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Performance of Exiting Firms in Japan: An Empirical Analysis Using Exit Mode Data

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Abstract

Studies on firm performance have found that exiting firms in Japan persistently show better performance than surviving firms, and this persistence adversely affects aggregate productivity. We use the panel data of business enterprises along with unique information on their exit modes (i.e., default, voluntary closure, and merger) to show that a large part of such a "negative exit effect" is attributed to the firms exiting through mergers. Further, we confirm that the causal effect of those mergers results in positive growth in the productivity of merging firms. Given that the size of such a positive causal effect overwhelms the negative exit effect, resource reallocation through mergers positively contributes to the aggregate growth in productivity for Japanese firms.

Keywords: Productivity dynamics; Exit effects; Mergers
JEL classification: D24, G33, G34, O47

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I. Introduction

The dynamics of heterogeneous firms comprise the growth of their productivity and output, the reallocation of resources among them, entries, and exits. These factors drive the dynamics of aggregate productivity (Foster et al. 2001, Disney et al. 2003, Caballero et al. 2008, Alon et al. 2017, Acemoglu et al. 2018). Among those firm dynamics, studies on performance have shown that exits make a positive contribution to the growth of aggregate productivity in many countries (Aw et al. 2001, Lents and Mortensen 2008, Riley et al. 2015, Alon et al. 2017, Acemoglu et al. 2018).

Surprisingly, this is not necessarily the case in Japan. Most of the empirical studies on Japan's productivity dynamics have reported a "negative" exit effect. For example, a series of studies like Fukao and Kwon (2006) have applied the method developed by Foster et al. (2001) to Japanese micro data and have confirmed the negative exit effect. Given natural selection that dictates worse firms in terms of performance have to exit the market through competition, this empirical finding in Japan creates a puzzle that may partially explain Japan's low growth since the 1990s.

This negative exit effect is a concern of Japan as the country could lose opportunities to use scarce resources when the exiting firms abandon those resources. However, this negative exit effect is not necessarily problematic if the resources continue to be used by other firms through, for example, mergers.[1] This indicates the importance of examining the negative exit effect by explicitly accounting for exit modes. As far as we know, no other study has decomposed the exit effect into the ones associated with various exit modes.

Against this background, we revisit this puzzling but largely confirmed empirical fact on the negative exit effect by using firm-level panel data along with unique information on exit modes. Our data on exit modes comprehensively displays the bankruptcies, voluntary closures, and mergers. This dataset allows us to decompose the aggregate exit effect into links with various exit modes.

Our main findings are summarized as follows: First, over the period from 2001 to 2018, we find that on average, about 80% of the negative exit effect observed for Japanese firms is mostly attributed to mergers.[2] This negative merged effect occurs in most of the years in our dataset and is confirmed regardless of whether the mergers are intra-industry, inter-industry, within transaction relationships, within shareholding relationships, or without any relationships. We also confirm that the negative merged effect is a common feature for most of the industries in Japan. Second, we also show that the causal effect of the mergers that are associated with the negative exit effect result in positive growth in the productivity of the "merging"

[1] Merger is a form of "Merger and Acquisitions" (M&As) and is associated with the exit of at least one firm. This firm exit might not occur in the event of acquisitions as it is usually accompanied only by the transfer of corporate control. In this study, we focus on the merger as it is associated with firm exit while the acquisition is not.

[2] The merged effect accounts for 78% of the total exit effect from 2001 to 2018.

firms. Given that the size of this positive causal effect is larger than the negative exit effect, resource reallocation through mergers positively contributes to the productivity growth of firms in Japan.

These empirical finding on the negative merged effect provides an important implication on M&A market. Namely, resource reallocation through merger markets has been working in a proper way. Given that the net merger effect (i.e., the sum of the positive causal effect of mergers on the merging firms and the negative merged effect associated with exiting firms) has been positive until recently, it could be effective for the Japanese economy to grow by fostering merger markets.

The structure of the paper is as follows: Section 2 covers the related literature on the productivity dynamics in general as well as the empirical studies on Japanese productivity dynamics. Section 3 presents the standard method of decomposing productivity dynamics as introduced by Foster et al. (2001) and further decomposition of the exit effect used in our study. Sections 4 and 5 provide the descriptions of the data and the empirical results. Given that there could be many extended analyses to the present ones, section 6 is used to list the potential directions for further study. Section 7 concludes.

II. Related Literature

Foster et al. (2001) have developed a standard method (FHK decomposition) to analyze the sources of aggregate productivity by using firm data. They decompose the dynamics of aggregate productivity into the components associated with various dimensions of firm dynamics. Those elements consist of firms' productivity growth under their initial size (within effect), their share growth under their initial productivity (share effect), the combination of those (covariance effect), aggregate productivity growth through entry (entry effect), and aggregate productivity growth that is associated with exit (exit effect). [3] Related to the context of the present study, they also report that the entries and exits of firms are the main driver of aggregate productivity growth. Specifically, they use US manufacturing data from 1987 to 1992 to empirically show that as firms with better (worse) performance compared to the incumbents enter (exit from) markets, aggregate labor productivity and total factor productivity (TFP) increase.

[3] As a brief history of the methods for decomposing aggregate productivity, the first method was developed by Baily et al. (1992) and was later criticized as always attributing positive contributions to entering firms and negative contributions to exiting firms. In order to eliminate these biases, Griliches and Regev (1995) and Foster et al. (2001) proposed improved variations of the decomposition. Both of which introduced reference productivity values in the calculation of contributions of entering and exiting firms. We should note that the two newly proposed decompositions have still suffered from the biases as business dynamics that are associated with market share change, the entering, and exiting firms are not fully incorporated into the reference productivity. See Section 3 of the present paper for details.

Many other studies have confirmed this "positive" exit effect. For example, Alon et al. (2017) use the US data from 1996 to 2012 and confirm that the exits of low productivity firms contribute to the improvement in firms' sales per employee, and this a pattern is more apparent for younger firms. Apart from the US, Disney et al. (2003) use UK manufacturing data from 1980 to 1992 and report the positive exit effect for most industries and periods. They emphasize that this positive exit effect becomes more pronounced during economic downturns that shares the view of the "cleansing effects" proposed by Foster et al. (2014). Although the method is not necessarily the same as what Foster et al. (2001) proposes, Bellone et al. (2008) report the same finding for the TFP of French manufacturing firms from 1990 to 2002, Lents and Mortensen (2008) for the labor productivity of Denmark firms from 1992 to 1997, Grilliches and Regev (1995) for the labor productivity of Israel manufacturing and mining firms from 1979 to 1988, Hahn (2000) for the TFP of Korean manufacturing firms from 1990 to 1998, and Aw et al. (2001) for the TFP of Taiwanese manufacturing firms from 1983 to 1993. Muendler (2004) reports a positive exit effect for Brazilian manufacturing firms from 1986 to 1998, which becomes higher during the periods of trade liberalization. Pavcnik (2002) reports the consistent fact with the positive exit effect for Chilean manufacturing firms from 1979 to 1986. Brandt et al. (2012) reports the positive exit effect for TFP of Chinese firms from 1998 to 2007.

Against the rich set of empirical findings on positive exit effects, only a few studies find “negative” exit effects. One of those few is Cincera and Galgau (2005) who use firm-level data from nine EU countries for 1997–2003 to find that high performing firms in capital-intensive industries, such as textiles, tend to exit. Cantner and Kruger (2008) use German manufacturing firms’ data from 1981–1998 to show that a small but negative exit effect occurs in the German manufacturing industry (esp., textile industry). Although there are some recent theoretical discussions on the measurement of exit effects and negative exit effects (e.g., Melitz and Polanec 2015; Asturias et al. 2019), the majority of studies support the positive exit effect.

However, the research on productivity considers the Japanese economy as a stark exception to this positive exit effect. In a prominent study, Fukao and Kwon (2006) apply the method proposed in Foster et al. (2001) to data from Japanese manufacturing firms for the period from 1994 to 2001 and report negative exit effects. A large number of subsequent studies have conducted similar analyses using a variety of Japanese firm- and plant-level data that consistently confirms the negative exit effect (e.g., Nishimura et al. 2005; Fukao and Kwon 2006; Kim et al, 2007; Kwon et al. 2008; Inui et al. 2011; Ikeuchi et al. 2018; Fukao et al. 2021).

Consequently, the contribution of this study is summarized as follows: We use unique firm-level data that account for the history of firm exits along with exit modes—bankruptcy, voluntary closure, and merger. As already mentioned, the source of the negative exit effect in terms of exit mode is informative for policy discussions. In addition, the recent discussion on firm exits during the Covid-19 pandemic in Japan (e.g., Miyakawa et al. 2021; Hong and Saito 2021) highlights that the patterns could be different among different exit modes. Coad and Kato (2020) also employ the data on exit mode and examine how the pre-exit dynamics of firm performance depends on the type of exit modes. Thus, a quantitative analysis on how different modes of exits contribute to the reported negative exit effect can be informative. This information helps us better understand what the source of resource misallocation is that is associated with the negative exit effect.

III. Empirical Strategies

This section first presents the standard method in Foster et al. (2001) (FHK) that we use to decompose aggregate productivity growth into multiple components associated with various dimensions of firm dynamics. Then, we explain how to further decompose one of the components (i.e., exit effect) into multiple subcomponents of exit modes.

A. FHK

We start by defining aggregate productivity. It is the sum of the weighted log productivity for each firm. Here, $\ln X_t$ denotes the log of aggregate productivity in period t, while $\ln X_{f,t}$ is that of firm f in period t. The productivity of each firm is weighted by its relevant share and is summed to obtain the aggregate productivity.

$$\ln X_t = \sum_{f=1}^{n} \theta_{f,t} \ln X_{f,t} \quad (1)$$

Then, we compute the difference in this aggregate productivity from period $t-1$ to period t.

$$\Delta \ln X_{t-1 \to t} = \sum_{f=1}^{n} \theta_{f,t} \ln X_{f,t} - \sum_{f=1}^{n} \theta_{f,t-1} \ln X_{f,t-1} \quad (2)$$

This equation accounts for the growth of the aggregate productivity and is decomposed into the following five components:

"Within effect"—The first component accounts for the change in an individual firm's productivity growth. To focus solely on this internal effect, we fix the share as $\theta_{f,t-1}$ and compute the difference from $\ln X_{f,t-1}$ to $\ln X_{f,t}$ that is denoted by $\Delta \ln X_{f,t-1 \to t}$, as follows:

$$\sum_{f=1}^{n} \theta_{f,t-1} \Delta \ln X_{f,t-1 \to t} \quad (3)$$

As the share of each firm is fixed at the end of the previous period, this within effect will be higher, for example, when firms with a larger share as of period $t-1$ show higher growth in their productivity from period $t-1$ to period t.

"Share effect"—The second component accounts for the change in an individual firm's share. To focus solely on this effect, we fix the level of productivity $\ln X_{f,t-1}$ and compute the difference in the share from $\theta_{f,t-1}$ to $\theta_{f,t}$ that is denoted by $\Delta\theta_{f,t-1\to t}$, as follows:

$$\sum_{f=1}^{n} \Delta\theta_{f,t-1\to t}\left(\ln X_{f,t-1} - \ln\bar{X}_{t-1}\right) \quad (4)$$

One important remark here is that the productivity of an individual firm in period $t-1$ is measured as the deviation from the average level of the productivity in period $t-1$ (i.e., $\ln\bar{X}_{t-1}$). As this relative productivity of each firm is fixed at the previous period, this share effect will be higher, for example, when firms with relatively higher productivity compared to the average of incumbent firms as of period $t-1$ show higher growth in their share from period $t-1$ to period t.

"Covariance effect"—Firms can experience their growth both in productivity and in share. The third component accounts for this interaction and is computed as follows:

$$\sum_{f=1}^{n} \Delta\theta_{f,t-1\to t} \Delta \ln X_{f,t-1\to t} \quad (5)$$

In most studies, the sum of the share effect and covariance effect is often called the "reallocation effect".

"Entry effect"—The fourth component accounts for the change in the aggregate productivity that originates from new entrants. To measure the contribution of entering firms to the aggregate productivity growth, we compute the weighted average of the deviation in the productivity of new entrants that is benchmarked by the average productivity level of incumbent firms in period $t-1$ as follows where NEW denotes the set of entering firms.

$$\sum_{f\in NEW} \theta_{f,t}\left(\ln X_{f,t} - \ln \bar{X}_{t-1}\right) \quad (6)$$

We should note that the relative productivity level of entering firms is benchmarked by the average productivity level as of period $t-1$. Thus, this entry effect will be high, for example, when firms with relatively higher productivity compared to the average of incumbent firms as of period $t-1$ enter the economy in period t.

"Exit effect"—The fifth component accounts for the change in the aggregate productivity that comes from firm exits. To measure the contribution of exiting firms to the aggregate productivity growth, we compute the weighted average of

the deviation in the productivity of exit firms from the average productivity level of incumbent firms in period $t-1$ as follows where $EXIT$ denotes the set of exiting firms.

$$\sum_{f \in EXIT} \theta_{f,t-1} \left(\ln\bar{X}_{t-1} - \ln X_{f,t-1}\right) \quad (7)$$

Consequently, the individual productivity is subtracted from the average level of productivity as of period $t-1$. Thus, this exit effect will be high, for example, when firms with relatively lower productivity compared to the average of incumbent firms as of period $t-1$ exit in period t.

A subtle issue to measure the exit effect — as intensively discussed in Melitz and Polanec (2015), size of some components could vary depending on the way to define it. In particular, the entry and exit effect are susceptible to the definition of the benchmark. As demonstrated above, the FHK method used in this study employs the average productivity as of period $t-1$ (i.e., $\ln\bar{X}_{t-1}$) for benchmarking each firm's productivity. This use means that the entrants' productivity is measured as a deviation between surviving and exiting firms. Similarly, the exit firms' productivity is also benchmarked by $\ln\bar{X}_{t-1}$(i.e., surviving and exiting firms). This benchmark means that the productivity of entering firms only shows up in the computation of the entry effect. Suppose an economy is facing extremely high churning where most of the firms routinely exit from the market while very productive firms continuously enter. Under this circumstance, which resembles an emerging economy, the exit effect will be small as firms will be benchmarked mostly with concurrently exiting firms while the benchmarked productivity of new entrants will be very high as the high productivity of entrant themselves will not be accounted for by the benchmarking. In this sense, the FHK method is more appropriate for decomposing aggregate productivity under a moderately growing economy. Given that it is natural to characterize the Japanese economy as experiencing low growth, we use FHK in this study.[4]

B. Decomposing exit effect

After decomposing aggregate productivity growth into the five components, we further decompose the exit effect in equation (7) into four subcomponents as in equation (8), where $EXIT(type)$ is the set of firms exiting by exit type. The first category of $type$ is $bankruptcy$ which accounts for the failure to repay debt and going through the legal process of bankruptcy. The second category is $closure$ that accounts for the exit without failure to pay debt. This type comprises the temporary or permanent closure and dissolution.[5] The third category is $merged$ that accounts

[4] It is still informative to use, for example, the method proposed in Melitz and Polanec (2015) to decompose the growth of aggregate productivity in Japan. We set this as our future research theme.

[5] As discussed, Crane et al. (2020), for example, it is not necessarily clear how we should define the voluntary closure that is not accompanied by the failure to repay debt. In this study, we simply use the information on exit modes from the data provider.

for the firms that exit through a merger. As we detail more in the data section, the case contains a typical merger as well as some sort of reorganization of companies belonging to a large business enterprise. The fourth category is $indout$ that accounts for the firms that move out of their original industry classification. Although we can omit this category as we are not highlighting the productivity dynamics of each industry as our main target, we add it as the effect has recently gotten great attention in the literature (e.g., Fukao et al. 2021).

$$\sum_{f\in EXIT(type)} \theta_{f,t-1}\left(\ln\bar{X}_{t-1} - \ln X_{f,t-1}\right) \quad (8)$$

Corresponding to $indout$, in the decomposition of the entry effect, we also decompose it into two subcomponents, that is, $establish$ and $indin$. The first case accounts for pure entry into the economy, while the second case accounts for the firms that move into a new industry classification.

$$\sum_{f\in NEW(type)} \theta_{f,t}\left(\ln X_{f,t} - \ln\bar{X}_{t-1}\right) \quad (9)$$

IV. Data

To conduct the decompositions, we use the datasets provided by TSR (Tokyo Shoko Research Ltd.), which is one of the largest credit reporting agencies in Japan, through a joint research agreement between Hitotubashi University and TSR. TSR is a private company that operates in the areas of credit research and database distribution. The central product that TSR provides is the unsolicited report on the performance of each targeted firm. A typical report consists of more than 10 pages and comprises firms' basic characteristics and financial statement information.

A. Firm-level panel data

Our first data source is the "KJ file" that is an annual-frequency panel of Japanese firm data on their financial statement information as well as basic characteristics, such as the number of employees, listed status, and the list of products and services for the period from period $t = 2000$ to 2018.

There are some remarks regarding the dataset we use for our empirical analysis. First, the original KJ file included some firms that had abnormal values for sales. For example, the number of digits in sales for a limited number of firms dramatically changed depending on the years that was possibly due to changes in the reporting unit from a million JPY to a thousand JPY. Thus, we drop these firms from our data by checking the time series variation in sales.[6] Second, in order to

[6] We excluded firms whose coefficient of variation, which is the standard deviation divided by the mean value, is greater than 10. Since at least two years of observations are required to measure the coefficient of variation, firms with only one year of data during the observation period (2000-2018) are also excluded. For this reason, the exit occurs for the first time in 2001 and the entrances occur for the last time in 2017.

prevent a very small number of firms from significantly influencing the results of the analysis, we exclude firms whose number of employees or productivity are at the edge of the distribution for the entire sample.[7] Third, given that some firms do not report data for multiple years but resume reporting later, we interpolate the data for the missing years with the most recent available values. Fourth, financial institutions and public institutions are excluded.

Further, the year identifier t accounts for the timing of data collection and means that the data labeled year t consists of the data collected as of the end of December of year t. Given that most Japanese firms use an accounting period that ends at the end of March, the file labeled $t = 2012$, for example, consists of a large amount of firm information that corresponds to the accounting period that ended in March 2012.

Table 1 presents the number of firms stored for each year t. The data record slightly less than one million firms in each year that covers 27% of Japanese firms in terms of the number.[8] This coverage corresponds to 74% and 45% of aggregate sales and employees respectively as of 2016. That said, the KJ file covers a substantial portion of sales and employees for Japanese firms. Given that we use

[7] Specifically, in the baseline analysis using sales per employee as a productivity measure, we exclude firms whose number of employees or sales per worker falls outside the upper or lower the 0.1th percentile of the total sample for each year. In analyses using labor productivity and TFP as productivity measures, the threshold for the exclusion is set at the 0.5th percentile, so that an appropriate number of firms can be excluded even when the total sample size is small.

[8] We calculate this coverage in comparison with the Economic Census.

the number of employees as well as sales as the weights in the FHK decomposition, this high coverage enables us to depict a complete picture of the business dynamics in Japanese firms. Regarding the coverage by exit mode, the data we use for our empirical analysis cover 40% of bankruptcies, 40% of closures, and 70% of mergers.[9]

Table 1: Dynamics of observations

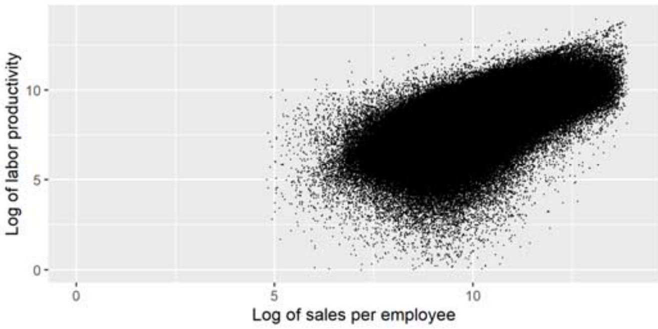
	All firms	Survivors	Entrants	Exit firms			
					Bankruptcy	Closure	Merged
2001	841,278	807,639	11,330	20,122	8,291	10,019	1,812
2002	864,992	826,958	8,562	21,436	8,318	10,984	2,134
2003	870,346	830,568	8,824	20,642	6,845	11,674	2,123
2004	871,998	834,601	10,456	20,553	6,304	12,174	2,075
2005	877,664	840,644	10,952	20,476	6,380	12,011	2,085
2006	881,460	845,447	11,798	20,588	6,844	11,549	2,195
2007	888,737	850,427	13,429	21,708	7,528	11,840	2,340
2008	896,508	857,804	13,139	20,769	6,471	12,201	2,097
2009	905,826	867,585	12,044	19,176	5,387	11,698	2,091
2010	918,954	881,142	11,938	17,715	4,925	10,989	1,801
2011	927,191	885,649	12,576	17,989	5,019	11,110	1,860
2012	937,133	895,052	11,636	16,849	4,109	10,795	1,945
2013	939,838	898,405	11,014	14,840	3,312	9,732	1,796
2014	929,815	886,378	11,639	13,047	2,760	8,500	1,787
2015	918,125	869,233	11,619	12,583	2,603	8,304	1,676
2016	898,575	839,458	9,759	11,105	2,083	7,423	1,599

[9] These coverages are based on the average number of firms from 2001-2017 and we calculate them in comparison with the corresponding business surveys conducted by the following research agencies: TSR for bankruptcy and closure, and RECOF for mergers. As for temporary closures, the TSR survey reports the number of those on a cumulative basis, while our data count the number of closures for each year, which may cause our coverage to be underestimated.

To measure firms' productivity and share, we choose to use basic firm attributes stored in the KJ file since it covers a large number of firms in each year. The data consist of firm size measured by sales and its change and profit (also the binary status of loss or not) and its change as well as the number of employees, their stated capital, and the status of the dividend payment and its change. The KJ file also includes firm age, owner age, the year of establishments, and their listed status. As the KJ file does not contain the information needed to measure value-added and capital, we cannot measure labor productivity and the TFP for the entire dataset. Given the trade-off between the sample size and the variety of productivity measurements, we use sales per employee as the main productivity measure as in Alon et al. (2017). Here, the raw number of sales is deflated for each industry.[10] For the robustness check of our empirical findings, we also use the financial statement information provided by TSR with which we can compute the labor productivity and TFP. However, the data coverage becomes substantially smaller as only 9% of firms that corresponds to 20% in aggregate sales are covered as of 2016. In Figure 1, we depict a scatter plot for the log of sales per employee (horizontal axis) and the log of labor productivity. We can confirm the positive association between those two productivity measures

[10] Industry groups are roughly in line with the major classification in National Accounts of Japan. Sales in wholesale and retail trade industry are deflated by the CPI (from the Statistics Bureau, Ministry of Internal Affairs and Communications), the construction sector by the Construction Cost Deflators (from the Ministry of Land, Infrastructure, Transport and Tourism), and other industries by the Corporate Goods Price Index (from Bank of Japan).

Figure 1: Sales per employ and labor productivity



Note: The figure depicts the log of sales per employ on the horizontal axis and the log of labor productivity on the vertical axis using data from period t=2000 to 2018.

The share used in the calculation of the aggregate productivity and its decomposition is measured on the number of employees in the case of using sales per employee or labor productivity as our proxy for productivity. When using TFP as our productivity measure, we employ sales as the share. As the KJ file also contains industry classifications in each period t, we can measure the change in each firm's industry classification, which we used to define $indout$ and $indin$ in the previous section.[11]

[11] In a companion project (Ito and Miyakawa 2022), we also study the prefecture productivity dynamics. In such analysis, it is necessary to take into account firm relocation.

B. Exit data

The TSR's KJ FLG file stores the record of firm exits with their time stamps and the information on their exit modes. This dataset facilitates not only the timing of firm exits but also the classification of the type of exit. As denoted in the previous section, we consider three modes of exits (i.e., $bankruptcy$, $closure$, and $merger$). We also consider the change in firms' industry classification as the other exit mode (i.e., $indout$).

C. Merger data

A part of the KJ FLG file is accompanied by the list of merging firm(s) in the case that $merged$ is the exit mode. Further combining the TSR's SK file, which accounts for the transaction (i.e., customer and supplier) and shareholding relationship of each firm, with the KJ FLG file, we can identify the type of mergers such as horizontal, vertical, corporate group

D. Entry data

As the KJ FLG file contains the date of firm establishment, we can identify the timing of its entry. If the establishment date is not available, we use the date of its founding instead. Here, one issue is that the data as of the timing of entry is not necessarily available in the dataset that means we cannot measure the entry effect precisely for all the entrants. Given this data constraint, we define the entering firms as those that show up in TSR within four years of the time of entry.

E. Variable definition

As already noted, we mainly use a ratio of the sales to the number of employees as our productivity measure ($\ln X1_{f,t}$). We also use the labor productivity defined as a ratio of value-added to the number of employees ($\ln X2_{f,t}$) and TFP ($\ln X3_{f,t}$) as two alternative productivity measures.

V. Empirical Results

A. Productivity dynamics

Table 2 is a summary of the results of our decomposition exercise using $\ln X1$ as our productivity measure. The second column labeled as $\Delta \ln X1$ denotes the annual average growth of the productivity measure (i.e., sales per employee) over the periods indicated in the first column. The number in the second column is decomposed into the four components of within, reallocation, entry, and exit effects.

Table 2: Baseline results

periods	ΔlnX1 a= b+c+f+i	Within b	Reallocation c=d+e	Share d	Covariance e	Entry f	Exit i
2000-2010	-0.65	1.53	-1.74	1.27	-3.01	0.03	-0.46
2010-2018	1.42	1.88	-0.23	2.60	-2.83	0.10	-0.33
2000-2004	0.08	2.79	-2.34	0.52	-2.86	0.13	-0.51
2004-2008	-0.11	1.68	-1.36	1.72	-3.08	-0.01	-0.41
2008-2010	-3.19	-1.31	-1.30	1.87	-3.18	-0.12	-0.46
2010-2014	1.16	2.45	-0.99	1.83	-2.82	0.01	-0.31
2014-2018	1.69	1.32	0.54	3.38	-2.84	0.19	-0.35

Note: The table presents the results of our decomposition exercise.

Before examining the exit effect in detail, we briefly go over the other effects measured in our exercise. Note that most of the other studies on the productivity dynamics of Japanese firms suffer from data truncation. For example, studies using BSJBSA, which is one of the major firm datasets obtained from a governmental compulsory survey, do not include firms with less than 50 employees or with paid-up capital of less than 30M JPY. One advantage of the TSR data is that we do not suffer from this truncation.

First, regarding the aggregate productivity growth, the Japanese economy experienced a large drop during the Global Financial Crisis (GFC) from 2008 to 2010. After that, the aggregate productivity shows moderate growth. Second, the within effect also experienced a large drop during the periods of the GFC. Third, the reallocation effect has been gradually improving over the periods that is driven by the share effect. Fourth, while the entry effect tends to be positive and contributes to productivity growth, it becomes negative during the GFC. Fifth, as the most important feature of this study, the exit effect is always negative as most other studies have reported. This negative sign means that firms exiting from the economy show higher productivity compared to the surviving firms. The result that the negative effect is also prevalent during the economic downturn is inconsistent with the cleansing effect proposed by Foster et al. (2014). In one related study, Riley et al. (2015) points out that the churning of the UK economy becomes lower after the GFC. As already mentioned, our results show that the impact of the entry effect is negative after the GFC. Japanese firms seem to show a similar mechanism as to that documented in Riley et al. (2015) that after the GFC, the churning mechanism in terms of extensive margin in total becomes lower.

B. Decomposition of exit effect and entry effect

In this section, as the main part of the present study, we further decompose the exit effect by using the information on exit modes. Table 3 has a summary of the results. Namely, we decompose the exit effect with bankruptcy (bankruptcy effect), voluntary closure (closure effect), merger (merged effect), and the changing industry classification (indout effect). We also show the result of our decomposition exercise for the entry effect with firm establishment (establishment effect) and an alternative change in industry classification (indin effect).

Table 3: Decomposition of entry effect and exit effect

periods	Entry			Exit				
		Establishment	Indin	i=	Bankruptcy	Closure	Merged	Indout
	f=g+h	g	h	j+k+l+m	j	k	l	m
2000-2010	0.03	-0.17	0.20	-0.46	-0.06	0.09	-0.33	-0.16
2010-2018	0.10	-0.11	0.21	-0.33	-0.00	0.13	-0.29	-0.17
2000-2004	0.13	-0.16	0.29	-0.51	-0.08	0.04	-0.25	-0.22
2004-2008	-0.01	-0.16	0.15	-0.41	-0.04	0.12	-0.37	-0.13
2008-2010	-0.12	-0.22	0.10	-0.46	-0.06	0.12	-0.41	-0.11
2010-2014	0.01	-0.16	0.17	-0.31	-0.01	0.14	-0.32	-0.13
2014-2018	0.19	-0.06	0.25	-0.35	-0.00	0.11	-0.26	-0.20

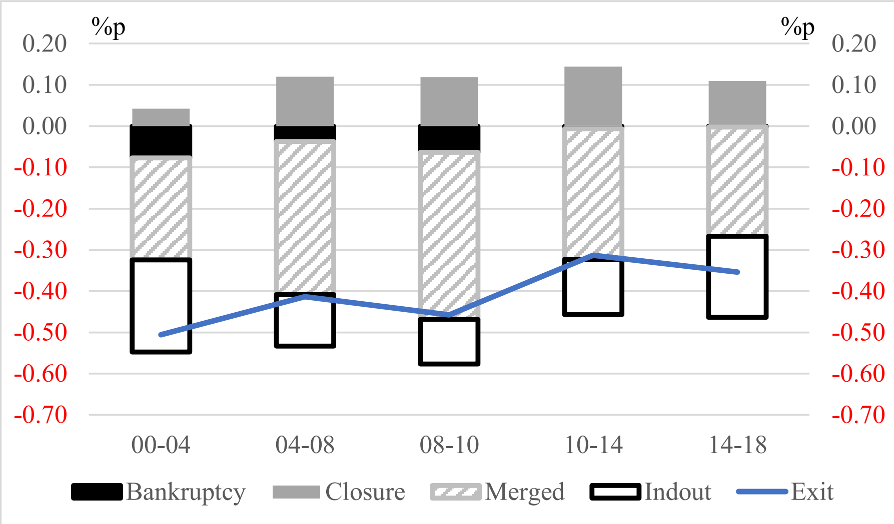
Note: The table gives the results of our decomposition exercise for the entry effect and the exit effect.

First, as the most important result, the negative exit effect is mainly driven by the merged effect. It means that firms with relatively high productivity exit from the market through mergers. Our empirical exercise highlights that the reported puzzling effect in the literature is not solely attributed to an “unnatural” selection mechanism but could rather come from the merged effect. Given that the motivation behind mergers could be for the merging firm to gain quick access to productive resources held by the target firm in order to achieve growth, it is in fact quite natural to observe such a negative merged effect. Second, in contrast to the constantly negative merged effect, the closure effect is in most of the cases positive and stays substantially large during the economic downturn of 2008–2010. This is consistent with the results reported in most studies on countries other than Japan. Third, as a still remaining a puzzle, the default effect is in some of the periods still negative. Fourth, the indout effect is always negative. This sign means that firms that are considered relatively productive in their industry move to other industries.

Regarding the entry effect, the establishment effect and the indin effect are always negative and positive, respectively. First, this result suggest that compared to the incumbent firms, entrant firms are not necessarily productive when we measure the productivity by sales per employee. Second, the positive indin effect is sizable in comparison with the negative indout effect. This difference means that firms that are considered relatively productive in their old industry are still considered productive in their new industry. As the sum of the indin and indout effects are in many cases positive or almost zero, the reallocation of resource among industries have been on average slightly contributing to aggregate productivity growth.

Figure 2 depicts the share of each exit effect for subperiods. It shows that the large fraction of the dynamics of the exit effect is attributed to merged effect. The absolute size of this effect increases is large in 2008 to 2010, which indicates that productive firms tend to exit through merger under economic downturn.

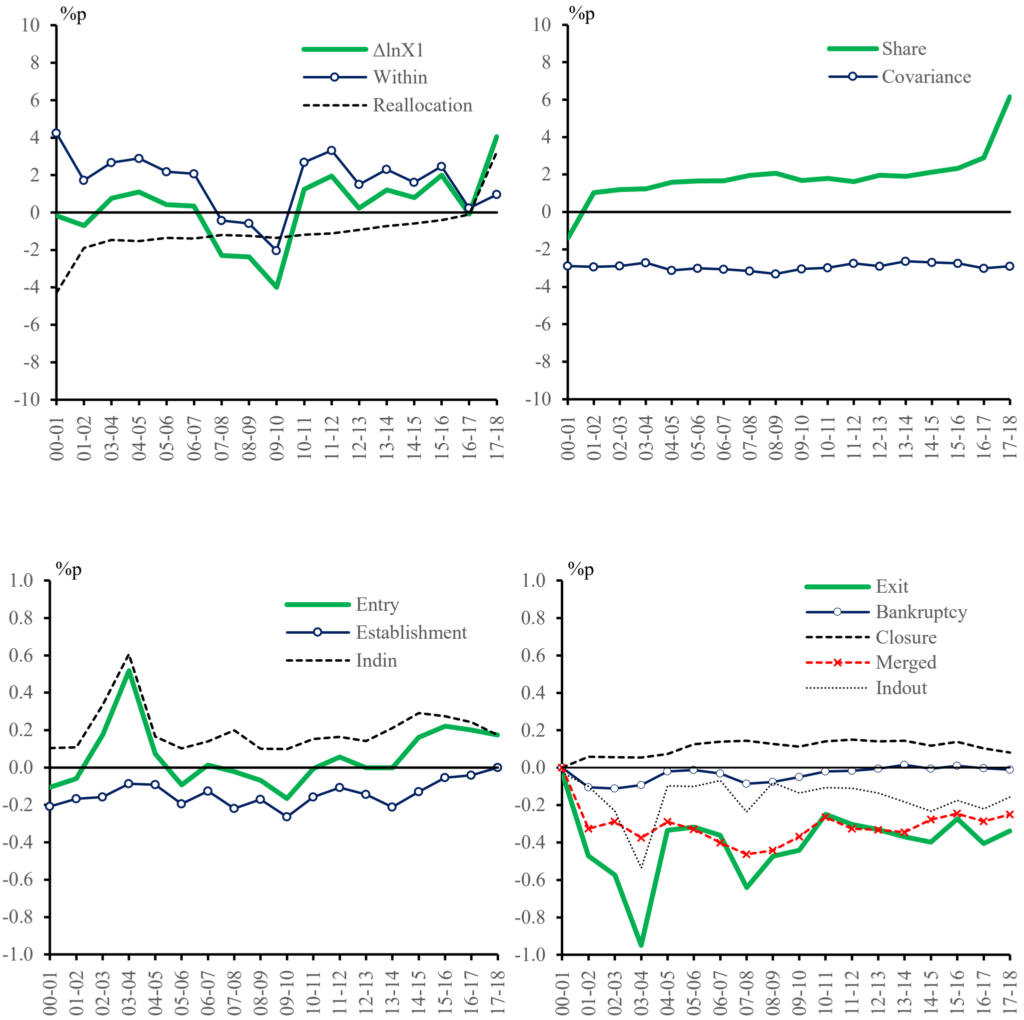
Figure 2: Decomposition of exit effect



Note: The figure depicts the results of our decomposition exercise of exit effect.

To confirm that the aforementioned results are robust against the definition of a subperiod, Figure 3 shows the time series of the decomposition year by year: We find that (a) the aggregate productivity growth and within effect have sharp drops in 2008–2009; (b) the reallocation effect is negative due to the stably negative covariance effect; (c) merged effect is consistently negative; (d) the negative exit effect is prevalent over the periods; (e) the entry effect gradually improves recently; (f) the negative default effect, the remaining puzzle, is small compared to the other components of exit effect.

Figure 3: Decomposition of $\Delta\ln X1$ (year by year)



Note: The figures depict the results of our decomposition exercise.

Most of the literature that reports the negative exit effect in Japan has paid great attention to the following two mechanisms. The first is based on firms' relocation to overseas. While moving is plausible for large manufacturing firms, it is not for small and medium-sized enterprises (SMEs) accounting for a certain part of

Japanese economy, which do not have a great chance to go abroad. The same argument could be applied to non-manufacturing firms. While we do not claim such an overseas relocation effect is absent in general, at least for SMEs in non-manufacturing industries, the potential explanatory power is quite limited.

The other mechanism is so-called zombie firms. In this exposition, firms with low productivity could somehow obtain financial support from financial institutions and survive. As these unproductive firms do not exit the economy, the likelihood of productive firms exiting becomes higher than in the case without zombie firms. This conjecture is somewhat consistent with the low entry and exit rates observed in Japan. Furthermore, the negative default effect reported in the present paper suggest that such a story is plausible although the quantitative impact is quite limited as we have already shown.

To check the robustness of our results regarding the decomposition of exit effect, Table 4 shows the decomposition exercise based on the labor productivity and TFP measure ($\Delta \ln X2$ and $\Delta \ln X3$, respectively) as our productivity measure.[12] As already mentioned, we employ the number of employee and the sales as the shares for each productivity measure, respectively. The merged effect kept negative as a whole as we presented in our baseline analysis.

[12] For the calculation of the TFP, we estimate the production function using the method of Ackerberg et al. (2016), which is currently considered the standard method, and measure it as the residual of the change in value-added minus the contributions of the changes in labor and capital. Here, value-added is deflated by using the ratio of real and nominal value-added (obtained from JIP database by Research Institute of Economy, Trade and Industry) as a deflator.

Table 4: Decomposition of exit effect based on labor productivity and TFP

periods	ΔlnX2	Exit				
		i=	Bankruptcy	Closure	Merged	Indout
	a	j+k+l+m	j	k	l	m
2000-2010	2.05	0.17	0.06	0.04	-0.01	0.08
2010-2018	1.06	0.09	0.03	0.05	-0.00	0.01
2000-2004	8.37	0.04	0.03	0.02	-0.00	-0.01
2004-2008	-1.38	0.30	0.09	0.04	0.01	0.16
2008-2010	-3.76	0.15	0.07	0.06	-0.06	0.08
2010-2014	1.28	0.12	0.04	0.07	-0.00	0.01
2014-2018	0.83	0.06	0.02	0.03	0.00	0.01

periods	ΔlnX3	Exit				
		i=	Bankruptcy	Closure	Merged	Indout
	a	j+k+l+m	j	k	l	m
2000-2010	-1.02	-1.42	-0.14	-0.04	-0.49	-0.75
2010-2018	3.48	-1.26	-0.05	-0.02	-0.48	-0.70
2000-2004	2.93	-1.29	-0.13	-0.01	-0.37	-0.77
2004-2008	-2.56	-1.42	-0.15	-0.03	-0.41	-0.84
2008-2010	-5.81	-1.69	-0.17	-0.12	-0.89	-0.51
2010-2014	0.83	-1.30	-0.06	-0.04	-0.54	-0.67
2014-2018	6.13	-1.22	-0.04	-0.01	-0.43	-0.74

Note: The table presents the results of our decomposition exercise for labor productivity and TFP.

D. Further decomposition of the negative merged effect

Since we have confirmed the robust negative merged effect, one natural question to ask is whether specific types of mergers are more closely associated with that effect. These types consist of intra- and inter-industry (horizontal merger or not).

In a different context, mergers could be also done between firms that are transacting with each other (e.g., customers and suppliers) and be connected with shareholdings (vertical mergers and corporate-group mergers, respectively). The number of cases categorized in each type of merger are shown in Table 5. There are more mergers for intra- than inter-industries and the largest number of mergers are observed with no transaction or shareholding relationship.

Table 5: The number of merger cases categorized by type

Total		1,939
Industry	Inter	706
	Intra	1,138
	Unknown	95
Relationship	Transaction	226
	Capital	206
	Both	363
	None	1,048
	Unknown	95
Salvaging	Yes	494
	No	1,445

Note: The table shows the average number of mergers from 2001 to 2017 by merger type.

The results of the decomposition by merger type and by industry are presented in Tables 6 and 7 and Figure 4, respectively. First, those results show that all types of mergers and mergers for most of the industries exert negative merged effects. There is a widespread tendency for merging firms to target high-performing firms across those types of mergers and across industries, which confirms the robustness of our result on the negative merged effect[13]. Second, we see a clear difference in the absolute effects of merged effects between intra- and inter-industry mergers. Namely, the magnitude is more than double in the case of intra-industry mergers. Third, we find that mergers involving firm-pairs with transaction and capital relationships have smaller magnitude (i.e., negative merged effects with smaller absolute value). This result is somewhat surprising as we conjecture that in those type of merger, the merging firms are familiar with the target firms, and hence successfully find high-performing firms to merge with. Further, we consider a comparative analysis with salvaging firms. In this analysis, a salvaging merger is defined as one in which the merging firm records a loss in the year prior to the merger. Note that we consider a merger to be non-salvaging when the information on profits is not available. The merged effect has remained around zero for a salvaging merger, while non-salvaging mergers show sizable negative effect throughout the period. Logically, the productivity of target firms in the case of salvaging mergers is not very high, and it does not contribute much to the negative merged effect.

[13] It should be noted that we need to be careful about measuring the output for specific industries such as wholesale, which we recognize as our future work.

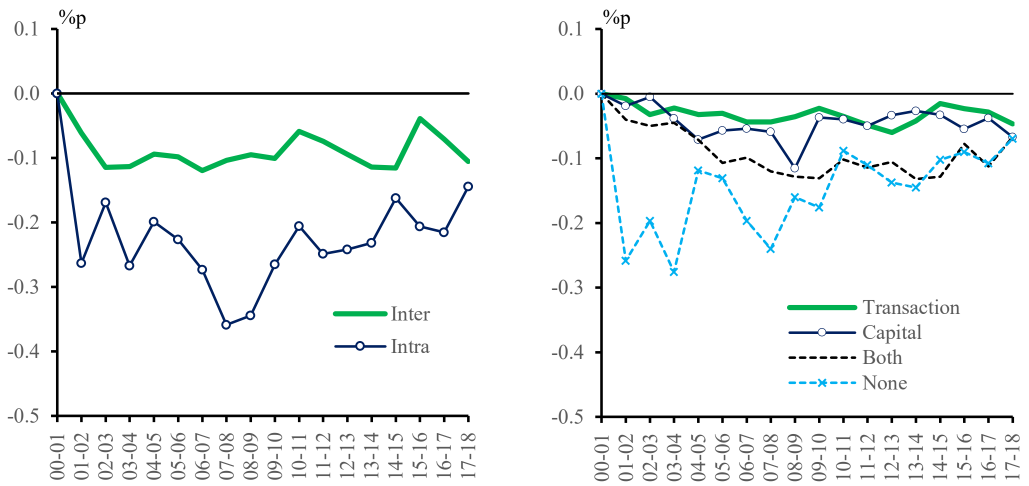
Table 6: Decomposition of the merged effect

periods	Merged								
		Industry		Relationship				Salvaging	
	l= q+r or s+t+u+v or w+x	Inter q	intra r	Transaction s	Capital t	Both u	None v	Yes w	No x
2000-2010	-0.33	-0.09	-0.24	-0.03	-0.05	-0.08	-0.18	-0.08	-0.25
2010-2018	-0.29	-0.08	-0.21	-0.04	-0.04	-0.10	-0.11	-0.05	-0.24
2000-2004	-0.25	-0.07	-0.17	-0.02	-0.02	-0.03	-0.18	-0.07	-0.18
2004-2008	-0.37	-0.10	-0.26	-0.04	-0.06	-0.10	-0.17	-0.06	-0.31
2008-2010	-0.41	-0.10	-0.30	-0.03	-0.08	-0.13	-0.17	-0.12	-0.28
2010-2014	-0.32	-0.09	-0.23	-0.05	-0.04	-0.11	-0.12	-0.06	-0.26
2014-2018	-0.26	-0.08	-0.18	-0.03	-0.05	-0.10	-0.09	-0.04	-0.22

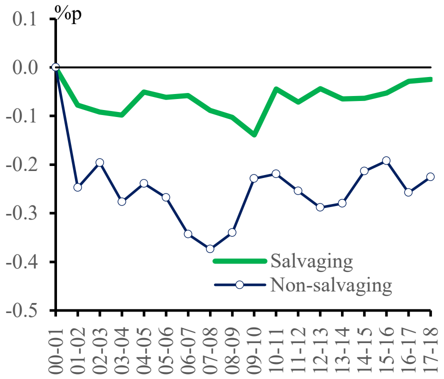
Note: The table presents the results of our decomposition exercise on the merged effect by merger type. The merged effects for cases where the types are unknown are negligibly small and therefore not included.

Figure 4: Decomposition of the merged effect (year by year)

(a) Industry (b) Relationship



(c)Salvaging



Note: The figure depicts the results of our decomposition exercise on merged effect by merger type. The merged effects for cases where the types are unknown are negligibly small and therefore not included.

Table 7: Decomposition of the merged effect by industry

	00-10	10-18	00-04	04-08	08-10	10-14	14-18
Overall	-0.33	-0.29	-0.25	-0.37	-0.41	-0.32	-0.26
Manufacturing	-0.11	-0.11	-0.10	-0.12	-0.12	-0.12	-0.11
Wholesale and retail trade	-0.11	-0.09	-0.10	-0.12	-0.13	-0.11	-0.07
Service activities	-0.03	-0.03	-0.01	-0.04	-0.06	-0.02	-0.04
Construction	-0.03	-0.02	-0.03	-0.03	-0.03	-0.02	-0.02
Information and communications	-0.03	-0.02	-0.01	-0.03	-0.05	-0.03	-0.01
Real estate	-0.01	-0.01	-0.00	-0.02	0.00	-0.01	-0.01
Transport	-0.00	-0.00	-0.00	-0.01	0.00	-0.00	-0.00
Agriculture, forestry and fishing	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00
Mining	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
Electricity, gas and water supply, waste management service	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00

Note: The table gives the results of our decomposition exercise on merged effect by industry.

E. Further decomposition of the voluntary closure effect

While our empirical findings partly resolve the puzzling negative exit effect reported in the Japanese economy, we have also confirmed that the positive closure effect is observed. In this subsection, we examine this empirical fact by using a more detailed exit flag that we can use to further decompose the current closure effect into that associated with the temporary closure, permanent closure, and dissolution. Here the temporary closure is recorded when the TSR analysts find a firm closing their business only temporarily while planning to resume the business in the near future. Contrary to this category, permanent closure means that TSR analysts do not expect the firms to resume business again.

As apparent from this description, the distinction between temporary and permanent is essentially subjective. Although a type of non-temporary closure (i.e., dissolution) is somewhat objectively identified as it requires a legal procedure, the distinction between temporary closure and permanent closure is still vague and could potentially suffer from measurement error. Nonetheless, examining the exit effect associated with temporary and non-temporary types of closure is worthwhile because they could have different implications for long-term macroeconomic productivity. If a less productive firm chooses to close its business permanently rather than temporarily, this closure positively affects the aggregate productivity in the long run. On the other hand, if a firm with relatively low productivity only temporarily closes its business, it will have a productivity effect on macroeconomic productivity at that point, but that positive effect will disappear when the firm resumes its operation (if the productivity remains unchanged).

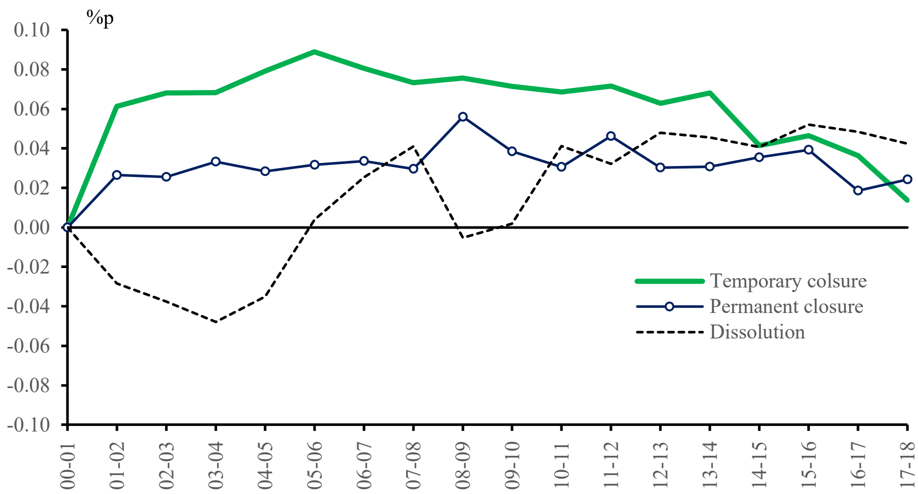
Table 8 and Figure 5 show the decomposition of the closure effects. The results show that the closure effect for temporary closure is always positive, while those for permanent closure are positive but smaller for most periods and the year. First, the positive sign for the temporary closure means that low-performing firms choose temporary closure rather than permanent closure or dissolution. From the perspective of churning, the temporary closure by low performers does not contribute to the aggregate productivity growth if they resume their business sometime later. Second and more importantly, the smaller positive closure effect occurs for the permanent closure. As already discussed, it is unnatural that the permanent closure is less pronounced than the temporary closure in the exits of less productive firms. It is an open question why such unnatural selection occurs.

Table 8: Decomposition of the closure effect

periods	k= n+o+p	Closure: Temporary Closure n	Closure: Permanent Closure o	Closure: Dissolution p
2000-2010	0.09	0.07	0.03	-0.01
2010-2018	0.13	0.05	0.03	0.04
2000-2004	0.04	0.05	0.02	-0.03
2004-2008	0.12	0.08	0.03	0.01
2008-2010	0.12	0.07	0.05	-0.00
2010-2014	0.14	0.07	0.03	0.04
2014-2018	0.11	0.03	0.03	0.05

Note: The table presents the results of our decomposition exercise on the closure effect.

Figure 5: Decomposition of closure effect (year by year)



Note: The figure depicts the results of our decomposition exercise on the closure effect.

F. "Net" effect of exit through a merger

While we have confirmed the negative merged effect, a natural question is whether or not the growth of "merging" firms could offset it. Such a discussion is informative in the sense that the causal effect represents the quantitative implication of resource reallocation from target firms to merging firms. To illustrate, the bad scenario is that merging firms obtain the resources originally held by highly productive target firms but could not perform well afterwards, which simply leads to a waste of resources. The good scenario is that merging firms grow more than what the target firms could have eventually achieved. Although each case could show different quantitative effects on the economy, it is informative to understand the average effect associated with those mergers.

Against this background discussion, we estimate the causal effect that runs from mergers to the productivity of merging firms. After quantifying the causal effect by estimating the average treatment effect on the treated (ATT) on the merging firms' productivity, we compare the aggregate causal effect (the merging effect) and the already measured merged effect.[14][15]

For this causal inference, we use the inverse probability weighting (IPW) that is based on the propensity score to estimate the causal effect of mergers on

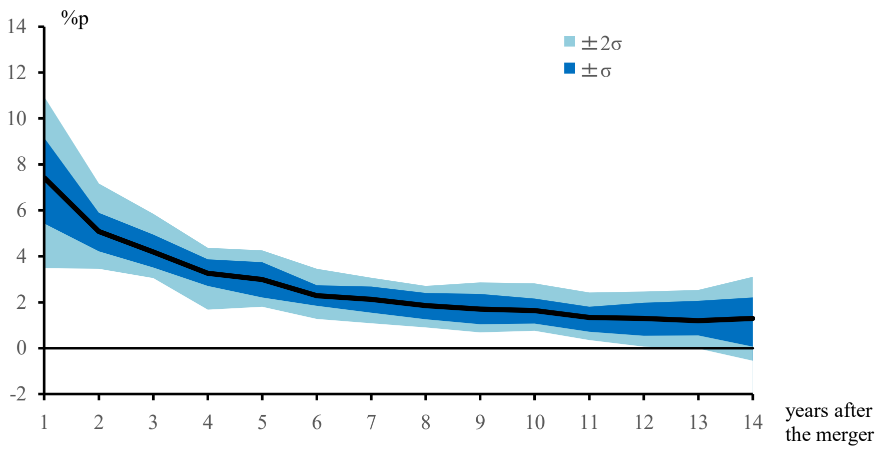
[14] See Appendix for details on how to estimate the merging effect.

[15] As an important limitation of our exercise, we do not analyze cross-border mergers that have been one of the important research issues in the context of firm performance (e.g., Fukao et al. 2008).

productivity growth. The covariates of the propensity score are (a) the log of sales, (b) the log of sales per employee, (c) the recent 3-year average productivity (sales per employee) growth before the merger, and (d) the number of industries in which each firm operates. After computing the propensity score through a logit estimation, we use the IPW method to estimate the ATT for the merger events. Given it might take time for merging firms to experience the causal effect of mergers, we estimate the ATT for multiple windows that range from 1–14 years after the timing of mergers with pooling data.

Figure 6 depicts the estimated ATTs for the merger events for multiple-year windows. We confirm that the estimates of ATTs are positive and statistically away from zero for at least the windows from 1–12 years. This sign means that merger with more productive firms on average is not a waste of resources for Japanese firms.

Figure 6: Causal effects of mergers on merging firms' productivity

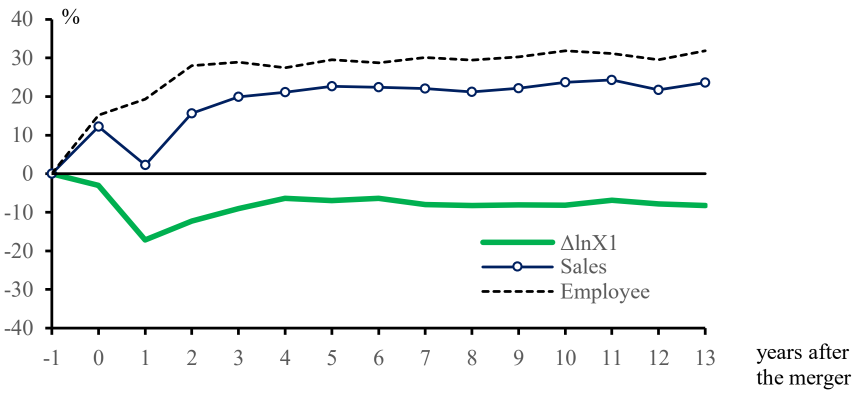


Note: The figure depicts the ATTs for the average growth rates in firms' productivity during the numbers of years shown on the horizontal axis after the merger. The line and the shaded area indicate the mean value and the standard deviation ($\pm\sigma$ and $\pm 2\sigma$) respectively which we calculate with the bootstrap method.

Moreover, the causal effect of the first year after the merger is quite sizable. This result raises the concern that the effect is merely brought by the mechanical aggregations of sales and employees for low-performing merging firms and high-performing target firms. To examine this, we analyze the evolutions of sales, employees, and productivity for merging firms before and after the merger through an aggregation. In order to clarify the effect of the aggregations, we consider the two summations of merging and target firms for sales and number of employees and the "hypothetical" productivity that is not obtained from the financial statements. If the abovementioned causal effect is simply due to the summation of two firms, this hypothetical productivity measure shows that the dynamics are similar to those obtained from the causal inference.

Figure 7 shows the result of this analysis. We confirm that the summations of sales and the number of employees does not lead to a clear improvement in the merging firm's productivity. More importantly, we confirm that there is a rather significant drop in productivity at the following year that is driven by a large drop in sales while the number of employees slightly grows. This discussion indicates that the causal effect overwhelms the aggregation effect as of one year after the merger.

Figure 7: Effects of mergers on merging firms' productivity



Note: The figure depicts cumulative growth rates for $X1$ *(sales per employee), sales and employees from the year previous to the merger. In the horizontal axis, sales and employees at 0 indicate the growth rate from the previous year's values to the sum of the values of the target and merging firms as of the merger year.* $\Delta\ln X1$ *at 0 is the growth rate from the previous year's* $X1$ *to the one which we calculate by taking the ratio of the two summations for sales and employees.*

Next, we compare the sum of the within effect defined in equation (3) and the covariance effect in equation (5) with the sum of following two effects:

$$\sum_{f \in merging} \theta_{f,t-1} ATT_{f,t-1\to t} \quad (10)$$

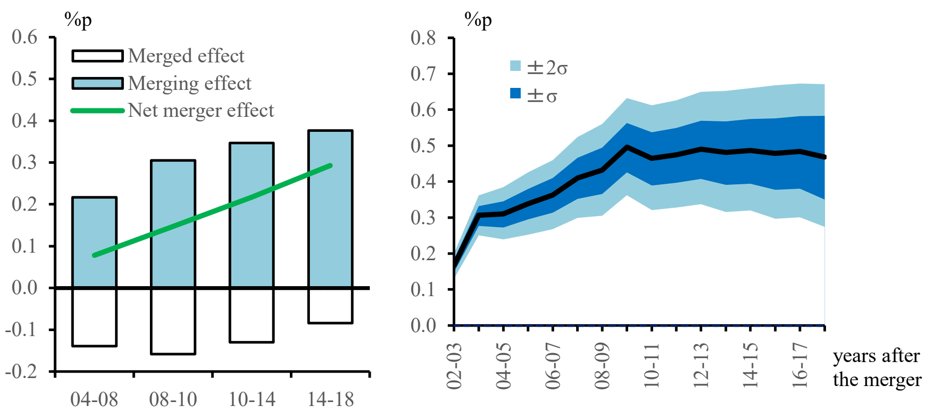
$$\sum_{f \in merging} \Delta\theta_{f,t-1} ATT_{f,t-1\to t} \quad (11)$$

Here, equation (10) accounts for the hypothetical within effect that originates from mergers. It sums up the merging firms' ATT weighted by their share. In the same form, equation (11) accounts for the covariance effect that consists of the change in sales share and the ATT. Using the standard deviations in the ATT that we calculate with the bootstrap method, we also measure the standard deviations for equations (10) and (11).

Figure 8 depicts the gross merging effect, gross merged effect, and the net merger effect from those two effects. Based on our estimation, the net merger effect is positive and sizable given that the annual growth rate of the aggregate productivity measure is at most around 1 to 2% as shown in Table 2. Looking at the time series of those estimates, the net merger effect gets larger as time passes. This is partly because the merging effect on a single merger affects the productivity growth in the following years as long as the firm continues to exist after the merger, while the merged effect on a single merger occurs on a one-shot basis.[16]

Figure 8: Merging effect and merged effect

(a) Net merger effect (b) Net merger effect with error bands



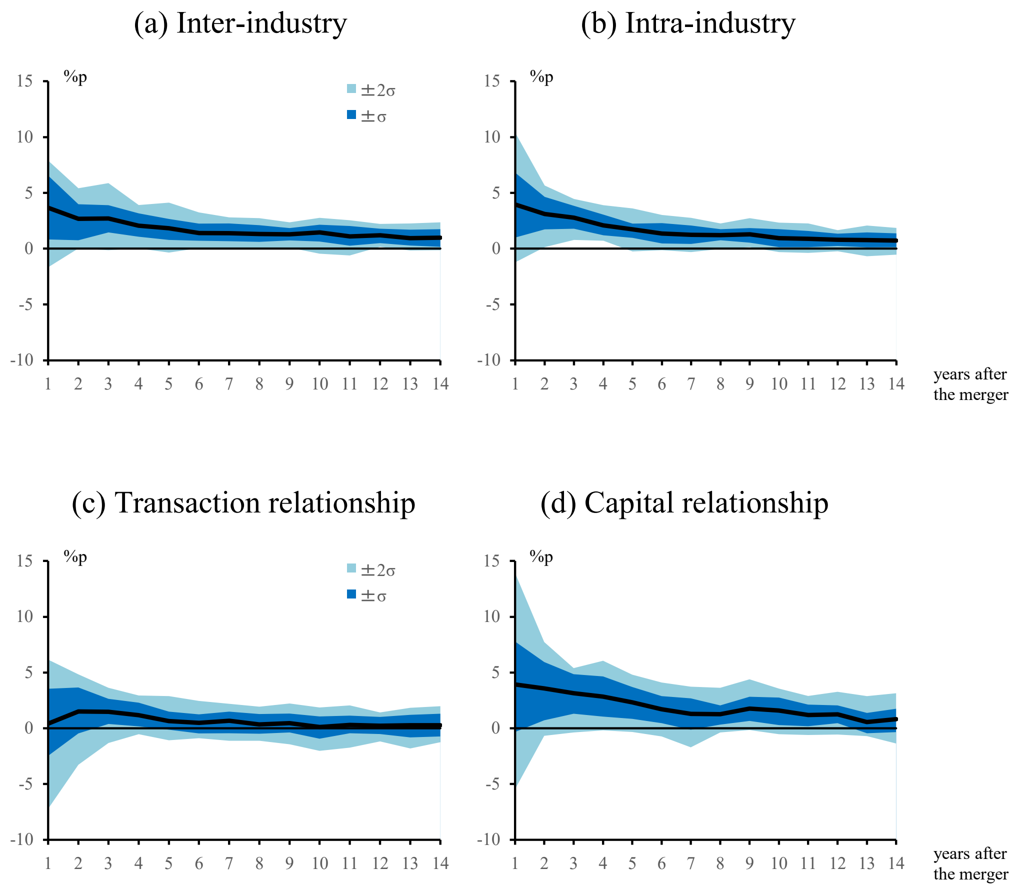
Note: (a) depicts the net merger effects for each period; (b) depicts the values for each year. We calculate the net merger effect in (b) by adding up the merged effect to both the mean value and the standard deviation ($\pm\sigma$ and $\pm 2\sigma$) of the merging effect.

Figure 9 shows the ATTs by type of merger. The results show that the industry relationship and whether it is a salvaging merger or not does not make a large difference in the merging effect. In terms of transaction and capital relationship, the highest effect is observed for the mergers between firms with no relationships. This is consistent with the previous result that the absolute size of the negative merged effect between firms without transaction or capital relationships was large. While

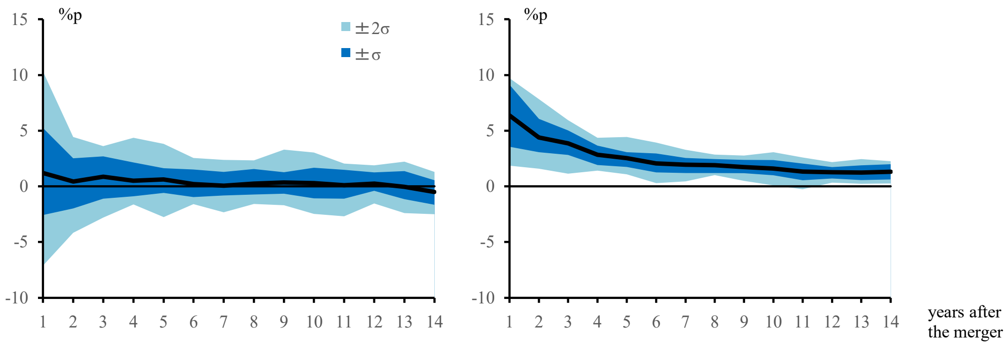
[16] Note that the merging effects for mergers that may have actually occurred before 2001 are not taken into account because that information is not available in our dataset.

mergers without any relationships involve target firms with higher productivity than other types of mergers, the merging firms in fact exert higher merging effects than those with the other types of mergers.

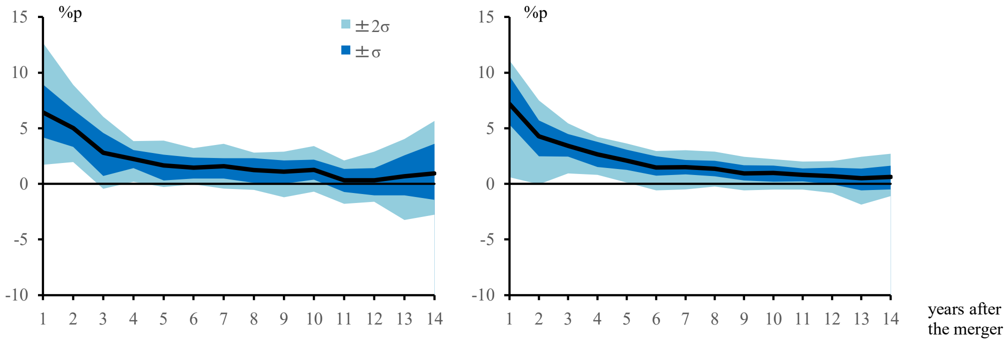
Figure 9: Causal effects by merger type



(e) Transaction and capital relationship (f) No relationship



(g) Salvaging (h) Non-salvaging



Note: The figures depict the ATTs by merger type for the average growth rate in productivity during the numbers of years shown on the horizontal axis after the merger. The line and the shaded area indicate the mean value and the standard deviation (±σ and ±2σ) respectively which we calculate with the bootstrap method.

To see this point more clearly, using the ATTs by merger type described above, we calculate the net merger effects by merger type. The number of mergers by type for this exercise is shown in Table 9. We only use merger pairs in which both the merging and target firms are included in our dataset in this analysis, and therefore the number of mergers differs from that in Table 5.

Table 9: The number of mergers (by merger type)
(for the analysis on net merger effect)

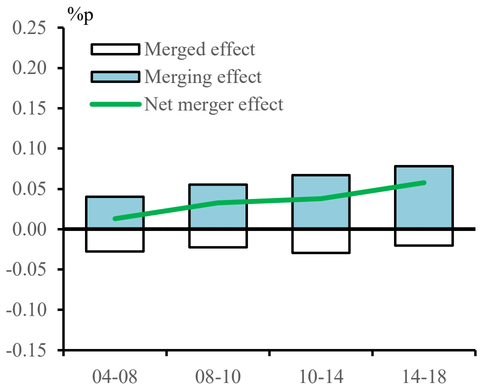
Total		1,295
Industry	Inter	468
	Intra	827
Relationship	Transaction	184
	Capital	145
	Both	249
	None	718
Salvaging	Yes	336
	No	959

Note: The table shows the average number of mergers from 2001 to 2017 by merger type. For the analysis of the net merger effect, mergers where the merging firms are not found in the TSR data are excluded.

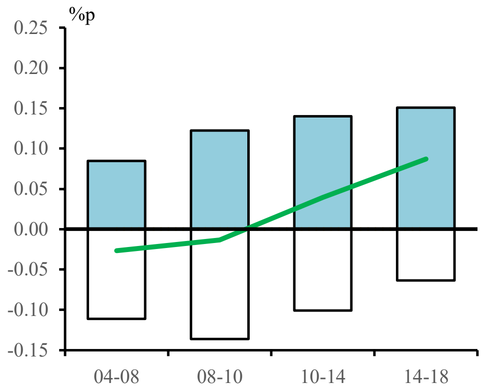
The results are as follows. From Figures 10(a) and 10(b), we confirm that the intra-industry mergers have a larger net merger effect than the inter-industry mergers. This is because although the negative merged effect was more apparent for between industries than within industries, the merging effect was in fact much larger for between industries. This result can be interpreted as firms are more likely to find better firms to merge with and as a result the merger is more likely to be successful in the case of between the industry.

Figure 10: Merging effect and merged effect (by merger type)

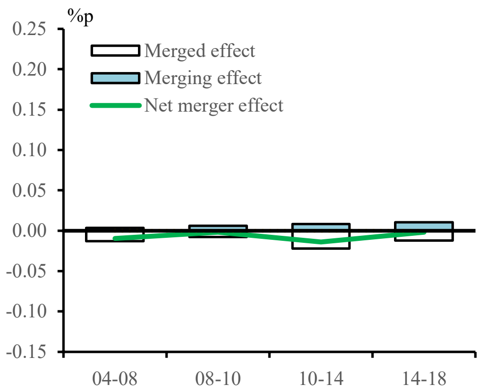
(a) Inter-industry



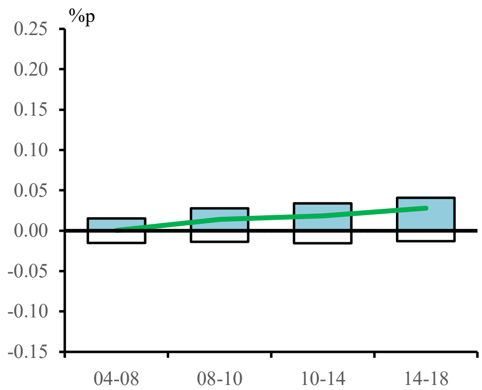
(b) Intra-industry



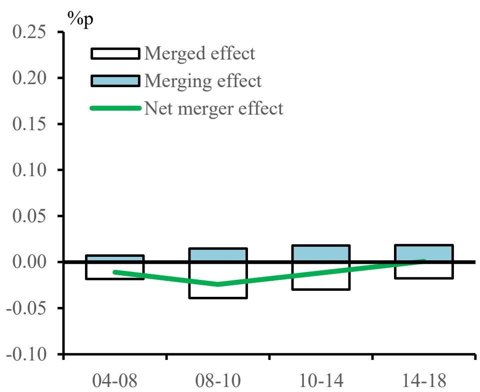
(c) Transaction relationship



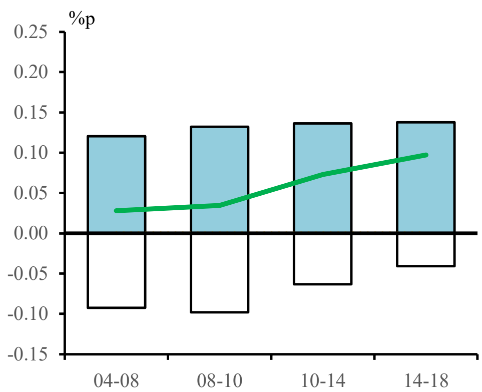
(d) Capital relationship

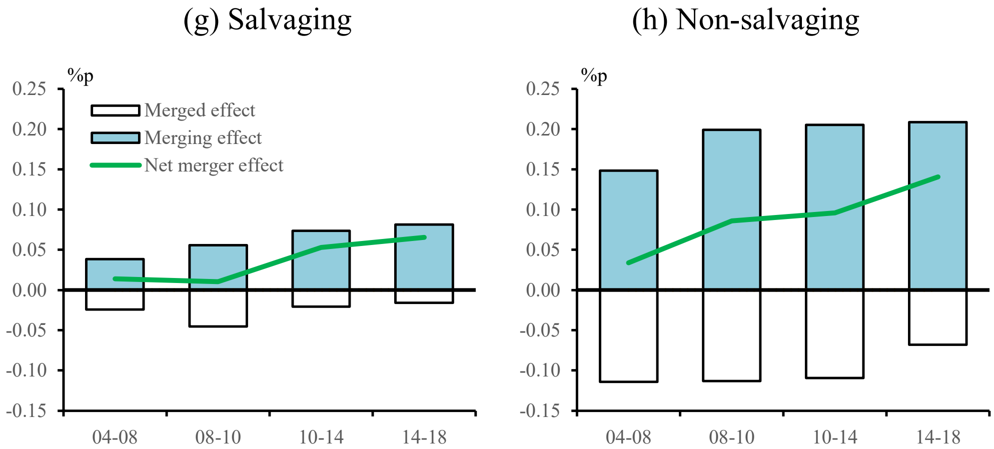


(e) Transaction and capital relationship



(f) No relationship





Note: The figures depict the net merger effects for each period by merger type.

Figures 10(c)–10(f) show the net merger effect by transaction or capital relationship. Interestingly, the effect is the most dominant for the merger with "no transaction or capital relationship", that is, the merger type that showed the largest ATT in the previous analysis. On the other hand, the effects for the mergers with transaction or transaction and capital relationships were relatively tiny although negative merged effect is more pronounced for the cases with transaction and capital relations. The fact that we find a high net merger effect for the merger with no transaction or capital relationship indicates that contrary to the cases with some relations prior to the mergers, the synergies originating from the cases without any previous relations could be large. As a future task, it is necessary to investigate what makes the net merger effect of each type differ.

Figures 10(g) and 10(h) show the net merger effects in each case of a salvaging merger or not. In both cases, the net merger effect is positive. In the case of salvage mergers, the positive merger effect is quite large, even though the negative merged effect is small. This contribution indicates well the efficacy in resource reallocation. Furthermore, in the case of the non-salvaging merger, large merging effects occur, and the net merger effect is much larger than that of the salvaging merger.

VI. Discussion

There are several important issues and concerns regarding our empirical analysis, some of which in turn lead to important extensions of the current analyses. First, as we repeatedly emphasized, the plausibility of our decomposition exercise needs to be carefully examined. For this purpose, it is useful to consult not only the sales per employee but also the labor productivity and the TFP. Although we show that the main result of our analysis is not susceptible to the choice of our productivity measure, it is necessary to compare the size of each effect with that reported in other studies. Second, as already mentioned, it is important to examine the backgrounds of heterogeneity in terms of net merger effects by merger type. This implication would be highly informative for designing related policy. Third, given the default effect is still one of the drivers of the negative exit effect, we should dig more into the background behind it. This should be accompanied by prefecture level and industry level analyses, which we can implement by using the current dataset.

VII. Conclusion

In this study, we revisit the negative exit effect by using firm-level panel data on Japanese firms with unique information on exit modes. We find a robust result that a large part of the negative exit effect is attributed to firms that exit through mergers. We also confirm that the causal effect of those mergers results in positive growth in the merging firms' productivity. The size of this positive causal effect is larger than the negative exit effects associated with mergers. Thus, resource reallocation through mergers positively contributes to productivity growth in Japanese firms.

Appendix

In this section, we explain the analysis method of merging effects. We calculate the merging effect in three steps: (i) estimating the propensity score, (ii) estimating the average treatment effect on the treated (ATT) using the inverse probability weighting (IPW) , and (iii) measuring the merger effect using the ATT. The propensity score, in this case, is an estimate of the propensity to become a merging firm on a scale of 0 to 1 using regression analysis. IPW is a standard method of causal inference for estimating ATT based on the propensity score. Regarding the time-series relationship of the variables, we use the variables before the merger for the propensity score estimation and the productivity growth rate after the merger for the ATT estimation. These three steps are described in detail in the following.

First, we estimate the propensity score by logistic regression analysis. The dependent variable is a dummy variable representing whether the firm conduct a merger or not, and the explanatory variables are ones that may affect the propensity of the merger. The sample size of this estimation is about 2,000 firms per year. This includes about 1,000 merged firms and about 1,000 other firms randomly selected. Table 10 shows the results of the logistic regression for five different sets of dependent variables. We have adopted equation (5), which is reasonable in terms of the value of Area Under the Curve (AUC), which indicates the discriminatory ability of the model, as well as the significance of variables. Second, we estimate the ATT from period $t-1$ to period t using the formula of IPW as follows:

$$\bar{y}_{mrg,t-1\to t} - \left[\sum_{f\in nonmrg} \frac{1}{1-e(x_f)} y_{f,t-1\to t}\right] \Big/ \left[\sum_{f\in nonmrg} \frac{1}{1-e(x_f)}\right] \quad (12)$$

Here, $y_{f,t-1\to t}$ denotes the productivity growth for the firm from period $t-1$ to period t, $\bar{y}_{mrg,t-1\to t}$ denotes the average productivity growth during those periods for the firms that have conducted the merger in period $t-2$, and $nonmrg$ denotes the set of firms that have not conducted a merger in period $t-2$. Finally, we apply the estimated ATT to equation (10) and (11) in Section 5 and take the sum of them to get the merging effect. In other words, we calculate the merging effect by replacing the growth rate of individual firms with the average treatment effect of mergers, i.e., ATT, in the normal decomposition formula shown in equation (3) and (5). Note that the share effect is not taken into account in the estimation of the merging effect.

Table 10: Results of the logistic regression of propensity scores

	(1)	(2)	(3)	(4)	(5)
(Constant)	-12.544 ***	-11.770 ***	-11.616 ***	-11.517 ***	-11.404 ***
	(1.059)	(1.030)	(1.035)	(1.031)	(1.030)
log(Sales)	1.035 ***	1.296 ***	1.266 ***	1.260 ***	1.242 ***
	(0.165)	(0.160)	(0.160)	(0.160)	(0.159)
log(Sales)^2	-0.005	-0.010 *	-0.009	-0.009	-0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
log(Sales per employee)		-0.317 ***	-0.321 ***	-0.322 ***	-0.328 ***
		(0.023)	(0.023)	(0.023)	(0.023)
Δlog(Sales per employee)		-0.879 ***	-0.857 ***	-0.844 ***	-0.858 ***
		(0.099)	(0.099)	(0.099)	(0.099)
Firm age		0.000	0.001	0.001	
		(0.004)	(0.004)	(0.004)	
(Firm age)^2		0.000	0.000	0.000	
		(0.000)	(0.000)	(0.000)	
TSE 1st section			0.503	0.509	
			(1.020)	(1.020)	
TSE 2nd section			-0.675	-0.676	
			(0.753)	(0.752)	
Listed in other markets			0.834 *	0.843 *	
			(0.450)	(0.449)	
2 industries			0.190 **	0.188 **	0.149 ***
			(0.079)	(0.079)	(0.045)
>3 industries			0.390 ***	0.391 ***	0.248 ***
			(0.091)	(0.091)	(0.042)
2 product lines			-0.010	-0.007	
			(0.083)	(0.083)	
3 product lines			-0.191 **	-0.189 **	
			(0.095)	(0.095)	
4 product lines			-0.183 *	-0.178 *	
			(0.103)	(-0.065)	
5 product lines			-0.072	-0.065	
			(0.111)	(0.111)	
>6 product lines			-0.148	-0.140	
			(0.113)	(0.113)	
Year dummy	Y	Y	Y	N	Y
N	21,942	21,942	21,942	21,942	21,942
AUC	0.857	0.862	0.863	0.863	0.862

Note: The table gives the results of the logistic regression of propensity scores. "TSE 1st section" to ">6 product lines" represent the dummy variables corresponding to each description. TSE *denotes Tokyo Stock Exchange. The number of industries represents one in which the firm operates. The number of product lines represents one which the firm produces.*

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The research data for this article

The data used in this study are proprietary, and we gained access to the data through a joint research contract between Miyakawa's institute and TSR.

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