In fact, the R&D stock comprises only a third of the total stock of intangible assets (Corrado et al., 2017), leading to the high elasticity of non-R&D intangible assets concerning output. We explore the role of intangible assets in productivity dynamics utilizing the Orbis database published by Bureau van Dijk, enabling us to use the exact definition for intangible assets across countries.

A novel and value-added aspect of our study comprises three contributions. First, against the backdrop of the abovementioned role of advancement of digital technology in the food industry, there is a lack of literature on the productivity drivers of detailed food industries in relation to intangible assets. The extant literature has studied the manufacturing sector (Roth et al., 2023) but did not dig further into the subcategories of the food manufacturing industry. For example, in a certain food industry such as bakery, brand equity as an intangible asset might be more important for improving productivity compared to other industries that rely on economies of scale (e.g., grain sector). Therefore, this study delves into the productivity dynamics of detailed subcategories of the food manufacturing sector to derive policy implications for the agrifood industry.

[3] Digitalization of the agrifood sector has become prominent (Fielke et al., 2020) and intangible assets (e.g., big data analytics, precision technologies, real-time monitoring via sensors, automation technology, machine learning, cloud computing, brand equity, and knowledge products) are accumulated (Bramley and Ouzman, 2019; Capalbo et al., 2017; Harris and Pike, 1996; Wolfert et al., 2017; Wu and Bjornson, 1996). For instance, food manufacturers use automation technology (e.g., AI) to detect quickly changing food demand.

The second novelty of this paper is the nonlinear effects of intangible assets on productivity growth, which have never been analyzed despite the possibility that the effects of asset intangibility on TFP growth may not neccesarily be a linear relationship.

Third, we investigate how intangible assets and other productivity-enhancing factors affect the productivity growth of start-up food companies. To the best of our knowledge, our study is the first to examine the role of intangible assets on the TFP growth of start-ups, not only in the field of agribusiness but also in other broader industries. Our hypothesis is that start-up companies may not be able to utilize the benefits from intangible assets because they have just entered the new markets, and therefore are in the learning process of obtaining new technology and other resources with limited finances.

The remainder of the paper is organized as follows. We discuss theories of TFP and provide a literature survey on the productivity of food manufacturing as well as clarificaiton of contributions of this article in the next section, after which we describe our empirical strategy (econometric approach and data). We then discuss our cross-country analysis using the generalized method of moments (GMM) and a panel fixed effects estimation method. Next, we conduct an industrial-level analysis across countries, which is the focus of this study. Finally, we conclude the study by deriving and discussing important and practically valuable policy implications for the food sector.

2. Literature Review

In this section, we discuss drivers of TFP relevant to our empirical analysis, including a discussion of the empirical literature that studied productivity dynamics of food manufacturing companies, which are the main focus of this article. Our empirical study builds on several theories of productivity. Specifically, we analyze five factors (variables) to explain productivity dynamics: technological convergence captured by the level of multifactor productivity, the intangibility of assets (i.e., the share of intangible assets in total assets), financing measured by leverage, the lifecycle of firms (the age of firms), and economies of scale measured by the size of firms.

The adoption of new technology can drive firm-level productivity growth. Hertel et al. (2020) studied the mechanism through which agricultural companies' productivity converges with the world technology frontier as they copy and adopt technology from the frontier and engage in innovation. These scholars' theoretical model implies that the distance to the technology frontier matters for productivity growth. In the field of food industry, Chang et al. (2019) found that technical progress has been a major driving force of Taiwanese bakery. Baležentis and Sun (2020) found that technical change is one of major factors affecting TFP growth in the dairy sector in Lithuania. Náglová and Pechrová (2021) used data on Czech food and drink companies, revealing that the bakery and milk industries demonstrated the highest technical efficiency, while fruit and vegetable processing demonstrated the lowest efficiency. Kim (2015) analyzed Japanese manufacturing and found that the existence of considerable embodied technical progress and interindustry externalities of capital investments positively affected productivity growth. Using Malaysian manufacturing data, Kim and Shafi'i (2009) found that technical progress and scale/allocative efficiency exerted significant influences on TFP.

The main driver of agricultural productivity growth is R&D-based innovation (Baldos et al., 2019; Jorgenson, 2011). This has led to the accumulation of intangible assets on the corporate balance sheets of the digital economy. Digitalization in the agriculture and food sectors can enhance the accumulation of intangible assets and improve TFP by reducing transaction costs (Ehlers et al., 2021). Using intangible assets as a variable to represent TFP enhancement is preferable to relying on R&D expenses, as R&D investments do not always guarantee successful commercial outcomes. Moreover, intangible assets are the actual assets that contribute to value-addition, which is crucial since the stock of R&D research does improve TFP growth (Wang et al., 2013). By focusing on intangible assets, we can avoid the challenges associated with modeling and measuring the productivity effects of R&D, such as accounting for the time lag between R&D and TFP growth (Alston and Pardey, 2001; Fuglie, 2018; Huffman and Evenson, 1993; Pardey and Craig, 1989; Sumner et al., 2010). Corrado et al. (2017) discovered that the stock of R&D represents only one-third of the total stock of intangible assets, highlighting the significant impact of non-R&D intangible assets on economic growth and their high elasticity with respect to output. This indicates that both the R&D component and non-R&D intangible assets have a substantial influence on economic growth by improving TFP. Kim (2015) found that the impact of R&D was realized only after being embodied in other capitals. Dettori et al. (2012) found that a large part of TFP differences across the European regions were explained by the disparities in the endowments of intangible assets. We analyzed the effects of broad intangible assets beyond R&D on TFP growth using cross-country firm-level data. We particularly studied the productivity effects of intangible assests for detailed food manufactring indusries, as well as the possible nonlinear effects of intangible assets on TFP growth.

Financing is another important determinant of productivity (Heil, 2018). Brander and Lewis (1986) theoretically showed that greater use of leverage tends to lead firms to compete more aggressively because leveraged firms have incentives to use their financial structures to influence the output markets. Better access to credit makes it easier for firms to innovate and become competitive. In fact, Rada and Buccola (2012) argued that agricultural/food productivity benefits from credit expansion, notably in rural areas. Khafagy and Vigani (2023) found a nonlinear relationship between external finance and agricultural productivity. Leverage can also be treated as an indicator of resource mobilization through financing (Beck et al., 2000). For example, ICT investment (which enhances productivity improvement and leads to an accumulation of intangible capital such as digital assets) is sensitive to financial constraints (Bacchini et al., 2018). Guevara-Rosero (2021) also found that credit and ICT are important TFP drivers for manufacturing. Moreover, leverage may be a valuable tool for reducing agency costs (Hall and Lerner, 2010). From the empirical viewpoint concerning the intangibility of assets articulated above, Bartoloni (2013) found evidence that intangible asset intensity has a significant effect on firms' leverage behavior. Bontempi (2016) also found that intangibles (R&D and non-R&D) are affected by debt financing. Moreover, Grashuis (2019) found that brand equity is positively related to the financial performance of farmer cooperatives. Therefore, we include leverage and asset intangibility as separate contributors to TFP growth to examine each variable’s ceteris paribus effect. Furthermore, Ibhagui and Olokoyo (2018) found that the negative impact of leverage on firm performance is most prominent for small firms and that this effect diminishes as a firm grows.

Consequently, it is essential to control for firm characteristics such as age and size when analyzing the ceteris paribus effects of leverage on TFP and to avoid omitted variable bias.

It is imperative to control for relevant firm characteristics when studying TFP dynamics. The literature has shown that young firms are important for job creation and productivity growth (Haltiwanger, 2015). As the life-cycle theory of firm dynamics predicts, new entrants and young firms tend to increase their productivity faster than old firms through learning by doing in new markets (Bahk and Gort, 1993). Using U.S. firm data, Foster et al. (2008) found that the productivity of new firms is higher than that of old firms. Geylani and Stefanou (2013) found that the productivity gains from learning-by-doing tended to be fully realized with a five-year technology learning period in the U.S. food manufacturing industry. Blažková et al. (2020) found that younger food companies achieved higher TFP growth than older ones in the Czech Republic. In the context of the lifecycle of food companies, we particulary analyze the effects of intangible assets on the TFP growth of start-up companies, which has not been explored in the literature.

Firm size is another critical characteristic of firms. Kim and Shafi'i (2009) discovered variations in the impact of firm size on scale economies across manufacturing industries. Dvoulety and Blazkova (2021) identified a positive association between TFP and firm size, as measured by assets. The presence of economies of scale, measured by firm or plant size, has been established as a significant driver of TFP for food processing firms (Azzam et al., 2004) and various food sectors, including the grain sector (Sheng and Chancellor, 2019; Key, 2019), the rice sector (Majumder et al., 2016), and the dairy sector (Mosheim and Lovell, 2009; Baležentis and Sun, 2020; Alem, 2023). Our analysis confirms this finding.

However, as we already mentioned, there still remain three gaps, which we fill in this article, since little literature has studied (i) the effects of intangible assets on detailed food manufacturing industries, (ii) the possible nonlinear effects of intangible assets on TFP growth, and (iii) the effects of intangible assets on start-up companies. All these topics are practically useful for providing industrial policy advices to food companies as we do in the conclusion section of this article. To do so, we explain the empirical strategy to analyze these research topics in the next section.

3. Empirical Strategy

3.1. Econometric Approach

The empirical model used to identify firm-specific factors that could lead to TFP growth is defined as follows:

$$\Delta ln\left(TFP_{i,j,t}\right) = \beta_1 + \beta_2 ln\left(TFP_{i,j,t-1}\right) + \beta_3 Leverage_{i,j,t-1} + \beta_4 ln\left(Size_{i,j,t}\right)$$
$$+\beta_5 ln\left(Age_{i,j,t}\right) + \beta_6 Intangible\ Assets_{i,j,t-1} + \mu_{j,t} + \gamma_t + v_i + \varepsilon_{i,j,t}$$

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

$Leverage_{i,t}$ is liabilities divided by total assets; $ln(Size_{i,t})$ is the natural logarithm of total assets[4]; $ln(Age_{i,t})$ is the natural logarithm of firm age; $Intangible\ Assets_{i,t}$ is intangible fixed assets divided by total assets; $\mu_{j,t}$ represents the industry-specific time fixed effects; γ_t represents the time fixed effects; v_i represents the firm fixed effects; and $\varepsilon_{i,j,t}$ is an error term.

The dependent variable of the differenced natural logarithm of TFP approximates the TFP growth rate. We include the logarithm of the previous year TFP level as an explanatory variable to capture the productivity convergence with the technology frontier. Namely, firms with a low level of TFP could improve TFP faster by adopting frontier technology. We also take the natural logarithm of firm size and firm age as explanatory variables because the relationship between TFP growth and firm characteristics (size, age) could be nonlinear.

To avoid endogeneity problems arising from firms' simultaneous decisions, the relevant explanatory variables (i.e., leverage and intangible assets[5]) are lagged. Note that since firm age is not a choice variable of firms and firm size is based on a stock variable, these two variables are less prone to endogeneity problems. We use a system GMM estimator for the baseline estimation because it can address endogeneity, unobservable firm heterogeneity, and persistence, with the dramatic efficiency gains over the first-difference GMM estimator (Baltagi, 2021). We also use a fixed-effects estimator for the robustness check as we can estimate the firm-fixed effects.

Although we make the best use of the Orbis database, there is a potential omitted variable bias that should be acknowledged, particularly because the following variables are not included: management capabilities (Bloom et al., 2019), exports (Kapelko and Lansink, 2013), imports (Olper et al., 2014), foreign direct investment (i.e., foreign ownership) (Nakatani et al., 2017), business environment (Commander and Svejnar, 2011), regulatory environment (Aterido et al., 2011), security costs (Besley and Mueller, 2018), electricity (Allcott et al., 2016), water infrastructure (Islam and Hyland, 2019), corruption (Fisman and Svensson, 2007), investment spikes (Kapelko et al., 2015; Geylani and Stefanou, 2013), formal training, physical environment, and political stability. However, to include these factors in our regression, firm-level surveys would need to be conducted to obtain these institutional variables. Unfortunately, in our database, there are no data or information on these factors. Therefore, we cannot include all these factors in our empirical analyses. Nevertheless, we believe that omitted variable bias

[4] 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. Economies of scale captured in this study are scale economies with respect to the firm size; economies of scale at the plant level are not considered.

[5] There is an issue of simultaneity such that intangible assets are more likely to be acquired by more productive firms. To be more precise, in our baseline simulations, this concern is mitigated by using TFP growth rather than TFP levels as a regressand. This is because only a portion of the regressand (i.e., TFP level in the previous period) is influenced by the simultaneity issue when lagged intangible assets are used as the regressor, as TFP growth reflects the change in the current TFP level from that of the previous period.

is not a severe problem in our econometric specification; our empirical results are not affected by these factors for the following reasons: most of these omitted variables are captured by various fixed effects. For example, nationwide factors such as political stability and corruption could be captured by the inclusion of time fixed-effects (γ_t). In addition, other omitted variables that are common for the same industry, such as business/regulatory environment, are also well-captured and controlled by the four-digit-level industry-specific time-varying fixed effects ($\mu_{j,t}$). Furthermore, firm-specific omitted variables, such as export/import status, security costs, investment spikes, training, physical environment, and geographic factors such as electricity and water infrastructure, are captured by the firm-specific fixed effects (v_i) in our regression. Therefore, most omitted variables listed above are likely to be controlled by the industry-specific time-varying and firm-specific fixed effects, $\mu_{j,t}$ and v_i, respectively. However, a possible omitted variable bias could still exist if there are unobservable factors in the dynamics of the decision-making process for the firm such as management capabilities (see footnote 11).

TFP is calculated using Gandhi et al.'s (2020) method, which estimates production functions for gross output with flexible inputs (e.g., intermediate inputs) represented by proxy variables (see Appendix). The production function determines value added as turnover revenue minus material costs. Labor input is the cost of employees, and capital input includes tangible fixed assets like buildings and machinery. Intangible fixed assets are not considered in TFP estimation but are treated as factors influencing TFP dynamics in our empirical model. We deflate nominal variables using the industry-level producer price index. The producer input price index is used to deflate capital inputs, while the producer output price index is used to deflate output. For countries lacking both types of price indices, a single producer price index is used for input and output deflation. Intangible fixed assets are calculated as the total value of assets from formation, research, goodwill, development expenses, and other long-term impact items on firms' balance sheets. The definition of intangible assets is consistent across all countries in the Orbis database, facilitating comparative analysis.

3.2. Data

We use firm-level data from the Orbis database published by Bureau van Dijk. The Orbis database is a cross-country longitudinal dataset of both listed and unlisted firms with their balance sheets and income statements. We use NACE (and ISIC) four-digit industry classifications to control for industry-specific time-fixed effects, such as changes in product market regulations. The four-digit NACE code for the food manufacturing sector is 1,000, and industry classification details are shown in Table A1.

We follow the method proposed by Kalemli-Özcan et al. (2015) and Gopinath et al. (2017) to construct our database. Our database is different from their databases in two respects: (1) as the Orbis database collects more data from various sources over time, we have more cross-sectional data than the older data used in the aforementioned studies; and (2) our firm-level panel data covers an extended period—up to 2015—for all countries.

One major issue to consider when constructing firm-level data is the need for data cleaning. We clean the Orbis database as follows: (1) we drop observations that include apparent reporting mistakes. For example, we drop firms with negative values for (total, tangible, or intangible) assets, sales, or the number of employees in any year; (2) we drop observations for which the cost of materials or cost of employees are missing or have nonpositive values; (3) we drop firms that lack the NACE codes because we cannot create their industry-specific time-fixed effects; (4) we drop observations with a negative firm age or negative liability; and (5) we drop firms whose ratio of liability to total assets or ratio of intangible assets to total assets exceeds unity. We also remove duplicate data; When we find duplicate accounts, we drop the accounts that are not used for annual reporting.

The dependent variable is the TFP growth approximated by the difference of natural logarithm of TFP estimated by the method explained in the last paragraph of the previous econometric approach subsection. We use five explanatory variables: (i) lagged TFP; (i) leverage; (ii) firm size; (iii) firm age; and (iv) intangible assets. The lagged TFP variable is the previous year's TFP level. Leverage is calculated as liabilities divided by total assets. Firm size is the natural logarithm of total assets. Firm age is the natural logarithm of firm age in years. Intangible assets are defined as the ratio of intangible assets to toal assets.

We employ criteria for selecting sampled countries. First, we include countries that have at least 2,000 observations in our analysis. The reason for this criterion is to avoid a small sample bias.[6] The second criterion is that we include countries with sufficient numbers of small and medium-sized enterprises (SMEs). Specifically, we include countries in which at least three fourths of the data samples consist of SMEs. There are two reasons for this second criterion: (1) we focus on the representativeness of our firm-level data when we perform a cross-country comparison; and (2) this is also to overcome the tendency of the Orbis data to be skewed toward large companies. The third criterion is that the sampled countries should have at least one hundred data observations for each sub-category of the food industry. The purpose of this third criterion is to enable us to conduct cross-country comparisons at the granular food industry level. The fourth criterion is to consider the characteristics of financial markets because we investigate the effects of financing on productivity. Using the IMF Financial Development Index database, we include countries with financial market depths higher than the average of all countries during the sample period so that we can compare the effects of financing for countries with similar degrees of financial market depth. Finally, as the fifth criterion for selecting sample countries, we take into account the regulatory quality of the countries. Namely, we only include countries with regulatory quality indices from the World Governance Indicators higher than the average of lower middle income countries. Put differently, we only include countries with governments' regulatory quality equivalent to that of upper-middle income and advanced countries. This is motivated by the fact that regulatory policies such as quality control of food products and transparency of the supply chain (e.g., inspection process, safety protocol, quality checking, sanitation requirement, procurement guideline) are vital factors that influence productivity and efficiency advancements of

[6] Although we do not have information about the firms' business status, it might be possible that the sample reflects the entry and exit of firms and is subject to potential sample selection bias.

food manufacturing companies. As a result, ten countries are included in our analysis: China, France, Germany, Italy, Japan, South Korea, Spain, Thailand, Turkey, and the United Kingdom (UK).

The number of sample firms, sample period, and descriptive statistics for each country are summarized in Table 1. A mean TFP of around 2 in China/Italy means that the ratio of output to labor and capital inputs is two; firms produce two units of output by using one unit of aggregate inputs. The mean TFP level depends on each country's food market structure. For example, the mean firm size is the smallest in France, which indicates the highest share of SMEs in France, because French food markets are too fragmented and the majority of food companies are small family-owned food processing businesses. The French meat industry (the largest food subsector in France) is composed mainly of small companies, and even French groups are quite small compared to their foreign competitors. An industrial composition also affects the national TFP average. Namely, food subsectors that have relatively low TFP levels (e.g., bakery) account for the larger shares in France relative to peers. As a result of the highest share of SMEs (with low TFP due to lack of scale economies) and the large shares of low-productivity food subsectors, the mean TFP level in France is the lowest in Table 1. The detailed distribution of the data sample across different food manufacturing industries for each country is shown in Table A2 in the Appendix. Table A2 shows the difference in food manufacturing distribution across countries, reflecting their different food cultures. For example, there are many bakeries in France and fish processing factories in Japan. Table A3 shows the average yearly growth rates of TFP across countries, demonstrating heterogeneity in TFP dynamics. For instance, the TFP of food manufacturing continued to grow over the past decade or so in South Korea and China, while it declined in Italy.

We compare our regression analyses across countries, but we do not attempt to generate a pooled estimate across countries. Note that it is not so simple to merge all country data for a pooled estimation because some companies are multinational corporations (MNCs). A MNC is headquartered in one country and have 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, organizational capital) and sell the same products.[7] MNCs often engage in transfer pricing and intra-firm financing for a global tax planning purpose, both of which further make it difficult to capture their real economic activities if their data are merged across borders.

Our empirical analysis shares similarities with Rajan and Zingales (1995). They utilized consistent samples of balance sheet variables for each country and reported within-country regressions. While they examined the stability of regression coefficients across countries and proposed explanations for variations based on institutional differences, their study did not investigate productivity.

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[7] In the case of Japanese multinationals, sharing the same intellectual property is evidenced by the repatriation of royalties from foreign affiliates to parent companies (Tajika and Nakatani, 2008).

4. Cross-country Analysis

In this section, we summarize the baseline results using the system GMM estimator in Table 2. Almost all countries' results indicate that productivity tends to catch up to the technology frontier of food manufacturing. This is manifested by the highly statistically significant negative coefficients of lagged TFP variables. Food companies with low TFP levels (that are distant from the frontier) experience higher TFP growth rates because they can increase their TFP by adopting the frontier technology to catch up with the productivity frontier. Conversely, high-productivity food companies (that are on the technology frontier) have less room for productivity improvement since they require new, expensive technologies and innovations to further increase productivity. The positive effects of leverage on TFP growth in the food manufacturing sector are also observed in most countries. We find that the impact of firm size on productivity growth is positive in most countries. Furthermore, we find mixed results on the effect of firm age on TFP growth. That is, in some countries, younger food companies tend to have higher TFP growth rates, while the opposite is true for other countries. The effects of intangible assets on TFP growth in the food manufacturing sector are heterogeneous across countries. We also conducted dynamic GMM estimations with the lagged dependent variables in Table A4 in the Appendix. We chose not to include the autoregressive term in our baseline estimation for two reasons: (1) the main stories from the results did not change; and (2) the lack of theoretical underpinnings—there is no theory to show that firms growing their TFP levels experience negative TFP growth in the next period (i.e., negative coefficient of lagged TFP growth rates) or experience positive TFP growth in the next period (i.e., positive coefficients of lagged TFP growth). Furthermore, we examined the difference in GMM estimation, and the empirical results did not change much. A detailed discussion of each explanatory variable is provided below.

First, lagged TFP variables are statistically significant at the one percent level, with the expected negative signs for all countries except China in Table 2. Namely, food manufacturing firms with low TFP levels experience higher levels of TFP growth across countries. This finding is consistent with the idea that TFP tends to catch up to the technology frontier, as low-productivity firms can increase their TFP by acquiring the existing technology capable of increasing TFP. This finding is consistent with Chang et al. (2019), who found that technical progress has been a major driving force of Taiwanese bakery. In contrast, high productivity firms have less room for TFP improvement as they require innovation to increase TFP further. The new technology is typically costly, and making such an investment to succeed in innovation involves high uncertainty levels. In terms of the size of the estimated coefficients, we find that the TFP convergence speed toward the frontier is slower in the food manufacturing sector compared to the ICT sector in Nakatani (2021a). The exceptional outcome of the positive coefficient of lagged TFP for China is driven by several specific food industries, such as the meat, vegetable, and bakery sectors. However, please note that the typical catching-up phenomenon of productivity convergence (i.e., negative coefficients of TFP level) holds for the dairy, grain, and starch sectors as well as start-up firms in China. Therefore, a possible explanation behind the results for China is that while some old meat/vegetable/bakery firms continue to expand the productivity frontier, at the same time, other old low-productivity companies in the same industries continue to deteriorate TFP further without exiting from the meat, vegetable, or bakery markets.

Second, the results for leverage show the expected signs, and the results are highly statistically significant for most countries except China. Our results show that leverage generally has a positive relationsihp with TFP growth of food manufacturing. This result indicates that leveraging financial resources can be key for firm performance in the food manufacturing sector. This finding is consistent with the empirical literature (e.g., Guevara-Rosero (2021)). In contrast, the leverage effect in China is likely to be influenced by the fact that more state-owned public banks and public companies exist in China compared to the Western countries. If bank credit is provided to companies that do not perform well but through other connections, such as political ties or family ties, financial leverage can actually lead to moral hazard owing to informational asymmetry between lenders (banks) and borrowers (companies). Furthermore, it could reduce productivity by allowing low-performance zombie firms. In fact, Shao et al. (2022) recently found empirical evidence citing that political connections were associated with zombification of Chinese manufacturing firms. To confirm this institutional hypothesis, in Figure 1, we plot the estimated coefficients of leverage on the vertical axis and the degree of financial access taken from the IMF Financial Development Index database on the horizontal axis. The financial access is calculated as the average value of the financial institution access indicator during the same data period as Table 1 for each country that has a statistically significant coefficient of leverage. We find that the low (negative) effects of leverage on productivity in China can be explained by the exceptionally low financial access due to the low quality of the financial institution in Figure 1.

Third, the coefficients of firm size are statistically significant at the one percent level for all countries. Among these ten countries, eight countries show positive coefficients, while two countries show negative coefficients.[8] The positive coefficients indicate that larger food manufacturing firms experience faster TFP growth than smaller firms. The positive coefficient of firm size indicates economies of scale in the food industry. The magnitude of scale economies (i.e., the size of estimated coefficients of firm size) in the food sector is found to be slightly smaller than that in the infrastructure sector studied by Nakatani (2023ad). We also examined a different definition of firm size for a further robustness check by using a lagged natural logarithm of sales in Table A5 in the Appendix. We found statistically significant positive coefficients in most countries.[9] This is not surprising because larger food manufacturing firms have more resources to invest in innovative activities to increase TFP. By contrast, in some advanced countries (Italy and Spain), smaller food manufacturing firms tend to show higher TFP growth.

Fourth, firm age exhibits statistical significance at the one percent level across nine countries. Among these, six countries (China, Japan, South Korea, Thailand, Turkey, and the UK) demonstrate a negative relationship between firm age and TFP growth, while the remaining countries (France, Italy, and Spain) show a positive association. The negative coefficient supports the life-cycle hypothesis of TFP dynamics

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[8] The coefficients of firm size are negatively statistically significant in Italy and Spain. The literature points out that the presence of market imperfections is a possible explanation of the inverse productivity-firm size relationship (Barrett et al., 2010; Chen et al., 2011).

[9] Turkey and the UK's results are dropped from Table A5 due to sample sizes too small for this specification.

(Huergo and Jaumandreu, 2004) and is consistent with Power's (1998) findings on U.S. manufacturing plants. Conversely, in the latter group of countries, TFP growth is positively correlated with firm age, indicating that younger food companies experience lower rates of productivity growth. This highlights the importance of considering country-specific circumstances when applying a uniform research framework to different economies. Additionally, we explore the potential nonlinear impact of firm size and firm age by including an interaction term in Table A6 of the Appendix.[10] However, we did not observe a clear pattern in this analysis.

Fifth, the results for intangible assets are heterogeneous. In our sample of ten countries, five countries have positive coefficients for intangible assets, implying that intangible assets are positively associated with TFP growth in the food manufacturing sector. For all five countries (Japan, Spain, Thailand, Turkey, and the UK), the coefficients are statistically significant at the one percent level. In contrast, the value of intangible assets' coefficient is negative and statistically significant at the one percent level in China, France, and South Korea. Our findings show the heterogeneous effects of intangible assets on TFP growth in the food manufacturing sector across countries.[11] We will dig into more details of intangible assets' effects in the industry-level analysis later in this paper, but at the cross-country level, we study the possible nonlinear effects of intangible assets in Table 3 by including its square term. We find that the coefficients of the squared term of intangible assets in Table 3 are positive and statistically significant in the majority of cases. Therefore, we conclude that intangible assets could nonlinearly affect TFP growth. Figure 2 shows the nonlinear effects of intangible assets on TFP growth, using the estimated linear and quadratic coefficients for countries with statistically significant coefficients. The figure shows that in most countries, the relationship between intangible assets and productivity growth is a convex function (e.g., Japan, the UK, Turkey). Figure 2 also indicates that in most countries, a higher share of intangible assets in total assets is nonlinearly associated with higher TFP growth.

Table A7 presents the results of the fixed effects estimation. The findings align closely with the GMM results, with the exception of intangible assets. Across the nine countries examined, positive coefficients for intangible assets are observed. Notably, the coefficients for France and Italy are statistically significant, indicating a meaningful relationship at least at the five percent level. In contrast, Japan exhibits a negative and statistically significant coefficient for intangible assets at the five percent

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[10] Aghion et al. (2019) and Nakatani (2023ad) found the nonlinear effect of leverage on TFP growth, which is analogous to the inverted U-shaped relationship between public debt and fiscal performance because net benefits to debt financing arise for firms or countries with low debt levels for better resource allocation but decrease as leverage reaches high levels, inducing moral hazard (Nakatani 2021b).

[11] An important time-variant omitted variable is managment capability, which is likely to be correlated with intangible assets. In this regard, the estimated coefficients of intangible assets may capture some effects from managment capability and the size of the coefficients could be somewhat overestimated, although this concern is mitigated by the fact that productivity is affected to a larger extent by innovation than management practices in high-income countries (Bartz-Zuccala et al., 2018), which is the case for our data.

level. These results from our robustness check underscore the diverse effects of intangible assets on TFP growth within the food manufacturing sector across different countries.

To compare our results for stocks of intangible assets to conventional estimates for the effects of R&D, we show the effects of R&D in Table A8. The R&D variable is defined as the ratio of R&D expenses to total expenses. As R&D was a major cause of the accumulation of intangible assets and these two variables were highly correlated, we excluded intangible assets from the explanatory variables in the regressions to avoid a multicollinearity problem. Due to a scarcity of R&D data available in our Orbis database, we could only estimate for six countries. Table A8 shows that the coefficients of R&D are statistically insignificant for the food industry. This supports our claim that it is better to use intangible assets as a variable representing a TFP enhancer rather than R&D expenses because intangible assets (e.g., intellectual property rights) are the actual assets that actuate value-addition. Our result is also consistent with the extant literature that found very lengthy lags between R&D and TFP growth in the agricultural/food sector.

To check whether the results are sensitive to the definition of TFP, we examine the alternative TFP measurement method of De Loecker and Warzynski (2012) in Table A9.[12] Compared to the baseline estimation in Table 2, more coefficients of intangible assets become positive and statistically significant in Table A9. The number of countries that showed positive effects of intangible assets on the TFP growth of food companies slightly increased from five to seven. The sign of the coefficients of firm age turned positive in a few countries. Aside from this, the main conclusions did not change significantly when we used a different definition of TFP.

As a final exercise for cross-country analysis, we study whether the TFP drivers are different for start-up firms, as shown in Table 4. To allow estimation of lagged TFP level in the regressions, we define start-up food companies as those whose firm age is less than two years. Due to the very small sample size of start-ups in some countries, we only show the estimation results that have more than 100 data points. Our results show that the catching-up of TFP to the technology frontier, as captured by the lagged TFP level, is the main productivity engine for start-ups. Since start-ups are at the beginning stage of financing from lenders, they cannot mobilize enough financial resources to reap productivity benefits. For this reason, the coefficients of the leverage variable are found to be negative and statistically significant in some countries.[13]

5. Industrial Analysis

We further analyze the TFP dynamics across different food manufacturing industries by splitting our cross-country data sample into six industries: (1) the meat and fish sector (NACE industry classification

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[12] De Loecker and Warzynski (2012) use revenue as a proxy for physical output, which presents a problem since it is justified as a local approximation and the variation in production data is large.

[13] It could also be the case that maturity of debt affected productivity (Nakatani, 2023bc) as start-up firms have just started to borrow money from lenders.

codes 1011-1020 in Table A1); (2) the fruit and vegetable sector (NACE codes 1031–1042); (3) the dairy sector (NACE codes 1051–1052); (4) the grain and starch sector (NACE codes 1061–1062); (5) the bakery sector (NACE codes 1071–1073); and (6) the other food sector (NACE codes 1081–1092). The results for each food manufacturing sector are shown in Tables 5–10.

Before we elaborate on each food industry's findings, we present some interesting patterns across countries. For instance, we find that intangible assets are negatively correlated with TFP dynamics in China's food manufacturing industries. This is consistent with the existing empirical literature on a recent surge in non-innovation-related Chinese patents. In China, the negative effects of intangible assets are statistically significant at the one percent level for the meat and fish sector, the bakery sector, and the other food sector as shown in Tables 5, 9, and 10, respectively. Hu et al. (2017) provides evidence that the number of patents has skyrocketed in China in recent years. However, these patents are not necessarily of high enough quality to increase productivity. Santacreu and Zhu (2018) found that the largest increase in the number of China's patents was for the utility category, followed by design patents, rather than invention patents. Furthermore, they stated that the actual technological improvement in China was not significant when compared with its escalating number of patents. Although food R&D in China has increased in recent years, it continues to lag behind that in high-income countries, such as Japan (Chai et al., 2019). Long and Wang (2019) found that patent promotion policies in China prompted a quantitative increase in patents but negatively affected the average patent quality, which could explain our findings regarding the negative coefficient for intangible assets in China.

This finding is a stark contrast to Japan's results as we find that the coefficients of intangible assets are always positive and statistically significant at the one percent level for all Japanese food manufacturing industries, as shown in Tables 5–10. This reflects the fact that Japanese manufacturing is the global technology frontier[14] and has better intellectual property (rights) protection of its high-quality patents. In contrast, we find that intangible assets are negatively correlated with TFP growth in almost all food manufacturing industries in South Korea. Different types of intangible assets could explain the contrast between Japan and South Korea. Chun et al. (2012) showed that innovative properties such as R&D and copyright account for the large share of intangible assets in the Japanese food manufacturing sector. In contrast, in the South Korean food manufacturing sector, economic competency such as brand equity accounts for the majority of intangible assets. Chun et al. (2012) empirically found that only investment in innovative property has a positive and significant effect on productivity growth; not economic competency. These conclusions explain why we find positive coefficients of intangible assets for Japan and negative coefficients of intangible assets for South Korea.

From here, we summarize our industrial findings by focusing on each TFP enabler. First, we find that TFP convergence toward the technology frontier is prevalent for all six food manufacturing industries. This is evidenced by the negative and highly statistically significant coefficients of lagged TFP levels in

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[14] In relation to food manufacturing, Japan is the global technology frontier also in the agriculture sector. Alston and Pardey (2014) find that Japan exhibits the highest agricultural labor productivity in the world.

Tables 5–10, except for a few industries in China. In terms of the convergence speed of TFP toward the productivity frontier, we find that two sectors are noteworthy. Namely, we find that the convergence speed of the dairy sector is the fastest in China, Germany, and the UK and that of the grain and starch sector is the fastest in Italy and Thailand. Technological adoption in the dairy sector was recently studied by Bonjean (2019), who found that dairy producers who crossed the entry threshold to the high-value market managed to obtain significantly higher returns, which happened through the increase in their production, facilitated by an improvement in their per-cow productivity and through the large set of improved agricultural practices. Further, Brümmer et al. (2002) found that TFP growth in the German dairy sector is driven by technical change (not by other reasons such as resource allocation). Our results on technological adoption may reflect such a practice in the dairy sector. An example of the latest frontier technology in the dairy industry is smart farming technology such as automatic milking systems (Rodenburg, 2017).

Second, the industrial analysis corroborates our main finding that leverage is positively associated with TFP growth in the broad range of food manufacturing industries across countries. For instance, the coefficients of leverage are positive and statistically significant at least at the five percent level for the meat and fish sector, the dairy sector, and the other food sector (of seven countries), as shown in Tables 5, 7, and 10, respectively. This finding reflects the financial needs to expand processing capacity in the meat and seafood industries.

Third, economies of scale are found to be an important TFP enhancer for most food industries. Our findings are consistent with those of Azzam et al. (2004), who found that economies of scale contribute to TFP growth in food processing firms, and those of Morrison et al. (2004), who found that small agricultural firms (e.g., family farms) are scale-inefficient. Table 8 shows that firm size's positive coefficients are statistically significant, at least at the five percent level for all ten counties' grain and starch sector. This is a very robust empirical finding, and is also supported by the fact that the coefficients of firm size are the largest for the grain and starch sector among all food industries in France, Germany, and Italy. This finding of economies of scale in the grain sector is consistent with the recent finding by Sheng and Chancellor (2019) and Key (2019), who documented the scale economies for grain producers in Australia and the United States, respectively. Majumder et al. (2016) also found evidence of scale economies in the rice sector in Bangladesh. An economic intuition behind this finding is that the grain and starch sector benefits more from scale economies because (1) it needs more capital equipment than other food sectors and (2) the sector produces less diversified products (i.e., fewer niche products), which minimizes sunk costs. Furthermore, Table 6 shows that the coefficients of firm size are positive and highly statistically significant for the fruit and vegetable sector of nine countries. Table 7 shows a similar story for the dairy sector, consistent with scale economies in dairy farms found by Mosheim and Lovell (2009), Baležentis and Sun (2020), and Alem (2023). Tables 9 and 10 indicate that economies of scale (positive and statistically significant coefficients of firm size) are widespread in the bakery and the other food sectors as well. Therefore, we conclude that economies of scale are imperative for the grain and starch sector to improve TFP, followed by the fruit and vegetable sector, dairy sector, bakery sector, and the other food sector.

Fourth, firm age is an important determinant of TFP growth in the fruit and vegetable sector and the other food sector. This is evidenced by the fact that Tables 6 and 10 show that firm age's negative coefficients are statistically significant, at least at the five percent level in seven out of the ten sample countries. This means that young fruit and vegetable processing firms tend to show higher TFP growth rates than old ones, indicating that firm dynamics are crucial for the fruit and vegetable sector.

Finally, intangible assets are positively correlated with TFP growth in some food manufacturing industries. We find that the coefficients of intangible assets are highly statistically significant for the bakery sector in nine countries (as shown in Table 9) and the other food sector in eight countries (as shown in Table 10). This may reflect the inference that brand image is sometimes vital for the bakery industry. The size of the positive coefficients of intangible assets is the largest for the grain and starch sector in France, Japan, and Turkey, and the meat and fish sector in Italy and the UK. Our results also indicate that intangible assets are statistically significant for all food manufacturing industries and positively correlated with TFP growth in two advanced countries: Japan and Spain. In addition to our abovementioned explanation about Japan, this finding is also consistent with the fact that Spain is the country that accumulated intangible capital in the manufacturing sector at the fastest speed in our sample of European countries (Jona-Lasinio and Meliciani, 2019). Moreover, five out of six food manufacturing industries in the UK exhibit the favourable and highly statistically significant coefficients of intangible assets. This finding of advanced economies can be supported by the claim by Johnson and Evenson (1999), who found that most international technology transfer (through patents) in agriculture occurs between high-income countries.

6. Conclusion and Policy Implications

This research derives five novel findings that the extant literature on TFP has not explored so far: (i) heterogeneous, nonlinear effects of intangible assets on TFP (Table 3 and Figure 2); (ii) product market regulations and the effects of intangible assets on TFP growth (Figure 3); (iii) detailed TFP drives of different food manufacturing industries (Tables 5–10); (iv) the institutional impact of financial development on leverage effects on TFP growth (Figure 1); and (v) the productivity effects of intangible assets for start-up food manufacturing companies (Table 4). The detailed discussions on these new findings and related policy advice for agrifood business are as follows.

First, we found that intangible assets nonlinearly influence TFP growth (Table 3). Using the estimated coefficients of intangible assets, Figure 2 indicates that higher asset intangibility would improve the TFP growth of food manufacturing companies nonlinearly in most countries. The policy implication of this finding is that incentives for intangible investment should be encouraged for countries with prudent intangible assets and intellectual protection schemes (e.g., patent; licensing). Doing so will promote innovation and raise TFP. For example, patents can incentivize agricultural and food processing firms to conduct an expensive and long-lasting research program (Lence et al., 2016). Protecting intellectual property rights is important for production companies to avoid getting discouraged by the illegal imitation of property rights and avoid being disincentivized from such abuses. Otherwise, incentives for conducting productive R&D and other legally adopted productivity-enhancing technologies will not be warranted. A well-targeted tax policy for R&D, such as an R&D tax credit, could be an option to stimulate R&D investment (Rao, 2016; Nakatani, 2019b). Contrastingly, direct subsidies to the R&D of incumbent food manufacturers should be carefully reviewed because they encourage the survival and expansion of low-productivity firms (Acemoglu et al., 2018). Moreover, Pisulewski and Marzec (2022) found that subsidies increase persistent technical inefficiency in the dairy sector.

Second, we found that it is fundamental to raise the quality of intangible assets. As discussed in the industrial analysis section, increasing patents unrelated to technological improvement (e.g., utility and design patents) in China did not increase their productivity (Santacreu and Zhu, 2018). Therefore, patent policies should focus on quality instead of quantity. Further, as the contrast between Japanese food manufacturing companies and South Korean ones was discussed in detail in the industrial analysis section, we learned that the types of intangible assets may matter for TFP growth. In other words, innovative intellectual property such as R&D can increase the TFP levels of food manufacturing, although different intangible assets such as goodwill may not contribute to productivity growth. Thus, policymakers should carefully formulate policies to enhance productive intangible investment to raise TFP levels of the food sector in the digitalization era. To enhance the quality of intangible assets, regulatory obstacles must also be considered. Figure 3 shows the relationship between product market regulations (PMRs) and the effects of intangible assets on TFP growth for countries with available data. In Figure 3, the coefficients of intangible assets are shown on the vertical axis, taken from our baseline estimation in Table 2. On the horizontal axis, the ecnomy-wide PMR indicators in 2013 are taken from OECD data.[15] Figure 3 clearly shows that countries with fewer PMRs show larger productivity-enhancing effects from intangible assets.

Third, we found that the main TFP drivers differ across different food manufacturing industries. For instance, it is crucial to increase the share of young firms in the vegetable and fruit sector and the other food sector to improve TFP growth.[16] Therefore, any obstacles that hinder the entry of new firms into these sectors should be removed. Newcomers in the market would also enhance incumbents' productivity growth by increasing competition (Fritsch and Changoluisa, 2017). Policies to promote entry include lifting barriers to competition in food markets and promoting labor market flexibility to facilitate resource reallocation. The latter is important because labor-saving automation technology in the fruit and vegetable sector—that is, mechanical harvesting of fruits/vegetables (e.g., self-propelled harvester for processed tomatoes, self-propelled catch harvester for oranges, self-propelled mechanical harvester for fresh-market apples or sweet cherries, etc.)—generally lag behind other food sectors because consumers demand fresh market products with minimal blemishes, bruises, or damage (Huffman, 2012). Although our results indicate that old food companies tend to show slower TFP

[15] Data on economy-wide regulations are used here because we do not have data on food-industry specific regulations comparable across countries. The previous study by Kapelko et al. (2015) found that food safety regulation increases production costs, such as costs for additional hygiene measures and costs for implementing tracing systems, leading to organizational disruptions in implementing technologies.

[16] The caveat of young firms includes that they often do not have vertical relationships developed, which can make them less effective, and they lack experience in learning by doing.

growth, this does not necessarily imply that they should exit from fruit and vegetable markets. For example, if we investigate the TFP growth rates and TFP levels of Korean vegetable and fruit companies classified by their firm age, Figure 4 shows that as companies get older, their average TFP level becomes higher and their average TFP growth rate decelerates. This is attributed to the importance of selection effects—that is, the best companies survive longer in the markets.

In contrast, economies of scale[17] are prevalent in many food manufacturing sectors (the grain and starch sector, the fruit and vegetable sector, the dairy sector, the bakery sector, and the other food sector), and are most prominent in the grain and starch sector. Firms can achieve economies of scale by specializing labor and utilizing more efficient capital equipment, allowing them to produce greater output with fewer inputs. However, it is important to note that economies of scale are not always productivity-enhancing. In many cases, there are diseconomies of scale, which entail a tradeoff between the size and efficiency of the economy. The growth in scale can lead to either productivity-enhancing economies of scale or productivity-depleting diseconomies of scale. To harness the potential benefits of economies of scale, it may be prudent to implement a competition policy that encourages mergers and acquisitions (M&A) in the food manufacturing sectors. Such a policy would enable these sectors to fully exploit economies of scale, leading to increased TFP in the food sector and improved national food security. The presence of competitive domestic food manufacturing companies can be advantageous during unforeseen events like wars or natural disasters that disrupt the global supply chain. One downside risk of M&As for consumers is the potential for markets to become oligopolistic, allowing food manufacturing firms to earn monopolistic rents. However, the abundance of local bakeries, greengroceries, and other food markets across countries mitigates this concern and makes it less significant for consumers.

Fourth, our results indicate that improving financing is crucial for the broad food industries, including the meat[18] and fish sector, the dairy sector, and the other food sector. Food manufacturing companies can improve TFP growth by increasing the availability of financial resources. Better access to financing for food companies could lead to better resource allocation and eventually raise TFP levels. Agricultural/food productivity would benefit more from credit access and expansion (Sabasi et al., 2021), especially in rural areas (Rada and Buccola, 2012). Government programs that promote access to credit for limited-resource firms would increase investment and productivity (Key, 2020). In contrast, credit constraints could hamper optimal resource allocation for food manufacturing firms and deter productivity-enhancing investments. The effects of credit on technology adoption are larger for credit-constrained producers compared to credit non-users (Regassa et al., 2023). Countries should also

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[17] The extant literature found that economies of scale or economies of scope are achieved by vertical integration of the production process (see Parcel et al., 2018; Azzam and Skinner, 2007; and Azzam, 1998 for the case of hog production; and Azzam and Schroeter, 1995 for the beef-packing industry). Kapelko and Lansink (2013) also found larger Spanish dairy processing firms were more efficient than smaller ones.

[18] Xia and Buccola (2002) found that technical change appears to be capital-using in the meat processing industries. This implies that financing capital equipment is necessary to improve technological improvement in the meat processing sector.

improve the quality of financial institutions because better access to financing could utilize the productivity-enhancing effect of leverage, as seen in Figure 1. It would also be useful to develop macroprudential policies to avoid distress in the banking sector (Nakatani, 2020) and address non-performing loans so that commercial banks do not constrain food manufacturing companies' financing.

Finally, we found that intangible assets play a relatively minor role in enhancing the productivity growth of start-up companies (Table 4). This might reflect a business reality: new entrants continue to be in the learning process of new food markets, so companies may not be able to achieve leverage entirely from purchasing or accumulating intangible assets and mobilizing financial resources. Instead, we found that the main productivity driver of start-up firms is productivity convergence toward the technological frontier, consistent with the learning-by-doing hypothesis of entrepreneurship.

A limitation of this research is the application of a single-producer price index for countries where producer-input and -output price indices are not available; we believe this might have impacted the estimation of TFP. A caveat of this research is that the data in the current study ends in 2015, so future research could extend the time period and use more recent data on food companies.

Possible future research areas include elucidating the mechanism and theory by which intangible assets nonlinearly affect productivity growth. This might be due to the difference in the types of intangible assets. Future research could also decipher the effects of specific food regulations on the effects of intangible assets on productivity, although we imposed a threshold of regulatory quality for selecting our sample countries. Focusing on single-country analysis is likely to be desirable for regulation analysis, as the specificities of food regulations might differ across food industries in different countries.

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Table 1: Summary Statistics

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Number of Firms	12694	18054	874	9058	3093	4289	11513	1588	651	1582
TFP										
Mean	2.0991	0.4656	6.1275	2.0375	2.4251	2.2143	1.1589	2.2911	1.4539	3.5588
Standard Deviation	0.1746	0.6124	0.8045	0.6126	0.2766	0.2336	0.5964	0.3470	0.1674	0.4636
Min.	0.5010	-6.6871	2.0899	-3.3915	0.5409	0.7467	-4.1787	0.2621	0.5680	0.9967
Max.	2.9198	3.8997	8.3203	5.1022	4.2688	2.9949	4.1311	3.4904	2.0696	5.1059
Leverage (=liabilities/total assets)										
Mean	0.4756	0.6501	0.7009	0.7482	0.6725	0.6288	0.6043	0.5063	0.6239	0.5910
Standard Deviation	0.2600	0.2203	0.2196	0.2001	0.2318	0.2088	0.2533	0.2893	0.2145	0.2280
Min.	0	0.0152	0.0368	0	0.0168	0	0.0018	0.0002	0.0029	0.0032
Max.	1	1	1	1	0.9986	1	1	1	0.9913	1
Size (=log total assets)										
Mean	14.7718	13.1500	16.4064	14.8522	16.1209	14.7592	13.8597	14.7127	16.0112	15.9530
Standard Deviation	1.3830	1.4325	1.8389	1.5933	1.4801	1.3184	1.7358	2.1755	1.7688	2.1089
Min.	9.2860	7.7553	9.2445	7.3238	10.7180	6.7935	7.8850	7.5240	9.6738	7.0825
Max.	23.1470	21.8581	22.6039	21.8405	22.8676	21.0712	21.6629	23.3404	21.3507	24.7237
Age (=log age)										
Mean	1.9952	2.4414	3.2513	2.7787	3.5018	2.1462	2.6719	2.6890	2.7073	2.9740
Standard Deviation	0.5984	0.8183	0.9729	0.8499	0.6035	0.7260	0.6782	0.7086	0.7132	0.8766
Min.	0	0.6931	0	0	0.6931	0	0	0	0	0
Max.	4.9767	4.8363	6.5280	4.8442	4.8442	4.1589	4.9767	4.3307	4.5218	4.8675
Intangible Assets (=intangible assets/total assets)										
Mean	0.0293	0.4325	0.0383	0.1169	0.0109	0.0231	0.0672	0.0033	0.0574	0.0540
Standard Deviation	0.0948	0.3580	0.1093	0.1883	0.0398	0.0912	0.1489	0.0282	0.1185	0.1536
Min.	0	0	0	0	0	0	0	0	0	0
Max.	0.9539	0.9999	0.9999	0.9987	1	0.9796	1	0.9730	0.9334	0.9998
Year	2005–14	2006–15	2003–14	1998–15	2002–15	2003–15	1996–15	2003–15	2005–15	1997–15
Cleansed Portion (%)	0.012	0.004	0.785	0.008	0.000	0.005	0.007	0.000	0.000	0.000

Table 2: Baseline System GMM Estimation

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	0.0631***	-0.7693***	-0.1037***	-0.0701***	-0.3953***	-0.3374***	-0.1028***	-0.1408***	-0.3970***	-0.4262***
	(0.0132)	(0.0210)	(0.0156)	(0.0074)	(0.0159)	(0.0268)	(0.0093)	(0.0015)	(0.0090)	(0.0031)
Leverage	-0.2101***	0.1700***	0.1534***	0.1790***	-0.0205	0.0274	0.1379***	0.0511***	0.0532***	0.1100***
	(0.0046)	(0.0201)	(0.0206)	(0.0193)	(0.0158)	(0.0184)	(0.0139)	(0.0017)	(0.0020)	(0.0011)
Size	0.0100***	0.0765***	0.0427***	-0.0161***	0.0215***	0.0311***	-0.0110***	0.0113***	0.0231***	0.0761***
	(0.0005)	(0.0061)	(0.0065)	(0.0038)	(0.0025)	(0.0045)	(0.0031)	(0.0004)	(0.0006)	(0.0008)
Age	-0.0436***	0.0623***	-0.0116	0.0404***	-0.0366***	-0.0313***	0.0226***	-0.0340***	-0.0309***	-0.0189***
	(0.0019)	(0.0046)	(0.0081)	(0.0058)	(0.0057)	(0.0054)	(0.0053)	(0.0007)	(0.0007)	(0.0019)
Intangible Assets	-0.0450***	-0.0429***	-0.2932*	-0.0139	0.1987***	-0.0636***	0.0613***	0.0921***	0.1001***	0.1933***
	(0.0024)	(0.0158)	(0.0166)	(0.0169)	(0.0182)	(0.0181)	(0.0108)	(0.0008)	(0.0075)	(0.0030)
Constant	-0.0801***	-0.8939***	-0.1262**	0.1301***	0.7486***	0.3537***	0.1137***	0.2259***	0.2574***	0.2948***
	(0.0199)	(0.0748)	(0.5766)	(0.0435)	(0.0692)	(0.0763)	(0.0435)	(0.0019)	(0.0055)	(0.0139)
Wald Chi^2 (5)	149267.54	1826.83	111.39	351.19	851.42	757.12	553.62	168197.29	87830.60	110805.55
Observations	45,677	106,968	5,102	75,289	22,104	22,052	102,271	11,229	2,579	10,899

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 3: Results for Nonlinear Effects of Intangible Assets

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	0.0564***	-0.7438***	-0.1311***	-0.0750***	-0.3328***	-0.3170***	-0.1203***	-0.1332***	-0.4428***	-0.3868***
	(0.0113)	(0.0191)	(0.0024)	(0.0067)	(0.0006)	(0.0067)	(0.0087)	(0.0000)	(0.0012)	(0.0000)
Leverage	-0.2058***	0.1842***	0.1785***	0.1722***	-0.0064***	0.0203***	0.1094***	0.0491***	0.0479***	0.1039***
	(0.0060)	(0.0182)	(0.0014)	(0.0178)	(0.0012)	(0.0053)	(0.0129)	(0.0000)	(0.0004)	(0.0000)
Size	0.0113***	0.0807***	0.0543***	-0.0122***	0.0236***	0.0382***	-0.0098***	0.0108***	0.0259***	0.0687***
	(0.0004)	(0.0058)	(0.0009)	(0.0034)	(0.0003)	(0.0023)	(0.0029)	(0.0000)	(0.0002)	(0.0000)
Age	-0.0466***	0.0515***	0.0050	0.0362***	-0.0181***	-0.0416***	0.0205***	-0.0326***	-0.0230***	-0.0127***
	(0.0021)	(0.0044)	(0.0011)	(0.0053)	(0.0008)	(0.0027)	(0.0050)	(0.0000)	(0.0004)	(0.0000)
Intangible Assets	-0.1166***	-0.4959***	-0.1197***	0.0353	-0.0831***	-0.1721***	0.2612***	0.0593***	-0.0153***	-0.1302***
	(0.0065)	(0.0480)	(0.0036)	(0.0321)	(0.0024)	(0.0116)	(0.0269)	(0.0001)	(0.0010)	(0.0000)
Intangible Assets Squared	0.1611***	0.4851***	0.1892***	-0.0600	0.5290***	0.2094***	-0.3589***	0.0262***	0.2296***	0.4728***
	(0.0159)	(0.0432)	(0.0042)	(0.0453)	(0.0053)	(0.0089)	(0.0468)	(0.0001)	(0.0008)	(0.0001)
Constant	-0.0820***	-0.9030***	-0.2204**	0.0971**	0.4921***	0.2323***	0.1362***	0.2136***	0.2652***	0.2631***
	(0.0168)	(0.0711)	(0.0132)	(0.0890)	(0.0057)	(0.321)	(0.0409)	(0.0000)	(0.0029)	(0.0003)
Wald Chi^2 (5)	412509.70	2096.46	36988.02	257.01	333156.56	6892.13	444.09	4.74e+09	4.56e+07	2.58e+10
Observations	45,677	106,968	5,102	75,289	22,104	22,052	102,271	11,229	2,579	10,899

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 4: Results for Start-ups

Country	China	France	Italy	South Korea	Spain	Thailand
Lagged TFP	-0.3792***	-0.2725***	-0.0908***	-0.3538***	-0.1322*	-0.1453***
	(0.0515)	(0.1068)	(0.0853)	(0.0314)	(0.0767)	(0.0848)
Leverage	-0.1126***	-0.5254	-0.0138	-0.0275	0.2846	-0.0685***
	(0.0380)	(0.8486)	(0.4937)	(0.0708)	(0.2847)	(0.0867)
Size	0.0023	-0.0027	0.0002	-0.0182**	0.0199	-0.0060***
	(0.0079)	(0.1161)	(0.0238)	(0.0074)	(0.0255)	(0.0114)
Intangible Assets	0.0262	-0.2270	0.6571**	-0.2203***	0.0887	0.5509
	(0.0533)	(0.3464)	(0.3063)	(0.0204)	(0.2301)	(1.7421)
Constant	0.8301***	0.6197	-0.0003	1.1192***	-0.3456	0.5232***
	(0.1219)	(1.0578)	(0.4111)	(0.1116)	(0.3670)	(0.1609)
Wald Chi^2 (5)	81.44	7.67	15.63	392.49	4.91	10.75
Observations	1,887	1,457	1,357	1,095	1,122	186

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 5: Results for the Meat and Fish Sector

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	0.0531**	-0.3182***	-0.1179***	-0.0730***	-0.2676***	-0.4636***	-0.3114***	-0.0945***	-0.1888***	-0.2316***
	(0.0224)	(0.0297)	(0.0052)	(0.0090)	(0.0080)	(0.0062)	(0.0151)	(0.0006)	(0.0110)	(0.0005)
Leverage	-0.1655***	0.2074***	0.1489***	0.1297***	-0.0274***	0.0482***	0.2563***	-0.0258***	0.0431***	0.0555***
	(0.0154)	(0.0302)	(0.0026)	(0.0238)	(0.0101)	(0.0086)	(0.0258)	(0.0002)	(0.0021)	(0.0007)
Size	0.0130***	0.0005	0.0326***	-0.0009	0.0079***	0.0354***	-0.0328***	0.0173***	0.0219***	0.0359***
	(0.0024)	(0.0077)	(0.0022)	(0.0049)	(0.0016)	(0.0012)	(0.0050)	(0.0000)	(0.0006)	(0.0002)
Age	-0.0511***	0.0375***	-0.0007	0.0052	-0.0313***	-0.0379***	-0.0032	-0.0327***	-0.0100	-0.0238***
	(0.0085)	(0.0075)	(0.0025)	(0.0076)	(0.0029)	(0.0023)	(0.0084)	(0.0001)	(0.0068)	(0.0004)
Intangible Assets	-0.0666***	0.0382*	-0.0420***	0.0439**	0.1500***	-0.0179***	0.0495***	-0.0396***	-0.1218***	0.1769***
	(0.0129)	(0.0221)	(0.0042)	(0.0214)	(0.0055)	(0.0038)	(0.0165)	(0.0002)	(0.0115)	(0.0004)
Constant	-0.1086***	0.0172	0.1054***	0.0447	0.6614***	0.5991***	0.7371***	0.0616***	-0.0693***	0.3097***
	(0.0277)	(0.0996)	(0.0193)	(0.0684)	(0.0353)	(0.0197)	(0.0711)	(0.0014)	(0.0082)	(0.0057)
Wald Chi^2 (5)	7.67e+06	193.32	12378.32	179.07	1526.92	7913.44	511.04	6.64e+06	1.18e+06	9.67e+06
Observations	7,787	19,048	1,351	16,964	6,490	6,343	26,800	981	178	2,317

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 6: Results for the Fruit and Vegetable Sector

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	0.2977***	-0.4149***	-0.0619***	-0.0983***	-0.2346***	-0.3462***	-0.3199***	-0.2253***	-0.3048***	-0.2412***
	(0.0119)	(0.0080)	(0.0027)	(0.0096)	(0.0003)	(0.0065)	(0.0109)	(0.0031)	(0.0096)	(0.0002)
Leverage	-0.1498***	0.0184	0.3204***	0.1912***	-0.0380***	-0.0564***	0.2808***	0.0229***	0.0545***	0.0204***
	(0.0148)	(0.0144)	(0.0020)	(0.0336)	(0.0002)	(0.0052)	(0.0238)	(0.0040)	(0.0026)	(0.0003)
Size	0.0002***	0.0526***	0.0151***	0.0055	0.0156***	0.0321***	0.0274***	0.0150***	0.0203***	0.0362***
	(0.0015)	(0.0052)	(0.0022)	(0.0055)	(0.0000)	(0.0017)	(0.0050)	(0.0008)	(0.0002)	(0.0001)
Age	-0.0291***	-0.0336***	-0.0285***	0.0140	0.2186***	-0.0394***	-0.0224**	-0.0243***	-0.0019*	-0.0077***
	(0.0044)	(0.0060)	(0.0027)	(0.0099)	(0.0001)	(0.0016)	(0.0089)	(0.0018)	(0.0011)	(0.0001)
Intangible Assets	-0.0174	-0.0643***	0.0054	0.0141	0.2063***	0.0052	0.1996***	0.2158***	0.1366***	0.0619***
	(0.0162)	(0.0114)	(0.0164)	(0.0220)	(0.0006)	(0.0045)	(0.0204)	(0.006)	(0.0027)	(0.0001)
Constant	0.0768***	-0.2877***	-0.0045	-0.0656	0.2547***	0.4186***	-0.0700	0.3504***	0.0830***	0.2948***
	(0.0178)	(0.0702)	(0.0193)	(0.0614)	(0.0006)	(0.0206)	(0.0757)	(0.0070)	(0.0167)	(0.0013)
Wald Chi^2 (5)	1387.54	3260.39	5.48e+06	199.60	5.43e+07	12861.29	1089.12	2.99e+06	1.84e+06	9.91e+07
Observations	9,185	2,966	594	11,617	2,195	3,830	10,444	1,924	586	1,365

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 7: Results for the Dairy Sector

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	-0.2951***	-0.2236***	-0.1793***	-0.2046***	-0.1531***	-0.0556***	-0.1627***	-0.1048***	-0.1276***	-0.3747***
	(0.0610)	(0.0135)	(0.0029)	(0.0112)	(0.0046)	(0.0044)	(0.0030)	(0.0061)	(0.0055)	(0.0010)
Leverage	-0.0855***	0.0324	0.3509***	0.1846***	-0.0141	0.0357***	0.0592***	0.0142***	0.0486***	0.0586***
	(0.0205)	(0.0280)	(0.0065)	(0.0219)	(0.0049)	(0.0031)	(0.0039)	(0.0045)	(0.0060)	(0.0019)
Size	0.0394***	0.0524***	0.0314***	0.0088*	0.0251***	0.0028**	0.0189***	0.0106***	0.0065***	0.0625***
	(0.0059)	(0.0078)	(0.0012)	(0.0048)	(0.0007)	(0.0012)	(0.0012)	(0.0008)	(0.0003)	(0.0004)
Age	-0.0758***	0.0442***	0.0638***	0.0092	-0.0046***	0.0046***	-0.0234***	-0.0070***	-0.0034*	0.0013**
	(0.0089)	(0.0096)	(0.0004)	(0.0065)	(0.0009)	(0.0008)	(0.0019)	(0.0037)	(0.0019)	(0.0006)
Intangible Assets	-0.0303	-0.0263	-0.0350***	0.0107	0.1257***	-0.0483***	0.1371***	-0.0444***	0.0080***	0.0479***
	(0.0254)	(0.0250)	(0.0022)	(0.0168)	(0.0093)	(0.0048)	(0.0028)	(0.0152)	(0.0011)	(0.0025)
Constant	0.2170***	-0.6589***	0.2159***	0.1411**	0.0065	0.0620***	-0.0522***	0.1007***	0.0669***	0.3136***
	(0.0548)	(0.0959)	(0.0133)	(0.0603)	(0.01238)	(0.0196)	(0.0138)	(0.0121)	(0.0086)	(0.0020)
Wald Chi^2 (5)	1707.60	379.94	258448.70	404.03	251119.08	283168.40	5993.89	18537.47	2.17e+06	1.08e+09
Observations	1,553	4,528	679	12,079	844	407	6,026	397	223	883

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 8: Results for the Grain and Starch Sector

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	-0.1807***	-0.5059***	-0.1120***	-0.3463***	-0.1083***	-0.2211***	-0.3822***	-0.2805***	-0.3287***	-0.1059***
	(0.0476)	(0.0038)	(0.0170)	(0.0003)	(0.0052)	(0.0000)	(0.0002)	(0.0009)	(0.0130)	(0.0127)
Leverage	-0.1412***	0.2401***	0.1370***	0.3150***	-0.0043	-0.0453***	0.2524***	0.1311***	0.0544***	0.0157
	(0.0194)	(0.0093)	(0.0526)	(0.0005)	(0.0027)	(0.0001)	(0.0003)	(0.0001)	(0.0030)	(0.0242)
Size	0.0191***	0.0891***	0.0361***	0.0204***	0.0094***	0.0362***	0.0039***	0.0123***	0.0006**	0.0188***
	(0.0042)	(0.0033)	(0.0079)	(0.0002)	(0.0018)	(0.0000)	(0.0001)	(0.0002)	(0.0003)	(0.0046)
Age	-0.0159**	0.0380***	0.0072	-0.0113***	0.0194***	-0.0409***	-0.0151***	-0.0157***	0.0515***	-0.0084
	(0.0064)	(0.0028)	(0.0193)	(0.0003)	(0.0021)	(0.0000)	(0.0002)	(0.0003)	(0.0016)	(0.0115)
Intangible Assets	-0.0120	0.2278***	-0.0755	-0.1279***	0.5358***	-0.1264***	0.1320***	0.1635***	0.1890***	-0.0299
	(0.0172)	(0.0113)	(0.0569)	(0.0005)	(0.0688)	(0.0001)	(0.0002)	(0.0038)	(0.0017)	(0.0708)
Constant	0.2135***	-1.0337***	0.0087	0.3270***	0.0283	0.1026***	0.4253***	0.4582***	0.2952***	0.1009
	(0.0508)	(0.0457)	(0.0491)	(0.0026)	(0.0285)	(0.0002)	(0.0010)	(0.0042)	(0.0198)	(0.0813)
Wald Chi^2 (5)	1743.26	35068.68	1096.34	2.34e+06	1086.81	5.43e+08	1.87e+09	5.49e+07	5.33e+06	1216.73
Observations	8,398	2,276	235	4,347	714	2,056	3,114	2,512	372	472

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 9: Results for the Bakery Sector

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	0.0524***	-0.6799***	-0.0633***	-0.1771***	-0.2113***	-0.2099***	-0.4535***	-0.2669***	-0.2982***	-0.2302***
	(0.0120)	(0.0219)	(0.0007)	(0.0104)	(0.0003)	(0.0005)	(0.0192)	(0.0093)	(0.0225)	(0.0001)
Leverage	-0.1395***	-0.0049	0.0005	0.1449***	0.0098***	-0.0324***	0.0156	-0.0069	0.0286***	0.0978***
	(0.0123)	(0.0167)	(0.0005)	(0.0153)	(0.0004)	(0.0003)	(0.0166)	(0.0054)	(0.0065)	(0.0000)
Size	-0.0015	0.0826***	0.0216***	0.0064**	0.0075***	0.0229***	0.0077*	0.0158***	0.0236***	0.0304***
	(0.0018)	(0.0068)	(0.0002)	(0.0030)	(0.0001)	(0.0001)	(0.0040)	(0.0011)	(0.0014)	(0.0000)
Age	-0.0184**	0.0123***	0.0037***	0.0171***	0.0137***	-0.0181***	-0.0235***	-0.0020	-0.0070***	0.0028***
	(0.0073)	(0.0042)	(0.0001)	(0.0053)	(0.0002)	(0.0002)	(0.0054)	(0.0028)	(0.0023)	(0.0000)
Intangible Assets	-0.0970***	0.1705***	0.0682***	0.0196	0.3204***	-0.0089***	0.1399***	0.0990***	0.0346***	0.0231***
	(0.0229)	(0.0134)	(0.0003)	(0.0128)	(0.0003)	(0.0007)	(0.0120)	(0.0153)	(0.0059)	(0.0000)
Constant	0.0285	-1.0210***	-0.0042**	0.0489	0.3101***	0.1868***	0.2621***	0.3800***	0.0520***	0.2454***
	(0.0255)	(0.0867)	(0.0017)	(0.0319)	(0.0015)	(0.0016)	(0.0506)	(0.0078)	(0.0190)	(0.0002)
Wald Chi^2 (5)	325.20	1471.09	1.83e+08	376.92	3.18e+06	1.07e+06	728.30	57651.44	2.36e+07	1.22e+09
Observations	3,095	66,820	919	16,925	2,716	1,934	33,225	524	238	1,910

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 10: Results for the Other Food Sector

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	-0.0001	-0.5392***	-0.1324***	-0.2083***	-0.4450***	-0.2904***	-0.1283***	-0.1441***	-0.4617***	-0.2360***
	(0.0151)	(0.0307)	(0.0038)	(0.0124)	(0.0035)	(0.0187)	(0.0141)	(0.0009)	(0.0037)	(0.0001)
Leverage	-0.2031***	0.1293***	0.0423***	0.1789***	-0.0441***	0.0226	0.1116***	0.0360***	0.0199***	0.0720***
	(0.0095)	(0.0483)	(0.0032)	(0.0233)	(0.0112)	(0.0172)	(0.0229)	(0.0007)	(0.0018)	(0.0001)
Size	0.0149***	0.0610***	0.0315***	-0.0005	0.0292***	0.0363***	-0.0041	0.0104***	0.0307***	0.0402***
	(0.0018)	(0.0120)	(0.0011)	(0.0048)	(0.0017)	(0.0047)	(0.0043)	(0.0001)	(0.0003)	(0.0000)
Age	-0.0540***	0.0286**	-0.0165***	0.0345***	-0.0456***	-0.0333***	0.0195**	-0.0192***	-0.0497***	-0.0036***
	(0.0059)	(0.0144)	(0.0021)	(0.0069)	(0.0039)	(0.0062)	(0.0082)	(0.0002)	(0.0017)	(0.0000)
Intangible Assets	-0.0428***	-0.0205	0.0503***	-0.0077	0.3982***	-0.0387***	0.0335**	0.0629***	0.0866***	0.1443***
	(0.0065)	(0.0346)	(0.0030)	(0.0163)	(0.0075)	(0.0121)	(0.0144)	(0.0002)	(0.0016)	(0.0000)
Constant	-0.0022	-0.6074	0.3256***	0.1883***	0.7746***	0.1648***	0.0986	0.2136***	0.3095***	0.1681***
	(0.0168)	(0.1403)	(0.0188)	(0.0703)	(0.0338)	(0.0636)	(0.0668)	(0.0028)	(0.0040)	(0.0003)
Wald Chi^2 (5)	180078.93	367.55	11997.70	346.36	103455.80	601.15	230.17	7.51e+07	91484.86	4.48e+09
Observations	15,659	11,330	1,324	13,357	9,145	7,482	22,662	4,891	982	3,952

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Figure 1: Financial Development and Leverage Effects

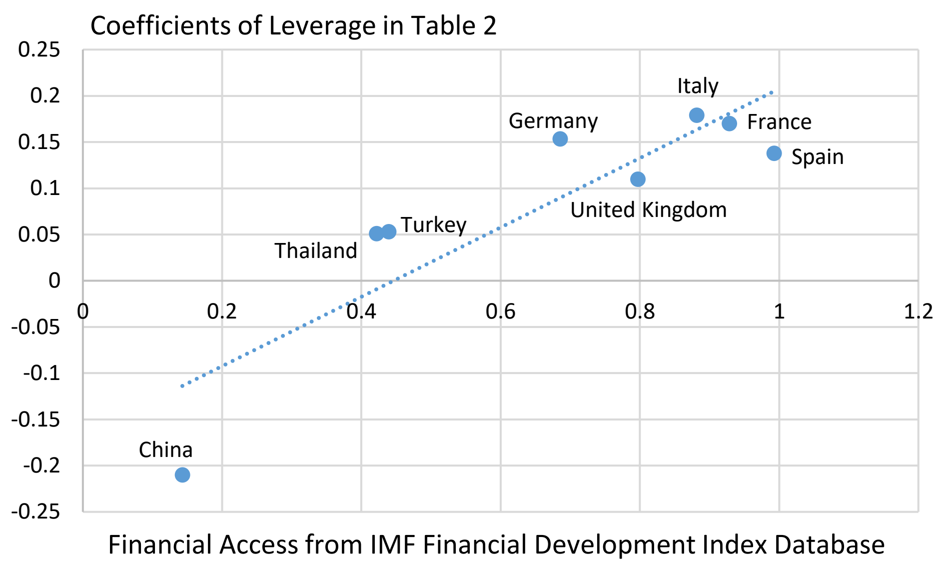


Figure 2: Nonlinear Effects of Intangible Assets on Productivity Growth

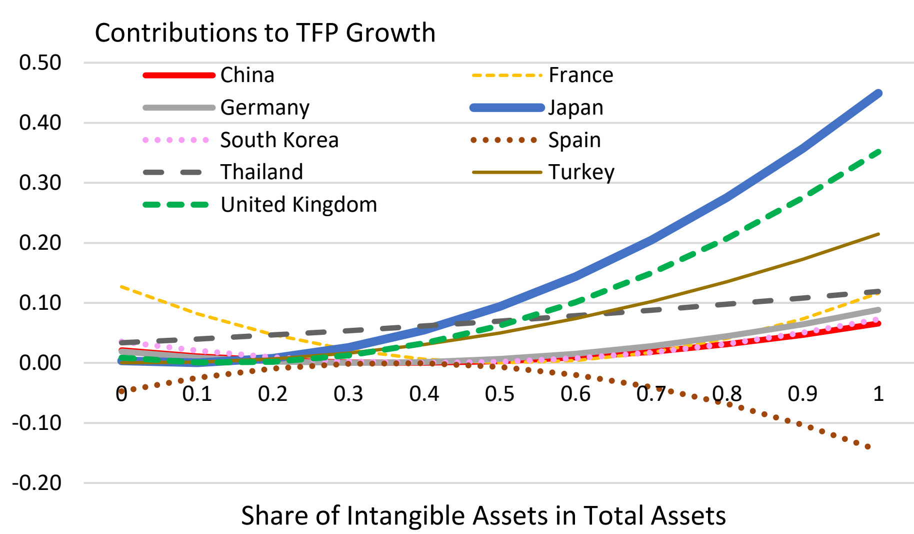


Figure 3: Product Market Regulations and Effects of Intangible Assets

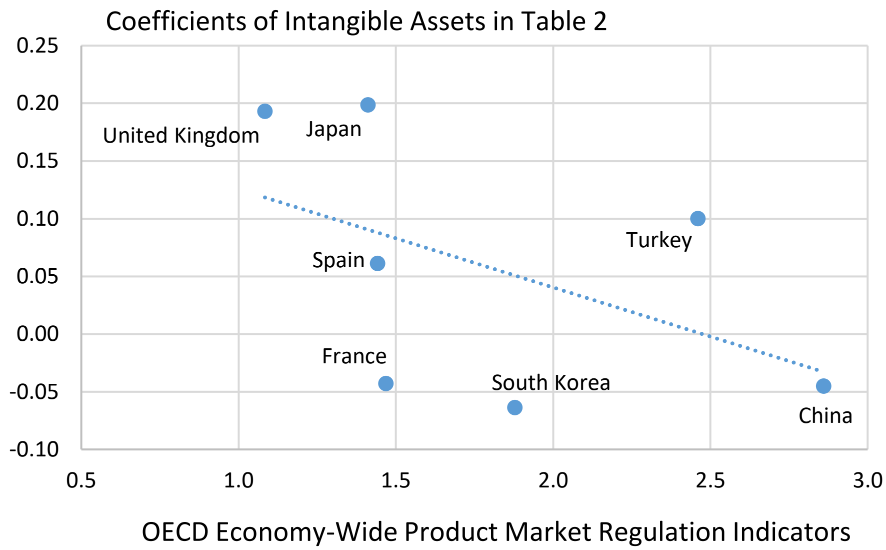
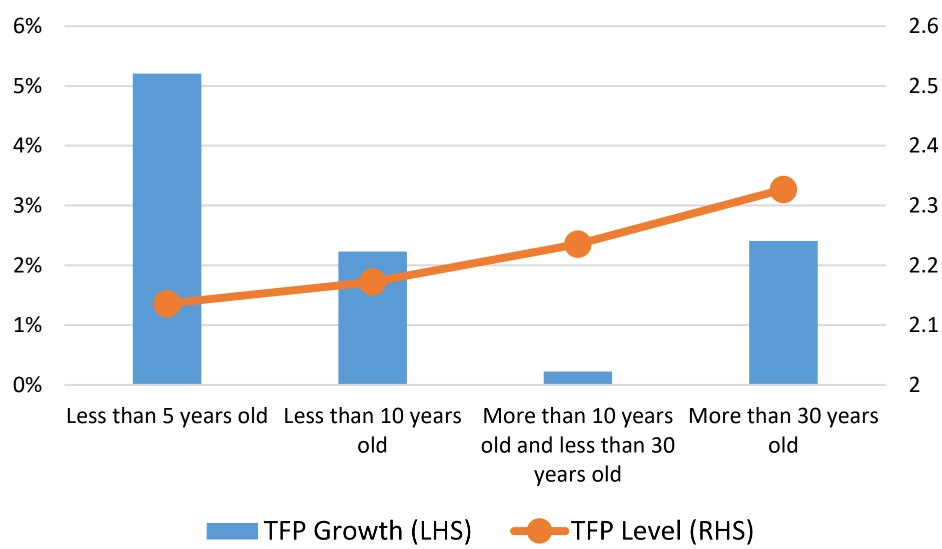


Figure 4: Vegetable and Fruit Companies in South Korea



Appendix

Here, we explain the estimation method of TFP. Gandhi et al. (2020) developed a nonparametric identification strategy for gross output production functions that is employed when additional sources of variation in the demand for flexible inputs are unavailable. Their identification strategy is to regress revenue shares on inputs to identify the flexible input elasticity, solve the partial differential equation, and integrate 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 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 can be decomposed into the Markovian component ω_{jt} and ex-post productivity shock ε_{jt}. The production function is differentiable at all inputs and strictly concave in intermediate input. The intermediate-input demand $m_{jt} = M_t(k_{jt}, l_{jt}, m_{jt})$ is postulated to be strictly monotone in a single unobservable ω_{jt}. Firms are price takers in the output and intermediate input markets. They demonstrate 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 $d_t \equiv ln(\rho_t/P_t) - ln\mathcal{E}$ 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, the authors 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 show that the restrictions implied by the optimizing behavior of the firm, 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 productivity, even absent additional sources of exogenous variation in flexible inputs. 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 the flexible input elasticity. Then, we can 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: Four-digit Industry Classifications in Food Manufacturing

1000 Manufacture of food products
1010 Processing and preserving of meat and production of meat products
1011 Processing and preserving of meat
1012 Processing and preserving of poultry meat
1013 Production of meat and poultry meat products
1020 Processing and preserving of fish, crustaceans, and mollusks
1020 Processing and preserving of fish, crustaceans, and mollusks
1030 Processing and preserving of fruit and vegetables
1031 Processing and preserving of potatoes
1032 Manufacture of fruit and vegetable juice
1039 Other processing and preserving of fruit and vegetables
1040 Manufacture of vegetable and animal oils and fats
1041 Manufacture of oils and fats
1042 Manufacture of margarine and similar edible fats
1050 Manufacture of dairy products
1051 Operation of dairies and cheese making
1052 Manufacture of ice cream
1060 Manufacture of grain mill products, starches, and starch products
1061 Manufacture of grain mill products
1062 Manufacture of starches and starch products
1070 Manufacture of bakery and farinaceous products
1071 Manufacture of bread; manufacture of fresh pastry goods and cakes
1072 Manufacture of rusks and biscuits; manufacture of preserved pastry goods and cakes
1073 Manufacture of macaroni, noodles, couscous, and similar farinaceous products
1080 Manufacture of other food products
1081 Manufacture of sugar
1082 Manufacture of cocoa, chocolate, and sugar confectionery
1083 Processing of tea and coffee
1084 Manufacture of condiments and seasonings
1085 Manufacture of prepared meals and dishes
1086 Manufacture of homogenized food preparations and dietetic food
1089 Manufacture of other food products not elsewhere classified
1090 Manufacture of prepared animal feeds
1091 Manufacture of prepared feeds for farm animals
1092 Manufacture of prepared pet foods

Source: Eurostat

Table A2: Sample Size Across Detailed Food Manufacturing Industries (number of data points [number of firms])

Industry	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Processing and preserving of meat and production of meat products	5157	18002	1207	14974	1835	4297	23153	314	149	1729
	[1201]	[2612]	[233]	[1642]	[271]	[890]	[2363]	[41]	[40]	[253]
Processing and preserving of fish, crustaceans, and molluscs	3271	1045	135	1989	4638	2040	3563	667	29	568
	[799]	[164]	[25]	[234]	[650]	[402]	[363]	[82]	[5]	[88]
Processing and preserving of fruit and vegetables	6820	2304	403	7062	1839	2358	5855	1444	412	1199
	[1564]	[360]	[67]	[831]	[253]	[473]	[619]	[198]	[103]	[180]
Manufacture of vegetable and animal oils and fats	3322	662	190	4555	338	1468	4546	480	174	150
	[791]	[103]	[24]	[637]	[36]	[274]	[598]	[65]	[46]	[20]
Manufacture of dairy products	1664	4528	675	12077	842	407	6003	397	223	877
	[406]	[677]	[98]	[1335]	[110]	[68]	[711]	[52]	[57]	[132]
Manufacture of grain mill products, starches, and starch products	9459	2276	235	4347	711	2055	3100	2511	372	469
	[2090]	[304]	[33]	[426]	[88]	[399]	[307]	[409]	[102]	[48]
Manufacture of bakery and farinaceous products	3376	66817	895	16923	2708	1933	33141	524	238	1910
	[765]	[12127]	[173]	[2502]	[417]	[359]	[4190]	[68]	[68]	[313]
Manufacture of other food products	11479	9121	951	10124	8498	5885	16669	3839	662	2961
	[2671]	[1409]	[158]	[1123]	[1183]	[1143]	[1764]	[531]	[157]	[426]
Manufacture of prepared animal feeds	5531	2209	367	3232	605	1590	5893	1051	320	970
	[1289]	[298]	[63]	[328]	[91]	[280]	[602]	[142]	[73]	[128]

Table A3: Average Yearly TFP Growth Rates (percent)

Year	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Before 2000	N/A	N/A	N/A	-2.367	N/A	N/A	-1.810	N/A	N/A	0.278
2000–2005	0.764	N/A	0.762	-1.518	-0.081	1.111	-1.201	0.978	-1.355	1.755
2006–2010	1.075	-0.114	0.701	-0.967	-0.682	1.283	-1.680	0.324	0.322	0.685
2011–2015	1.090	-0.233	0.472	-0.149	0.267	1.549	0.353	0.483	0.749	0.537

Table A4: Dynamic GMM Estimation

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP Growth	-0.5797***	0.2877***	-0.1517***	-0.1120***	-0.1691***	-0.0721***	-0.0584***	-0.1448***	-0.0981***	-0.0455***
	(0.0115)	(0.0202)	(0.0210)	(0.0220)	(0.0095)	(0.0252)	(0.0193)	(0.0017)	(0.0095)	(0.0019)
Lagged TFP	-0.5587***	-0.9253***	-0.0933***	-0.0576***	-0.3335***	-0.2164***	-0.1128***	-0.0951***	-0.3594***	-0.3064***
	(0.0188)	(0.0288)	(0.0189)	(0.0074)	(0.0181)	(0.0338)	(0.0092)	(0.0018)	(0.0152)	(0.0015)
Leverage	-0.1898***	0.2089***	0.0925***	0.1435***	-0.0215	0.0702***	0.0872***	0.0596***	0.0565***	0.0832***
	(0.0073)	(0.0205)	(0.0215)	(0.0159)	(0.0140)	(0.0164)	(0.0117)	(0.0018)	(0.0030)	(0.0010)
Size	0.0477***	0.1129***	0.0402***	-0.0187***	0.0171***	0.0260***	-0.0080***	0.0071***	0.0126***	0.0543***
	(0.0022)	(0.0076)	(0.0078)	(0.0037)	(0.0028)	(0.0052)	(0.0029)	(0.0004)	(0.0013)	(0.0006)
Age	-0.1120***	0.0601***	-0.0114	0.0336***	-0.0299***	-0.0209***	0.0168***	-0.0356***	0.0267***	-0.0091***
	(0.0057)	(0.0050)	(0.0089)	(0.0061)	(0.0055)	(0.0060)	(0.0057)	(0.0006)	(0.0037)	(0.0013)
Intangible Assets	-0.0241***	-0.0220	0.0676***	-0.0035	0.2857***	-0.0320**	0.0856***	0.1003***	0.0872***	0.1460***
	(0.0035)	(0.0173)	(0.0140)	(0.0153)	(0.0253)	(0.0156)	(0.0115)	(0.0008)	(0.0061)	(0.0021)
Constant	0.8128***	-1.3334***	-0.1100***	0.1888***	0.6499***	0.1096	0.1318***	0.1869***	0.2124***	0.2048***
	(0.0165)	(0.0946)	(0.0603)	(0.0412)	(0.0777)	(0.0733)	(0.0405)	(0.0021)	(0.0312)	(0.0096)
Wald Chi^2 (6)	1.58e+07	1196.75	124.41	287.83	1881.32	355.06	503.72	168197.29	87830.60	237745.50
Observations	25,908	82,369	3,446	62,589	17,504	15,450	82,306	11,229	1,689	8,484

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table A5: Alternative Measure of Firm Size

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand
Lagged TFP	-0.2144***	-0.6540***	-0.1332***	-0.0811***	-0.3636***	-0.4696***	-0.1288***	-0.3002***
	(0.0075)	(0.0166)	(0.0128)	(0.0079)	(0.0105)	(0.0177)	(0.0086)	(0.0010)
Leverage	-0.0604***	0.0800***	0.0794***	0.1266***	0.0010	0.0689***	0.1027***	0.0138***
	(0.0017)	(0.0147)	(0.0143)	(0.0160)	(0.0118)	(0.0111)	(0.0120)	(0.0016)
Log Sales	0.0269***	0.0914***	0.0615***	-0.0045	0.0292***	0.0523***	-0.0109***	0.0296***
	(0.0008)	(0.0048)	(0.0057)	(0.0033)	(0.0019)	(0.0030)	(0.0027)	(0.0003)
Age	-0.0455***	0.0341***	-0.0567***	0.0288***	-0.0119***	-0.0163***	0.0179***	-0.0140***
	(0.0017)	(0.0037)	(0.0075)	(0.0042)	(0.0044)	(0.0022)	(0.0043)	(0.0007)
Intangible Assets	-0.0127***	-0.0197	0.0169	-0.0118	0.1898***	-0.0754***	0.0861***	0.0756***
	(0.0012)	(0.0131)	(0.0133)	(0.0156)	(0.0154)	(0.0149)	(0.0102)	(0.0008)
Constant	0.1635***	-1.0745***	-0.1177**	0.0523	0.0438***	0.2567***	0.1773***	0.2720***
	(0.0100)	(0.0608)	(0.0498)	(0.0358)	(0.0474)	(0.0358)	(0.0351)	(0.0027)
Wald Chi^2 (6)	6.35e+06	2181.35	256.91	461.07	1372.84	1504.00	858.08	259746.31
Observations	45,677	106,949	5,102	75,255	20,646	22,052	102,180	11,224

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table A6: Inclusion of the Interaction Term of Firm Size and Firm Age

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	0.0144	-0.7788***	-0.1042***	-0.0684***	-0.4210***	-0.2965***	-0.1099***	-0.2049***	-0.4141***	-0.4229***
	(0.0189)	(0.0218)	(0.0160)	(0.0079)	(0.0162)	(0.0270)	(0.0094)	(0.0014)	(0.0106)	(0.0031)
Leverage	-0.1943***	0.1670***	0.1580***	0.1828***	-0.0374**	0.0366**	0.1389***	0.0344***	0.0523***	0.1115***
	(0.0035)	(0.0204)	(0.0214)	(0.0207)	(0.0167)	(0.0186)	(0.0139)	(0.0019)	(0.0025)	(0.0012)
Size	0.1100***	0.0529**	0.0681***	-0.0218*	-0.1040***	-0.0261***	-0.0751***	-0.0116***	0.0236***	0.0701***
	(0.0020)	(0.0225)	(0.0149)	(0.0118)	(0.0159)	(0.0095)	(0.0121)	(0.0006)	(0.0048)	(0.0030)
Age	0.4722***	-0.0509	0.1198	0.0127	-0.6018***	-0.3555***	-0.2931***	-0.1997***	-0.0260	-0.0536***
	(0.0159)	(0.1019)	(0.0745)	(0.0547)	(0.0702)	(0.0500)	(0.0578)	(0.0026)	(0.0262)	(0.0148)
Size*Age	-0.0376***	0.0087	-0.0080*	0.0019	0.0356***	0.0224***	0.0234***	0.0110***	-0.0003**	0.0022**
	(0.0009)	(0.0079)	(0.0045)	(0.0038)	(0.0045)	(0.0034)	(0.0043)	(0.0002)	(0.0016)	(0.0009)
Intangible Assets	-0.0584***	-0.0432***	-0.0217	-0.0155	0.2164***	-0.0630***	0.0602***	0.0839***	0.0967***	0.1856***
	(0.0016)	(0.0159)	(0.0165)	(0.0171)	(0.0206)	(0.0176)	(0.0109)	(0.0008)	(0.0079)	(0.0028)
Constant	-1.3752***	-0.5851**	-0.5384**	0.2053	2.7996***	1.0777***	0.9768***	0.7251***	0.2758***	0.3759***
	(0.0499)	(0.2916)	(0.2436)	(0.1535)	(0.2574)	(0.1343)	(0.1634)	(0.0099)	(0.0859)	(0.0510)
Wald Chi^2 (6)	3.92e+06	1853.64	111.13	352.61	1019.24	754.99	581.96	52084.22	30437.83	103400.87
Observations	45,677	106,968	5,102	75,289	22,104	22,052	102,271	11,229	2,579	10,899

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table A7: Fixed-effects Estimation

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	-0.6715***	-0.5670***	-0.4170***	-0.4874***	-0.3827***	-0.6068***	-0.4292***	-0.5005***	-0.7600***	-0.4350***
	(0.0057)	(0.0029)	(0.0183)	(0.0034)	(0.0055)	(0.0066)	(0.0028)	(0.0094)	(0.0236)	(0.0091)
Leverage	-0.0016	0.1011***	0.0417	0.0628***	0.0428***	0.0268***	0.0805***	0.0404***	0.0148	0.0506***
	(0.0025)	(0.0048)	(0.0287)	(0.0078)	(0.0059)	(0.0045)	(0.0048)	(0.0084)	(0.0132)	(0.0078)
Size	0.0034***	-0.0290***	0.1285***	0.0240***	-0.2550***	0.0276***	-0.0054***	0.0252***	0.0025	0.0468***
	(0.0009)	(0.0020)	(0.0115)	(0.0025)	(0.0021)	(0.0017)	(0.0017)	(0.0033)	(0.0049)	(0.0029)
Age	0.0271***	0.0284***	-0.0336	-0.0094**	-0.0077	-0.0206***	0.0026	-0.0166**	-0.0088	-0.0012
	(0.0033)	(0.0036)	(0.0216)	(0.0045)	(0.0056)	(0.0034)	(0.0035)	(0.0077)	(0.0134)	(0.0061)
Intangible Assets	0.0004	0.0360***	0.0677	0.0182**	-0.0421**	0.0107	0.0081	0.0693	0.0092	0.0132
	(0.0051)	(0.0042)	(0.0443)	(0.0072)	(0.0199)	(0.0114)	(0.0053)	(0.0500)	(0.0179)	(0.0142)
Constant	1.3207***	0.4893***	0.5387***	0.6077***	1.3383***	0.9784***	0.5071***	0.8067***	1.0088***	0.7846***
	(0.0177)	(0.0279)	(0.1989)	(0.0395)	(0.0384)	(0.0244)	(0.0242)	(0.0522)	(0.0808)	(0.0516)
4 Digit Industry-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,867	103,284	4,519	73,763	21,520	20,682	100,422	11,020	2,385	10,418
R-squared	0.557	0.441	0.407	0.366	0.380	0.512	0.324	0.362	0.600	0.403

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table A8: Results of R&D

Country	China	Japan	South Korea	Thailand	Turkey	United Kingdom
Lagged TFP	-0.7306***	-0.7759***	-0.6071***	-0.6032***	-0.7587***	-0.8948***
	(0.1766)	(0.0264)	(0.0066)	(0.0152)	(0.0234)	(0.0870)
Leverage	0.2033***	0.1374***	0.0264***	0.0481***	0.0149	0.0936
	(0.0683)	(0.02896)	(0.0045)	(0.0134)	(0.0132)	(0.0564)
Size	0.0623**	-0.0878***	0.0277***	0.0457***	0.0024	0.0548***
	(0.0280)	(0.0109)	(0.0017)	(0.0050)	(0.0049)	(0.0204)
Age	-0.0320	-0.0288	-0.0207***	-0.0314**	-0.0080	0.0355
	(0.1013)	(0.0292)	(0.0033)	(0.0154)	(0.0135)	(0.1013)
R&D	-0.0598	0.0231	0.0045	0.0146	-0.0120	-0.1075
	(0.1847)	(0.1000)	(0.0135)	(0.06487)	(0.0287)	(0.1424)
Constant	0.4691	3.3002***	0.9796***	0.8119***	1.0867***	2.2747***
	(0.5900)	(0.0206)	(0.0245)	(0.0857)	(0.0810)	(0.5736)
4 Digit Industry-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114	1,895	20,676	5,307	2,383	212
R-squared	0.771	0.671	0.512	0.435	0.600	0.717

Dependent variables are TFP growth calculated by the method of Gandhi et al. (2020). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table A9: Different TFP Measure

Country	China	France	Germany	Italy	Japan	South Korea	Spain	Thailand	Turkey	United Kingdom
Lagged TFP	-1.2316***	-0.3085***	-0.2659***	-0.1760***	-0.3303***	-0.2775***	-0.1056***	-0.1018***	-0.5062***	-0.2284***
	(0.0027)	(0.0072)	(0.0095)	(0.0116)	(0.0088)	(0.0189)	(0.0055)	(0.0012)	(0.0059)	(0.0013)
Leverage	0.0634***	-0.1038***	0.0797***	0.1158***	-0.0149**	-0.0155	0.0667***	0.0273***	-0.0169***	-0.0004*
	(0.0016)	(0.0077)	(0.0118)	(0.0126)	(0.0060)	(0.0304)	(0.0063)	(0.0006)	(0.0026)	(0.0002)
Size	0.0113***	0.1405***	0.0207***	-0.0417***	0.0188***	-0.0011	-0.0098***	0.0068***	0.0216***	-0.0039***
	(0.0002)	(0.0024)	(0.0025)	(0.0025)	(0.0009)	(0.0073)	(0.0015)	(0.0001)	(0.0003)	(0.0001)
Age	-0.0039***	0.0197***	0.0139**	0.0971***	-0.0144***	0.0232***	-0.0236***	0.0004	0.0089***	0.0060***
	(0.0008)	(0.0020)	(0.0056)	(0.0037)	(0.0019)	(0.0084)	(0.0021)	(0.0004)	(0.0012)	(0.0003)
Intangible Assets	-0.0053***	0.0481***	0.1711***	-0.0387***	0.1022***	-0.0526**	0.1241***	0.0399***	0.0242***	0.0444***
	(0.0006)	(0.0063)	(0.0095)	(0.0114)	(0.0091)	(0.0524)	(0.0052)	(0.0005)	(0.0016)	(0.0004)
Constant	0.4456***	-0.4716***	-0.1163***	0.6725***	0.2018***	0.6320***	0.5815***	0.0949***	0.1126***	0.4285***
	(0.0039)	(0.0415)	(0.0400)	(0.0321)	(0.0238)	(0.1082)	(0.0235)	(0.0011)	(0.0059)	(0.0033)
Wald Chi^2 (5)	3.77e+08	5017.70	1171.65	1088.41	2645.97	240.53	1982.21	84676.35	1.92e+06	51685.40
Observations	45,605	106,968	5,102	75,289	22,090	22,052	102,271	11,180	2,567	10,899

Dependent variables are TFP growth calculated by the method of De Loecker and Warzynski (2012). Notations of independent variables are the same as in Table 1. Standard errors are in parentheses.
*p<0.1, **p<0.05, ***p<0.01.