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Productivity Dynamics during Major Crises in Japan: A Quantile Approach[1]

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Abstract

This paper presents a new approach to estimating changes in firm productivity. Particular focus is placed on how productivity changed before, during, and after recessions accompanied by crises, using micro data on Japanese manufacturing firms. We depart from the traditional method of comparing (weighted) average productivity before and after a crisis and apply the quantile approach, which estimates the changes in the productivity distribution of surviving firms. The main results indicate that crises have different impacts on firms with different initial productivity levels. First, when productivity improves the industry as a whole, productivity growth is relatively high for firms with lower productivity. Second, in the event of major crises, the productivity decline is more pronounced for firms with lower productivity, whereas the impact on firms with higher productivity is relatively small. Finally, the productivity level required to survive in the market did not rise at the times of crisis and therefore we did not find that firms with low productivity were particularly forced to withdraw from the market.

Keywords: Quantile approach, Firms' productivity, Crisis

JEL classification: D24, L11, O47, O53, R12

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1 Introduction

Economic growth is essential to improve our standards of living, and the key factor to such growth is productivity. Productivity indices typically measure how much production or added value is produced by inputs such as labor and capital, and R&D investment and the qualitative improvement in human capital are considered to be crucial to productivity growth. When the competitive market works well, productivity can grow by increasing such factors. However, if the market fails to function properly because of the occurrence of a large crisis, any productivity improvement may be impaired. Specifically, declines in R&D investment due to an uncertain future outlook and the borrowing constraints faced by emerging firms because of the credit crunch lower productivity. In addition, the insufficient adjustment of inputs against a decline in demand results in the inefficient allocation of inputs, which hampers any productivity rise that could have been realized. Representative examples of such situations include Japan in the 1990s and western Europe after 2000 (Hayashi and Prescott, 2002; Fukao and Kwon, 2006; Burda and Severgnini, 2009). Rising productivity is critical to maintaining solid growth not only in emerging countries aiming to join the ranks of first world status but also particularly in developed but aging countries. This has led many researchers to measure productivity, typified by total factor productivity (TFP), and understand its changes over time. This study is an attempt to contribute to this field using a new analytical method, called the quantile approach.

When measuring productivity and its changes in an industry, the simplest approach is to compare the (weighted) average productivity of the firms operating in the industry between two periods. Such a comparison of average values is also used to examine whether the productivity of the industry rises through natural selection (i.e., firms with high productivity survive instead of firms with lower productivity).[1] However, this approach has several potential weaknesses. First and most importantly, it is only a descriptive comparison. While descriptive statistics provide useful information, the absence of the statistical testing of hypotheses prevents us from concluding whether there is a significant difference in productivity levels between periods or between surviving and exiting firms. The second is the pitfalls of using mean values. For instance, suppose there are two firms with a productivity of 2 and one firm with a productivity of 5. For the sake of simplicity, assume that the market share is equal for all firms. In this case, average productivity is 3. Now, suppose that the productivity of the former firms drops to 1 in the next year because of the onset of a crisis, while the productivity of the remaining firm increases to 7. Average productivity remains at 3. The average productivity has not changed in the two cases, but it is not reasonable to conclude that the crisis had no influence. Actually, the productivity of two of the three firms halved. This sometimes happens as firms with lower productivity might be more vulnerable, suggesting that an analysis considering that less-productive firms are more vulnerable to crises is required. A similar example can be offered for firms' exits. Suppose the four firms exit the market. Three firms have a productivity of 1 and the remaining one has a productivity of 9. Assume also that many firms with a productivity of 2 survive. In this example, under the assumption of an equal market share, the average productivity of exiting firms is 3, while that of surviving firms is 2, which shows a pseudo-illustration of adverse selection. However, since three firms with the lowest productivity exit the market, it is plausible to see that firms are selected naturally. These examples suggest that to ensure a more accurate judgment, it is important to consider not only the (weighted) "average" but also the productivity "scatter," or more strictly speaking, the "distribution" of firms' productivity.

To deal with these problems, we depart from the approach taken in previous studies and apply the quantile method proposed by Combes et al. (2012) to decompose the sources of productivity changes. The stylized fact in the urban economics literature is that firms are, on average, more productive in dense regions. Theoretically, agglomeration economies, advocated by Marshall (1890) and Jacobs (1969), and the natural selection of firms modeled by Melitz (2003) and Melitz and Ottaviano (2008) have been used to explain this fact; however, it is difficult to distinguish between these two factors in empirical research. The quantile approach makes it possible to separate them, and hence recent studies have adopted it to decompose the sources of productivity changes in the regional economics context (Arimoto et al., 2014; Kondo, 2016; Accetturo et al., 2018). Our idea in this study is to apply the quantile approach, which was created to compare the productivity distribution between regions with different densities, to compare productivity distributions between two periods. Specifically, using Japan as an example, we apply the

[1] For instance, Nishimura et al. (2005) use cohort analysis to assess the effects of the severe recession in the mid-1990s in Japan. Comparing the average productivity of firms withdrawing from and surviving in the market, they point out the possibility of adverse selection that productive firms withdrew and firms with low productivity survived in 1996 and 1997.

new method to understand how the productivity distribution changed for a period that is considered to have reduced productivity. In our approach, we can decompose the changes in firms' productivity into three parts: (i) changes in the cut-off level of productivity making it possible to survive in the market, (ii) the common productivity change in all surviving firms, and (iii) disparities among surviving firms in the impacts of the crisis on productivity. The advantage of our approach is that such a decomposition allows us to test changes in the distribution rather than descriptively comparing average productivity before and after the crisis occurred. In addition, it is effective for explaining the impact of the crisis on firms' productivity to identify which of points (i) to (iii) above strongly influenced firms' productivity distributions before and after serious recessions triggered by major crises such as the global financial crisis of 2008. Some studies may quantify the three changes artificially assuming the other two remain constant. However, such an estimation would be biased since the crisis impacts are absorbed by one factor. The quantile approach can solve this problem and, to the best of our knowledge, this is the first study that applies it to capture changes in the productivity distribution and the impacts of major crises.

Analyzing the impact of crises on firms' productivity and its distribution involves another difficulty: large crises rarely occur and their causes are varied. Hence, it is not necessarily the case that changes in the productivity distribution occur in the next crisis even though it has occurred in the past. To analyze many cases using the same methodology, this study thus targets Japan.[2] The Japanese economy has experienced four severe recessions over the past quarter-century, and their causes are diverse. The recession in the early 1990s was caused by the collapse of the overheating domestic economy, whereas the rapid economic deterioration at the end of the 1990s was one in which the domestic financial system was at risk. Crises can also be brought about by natural disasters such as large earthquakes. Specifically, in 2007, the massive disruption of the supply chain caused by an earthquake had a major impact on the economy, particularly the manufacturing industry. Finally, the historical economic downturn in 2008 was triggered by the overseas subprime mortgage crisis that spread to Japan. Hence, studying several crises with the same methodology allows us to clarify the similarities and differences of the resulting impacts on firms' productivity.

There is also another practical advantage of analyzing Japan. Establishment-level data are essential when analyzing the productivity of a firm, and we can use high-quality panel data based on the *Census of Manufacture* (CM), which many researchers have used to study firms' productivity (Norsworthy and Malmquist, 1983; Nakamura, 1985; Jorgenson et al., 1987; Kondo, 2016). The availability of long-term micro data over a quarter of a century is also an advantage of using the CM and Japan as the target country. In this study, taking advantage of these benefits, we build panel data on the manufacturing industry in Japan to target the several severe recessions during 1986–2010 and estimate changes in firms' productivity distributions.

Among our findings, the followings are peculiar to our analysis. First, when productivity improved in the industry as a whole, productivity growth was relatively high for firms with lower productivity. This contributed to reducing the productivity gap between firms. Second, in the event of a major crisis such as the global financial crisis of 2008, the industry's productivity declined. In this case, the productivity decline was more pronounced for firms with lower productivity and the impact on firms with higher productivity was relatively small. Third, the productivity level required to survive in the market did not rise, and therefore we did not find that firms with low productivity were particularly forced to leave the market. Specifically, at the time of the global financial crisis in 2008, there was no evidence that firms with lower productivity were more likely to withdraw from the market. In addition to these findings, our quantile approach solves the paradox that productivity hardly decreased during the global financial crisis. Indeed, the decline in weighted average productivity was just 0.2%. Our analysis shows that this figure represents the shortcoming of using "average" productivity and reveals that the crisis shifted the productivity distribution by more than 22% to the left. The reason for this gap in our analysis is that the impact of the crisis was concentrated on firms with low productivity, and productive firms escaped the negative influence of the crisis, which reduced the productivity drop to only 0.2%.

The first two results imply that productivity changes do not occur uniformly among firms with different productivity levels. Firms with low productivity benefit relatively greatly during ordinary times, which raises productivity at the industry level, whereas they experience a large productivity decline at the time of a crisis. The third result suggests that the policy to bail out small and medium-sized enterprises (SMEs), which are less productive on average, played a major role in helping them survive, and the final

[2]There is an enormous number of studies that measured productivity for Japan. See, for example, Table 1 of Fukao and Kwnon (2006, p.198) which summarizes the results of researches that measure changes in Japan's TFP.

remark shows the usefulness of the quantile approach, which can consider firms' heterogeneity in the form of the productivity distribution.

The remainder of this paper is organized as follows. The next section presents the dataset and explains the recessions that occurred during the analysis period. Section 3 introduces the quantile approach and defines productivity. Section 4 shows our main results. Here, we present the dynamics of the changes in the productivity distribution to examine how each recession changed firms' productivity distributions. The advantages of using the quantile approach over comparing weighted average productivity are also described here. Section 5 discusses the main analysis, which is extended to include the productivity measurement in different ways, sample decomposition, and constrained estimation. The final section concludes.

2 Data

2.1 Dataset

Our study focuses on the productivity changes in the Japanese manufacturing sector for two reasons. First, this sector is, at least in Japan, a key industry. Specifically, the roles of manufacturing sectors are the most significant in terms of both added value and employment, which are always important concerns for policymakers.[3] Second, firms in the manufacturing sectors produce durable goods. Consumers and firms find it easy to postpone their consumption and purchase, and thus firms producing durable products tend to be strongly influenced by crises.

We follow Kondo (2016) by using the CM datasets provided by the Ministry of Economy, Trade and Industry. The scope of this survey covers not only large establishments but also SMEs. The advantage of using CM data is that code numbers are given to all establishments. This enables us to trace their changes over time and construct a firm-level panel dataset. In addition, the CM covers a wide range of firms by size. Both firms listed on the stock market and unlisted firms are included in the data.

This survey includes two forms: the first one is *Kou*, which is for establishments with 30 or more employees, and the second is *Otsu*, which is for establishments with 29 or fewer employees. We only use the data from *Kou*, focusing on all establishments having 30 or more employees. There are two reasons for this. First, the data in *Otsu* contain a large number of missing values that impairs the reliability of the analysis. Second, using the data only from *Kou* allows us to exclude dormant firms that may be established in Japan to avoid paying tax. It is thus desirable to use *Otsu* data to exclude from the analysis those establishments that are not actually doing business. In addition to establishments with 29 or fewer employees, we exclude samples in which the variables necessary for estimating the production function take negative values.

In the analysis, two types of TFP are measured: TFP with the production value as the output (added to the left-hand side of the estimation equation) and TFP with added value as the output, defined as the production value minus the intermediate input cost. Intermediate inputs include materials, fuel, energy, and production outsourcing. Since both formulations have advantages and disadvantages, this paper mainly shows the results based on the latter following previous research. Hence, the input variables, when we take added value as the output variable, are labor and capital stock. Labor is represented by the number of employees and capital stock is measured by the end of year book value. All nominal values are deflated by each price index. The deflators are available from the Bank of Japan and Cabinet Office of Japan. Table 1 reports the descriptive statistics of the full sample. Establishments whose added value takes a negative value are excluded from the sample, taking into consideration the possibility that such establishments are intangible.

One point about our dataset should be noted. The CM data that we can use run from 1986 to 2014. However, the CM survey was not conducted in 2011. Although we could replace the 2011 data with data taken the *Economic Census for Business Activity* jointly conducted by the Ministry of Economy, Trade

[3]Although manufacturing industries, including mining industries, accounted for 18% of Japanese GDP in 2012, some industries, including the wholesale industry, retail industry, and transport industry, are closely connected with production activities through the distribution of mining and manufacturing products. For this reason, when these relevant industries are taken into account, the weight of the mining and manufacturing industries amounted to approximately 40% of GDP in Japan in 2012. See Ministry of Economy, Trade and Industry, Mechanism of and way to understand Indices of Industrial Production (`http://www.meti.go.jp/english/statistics/tyo/iip/pdf/b2010_mechanism_iipe.pdf`), accessed on January 16, 2019.

Table 1: Descriptive statistics

	Mean	Std. Dev.	Min	Max
Value added	2562.19	13231.60	0.00	2301647.00
Production value	5334.58	29344.54	1.04	7286348.00
Capital	1104.31	5865.60	0.01	596855.60
Labor employment	1568.70	3719.98	0.00	269176.00
Intermediate goods	2772.39	18693.65	0.01	4984702.00

Note. These descriptive statistics show the full sample of our data, 1986–2014. The number of establishments is 1,233,244.

and Industry and the Ministry of Internal Affairs and Communications, the latter are not necessarily consistent with the CM and there are many missing values. Therefore, the descriptive statistics and estimation of the production functions in the following analysis use the CM data from 1986 to 2014, but the data in 2011 are not included.

2.2 Recessions during the analysis period

Figure 1 shows the major recessions that have occurred in Japan since 1986. The time series line shows the Index of Industrial Production (IIP) of the manufacturing sector in Japan.[4] The IIP explains activities related to production, shipment, and inventory in the country. It is a comprehensive indicator of the wide-ranging production activities for products manufactured in Japan. As well as being used to understand production trends in the mining and manufacturing industries, the index is used to assess changes in the whole economy caused by economic activities related to goods, such as whether products are used as final demand goods or as producer goods. Moreover, the IIP is a quantity index representing quantitative fluctuations excluding price fluctuations. It is expressed in the form of a ratio with 100 in the base period (2010).[5]

There was at least four recessions between 1986 and 2010. The first recession in Figure 1, starting at the beginning of the 1990s, was triggered by the bursting of the overheated economy. By December 1989, the benchmark Nikkei 225 stock average had reached 38,915 yen. However, from 1990, the stock market began a downward spiral. On October 1, 1990, the stock price dropped below 20,000 yen, falling by close to half in just nine months. By the end of 1993, the total share value of Japan had decreased to 59% of the stock price at the end of 1989. The IIP continued to be sluggish for 32 months until it hit the bottom at 93.8 in January 1994 with a peak at 109.6 in May 1991.

The second was the recession that started in 1997. Because of the nonperforming loan problem, financial institutions with weak capital positions were successively brought into bankruptcy and nationalized. Capital investment contracted dramatically, especially among SMEs, which was caused by the credit crunch triggered by the failures of many financial institutions (Cabinet Office of Japan, 1998). In addition, the Asian currency and financial crisis started in Thailand with the collapse of the Thai baht in July 1997, resulting in the sharp shrinking of demand in Asian countries. The Japanese export industry, especially the manufacturing industry, was particularly hit. Specifically, export-oriented manufacturing production stagnated. In July 1997, the IIP was 109.1; however, it declined over 17 months until it bottomed out at 97.9 in December 1998.

The third was the dotcom bubble crash. Thanks to the IT boom, the Nasdaq Composite Index reached 5048 on March 10, 2000. Thereafter, the overheated stock markets burst and stock prices fell rapidly. With the effects of the terrorist attacks in the United States on September 11, 2001, the index fell to 1000 in 2002. Since firms were behind the IT investment in Japan, they were not damaged as much as those in the United States. Nonetheless, because of the sharp drop in demand including in the United States, the index decreased from February 2001 to January 2002. Furthermore, owing to the effect of the global stagnation of transactions caused by the terrorist attacks in the United States, the index did not rise for the following 22 months.

[4]The Ministry of Economy, Trade and Industry publishes IIP, which can be downloaded from `https://www.meti.go.jp/english/statistics/tyo/iip/index.html`.

[5]For how to create the index, see Ministry of Economy, Trade and Industry, Mechanism of and way to understand Indices of Industrial Production (`http://www.meti.go.jp/english/statistics/tyo/iip/pdf/b2010_mechanism_iipe.pdf`), accessed on January 16, 2019.

Figure 1: The IIP of the manufacturing sector in Japan

Note. 100 in the base year, 2010.

The fourth was the financial crisis of 2008 that drastically reduced global demand, with the Japanese manufacturing sector hit hard even though its relatively resilient financial system initially limited the direct impact. Kawai and Takagi (2009) point out that Japan was particularly vulnerable because of the changes in its trade and industry structures over the past decade, which meant Japanese output had become much more responsive to output shocks in the advanced markets of the United States and Western Europe. The impact of the crisis not only led the index to drop sharply in the short run; it has not yet recovered to the pre-crisis level. The IIP in September 2008 was 110.0, but it fell sharply to 76.6 in only four months.

3 Estimation Methodology

3.1 Quantile approach

To clarify how firm productivity changed between two periods, this study applies the quantile approach developed by Combes et al. (2012), which enables us to estimate the crisis effects using productivity distributions. We categorize the changes in the productivity distribution in the manufacturing industry into three factors. The first is the selection effect. If selection is tough at the time of recession, fewer less-productive firms will survive. Stronger selection should thus lead to a greater right truncation of firms' productivity distribution in the recession period. Second, the recession may shift the distribution to the right or left by improving or worsening the productivity of all firms. It intensifies competition over reduced demand, which may increase the productivity of surviving firms. Alternatively, it might make future prospects unclear, so that firms reduce incentives for investing in technology and improving skills for the future, resulting in a decline in productivity. Third, the impacts of recessions vary across firms. For example, less-productive firms tend to be more affected by recessions. Alternatively, intense competition may increase the productivity of firms with relatively high productivity. If this happens, the productivity distribution after the crisis will be dilated and right-shifted compared with beforehand. The quantile approach, which can account for these factors, thus frees us from the visual comparison of distributions and the comparison of average productivity using descriptive statistics.

Figure 2 illustrates the approach by plotting the distributions of firm log productivity.[6] To explain this, consider two time periods, $t = 0, 1$, which respectively mean before and after the crisis. Hence, a crisis occurs between these two time periods. The distribution of log productivity for active firms before the crisis ($t = 0$) is represented by the dashed lines. The solid lines represent firms' productivity distributions after the crisis ($t = 1$). Firms that do not meet certain productivity thresholds are not active in the market, so the left side of the distribution is truncated. Panel (a) shows the case that the crisis has brought about the natural selection of firms. Among firms active before the crisis, the financial

[6]The variables S, D, and T shown in the caption will be explained later.

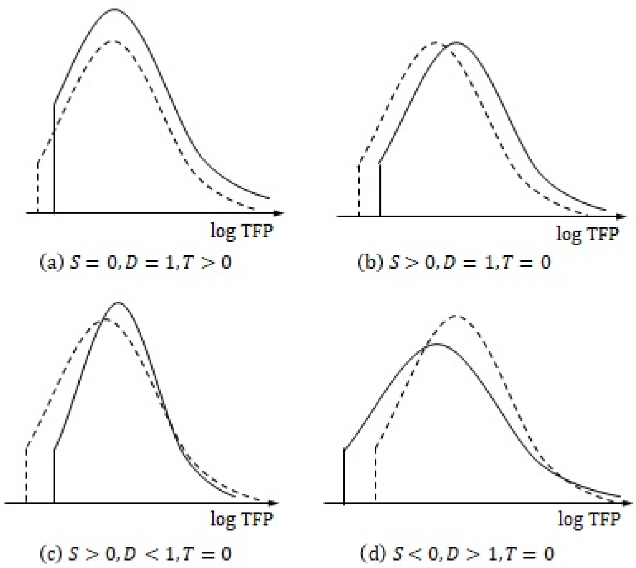

Figure 2: Log TFP distribution before and after the crisis
Note. The solid (dashed) line shows the distribution after (before) the crisis.

turmoil caused less-productive firms to exit the market but nothing changed for surviving firms. In Panel (b), the crisis shifts the distribution to the right by improving the productivity of all firms. This might happen when competition over reduced demand is intensified and the productivity of all firms surviving the market is increased. Panel (c) plots the variant of Panel (b) in which the crisis shifts the productivity distribution to the right without changing the truncation. Panel (c) differs from Panel (b) in that the productivity improvement is brought about mainly by improving the productivity of firms that originally had relatively low productivity. In this case, the width of the distribution narrows. Finally, Panel (d) represents the opposite case to Panel (c): the crisis shifts the distribution to the left, but firms with higher productivity achieve a higher productivity rise. In this case, the distribution of log productivity after the crisis is dilated relative to beforehand.

3.1.1 Basic setup

We assume that the underlying (log) distribution with cumulative density function $\tilde{F}$ is unchanged regardless of the time. However, we cannot observe this distribution. One of the advantages of the quantile approach is that it is not necessary to identify the unobservable distribution of log productivity $\tilde{F}$. To explain this, consider the two time periods again, $t = 0, 1$, with a crisis occurring between them. The cumulative density function of the distribution of log productivity for active firms at $t = 0$ (before the crisis) is observable and is represented by F_0, which can obtained from the three parameters representing the left truncation, T_0, the dilation, D_0, and the shift, S_0:

$$F_0(\phi) = \max \left\{ 0, \frac{\tilde{F}\left(\dfrac{\phi - S_0}{D_0}\right) - T_0}{1 - T_0} \right\} \text{ where } T_0 \in [0, 1). \tag{1}$$

In addition, we can describe the cumulative density function of the distribution of log productivity for surviving firms at $t = 1$ (after the crisis) by F_1:

$$F_1(\phi) = \max \left\{ 0, \frac{\tilde{F}\left(\dfrac{\phi - S_1}{D_1}\right) - T_1}{1 - T_1} \right\} \text{ where } T_1 \in [0, 1). \tag{2}$$

Here, T_t captures the relative strength of the truncation compared with the previous period. If the natural selection mechanism is enhanced when the crisis hits, the left truncation should move to the right after the crisis, $T_t > 0$. D_t measures the ratio of dilation compared with the previous period. More specifically, $D_t > (<) 1$ means that the productivity of firms with relatively high (low) productivity grows relatively large, so that the tail of the distribution spreads (shrinks). S_t indicates that surviving firms are equally affected by the crisis, that is, $S_t > (<) 0$ means that firms equally increase (decrease) their productivity by the crisis.

We compare two distributions with the cumulative density functions F_0 and F_1. According to equations (1) and (2), the unobserved distribution $\tilde{F}$ can mediate these two distributions. Then, the following relationship between F_0 and F_1 can be obtained: [7]

$$F_1(\phi) = \max\left\{0, \frac{F_0\left(\dfrac{\phi - S}{D}\right) - T}{1 - T}\right\} \quad \text{if} \quad T_0 > T_1, \tag{3}$$

$$F_0(\phi) = \max\left\{0, \frac{F_1(D\phi + S) - \dfrac{-T}{1-T}}{1 - \dfrac{-T}{1-T}}\right\} \quad \text{if} \quad T_0 < T_1, \tag{4}$$

where $D \equiv D_1/D_0$, $S \equiv S_1 - DS_0$, and $T \equiv (T_1 - T_0)/(1 - T_0)$. (3) and (4) are used to obtain an econometric specification that can be estimated from the data. We identify T, D, and S instead of T_t, S_t, and D_t. The parameter T measures the relative strength of the left truncation by comparing T_0 with T_1. For instance, $T > 0$ means that the lower limit of productivity required to survive in the market has risen after the crisis, which corresponds to Panel (a) of Figure 2. By contrast, $T < 0$ means that the crisis has reduced the lower limit of productivity for operating in the market. The parameter S measures how much the distribution shifts to the left or right due to the crisis. If $S > 0$, the crisis increases the productivity of surviving firms equally, which corresponds to Panel (b) of Figure 2. On the contrary, if $S < 0$, the crisis lowers the productivity of surviving firms evenly. The parameter D measures the dilation of the log productivity of distribution for active firms before and after the crisis. $D > 1$ shows that firms with relatively high productivity have a greater productivity improvement than firms with lower productivity. This corresponds to Panel (c) of Figure 2. On the contrary, when $D < 1$, the productivity of relatively less-productive firms is improved compared with firms with high productivity, which corresponds to Panel (d) of Figure 2.

3.1.2 Quantile specification

We transform equations (3) and (4) into quantile functions to identify T, D, and S. Suppose that $\tilde{F}$ is invertible and that F_0 and F_1 are also invertible. $\lambda_0(u) \equiv F_0^{-1}(u)$ and $\lambda_1(u) \equiv F_1^{-1}(u)$ are introduced to denote the u^{th} quantile of F_0 and F_1. If $S > 0$, (3) applies and can be rewritten as

$$\lambda_1(u) = D\lambda_0(T + (1 - T)u) + S \quad \text{for} \quad u \in [0, 1]. \tag{5}$$

If $S < 0$, (4) applies and can be rewritten as

$$\lambda_0(u) = \frac{1}{D}\lambda_1\left(\frac{u - T}{1 - T}\right) - \frac{S}{D} \quad \text{for} \quad u \in [0, 1]. \tag{6}$$

We make the change of the variable by $u \to T + (1 - T)u$ in (6):

$$\lambda_0(T + (1 - T)u) = \frac{1}{D}\lambda_1(u) - \frac{S}{D} \quad \text{for} \quad u \in \left[\frac{-T}{1 - T}, 1\right]. \tag{7}$$

Combining (5) and (7) for all S yields

$$\lambda_1(u) = D\lambda_0(T + (1 - T)u) + S \quad \text{for} \quad u \in \left[\max\left(0, \frac{-T}{1 - T}\right), 1\right]. \tag{8}$$

[7] Appendix A presents the derivation of this relationship.

(8) cannot be estimated because the set of rank u includes the unknown parameter T. Hence, we make a final change of the variable $u \to r_T(u)$, where

$$r_T(u) = \max\left(0, \frac{-T}{1-T}\right) + \left[1 - \max\left(0, \frac{-T}{1-T}\right)\right] u.$$

This transforms (8) into

$$\lambda_1(r_T(u)) = D\lambda_0(T + (1-T)r_T(u)) + D \qquad \text{for} \qquad u \in [0,1]. \tag{9}$$

3.1.3 Estimating the quantile functions

Let $\theta = (T, D, S)$ denote the parameter vector. To estimate θ, we use the infinite set of equalities given by (9), which can be rewritten in more general terms as $m_\theta(u)$ for $u \in [0,1]$ and

$$m_\theta(u) = \lambda_1(r_T(u)) - D\lambda_0(T + (1-T)r_T(u)) - S, \qquad \text{for} \qquad u \in [0,1].$$

To consider the asymmetric relationship between two distributions arising from the opposite transformation, we use the infinite set of equalities:

$$\tilde{m}_\theta(u) = \lambda_1(\tilde{r}_T(u)) - \frac{1}{D}\lambda_0\left(\frac{\tilde{r}_T(u) - T}{1-T}\right) + \frac{S}{D} \qquad \text{for} \qquad u \in [0,1],$$

where $\tilde{r}_T(u) = max(0,T) + [1 - max(0,T)]u$. The estimator we use is

$$\hat{\theta} = \text{argmin}_\theta M(\theta) = \int_0^1 [\hat{m}_\theta(u)]^2 du + \int_0^1 [\hat{\tilde{m}}_\theta(u)]^2 du.$$

Let $\hat{m}_\theta(u)$ and $\hat{\tilde{m}}_\theta(u)$ denote the empirical counterparts of $m_\theta(u)$ and $\tilde{m}_\theta(u)$, where the true quantiles λ_0 and λ_1 have been replaced by some estimators $\hat{\lambda}_0$ and $\hat{\lambda}_1$. We state the result, $\hat{\theta} = (\hat{T}, \hat{D}, \hat{S})$, and measure of goodness of fit R^2, which is as follows:

$$R^2 = 1 - \frac{M(\hat{T}, \hat{D}, \hat{S})}{M(0,1,0)}.$$

In addition, the standard errors of the estimated parameters, $\hat{\theta}$, are bootstrapped. For each bootstrap replication, we draw observations of the same sample size as data with replacement, and estimate θ.

3.2 TFP estimation

To derive the TFP level, we assume the following Cobb–Douglas production function:

$$V_{it} = \Phi_{it} K_{it}^{\beta_k} L_{it}^{\beta_l}, \tag{10}$$

where K_{it} and L_{it} indicate the capital and labor inputs used to generate added value by firm i in year t, V_{it}. β_k and β_l are the production function coefficients. Φ_{it} denotes TFP. We take the logarithm of (10)

$$v_{it} = \phi_{it} + \beta_k k_{it} + \beta_l l_{it}, \tag{11}$$

where the lower case letters denote the logs. From this equation, we can compute TFP using consistent estimates of the production function coefficients:

$$\hat{\phi_{it}} = v_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}. \tag{12}$$

The ordinary least squares (OLS) estimation may cause the problem that it derives the inconsistent estimates of β_k and β_l because the capital input might be correlated with productivity. To account for this endogeneity, Levinsohn and Petrin (2003) propose a method under which unobserved productivity is approximated by intermediate inputs. Our main results use TFP estimated using Levinsohn and Petrin (2003)'s approach.[8]

[8]Appendix B explains the details of Levinsohn and Petrin (2003)'s estimation approach.

4 Results

4.1 Changes in the productivity distribution

Appendix C shows the estimation results of the production function and time series change in TFP. Using estimated TFP, we can draw the distribution of TFP and estimate the time series change in the distribution.[9] Table 2 shows the main results of the estimation, particularly the year-by-year changes in the productivity distribution.[10]

For example, in Table 2, the number in the top row shows how the productivity distribution in 1987 changed with reference to that in 1986. Only the estimated value (0.053) representing the *shift* is significant at the 1% level, while the estimates of dilation and truncation are not significant in the first row. This finding means that the productivity distribution shifted parallel to the right from 1986 to 1987, suggesting that the productivity of all establishments increased almost equally. Panel (b) in Figure 2 depicts the change in the productivity distribution from 1986 to 1987. In a similar manner, we can understand the changes in the productivity distribution in 1988. In the second row, representing how the distribution changes from 1987 to 1988, the estimates of the variables indicating shift and dilation are significant at the 1% level for the former and 10% for the latter, $S = 0.101$ and $D = 0.987$. This finding suggests that the productivity distribution shifts to the right and, at the same time, the productivity growth of firms with low productivity is relatively large. Panel (c) of Figure 2 shows this change.

Three noteworthy features can be pointed out from Table 2. First, the estimates of T did not reach significance throughout the study period, suggesting that in times of crisis, there is no evidence that firms with low productivity are particularly forced to withdraw from the market (i.e., no selection effect is observed in Japan). It seems to be a strong result that T did not reach significance during the study period despite having experienced massive crises. Hence, we carried out an additional analysis to estimate the changes in the productivity distribution every two years instead, finding that $T = 0.006$ at the 1% significance level between the two distributions based on the average value from 1998 and 2001. In this sense, the significance of T may change depending on how we define the length of the "before" and "after" periods. However, in our additional estimation, T still does not reach significance during the two financial crisis in the late 1990s and 2008–2009. This finding suggests that in the event of a serious financial crisis, there is no evidence that the minimum level of productivity necessary to survive the market rises.

The second and most important point is that the productivity distribution has significantly shifted to the left twice in the past. The first shift to the left occurred in 1998 and 1999 (-0.074 in 1998 and -0.037 in 1999). The second shift occurred over the three years after 2007 (-0.034 in 2007, -0.031 in 2008, and -0.251 in 2009). Despite improved productivity the year before (0.049 in 1997 and 0.037 in 2006), the fact that the productivity distribution shifted to the left from 1998 and 2007 shows the significant negative impacts of the crises during this period. Specifically, the estimated value showing the shift in 2009 was probably caused by the 2008 global financial crisis. Indeed, this shows a large absolute value of -0.251, suggesting that productivity greatly declined from 2008 to 2009.

Third, if S and D are both significant, S and $D - 1$ take the opposite sign. For instance, both D and S have significant values in 1988, 2001, 2008, and 2009. In 1988 and 2001, $S > 0$ and $D < 1$, while $S < 0$ and $D > 1$ in 2008 and 2009. Hence, when productivity improves at the industry level ($S > 0$), the degree of improvement in the productivity of firms with low productivity is relatively large ($D < 1$). On the contrary, the productivity of firms with low productivity declines relatively greatly ($D < 1$) when productivity at the industry level declines ($S < 0$). For a further visualization, in Figure 3, we place the estimated values of S and D in each year on the horizontal axis and vertical axis, respectively. Each point in the figure denotes the year of analysis. In the second (fourth) quadrant, there is a shift to the left (right) of the productivity distribution and an expansion (reduction) of the width of the distribution. This figure thus suggests a negative relationship between the direction of the shift and change in the width of the distribution. This shows the dynamics of the productivity change in the Japanese manufacturing industry. In other words, in normal times, the productivity of the industry as a whole is stable or gradually increases. In this case, firms with low productivity improve productivity to a relatively large extent and the productivity gaps between heterogeneous firms shrink. However, when productivity declines in crisis

[9] Appendix D provides the descriptive statistics of the TFP distribution.

[10] As explained in Section 2.1, our dataset does not include the data in 2011, which makes it impossible for us to estimate changes in the productivity distribution from 2010 to 2011 and from 2011 to 2012. Therefore, we estimate the change in the distribution until 2010.

Table 2: Estimation results

	Shift	Dilation	Truncation	R2
1987	0.053***	1.000	0.000	0.795
	(2.76)	(0.03)	(0.24)	
1988	0.101***	0.987 *	0.000	0.975
	(5.38)	(-1.82)	(-0.49)	
1989	0.029	1.003	0.000	0.914
	(1.62)	(0.53)	(-0.34)	
1990	0.066***	0.988	0.000	0.889
	(3.00)	(-1.54)	(-0.59)	
1991	0.044**	0.988	0.000	0.901
	(2.00)	(-1.44)	(1.30)	
1992	-0.003	0.989*	0.000	0.796
	(-0.20)	(-1.69)	(-0.49)	
1993	-0.002	0.986*	0.000	0.788
	(-0.12)	(-1.87)	(-0.18)	
1994	-0.008	1.003	0.000	0.231
	(-0.36)	(0.33)	(-0.08)	
1995	0.057**	0.992	0.000	0.847
	(2.41)	(-0.92)	(0.38)	
1996	0.016	1.006	0.000	0.747
	(0.73)	(0.71)	(0.49)	
1997	0.049**	0.992	0.000	0.772
	(2.40)	(-0.99)	(0.34)	
1998	-0.074***	1.004	0.000	0.968
	(-3.27)	(0.51)	(0.11)	
1999	-0.037*	1.008	0.000	0.806
	(-1.71)	(0.97)	(-0.45)	
2000	0.024	1.009	0.000	0.916
	(1.15)	(1.14)	(-0.27)	
2001	0.133***	0.936***	0.002	0.731
	(3.66)	(-4.89)	(1.22)	
2002	-0.006	0.999	0.000	0.556
	(-0.30)	(-0.09)	(-0.48)	
2003	0.069***	0.994	0.000	0.940
	(3.59)	(-0.83)	(0.35)	
2004	0.051***	1.001	0.000	0.969
	(2.88)	(0.16)	(0.37)	
2005	0.010	1.003	0.000	0.664
	(0.53)	(0.45)	(-0.11)	
2006	0.037**	0.996	0.000	0.775
	(2.48)	(-0.81)	(-0.18)	
2007	-0.034*	1.010	0.000	0.279
	(-1.75)	(1.39)	(0.20)	
2008	-0.031*	1.012*	0.000	0.455
	(-1.78)	(1.69)	(-0.24)	
2009	-0.251***	1.042***	0.000	0.975
	(-13.46)	(6.14)	(-0.15)	
2010	0.065***	1.011	0.000	0.927
	(3.14)	(1.32)	(0.25)	

Note. Each entry represents the coefficients of S, T, and D. We use the estimation methodology suggested by Combes et al. (2012). Z-values are in parentheses, which are calculated by bootstrapping. The null hypotheses are that average productivity is unchanged before and after each crisis; in other words, the null hypotheses are $S = 0$, $T = 0$, and $D = 1$. ***, **, and * denote that the estimates are significant at the 1%, 5%, and 10% levels, respectively.

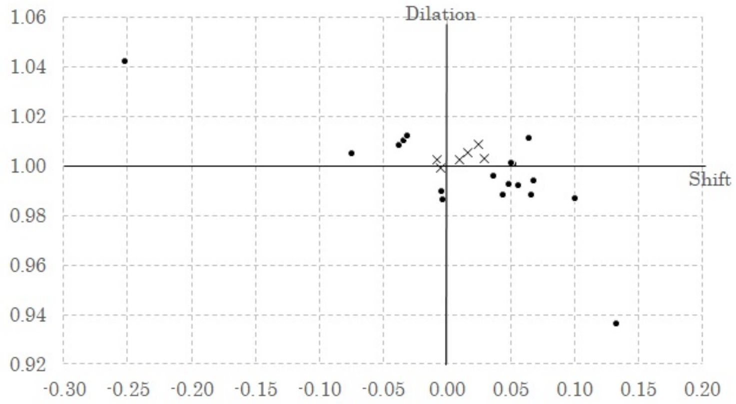

Figure 3: Change in the productivity distribution: direction and width

Note. A black dot represents the year in which the estimate of either D or S is significant, or both are significant. The crosses indicate the years in which both estimates are not significant.

periods, the productivity gaps among firms increase because firms with low productivity are affected to a relatively greater degree.

Why is it likely that $D < 1$ when $S > 0$? One possible explanation is that there is a spillover of technology and information from productive firms to unproductive ones. In addition to raising the productivity of the industry as a whole, this would reduce the productivity gaps among firms by catching up technologies, and thus the spread of the distribution narrows. Conversely, when the industry-level productivity distribution shifts to the left in a crisis, $D > 1$ is likely. This might be because productive firms, which tend to be relatively large, have room to adjust their inputs. For instance, they can refrain from investing or change the level of intermediate inputs. Indeed, even if productive firms cannot change their input levels (e.g., labor inputs) in the short run, they have room to improve labor efficiency by changing the structure of the workforce. These measures lead to the efficient use of inputs and, in some cases, improved productivity. As it is difficult for unproductive SMEs to respond in the same way, at least in the short term, the crisis must have had a relatively large impact on small and less-productive firms.[11]

4.2 Quantification

The estimates in Table 2 can be used to quantify the following two points: (i) how much the productivity distribution shifts right or left and (ii) how much the spread of the distribution changes. For example, the estimate of S in 1987 is 0.053 in Table 2, which can be used to quantify the shift in the distribution. That is, the estimate of 0.053 means an increase in average productivity of $e^{0.053} - 1$, which is equivalent to a 5.5% increase in mean productivity, generated by the shift in the distribution. The numbers in the third column of Table 3 labeled *Shift in the TFP distribution* show this change. In particular, there were large shifts in the productivity distributions in 2001 and 2009, shifting 14.2% in the right direction in 2001 and 22.2% in the left direction in 2009. In addition, the estimation results in Table 2 can be used to quantify the changes in the spread of the distribution by calculating the inter-quantile range of each distribution. Figure 4 shows the inter-quantile range, which can be derived year by year. In the fourth column of Table 3, the percentage changes in the interquartile range (i.e., the rate of changes in the range between the top 25th percentile and bottom 25th percentile) are shown with the changes in the range between the other two quantiles. For example, in 2001, the interquartile range decreased by 3.4%. The

[11] We confirm that the changes in intermediate inputs at the time of crisis are greater for firms with higher productivity, leading us to support this hypothesis. For example, from 2008 to 2009, intermediate inputs reduced by 16.9% for the top 25% of firms measured by productivity. That figure was 9.7% and 6.8% for the next two 25% categories. In the bottom 25% of firms, the reduction in intermediate inputs was 1.9%, which was only about 2/17th of the top 25%. The same can be said for the economic recovery period. For example, from 2009 to 2010, productive firms changed input volumes significantly. The top 25% of firms increased intermediate input costs by 15.5%. Those figures were 9.0%, 4.6%, and 7.0% in the following categories. Compared with these, during the global financial crisis, the rates of change in capital and labor inputs were about the same and small, approximately 3% or less, regardless of firms' productivity level.

Table 3: Changes in average productivity and inter-quantile range

	Change in avg. TFP	Shift in the TFP distribution	Interquartile range	Range b/w 10th and 90th percentiles	Range b/w 5th and 95th percentiles
1987	3.7%	5.5%^{a}	0.0%	0.3%	-0.7%
1988	1.9%	10.6%^{a}	-0.9%^{b}	-1.8%^{b}	-1.1%^{b}
1989	1.0%	3.0%	0.5%	-0.1%	-0.6%
1990	-0.9%	6.9%^{a}	-0.2%	-0.1%	-1.9%
1991	-0.3%	4.5%^{a}	-0.8%	-1.6%	-1.3%
1992	0.4%	-0.3%	-1.6%^{b}	-0.7%^{b}	-0.4%^{b}
1993	-0.8%	-0.2%	-1.6%^{b}	-2.1%^{b}	-2.1%^{b}
1994	0.8%	-0.8%	-1.2%	-0.4%	-0.5%
1995	1.0%	5.8%^{a}	-0.6%	-0.7%	0.0%
1996	0.7%	1.6%	0.7%	1.0%	0.7%
1997	-0.2%	5.0%^{a}	-0.1%	-0.7%	-0.7%
1998	-1.0%	-7.1%^{a}	0.1%	0.4%	0.6%
1999	0.7%	-3.6%^{a}	0.5%	1.0%	0.5%
2000	0.4%	2.4%	2.4%	1.3%	1.5%
2001	-2.1%	14.2%^{a}	-3.4%^{b}	-4.6%^{b}	-8.1%^{b}
2002	1.1%	-0.6%	-0.4%	-0.8%	0.0%
2003	0.9%	7.1%^{a}	-0.1%	0.0%	-0.4%
2004	1.1%	5.2%^{a}	0.6%	1.4%	0.2%
2005	0.7%	1.0%	1.5%	0.0%	0.6%
2006	1.5%	3.8%^{a}	0.5%	0.1%	-0.6%
2007	0.2%	-3.3%^{a}	0.5%	0.6%	1.1%
2008	0.4%	-3.0%^{a}	0.9%^{b}	1.3%^{b}	1.2%^{b}
2009	-0.2%	-22.2%^{a}	3.2%^{b}	2.7%^{b}	2.9%^{b}
2010	3.9%	6.7%^{a}	1.4%	1.4%	1.1%

Note. *Change in avg. TFP* means the ratio of change in average TFP weighted by the share of added value. The numbers in the column *Shift in the TFP distribution* indicate how much the productivity distribution shifted in the left or right direction, eliminating the effects of dilation and truncation. This is obtained by inserting the value x in the second column of Table 2 into $e^x - 1$. TFP is estimated following Levinsohn and Petrin (2003)'s method. Each entry in the last three columns indicates the effect of dilation. The fourth column shows the width of the ranges of the top and bottom quantiles. The fifth and sixth columns show the results when the ranges are the 10th-90th percentiles and 5th–95th percentiles, respectively. The superscript a (b) indicates that the estimates of S (D) are significant in the estimation.

rate of range reduction is larger at the point closer to the margin of the distribution than the quartile; the rate of change in the range between the 10th (5th) and 90th (95th) percentiles was -4.6% (-8.6%).

In Table 3, the rate of change in standard average TFP, weighted by the share of added value, is also presented in the second column.[12] a (b) indicates that the estimate of S (D) is significant in the estimation, and therefore it is meaningful to compare the numbers in the second and third columns of such a year. Specifically, the comparison of these numbers describes the features of the quantile approach well.

For example, let us see how average productivity in 2009 changed. The rate of change in productivity calculated by the weighted average method is just -0.2%, which implies that average productivity hardly changed during the crisis of 2008. However, its value seems to be too small, as the global financial crisis was of a scale rarely seen historically. The rate of change in average productivity under the quantile approach presented in the third column of the table answers this doubt. It shows the change in average productivity accompanying the shift in the distribution after the effects of dilation and truncation are eliminated. Looking at the third column of Table 3 in 2009, the change in average productivity under the quantile approach is -22.2%, which is large. This means that the productivity distribution shifted 22.2% to the left, which would lead to a sharp decline in average productivity at the industry level. At the same time, it can also be confirmed in Table 2 that $D = 1.043 > 1$ in 2009, showing a strong dilation of the distribution in that year. This finding suggests that the productivity of firms with low productivity dropped sharply, whereas that of firms with high productivity did not, which dilated the distribution. Indeed, the fourth column of Table 3 shows that the rate of change of the interquartile range in 2009

[12] See the definition of weighted average TFP and its time series change (Figure 6) in Appendix C.

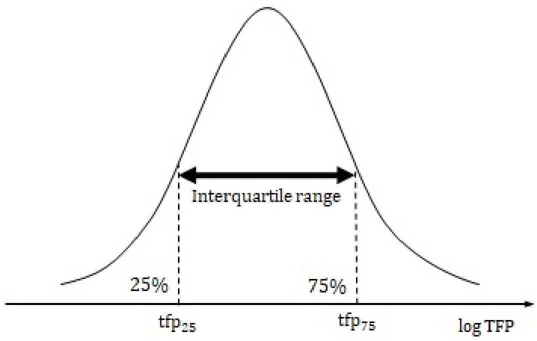

Figure 4: Inter-quantile range

was 3.2%, suggesting that the width of the distribution expanded in that year. Therefore, we can argue that the decrease in weighted average productivity in 2009 of only 0.2% does not mean that there was no decrease in productivity. Rather, the productivity distribution moved more than 22% in the left direction overall, with the concentration of the negative impact of the crisis on firms with low productivity. At the same time, however, firms with originally high productivity were able to avoid a sharp fall in productivity and may have even raised productivity during this period. This effect halted the drastic reduction in average productivity and thus the decline in productivity remained at only 0.2%.[13]

In the same manner, we can interpret the significant difference in the two numbers in 2001 as well. In 2001, average productivity at the industry level decreased by 2.1% (see the second column in 2001 of Table 3). However, the estimates of the shift in the productivity distribution measured by the quantile approach are at least 14.2%, which means that the productivity distribution shifted to the right. At the same time, Table 2 shows that the estimate of D is 0.936 in 2001, which is extremely small compared with the other years. This result means that while the productivity improvement was biased toward firms with lower productivity, the productivity may have declined in firms with high productivity. In fact, according to Table 3, the percentage change in the interquartile range is -3.4% in 2001, which means the spread of the distribution narrows. These findings suggest that a rise in productivity (in the sense that the distribution shifts to the right) has certainly occurred. However, this is a result mainly of low productivity firms raising productivity. Indeed, the productivity of firms with high productivity may have declined, which results in an average growth rate of -2.1%.

In this way, our approach makes it possible to capture the characteristics of productivity changes in more detail by comparing them with the descriptive results using average values. As firms are heterogeneous, it is natural to think that the impact of the crisis would also differ by firm. The approach we propose here can thus better explain the different impacts of crises on firms that are inherently heterogeneous.

4.3 Several interpretations

To provide some insights into our results, we use the findings provided by the Ministry of Economy, Trade and Industry on the factors that affect establishment-level TFP in Japan.[14] It built a panel dataset from 2001 to 2008 using 155,515 establishment-level samples and performed a regression with 18 possible factors as the explanatory variables. The analysis shows that among these 18 factors, four factors, namely the export ratio, overseas investment ratio, R&D investment ratio, and IT investment ratio, significantly affect productivity.[15] We here present a possible explanation of our results, partly relying on these findings. In

[13] When the rate of TFP growth is calculated as a simple average rather than a weighted average, the decrease in productivity in 2009 was about 5%, which still has a large divergence from the result that the distribution shifted to the left by 22% or more.

[14] Ministry of Economy, Trade and Industry, The role of international expansion in productivity improvement, *White Paper on International Economy and Trade* 2013 (`https://www.meti.go.jp/english/report/downloadfiles/2013WhitePaper/1-2.pdf`), accessed on March 13, 2019.

[15] Some of these are also included in the following items found to be determinants of TFP growth by previous studies: R&D expenditure and the adoption of ICT-intensive technologies (McMorrow et al., 2010, Van der Marel, 2012), trade openness (Miller and Upadhyay, 2000; Danquah et al., 2014), human capital (Miller and Upadhyay, 2000; Di Liberto et al., 2011; Mastromarco and Zago, 2012), regional banking efficiency (Mastromarco and Zago, 2012), policies to attract

particular, we focus on the shifts in the productivity distribution to the left in 1998 and 2007–2009 and to the right in 2001.

Financial institution crisis in 1998. In the second half of 1997, three large banks and securities companies became bankrupt, which triggered the financial system crisis in 1998. The Japanese government took measures to close down banks with weak financial positions. These banks had weighed heavily on SMEs, and this measure had a profound impact, especially on SMEs, in the form of a sharp fall in investment due to the restrictions on borrowing.[16] An additional misfortune was that the Asian currency and financial crisis occurred at the same time. The direct impact was a sharp decline in demand in Asian countries. Because manufacturing firms in Japan rely on exports, they suffered a blow. Two factors, a decrease in investment resulting from the stricter lending of banks and a decline in exports accompanying a sharp drop in overseas demand, may have led to the shift in the productivity distribution to the left in 1998.

Right shift in the distribution in 2001. Since the estimate representing the shift in 2001 is positive and significant at the 1% level (0.133), it turns out that the productivity distribution shifted significantly to the right between 2000 and 2001. In particular, the estimated value representing dilation is 0.936, which is the smallest during the sample periods. This means that the productivity growth of establishments with low productivity—mostly small businesses—was relatively large. The reason that the productivity of establishments with relatively low productivity increased greatly may be related to the development of IT in less-productive firms.[17] By 2000, while the internet penetration rate of establishments with more than 100 employees was 90%, it was only 44% for smaller firms. In 2001, as IT investment grew, the internet penetration rate of small establishments rose to 68% in just a year and expanded to 80% in the next year.[18] This can be regarded as a spillover of technology from productive firms to firms with lower productivity. At the same time, there was also a strong boost by the government. To promote the diffusion of IT to SMEs, the Japanese government enacted the Basic Law on the Formation of an "Advanced Information and Telecommunications Network Society" in December 2000 and formulated the "e-Japan Strategy." This was an effective strategy with tax incentives and subsidies, aiming to conduct e-commerce in more than half of SMEs by March 2004 (Morikawa, 2004).

Although the productivity distribution shifted to the right, the second column of Table 3 shows that weighted average productivity in 2001 decreased by 2.1% because of the productivity decline in firms with high productivity. Outside Japan, 2001 was the year in which the economy fell into recession in Europe and the United States. In addition, the 9/11 terrorist attacks in the United States reduced transactions worldwide. Global trade volume in 2000 had achieved 13.1% growth over the previous year; however, in 2001, the growth of trade volume plummeted to 0%. Moreover, the drop in Japan's exports was the largest in the world, and the export volume in 2001 was −0.8% compared with the previous year (Ministry of Economy, Trade and Industry, 2013), damaging productive firms with a high export ratio.[19] This resulted in the shrinking of the right end of the productivity distribution and decline in average productivity in 2001.

Left shift in the distribution in 2007. The estimated value had a significant negative value from 2007 to 2009, but the cause might differ. The shift in the productivity distribution in 2007 may have been caused by the supply chain shock, which originated from the Niigata Chuetsu-offshore Earthquake on July 16, 2007. It hit a mother factory of a leading supplier of piston rings, which was an indispensable part for the production of automobiles. However, when it stopped supplying this part, as many as four major auto manufacturers were forced to suspend vehicle production and this caused 12 auto manufacturers in Japan to stop operating in part or in whole for at least several weeks.

manufacturing industries and investment (Domazlicky and Weber, 1998), and out-in M&A (Fukao et al., 2005). See also Isaksson (2007) for a review of the determinants of TFP growth.

[16]See, for instance, Ueda (2000) and Hoshi (2000) for reviews of the Japanese banking crisis in the late 1990s. Our interpretation here is consistent with the view presented by Akiyoshi and Kobayashi (2010) which shows that deterioration in the financial health of banks decreased the productivity of their borrowers in 1997 and 1998.

[17]Using 1998 data, Morikawa (2004) finds a positive and statistically significant relationship between IT penetration and firm profitability and innovation in Japan, but only for small firms.

[18]Ministry of Internal Affairs and Communications, *White Paper on Information and Communications in Japan* (`www.soumu.go.jp/johotsusintokei/field/data/gt010102.xls`), accessed on January 5, 2019.

[19]Ministry of Economy, Trade and Industry, Trends in Japan's international trade and investment, *White Paper on International Economy and Trade* 2013 (`https://www.meti.go.jp/english/report/downloadfiles/2014WhitePaper/1-2-1.pdf`), accessed on March 13, 2019.

Global financial crisis of 2008. Between the third quarter of 2008 and second quarter of 2009, global trade volumes declined by approximately 15%. This was much more steeply than global GDP, which fell by around 2% over the same period (European Central Bank, 2010). Because investment declined as the outlook for the future became uncertain, and demand dropped sharply globally, we are not surprised to find that the productivity distribution shifted to the left largely during 2008–2009. However, noteworthily, the estimates representing truncation (T) at the time of the global financial crisis of 2008 are almost zero and insignificant, suggesting that truncation did not occur during this period of historic financial turmoil. This finding can be explained by the strong intervention by the government. The impact of the economic crisis triggered by the global financial crisis of 2008 deteriorated the financial position of SMEs. It raised the difficulty of borrowing from financial institutions, and loan conditions became severe. In light of this situation, the government acted to support SME financing by establishing two unprecedented policies in October 2008: the Emergency Guarantee Program (EGP) and Safety Net Lending Program (SNLP). The EGP initially covered SMEs in 545 industries that had been hit by escalating crude oil and raw material prices and rising purchase prices. Since its launch, the range of designated industries and size of guarantees available have progressively expanded. The total amount of guarantees available was raised by 6 trillion yen in 2008 to 36 trillion yen by the end of March 2011. The SNLP has expanded the lending available, lowered interest rates, and increased the range of uses to which loans may be put. Total available lending in the SNLP increased from 4 trillion yen in 2008 to 21 trillion yen by the end of March 2011. This extraordinary policy supported SMEs at such a large scale, and many benefited from this measure. For example, the number of bankruptcies caused by the shortage of funds peaked in September 2008; however, after March 2009, as the policy effects appeared gradually, the number of bankruptcies turned negative compared with the same month of the previous year, suggesting that the EGP and SNLP were starting to contribute in preventing fragile SMEs from leaving the market (Japan Small Business Research Institute, 2010).

5 Robustness and Discussion

In this section, we check whether the main results of our study are robust. First, we check the results using other specifications of TFP. Second, we decompose our sample into subgroups. We also conduct a constrained specification to discuss the results.

5.1 Other specifications

The estimation was conducted by estimating TFP following Levinsohn and Petrin (2003). There are several ways to estimate TFP, however. As explained in Appendix C, representative ways include simple OLS, OLS with fixed effects, and the Wooldridge (2009) approach. Table 4 describes the estimation results generated using these three other specifications. Specifically, the left, middle, and right panels show the estimation results obtained using the Wooldridge (2009) approach, OLS, and OLS with fixed effects, respectively.

Table 4 allows us to understand whether the three findings pointed out in Section 4.1 are robust when TFP is measured using other specifications. First, no truncation occurred in Table 2, but the estimates of T are positive and significant in 2001 in the three cases in Table 4. This suggests truncation may have occurred in 2001 although we cannot strongly argue it as the estimate of T was not significant in 2001 under Levinsohn and Petrin (2003)'s specification. Except for 2001, we find no significant estimates for T, suggesting that the result that truncation did not occur in most of the periods is maintained. Second, the result that the productivity distribution shifted to the left in the late 1990s (specifically in 1998 and 1999) and 2009 remains. In particular, in the latter case, the absolute value of the estimate is still large compared with the estimates obtained in other years. This means that the global financial crisis of 2008 did shift the distribution in the left direction to a large extent. Third, the result that the signs of S and $D-1$ are reversed is also almost unchanged. This can be confirmed in the estimates of 1988, 2001, and 2009, but not for 2008.

Table 4: Estimation results: Wooldridge, OLS, and OLS with fixed effects approaches

	Wooldridge				OLS				Fixed Effects			
	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2
1987	0.053***	1.000	0.000	0.796	0.048***	0.985**	0.000	0.747	0.055***	0.999	0.000	0.786
	(3.02)	(0.04)	(0.23)		(10.11)	(-2.09)	(-0.09)		(8.45)	(-0.11)	(0.23)	
1988	0.101***	0.987**	0.000	0.975	0.061***	0.981**	0.000	0.972	0.069***	0.985*	0.000	0.971
	(6.07)	(-2.09)	(-0.58)		(10.32)	(-2.10)	(-0.36)		(11.72)	(-1.72)	(-0.41)	
1989	0.029	1.003	0.000	0.914	0.025***	1.006	0.000	0.791	0.038***	1.004	0.000	0.915
	(1.44)	(0.41)	(-0.34)		(4.66)	(0.82)	(-0.29)		(5.89)	(0.47)	(-0.42)	
1990	0.071***	0.986**	0.000	0.888	0.027***	0.983*	0.000	0.812	0.039***	0.985*	0.000	0.897
	(3.84)	(-2.09)	(-1.07)		(5.08)	(-1.95)	(-0.76)		(6.01)	(-1.90)	(-0.66)	
1991	0.044**	0.988	0.000	0.901	-0.001	0.990	0.000	0.833	0.017***	0.987	0.000	0.883
	(2.05)	(-1.63)	(1.08)		(-0.12)	(-1.09)	(1.38)		(3.02)	(-1.55)	(1.61)	
1992	-0.003	0.989	0.000	0.795	-0.043***	0.995	0.000	0.896	-0.028***	0.989	0.000	0.780
	(-0.15)	(-1.60)	(-0.71)		(-7.12)	(-0.51)	(-0.46)		(-4.04)	(-1.21)	(-0.79)	
1993	0.010	0.982***	0.000	0.624	-0.045***	0.986	0.000	0.854	-0.036***	0.984**	0.000	0.787
	(0.50)	(-2.69)	(-0.97)		(-8.28)	(-1.47)	(-0.17)		(-7.28)	(-1.97)	(-0.18)	
1994	-0.008	1.003	0.000	0.230	-0.004	0.996	0.000	0.253	0.000	1.000	0.000	0.250
	(-0.41)	(0.37)	(-0.09)		(-0.75)	(-0.49)	(-0.11)		(0.07)	(0.05)	(-0.23)	
1995	0.057***	0.992	0.000	0.846	0.034***	0.981**	0.000	0.846	0.037***	0.989	0.000	0.850
	(2.72)	(-1.02)	(0.27)		(7.04)	(-2.18)	(0.43)		(5.26)	(-1.19)	(0.10)	
1996	0.016	1.006	0.000	0.747	0.027***	1.002	0.000	0.741	0.033***	1.006	0.000	0.778
	(0.70)	(0.71)	(0.37)		(4.87)	(0.18)	(0.59)		(6.02)	(0.67)	(0.35)	
1997	0.063***	0.987*	0.000	0.672	0.023***	0.987*	0.000	0.709	0.030***	0.991	0.000	0.754
	(3.03)	(-1.71)	(-0.73)		(4.07)	(-1.83)	(-0.11)		(4.51)	(-1.37)	(0.07)	
1998	-0.070***	1.003	0.000	0.966	-0.072***	1.015*	0.000	0.973	-0.061***	1.006	0.000	0.967
	(-3.04)	(0.37)	(-0.17)		(-13.76)	(1.70)	(0.13)		(-10.98)	(0.72)	(0.21)	
1999	-0.037*	1.008	0.000	0.806	-0.017***	1.005	0.000	0.673	-0.015**	1.009	0.000	0.813
	(-1.87)	(1.07)	(-0.42)		(-3.0)	(0.78)	(-0.43)		(-2.06)	(1.15)	(-0.48)	
2000	0.023	1.009	0.000	0.917	0.049***	1.003	0.000	0.926	0.047***	1.009	0.000	0.902
	(1.19)	(1.20)	(-0.35)		(8.71)	(0.33)	(-0.33)		(7.23)	(1.14)	(-0.20)	
2001	0.088***	0.952***	0.004**	0.730	-0.003	0.921***	0.001**	0.710	-0.033***	0.947***	0.003**	0.729
	(2.71)	(-4.47)	(2.46)		(-0.61)	(-7.44)	(1.97)		(-4.28)	(-4.71)	(2.12)	
2002	-0.004	0.999	0.000	0.544	-0.011**	0.991	0.000	0.666	-0.004	0.995	0.000	0.447
	(-0.22)	(-0.19)	(-0.59)		(-2.34)	(-1.27)	(-0.39)		(-0.85)	(-0.68)	(-0.82)	
2003	0.069***	0.994	0.000	0.940	0.052***	0.982**	0.000	0.937	0.052***	0.991	0.000	0.934
	(3.68)	(-0.83)	(0.37)		(10.85)	(-2.39)	(0.28)		(10.03)	(-1.17)	(0.39)	
2004	0.051**	1.001	0.000	0.958	0.053***	0.989*	0.000	0.967	0.052***	0.998	0.000	0.967
	(2.50)	(0.14)	(0.27)		(12.64)	(-1.74)	(0.54)		(9.01)	(-0.29)	(0.30)	
2005	0.008	1.003	0.000	0.662	0.020***	1.002	0.000	0.794	0.015**	1.002	0.000	0.631
	(0.49)	(0.57)	(0.07)		(3.76)	(0.23)	(-0.42)		(2.41)	(0.35)	(-0.25)	
2006	0.031*	0.998	0.000	0.798	0.023***	0.993	0.000	0.811	0.024***	0.993	0.000	0.840
	(1.78)	(-0.36)	(0.24)		(4.33)	(-1.08)	(0.52)		(4.70)	(-0.98)	(0.44)	
2007	-0.034	1.010	0.000	0.281	-0.010*	1.006	0.000	0.565	-0.011*	1.006	0.000	0.401
	(-1.52)	(1.14)	(0.16)		(-1.85)	(0.88)	(-0.29)		(-1.93)	(0.83)	(-0.20)	
2008	-0.023*	1.009*	0.000	0.076	-0.007	1.018**	0.000	0.553	-0.004	1.009	0.000	0.092
	(-1.76)	(1.73)	(-0.69)		(-1.41)	(2.26)	(-0.16)		(-0.71)	(1.29)	(-0.62)	
2009	-0.248***	1.041***	0.000	0.975	-0.148***	1.065***	0.000	0.980	-0.141***	1.046***	0.000	0.971
	(-16.47)	(7.07)	(-0.39)		(-23.94)	(7.62)	(-0.16)		(-22.04)	(8.03)	(-0.19)	
2010	0.072***	1.008	0.000	0.939	0.096***	0.992	0.000	0.959	0.091***	1.003	0.000	0.955
	(3.15)	(0.97)	(-0.30)		(19.46)	(-1.06)	(0.02)		(16.79)	(0.46)	(-0.34)	

Note. Each entry represents the coefficient of S, T, and D. We use the estimation methodology suggested by Combes et al. (2012). Z-values are in parentheses, which are calculated by bootstrapping. The null hypotheses are that average productivity is unchanged before and after each crisis; in other words, the null hypotheses are $S = 0$, $T = 0$, and $D = 1$. ***, **, and * denote that the estimates are significant at the 1%, 5%, and 10% levels, respectively.

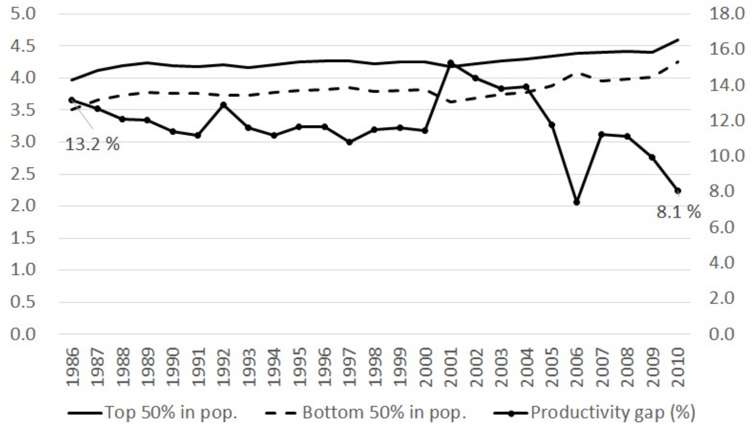

Figure 5: Productivity: populated regions vs. less-populated regions

Note. The solid (dashed) line denotes weighted average log TFP in the regions within the top (bottom) 50% of the population. A line with a dot represents the productivity gap between the two regions. TFP is estimated following Levinsohn and Petrin (2003).

5.2 Regional differences

5.2.1 Population

One might question how our results would change if firms' productivity distribution was estimated by dividing the sample into large and small cities. The standard argument in urban and regional economics is that firms' productivity varies by location: firms are more productive, on average, in larger cities. In particular, the quantile approach was developed to explain why firms in large cities are more productive, focusing on firm selection and agglomeration economies.

Figure 5 shows the trend in weighted average log TFP divided into areas with an above-average population (populated regions) and with a below-average population (less-populated regions). All firms are classified into these two groups based on their location, which is grouped based on the regional (municipal) population. We here classify the size of the region at the municipality level, which is the smallest administrative unit in Japan.

Figure 5 illustrates that productivity is consistently high in large areas, suggesting that agglomeration economies in production work. In addition, comparing both areas shows that except for the first half of the 2000s, the disparity between the two areas has been shrinking gradually. For example, in 1986, the productivity in populated areas was about 13.2% higher than that in less-populated areas, but this fell to around 8.1% in 2010.

Table 5 classifies the estimation results by population size. The results divided into the two areas are similar to the main results in Table 2 for populated regions. However, they are not consistent with the results in Table 2 for less-populated regions. We point out three characteristic results. First, since we have less evidence of truncation, except for large regions in 2001, and average productivity in populated regions is larger than that in less-populated regions, we conclude that agglomeration economies, rather than the severe selection of unproductive establishments in larger regions, explain the regional productivity differences in Japan. This is consistent with the findings of Kondo (2016). Second, the two panels in Table 5 clearly show that the changes in the productivity distribution mainly occur in establishments that operate in populated areas. In particular, in Table 5, most of the estimates in the 1990s are not significant in less-populated areas. This finding suggests little change in the productivity distribution in less-populated areas at that time. Specifically, given the effects of the crisis of 1998, the shift to the left of the productivity distribution is now observed only in populated areas, implying that most of the impact of the financial system crisis in 1998 occurred in the form of a decline in productivity in establishments in populated areas. One possible reason to explain this finding is that the financial system crisis of 1998 was serious in urban areas. In Japan, major city banks have large market share in cities with large populations such as Tokyo and Osaka, whereas other regional banks are active in areas with a lower population. In September 1998, the amount of nonperforming loans held by those banks was 1,544 billion yen per city bank compared with 848 billion yen per regional bank and less than 5 billion yen for second-tier regional banks (Economic and Social Research Institute, 2011). These amounts show that city banks had a large amount of nonperforming loans and needed to improve their financial position. Indeed, most banks that went bankrupt or were nationalized in the year after one of the major city banks failed in 1997 were financial institutions based in Tokyo, Osaka, and other urban areas. Hence, the financial position of banks in urban areas was relatively bad in 1998 and consequently a credit crunch against manufacturers in populated regions occurred, which made it difficult to finance investment in these firms.

Third, the fact that the estimates of S in both populated and less-populated regions are negative and significant (-0.251 and -0.206) in 2009 shows that the global financial crisis in 2008 shifted the productivity distribution to the left irrespective of which area establishments were located in. However, the recovery of productivity growth from the crisis was different by area: the coefficient of S in 2010 is positive and significant in populated areas, but not in less-populated areas. This finding suggests that productivity improvement from the crisis has advanced mainly in populated areas, but been delayed in less-populated areas.

5.2.2 Financial institutions

The shift in the productivity distribution to the left arises in connection with the crises of the financial system in 1998 and 2008. This fact suggests that the efficiency and stability of financial institutions may influence the productivity of manufacturing industries through changes in banks' supply of funding to establishments. Here, we present the estimation results by decomposing areas based on the competitiveness of financial institutions.

As the competition of banks intensifies, the efficiency of financial institutions will increase. While the efficient financial institutions may control the impact of the crisis well, the effect of the crisis cannot be handled within the financial institution because of intense competition in the loan market, and as a result, the supply of funds to establishments may be restricted. The relationship between bank efficiency and productivity is studied by Mastromarco and Zago (2012).[20] They use Italian microdata in 2002 and 2004, which include all Italian manufacturing firms with more than 500 workers and a representative subsample of firms with 11–500 workers. Their finding is that the estimated parameter of regional bank technical inefficiency taking into account credit quality is negative, suggesting that an increase in bank efficiency enhances firms' TFP.

To clarify the relationship between the efficiency of financial institutions and productivity distribution of establishments, we estimate the changes in the productivity distribution by dividing our sample into two and using the competitiveness of financial institutions as a proxy index of efficiency. As an indicator of the degree of competition among financial institutions within a particular area, we use the Herfindahl–Hirschman Index (HHI) of regional financial institutions. Harimaya and Ozaki (2017) construct the HHI to represent the competitiveness of financial institutions in Japanese municipalities. In this study, we use their index in 2008 and estimate the changes in the productivity distribution at the time of the global financial crisis by dividing the sample into regions whose HHI value is within the top 50% and regions within the lower 50%.

Table 6 shows the estimation results. The estimated values of S (D) are -0.231 (1.036) and -0.255 (1.043) in these two regions, both of which are significant at the 1% level, showing that the results in Table 6 are similar to our main results in Table 2. The crisis shifted the productivity distribution overall to the left, with a significant drop in the productivity of firms with low productivity. This tendency does not differ according to region divided by the competitiveness of financial institutions, whereas the absolute value of the estimate of S is about 10% smaller in competitive regions. More specifically, the productivity distribution in competitive regions moved 20.6% to the left, whereas in those areas where competition was moderate, the distribution shifted by 23%. This means that the shift in the productivity distribution to the left was slightly smaller in competitive regions, suggesting that competition between financial institutions may have alleviated the negative impact of the crisis on firms' productivity.

5.3 Constrained specification

In Section 4, we found that less-productive firms benefit more in improving their productivity when productivity at the industry level rises in ordinary times. We also found that the productivity of less-

[20]The inefficiency of banks in their study is measured by the directional distance function employed by Zago and Dongili (2011).

Table 5: Estimation results: Top 50% vs. bottom 50% of the population

	Top 50% of the population				Bottom 50% of the population			
	S: Shift	D: Dilation	T: Truncation	R2	S: Shift	D: Dilation	T: Truncation	R2
1987	0.062***	0.997	0.000	0.742	0.001	1.024	0.000	0.720
	(2.88)	(-0.34)	(0.18)		(0.01)	(1.02)	(0.08)	
1988	0.090***	0.991	0.000	0.965	0.181***	0.951***	0.000	0.844
	(4.67)	(-1.16)	(-0.50)		(3.84)	(-2.87)	(-0.02)	
1989	0.046*	0.998	0.000	0.892	-0.051	1.033	0.000	0.635
	(1.89)	(-0.22)	(-0.34)		(-0.84)	(1.36)	(-0.05)	
1990	0.065***	0.988*	0.000	0.910	0.104**	0.977	0.000	0.708
	(3.52)	(-1.77)	(-0.92)		(2.11)	(-1.21)	(-0.14)	
1991	0.041**	0.989	0.000	0.849	0.065	0.983	0.000	0.746
	(2.22)	(-1.56)	(1.01)		(1.06)	(-0.67)	(0.44)	
1992	-0.007	0.991	0.000	0.799	-0.017	0.996	0.001	0.524
	(-0.31)	(-1.11)	(-0.81)		(-0.37)	(-0.19)	(0.77)	
1993	-0.007	0.987*	0.000	0.875	0.052	0.973	0.000	0.715
	(-0.30)	(-1.72)	(-0.21)		(0.98)	(-1.24)	(-0.83)	
1994	-0.023	1.007	0.000	0.279	0.072	0.983	0.000	0.590
	(-0.96)	(0.76)	(-0.06)		(1.58)	(-0.94)	(-0.20)	
1995	0.069***	0.988	0.000	0.793	0.000	1.012	0.000	0.506
	(3.02)	(-1.35)	(0.08)		(-0.01)	(0.60)	(0.13)	
1996	0.013	1.007	0.000	0.742	-0.012	1.017	0.001	0.849
	(0.55)	(0.77)	(0.29)		(-0.23)	(0.77)	(1.02)	
1997	0.043*	0.995	0.000	0.776	0.095	0.974	-0.001	0.676
	(1.93)	(-0.67)	(0.61)		(1.49)	(-1.10)	(-0.71)	
1998	-0.080***	1.006	0.000	0.974	-0.077	1.009	0.000	0.763
	(-3.09)	(0.61)	(0.17)		(-1.34)	(0.37)	(0.69)	
1999	-0.041*	1.009	0.000	0.820	0.011	0.997	0.000	0.458
	(-1.78)	(0.99)	(-0.47)		(0.20)	(-0.11)	(-0.53)	
2000	0.014	1.010	0.000	0.863	0.022	1.006	0.000	0.821
	(0.60)	(1.21)	(0.39)		(0.35)	(0.23)	(-1.05)	
2001	0.109***	0.947***	0.003***	0.733	0.007	0.965	0.007	0.735
	(3.49)	(-4.56)	(2.81)		(0.08)	(-1.12)	(1.61)	
2002	-0.008	0.999	0.000	0.642	0.027	0.994	0.000	0.447
	(-0.53)	(-0.08)	(-0.66)		(0.58)	(-0.35)	(0.18)	
2003	0.060***	0.997	0.000	0.933	0.104**	0.980	0.000	0.850
	(3.92)	(-0.51)	(0.63)		(2.24)	(-0.98)	(0.10)	
2004	0.054	0.998	0.000	0.940	0.014	1.017	0.000	0.797
	(0.02)	(0.01)	(0.0)		(0.29)	(0.81)	(-0.45)	
2005	0.014	1.002	0.000	0.651	-0.023	1.030	0.000	0.779
	(0.79)	(0.24)	(-0.09)		(-0.37)	(1.31)	(0.11)	
2006	0.030*	0.995	0.000	0.725	0.005	1.018	0.000	0.791
	(1.86)	(-0.78)	(0.36)		(0.09)	(0.78)	(-0.37)	
2007	-0.035*	1.011	0.000	0.613	-0.003	0.994	0.001	0.868
	(-1.92)	(1.61)	(-0.21)		(-0.05)	(-0.25)	(0.94)	
2008	-0.033*	1.013*	0.000	0.488	0.007	0.998	0.000	0.253
	(-1.84)	(1.75)	(-0.16)		(0.13)	(-0.08)	(-0.22)	
2009	-0.251***	1.043***	0.000	0.971	-0.206***	1.022	-0.001	0.955
	(-13.55)	(6.31)	(-0.14)		(-3.67)	(0.95)	(-0.46)	
2010	0.081***	1.008	0.000	0.929	0.048	1.033	0.000	0.941
	(3.77)	(0.95)	(-0.33)		(0.99)	(1.53)	(0.26)	

Note. Each entry represents the coefficient of S, T, and D. We use the estimation methodology suggested by Combes et al. (2012). Z-values are in parentheses, which are calculated by bootstrapping. The null hypotheses are that average productivity is unchanged before and after each crisis; in other words, the null hypotheses are $S = 0$, $T = 0$, and $D = 1$. ***, **, and * denote that the estimates are significant at the 1%, 5%, and 10% levels, respectively. TFP is estimated following Levinsohn and Petrin (2003).

Table 6: Estimation results: Intense vs. moderate inter-bank competition

	Intense inter-bank competition				Moderate inter-bank competition			
	S: Shift	D: Dilation	T: Truncation	R2	S: Shift	D: Dilation	T: Truncation	R2
2008	-0.006	1.005	0.000	0.345	-0.029	1.011	0.000	0.809
	(-0.20)	(0.47)	(-0.43)		(-1.49)	(1.48)	(-0.41)	
2009	-0.231***	1.036***	0.000	0.962	-0.255***	1.043***	0.000	0.974
	(-6.20)	(2.73)	(-0.39)		(-10.06)	(4.91)	(-0.29)	

Note. Each entry represents the coefficient of S, T, and D. We use the estimation methodology suggested by Combes et al. (2012). Z-values are in parentheses, which are calculated by bootstrapping. The null hypotheses are that average productivity is unchanged before and after each crisis; in other words, the null hypotheses are $S = 0$, $T = 0$, and $D = 1$. ***, **, and * denote that the estimates are significant at the 1%, 5%, and 10% levels, respectively. TFP is estimated following Levinsohn and Petrin (2003).

productive firms declines sharply, while productive firms could avoid a sharp fall in productivity and could have even raised it shortly after the crisis. In this section, we study the importance of allowing such different impacts of the crisis on firms with different productivity levels. To do this, following the constrained specification conducted by Combes et al. (2012), we impose a constraint of $D = 1$ when estimating the changes in the distribution. This estimation is equivalent to assuming that all firms are affected equally by the crisis. We compare the results under the constraint with those derived in the standard estimation in which no such constraint is imposed.

The left panel of Table 7 replicates the results in Table 2 and the right panel presents the estimates of S and T when assuming that firms' productivity always changes uniformly regardless of the level of original productivity, $D = 1$.

Comparing the numbers in the second and sixth rows showing whether the distribution shifts reveals the following. First, if we impose the assumption that $D = 1$, the absolute value of the estimate for S is smaller than if we do not impose it. That is, if we do not consider that the change in productivity varies according to the heterogeneity of firms measured at the original productivity level, the parameter estimates representing the shift in the productivity distribution should be biased: we underestimate the shift in the distribution. On average, the estimates representing a shift in the distribution is about 25% less if we do not account for the fact that heterogeneous firms receive different influences from the crisis.[21] Second, if dilation or contraction is not taken into consideration, although there was no change in the productivity distribution, it would make a misidentification that it was there. For instance, for the columns of 1992 and 1993, in the left panel, only the coefficient of D is significant, which is smaller than one. From this, we could argue that in these years, the productivity improvement of firms with low productivity was offset by the productivity decline of firms with higher productivity; hence, overall, there was no parallel shift in the productivity distribution. However, if we work from the results in the right panel, the interpretation changes: there was a shift in the productivity distribution to the left in 1992 and 1993. Third, incorrect information might be provided in the opposite form to the above. As described in the rows of 2007 and 2008, the estimates assuming no dilation show no shift in the distribution since they are not significant. However, the estimates on S in 2007 and 2008 for left panel are negative and significant; therefore, the distribution did actually shift to the left.

The supplementary appendix shows the estimation results based on other constraints including the case of imposing the constraint of $T = 0$. One important conclusion that can be deduced from these results is that the measurement of shifts in the productivity distribution ignoring dilation involves strong bias, at least in Japan. This means that firms with different productivity levels are significantly affected differently in times of crisis, suggesting that although firms belong to the same industry, a uniform policy intervention to such heterogeneous firms does not necessarily produce the results intended by the government.

6 Conclusion

In this study, we proposed a new approach to measure the change in the productivity of the manufacturing industry in Japan. As firms belonging to the same industry can still have different productivity levels,

[21] This number is obtained by comparing the second and sixth columns of Table 7.

Table 7: Estimation results: Constrained specification

	No constraint				Constraint: $D = 1$			
	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2
1987	0.053***	1.000	0.000	0.795	0.054***	–	0.000	0.834
	(2.76)	(0.03)	(0.24)		(9.01)		(0.20)	
1988	0.101***	0.987*	0.000	0.975	0.069***	–	0.000	0.948
	(5.38)	(-1.82)	(-0.49)		(12.0)		(0.28)	
1989	0.029	1.003	0.000	0.914	0.037***	–	0.000	0.807
	(1.62)	(0.53)	(-0.34)		(5.72)		(-0.29)	
1990	0.066***	0.988	0.000	0.889	0.037***	–	0.000	0.810
	(3.0)	(-1.54)	(-0.59)		(6.07)		(-0.32)	
1991	0.044**	0.988	0.000	0.901	0.014***	–	0.000	0.848
	(2.0)	(-1.44)	(1.30)		(2.81)		(1.07)	
1992	-0.003	0.989*	0.000	0.796	-0.030***	–	0.000	0.942
	(-0.20)	(-1.69)	(-0.49)		(-4.97)		(-0.64)	
1993	-0.002	0.986*	0.000	0.788	-0.036***	–	0.000	0.776
	(-0.12)	(-1.87)	(-0.18)		(-6.37)		(0.31)	
1994	-0.008	1.003	0.000	0.231	-0.001	–	0.000	0.032
	(-0.36)	(0.33)	(-0.08)		(-0.19)		(-0.18)	
1995	0.057**	0.992	0.000	0.847	0.037***	–	0.000	0.864
	(2.41)	(-0.92)	(0.38)		(6.48)		(0.91)	
1996	0.016	1.006	0.000	0.747	0.031***	–	0.000	0.695
	(0.73)	(0.71)	(0.49)		(5.16)		(0.17)	
1997	0.049**	0.992	0.000	0.772	0.029***	–	0.000	0.931
	(2.40)	(-0.99)	(0.34)		(4.44)		(0.77)	
1998	-0.074***	1.004	0.000	0.968	-0.062***	–	0.000	0.980
	(-3.27)	(0.51)	(0.11)		(-9.72)		(-0.56)	
1999	-0.037*	1.008	0.000	0.806	-0.016***	–	0.000	0.952
	(-1.71)	(0.97)	(-0.45)		(-2.04)		(-0.48)	
2000	0.024	1.009	0.000	0.916	0.046***	–	0.000	0.890
	(1.15)	(1.14)	(-0.27)		(5.96)		(-0.26)	
2001	0.133***	0.936***	0.002	0.731	-0.037***	–	0.004	0.550
	(3.66)	(-4.89)	(1.22)		(-4.34)		(2.13)	
2002	-0.006	0.999	0.000	0.556	-0.007	–	0.000	0.731
	(-0.30)	(-0.09)	(-0.48)		(-1.10)		(-1.31)	
2003	0.069***	0.994	0.000	0.940	0.053***	–	0.000	0.832
	(3.59)	(-0.83)	(0.35)		(8.78)		(0.12)	
2004	0.051***	1.001	0.000	0.969	0.054***	–	0.000	0.966
	(2.88)	(0.16)	(0.37)		(9.78)		(0.28)	
2005	0.010	1.003	0.000	0.664	0.017***	–	0.000	0.572
	(0.53)	(0.45)	(-0.11)		(2.71)		(-0.20)	
2006	0.037**	0.996	0.000	0.775	0.025***	–	0.000	0.863
	(2.48)	(-0.81)	(-0.18)		(5.59)		(0.25)	
2007	-0.034*	1.010	0.000	0.279	-0.007	–	0.000	0.816
	(-1.75)	(1.39)	(0.20)		(-0.99)		(-0.35)	
2008	-0.031*	1.012*	0.000	0.455	0.001	–	0.000	0.032
	(-1.78)	(1.69)	(-0.24)		(0.19)		(-0.21)	
2009	-0.251***	1.042***	0.000	0.975	-0.140***	–	0.000	0.911
	(-13.46)	(6.14)	(-0.15)		(-20.91)		(-0.06)	
2010	0.065***	1.011	0.000	0.927	0.093***	–	0.000	0.950
	(3.14)	(1.32)	(0.25)		(13.02)		(-0.39)	

Note. Each entry in the left panel replicates Table 2. The right panel represents the estimates of the constrained specification with $D = 1$. ***, **, and * denote that the estimates are significant at the 1%, 5%, and 10% levels, respectively. TFP is estimated following Levinsohn and Petrin (2003).

the impacts of crises differ by firm. Taking this firm heterogeneity into consideration, we attempted to obtain new findings by applying a method that can statistically prove the annual changes in the productivity distribution. Specifically, taking advantage of the quantile technique, we divided the sources of productivity changes accompanied by each of the several crises to reveal which worked most hard in which recessions and changed productivity at the industry level.

The main conclusions can be divided into the finding on the facts about changes in the productivity distribution and technical findings obtained by applying new methods. The findings on the changes in the productivity distribution in Japan can be briefly summarized as follows. First, when productivity improved in the industry as a whole, productivity growth was relatively high for firms with lower productivity. This contributed to reducing the productivity gap between firms. Second, in the event of a major crisis such as the global financial crisis of 2008, the industry's productivity declined. In this case, the productivity decline was more pronounced for firms with lower productivity and the impact on firms with higher productivity was relatively small. Third, the productivity level required to survive in the market did not rise and therefore we did not find that firms with low productivity were particularly forced to withdraw from the market. Specifically, at the time of the global financial crisis in 2008, there was no evidence that firms with lower productivity were more likely to exit the market. This finding suggests that policies to bail out SMEs were effective. Fourth, the productivity improvement from the crisis of 2008 has advanced mainly in populated areas. Fifth, agglomeration economies, rather than the severe selection of unproductive establishments in larger regions, explain the regional productivity differences in Japan.

We also derive two technical implications when estimating productivity using the quantile method. First, if we do not consider that the change in productivity varies according to the heterogeneity of firms measured at the original productivity level, the estimates of the parameter representing the shift in the productivity distribution should be underestimated. For instance, applying the Welch's test to see if the estimate with and without the constraint $D = 1$ are significantly different in 2009 shows that the estimate representing the shift in the distribution is about 45% less if we do not account for the fact that heterogeneous firms receive different influences from the crisis. Second, the quantile approach can explain the slightly unnatural result derived from conventional analysis using weighted average productivity. For example, at the time of the global financial crisis, a crisis rarely seen in history, productivity hardly changed when looking at the rate of change in weighted average productivity. However, using the quantile approach, we find that the distribution shifted by more than 22% to the left driven the decline in the productivity of unproductive firms. Firms with high productivity not only escaped a decline in productivity but might also have achieved a productivity increase, which contributed to maintaining average productivity at almost the zero level.

In closing the paper, we mention some issues to be addressed in the future. First, in the quantile approach, it is difficult to clearly reveal whether the change in the productivity distribution is the result of firms' entry and exit. That is, when a firm with low productivity disappears, it cannot be identified whether this is due to withdrawing from the market or because the productivity of the firm has increased. To analyze changes in the productivity distribution through firms' entry and exit, we thus need to take other approach. In addition, our study only examined the truncation on the left side of the distribution. Analyzing the truncation on the right side of the distribution, we might see if the adverse selection that productive firms are forced to exit the market happened. Second, one of the problems remaining in this study is to separate the demand factors from the productivity measurement. In the financial crises that occurred in 1998 and 2008, our study confirmed that the productivity distribution of the manufacturing industry shifted to the left. However, we were silent about the identification of the mechanism throughout which the crisis affects the productivity distribution. A demand reduction is heavily involved in this shift, however. Because methods for separating demand factors to measure productivity have been proposed by Konishi and Nishiyama (2013), it would be useful to conduct the quantile approach using them to investigate the robustness of the results of our study. Third, in this study, we estimated changes in the productivity distribution in the manufacturing industry, but it is also important to extend the quantile approach to other industries. In particular, the role of the service industry in a narrow sense, excluding the financial industry, is significant since it accounts for a slightly larger share than the manufacturing industry, and thus studies have tried to estimate the productivity in service industries (Konishi and Nishiyama, 2010; Morikawa, 2011, 2012). The analysis of the service industry using the quantile approach would contribute to the discussion and add to the comprehensive understanding of the productivity of the entire economy.

Appendix A: Derivation of (3) and (4)

If $T_1 > T_0$, the change in variable $\phi \to (\phi - S)/D$ turns F_0 into

$$F_0\left(\frac{\phi - S}{D}\right) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - S_1}{D_1}\right) - T_0}{1 - T_0}\right\}.$$

Dividing by $1 - T$ and adding $-T/(1-T)$ to all terms leads to

$$\frac{F_0\left(\frac{\phi - S}{D}\right) - T}{1 - T} = \max\left\{\frac{-T}{1-T}, \frac{\tilde{F}\left(\frac{\phi - S_1}{D_1}\right) - T_1}{1 - T_1}\right\}.$$

We obtain

$$\max\left\{0, \frac{F_0\left(\frac{\phi - S}{D}\right) - T}{1 - T}\right\} = \max\left\{\frac{-T}{1-T}, \frac{\tilde{F}\left(\frac{\phi - S_1}{D_1}\right) - T_1}{1 - T_1}\right\} = F_1(\phi).$$

Next, if $T_1 < T_0$, the change in variable $\phi \to D\phi + S$ turns F_0 into

$$F_0\left(D\phi + S\right) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - S_1}{D_1}\right) - T_0}{1 - T_0}\right\}.$$

Dividing by $1 - T$ and adding $-T/(1-T)$ to all terms leads to

$$\frac{F_0\left(D\phi + S\right) - \frac{-T}{1-T}}{1 - \frac{-T}{1-T}} = \max\left\{\frac{-T}{1-T}, \frac{\tilde{F}\left(\frac{\phi - S_1}{D_1}\right) - T_1}{1 - T_1}\right\}.$$

We obtain

$$\max\left\{0, \frac{F_0\left(D\phi + S\right) - \frac{-T}{1-T}}{1 - \frac{-T}{1-T}}\right\} = \max\left\{\frac{-T}{1-T}, \frac{\tilde{F}\left(\frac{\phi - S_1}{D_1}\right) - T_1}{1 - T_1}\right\} = F_1(\phi).$$

Appendix B: Levinsohn and Petrin (2003)'s approach

We here present the estimation methodology proposed by Levinsohn and Petrin (2003). This method takes account of the endogeneity problem that capital inputs and productivity are correlated. According to Levinsohn and Petrin (2003), the production function is represented as

$$v_{it} = \beta_k k_{it} + \beta_l l_{it} + \varepsilon_{it},$$

where $\varepsilon_{it} = \phi_{it} + e_{it}$, and e_{it} is the error term that cannot be observed. ϕ_{it} is likely to be correlated with the capital inputs. In addition, ϕ_{it} has a positive relationship with intermediate inputs m_{it},

$$m_{it} = g(k_{it}, \phi_{it}).$$

This can be inverted $\phi_{it} = h(m_{it}, k_{it})$. Substituting this into production function leads to

$$v_{it} = \beta_l l_{it} + \Phi(k_{it}, m_{it}) + e_{it}, \tag{13}$$

Table 8: Estimation results of the production function

	Model			
	OLS	FE	LP	W
$\log k$	0.340***	0.071***	0.129***	0.130***
	(499.07)	(78.75)	(57.05)	(76.38)
$\log l$	0.780***	0.768***	0.493 ***	0.487***
	(646.66)	(376.13)	(113.4)	(463.99)
Obs.	1,233,232	1,233,230	1,233,232	1,061,229

Note. Each entry represents the production function coefficients. Z-values are in parentheses. *** denotes that the estimate is significant at 1%. OLS, FE, LP, and W mean that the estimation method of the production function is by the OLS, OLS with fixed effects, Levinsohn and Petrin (2003), and Wooldridge (2009) approaches, respectively. *Obs.* stands for the sample size.

where $\Phi(k_{it}, m_{it}) = \beta_k k_{it} + h(m_{it}, k_{it})$. $\Phi(k_{it}, m_{it})$ is replaced with a multi-order polynomial in m_{it} and k_{it}, $\hat{\Phi}$. Then, (13) can be estimated by OLS. In addition, $\phi_{i,t-1}$ can be approximated by $\Phi(k_{i,t-1}, m_{i,t-1}) - \beta_k k_{i,t-1}$. From the above, the production function is rewritten as

$$v_{it} = \beta_l l_{it} + \gamma(\hat{\Phi}(k_{i,t-1}, m_{i,t-1}) - \beta_k k_{i,t-1}) + e_{it}, \tag{14}$$

where $\gamma(\cdot)$ is an approximated term. (14) is estimated by nonlinear least squares, and k_{it} does not have a correlation with the error term. Hence, we obtain consistent estimates of the production function coefficients.

Appendix C: TFP

In the analysis, we used the estimation results mainly based on Levinsohn and Petrin (2003). Another representative method is to use the method proposed by Wooldridge (2009). Using the generalized method of moments approach, Levinsohn and Petrin (2003) build the identification production function following Olley and Pakes (1996), whereas Wooldridge (2009) proposes a single-equation instrumental variable approach to control for the correlation between the inputs and unobserved productivity of establishments. Table 8 shows the estimation results of the production function derived using the Levinsohn and Petrin (2003) and Wooldridge (2009) approaches as well as OLS and OLS with fixed effects. The coefficients of $\ln k$ and $\ln l$ of both the Levinsohn and Petrin (2003) and the Wooldridge (2009) approaches are almost the same. They also have the expected signs and are statistically significant at the 1% level.

Using the data on the TFP of each establishment $i = 1, 2, ...$, weighted average ln TFP in the industry at year t is calculated by the following formulation:

$$TFP_t = \sum_i \theta_{it} \ln TFP_{ti},$$

where θ_{it} is the added-value share of establishment i in year t. Figure 6 depicts the annual growth rate of weighted average TFP in the manufacturing sector. This figure shows that the TFP growth rate in the 1990s was lower than before and had already decreased since 1987. The annual average growth rate of TFP for the three years after 1987 was 2.19%, while it decreased to 0.04% in the 1990s. The situation slightly improved after that, and the annual average growth rate of TFP for the 10 years from 2000 was 0.41%. A sharp drop in TFP was recorded in 2001, which was -2.08%, and the sharp increase in TFP in 2010 corresponds to the year in which the economy recovered from the global financial crisis.

Appendix D: Descriptive statistics of the productivity distribution

Table 9 presents the descriptive statistics of the productivity distribution. Compared with between 1986 and 2010, productivity increased by 30% from 1.17 to 1.52 at the 10th percentile. On the contrary, the productivity rise at the 90th percentile remained at 8.7% from 3.43 to 3.73. This implies that the increase in productivity in firms with low productivity was relatively large and that the productivity gap between firms narrowed. This can also be confirmed by reading the table from left to right. In 1986, productivity

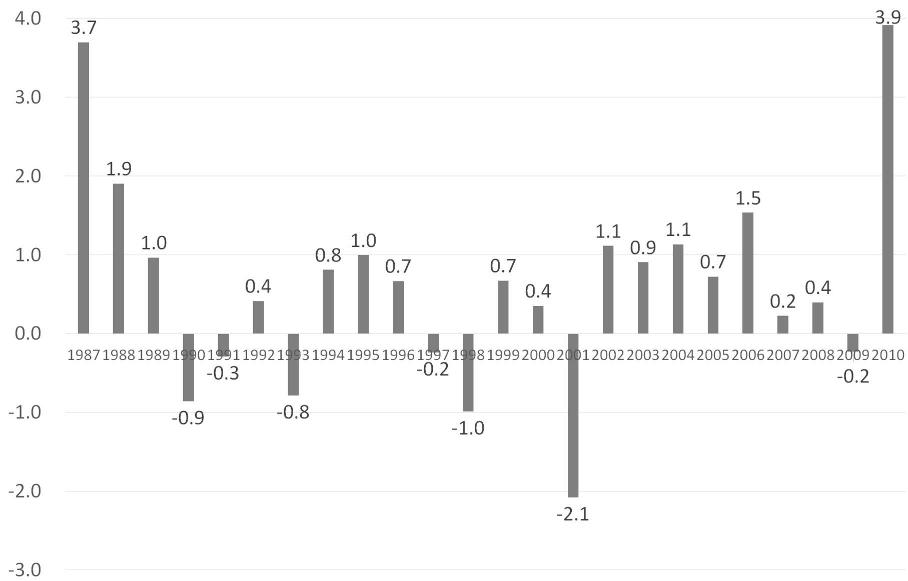

Figure 6: Annual growth in weighted average TFP (%)

at the 90th percentile was 2.9 times greater than that at the 10th percentile. That figure was 2.45 in 2010.

Table 9: Descriptive statistics of the productivity distribution

	Percentile						
	5th	10th	25th	50th	75th	90th	95th
1986	0.61	1.17	1.79	2.31	2.86	3.43	3.82
1987	0.72	1.22	1.83	2.35	2.90	3.49	3.91
1988	0.81	1.32	1.90	2.42	2.96	3.54	3.97
1989	0.87	1.36	1.93	2.45	3.00	3.59	4.00
1990	0.95	1.40	1.97	2.49	3.03	3.62	4.02
1991	0.97	1.42	1.99	2.51	3.04	3.61	4.01
1992	0.95	1.41	1.96	2.47	3.00	3.58	3.98
1993	0.96	1.39	1.93	2.42	2.95	3.52	3.93
1994	0.97	1.40	1.94	2.42	2.95	3.52	3.92
1995	1.01	1.45	1.97	2.46	2.98	3.55	3.96
1996	1.04	1.47	2.00	2.49	3.01	3.59	4.00
1997	1.09	1.51	2.03	2.51	3.04	3.61	4.04
1998	1.01	1.44	1.97	2.45	2.98	3.55	3.98
1999	0.99	1.42	1.95	2.44	2.96	3.55	3.97
2000	1.02	1.45	1.98	2.48	3.02	3.61	4.04
2001	1.16	1.47	1.95	2.44	2.96	3.54	3.94
2002	1.17	1.48	1.95	2.43	2.95	3.52	3.95
2003	1.23	1.53	2.00	2.48	3.00	3.58	4.00
2004	1.28	1.57	2.05	2.53	3.06	3.65	4.05
2005	1.29	1.59	2.06	2.54	3.08	3.67	4.07
2006	1.33	1.62	2.08	2.57	3.11	3.70	4.10
2007	1.30	1.61	2.07	2.56	3.11	3.70	4.11
2008	1.28	1.60	2.07	2.56	3.11	3.71	4.12
2009	1.11	1.44	1.92	2.43	2.99	3.61	4.03
2010	1.21	1.52	1.99	2.50	3.08	3.73	4.15

Note. Each entry shows the TFP of each percentile. TFP is estimated following Levinsohn and Petrin (2003).

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Supplemental Appendix

Table 10: Estimation results: Constrained specification

	No constraint				Constraint: $S = 0$				Constraint: $T = 0$			
	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2
1987	0.053***	1.000	0.000	0.795	–	1.020***	0.000	0.730	0.071***	0.993	–	0.666
	(2.76)	(0.03)	(0.24)			(7.59)	(0.21)		(2.69)	(-0.72)		
1988	0.101***	0.987*	0.000	0.975	–	1.023***	0.000	0.706	0.100***	0.987*	–	0.975
	(5.38)	(-1.82)	(-0.49)			(8.96)	(0.26)		(5.07)	(-1.70)		
1989	0.029	1.003	0.000	0.914	–	1.013***	0.000	0.713	0.028	1.004	–	0.760
	(1.62)	(0.53)	(-0.34)			(5.37)	(-0.26)		(1.10)	(0.41)		
1990	0.066***	0.988	0.000	0.889	–	1.011***	0.000	0.546	0.056***	0.992	–	0.820
	(3.00)	(-1.54)	(-0.59)			(4.96)	(0.04)		(3.06)	(-1.25)		
1991	0.044**	0.988	0.000	0.901	–	1.003	0.0001*	0.773	0.067***	0.979***	–	0.418
	(2.00)	(-1.44)	(1.30)			(1.51)	(1.73)		(3.15)	(-2.65)		
1992	-0.003	0.989*	0.000	0.796	–	0.988***	0.000	0.955	-0.054**	1.009	–	0.173
	(-0.20)	(-1.69)	(-0.49)			(-4.66)	(-0.96)		(-2.26)	(0.96)		
1993	-0.002	0.986*	0.000	0.788	–	0.985***	0.000	0.823	0.011	0.981*	–	0.831
	(-0.12)	(-1.87)	(-0.18)			(-6.97)	(-0.18)		(0.42)	(-1.88)		
1994	-0.008	1.003	0.000	0.231	–	1.000	0.000	0.031	-0.003	1.001	–	0.005
	(-0.36)	(0.33)	(-0.08)			(-0.15)	(-0.17)		(-0.11)	(0.07)		
1995	0.057**	0.992	0.000	0.847	–	1.012***	0.000	0.697	0.068***	0.987	–	0.769
	(2.41)	(-0.92)	(0.38)			(4.96)	(0.54)		(3.07)	(-1.54)		
1996	0.016	1.006	0.000	0.747	–	1.011***	0.000	0.682	0.019	1.005	–	0.691
	(0.73)	(0.71)	(0.49)			(5.06)	(0.14)		(0.84)	(0.54)		
1997	0.049**	0.992	0.000	0.772	–	1.009***	0.000	0.830	0.070***	0.984**	–	0.503
	(2.40)	(-0.99)	(0.34)			(3.46)	(0.61)		(3.45)	(-2.01)		
1998	-0.074***	1.004	0.000	0.968	–	0.979***	0.000	0.831	-0.080***	1.007	–	0.959
	(-3.27)	(0.51)	(0.11)			(-8.92)	(-0.36)		(-4.32)	(0.97)		
1999	-0.037*	1.008	0.000	0.806	–	0.995**	0.000	0.917	-0.067***	1.020**	–	0.230
	(-1.71)	(0.97)	(-0.45)			(-2.12)	(-0.57)		(-2.90)	(2.25)		
2000	0.024	1.009	0.000	0.916	–	1.018***	0.000	0.898	0.014	1.013	–	0.880
	(1.15)	(1.14)	(-0.27)			(7.24)	(-0.12)		(0.43)	(1.12)		
2001	0.133***	0.936***	0.002	0.731	–	0.982***	0.004**	0.583	0.251***	0.893***	–	0.474
	(3.66)	(-4.89)	(1.22)			(-7.05)	(2.46)		(12.64)	(-14.31)		
2002	-0.006	0.999	0.000	0.556	–	0.997	0.000	0.738	-0.013	1.002	–	0.198
	(-0.30)	(-0.09)	(-0.48)			(-1.23)	(-0.72)		(-0.75)	(0.30)		
2003	0.069***	0.994	0.000	0.940	–	1.019***	0.000	0.727	0.058**	0.998	–	0.822
	(3.59)	(-0.83)	(0.35)			(7.15)	(0.11)		(2.55)	(-0.21)		
2004	0.051***	1.001	0.000	0.969	–	1.019***	0.000	0.882	0.063**	0.996	–	0.886
	(2.88)	(0.16)	(0.37)			(8.29)	(0.21)		(2.37)	(-0.33)		
2005	0.010	1.003	0.000	0.664	–	1.006***	0.000	0.539	0.012	1.002	–	0.570
	(0.53)	(0.45)	(-0.11)			(2.81)	(0.23)		(0.59)	(0.27)		
2006	0.037**	0.996	0.000	0.775	–	1.008***	0.000	0.783	0.044**	0.993	–	0.584
	(2.48)	(-0.81)	(-0.18)			(3.66)	(0.30)		(2.31)	(-0.91)		
2007	-0.034*	1.010	0.000	0.279	–	0.998	0.000	0.806	-0.063**	1.021**	–	0.165
	(-1.75)	(1.39)	(0.20)			(-0.88)	(-0.33)		(-2.21)	(2.04)		
2008	-0.031*	1.012*	0.000	0.455	–	1.001	0.000	0.053	-0.017	1.007	–	0.108
	(-1.78)	(1.69)	(-0.24)			(0.47)	(-0.14)		(-0.67)	(0.71)		
2009	-0.251***	1.042***	0.000	0.975	–	0.956***	0.000	0.654	-0.237***	1.037***	–	0.960
	(-13.46)	(6.14)	(-0.15)			(-19.88)	(-0.23)		(-11.10)	(4.36)		
2010	0.065***	1.011	0.000	0.927		1.034***	0.000	0.905	0.043	1.020*		0.802
	(3.14)	(1.32)	(0.25)			(12.39)	(-0.15)		(1.55)	(1.79)		

Note. Each entry of the left panel replicates Table 2. The middle panel shows the estimates of the constrained specification with $S = 0$. The right panel represents the estimates of the constrained specification with $T = 0$. ***, **, and * denote that the estimates are significant at 1%, 5%, and 10% levels, respectively. TFP is estimated following Levinsohn and Petrin (2003).

Table 11: Estimation results: Constrained specification

	Constraint: $S=0$, $D=1$				Constraint: $D=1$, $T=0$				Constraint: $S=0$, $T=0$			
	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2	Shift	Dilation	Truncation	R2
1987	–	–	0.000	0.202	0.055***	–	–	0.654	–	1.019***	–	0.480
			(0.21)		(7.75)					(7.26)		
1988	–	–	0.000	0.020	0.070***	–	–	0.940	–	1.023***	–	0.668
			(0.26)		(9.11)					(8.20)		
1989	–	–	0.000	0.036	0.036***	–	–	0.753	–	1.013***	–	0.696
			(-0.39)		(5.31)					(5.24)		
1990	–	–	0.000	0.000	0.036***	–	–	0.779	–	1.011***	–	0.546
			(0.03)		(5.08)					(5.87)		
1991	–	–	0.000	0.727	0.016**	–	–	0.150	–	1.003	–	0.028
			(0.75)		(2.37)					(1.13)		
1992	–	–	0.000	0.802	-0.032***	–	–	0.161	–	0.990***	–	0.110
			(-0.71)		(-5.53)					(-4.95)		
1993	–	–	0.000	0.108	-0.036***	–	–	0.649	–	0.985***	–	0.822
			(0.28)		(-5.59)					(-6.21)		
1994	–	–	0.000	0.431	-0.001	–	–	0.004	–	1.000	–	0.002
			(0.24)		(-0.18)					(-0.14)		
1995	–	–	0.000	0.203	0.038***	–	–	0.695	–	1.012***	–	0.454
			(0.34)		(5.27)					(5.66)		
1996	–	–	0.000	0.024	0.031***	–	–	0.677	–	1.011***	–	0.656
			(0.20)		(5.52)					(4.44)		
1997	–	–	0.000	0.367	0.031***	–	–	0.404	–	1.009***	–	0.230
			(0.55)		(5.27)					(3.55)		
1998	–	–	0.000	0.054	-0.062***	–	–	0.948	–	0.979***	–	0.757
			(-0.52)		(-8.88)					(-9.52)		
1999	–	–	0.000	0.865	-0.018**	–	–	0.105	–	0.996*	–	0.029
			(-0.55)		(-2.11)					(-1.78)		
2000	–	–	0.000	0.057	0.046***	–	–	0.815	–	1.018***	–	0.870
			(-0.27)		(6.11)					(7.62)		
2001	–	–	0.004**	0.497	-0.015***	–	–	0.009	–	0.981***	–	0.110
			(2.45)		(-2.78)					(-8.21)		
2002	–	–	0.000	0.573	-0.008	–	–	0.189	–	0.997	–	0.142
			(-0.57)		(-1.35)					(-1.11)		
2003	–	–	0.000	0.011	0.053***	–	–	0.821	–	1.019***	–	0.712
			(0.09)		(8.50)					(7.60)		
2004	–	–	0.000	0.099	0.054***	–	–	0.883	–	1.019***	–	0.757
			(0.10)		(9.92)					(8.13)		
2005	–	–	0.000	0.003	0.017***	–	–	0.563	–	1.006***	–	0.542
			(-0.16)		(3.13)					(2.70)		
2006	–	–	0.000	0.336	0.026***	–	–	0.552	–	1.008***	–	0.418
			(0.19)		(4.97)					(3.96)		
2007	–	–	0.000	0.798	-0.008	–	–	0.029	–	0.999	–	0.002
			(-0.34)		(-1.24)					(-0.38)		
2008	–	–	0.000	0.029	0.001	–	–	0.003	–	1.001	–	0.024
			(-0.22)		(0.17)					(0.48)		
2009	–	–	0.000	0.018	-0.141***	–	–	0.909	–	0.956***	–	0.670
			(-0.25)		(-25.34)					(-20.78)		
2010	–	–	0.000	0.160	0.092***	–	–	0.770	–	1.035***	–	0.781
			(-0.16)		(15.83)					(12.67)		

Note. Each entry of the left panel represents the estimates of the constrained specification with $S=0$ and $D=1$. The middle panel shows the estimates of the constrained specification with $D=1$ and $T=0$. The right panel represents the estimates of the constrained specification with $S,T=0$. *** and ** denote that the estimates are significant at the 1% and 5% levels, respectively. TFP is estimated following Levinsohn and Petrin (2003).