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Sources of Productivity Growth by Firm Size and Causes of the Negative Exit Effect[‡]

Kyoji Fukao[§], YoungGak Kim[*], and Hyeog Ug Kwon[†]

Abstract

This study examines the dynamics of total factor productivity (TFP) by firm size to clarify the recent drivers of productivity growth in the Japanese economy, utilizing firm-level financial data from Teikoku Databank (TDB) spanning the years 1999 to 2020. In particular, we examine Japan's distinctive "negative exit effect" by differentiating among various types of firm exit, including bankruptcy, closure, dissolution, and mergers. Our analysis shows that while within-firm productivity improvements at large firms played a dominant role in driving productivity growth through the 2000s, reallocation effects have become increasingly important since the 2010s. Notably, a substantial share of high-productivity firms exited the market through mergers, accounting for nearly half of the overall negative exit effect. Furthermore, while TFP among acquiring firms tends to stagnate in the short term after mergers, their labor productivity shows a significant and sustained increase, likely driven by capital deepening. These findings provide new insights into the shifting drivers of productivity growth in Japan—from within-firm productivity growth to market-driven resource reallocation—as well as into firm-size heterogeneity and the role of mergers in shaping productivity dynamics.

JEL Codes: O47, D24, L25, O53, G34

Keywords: productivity dynamics; firm size heterogeneity; negative exit effect; mergers and acquisitions; resource reallocation; total factor productivity; SMEs; Japan

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1. Introduction

Since the 1990s, numerous empirical studies using firm- and establishment-level data have been conducted to investigate the causes of Japan's sluggish productivity growth. These studies have yielded three key findings.

First, the primary cause of the slowdown in productivity growth has been a sharp decline in within-firm productivity improvements (Fukao and Kwon, 2006; Fukao, Kim, and Kwon, 2008). One possible explanation for this decline is the stagnation in firms' investments in intangible assets such as information and communication technology (ICT), research and development (R&D), and human capital (e.g., Takizawa, 2015; Fukao et al., 2016).

Second, Japan's market mechanism of creative destruction has not functioned properly. Bartelsman and Doms (2000), reviewing studies on productivity dynamics in developed economies, find that roughly 50% of productivity growth in these economies is attributable to the effects of entry and exit and the reallocation of resources among incumbent firms. In contrast, studies focusing on Japan have consistently shown that resource reallocation effects are markedly weaker than in other countries. Nishimura, Nakajima, and Kiyota (2005), Fukao and Kwon (2006), and Caballero, Hoshi, and Kashyap (2008) report that low-productivity firms that should exit or shrink remain in the market, while high-productivity firms that should survive or expand are instead shrinking or exiting. Such distortions hinder productivity growth at both the industry and macroeconomic levels. This phenomenon is referred to in prior research—and in this paper—as the "negative exit effect." According to Fukao, Kim, and Kwon (2006), who analyzed plant-level data from the Census of Manufactures since the mid-1980s, Japan's weak creative destruction and negative exit effects were already present in the late 1980s. Therefore, the sharp slowdown in TFP growth since the 1990s cannot be solely attributed to the rise in so-called zombie firms. Furthermore, Fukao, Kim, and Kwon (2019), who examined the productivity dynamics of virtually all publicly listed firms since the 1960s, find that even during the period of rapid economic growth, the main source of TFP growth in both manufacturing and non-manufacturing was internal within-firm productivity growth, not resource reallocation, suggesting that creative destruction in Japan has historically been weak.

Third, the performance of small and medium-sized enterprises (SMEs) has deteriorated more severely than that of large firms. Kim, Fukao, and Makino (2010) and Ikeuchi et al. (2013) show that even during the so-called "lost decades" from the 1990s onward, large factories (or large firms) continued to achieve relatively high TFP growth, whereas small factories (or SMEs) experienced substantial stagnation. Several factors may explain this stagnation among SMEs, including insufficient R&D investment (Yamaguchi et al., 2019), delayed globalization through exports and outward FDI (Kim, Fukao, and Makino, 2010), and underinvestment in ICT (Fukao et al., 2016). Belderbos et al. (2025) also point out that the relocation of production bases overseas by large firms may have weakened their transaction relationships with SMEs, thereby reducing positive technology spillovers.

While many studies have investigated the productivity dynamics of the Japanese economy since the 1990s, several gaps remain. First, existing research has not sufficiently examined differences across firm size groups. For example, Ikeuchi et al. (2022) analyze productivity dynamics using the Credit Risk Database (CRD), which primarily covers SMEs, and find that the negative exit effect is driven mainly by a small number of relatively large firms. However, the dataset they use does not include large firms. Fukao et al. (2021) and Kim (2024) analyze productivity dynamics by firm size using other datasets; however, these datasets provide limited coverage of SMEs.

Moreover, some exiting firms that appear to leave the data in fact merged with other firms. In such cases, if the productivity of the merged entity is higher than the combined productivity of the pre-merger firms, the exit may be welfare-enhancing for the economy.

Against this backdrop, this study conducts a productivity dynamics analysis by firm size group—large firms, mid-sized firms, and small firms—using Teikoku Databank (TDB) data. This dataset encompasses a substantial number of SMEs and provides information on mergers and acquisitions (M&As). We also examine whether the negative exit effect observed in Japan is primarily driven by M&As or by bankruptcies and closures.

This study makes significant contributions to the literature in several important ways. First, it indicates that the primary driver of productivity growth in Japan is shifting from within-firm improvements to reallocation across firms. Second, we find that the exit effect continues to be a substantial drag on aggregate productivity growth. Unlike the positive exit effect observed in the U.S. and European economies, Japan's exit effect continues to be negative—a distinctive feature of its productivity dynamics. Third, we demonstrate that a substantial portion of the negative exit effect can be attributed to exits through mergers. Fourth, we find that the labor productivity of acquiring firms tends to increase over time after mergers, suggesting that the exit of high-productivity firms through mergers may enhance economic welfare.

The rest of the paper is structured as follows. Section 2 describes the data and the methods used to measure productivity. Section 3 presents the main results of the productivity dynamics analysis. Section 4 discusses the nature of the negative exit effect in detail. Section 5 concludes.

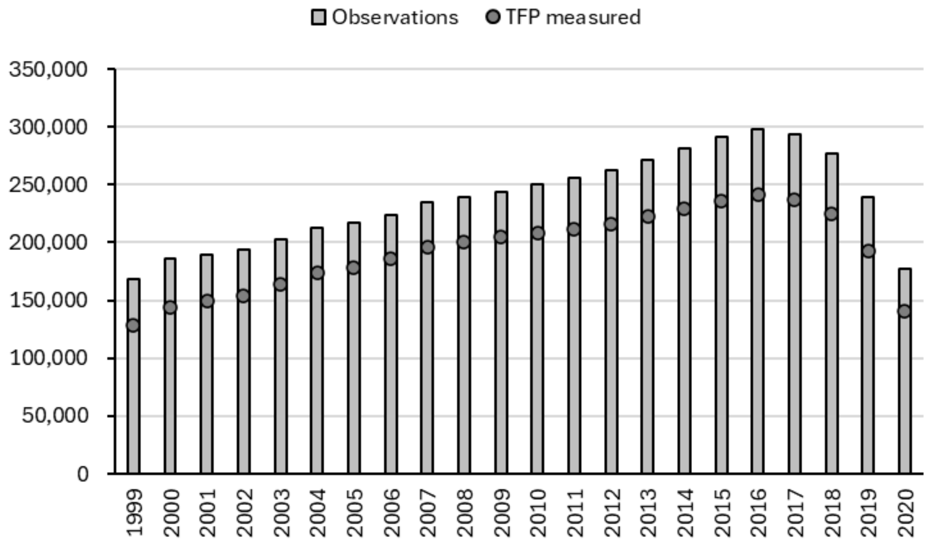
2. Data and Measurement of Productivity

2.1. Data

As described in the previous section, this study mainly uses the corporate financial data provided by Teikoku Databank (TDB), which covers a wide range of small and medium-sized enterprises

(SMEs).[1] The dataset spans from 1999 to 2020 and contains an annual average of 236,795 firms, amounting to over five million firm-year observations in total. Among these, TFP can be measured for approximately 81% of firm-year observations.

Figure 1. Number of Firms in the TDB database (by year)



Source: Authors' calculations using TDB data.
Note: "TFP measured" refers to observations for which TFP is calculated using Equations (1) and (2) below.

2.2. Definition of Firm Size

A key strength of the TDB data is its extensive coverage of small firms. For analytical purposes, we categorize firms into the following three groups based on size:

(1) Small firms: Firms classified as SMEs under the definition provided by the Basic Act on Small and Medium Enterprises and the Industrial Competitiveness Enhancement Act (see Appendix Table A1).

(2) Mid-sized firms: Firms with fewer than 2,000 employees (excluding those classified as SMEs) based on the revised 2024 definition in the Industrial Competitiveness Enhancement Act.

(3) Large firms: Firms with more than 2,000 employees.

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[1] Teikoku Databank (TDB) maintains several firm-level datasets, each compiled for different research purposes. These datasets vary in terms of their time coverage and the number of firms included. While some datasets cover a much larger number of firms than the financial dataset used in this study, we utilize the financial data because it allows for the measurement of firm-level productivity, which is essential for analyzing productivity dynamics.

Based on the TDB financial data, small firms account for 97% of the total number of firms on average throughout the sample period, mid-sized firms for about 2%, and large firms for less than 1%. In terms of total employment, the average shares are 51% for small firms, 22% for mid-sized firms, and 27% for large firms. For tangible fixed assets, the shares are 28%, 24%, and 48%, respectively, indicating that large firms own roughly half of all fixed capital. On average, tangible fixed capital per worker in large firms is approximately 3.3 times that of small firms and 1.7 times that of mid-sized firms, reflecting their higher capital intensity.

2.3. Measurement of Productivity

We focus on total factor productivity (TFP) as the key measure of firm-level performance. To decompose productivity growth, we adopt the index number approach proposed by Good, Nadiri, and Sickles (1997). This approach measures the TFP level of firm *f* in year *t* by comparing its inputs and outputs with those of a representative firm in the same industry during the base year. We define the base year as 2000 and measure TFP using the following equations:

$$\ln TFP_{f,t} = \left(\ln Q_{f,t} - \overline{\ln Q_{f,t}}\right) - \sum_{i} \frac{1}{2}\left(S_{f,i,t} + \overline{S_{\iota,t}}\right)\left(\ln X_{f,i,t} - \overline{\ln X_{\iota,t}}\right), \qquad for\ t = 2000, \tag{1}$$

and

$$\ln TFP_{f,t} = \left(\ln Q_{f,t} - \overline{\ln Q_{t}}\right) - \sum_{i} \frac{1}{2}\left(S_{f,i,t} + \overline{S_{\iota,t}}\right)\left(\ln X_{f,i,t} - \overline{\ln X_{\iota,t}}\right)$$
$$+ \sum_{s=1}^{t}\left(\overline{\ln Q_{s}} - \overline{\ln Q_{s-1}}\right) - \sum_{s=1}^{t}\sum_{i} \frac{1}{2}\left(\overline{S_{\iota,s}} + \overline{S_{\iota,s-1}}\right)\left(\overline{\ln X_{\iota,s}} - \overline{\ln X_{\iota,s-1}}\right), \qquad for\ t \geq 2001. \tag{2}$$

where $Q_{f,t}$ is the output of firm *f* in year *t*, $S_{f,i,t}$ is the cost share of firm *f*'s input *i* in year *t*, and $X_{f,i,t}$ is the input of factor *i* (capital, labor, or intermediate input) for firm *f* in year *t*. Bars (e.g., $\overline{\ln Q_t}$) denote industry averages. The representative firm is defined as a hypothetical firm with average inputs, output, and input cost shares in each industry.[2]

Equation (2) decomposes a firm's TFP level into the cross-sectional deviation from the representative firm at time *t* and the representative firm's TFP growth from the base year. This allows

[2] Labor productivity is measured using a similar approach; however, output is defined as real value-added, and the sole input is total labor hours. Because only labor is considered as an input, the cost share is set to one.

both cross-sectional and intertemporal comparisons of productivity distributions.

While we primarily use TFP as measured by Equations (1) and (2), this measure includes productivity trends at the industry level. Therefore, for descriptive comparisons across firms in different industries and years, we also use a cross-sectional TFP index defined as:

$$\mathrm{CSln}\,TFP_{f,t} = \left(\ln Q_{f,t} - \overline{\ln Q_{f,t}}\right) - \sum_{i} \frac{1}{2}\left(S_{f,i,t} + \overline{S_{\iota,t}}\right)\left(\ln X_{f,i,t} - \overline{\ln X_{\iota,t}}\right). \tag{3}$$

Here, comparisons are made against the representative firm in the same industry and year.

Because firm-level deflators and hours-worked data are not available in the TDB database, we use industry-level deflators and input-output data from the Japan Industrial Productivity Database (JIP) 2023.[3] The industry classifications in the TDB and JIP data are matched accordingly.

One advantage of the index number approach is that it accommodates heterogeneity in production technologies across firms and imperfect competition in product markets. However, it assumes constant returns to scale and perfect competition in input markets. As Van Biesebroeck (2007) notes, while the index number approach is sensitive to measurement errors, it performs well when such errors are minimal. Moreover, Kasahara, Nishida, and Suzuki (2017) caution that assuming uniform input levels across firms (as in some production function approaches) may overstate the resource reallocation effect. Therefore, to accurately measure TFP growth over time and derive macroeconomic insights, we adopt the index number approach.

Table 1 presents basic summary statistics of TFP measured using the index number approach.[4]

[3] https://www.rieti.go.jp/jp/database/JIP2023/

[4] The measurement of TFP is conducted in two stages. In the first stage, TFP is calculated and observations that deviate by more than three standard deviations from the industry-year mean are excluded. In the second stage, TFP is recalculated using the updated industry averages. If the outlier threshold is relaxed, some firms exhibit implausible productivity values. However, even when such observations are included, the main results of this study remain unchanged.

Table 1. Summary Statistics of ln*TFP* and CSln*TFP*

Variable	Obs.	Mean	S.D.	Min.	p25	Median	p75	Max.
lnTFP	4,253,043	-0.069	0.324	-3.862	-0.198	-0.014	0.119	3.791
CSlnTFP	4,253,043	0.000	0.308	-3.718	-0.129	0.049	0.176	3.476

Source: Authors' calculations using TDB data.
Note: lnTFP is calculated using Equations (1) and (2), and CSlnTFP using Equation (3).

Table 2 compares productivity levels—specifically, cross-sectional TFP (CSlnTFP)—by firm size. On average, large firms exhibit the highest productivity levels; however, it is noteworthy that mid-sized firms do not consistently outperform small firms. Small firms not only constitute the overwhelming majority of the sample but also display greater variability in productivity compared to mid-sized and large firms.

Table 2. Summary Statistics of Cross-Sectional TFP by Firm Size

Variable	Obs.	Mean	S.D.	Min.	p25	Median	p75	Max.
Small	4,180,158	0.000	0.308	-3.718	-0.129	0.049	0.177	3.476
Mid-sized	64,765	-0.012	0.327	-2.493	-0.132	0.032	0.161	3.182
Large	8,120	0.015	0.239	-1.545	-0.084	0.038	0.138	1.895
Total	4,253,043	0.000	0.308	-3.718	-0.129	0.049	0.176	3.476

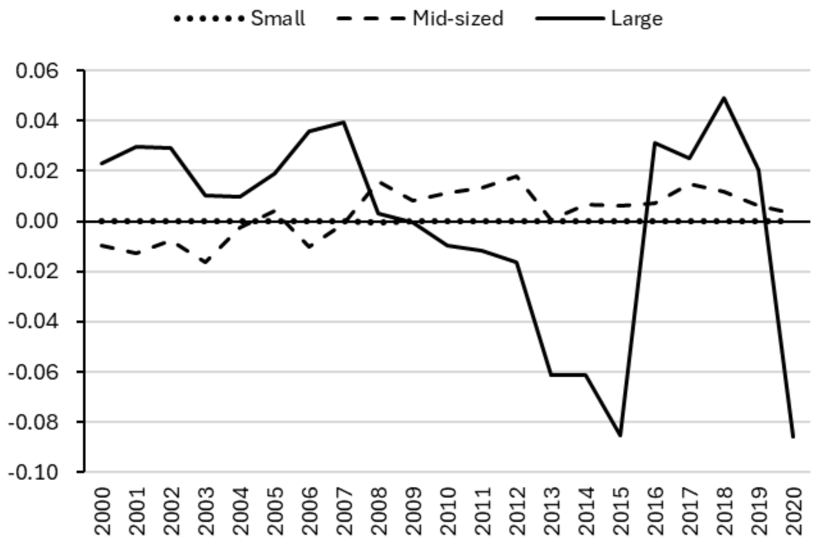
Source: Authors' calculations using TDB data.
Note: Calculated using Equation (3).

Figure 2 illustrates the weighted average of cross-sectional TFP (CSlnTFP) by firm size across all industries.[5] Until the global financial crisis in 2008, large firms consistently exhibited higher productivity than firms of other sizes. However, during the subsequent period of economic stagnation, their productivity declined substantially, falling below that of both mid-sized and small firms until around 2016. In the recovery period that followed, large firms' productivity once again surpassed that of small and mid-sized firms, although these were also the most affected by the negative impact of COVID-19 in 2020.

In contrast, mid-sized firms had lower productivity than small firms before the 2008 financial crisis, but since then, they have consistently maintained higher productivity levels than small firms.

[5] The weighted average of cross-sectional TFP is calculated by taking the firm-size-specific weighted average of each firm's cross-sectional TFP using nominal output (operating margin in the wholesale and retail industry) as weights, and then adjusting the values so that the weighted average across all firm sizes equals zero in each year.

Figure 2. Trends in the Weighted Average of Cross-Sectional TFP by Firm Size (All Industries)



Source: Authors' calculations using TDB data.

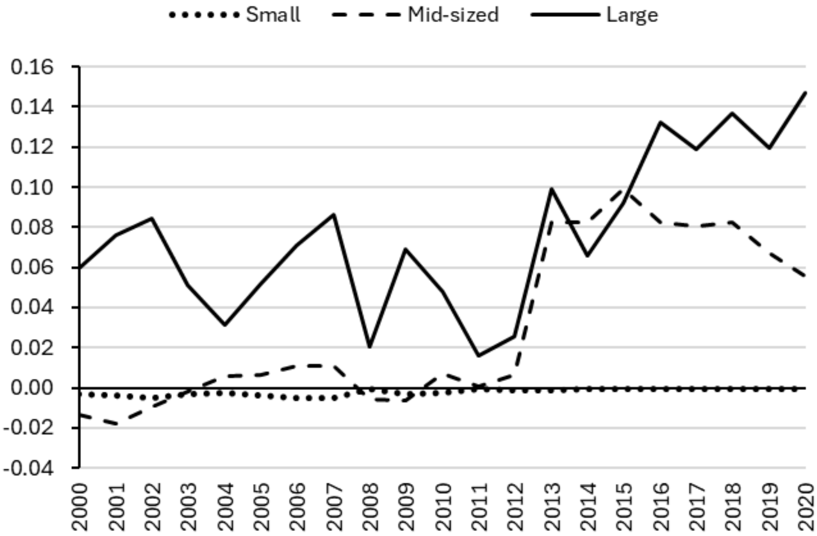
Note. The weighted average of cross-sectional TFP is calculated by taking the firm-size-specific weighted average of each firm's cross-sectional TFP using nominal output as weights, and then adjusting the values so that the weighted average across all firm sizes equals zero in each year. Cross-sectional TFP, CSln*TFP*, is calculated using Equation (3).

However, such patterns in productivity by firm size may vary across industries. Figure 3 presents the trends in the weighted average of cross-sectional TFP by firm size within the manufacturing sector. Large firms have consistently exhibited significantly higher productivity, maintaining levels about 5% above those of mid-sized and small firms up to around 2012. Since 2013, the gap has widened further, reaching approximately 15% by 2020.

For mid-sized firms, productivity levels were nearly identical to those of small firms until 2012; however, from 2013 onward, they have maintained a productivity advantage of approximately 8%.

Overall, in the manufacturing sector, the productivity gap between small firms and both mid-sized and large firms has widened notably since 2013.

Figure 3. Trends in the Weighted Average of Cross-Sectional TFP by Firm Size (Manufacturing)



Source: Authors' calculations using TDB data.

Note. The weighted average of cross-sectional TFP is calculated by taking the firm-size-specific weighted average of each firm's cross-sectional TFP using nominal output as weights, and then adjusting the values so that the weighted average across all firm sizes equals zero in each year. Cross-sectional TFP, CSln*TFP*, is calculated using Eq. (3).

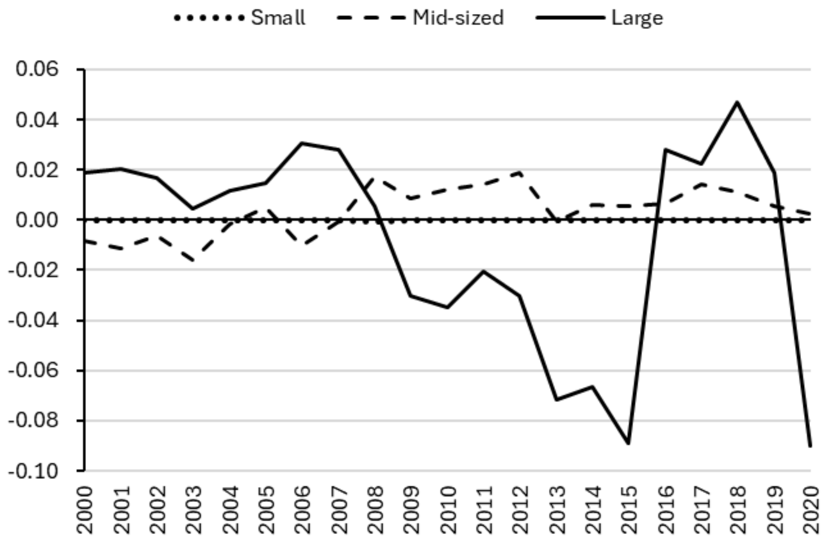
Figure 4 shows the trends in the weighted average of cross-sectional TFP by firm size in the non-manufacturing sector. In contrast to the manufacturing sector, these trends closely align with those observed across all industries. Large firms exhibited higher productivity than mid-sized and small firms up to 2007 and again from 2016 to 2019. However, their productivity declined significantly from 2008 to 2015 and again in 2020.

This suggests that large non-manufacturing firms were heavily affected by external shocks such as the global financial crisis, the Great East Japan Earthquake (Tohoku earthquake), and the COVID-19 pandemic.

The pattern that mid-sized firms have consistently outperformed small firms since 2008 is also consistent with the overall pattern observed across all industries.

Overall, since 2008, mid-sized firms in the non-manufacturing sector have shown increasing competitiveness relative to small firms. In contrast, the performance of large firms has been more vulnerable to external shocks.

Figure 4. Trends in the Weighted Average of Cross-Sectional TFP by Firm Size (Non-Manufacturing)



Source: Authors' calculations using TDB data.

Note. The weighted average of cross-sectional TFP is calculated by taking the firm-size-specific weighted average of each firm's cross-sectional TFP using nominal output as weights, and then adjusting the values so that the weighted average across all firm sizes equals zero in each year. Cross-sectional TFP, CSlnTFP, is calculated using Eq. (3).

2.4. Decomposition of Aggregate Productivity Growth

Next, we explain how we decompose aggregate productivity growth using firm-level TFP data as measured in the previous section. To aggregate firm-level TFP to the industry level, we adopt the method proposed by Baily, Hulten, and Campbell (1992). The log of TFP for an industry at time t, denoted as lnTFP_t, is defined as follows:

$$\ln TFP_t = \sum_f \theta_{f,t} \ln TFP_{f,t} \tag{4}$$

where ln$TFP_{f,t}$ denotes the log TFP level of firm f in year t, and $\theta_{f,t}$ represents the nominal output share of firm f within the industry.[6]

To decompose changes in industry-level productivity, we use the method developed by Foster, Haltiwanger, and Krizan (2001), hereafter referred to as the FHK decomposition. According to this

[6] For retail and wholesale firms, output is defined as the operating margin.

approach, the change in industry-level productivity between period $t-\tau$ and period t, denoted $\Delta \ln TFP_{t-\tau,t}$, can be decomposed into the following five components:

(a) Within effect: productivity growth within continuing firms.

(b) Between effect: shifts in market shares favoring more productive firms.

(c) Covariance effect: increases in market shares of firms with rising productivity.

(d) Entry effect: contribution from newly entering firms.

(e) Exit effect: contribution from firms that exited the market.

$$
\begin{aligned}
\Delta \ln TFP_{t-\tau,t} &= \ln TFP_t - \ln TFP_{t-\tau} \\
&= \textstyle\sum_{f\in S} \theta_{f,t-\tau} \Delta \ln TFP_{f,t} \quad \text{: within effect} \\
&\quad + \textstyle\sum_{f\in S} \Delta\theta_{f,t} \left(\ln TFP_{f,t} - \overline{\ln TFP_{f,t-\tau}}\right) \quad \text{: between effect} \\
&\quad + \textstyle\sum_{f\in S} \Delta\theta_{f,t} \Delta \ln TFP_{f,t} \quad \text{: covariance effect} \\
&\quad + \textstyle\sum_{f\in N} \theta_{f,t} \left(\ln TFP_{f,t} - \overline{\ln TFP_{f,t-\tau}}\right) \quad \text{: entry effect} \\
&\quad + \textstyle\sum_{f\in X} \theta_{f,t-\tau} \left(\overline{\ln TFP_{f,t-\tau}} - \ln TFP_{f,t-\tau}\right) \quad \text{: exit effect}
\end{aligned} \tag{5}
$$

where S is the set of continuing firms (those present in both periods), N is the set of entering firms (present only in period t), X is the set of exiting firms (present only in period $t-\tau$), $\theta_{f,t}$ is the output share of firm f in period t, $\Delta\theta_{f,,t}$ is the change in output share from $t-\tau$ to t, $\ln TFP_{f,t}$ is the TFP of firm f at time t, and $\overline{\ln TFP_{f,t-\tau}}$ is the industry average TFP at time t.

To perform this decomposition, we identify firms as follows: *Continuing firms* are those that exist in both period $t-\tau$ and period t; *Entering firms* are those that appear in the data in period t but not in $t-\tau$; and *Exiting firms* are those that appear in $t-\tau$ but not in t.[7]

In addition, when a firm's main industry classification changes between the initial and final periods, we account for the productivity impact of industry switching. Specifically, the switch-in effect captures the contribution of firms that newly enter an industry by changing their primary sector classification, while the switch-out effect reflects the impact of firms that leave an industry for another. These components represent the reallocation of resources across industries driven by firms' strategic repositioning.

3. Productivity Dynamics

3.1. All Firms

To analyze overall productivity growth, we divide the sample period from 2000 to 2019 into four

[7] Although information such as the year of establishment and records of bankruptcy or dissolution could, in principle, be used to more accurately define entry and exit, such information is incomplete in the dataset; therefore, this study does not utilize it.

five-year sub-periods and apply the FHK decomposition method described in the previous section. The four sub-periods are as follows:

- 2000–2005: a period of stable economic growth in Japan.
- 2005–2010: a period marked by the global financial crisis and the most severe recession in Japan's postwar history.
- 2010–2015: the post-crisis recovery period.
- 2015–2019: the Abenomics era before the outbreak of COVID-19.

The decomposition results of productivity growth for each period are summarized in Figure 5. The key findings are as follows.

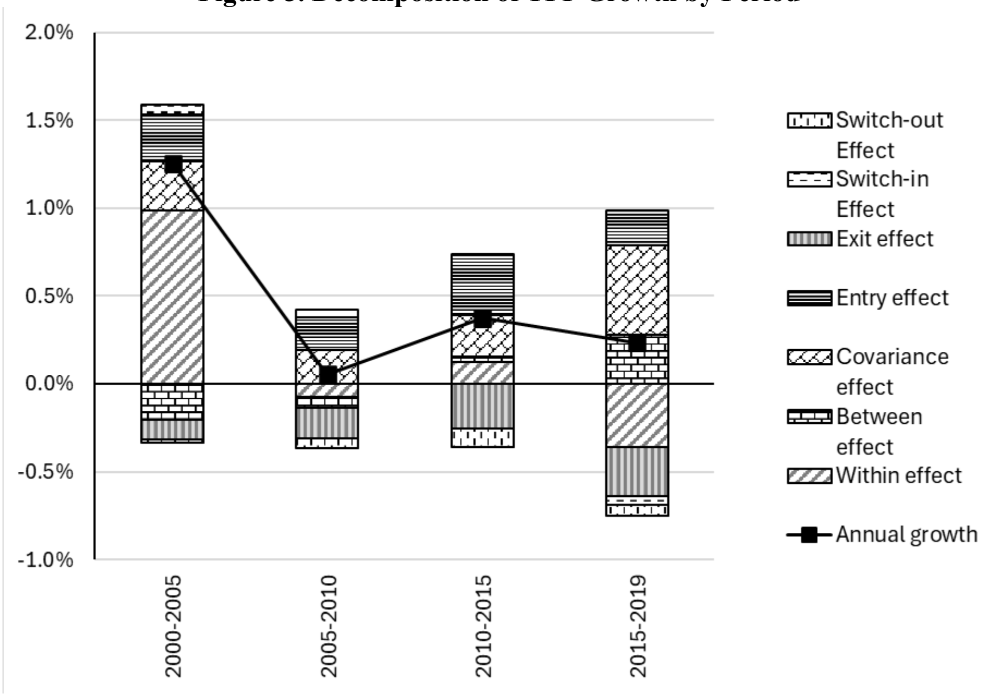
First, the within effect (i.e., productivity growth within continuing firms) consistently contributes the most to overall productivity changes across all periods. Variations in the within effect largely explain fluctuations in total productivity growth. Notably, however, the primary driver of productivity growth in recent years has shifted from within-firm productivity improvements to reallocation across continuing firms. As pointed out by Fukao et al. (2006), productivity growth in Japan had long been driven by the within effect even before the bursting of the asset price bubble. However, the contribution of the within effect has diminished over time and even turned negative during the 2015–2019 period. It is worth noting that this period ends just before the full onset of the COVID-19 pandemic, yet the within effect is significantly negative.

Second, the reallocation effect—comprising the between effect and the covariance effect, both stemming from competition among continuing firms—has become increasingly important since the Abenomics period. The between effect is positive when the market shares of highly productive firms expand or those of less productive firms shrink. Before 2015, this effect was negligible, but during 2015–2019, it made a substantial positive contribution. The covariance effect, which is positive when firms with rising productivity gain market share, had already been positive before 2015 but contributed nearly half of the positive part of the total productivity growth from 2015 to 2019. These results suggest that, in recent years, the Japanese market mechanism has become more effective in reallocating resources from inefficient to efficient firms. Nevertheless, as highlighted by Foster, Haltiwanger, and Krizan (2001) for the United States and by Disney, Haskel, and Heden (2003) for the United Kingdom, it is also possible that in times of economic downturn, reallocation effects temporarily outweigh within-firm improvements in their contribution to productivity growth.

Third, the entry effect is consistently positive and tends to be larger during periods of economic expansion (2000–2005, 2010–2015). In contrast to the exit effect, the entry of new firms has a positive impact on productivity growth.

Fourth, the exit effect is consistently negative throughout all periods, regardless of the business cycle. Moreover, the magnitude of the negative exit effect has been increasing over time. A negative exit effect indicates that firms exiting the market had higher productivity levels than the industry average. This finding is consistent with previous studies such as Fukao and Kwon (2006) and Ikeuchi et al. (2022), which also documented the negative nature of the exit effect in Japan.

Figure 5. Decomposition of TFP Growth by Period

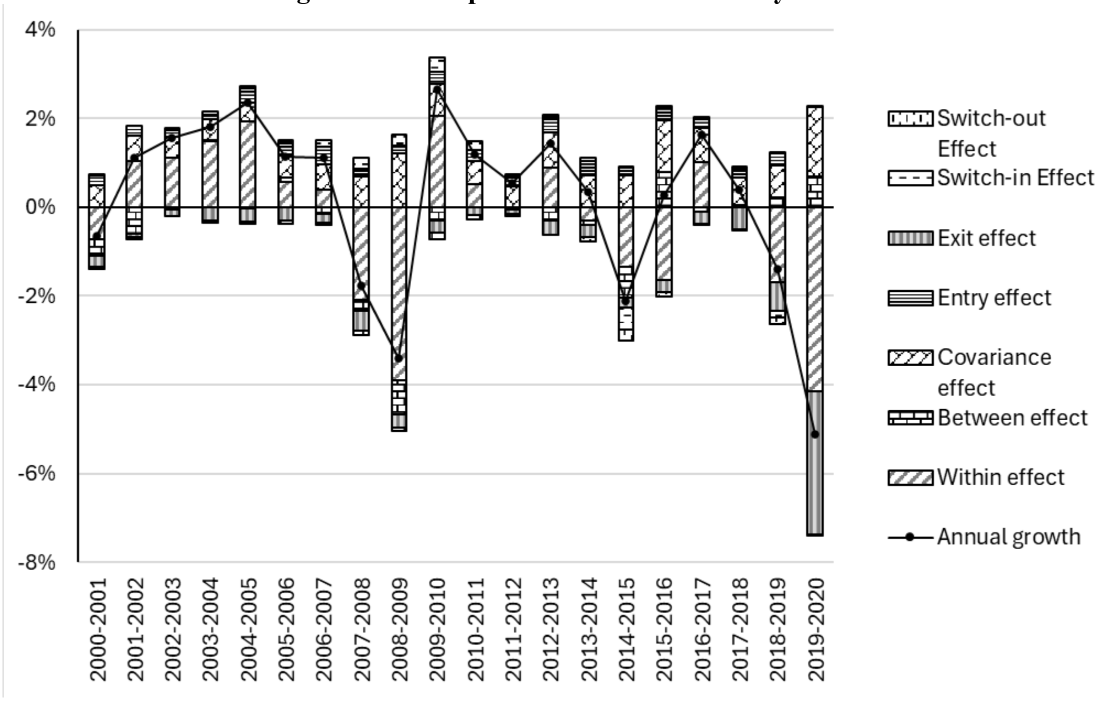


Source: Authors' calculations using TDB data.
Note: TFP is measured using Equations (1) and (2). The FHK method is employed.

Figure 6 shows the decomposition results of TFP growth for each year. Since entry and exit are determined annually, the values differ from the five-year aggregates shown in Figure 5. Nevertheless, the overall patterns remain consistent. As in Figure 5, macro-level TFP growth displays a procyclical movement—i.e., it tends to rise during booms and fall during recessions. Changes in the within effect mainly drive the fluctuations in TFP growth. The exit effect remains consistently negative, and has grown larger since around 2013. In contrast, the entry effect (including the switch-in effect) is consistently positive in almost all years except 2014, suggesting that newly entering firms tend to be more productive than the average.

Finally, the growing importance of the reallocation effect in recent years underscores the increasing role of market competition in driving productivity growth in Japan, especially in the context of persistently weak within-firm productivity improvements.

Figure 6. Decomposition of TFP Growth by Year



Source: Authors' calculations using TDB data.
Note: TFP is measured using Equations (1) and (2). The FHK method is employed.

3.2. By Firm Size

What roles have small, mid-sized, and large firms played in Japan's productivity dynamics? As discussed in the introduction, one hypothesis for Japan's prolonged stagnation is the persistent low productivity of SMEs. To assess the contribution of each firm size group to aggregate productivity growth, we divide the sample into three groups—small, mid-sized, and large firms—and analyze the decomposition results separately for each group.[8]

Figure 7 presents the decomposition results, highlighting several key trends in Japan's evolving economic structure. Until 2005, productivity growth was primarily driven by within-firm improvements among large firms. However, since the 2010s, the contribution of large firms has declined while that of small firms has increased. The contribution of each size group to aggregate productivity growth is calculated as the product of that group's productivity growth rate and its output share. For example, during 2010–2015, the productivity growth rates were 0.06% for large firms and 0.84% for small firms; during 2015–2019, they were 0.14% and 0.28%, respectively. These results indicate that small firms exhibited higher productivity growth than large firms in both periods.

In contrast, mid-sized firms contributed positively until around 2010, but their contribution

[8] While the size of continuing firms may change during the period, firms are classified into size groups based on their status at the beginning of the period.

declined thereafter and turned negative. Small firms appear more sensitive to business cycle fluctuations, whereas mid-sized firms are less affected. Large firms, on the other hand, tend to struggle during economic downturns.

The decomposition of productivity growth also reveals notable differences in the sources of growth by firm size.[9] Among small firms, the main drivers of productivity growth are the entry and covariance effects. Naturally, most of the entry effect in the economy originates from small firms. Moreover, consistent with the findings of Ikeuchi et al. (2022), the covariance effect—which reflects effective resource reallocation among small firms through market competition—is especially pronounced in this group. In contrast, the within effect is almost negligible for small firms and even contributes negatively during recessionary periods, such as the 2005–2010 period, which includes the global financial crisis. The negative exit effect is also predominantly observed among small firms.

Unlike among small firms, productivity growth among large firms is mainly driven by the within effect. The decline in the within effect since 2005 has been concentrated mainly among large firms. Interestingly, the recent rise in reallocation effects also appears to stem from increased resource shifts among large firms. Previous research on Japanese firms has suggested that productivity growth among large firms owes primarily to within-firm improvements, while among small firms it is more due to market reallocation. However, the recent trend among large firms seems to deviate from this conventional pattern.

The negative exit effect has been primarily observed among small firms and has gradually grown over time. The contributions by period are −0.08%, −0.15%, −0.17%, and −0.20%, respectively. However, it is also noteworthy that the negative exit effect has also increased among mid-sized firms. While almost no negative exit effect was observed for mid-sized firms up to 2010, it has become increasingly significant in the following periods. Interestingly, the number of exiting mid-sized firms declined from 439 (2000–2005) to 397 (2015–2019), suggesting that these exit effects reflect the exit of relatively large and productive mid-sized firms since 2010.

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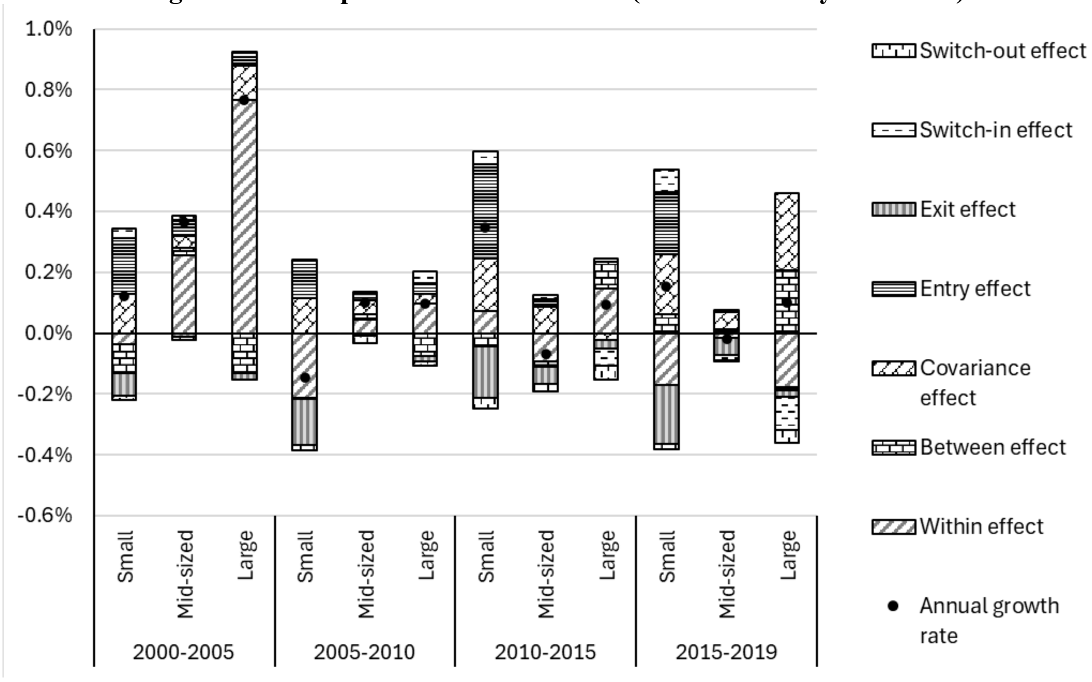
[9] For a summary of productivity growth by firm size in each period, see Figure A1 in the Appendix.

Figure 7. Decomposition of TFP Growth (Contribution by Firm Size)



Source: Authors' calculation using TDB data.
Note: TFP is measured using Equations (1) and (2). The FHK method is employed. The vertical axis indicates percentage point contributions.

4. The Negative Exit Effect

4.1. Productivity Levels by Type of Exit

In this section, we investigate the underlying causes of the negative exit effect discussed earlier. To conduct this analysis, it is necessary to identify firm exits accurately. Even in official government statistics, defining and measuring firm exit is inherently difficult. TDB, however, conducts follow-up investigations on firms that disappear from the dataset and, when available, records the reason for exit.[10]

We categorize the exit reasons into the following five types: closure, merger, dissolution, bankruptcy, and other (when the specific reason is unknown). The industries with the highest number of exits (see Table A2 in the Appendix) are construction, civil engineering, wholesale, retail, and real estate. These industries also account for the highest number of exits due to mergers.

Table 3 shows summary statistics of the cross-sectional TFP (measured in the final year of available financial data) of exiting firms by type of exit from 2000 onward.[11] Among the known

[10] It should be noted, however, that the identification of firm exits and the investigation of their reasons often lag behind the actual timing of exit. This is particularly true for small firms, for which exit reasons are frequently unknown.

[11] Some firms may exit for multiple reasons. In such cases, we classify the exit based on the reason

reasons for exit, bankruptcy (24%) and dissolution (20%) are the most frequent, while mergers account for only about 8% of total exits. The productivity level just before exit is lowest for firms exiting due to closure. Interestingly, firms exiting via bankruptcy show, on average, higher productivity than surviving firms, which contributes to the negative exit effect. Firms exiting via merger exhibit the highest productivity—about 8% higher than the average surviving firm.

Table 3. Summary Statistics of Cross-sectional TFP by Exit Type

Variable	Obs.	Mean	S.D.	Min.	p25	Median	p75	Max.
No exit	3,533,802	-0.002	0.304	-3.718	-0.130	0.046	0.172	3.476
Closure	111,114	-0.029	0.322	-2.559	-0.175	0.031	0.166	2.184
Merger	60,544	0.078	0.350	-2.585	-0.056	0.119	0.267	2.632
Dissolution	146,111	-0.004	0.302	-2.932	-0.129	0.054	0.176	2.001
Bankruptcy	173,114	0.004	0.288	-3.140	-0.128	0.050	0.178	2.093
Other	228,358	0.028	0.354	-2.978	-0.112	0.082	0.217	3.045
Total	4,253,043	0.000	0.308	-3.718	-0.129	0.049	0.176	3.476

Source: Authors' calculations using TDB data.
Note: Cross-sectional TFP is calculated using Equation (3).

However, these raw comparisons do not control for industry or year effects. Therefore, we conduct a regression analysis controlling for industry and year fixed effects, as well as firm-level characteristics such as firm age, the firm representative's age, number of employees, and whether the firm engages in R&D. Table 4 compares the pre-exit TFP of exiting firms with that of surviving firms. Across all specifications, firms that exit through mergers show 6–8% higher TFP than surviving firms. In contrast, firms exiting due to closure, dissolution, or bankruptcy exhibit significantly lower TFP levels. These results suggest that mergers may be the primary source of the negative exit effect. Nevertheless, since this is an average comparison, it is essential to recognize that the overall contribution to productivity dynamics also depends on the firm size and productivity distribution.

recorded closest to the final year of data (i.e., one year before disappearance from the dataset). For example, if a firm went bankrupt in 2010, was subsequently acquired through a merger in 2011, and the data in 2011 is the last observation, the exit reason is classified as a merger based on the final data year, 2011.

Table 4. TFP of Exiting Firms

	(1)	(2)	(3)	(4)
	lnTFP	lnTFP	lnTFP	lnTFP
ln(Firm age)			**-0.0898*** **	**-0.0898*** **
			[0.0119]	[0.0119]
ln(CEO age)			-0.0205	-0.0203
			[0.0178]	[0.0177]
ln(#Employees)			**0.0112***	**0.0110***
			[0.00655]	[0.00654]
1 if R&D			**0.0201*** **	**0.0201*** **
			[0.00261]	[0.00261]
Exit		-0.00625		**-0.0134*** **
		[0.00506]		[0.00336]
Closure	**-0.0606*** **	**-0.0544*** **	**-0.0653*** **	**-0.0522*** **
	[0.0109]	[0.0138]	[0.00821]	[0.0107]
Merger	**0.0814*** **	**0.0875*** **	**0.0594*** **	**0.0726*** **
	[0.0137]	[0.0103]	[0.0149]	[0.0134]
Dissolution	**-0.0330*** **	**-0.0269** **	**-0.0228*** **	-0.00981
	[0.00927]	[0.0117]	[0.00661]	[0.00915]
Bankruptcy	**-0.0281*** **	**-0.0219** **	**-0.0345*** **	**-0.0213** **
	[0.00721]	[0.00918]	[0.00813]	[0.00834]
Other	0.013	0.0189	**-0.0226*** **	-0.00982
	[0.00798]	[0.0116]	[0.00654]	[0.00755]
Observations	2,985,581	2,985,581	2,678,022	2,678,022
Adj. R sq.	0.075	0.075	0.121	0.121

Source: Authors' calculations using TDB data.
Note: ln*TFP* is measured using Equations (1) and (2). Robust standard errors in brackets. Clustered at the JIP 2018 industry level. * p<0.10, ** p<0.05, and *** p<0.01.

Table 5 shows the corresponding results using labor productivity as the dependent variable. Similar to TFP, firms exiting through mergers exhibit 26–30% higher labor productivity than surviving firms. Firms exiting due to bankruptcy also show higher labor productivity (17–20%), while firms exiting for other reasons tend to have lower productivity.

Table 5. Labor Productivity of Exiting Firms

	(1) lnLP	(2) lnLP	(3) lnLP	(4) lnLP
ln(Firm age)			**0.0537*****	**0.0534*****
			[0.0173]	[0.0173]
ln(CEO age)			**-0.144*****	**-0.141*****
			[0.0414]	[0.0412]
ln(#Employees)			0.0223	0.0195
			[0.0249]	[0.0249]
1 if R&D			**0.342*****	**0.341*****
			[0.0406]	[0.0406]
Exit		**-0.245*****		**-0.229*****
		[0.0328]		[0.0315]
Closure	**-0.395*****	**-0.155*****	**-0.353*****	**-0.131*****
	[0.0401]	[0.0329]	[0.0268]	[0.0185]
Merger	0.0628	**0.303*****	0.0386	**0.264*****
	[0.0530]	[0.0711]	[0.0527]	[0.0718]
Dissolution	**-0.454*****	**-0.216*****	**-0.416*****	**-0.196*****
	[0.0239]	[0.0230]	[0.0222]	[0.0152]
Bankruptcy	-0.0372	**0.205*****	-0.0573	**0.168*****
	[0.0424]	[0.0544]	[0.0415]	[0.0543]
Other	**-0.169*****	**0.0623****	**-0.130*****	**0.0867*****
	[0.0415]	[0.0244]	[0.0392]	[0.0291]
Observations	3,015,702	3,015,702	2,682,935	2,682,935
Adj. R sq.	0.046	0.047	0.057	0.058

Source: Authors' calculations using TDB data.
Note: ln*LP* is measured using Equations (1) and (2). Robust standard errors in brackets. Clustered at the JIP 2018 industry level. * p<0.10, ** p<0.05, and *** p<0.01.

Previous studies have documented that exiting firms often experience a decline in productivity prior to exit, referred to as the "shadow of death" effect. However, in the case of mergers, firms may intentionally present better performance prior to negotiations. Table 6 estimates this shadow of death effect for both TFP and labor productivity. Exit types are grouped into mergers and non-mergers. For non-merger exits, the results confirm a shadow of death effect: TFP is approximately 2.6% lower, and labor productivity is 15.6% lower in the final year relative to survivors. Moreover, labor productivity is 4.3% lower one year prior to exit. In contrast, firms exiting via mergers exhibit 6–7% higher TFP and 14–19% higher labor productivity, both in the year of exit and the year before.

Table 6. Shadow of Death Effect for Merger Exits

	(1) lnTFP	(2) lnLP
ln(Firm age)	-0.0907***	0.0557***
	[0.0122]	[0.0163]
ln(CEO age)	-0.0247	-0.163***
	[0.0173]	[0.0424]
ln(#Employees, t-1)	0.0112*	0.0129
	[0.00669]	[0.0219]
1 if R&D	0.0199***	0.337***
	[0.00256]	[0.0412]
Merger, exit -5+ year	0.0734***	0.153**
	[0.0204]	[0.0684]
Merger, exit -4 year	0.0789***	0.191***
	[0.0177]	[0.0606]
Merger, exit -3 year	0.0738***	0.194***
	[0.0150]	[0.0682]
Merger, exit -2 year	0.0667***	0.173***
	[0.0153]	[0.0594]
Merger, exit -1 year	0.0719***	0.142***
	[0.0154]	[0.0536]
Merger, exit year	0.0664***	0.0861
	[0.0147]	[0.0599]
Other exit, exit -5+ year	0.0159***	0.0176
	[0.00578]	[0.0112]
Other exit, exit -4 year	0.0089	-0.0102
	[0.00707]	[0.0105]
Other exit, exit -3 year	0.00929	0.00498
	[0.00658]	[0.0175]
Other exit, exit -2 year	0.000654	-0.0166
	[0.00655]	[0.0138]
Other exit, exit -1 year	-0.00831	-0.0431***
	[0.00673]	[0.0145]
Other exit, exit year	-0.0263***	-0.156***
	[0.00689]	[0.0163]
Observations	3,786,768	3,751,430
Adj. R sq.	0.124	0.055

Source: Authors' calculations using TDB data.
Note: ln*TFP* and ln*LP* are measured using Equations (1) and (2). Robust standard errors in brackets. Clustered at the JIP 2018 industry level. * p<0.10, ** p<0.05, and *** p<0.01.

4.2. Decomposition of the Negative Exit Effect

To what extent can exits through mergers explain the negative exit effect? In this section, we decompose the exit component of the FHK productivity growth decomposition by categorizing exits based on the reason identified in the TDB dataset. Specifically, we extract and evaluate the contribution of each exit type—excluding exits for which the reason is unknown—to determine how much each type accounts for the overall negative exit effect.

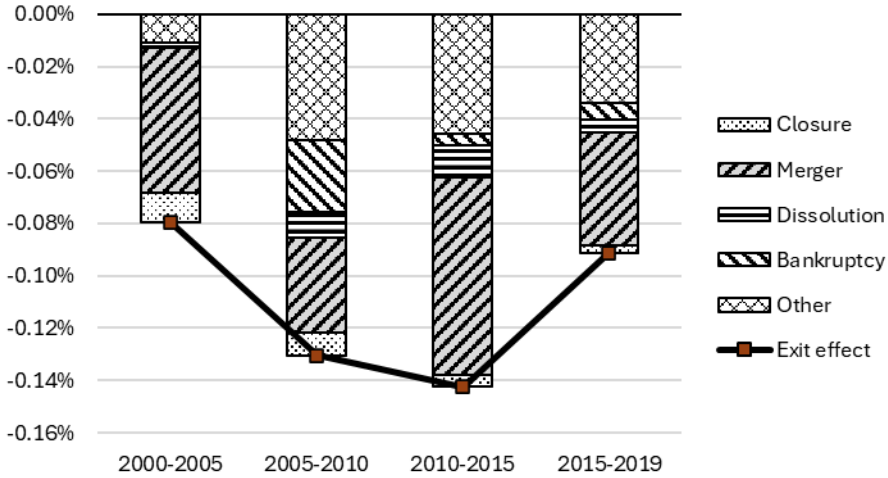
Figure 8 disaggregates the exit effect from Figure 5 by exit type, excluding exits for which the reason is unknown (N/A).[12] Although the regression results in the previous subsection indicated that

[12] Because the confirmation of firm exits and the investigation of the causes lag behind the actual timing of exit, the number of cases in which the exit reason is unknown is highest in the most recent years.

firms exiting via closure, dissolution, or bankruptcy have lower productivity than surviving firms—suggesting that these exits made a positive contribution to overall productivity growth—the aggregate contributions of these types of exits remain negative. This implies that, regardless of exit type, the negative exit effect is likely driven by the exit of a small number of highly productive large firms.

Moreover, in most periods, approximately half of the negative exit effect is attributable to firms exiting via mergers.

Figure 8. Contributions to the Exit Effect by Exit Type



Source: Authors' calculations using TDB data.
Note: FHK decomposition of TFP growth. TFP is measured using Equations (1) and (2). Exits for which the reason is unknown (N/A) are excluded.

4.3. Welfare Implications of Exit through Mergers

Given that exits via mergers account for a substantial share of the negative exit effect, the question that arises is whether such exits are desirable from an economic welfare perspective. In this section, we conduct a simple test of whether acquiring firms (i.e., firms that absorb exiting firms) experience an increase in productivity after the merger. The TDB dataset allows us to identify the acquirer in each merger-related exit.

To evaluate the performance of acquiring firms before and after mergers—particularly in terms of productivity—we construct firm-level data for merged entities. Specifically, we aggregate the nominal output and inputs of both the acquiring and acquired firms prior to the merger and then deflate them using industry-specific deflators and values from the industry of the acquiring firm. This yields real output and input data for calculating productivity levels.

Table 7 compares merger firms (before and after the mergers) with firms not involved in a merger. The analysis includes only mergers that occurred in the period from 2000 onward. In cases where a firm was involved in multiple mergers, we define the period following the first merger as "after the merger." Although the number of merging firms is relatively small compared to the full sample, several notable patterns emerge. Starting with TFP, while merging firms exhibit slightly higher productivity than non-merging firms before the merger, their TFP appears to decline after the merger. In contrast, merging firms' labor productivity is substantially higher than that of non-merging firms and increases further after the merger. Merging firms' capital intensity (tangible fixed assets per employee) is also higher and increases following the merger.[13]

Table 7. Summary Statistics of Merging and Non-Merging Firms

		Merger	
		Before	After
Observations	Did not merge	5,060,702	
	Merged	125,029	89,879
lnTFP (cross-sectional)	Did not merge	0.000	
	Merged	0.008	-0.018
lnLP (cross-sectional)	Did not merge	-0.013	
	Merged	0.310	0.359
Tangible capital /#Employees	Did not merge	7,594	
	Merged	11,890	15,699

Source: Authors' calculation using TDB data.
Note: Cross-sectional TFP and LP are measured using Equation (3). Tangible capital is expressed in thousands of yen at current prices.

Table 8 presents estimates of the change in productivity of merged entities by comparing their productivity after the merger with the combined productivity of the acquiring and acquired firms before the merger. Model (1) uses TFP as the dependent variable, while Model (2) uses labor productivity.

In both models, productivity declines by 2–3% in the year of the merger. In Model (1), TFP continues to decline significantly until the fourth year after the merger, although the statistical significance weakens over time. By the fifth year, the decline is no longer statistically significant.

In contrast, Model (2) shows that labor productivity increases substantially starting from the second year after the merger and remains about 10% higher than the pre-merger level in the long term.[14]

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[13] Note, however, that tangible fixed assets are measured in nominal terms, so that this result should be treated with caution.

[14] It should be noted, however, that this analysis does not address potential endogeneity issues.

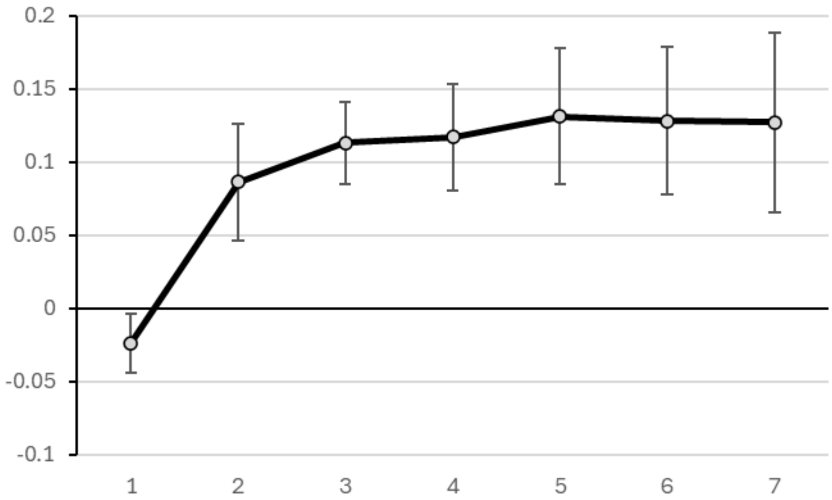
Table 8. Productivity Change of Merged Entities after the Merger

	(1) lnTFP	(2) lnLP
ln(Firm age)	**-0.0982*** **	**0.0581*** **
	[0.0177]	[0.0158]
ln(CEO age)	-0.0389	**-0.168*** **
	[0.0279]	[0.0427]
ln(#Employees, t-1)	0.0164	0.00386
	[0.0117]	[0.0219]
1 if R&D	**0.0251*** **	**0.328*** **
	[0.00408]	[0.0405]
1 if involved in a merger	-0.000793	**0.198*** **
	[0.0198]	[0.0643]
Merger year	**-0.0355*** **	**-0.0239** **
	[0.0129]	[0.0104]
2nd year after merger	**-0.0238*** **	**0.0862*** **
	[0.00757]	[0.0202]
3rd year after merger	**-0.0211* **	**0.113*** **
	[0.0110]	[0.0142]
4th year after merger	**-0.0213* **	**0.117*** **
	[0.0108]	[0.0186]
5th year after merger	-0.0191	**0.131*** **
	[0.0125]	[0.0237]
6th year after merger	-0.0148	**0.128*** **
	[0.0114]	[0.0256]
7th+ year after merger	-0.0153	**0.127*** **
	[0.0115]	[0.0312]
Observations	4,229,100	3,683,650
Adj. R sq.	0.094	0.034

Source: Authors' calculations using TDB data.
Note: Estimated using ordinary least squares (OLS). ln*TFP* and ln*LP* are measured using Equations (1) and (2). Robust standard errors in brackets. Clustered at the JIP 2018 industry level. * p<0.10, ** p<0.05, and *** p<0.01.

Figure 9 illustrates the estimated coefficients and 95% confidence intervals from Model (2) in Table 8, showing the trajectory of labor productivity following the merger.

Figure 9. Labor Productivity after the Merger



Source: Authors' calculations using TDB data.
Note: Coefficient estimates and 95% confidence intervals from Model (2) in Table 8. The horizontal axis indicates the number of years since the first merger.

Table 9 presents the results of a fixed effects model that controls for firm-specific characteristics. In this specification, TFP declines through the third year after the merger and does not exhibit significant declines thereafter. By contrast, labor productivity increases immediately in the year of the merger and remains stable at a level approximately 20% above the pre-merger baseline in subsequent years.

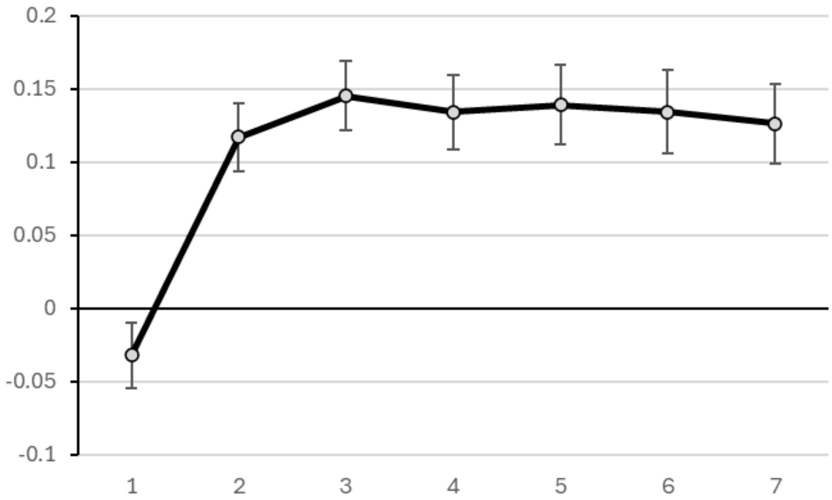
Table 9. Productivity after the Merger (Fixed Effects Estimation)

	(1) lnTFP	(2) lnLP
ln(Firm age)	**-0.0367*** **	**0.285*** **
	[0.00107]	[0.00407]
ln(CEO age)	**-0.0208*** **	0.00162
	[0.00158]	[0.00630]
ln(#Employees, t-1)	**0.00978*** **	**-0.524*** **
	[0.000939]	[0.00273]
1 if R&D	**0.0124*** **	**0.198*** **
	[0.000795]	[0.00377]
Merger year	**-0.0268*** **	**-0.0322*** **
	[0.00340]	[0.0116]
2nd year after merger	**-0.0121*** **	**0.117*** **
	[0.00337]	[0.0119]
3rd year after merger	**-0.00698* **	**0.145*** **
	[0.00364]	[0.0121]
4th year after merger	-0.00658	**0.134*** **
	[0.00402]	[0.0131]
5th year after merger	-0.0037	**0.139*** **
	[0.00423]	[0.0140]
6th year after merger	-0.00436	**0.134*** **
	[0.00445]	[0.0146]
7th+ year after merger	-0.00361	**0.126*** **
	[0.00489]	[0.0140]
Observations	4,229,100	3,683,650
Adj. R sq.	0.042	0.097
ρ	0.837	0.756

Source: Authors' calculations using TDB data.
Note: ln*TFP* and ln*LP* are measured using Equations (1) and (2). Robust standard errors in brackets. Clustered at the JIP 2018 industry level. * p<0.10, ** p<0.05, and *** p<0.01.

Figure 10 illustrates the coefficient estimates and 95% confidence intervals from Model (2) in the table. The fixed effects analysis also shows that labor productivity remains consistently higher following the merger.

Figure 10. Labor Productivity after the Merger



Source: Authors' calculations using TDB data.
Note: Coefficient estimates and 95% confidence intervals from the fixed effects model (Model 2). Labor productivity is measured using Equations (1) and (2).

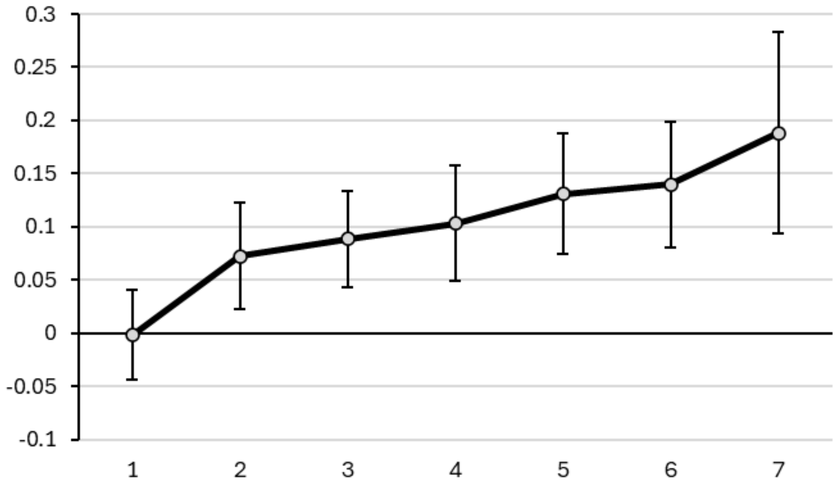
As TFP does not show significant improvement after mergers while labor productivity rose substantially, it is likely that capital deepening occurred—i.e., the capital-labor ratio increased following the mergers. Figure 11 shows the regression results estimates for changes in tangible fixed capital per employee following the mergers. From the second year onward, capital per employee increased by approximately 10%.[15]

While an increase in capital per employee could also be driven by a reduction in the number of employees, additional regressions using the number of employees as the dependent variable indicate that employment actually tended to increase after the mergers.[16] This suggests that the increase in capital per worker was due to capital investment by the acquiring firms.

[15] The estimation results are provided in the Appendix. The fixed effects estimation yields broadly similar results.

[16] Since the TDB data do not cover all mergers, there is a high likelihood that the number of employees before the mergers is underestimated. Therefore, caution is needed when comparing the number of employees before and after mergers. However, the impact of this underestimation on tangible fixed capital per employee is likely to be limited.

Figure 11. Tangible Fixed Capital per Employee after the Mergers



Source: Authors' calculations using TDB data.
Note: Coefficient estimates and 95% confidence intervals from Table A.3. The horizontal axis indicates the number of years since the first merger.

5. Conclusion

Since the 1990s, a large body of empirical research has examined the slowdown in productivity growth in the Japanese economy using firm- and establishment-level data. Existing studies have identified three key factors behind this slowdown:

(1) stagnation in within-firm productivity growth;

(2) inefficient resource allocation in the market, particularly the so-called negative exit effect; and

(3) the relatively poor performance of small and medium-sized enterprises (SMEs).

However, prior research has not sufficiently addressed differences across firm size categories, nor has it adequately distinguished between exits due to mergers and those caused by bankruptcies or closures.

Against this backdrop, the present study examined productivity dynamics by firm size using financial data from Teikoku Databank (TDB), while distinguish exit types to differentiate between mergers and bankruptcies/closures. Our main findings are as follows.

First, whereas overall productivity growth in the early 2000s was largely driven by within-firm productivity growth at large firms, since the 2010s, small firms have played a greater role, and resource reallocation across firms has become the primary driver of productivity growth. This shift suggests that the functioning of the market mechanism has improved in the Japanese economy.

Second, the distinctive negative exit effect persists in Japan. Not only among small firms but also, more recently, among mid-sized firms has there been a notable exit of high-productivity firms from the market. In addition to exits due to bankruptcy and closure, a substantial share of these exits occurred via mergers.

Third, firms that exit through mergers tend to exhibit above-average productivity and account for roughly half of the total negative exit effect. Although the total factor productivity (TFP) of acquiring firms stagnates immediately after mergers, their labor productivity increases significantly over the long term, likely due to capital deepening. This indicates that part of the negative exit effect may, in fact, reflect welfare-enhancing restructuring.

Taken together, these findings provide new insights into the changing nature of productivity dynamics in Japan. They suggest the need for policy measures tailored to different firm sizes, as well as the development of institutional frameworks that facilitate the smooth exit and restructuring of high-productivity firms to enhance overall economic efficiency.

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Appendix

Definition of Small and Medium-Sized Enterprises

Small and medium-sized enterprises (SMEs) are defined based on the criteria specified in the Small and Medium-sized Enterprise Basic Act and the Industrial Competitiveness Enhancement Act, as shown in Table A1.

Table A1. Definition of Small and Medium-Sized Enterprises (SMEs)

Industry Classification	Definition
Manufacturing and other	Companies with capital of ¥300 million or less, or individuals/companies with 300 or fewer regular employees
Wholesale trade	Companies with capital of ¥100 million or less, or individuals/companies with 100 or fewer regular employees
Retail trade	Companies with capital of ¥50 million or less, or individuals/companies with 50 or fewer regular employees
Services	Companies with capital of ¥50 million or less, or individuals/companies with 100 or fewer regular employee
Rubber products manufacturing (excluding certain subcategories)	Companies with capital of ¥300 million or less, or 900 or fewer employees
Lodging industry	Companies with capital of ¥50 million or less, or 200 or fewer employees
Software and information processing services	Companies with capital of ¥300 million or less, or 300 or fewer employees

Source: Small and Medium-sized Enterprise Basic Act; Industrial Competitiveness Enhancement Act

Definition of Mid-Sized Firms

In accordance with the 2024 revision of the Industrial Competitiveness Enhancement Act, medium-sized enterprises are defined as firms with 2,000 or fewer employees, excluding those classified as SMEs.”

In this study, we follow the same definition: firms not meeting the SME criteria specified in the Small and Medium-Sized Enterprise Basic Act and the Industrial Competitiveness Enhancement Act (see Table A1), but with 2,000 or fewer regular employees, are classified as mid-sized firms.

Number of Exits by Type and by Industry

Table A2 shows the number of exits by type of exit and by industry.

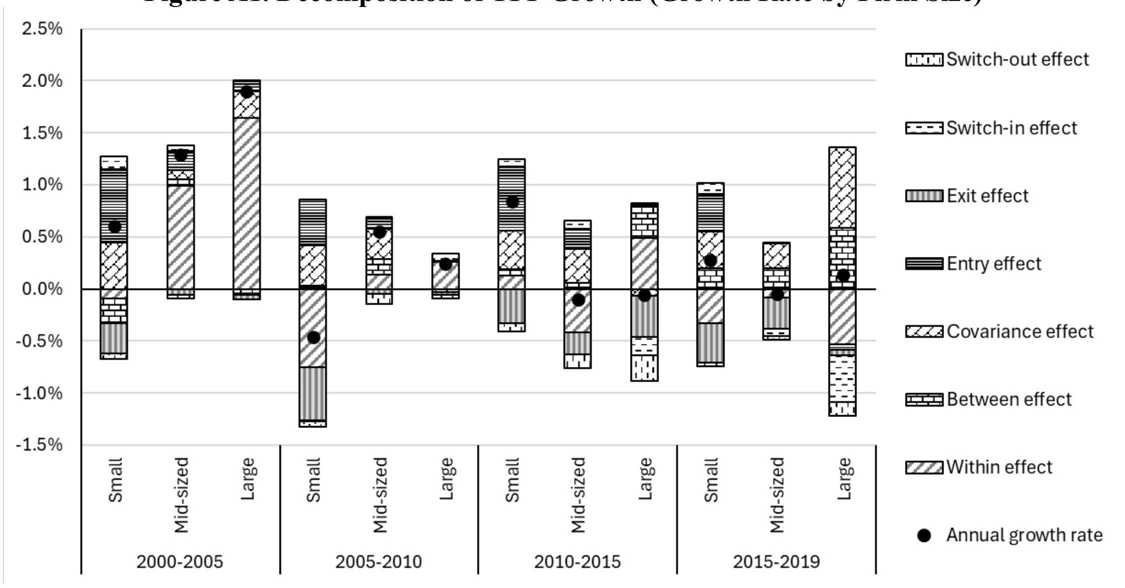
Table A2. Number of exits by type and by industry

Industry	Unknown	Closure	Merger	Dissolution	Bankruptcy	Other	Total	Total exits, excl. unknown
Agriculture	349	36	27	37	50	56	5,989	206
Agricultural services	31	5	3	4	0	3	439	15
Forestry	135	5	4	8	9	12	1,806	38
Fisheries	32	7	4	8	13	8	668	40
Mining	226	43	37	23	85	30	7,038	218
Livestock products	98	14	35	21	31	26	5,417	127
Seafood products	162	41	25	25	89	43	8,146	223
Flour and grain mill products	11	3	4	4	0	4	1,015	15
Miscellaneous foods and related products	745	102	178	100	293	234	28,634	907
Beverages	116	8	25	8	26	25	4,347	92
Prepared animal foods and organic fertilizers	46	8	11	8	15	10	1,909	52
Tobacco	0	0	0	0	0	0	21	0
Textile products (except chemical fibers)	375	107	79	75	271	73	16,486	605
Chemical fibers	5	1	2	0	0	0	194	3
Pulp, paper, and coated and glazed paper	30	5	26	7	16	10	2,669	64
Paper products	139	11	60	9	49	27	8,923	156
Chemical fertilizers	5	0	5	0	4	2	664	11
Basic inorganic chemicals	33	1	13	4	4	8	2,783	30
Basic organic chemicals	3	1	4	0	0	0	293	5
Organic chemicals	37	7	27	5	9	7	4,345	55
Pharmaceutical products	42	3	25	11	8	12	3,828	59
Miscellaneous chemical products	127	21	47	20	40	43	9,114	171
Petroleum products	19	6	7	2	1	11	1,234	27
Coal products	30	4	9	4	6	3	1,203	26
Glass and its products	43	3	14	3	9	9	1,957	38
Cement and its products	291	77	88	60	126	66	14,058	417
Pottery	22	3	5	5	8	2	1,206	23
Miscellaneous ceramic, stone and clay products	136	20	21	13	49	24	5,798	127
Pig iron and crude steel	0	2	8	2	3	2	999	17
Miscellaneous iron and steel	167	29	66	42	36	33	11,768	206
Smelting and refining of non-ferrous metals	7	3	8	4	2	11	1,580	28
Non-ferrous metal products	94	14	48	13	31	19	6,883	125
Fabricated constructional and architectural metal products	447	68	56	71	233	78	19,941	506
Miscellaneous fabricated metal products	1,155	81	110	101	276	145	43,449	713
General-purpose machinery	779	64	121	79	204	129	34,045	597
Production machinery	945	96	186	97	358	171	44,702	908
Office and service industry machines	43	6	19	5	39	24	2,648	93
Miscellaneous business-oriented machinery	181	13	46	25	47	41	8,789	172
Ordnance	1	1	0	0	0	0	19	1
Semiconductor devices and integrated circuits	12	5	17	9	9	6	1,373	46
Miscellaneous electronic components and devices	192	34	76	43	97	61	10,712	311
Electrical devices and parts	407	33	63	46	106	63	16,662	311
Household electric appliances	28	8	13	4	24	16	1,780	65
Electronic equipment and electric measuring instruments	135	18	35	24	69	48	8,068	194
Miscellaneous electrical machinery equipment	38	6	25	5	23	25	2,613	84
Image and audio equipment	12	3	10	4	8	8	1,027	33
Communication equipment	44	4	22	12	23	18	3,249	79
Electronic data processing machines, digital and analog computer equipment and accessories	27	4	22	10	27	19	2,269	82
Motor vehicles (including motor vehicle bodies)	38	2	8	3	16	7	1,614	36
Motor vehicle parts and accessories	170	16	51	19	36	29	8,929	151
Other transportation equipment	500	32	80	55	50	62	12,841	279

Table A2. Number of exits by type and by industry (cont.)

Industry	Unknown	Closure	Merger	Dissolution	Bankruptcy	Other	Total	Total exits, excl. unknown
Printing	352	50	74	45	210	110	16,340	489
Lumber and wood products	248	62	48	47	134	41	10,311	332
Furniture and fixtures	373	52	37	62	159	53	10,737	363
Plastic products	539	62	132	64	195	93	28,311	546
Rubber products	86	4	13	14	18	16	4,737	65
Leather and leather products	33	13	5	4	35	12	1,420	69
Watches and clocks	1	0	2	0	2	1	220	5
Miscellaneous manufacturing industries	644	62	40	65	144	125	16,213	436
Electricity	197	3	19	5	2	28	2,167	57
Gas, heat supply	54	0	11	2	1	2	2,172	16
Waste disposal	1,361	82	55	61	136	230	30,953	564
Construction	18,472	4,462	734	3,950	7,553	3,398	442,909	20,097
Civil engineering	84,705	9,785	1,960	13,700	14,535	12,532	1,405,867	52,512
Wholesale	12,202	2,185	3,317	2,321	4,743	4,612	550,571	17,178
Retail	4,287	708	1,000	558	1,129	1,670	112,977	5,065
Railway	30	3	2	5	2	2	1,777	14
Road transportation	2,851	188	300	162	585	515	68,796	1,750
Water transportation	358	46	78	43	55	61	11,522	283
Air transportation	24	3	4	5	3	3	671	18
Other transportation and packing	369	50	101	55	76	131	10,459	413
Hotels	292	65	83	58	100	109	6,053	415
Eating and drinking services	1,019	158	248	76	263	491	19,161	1,236
Communications	2,200	257	531	212	285	1,049	40,597	2,334
Broadcasting	110	3	29	8	6	11	3,769	57
Information services	3,076	252	649	268	518	1,339	76,863	3,026
Image information, sound information and character information production	561	71	112	60	196	349	13,930	788
Finance	523	40	211	63	34	233	13,489	581
Real estate	10,374	1,105	810	884	935	4,166	117,555	7,900
Advertising	440	60	83	58	120	250	10,898	571
Rental of office equipment and goods	818	103	242	119	154	196	26,698	814
Automobile maintenance services	576	32	105	46	40	64	9,669	287
Other services for businesses	7,614	707	725	760	712	2,106	112,064	5,010
Education	126	12	19	10	11	35	1,581	87
Medical services, health and hygiene	2,152	63	110	72	59	210	30,361	514
Social insurance and social welfare	593	21	48	12	25	108	6,774	214
Entertainment	467	117	211	84	211	328	14,386	951
Laundry, beauty and bath services	297	49	48	39	61	115	6,092	312
Other services for individuals	723	71	79	65	74	171	9,842	460
Membership organizations	346	14	39	54	10	41	5,232	158
	168,203	22,104	14,189	25,253	36,459	36,769	3,640,288	134,774

Figure A1. Decomposition of TFP Growth (Growth Rate by Firm Size)



Source: Authors' calculations using TDB data.
Note: TFP is measured using Equations (1) and (2). The FHK method is employed.

Table A3. Tangible Fixed Capital and Number of Employees in the *t*-th Year after the Merger (OLS)

	ln(Tangible capital / #Employees)	ln(#Employees)
	(1)	(2)
1 if involved in a merger	**0.425*** **	**1.758*** **
	[0.0330]	[0.0547]
Merger year	-0.00172	**0.0578*** **
	[0.0213]	[0.0178]
2nd year after merger	**0.0725*** **	**0.161*** **
	[0.0257]	[0.0202]
3rd year after merger	**0.0887*** **	**0.215*** **
	[0.0230]	[0.0270]
4th year after merger	**0.103*** **	**0.244*** **
	[0.0278]	[0.0302]
5th year after merger	**0.131*** **	**0.266*** **
	[0.0289]	[0.0311]
6th year after merger	**0.140*** **	**0.312*** **
	[0.0301]	[0.0352]
7th+ year after merger	**0.188*** **	**0.454*** **
	[0.0483]	[0.0433]
Observations	4,598,108	5,137,473
Adj. R sq.	0.208	0.286

Source: Authors' calculations using TDB data.

Note: Estimated using OLS. Industry and year dummies are included. Robust standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01. Clustered at the JIP 2018 industry level.

Table A4. Tangible Fixed Capital and Number of Employees in the *t*-th Year after the Merger (Fixed Effect Estimation)

	ln(Tangible capital / #Employees)	ln(#Employees)
	(1)	(2)
Merger year	-0.00143	-0.00362
	[0.0110]	[0.00713]
2nd year after merger	**0.0833*** **	**0.0711*** **
	[0.0111]	[0.00706]
3rd year after merger	**0.0781*** **	**0.0794*** **
	[0.0119]	[0.00765]
4th year after merger	**0.0736*** **	**0.0807*** **
	[0.0125]	[0.00809]
5th year after merger	**0.0588*** **	**0.0678*** **
	[0.0134]	[0.00874]
6th year after merger	**0.0424*** **	**0.0608*** **
	[0.0141]	[0.00914]
7th+ year after merger	0.00475	**0.0168* **
	[0.0147]	[0.00974]
Observations	4,598,108	5,137,473
Adj. R sq.	0.015	0.030
ρ	0.839	0.920

Source: Authors' calculations using TDB data.

Note: Fixed effect estimations. Industry and year dummies are included. Robust standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01. Clustered at the JIP 2018 industry level.