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Resource Reallocation and Zombie Lending in Japan in the '90s

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Abstract

We investigate the efficiency of resource reallocation in Japan during the 1990s, a decade of economic recession, by measuring aggregate productivity growth (APG) using a plant-level data set of manufacturers from 1981-2000. We find that resource reallocation contributed negatively to APG, mainly due to inefficient labor reallocation. A possible reason for the inefficient labor reallocation is misdirected bank lending or "zombie lending" to otherwise defunct plants. To quantify its impact, we develop a model with plant-level heterogeneity, calibrate it based on the results of plant-level productivity estimation, and conduct a counterfactual exercise. The results show that 37% of the actual decline in APG due to inefficient labor reallocation in Japan in the '90s is attributable to "zombie lending."

Keywords: Japan, Plant-level data, Productivity, Proxy estimation, Reallocation, Zombie lending.

JEL Classification Number: E23, E32, G21, O47.

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1 Introduction

The collapse of the bubble economy of the early 1990s was followed by a decade of economic stagnation and financial crisis. During the severe economic recession, it was prevalent that Japanese banks continued to lend to otherwise insolvent firms (Peek and Rosengren (2005) and Caballero et al. (2008)). Such "zombie lending" must have impeded efficient resource reallocation by causing resources to reallocate from profitable firms to unprofitable firms. In this paper, we investigate how effectively resources were reallocated and how much zombie lending distorted resource reallocation during the 1990s.

In order to measure the efficiency of resource reallocation, we estimate its contribution to aggregate productivity growth (APG) using the method proposed by Petrin and Levinsohn (2008). APG is defined as aggregate change in output holding input use unchanged, and its reallocation component captures the change in output resulting from resource reallocation among existing plants.[1] Resource reallocation contributes to APG if inputs are reallocated from plants with lower marginal product to plants with higher marginal product, because output increases without additional input use. Therefore, from the estimated reallocation term, we can learn whether resources were reallocated in the way to increase output and how much change in output was generated by the reallocation.

We estimate the reallocation term using a plant-level panel data set of manufacturers from 1981 to 2000 and find that resources were reallocated in the way to decrease output, especially during the 1990s. The average reallocation term was -0.18% during the 1980s and it was -0.85% during the 1990s. This result is in stark contrast with findings for Chile, Columbia, and the United States, where the reallocation term is typically positive (Petrin and Levinsohn (2008) and Petrin et al. (2009)).

When we further decompose the reallocation term into input-specific reallocation terms, we find that labor reallocation made a large negative contribution to APG during the 1990s. The average labor reallocation term during the 1990s was -0.66% and it accounted for 78% of the undecomposed reallocation term. The capital and material reallocation terms were also negative on average during the 1990s.

[1] APG consists of three components: technical efficiency, reallocation effect, and net-entry effect. We estimate each component at plant-level and obtain APG by aggregating them up over all plants.

Now, the question is why resource reallocation negatively contributed to growth in Japan. The negative reallocation effect means that inputs were reallocated from higher margin plants to lower margin plants. However, in a fully functioning market, resources must be reallocated in the opposite way.

As a possible cause of the negative reallocation effect, we will investigate the effect of misdirected bank lending. As Peek and Rosengren (2005) and Caballero et al. (2008) document, Japanese banks provided subsidized credit to failing firms during the 1990s. Such zombie lending must have caused resources to be reallocated from higher margin plants to lower margin plants.

In order to measure the distortion of zombie lending in reallocation effect, we developed a model with plant-level heterogeneity based on Restuccia and Rogerson (2008). Subsidized credit for zombies is captured by effective tax rates in the model. We define zombies as plants whose technical efficiency has fallen below 20th percentile of its distribution for a consecutive five years. Then, we calibrate effective tax rates of labor and capital using the averages of the corresponding estimated margins for zombies and nonzombies, respectively. Using the calibrated model, we conduct a counterfactual exercise of the no-zombie-lending case and show that the decline in labor reallocation effect due to zombie lending is 37% of the estimated negative labor reallocation effect.

This paper contributes to the literature on Japan's 1990s by providing new evidence that resource reallocation was not efficient. Fukao et al. (2006) showed that the contribution of resource reallocation was strong in the 1990s by using a measure which was originally proposed by Bailey et al. (1992). However, their measure of reallocation effect is based on plant-level TFP, rather than marginal product, and thus its implication is misleading in some cases as Petrin and Levinsohn (2008) argued. We use the newly proposed measure by Petrin and Levinsohn (2008) and document that resources were reallocated in the way to decrease output.

In addition, the quantitative measure of the zombie distortion contributes to the ongoing discussion about why APG in the manufacturing sector slowed down during the 1990s. Fukao and Kwon (2006) questioned the quantitative implication of the "zombie lending hypothesis" by Caballero et al. (2008). They pointed out the fact that the slowdown of APG in the manufacturing sector was most severe although zombie lending was least prevalent in the sector. We provided a quantitative implication of zombie lending on the estimated reallocation effect and showed that zombie lending had a non-negligible negative impact on APG in the manufacturing sector.

The rest of the paper consists of four sections. Section 2 explains the APG measures and their decomposition which we will use in our analysis. We also discuss how we estimate plant-level technical efficiency using plant-level panel data. Section 3 describes the data we use, and section 4 demonstrates the empirical results. Section 5 describes the model and the counterfactual exercise. Section 6 concludes.

2 Method

There are two conceptually different types of measures of aggregate productivity growth suggested in the literature; one is proposed by Petrin and Levinsohn (2008) and the other is proposed by Bailey et al. (1992). First, we explain the index proposed by Petrin and Levinsohn (2008), which we mainly use in the data analysis. Second, we explain the other index by Bailey et al. (1992), focusing on similarities and differences. We also explain that Petrin and Levinsohn (2008) captures the reallocation effect on the aggregate productivity growth more precisely than Bailey et al. (1992). Third, we explain how we measure these continuous-time indexes using discrete-time data, and how entry and exit effects are captured in this setting. Finally, we explain how we estimate production functions and unobserved productivity.

2.1 PL Aggregate Productivity Growth

Petrin and Levinsohn (2008) propose the following index, PL^{level}, in a continuous time setting as aggregate productivity growth:

$$dPL^{level} := \sum_i dV_i - \sum_i \sum_k W_{ik} dX_{ik}, \tag{1}$$

where dV_i is the change in the real value added, W_{ik} is the price of primary input k, and dX_{ik} is the change in primary input k in plant i. Subscript $k \in \{L, K\}$ for primary inputs represents either labor hours, L, or capital stocks, K.

In this way, aggregate productivity growth is defined by the change in aggregate real value added minus the change in aggregate input cost. Since the index is defined in a continuous time setting, all variables are the functions of time t. We suppress time index t in most cases, but sometimes explicitly write it as a subscript, such as V_{it}.

Entrants (exiters) are considered as plants with zero variables before entry (after exit). Therefore, a variable may not be a continuous function of time, and may include jumps. For example, if plant i starts operating at time t^*, then value added in plant i, V_i, takes zero for all $t < t^*$, and takes positive values after $t \geq t^*$. In this setting, the sum of a variable over plants who exist at a point of time is equal to the sum over all plants, including those who may not exist at the point of time. We use $\sum_i$ as the sum over all plants in the latter sense, and thus the domain of the summation does not change over time.

We consider gross output production function of the Cobb-Douglas form with plant-specific technical efficiency:

$$Y_i = A_i L_i^{\beta_L} K_i^{\beta_K} M_i^{\beta_M}, \tag{2}$$

where A_i is the level of technical efficiency, L_i is the labor-hour input, K_i is the real capital stock in plant i, and β's are coefficients for each input.

For each plant, the real value added, V_i, is calculated by subtracting real intermediate materials from real gross output, that is,

$$V_i := P_i Y_i - P_i^M M_i,$$

where P_i is the gross output price, Y_i is the real gross output, P_i^M is the price of intermediate materials, and M_i is the real intermediate materials in plant i.

To make it the growth rate, we divide (1) by the sum of the real value added over all plants, denoted by $V = \sum_i V_i$.

$$\begin{aligned} dPL &:= \frac{dPL^{level}}{V} = \sum_i \frac{dV_i}{V} - \sum_i \sum_k \frac{W_{ik} dX_{ik}}{V} \\ &= \sum_i \frac{P_i dY_i}{V} - \sum_i \frac{P_i^M dM_i}{V} - \sum_i \sum_k \frac{W_{ik} dX_{ik}}{V}, \\ &= \sum_i \frac{P_i dY_i}{V} - \sum_i \sum_{k'} \frac{W_{ik'} dX_{ik'}}{V}, \end{aligned} \tag{3}$$

where subscript $k' \in \{L, K, M\}$ represents one of the primary and intermediate inputs with notations $W_{iM} := P_i^M$ and $X_{iM} := M_i$. Thus, PL is an aggregate productivity growth measure in terms of a percentage to the current aggregate real value added.

We transform differentials in (3) into log differentials after separating the entrants and exiters from the summation over i. For entrants and exiters, log differentials such as $d\ln Y_i$ are not well defined because level variables such as Y_i are equal to zero before entry or after exit, while log of zero is not well defined or minus infinity. Let S be the set of plants who operate and neither enter nor exit at time t, and dNE be the effect on aggregate productivity growth of entry and exit of plants, which is specified later. Using the formula $d\ln Z = dZ/Z$, (3) can be written as

$$dPL \;=\; \sum_{i\in S} D_i d\ln Y_i - \sum_{i\in S} D_i \sum_{k'} s_{ik'} d\ln X_{ik'} + dNE, \tag{4}$$

where $D_i := P_iY_i/V$ is the Domar weight and $s_{ik'} := W_{ik'}X_{ik'}/P_iY_i$ is the ratio of cost to gross output for input $k' \in \{L, K, M\}$. We explicitly discuss the effect of entering and exiting plants in subsection 2.3.

The log differential form, (4), has an advantage that we can decompose PL and investigate the driving forces of aggregate productivity growth. As is stated in Petrin and Levinsohn (2008), PL can be decomposed into the technical efficiency term and the reallocation terms. By substituting $d\ln Y_i$ in (4) with

$$d\ln Y_i = d\ln A_i + \sum_{k'} \varepsilon_{ik'} d\ln X_{ik'}, \tag{5}$$

which is the log differential of (2), we obtain

$$dPL = \sum_i D_i d\ln A_i + \sum_i D_i \sum_{k'} (\varepsilon_{ik'} - s_{ik'}) d\ln X_{ik'} + dNE, \tag{6}$$

where $\varepsilon_{ik'} := \frac{\partial Y_i/Y_i}{\partial X_{ik'}/X_{ik'}}$ is the elasticity of output with respect to input $k' \in \{L, K, M\}$. In our Cobb-Douglas specification, each $\varepsilon_{ik'}$ is equal to $\beta_{k'}$ in (2) for all plant i for $k' \in \{L, K, M\}$. Note that (6) holds for any estimates of β's.

The first term in the right hand side of (6) represents the effect of technological improvement, which we call the technical efficiency term. The second term is the reallocation term, which represents the effect of resource reallocation across existing plants. It is the sum of the reallocation terms of each input $k' \in \{L, K, M\}$. Each term is the weighted sum of time differential of logged input. The weight, $(\varepsilon_{ik'} - s_{ik'})$, is the margin that captures the difference between marginal productivity and unit cost of the input. The reallocation terms give us more information about the contribution of resource reallocation to aggregate productivity growth. For example, we can ask how effectively labor was reallocated compared with capital. We can also ask which resource reallocation is induced the most due to a specific policy change.

We construct the technical efficiency term by estimating the residual productivity, A_i, for each plant. The estimation methods of the residual productivity will be discussed in the subsection 2.4. The decomposition (6) is independent of the method used to estimate production function. Calculating PL itself does not require the estimation of unobserved productivity of each plant.

2.2 BHC Aggregate Productivity Growth

A widely used alternative definition of aggregate productivity growth is the one originally proposed in Bailey et al. (1992). In this subsection, we will explain this type of index, focusing on similarities and differences compared to PL. We will also explain that Petrin and Levinsohn (2008) captures reallocation effects more precisely than Bailey et al. (1992). Among many versions of the measure, we use the version in Foster et al. (1998);

$$dBHC := \sum_i D_i d \ln A_i + \sum_i \ln A_i dD_i + dNE^{BHC}. \tag{7}$$

The first term captures changes in the technical efficiency , the second term captures the reallocation effect, and the third term, which is specified later, captures the net-entry effect. Calculating BHC requires the estimation of unobserved productivity, A_i. Once we obtain an estimate of A_i, we can calculate both the reallocation term and the technical efficiency term, and then we get BHC.

As is shown in Petrin and Levinsohn (2008), the technical efficiency term of BHC is equal to the technical efficiency term of PL under the use of the same weight, D_i. That is, the two measures capture the technical efficiency in the same way. Therefore, the difference lies in the reallocation term and the net-entry term.

Each measure captures a different aspect of resource reallocation. PL increases if resource reallocation leads to more output and/or less input cost. Namely, PL measures the current increase in output and/or decrease in input cost due to resource reallocation. On the other hand, BHC increases if resources are reallocated to more productive plants from less productive plants, in terms of plant-level productivity, A_i. That is, BHC measures the distribution of resources to plants with different levels of productivity.

PL is more precise than BHC in the sense that PL is based on the marginal revenue product of each input, whereas BHC is based on the total factor productivity of the plant where resources are allocated. PL always increases in the case where market competition results in reallocation of resources from plants with low marginal productivity to plants with high marginal productivity, while BHC may or may not increase according to the total factor productivity of plants associated with the resource reallocation.

There are several examples where PL is more favorable than BHC. Petrin and Levinsohn (2008) give an example of a neo-classical competitive setting where plants smoothly reallocate their resource according to the marginal revenue product. In such a case, the reallocation should not affect aggregate productivity in theory, and the reallocation term of PL always takes zero, whereas that of BHC may take the value other than zero. For another example, if the resource is reallocated from less productive plants to more productive plants, then BHC will increase, even if such a reallocation may decrease output and/or increase input cost. This is the case where plants with low productivity cannot increase their input up to the optimal level, and end up with decreasing their input due to some kind of friction, such as credit constraint. PL will decrease in this case, while BHC will increase.

Nonetheless, we also calculate BHC, as well as PL, because BHC gives us information on the pattern of resource reallocation. If BHC increases, then more resources are reallocated to plants with high levels of total factor productivity. Thus, we can infer the direction of resource reallocation in terms of productivity, A_i. This is why it is interesting to compare the reallocation terms of PL and BHC.

2.3 Approximation of Continuous-time Indexes

To measure these continuous-time indexes of aggregate productivity growth, we approximate them by discrete-time indexes as is often the case for the Divisia index (See Hulten (2008)). First, we integrate the index with respect to time from $t-1$ to t, and consider it as a *ideal* discrete-time index. Next, we approximate the integral, i.e., the *ideal* discrete-time index, by Tornqvist approximation(See Appendix A for a detail description, and also

Hulten (2008)). Therefore, as to (4), we obtain

$$\begin{aligned}\int_{t-1}^{t} dPL &= \int_{t-1}^{t} \sum_{i\in S} D_i d\ln Y_i - \int_{t-1}^{t} \sum_{i\in S} D_i \sum_{k'} s_{ik'} d\ln X_{ik'} + \int_{t-1}^{t} dNE \\ &\simeq \sum_{i\in S} \overline{D}_{it}\Delta \ln Y_{it} - \sum_{i\in S} \overline{D}_{it} \sum_{k'} \overline{s}_{ik't}\Delta \ln X_{ik't} + \int_{t-1}^{t} dNE, \end{aligned} \tag{8}$$

where $\overline{D}_{it} := \frac{D_{i,t-1}+D_{it}}{2}$, $\overline{s}_{ik't} := \frac{s_{ik',t-1}+s_{ik't}}{2}$, and $\Delta \ln Z_{it} := \ln Z_{it} - \ln Z_{i,t-1}$ for $Z_i = A_i$ or $X_{ik'}$ for $k' \in \{L, K, M\}$.

So far, we put aside the issue with entrants and exiters in measuring aggregate productivity growth, which is captured by the last term of (8), i.e., $\int_{t-1}^{t} dNE$. In theory, entry and exit of plants create a jump in the aggregate productivity growth measure since we employ a continuous time setting. We explain as follows how these jumps in a continuous time setting will be captured by an approximated integral in a discrete time setting.

First, we integrate (3) from time $t-1$ to t to obtain the *ideal* discrete-time index. Next, after exchanging the order of the integral and the sum over all plants, we split the sum into the sums over three sets of plants: stayers, entrants, and exiters[2]. Thus, we obtain

$$\begin{aligned}\int_{t-1}^{t} dPL &= \sum_{i} \left[\int_{t-1}^{t} \frac{P_i dY_i}{V} - \sum_{k'} \int_{t-1}^{t} \frac{W_{ik'} dX_{ik'}}{V}\right] \\ &= \sum_{i\in \mathcal{S}_t} \left[\int_{t-1}^{t} \frac{P_i dY_i}{V} - \sum_{k'} \int_{t-1}^{t} \frac{W_{ik'} dX_{ik'}}{V}\right] \\ &\quad + \sum_{i\in \mathcal{E}_t} \left[\int_{t-1}^{t} \frac{P_i dY_i}{V} - \sum_{k'} \int_{t-1}^{t} \frac{W_{ik'} dX_{ik'}}{V}\right] \\ &\quad + \sum_{i\in \mathcal{X}_{t-1}} \left[\int_{t-1}^{t} \frac{P_i dY_i}{V} - \sum_{k'} \int_{t-1}^{t} \frac{W_{ik'} dX_{ik'}}{V}\right], \end{aligned} \tag{9}$$

where $\mathcal{S}_t$ is the set of plants who operate throughout the period from time $t-1$ to time t, $\mathcal{E}_t$ the set of entrants who do not operate at time $t-1$ but start operating between time $t-1$ and time t, and $\mathcal{X}_{t-1}$ the set of exiters who operate at time $t-1$ but quit operating between time $t-1$ and time t. The sum of the last two terms are denoted by $\int_{t-1}^{t} dNE$ in (8).

[2] In fact, every plant belongs to one of the four sets of plants: plants who keep operating from time $t-1$ to time t, plants who are not operating at time $t-1$ but starting at some point before time t, plants who are operating at time $t-1$ but quitting at some point before time t, and plants who are not operating throughout the period from time $t-1$ to time t. The sum of any variable over the plants in the forth category is equal to zero.

Next, we approximate the integral under a reasonable assumption addressed in detail in Appendix A. For the first term in (9), we apply the Tornqvist approximation as we discussed above. For the rest of terms, we approximate them by ignoring the reasonably small terms. Finally, we obtain

$$\begin{aligned} APG_t^{PL} := \int_{t-1}^{t} dPL \quad &\simeq \quad \sum_{i \in \mathcal{S}_t} \overline{D}_{it} \Delta \ln Y_{it} - \sum_{i \in \mathcal{S}_t} \overline{D}_{it} \sum_{k'} \overline{s}_{ik't} \Delta \ln X_{ik't} \\ &+ \sum_{i \in \mathcal{E}_t} D_{it} \left[1 - \sum_{k'} s_{ik't} \right] - \sum_{i \in \mathcal{X}_{t-1}} D_{i,t-1} \left[1 - \sum_{k'} s_{ik',t-1} \right]. \end{aligned} \tag{10}$$

We refer to the last two terms in (10) as entry and exit effects, respectively. Note that we do not need to estimate production function when we use (10) to measure APG_t^{PL}. Thus, the measurement of APG_t^{PL} does not require to estimate unobserved productivity of plants.

By applying decomposition (6), equation (10) becomes

$$\begin{aligned} APG_t^{PL} \quad &\simeq \quad \sum_{i \in \mathcal{S}_t} \overline{D}_{it} \Delta \ln A_{it} + \sum_{i \in \mathcal{S}_t} \overline{D}_{it} \sum_{k'} (\varepsilon_{ik'} - \overline{s}_{ik't}) \Delta \ln X_{ik't} \\ &+ \sum_{i \in \mathcal{E}_t} D_{it} \left[1 - \sum_{k'} s_{ik't} \right] - \sum_{i \in \mathcal{X}_{t-1}} D_{i,t-1} \left[1 - \sum_{k'} s_{ik',t-1} \right]. \end{aligned} \tag{11}$$

We use (11) to measure the decomposed parts of aggregate productivity growth. At this point, we use the estimates of unobserved productivity and elasticity to measure each term of the decomposed APG_t^{PL}.

Similarly, BHC is also measured as the integral from time $t-1$ to t. Therefore, APG_t^{BHC} is defined as follows.

$$\begin{aligned} APG_t^{BHC} := \int_{t-1}^{t} dBHC \quad &= \quad \sum_{i \in \mathcal{S}_t} \overline{D}_{it} \Delta \ln A_{it} + \sum_{i \in \mathcal{S}_t} \overline{\ln A_{it}} \Delta D_{it} \\ &+ \sum_{i \in \mathcal{E}_t} [D_{it} \ln A_{it}] - \sum_{i \in \mathcal{X}_{t-1}} [D_{i,t-1} \ln A_{i,t-1}], \end{aligned} \tag{12}$$

where $\overline{\ln A_{it}} := \frac{\ln A_{i,t-1} + \ln A_{it}}{2}$. Note that equation (12) is not an approximation, but an identity, since the form of BHC allows us to exactly calculate the integral.

2.4 Production Function Estimation

Our estimation procedure consists of two steps: plant-level estimation of unobserved technical efficiency, and aggregation of those estimates over all plants. Specifically, decomposing PL and calculating BHC require the first step, that is, the estimation of the plant level technical efficiency A_i and the elasticities ε_{ik}. By taking log of both sides of (2), we have

$$\ln Y_{it} = \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_M \ln M_{it} + \ln A_{it}. \tag{13}$$

We estimate the logged production functions industry by industry, by assuming that there is no correlation in error terms between any two industries. We use the 2nd digit sic code in categorizing industries.

There are many ways to obtain an unbiased estimates of βs, depending the assumption on the error term, $\ln A_{it}$. The argument on endogeneity problem in the production function estimation is well discussed in Griliches and Mairesse (1995). In this paper, we estimate (13) with the Wooldridge-Levinsohn-Petrin (WLP) estimator as our benchmark. To see how the measures are sensitive to estimation methods, we also estimate them using other methods such as the pooled OLS.

The assumption on $\ln A_{it}$ behind the WLP estimator is

$$\ln A_{it} = \nu_{it} + e_{it} \tag{14}$$

where ν_{it} is the unobserved productivity, and e_{it} is the shock which is assumed to be conditional-mean independent of current and past inputs. According to Levinsohn and Petrin (2003), we assume that there exists a time-invariant function $g(\cdot)$ such that $\nu_{it} = g(\ln K_{it}, \ln M_{it})$.

In order to identify $\boldsymbol{\beta} = (\beta_L, \beta_K, \beta_M)'$, we assume

$$E[e_{it}|\boldsymbol{x}_{it}, \cdots, \boldsymbol{x}_{i1}] = 0 \tag{15}$$

$$E[\nu_{it}|\ln K_{it}, \boldsymbol{x}_{i,t-1}, \cdots, \boldsymbol{x}_{i1}] = E[\nu_{it}|\nu_{i,t-1}] \tag{16}$$

where $\boldsymbol{x}_{it} := [\ln L_{it} \ln K_{it} \ln M_{it}]'$. Also, we assume there exists a time-invariant function $f(\cdot)$ such that $E[\nu_{it}|\nu_{i,t-1}] = f(\nu_{i,t-1})$.

Define the innovation in ν_{it};

$$a_{it} := \nu_{it} - E[\nu_{it}|\nu_{i,t-1}]. \tag{17}$$

The equation (16) means that $\ln K_{it}$, $\boldsymbol{x}_{i,t-1}$, and all functions of these are uncorrelated with a_{it}. Note, however, that $\ln L_{it}$ is allowed to be correlated with a_{it}. Then, putting the assumptions into the equation (13) gives the following estimation equation;

$$\ln Y_{it} = \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_M \ln M_{it} + f[g(\ln K_{i,t-1}, \ln M_{i,t-1})] + u_{it}, \tag{18}$$

where $u_{it} := a_{it} + e_{it}$.

We non-parametrically estimate the two functions $g(\cdot)$ and $f(\cdot)$. For $g(\cdot)$, we use the 3rd order polynomial. For $f(\cdot)$, we use the 1st order polynomial, that is a linear function. One reason for these choices is a computational advantage that we can estimate (18) by linear GMM. Another reason is that high order polynomial regression leads to collinearity problems.

Since $\ln L_{it}$ and $\ln M_{it}$ can be correlated with a_{it}, we need instruments for them. Recall that $\ln K_{it}$, $\boldsymbol{x}_{it-1}$, and all functions of these are uncorrelated with a_{it} by (16). Therefore, we use $\ln L_{i,t-1}$, $\ln L_{i,t-2}$, and $\ln M_{i,t-2}$ as instruments.

3 Data

We use plant-level panel data on Japanese manufacturing sector for the period 1981-2000. The panel data is compiled from the annual *Census of Manufactures*, which covers all plants in the manufacturing sector that hire 4 or more employees.[3] The *Census of Manufactures* contains information on shipments, number of employees, the book value of tangible fixed assets, the wage bill, and other values. The census consists of two parts; one covers all manufacturing plants with more than 30 employees (Part A) and other covers those with 4-29 employees (Part B).[4] There are about 50,000 plants in Part A and about 550,000 plants in Part B in each year.

In this paper, we use Part A and B of the period 1981-2000 because Part B of the *Census of Manufactures* stopped asking the book value of tangible fixed assets in 2001. There are 8,149,190 plant-year observations in this period. We dropped plants that did not provide information on the book value of tangible fixed assets and plants that report zero wage bill and intermediate inputs. This treatment reduced 4,828,041 observations, mainly due to the lack of information on the book value of tangible fixed assets. As a result, there remain 3,321,149 observations in our sample.

[3] The construction of the panel data from the *Census of Manufactures* data was a part of the RIETI project named "Study on industry and firm level productivity in Japan". Since the census data are not stored in a panel format, the project converted them into panel data by assigning a relevant identification number to each plant.

[4] Part A is called "Kou Hyo" and Part B is called "Otsu Hyo" in Japanese. The manufacturing plants with 1-3 employees are also surveyed in the years ending in 0,3,5, and 8. However, the data on these small plants are not publicly available and were not treated in the RIETI project, either.

All nominal output and input variables are available at plant level. The nominal output is defined as the sum of shipments, the revenue from repairing and fixing services, and revenues from performing subcontracted work. The real output is defined as gross output deflated using sectoral output deflators derived from the JIP 2008 (2000 base index).[5] The nominal intermediate inputs are defined as the sum of the material, fuel, and electricity expenditures and subcontracting expenses for consigned production used by the plant. Intermediate inputs are deflated by the intermediate input deflators provided in the JIP 2008 (2000 base index). Labor input is obtained by multiplying the number of employees by the sectoral working hours from the JIP 2008. The real value of capital stock is obtained by deflating the nominal book value of capital stock with an industry-level price index of capital. The nominal book value is the beginning period book value of tangible fixed assets including buildings, machinery, tools and transport equipment. The industry-level price index of capital is calculated by dividing the sum of the nominal book values in the industry by the industry's real net capital stock, which is obtained from JIP 2008.

4 Results

Our estimation results reveal a sharp contrast between the pattern of APG during the 1980s and 1990s in the Japanese manufacturing sector. We document three main findings in comparison of the 1980s and the 1990s. In addition, we examine the sensitivity of the main findings to the estimation method used in productivity estimation. All main findings are fairly robust to different estimation methods, with a few exceptions.

4.1 Main Findings

We summarize the estimation results in three main findings. First, the estimated APG considerably dropped on average from the 1980s to the 1990s.

[5]The JIP 2008 Database was compiled as part of a RIETI research project. The database contains annual information on 108sectors, including 56 non-manufacturing sectors, from 1970 to 2005. These sectors cover the whole Japanese economy. The database includes detailed information on factor inputs, annual nominal and real input-output tables, as well as some additional statistics, such as Japan's international trade by trade partner, inward and outward FDI, etc., at the detailed sectoral level. An Excel file version of the JIP 2008 Database is available on RIETI's web site.

Second, all three components, i.e., the technical efficiency, reallocation, and net-entry terms, became lower on average in the 1990s than in the 1980s. Third, there was a huge drop in the labor reallocation term on average in the 1990s, which contributed the most to the negative reallocation effect in the 1990s. In this subsection, we document these findings as well as explain the main events during the 1980s and the 1990s.

The first column of Table 1 shows the estimated APG_t^{PL}. In the 1980s, APG_t^{PL} always took positive values and had an increasing trend until the late 1980s. However, it started decreasing in 1989 and turned to be negative in 1992-93 and 1998-99. The average of APG_t^{PL} in the 1990s was much lower than in the 1980s: 4.99% in the 1980s and 1.38% in the 1990s. Japan's economy was in an economic slump during the 1990s.

The movement of APG_t^{PL} agrees with what happened in Japan. In 1985, when the G5 countries agreed to intervene in currency markets to depreciate the overvalued U.S. dollar (the Plaza agreement), Japan went in a recession due to the acute devaluation of the U.S. dollar against the Japanese yen. The expansionary monetary policy issued in the following years boosted the economy, but it led to the Japanese asset price bubble during 1987-89. The estimated APG_t^{PL} took a relatively lower value in 1985 and rapidly increased in the late 1980s.

The bubble's collapse started in 1990 with a plunge in stock, land, and building values. The estimated APG_t^{PL} started decreasing in 1989 and tuned to be negative in 1992-93. In 1997, the government decided that the economy started recovering and increased taxes in April. However, the Asian financial crisis occurred in the summer and a series of failures of financial institutions occurred in the winter. The estimated APG_t^{PL} took negative values again during 1998-99.

Columns 2-4 show the decomposed terms of APG_t^{PL}; the technical efficiency, reallocation, and net-entry terms. This decomposition is based on equation (11) and shows the main sources of aggregate productivity growth. In most of the years, technical efficiency contributed the most to APG and reallocation of resources had the second largest impact on APG.

The growth rates of all terms became lower in the 1990s than in the 1980s. For example, the average technical efficiency term became less than a half in the 1990s: 4.72% in the 1980s and 2.31% in the 1990s. The reallocation term was always negative except for the bubble period, 1987-1991, and took large negative values in 1992-94 and in 1998-99. Also, we find that net-entry effect was almost always positive in the 1980s, but tend to be negative after

Table 1: PL Aggregate Productivity and Its Decomposition

year	**PL APG**	**Technical Efficiency**	**Reallocation**	**Net-Entry**
1982	3.19	3.02	-0.57	0.74
1983	3.57	4.14	-0.50	-0.07
1984	5.03	5.64	-1.05	0.45
1985	3.10	3.03	-0.36	0.43
1986	3.42	2.85	-0.82	1.38
1987	5.60	5.39	0.10	0.11
1988	8.54	7.43	0.94	0.17
1989	7.44	6.25	0.82	0.37
1990	5.31	4.84	0.02	0.45
1991	3.35	3.03	-0.07	0.39
1992	-1.27	0.44	-1.68	-0.02
1993	-2.85	-0.78	-1.68	-0.39
1994	1.53	3.32	-1.06	-0.73
1995	4.67	4.59	-0.04	0.13
1996	3.85	3.66	0.14	0.04
1997	2.83	3.44	-0.38	-0.23
1998	-2.01	-0.70	-1.61	0.30
1999	-1.60	1.24	-2.15	-0.69
2000	5.63	5.87	0.19	-0.42
1980s Average	4.99	4.72	-0.18	0.45
(Std. dev.)	(2.08)	(1.71)	(0.74)	(0.45)
1990s Average	1.38	2.31	-0.85	-0.07
(Std. dev.)	(3.05)	(2.09)	(0.88)	(0.42)

the collapse of the asset bubble.

The finding that reallocation effect deteriorated during the 1990s is different from what was reported in Fukao et al. (2006). They find that reallocation effect was stronger in the 1990s using the BHC definition. We also confirmed this BHC finding using our sample; the BHC reallocation term increased on average from -7.48% in the 1980s to -1.87% in the 1990s.[6]

[6] However, we also find that the BHC reallocation term is much more volatile than the PL reallocation term. The standard deviation of the BHC reallocation term (9.62) is more than 10 times larger than that of the PL reallocation term (0.86). Therefore, we have to be careful in comparing the averages of the BHC reallocation terms.

This difference comes from the different measures of reallocation effect. The BHC reallocation measures the contribution of input reallocation based on the level of productivity, $\ln A_{it}$. If inputs are reallocate from a lower $\ln A_{it}$ plant to a higher $\ln A_{jt}$ plant, the BHC reallocation term count it as positive contribution to aggregate productivity. On the other hand, the PL reallocation term is $\sum_i D_i \sum_{k'}(\varepsilon_{ik'} - s_{ik'})d\ln X_{ik'}$. If inputs are reallocated from a plant with a lower margin, $\varepsilon_{ik} - s_{ik}$, to a plant with a higher margin, $\varepsilon_{jk} - s_{jk}$, then the PL reallocation term count it as positive contribution to aggregate productivity. Recall that the margin captures the difference between marginal productivity and unit cost of the input.

To further investigate the negative PL reallocation term, we break it down into three terms by input: labor, capital stock, and intermediate materials. The estimates of the decomposed terms are reported in Table 2. On average, the contribution of labor and intermediate material reallocation decreased in the 1990s, whereas the contribution of capital reallocation slightly increased. Among them, the fall in the labor reallocation term was sizable: 0.02% in the 1980s and -0.66% in the 1990s.

Table 2 also shows that reallocating input did not always positively contribute to APG. The capital reallocation term was negative in most of the years although its magnitude was small. Growth generated by labor reallocation was positive in the late 1980s, but it became negative in the 1990s. Especially, the negative growth from labor reallocation largely contributed to the low APG in the 1990s. The contribution of material reallocation was positive in the late 1980s and the early 1990s. The standard deviation of the intermediate material reallocation term is fairly large in spite of the small magnitude of its mean.

Now the question is why resource reallocation negatively contributed to APG. If input markets were functioning well, inputs should have been reallocated from plants whose wedge was negative to those with positive wedge. Therefore, we expect that reallocating inputs always generate positive aggregate productivity growth. The negative reallocation effect implies that resource reallocation was not well functioning in Japan's manufacturing sector.

As a possible reason for the negative reallocation effect, we will investigate the effect of misdirected bank lending in Section 5. Caballero et al. (2008) show the wide-spread practice of Japanese banks of providing subsidized credit to otherwise insolvent firms. They also argue that this "zombie lending" deteriorated efficiency of resource reallocation. Peek and Rosengren

Table 2: Decomposition of Reallocation Effect

year	Reallocation	Decomposition		
		Labor	**Capital**	**Materials**
1982	-0.57	-0.53	-0.04	0.00
1983	-0.50	-0.36	-0.20	0.06
1984	-1.05	0.19	-0.32	-0.92
1985	-0.36	0.78	-0.22	-0.91
1986	-0.82	-0.57	-0.29	0.04
1987	0.10	-0.62	-0.29	1.01
1988	0.94	0.39	-0.13	0.68
1989	0.82	0.85	-0.10	0.07
1990	0.02	0.11	-0.06	-0.03
1991	-0.07	0.30	-0.22	-0.15
1992	-1.68	-0.80	-0.44	-0.45
1993	-1.68	-1.36	-0.43	0.12
1994	-1.06	-1.22	-0.18	0.35
1995	-0.04	-0.65	0.11	0.50
1996	0.14	-0.32	-0.01	0.47
1997	-0.38	-0.10	-0.14	-0.14
1998	-1.61	-0.89	-0.05	-0.67
1999	-2.15	-1.62	-0.02	-0.50
2000	0.19	-0.82	0.02	0.98
1980s Average	-0.18	0.02	-0.20	0.00
(Std. dev.)	(0.74)	(0.61)	(0.10)	(0.67)
1990s Average	-0.85	-0.66	-0.14	-0.05
(Std. dev.)	(0.88)	(0.65)	(0.18)	(0.41)

(2005) also document the misallocation of credit in Japan. In section 5, we measure the distortion of zombie lending in reallocation effect, using a model with plant-level heterogeneity of technical efficiency.

Figure 1 shows the stacked column of all terms so that we can compare the contributions of each source. In Figure 1, it is clear that the largest source of APG was technical efficiency. The high growth of aggregate productivity in the 1980s was mainly explained by the high growth of technical efficiency. We also find that technical efficiency growth was volatile during the 1990s. There were two troughs in 1992-93 and 1998-99.

The growth from net-entry was positive in the 1980s, but it tended to be

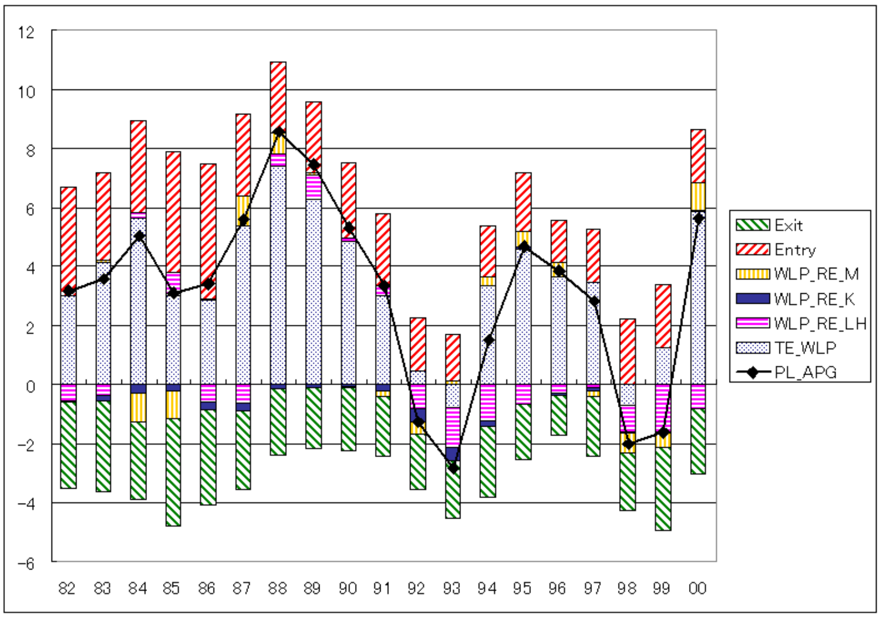

Figure 1: Aggregate Productivity Growth and Its Decomposition.

negative in the 1990s. If we look at entry and exit terms respectively, we can find that the negative net-entry effect was mainly explained by the decrease in the entry effect. In the 1990s, entries of new plants did not bring growth in productivity enough to cover the loss from exit.

4.2 Sensitivity Analysis

The estimation of APG consists of two stages: estimation of unobserved productivity for each plant, and aggregation over all plants. In this subsection, we demonstrate how the aggregation results change in the second stage if we use a different method in the first stage.

First of all, our findings on APG_t^{PL} and the net-entry effect are independent of the method used in productivity estimation. They are estimated without using productivity or elasticity estimates. The findings on technical efficiency and reallocation terms are affected by the choice of estimation methods in the first stage. Therefore, the first main finding will be unchanged and the second and third main findings can possibly be changed if we use a different estimator in productivity estimation. The results from different estimators show that both main findings are still observed with a few exceptions.

Our choice of different estimation methods is a variation of regression-type methods along the line with the base line proxy estimation. On estimation methods of productivity using panel data, Biesebroeck (2003) surveys five estimation methods and concludes that those five ways of measuring plant-level productivities are consistent in a sense that their estimates are highly correlated and give similar insights on the major topics on productivity. Biesebroeck (2004) also shows by Monte Carlo simulation that proxy estimation, introduced by Olley and Pakes (1996) and modified by Levinsohn and Petrin (2003) and Wooldridge (2005), is the most accurate and robust to measurement errors among proposed five estimators. This is why we use a proxy estimation method, the Wooldridge-Levinsohn-Petrin (WLP) estimator, in our base line results.

We show the results from four other estimation methods: the pooled OLS estimator (OLS), the fixed-effect estimator (FE), the first-differences estimator (FD), and the second-differences estimator (SD). Consistency of each estimator depends on the assumption on unobserved productivity ν_{it} in (14). We also show the results from the TFP estimator used in Fukao et al. (2006), with abbreviation (FKK). We briefly explain the advantage and disadvantage for each estimator.

OLS is one of the simplest methods to estimate (13). If plants choose labor inputs L_{it} and intermediate materials M_{it} without knowing unobserved productivity ν_{it}, there is no endogeneity problem and thus OLS leads to consistent estimates. However, if plants choose L_{it} and M_{it} after knowing ν_{it}, OLS leads to inconsistent estimates due to the endogeneity of labor inputs and intermediate materials with unobserved productivity. Since firms observe their productivity even though they are unobserved for econometrician, firm's decision on labor inputs and intermediate materials should be positively correlated with their productivity.

FE and FD resolve the endogeneity problem if ν_{it} is constant over time for each plant, i.e.,

$$\nu_{it} = \nu_{i0}, \qquad {}^{\forall}t = 1, \ldots, T. \tag{19}$$

For consistency, FE requires the strong exogeneity assumption that regressors at time t must be uncorrelated with $e_{i\tau}$ for all $\tau = 1, \ldots, T$. FD requires a relatively weak exogeneity assumption. That is, regressors at time t must be uncorrelated with e_{it} and $e_{i,t-1}$. However, we discard many variations in data by taking the first difference of all variables. FE also discards variations by taking the mean deviation of regressors. Such data transformations may deteriorate possible attenuation bias due to measurement errors, as is discussed in Griliches and Mairesse (1998). In addition, as for FD, the differencing transformation may deteriorate the attenuation bias due to positive autocorrelation in regressors in panel data (See Cameron and Trivedi (2005) for example).

SD resolves the endogeneity problem if ν_{it} grows over time at a plant-specific constant rate, i.e.,

$$\nu_{it} = \nu_{i0} + \eta_i \cdot t, \qquad {}^{\forall}t = 1, \ldots, T, \tag{20}$$

which includes (19) as a special case with $\eta_i = 0$. For consistency, SD requires that regressors at time t must be uncorrelated with $e_{i,t-2}$, $e_{i,t-1}$, and $e_{i,t}$. By taking the second difference of variables, we discard more variations in regressors than in the case of FD.

Finally, we show the results from FKK to compare our results with the ones in Fukao et al. (2006). FKK assumes that the output elasticities of each input varies across plants and are equal to the cost shares for each plant. See Fukao et al. (2006) for a detailed explanation. Note that the TFP estimates in Fukao et al. (2006) are not exactly the same as the ones used in this paper due to slight differences in the samples and deflator.

Table 3 summarizes the results in production function estimates by estimators. Since we estimate production functions by industry, we report the industry averages of the coefficients and the standard errors. The estimates of returns to scale are almost equal to one for WLP and OLS, a little less than one for FE, and near to a half for FD and SD. The low estimates for FD and SD can be attributed to the attenuation bias deteriorated by the loss of variations in regressors due to differencing transformations.

Tables 4 and 5 summarize the results by estimation method. Since the first main finding, that is, the fact that APG_t^{PL} declined on average from the 1980s to the 1990s, remains the same across different estimators, we only show the results associated with the second and third main findings. We omit the estimates of the net-entry effect since they are the same across estimators.

Table 4 shows the averages of the technical efficiency and reallocation terms in the 1980s and the 1990s, by estimation method. According to

Table 3: Production Function Estimates by Method

Method	**Coefficients**			**Returns**
	Labor	**Capital**	**Materials**	**To Scale**
WLP	0.305	0.037	0.617	0.959
	(0.009)	(0.004)	(0.026)	
OLS	0.420	0.096	0.522	1.038
	(0.008)	(0.003)	(0.005)	
FE	0.368	0.069	0.399	0.836
	(0.011)	(0.003)	(0.007)	
FD	0.296	0.022	0.279	0.597
	(0.010)	(0.003)	(0.007)	
SD	0.204	0.011	0.246	0.461
	(0.013)	(0.003)	(0.008)	
FKK	-	-	-	-

Standard errors are reported in parentheses. Our benchmark is WLP.
All values are the averages over industries.

Table 4, the second main finding is robust to estimation methods, except for the decline in the reallocation term. The first two columns show that the technical efficiency term declined on average from the 1980s to the 1990s for all estimates. Columns 3-4 show that the PL reallocation term also declined for the WLP, OLS, and FKK estimates, whereas it increased for the FE, FD, and SD estimates. Since the FD and SD estimates are much more volatile than the others, the increase in the reallocation term for FD and SD may result from amplified attenuation bias due to differencing transformations.

The last two columns in Table 4 show the averages of the BHC reallocation term by estimators. All the estimates increased on average from the 1980s to the 1990s. The implication on the reallocation effect differs across the two measurement ways; it was increased in the BHC way, but decreased in the PL way. This fact is observed for the WLP, OLS, and FKK estimates.

Table 5 shows the averages of the decomposed reallocation terms in the 1980s and the 1990s, by estimation method. Columns 1-2 show that the

Table 4: Technical Efficiency and Reallocation Terms
by Estimation Method

Method	**Technical Efficiency**		**PL Reallocation**		**BHC Reallocation**	
	1980s	**1990s**	**1980s**	**1990s**	**1980s**	**1990s**
WLP	4.72	2.31	-0.18	-0.85	-7.48	-1.87
	(1.71)	(2.09)	(0.74)	(0.88)	(10.94)	(7.17)
OLS	4.40	2.43	0.14	-0.97	-0.97	-0.24
	(2.99)	(2.78)	(1.08)	(1.10)	(1.63)	(1.52)
FE	5.37	2.11	-0.83	-0.66	-20.99	-1.83
	(4.81)	(3.93)	(2.89)	(1.40)	(20.78)	(11.14)
FD	7.23	2.34	-2.69	-0.89	-42.17	-4.75
	(6.50)	(5.23)	(4.59)	(2.57)	(39.75)	(19.93)
SD	7.68	1.99	-3.14	-0.53	-52.51	-6.61
	(7.19)	(5.86)	(5.29)	(3.15)	(52.05)	(26.93)
FKK	4.17	2.95	0.37	-1.50	0.28	0.33
	(1.75)	(1.20)	(1.81)	(2.15)	(0.32)	(1.47)

Standard deviations are reported in parentheses. Our benchmark is WLP.

labor reallocation term declined on average from the 1980s to the 1990s for all estimation methods. The decline was large, except for the SD estimate. For WLP and OLS, the decline in the labor reallocation effect contributed the most to the decline in the whole reallocation effect in the 1990s. For FE, the decline in the labor reallocation effect was large, but offset by the material reallocation effect. For FD and SD, the increase in the capital and intermediate material reallocation effects exceeded the decline in the labor reallocation effect, and the whole reallocation effect increased in the 1990s as in Table 4. Therefore, as to the third main finding, the labor reallocation effect robustly decreased, but was not necessarily the main driving force of the average change in the reallocation term from the 1980s to the 1990s.

Table 5: Decomposed Reallocation Terms by Estimation Method

Method	**Labor**		**Capital**		**Materials**	
	1980s	**1990s**	**1980s**	**1990s**	**1980s**	**1990s**
WLP	0.02	-0.66	-0.20	-0.14	0.00	-0.05
	(0.61)	(0.65)	(0.10)	(0.18)	(0.67)	(0.41)
OLS	-0.00	-1.22	0.80	0.30	-0.66	-0.05
	(1.14)	(1.19)	(0.35)	(0.40)	(1.54)	(0.74)
FE	-0.05	-0.92	0.51	0.18	-1.29	0.08
	(0.89)	(0.89)	(0.26)	(0.29)	(3.30)	(1.76)
FD	0.09	-0.74	-0.43	-0.24	-2.35	0.09
	(0.78)	(0.80)	(0.10)	(0.27)	(5.10)	(3.09)
SD	0.12	-0.30	-0.63	-0.33	-2.63	0.10
	(0.41)	(0.41)	(0.14)	(0.35)	(5.61)	(3.46)
FKK	-	-	-	-	-	-

Standard deviations are reported in parentheses. Our benchmark is WLP.

5 Effect of Zombie Lending

We measure the impact of misdirected lending, so-called "zombie lending", on the negative labor reallocation effect observed in Japan in the 1990s. We develop a version of the model with plant-level heterogeneity provided by Restuccia and Rogerson (2008) and conduct a counterfactual exercise. The exercise shows that the decline in labor reallocation effect due to the distortion of zombie lending is 37% of the negative labor reallocation effect observed in the data.

5.1 Model

There are a mass of plants and one infinitely-lived representative household in the economy. The plants produce the same goods using labor, capital, and intermediate input. They differ only in the level of technical efficiency

(TFP). TFP of a plant i is modeled as follows;

$$A_{it} = A_i \times A_t, \quad \text{where } A_i \sim h(A), \text{ and } A_t = \gamma^t A_0,$$

where $h(\cdot)$ is the density of the idiosyncratic component of TFP, A_i.

There is an unlimited mass of potential entrants and they can enter the market by paying a fixed cost c_e. After a new plant pays the cost, the idiosyncratic component of TFP A_i is revealed and it remains constant over time. Plants exit from the market at a probability $\lambda \in (0, 1)$.

Each plant faces different tax or subsidy rates on capital and labor. These taxes capture the government policy behind the zombie lending. The plant-level tax rates are revealed when A_i is. The probability that a plant with A_i faces a set of tax rates $\tau := (\tau^k, \tau^l)$ is denoted by $\mathcal{P}(A_i, \tau)$. The joint density of (A_i, τ) is $g(A_i, \tau) := h(A_i) \times \mathcal{P}(A_i, \tau)$

Since A_{it} grows at the rate γ, we detrend variables by $A_t^{\frac{1}{1-\beta_k}}$ in order to make the economy stationary. The detrended variables are denoted with tilde, $\tilde{x}$.

Household Problem:

$$\max_{\{\tilde{C}_t, \tilde{K}_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t u(\tilde{C}_t)$$

$$\text{s.t.} \quad \sum_{t=0}^{\infty} p_t(\tilde{C}_t + \gamma \tilde{K}_{t+1} - (1-\delta)\tilde{K}_t) = \sum_{t=0}^{\infty} p_t(r_t \tilde{K}_t + \tilde{w}_t L_t + \tilde{\Pi}_t + \tilde{T}_t)$$

$$K_0 \text{ is given, and } L_t = 1 \text{ for } \forall t.$$

where $\beta \in (0, 1)$ is the time discount factor, $\tilde{C}_t$ is consumption at time t, $\tilde{K}_t$ is capital at the beginning of period t, L_t is labor supply, p_t is the time zero price of consumption at time t, $\tilde{w}_t$ and r_t are the period t rental prices of labor and capital measured relative to period t consumption, $\delta \in (0, 1)$ is the capital depreciation rate, $\tilde{\Pi}_t$ is the total profit from all operating plants, and $\tilde{T}_t$ is the lump-sum transfer. Note that the household does not get utility from leisure and thus L_t always equals to 1.

Existing Plant's Problem:

$$\pi(A_i, \tau_i) := \max_{l,k \geq 0} \left\{ A_i \tilde{k}_i^{\beta_k} l_i^{\beta_l} - (1+\tau_i^l)\tilde{w}_t l_i - (1+\tau_i^k) r_t \tilde{k}_i - \tilde{c}_f \right\},$$

$$\beta_k, \beta_l \in (0, 1), \quad 0 < \beta_k + \beta_l < 1$$

where $\tilde{c}_f$ is a fixed cost of operation measured in units of output.[7]

The policy functions are as follows:

$$\tilde{\bar{k}}(A_i, \tau_i) = \left(\frac{\beta_k}{r_t}\right)^{\frac{1-\beta_l}{1-\beta_l-\beta_k}} \left(\frac{\beta_l}{\tilde{w}_t}\right)^{\frac{\beta_l}{1-\beta_l-\beta_k}} A_i^{\frac{1}{1-\beta_l-\beta_k}},$$

$$\bar{l}(A_{it}, \tau_i) = \left(\frac{\beta_k}{r_t}\right)^{-1} \left(\frac{\beta_l}{\tilde{w}_t}\right) \tilde{\bar{k}}(A_i, \tau).$$

Entering Plant's Problem:

$$W_e := \sum_{(A_i,\tau)} \max_{\bar{\chi}\in\{0,1\}} \{\bar{\chi}(A_i, \tau) W(A_i, \tau) - \tilde{c}_e\} \, g(A_i, \tau)$$

where $\bar{\chi}(A, \tau)$ is the optimal entry decision which takes 1 (enter) or 0 (not enter). $\tilde{c}_e$ is a fixed entering cost measured in units of output, and $W(A, \tau)$ denotes the discounted present value of an existing plant;

$$W(A_i, \tau_i) := \frac{\pi(A_i, \tau_i)}{1-\rho}$$

where $\rho := \frac{1-\lambda}{1+R}$, λ is the exogenous exit rate, and $R := r - \delta$.

Distribution of Plants: Let $\mu(A_i, \tau)$ be the distribution of operating plants over (A_i, τ). Then, its law of motion is

$$\mu'(A_i, \tau) = (1-\lambda)\mu(A_i, \tau) + \bar{\chi}(A_i, \tau) g(A_i, \tau) E$$

where E is the mass of entering plants.

We can now define a steady-state competitive equilibrium.

Equilibrium: A steady state competitive equilibrium in the detrended economy is prices $(\tilde{w}, \tilde{r})$, a lump-sum transfer $\tilde{T}$, a invariant distribution of plants $\mu(A_i, \tau)$, a mass of entry E, value functions $(W(A_i, \tau), \pi(A_i, \tau), W_e)$, policy functions $(\bar{\chi}(A_i, \tau), \tilde{\bar{k}}(A_i, \tau), \bar{l}(A_i, \tau))$, and aggregate variables $(\tilde{C}, \tilde{K})$ such that:

[7] Note that the value added production function exhibits decreasing returns to scale. This is a key assumption for a single-good model to allow plants with different levels of technical efficiency co-exist in equilibrium.

(1) (HH optimization) $r = \frac{1}{\tilde{\beta}} - (1-\delta)$, where $\tilde{\beta} := \beta/\gamma^{\frac{1}{1-\beta_l}}$.
(2) (Plant Optimization) Given prices, value functions solve existing and entering plant's problems and policy functions are optimal,
(3) (Free Entry) $W_e = 0$,
(4) (Market Clearing)

$$1 = \sum_{(A_i,\tau_i)} \bar{l}(A_i,\tau_i)\mu(A_i,\tau_i),$$

$$\tilde{K} = \sum_{(A_i,\tau_i)} \tilde{\bar{k}}(A_i,\tau_i)\mu(A_i,\tau_i),$$

$$\tilde{C} - (1-\delta-\gamma)\tilde{K} + \tilde{c}_e E = \sum_{(A_i,\tau_i)} (A_i \tilde{\bar{k}}^{\beta_k} \bar{l}^{\beta_l} - \tilde{c}_f)\mu(A_i,\tau_i),$$

(5) (Government Budget Constraint)

$$\tilde{T} = \sum_{(A_i,\tau_i)} \left\{ \tau_i^l \tilde{w}_t \bar{l}(A_i,\tau_i) + \tau_i^k r_t \tilde{\bar{k}}(A_i,\tau_i) \right\} \mu(A_i,\tau_i)$$

(6) (Invariant Distribution)

$$\mu(A,\tau) = E\frac{\bar{\chi}(A,\tau)}{\lambda} g(A,\tau), \quad \forall (A,\tau).$$

5.2 Calibration

We let one model period correspond to one year and assign 6% to R, implying $\beta = 0.994$. As in Restuccia and Rogerson (2008), we set $c_e = 1.0$, $c_f = 0.0$, and $\lambda = 0.1$. We assign 0.11 to δ so that the capital-output ratio in the model becomes equal to aggregate capital over aggregate value added in the manufacturing sector.

As Restuccia and Rogerson (2008) discussed, the most important parameter for a quantitative analysis of reallocation effect is the extent of decreasing returns to scale at plant-level because it affects the magnitude of reallocation effect. In order to obtain the extent of decreasing returns, we estimate the value-added production function by WLP, assuming the common production function across industries. Then, the estimates can be directly used as the values of βs and TFP. The resulting values of β's are $\beta_k = 0.10$ and $\beta_l = 0.52$.

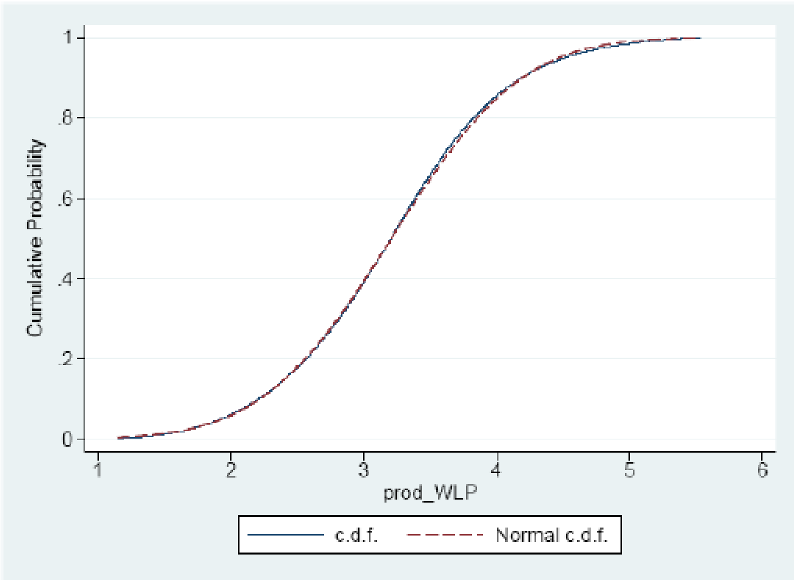

Figure 2: Cumulative Distribution of Plant-level TFP Estimates in 1989.

Manufacturing plants in Japan. Estimated by the WLP method, assuming a common value-added production function for all plants. The data less than 1%-tile and more than 99%-tile are trimmed. Normal c.d.f. shows a normal distribution function with the same mean and variance as the data.

As for $h(A)$, which is the density of the idiosyncratic component of TFP, we approximate the distribution of the estimated plant-level TFP, shown in Figure 2, with 20 grid points. As Restuccia and Rogerson (2008) discussed, h is a key determinant of the magnitude of distortion. The direct use of the estimates is our advantage.

5.3 Quantitative Analysis

If banks provided subsidized credits to the zombie plants (which we call "zombie lending"), it would deteriorate efficiency of resource reallocation. In this subsection, we measure the distortion of such lending in each reallocation term.

We assume that Japan's economy was in different steady states in 1989 and 1999. The steady state in 1989 was associated with $\gamma = \gamma_{89}$ (=4.72%) and another steady state in 1999 was associated with $\gamma = \gamma_{99}$ (=2.31%). We assume that the detrended economy attained the capital stock in the new steady state in 1990 and that the original economy grew at the rate of γ_{99}.[8]

We define a zombie plant as a plant whose TFP has fallen below the 20th percentile of the TFP distribution for 5 consecutive years. We assume that zombies and nonzombies faced different tax rates during the 1990s while they didn't during the 1980s.[9] The different tax rates during the 1990s captured subsidized credits to the zombie plants because a plant faced lower effective rental rates if it received subsidized credit. The percentage of zombie plants was 9% of all plants during the 1990s.

We calibrate the tax rates to match the average wedges of labor and capital. From the first order conditions of the existing plant's problem, we obtain the following theoretical relationship between the wedges and the tax rates:

$$\varepsilon_{ij} - s_{ij} = \beta_j \left(1 - \frac{1}{(1+\tau_i^j)}\right), \quad \text{for } j = k,\ l. \tag{21}$$

For the steady state in 1989, we calculate the average labor and capital wedges during the 1980s and solve for $(\tau_{89}^l,\ \tau_{89}^k)$ that satisfies (21) given the calculated wedges. For the steady state in 1999, we take the 90s' averages of the labor and capital wedges for zombies and non-zombies, respectively. Then we obtain $\{(\tau_{99,Z}^l, \tau_{99,Z}^k), (\tau_{99,NZ}^l, \tau_{99,NZ}^k)\}$ according to (21). The calibrated tax rates are shown in Table 6.

Table 6 shows that zombie plants actually received subsidized credit during the 1990s. This result confirms that our definition of a zombie plant is reasonable because it is consistent with the previous studies, such as Peek and Rosengren (2005) and Caballero et al. (2008). Table 6 also documents that non-zombies faced much higher tax rates than zombies during the 1990s. It implies that healthy plants had more difficulty to receive bank credit than unprofitable plants. This tax configuration will lead resource reallocation from profitable plants to unprofitable plants.

[8] Instead, we could compute the transitional path from the initial steady state to the new steady state. If we do so, we will provide a better measure on capital stocks. Since our approach assumes that the economy immediately attains the new steady state capital stock, the generated capital stock in 1999 was over-accumulated. However, since our focus is on labor reallocation effect and since it is not affected by capital accumulation, we took our approach to save our time.

[9] Peek and Rosengren (2005) documented that bank lending to unprofitable firms increased during the 1990s. Also, Caballero et al. (2008) showed that subsidized credits became prevalent during the 1990s.

Table 6: Capital and Labor Wedges, and Calibrated Taxes.

Wedges	1980s Ave.	1990s Ave.	
		Zombie	Non-Zombie
$\varepsilon_{il} - s_{il}$	0.20	-0.21	0.21
$\varepsilon_{ik} - s_{ik}$	-0.04	-0.07	-0.05

Calibrated Taxes	1989	1999	
		Zombie	Non-Zombie
τ^l	0.62	-0.29	0.68
τ^k	-0.28	-0.42	-0.32

Note: τ^l_{89} and τ^k_{89} are calibrated so that the average labor and capital wedges, $(\varepsilon_{il} - s_{il}, \varepsilon_{ik} - s_{ik})$, are respectively matched with the counterparts in the data in the 1980's. $(\tau^l_{99,Z}, \tau^k_{99,Z})$ and $(\tau^l_{99,NZ}, \tau^k_{99,NZ})$ are calibrated using (21) so that the average labor and capital wedges are respectively matched with the counterparts in the data in the 1990's for zombie and non-zombie plants, respectively.

In the model, zombies are the plants whose idiosyncratic component of TFP (A_i) is bellow the 20th percentile. In the final steady state in 1999, zombie plants face $(\tau^l_{99,Z}, \tau^k_{99,Z})$ and others face $(\tau^l_{99,NZ}, \tau^k_{99,NZ})$. In order to measure the distortion of zombie lending, we consider the case where there is no misdirected zombie lending. For this "no-zombie lending case," we assume that taxes didn't change at all, i.e. $(\tau^l_{99}, \tau^k_{99}) = (\tau^l_{89}, \tau^k_{89})$ for all plants.

The distortion of zombie lending in reallocation effect is measured as follows.

$$ZD_j := RE_j^{NZ} - RE_j^{Z}, \quad \text{for } j = k,\ l.$$

where RE_j^{NZ} is the reallocation term of input j in the no-zombie lending case and RE_j^{Z} is in the zombie lending case.

We explain how to calculate RE_j^{NZ} and RE_j^{Z}. First, we need to generate the 1989 and 1999 data from the model. We solve the detrended initial steady state and back out the level variables for the 1989 data. For the 1999 data, we solve the detrended final steady state in the zombie lending case. Then, we let all values grow to account for growth during 10 years from 1990 to 1999 and obtain the 1999 data in the zombie lending case. Similarly, we obtain the 1999 data in the no-zombie lending case.

The growth rate, denoted by $\hat{\gamma}$, is calibrated so that aggregate technical efficiency (TE) in the no-zombie case is equal to what we observed in the data from 1989 to 1999. Plant-level TFP grows at the rate of $\hat{\gamma}$ for all plants. Output, capital stock, and the wage rate are multiplied by $\hat{\gamma}^{\frac{1}{1-\beta_k}}$ to be consistent with the model.

We calculate PL-APG and its components in the same way as we calculate them from the data. First, at every grid point of the TFP distribution h, we calculate value added shares, cost shares over value added, and log differences of factor inputs and productivity. Second, we apply Tornqvist approximation and aggregate these numbers. At this point, we assume that the number of stayers is the minimum of the stationary distributions of plants between 1989 and 1999. That is, the distribution of the plants who stay from 1989 to 1999, denoted by $\mu_S(s)$, is calculated by $\mu_S(s) = \min(\mu_{89}(s), \mu_{99}(s))$ for each s.

In both final steady states, we adjust $\tilde{c}_e$ so that the wage rate in the final steady state is equal to the one in the initial steady state. If we don't control $\tilde{c}_e$, the model generates too much growth in the wage rate as opposed to the data. When the TFP growth rate is low, the rental rate of capital also becomes low. The cheap capital greatly attracts potential entrants because the net return from entering increases. In order to satisfy "free entry condition" in equilibrium, the wage rate becomes high enough to discourage the excess entry. As a result, all plants down-size their labor given the high wage rate. However, we don't observe such a large increase in the wage rate in the data.

Table 7 shows the benchmark results. It reports model-generated PL-APG and its component in each scenario: the zombie and no-zombie lending scenarios. It also reports the measures calculated by the data in the first row.

The second row of Table 7 shows the results for the no-zombie lending scenario. Without zombie (misdirected) lending, all indexes were positive, except for capital reallocation effect. Capital reallocation effect was negative due to the negative capital wedges[10], although capital was accumulated from 1989 to 1999.

The third row of Table 7 shows the results for the zombie lending scenario. In this case, reallocation effects of both labor and capital were negative. Due to the negative reallocation effects, the measured PL-APG was lower than that in the no-zombie case.

The size of the zombie distortion, ZD_j, is reported in the fourth row of

[10]The capital wedges were negative for all plants in the data. Since we calibrated τ_k^{NZ} to match the model capital wedge to that in the data, the wedges are also negative in the model, as well. Please note, however, that they they are close to zero, although they are negative.

Table 7: Distortion of the Zombie Lending

			Reallocation Effect	
	PL APG	**TE**	**Labor**	**Capital**
Data	10.01	14.47	-3.96	-0.50
No-Zombie Case	13.89	14.47	0.87	-1.44
Zombie Case	12.33	14.57	-0.62	-1.63
Distortion of Zombies	1.56	-0.10	1.48	0.18
As % of Data			37%	36%

Note: Table shows the results between 1989 and 1999. "Data" row shows the PL-APG and its components from 1989 to 1999, under a common value added production function for all plants estimated by the WLP method using intermediate input as proxy. All values are aggregated over the stayers, i.e., the plants who operated both in 1989 and 1999. "No-Zombie Case" and "Zombie Case" rows show the results in the model with and without zombie lending, respectively. "Distortion of Zombies" row shows the differences of values in the second row and the third row for each column, which is ZD_j, $j = l, k$. The last row shows ZD_j as a percentage of the values in the first row. TE in "No-Zombie Case" is equal to TE in "Data" because we calibrate plant-level TFP growth rate to let them have the same value. TE in "Zombie Case" differs a little from TE in "No-Zombie Case" because the number of stayers is different due to the zombie lending, although the plant-level TFP growth rate is the same in both cases.

Table 7. Each column shows the difference between the indexes in the zombie and the no-zombie lending cases. The zombie distortion in labor reallocation effect ZD_l was 1.48%. As reported in the last row, the magnitude of ZD_l was 37% of the negative labor reallocation effect observed in the data, which was -3.96%. The zombie distortion in capital reallocation effect ZD_k was 0.18%, and its size was 36% of the negative capital reallocation effect observed in the data, which was -0.50%.[11]

Conclusion

Subsidized bank credit to poorly performing plants was broadly discussed as a source of misallocation of resources in Japan in the late 1990s. To

[11]Please note that capital reallocation effect is biased as we discussed in footnote 7. Although labor reallocation effect is not affected by this assumption, PL-APG reflects the bias in capital reallocation effect.

the best of our knowledge, this is the first study that quantifies the loss in aggregate productivity growth (APG) from misdirected bank lending that led to inefficient resource reallocation across existing plants. Whereas Caballero et al. (2008) quantify the effect of "zombie lending" on the change in input and output for individual non-zombie firms, we quantify the aggregated effect of zombie lending on APG in the Japanese manufacturing sector.

Our approach consists of two parts. First, we measure the effect on APG of resource reallocation among manufacturing plants in Japan during the 1990s, by applying the APG measure of Petrin and Levinsohn (2008). Next, we calibrate a version of the model provided by Restuccia and Rogerson (2008) based on the results of plant-level productivity estimation, and quantify the effect of the misdirected lending on APG by conducting a counterfactual exercise.

In the first part, we find that resource reallocation was not functioning well in Japan's economy in the 1990s. Resource reallocation was less efficient in the 1990 than in the 1980s, especially due to deterioration of labor reallocation. Such negative reallocation effect observed in Japan is not common to other countries such as Chile, Columbia, and the United States, as reported by Petrin and Levinsohn (2008) and Petrin et al. (2009).

In the second part, we find that so-called zombie lending in the 1990s could induce the loss of 37% of the actual decline in APG due to inefficient labor reallocation in manufacturing plants. Therefore, zombie lending had a non-negligible impact on resource reallocation in the manufacturing sector, although zombie lending was less prevalent in the manufacturing sector than in the non-manufacturing sectors, as estimated by Caballero et al. (2008).

The novelty of our counterfactual exercise lies on the use of the results of plant-level productivity estimation in calibrating the model. We apply a version of the proxy estimation method, originally proposed by Olley and Pakes (1996), to our panel data of manufacturing plants. Such estimation results allow us to directly assign the parameter values that are important to resource reallocation, such as plant-level productivity and implied tax/subsidy schedule that represents distortions in the economy. A similar exercise can be applied to assess the efficiency of resource reallocation in other financial crises, such as the world-wide financial crisis starting in the United States in 2007, if a plant-level panel data set is available.

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Appendix A: A Detail Description of Discrete-time Approximation

A.1 Tornqvist Approximation

The Tornqvist approximation is a way to approximate a Riemann-Stieltjes integral by the values of functions at both endpoints of the domain of the integral. The general formula is as follows.

$$\int_{t-1}^{t} g(x)dF(x) \quad \simeq \quad \left[\frac{g(t-1)+g(t)}{2}\right][F(t)-F(t-1)].$$

This approximation is exactly the same as the true value if integrand $g(x)$ is a linear function of $F(x)$ in interval $[t-1,t]$. In other words, by applying the Tornqvist approximation, we approximate function $g(x)$ by a linear function of $F(x)$ on $[t-1,t]$: $g(x) \simeq aF(x)+b$, with some constants (a,b). See Hulten (2008) for a discussion on the relevance of the Tornqvist approximation.

In this paper, we apply the Tornqvist approximation in the following form.

$$\int_{t-1}^{t} s_i d\ln Z_i \quad \simeq \quad \left[\frac{s_{it-1}+s_{it}}{2}\right][\ln Z_{it} - \ln Z_{it-1}] \;=\; \overline{s}_{it}\Delta \ln Z_{it},$$

with notation $\overline{s}_{it} := \frac{s_{it-1}+s_{it}}{2}$.

A.2 Approximation of Entry and Exit Effects

In this subsection, we explain in detail how we deal with entrants and exiters when we derive (11). To begin with, we assume that there are only four possibilities for a plant during the period from time $t-1$ to time t; a plant keeps operating, enters once, exits once, or does not operates at all. That is, we exclude the case where a plant repeats entering and exiting more than once during the period time $t-1$ to time t.

For ease of exposition, we explain the idea by applying it to aggregate value added growth. The *ideal* discrete-time index for aggregate value added growth is the integral of the sum of $\frac{dV_i}{V}$ over all plants from time $t-1$ to time t. In this case, the integral has a closed-form solution as follows.

$$\int_{t-1}^{t} \sum_i \frac{dV_i}{V} = \int_{t-1}^{t} \frac{dV}{V} = \ln V_t - \ln V_{t-1}. \tag{22}$$

Alternately, we split the sum over all plants into the sums over three sets of plants: stayers, entrants, and exiters.

$$\begin{aligned} \int_{t-1}^{t} \sum_i \frac{dV_i}{V} &= \sum_i \int_{t-1}^{t} \frac{dV_i}{V} \\ &= \sum_{i\in S_t} \int_{t-1}^{t} \frac{dV_i}{V} + \sum_{i\in E_t} \int_{t-1}^{t} \frac{dV_i}{V} + \sum_{i\in X_{t-1}} \int_{t-1}^{t} \frac{dV_i}{V} \end{aligned} \tag{23}$$

We explain how to deal with (23) term by term. For the first term that is the sum over stayers, we transform the integrand into a log form and apply the Tornqvist approximation.

$$\sum_{i\in S_t} \int_{t-1}^{t} \frac{dV_i}{V} = \sum_{i\in S_t} \int_{t-1}^{t} \left(\frac{V_i}{V}\right) \frac{dV_i}{V_i} = \sum_{i\in S_t} \int_{t-1}^{t} s_{v_i} d\ln V_i \simeq \sum_{i\in S_t} \bar{s}_{v_i t} \Delta \ln V_{it}, \tag{24}$$

where $s_{v_i} := \frac{V_i}{V}$, and $\bar{s}_{v_i t} := \frac{s_{v_i t-1} + s_{v_i t}}{2}$.

For the second term that is the sum over entrants, we first split the domain of the integral into the three parts: before, at the time, and after the plant enters. Let τ_i^E denote the time when plant i starts operating. Since $V_i = 0$ for all $t < \tau_i^E$, the first term is equal to zero. The second term is calculated as a Riemann-Stieltjes integral. And then, we apply integral by parts to the third term.

$$\begin{aligned}
\sum_{i\in E_t}\int_{t-1}^{t}\frac{dV_i}{V} &= \sum_{i\in E_t}\left[\int_{t-1}^{\tau_i^E}\frac{dV_i}{V}+\int_{\tau_i^E}^{\tau_i^E}\frac{dV_i}{V}+\int_{\tau_i^E}^{t}\frac{dV_i}{V}\right] \\
&= \sum_{i\in E_t}\left[0+\left(\frac{V_i^{\tau_i^E}}{V^{\tau_i^E}}\right)+\int_{\tau_i^E}^{t}\frac{dV_i}{V}\right] \\
&= \sum_{i\in E_t}\left[\left(\frac{V_i^{\tau_i^E}}{V^{\tau_i^E}}\right)+\left(\frac{V_i^t}{V^t}\right)-\left(\frac{V_i^{\tau_i^E}}{V^{\tau_i^E}}\right)-\int_{\tau_i^E}^{t}V_i d\left(\frac{1}{V}\right)\right] \\
&= \sum_{i\in E_t}\left[\left(\frac{V_i^t}{V^t}\right)+\int_{\tau_i^E}^{t}\frac{V_i}{V^2}dV\right] \\
&\simeq \sum_{i\in E_t}\left(\frac{V_i^t}{V^t}\right)=\sum_{i\in E_t}s_{v_it} \qquad (25)
\end{aligned}$$

For the last approximation, we assume that $V_i << V^2$ and hence $V_i/V^2 \simeq 0$.

For the third term that is the sum over exiters, we take the same way for the sum over entrants. Thus, we obtain

$$\sum_{i\in X_{t-1}}\int_{t-1}^{t}\frac{dV_i}{V} \simeq \sum_{i\in X_{t-1}}-\left(\frac{V_i^{t-1}}{V^{t-1}}\right)=\sum_{i\in X_{t-1}}-s_{v_it-1}, \qquad (26)$$

in the same way as we use to obtain (25). Note that we have a negative sign in this case.

Combining (24), (25) and (26), we finally obtain

$$\int_{t-1}^{t}\sum_i\frac{dV_i}{V} \simeq \sum_{i\in S_t}\overline{s}_{v_it}\Delta\ln V_{it}+\sum_{i\in E_t}s_{v_it}-\sum_{i\in X_{t-1}}s_{v_it-1} \qquad (27)$$

In this way, we derive (11) from (9). We apply to each term of (9) the same way of calculation and approximation as we described so far, and hence obtain (11).

Appendix B: Supplemental Tables and Figures

In this appendix, we show several supplemental tables and figures as a reference.

B.1 Another Decomposition of APG_t^{PL}

Table 6 shows APG_t^{PL} and its components using (10), not using (11) as in the main text. As is shown in (10), APG_t^{PL} is calculated as aggregate gross output minus aggregate cost, which is the sum of aggregate labor cost, capital cost, and intermediate material cost, plus the entry and exit effects.

B.2 Time Series by Estimation Method

Figure 4 shows the time series of the technical efficiency term for each estimation method. All technical efficiency estimates are positively correlated, but the magnitude of movement over time differs across estimators. Figure 5 shows the time series of the PL reallocation term for each estimation method. Figure 6 shows the time series of the BHC reallocation term for each estimation method. Comparing Figures 5 and 6, we find that the BHC reallocation term fluctuates much more than the PL reallocation term. Figure 7 shows the time series of the BHC aggregate productivity growth, APG_t^{BHC}, for each estimation method. In general, all APG_t^{BHC} estimates show a similar pattern and are highly positively correlated. Most of the time variations of APG_t^{BHC} are attributed to the BHC reallocation term, because the BHC reallocation term varies much much more than the technical efficiency term as in Figures 4 and 6.

Table 6: PL Aggregate Productivity Growth and Its Components.

	PL	**Aggregate**	**Aggregate Cost**				
year	**APG**	**Gross Output**	**Labor**	**Capital**	**Materials**	**Entry**	**Exit**
1982	3.19	1.79	-0.54	1.10	-1.21	3.67	-2.92
1983	3.57	2.51	-0.30	0.98	-1.81	2.98	-3.05
1984	5.03	20.20	0.22	1.03	14.36	3.11	-2.66
1985	3.10	9.43	0.53	0.84	5.38	4.09	-3.65
1986	3.42	-10.81	-0.55	0.92	-13.21	4.60	-3.22
1987	5.60	12.69	-0.62	0.75	7.07	2.75	-2.65
1988	8.54	23.53	0.23	0.54	14.39	2.43	-2.26
1989	7.44	20.85	0.51	0.63	12.64	2.42	-2.05
1990	5.31	12.04	-0.05	0.75	6.48	2.59	-2.15
1991	3.35	5.87	-0.09	0.97	2.04	2.45	-2.05
1992	-1.27	-7.79	-0.85	1.08	-6.77	1.82	-1.85
1993	-2.85	-8.87	-1.49	0.87	-5.79	1.59	-1.98
1994	1.53	0.17	-1.29	0.31	-1.11	1.71	-2.44
1995	4.67	9.06	-0.50	-0.14	5.15	1.99	-1.86
1996	3.85	7.34	-0.24	0.00	3.78	1.43	-1.39
1997	2.83	10.77	-0.13	0.12	7.72	1.84	-2.06
1998	-2.01	-14.55	-1.02	0.14	-11.36	2.24	-1.94
1999	-1.60	-5.04	-1.52	0.09	-2.70	2.12	-2.81
2000	5.63	15.58	-0.55	-0.08	10.16	1.78	-2.20
1980s Average	4.99	10.02	-0.06	0.85	4.70	3.26	-2.81
(Std. dev.)	(2.08)	(11.76)	(0.49)	(0.20)	(9.67)	(0.79)	(0.52)
1990s Average	1.38	0.90	-0.72	0.42	-0.26	1.98	-2.05
(Std. dev.)	(3.05)	(9.43)	(0.59)	(0.45)	(6.35)	(0.37)	(0.38)

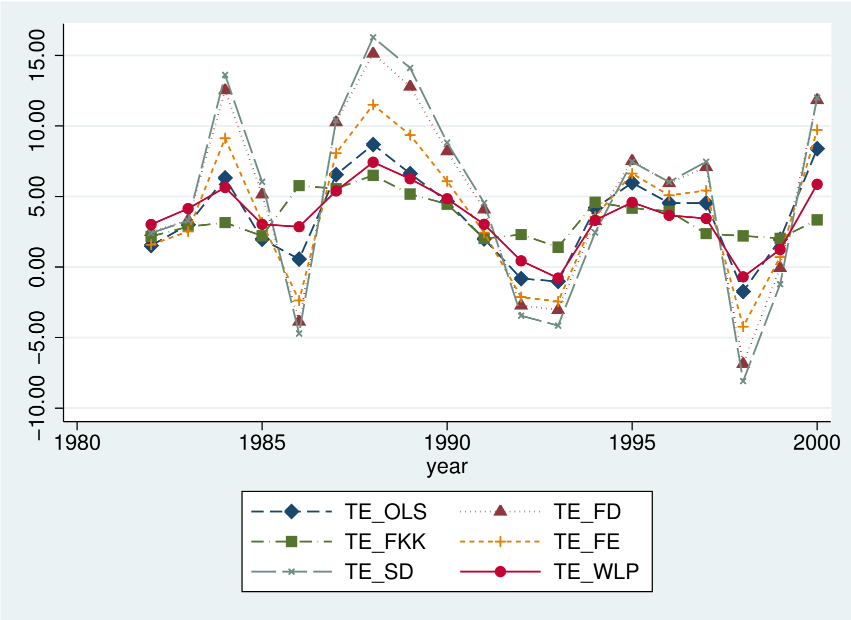


Figure 4: Technical Efficiency by Estimation Method.

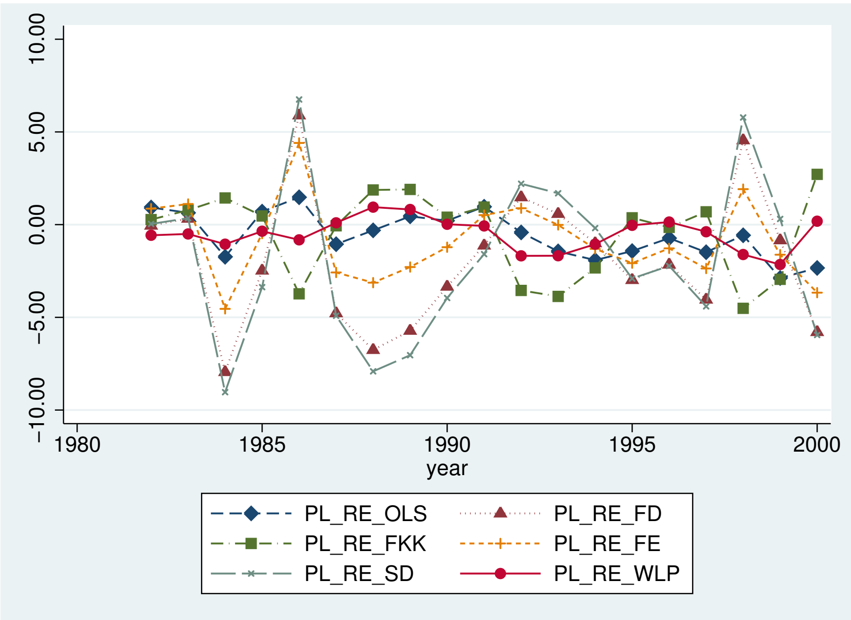


Figure 5: PL Reallocation Effect by Estimation Method.

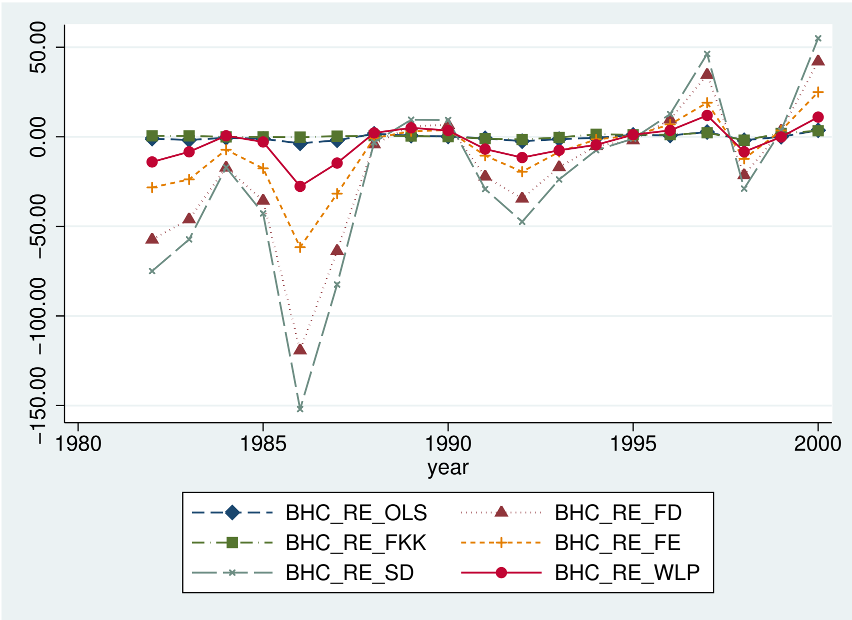


Figure 6: BHC Reallocation Effect by Estimation Method.

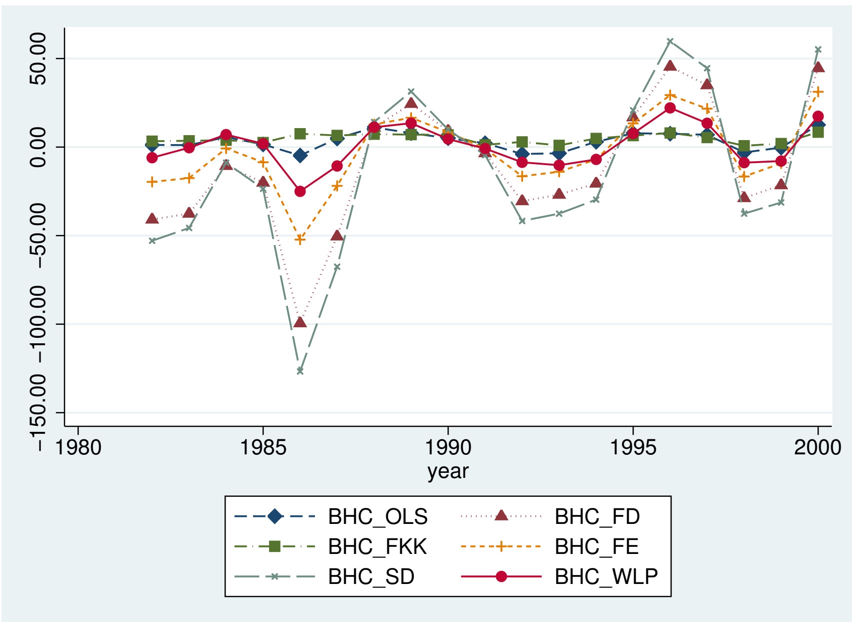


Figure 7: BHC Aggregate Productivity Growth by Estimation Method.

B.3 Comparison with Macro Data

Table VA and TFP compare value added and productivity estimates between macro and micro data. All the macro data are obtained from JIP 2008. The micro data are the plant-level panel data we use in this paper.

The first two columns of Table VA show growth rates of the economy-wide and manufacturing value added, which are highly positively correlated; the correlation coefficient is 0.89. Thus, the manufacturing sector seems to represent Japan's economy as a whole in terms of growth rate of value added. The last column shows growth rate of manufacturing value added obtained from our data set, which is highly positively correlated with the one obtained from JIP 2008; the correlation coefficient is 0.85. Therefore, our sample of plant-level data represents the manufacturing sector as a whole.

Table TFP shows growth rates of TFP (Total Factor Productivity) estimates in the whole economy and the manufacturing sector, and PL APG measured in this paper. The manufacturing TFP positively correlates with aggregate TFP with coefficient 0.50, which is smaller than in the case of value added growth rates. PL APG positively correlates with the manufacturing TFP with coefficient 0.69, although the two measures are conceptually different.

Table VA: Comparison of Growth Rate of Value Added.

year	Aggregate Value added (Macro Data)	Manufacturing Value added (Macro Data)	Manufacturing Value added (Micro Data)
1982	3.01	5.38	2.80
1983	3.11	4.86	2.97
1984	4.86	8.90	5.55
1985	5.01	9.80	3.93
1986	2.12	0.08	2.72
1987	4.23	5.32	5.66
1988	6.23	8.66	8.79
1989	5.04	7.35	8.57
1990	5.25	3.04	6.70
1991	3.95	5.34	4.39
1992	0.58	-1.81	-0.91
1993	0.31	-3.40	-4.08
1994	0.56	-1.73	-0.31
1995	1.82	3.98	4.24
1996	3.48	4.17	3.78
1997	1.43	2.33	3.01
1998	-1.92	-5.41	-3.04
1999	-0.08	-0.92	-3.64
2000	1.68	5.43	5.96
1980s Average	4.20	6.29	5.12
(Std. dev.)	(1.36)	(3.12)	(2.48)
1990s Average	1.54	0.56	1.01
(Std. dev.)	(2.14)	(3.67)	(3.88)

Correlation	AGG VA	MF VA	MF VA Micro
AGG VA	1.00	0.89	0.87
MF VA	.	1.00	0.85
MF VA Micro	.	.	1.00

The macro data are from JIP 2008. The micro data are what we use in this paper.

Table TFP: Comparison of TFP and PL APG.

year	**Aggregate TFP (Macro Data)**	**Manufacturing TFP (Macro Data)**	**PL APG (Micro Data)**
1982	0.10	1.27	3.19
1983	-0.09	0.51	3.57
1984	0.78	1.08	5.03
1985	1.26	2.25	3.10
1986	-0.24	-0.25	3.42
1987	0.62	1.76	5.60
1988	1.49	1.45	8.54
1989	1.00	1.53	7.44
1990	1.65	-0.13	5.31
1991	0.79	0.94	3.35
1992	-0.44	-0.62	-1.27
1993	0.24	-0.25	-2.85
1994	-0.16	-0.17	1.53
1995	-0.17	1.69	4.67
1996	1.15	1.37	3.85
1997	0.39	0.66	2.83
1998	-0.81	-0.76	-2.01
1999	0.33	0.34	-1.60
2000	-0.16	1.57	5.63
1980s Average	0.62	1.20	4.99
(Std. dev.)	(0.64)	(0.77)	(2.08)
1990s Average	0.30	0.31	1.38
(Std. dev.)	(0.75)	(0.83)	(3.05)

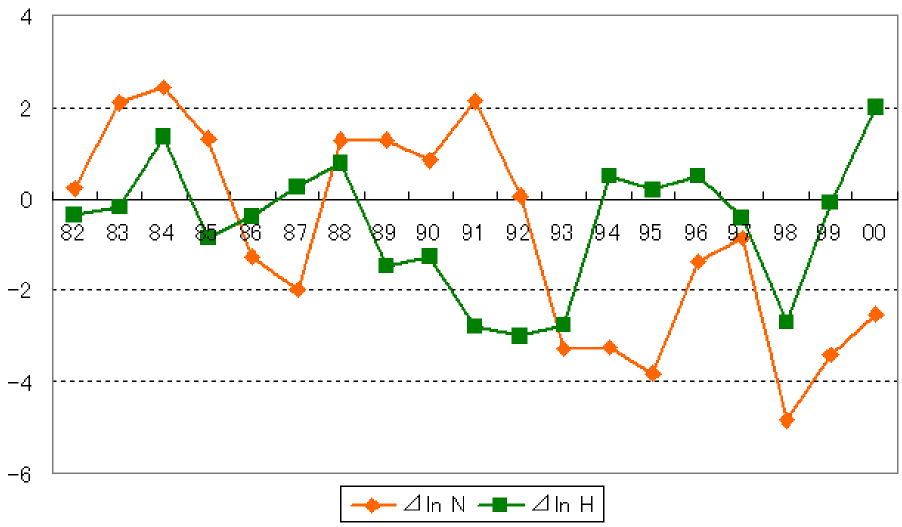
Correlation	AGG TFP	MF TFP	PL APG
AGG TFP	1.00	0.50	0.57
MF TFP	.	1.00	0.69
PL APG	.	.	1.00

The macro data are from JIP 2008. The micro data are what we use in this paper. JIP 2008 contains their estimates of TFP, using the following equation:

$$\Delta \ln TFP_t = \Delta \ln Y_t - \overline{\nu}_{L,t} \Delta \ln L_t - \overline{\nu}_{K,t} \Delta \ln K_t - \overline{\nu}_{M,t} \Delta \ln M_t, \tag{28}$$

where $\overline{\nu}_{X,t}$ is the average of the cost shares of input $X \in \{L, K, M\}$ in time $t-1$ and t. See Fukao et al. (2007), which is for JIP 2006, but the same applies to JIP 2008.

B.4 HoursWorked and Number of Employees



Note: L = Hours worked (H) × Number of workers (N). $\Delta \ln H$ was negative during 1989-93. Legislation on workweek: 44 hrs (1988) → 40 hrs (1993). $\Delta \ln N$ was negative after 1993.

B.5 Industry-level Results

Table PL80 : PL Aggregate Productivity and Its Decomposition
- Average in the 1980s by Industry.

SIC	Industry Name	PL APG	Technical Efficiency	Reallo -cation	Net-Entry
9	Foods	0.24	-0.32	0.50	0.06
10	Beverages and tabacco	3.30	0.85	0.09	2.37
11	Textile products	0.92	2.92	-0.53	-1.47
12	Wearing apparel and other textile products	4.45	2.65	0.52	1.28
13	Timber and wooden products	2.59	4.29	-0.69	-1.01
14	Furniture and fixtures	1.77	1.36	0.75	-0.34
15	Pulp and paper products	4.73	6.28	-1.45	-0.11
16	Printing	4.03	3.70	0.15	0.18
17	Chemical products	10.05	9.48	0.44	0.13
18	Petroleum and coal products	2.69	3.06	-0.18	-0.19
19	Plastic products	6.72	5.96	0.45	0.31
20	Rubber products	4.35	3.96	0.09	0.30
21	Leather and miscellaneous leather products	-0.67	-0.77	0.21	-0.11
22	Ceramic, stone and clay products	2.75	2.96	-0.06	-0.16
23	Iron and steel	4.16	5.62	-1.54	0.09
24	Non-ferrous metals	2.86	5.57	-2.40	-0.31
25	Metal products	3.91	3.10	0.25	0.56
26	General machinery	3.70	3.08	0.07	0.55
27	Other electrical machinery and apparatus n.e.c.	4.45	2.79	0.41	1.25
28	Electronic computing equipment and communication equipment	13.68	10.79	1.13	1.77
29	Semiconductor devices and electronic components	16.15	8.97	4.35	2.82
30	Transportation equipment	4.40	7.97	-3.39	-0.18
31	Precision instruments	4.69	5.09	0.11	-0.51
32	Miscellaneous manufacturing products	4.16	2.37	0.48	1.32
41	Publishing	1.26	-0.79	2.41	-0.36

All values are the averages in the 1980s. Industry is defined by 2-digit SIC code.

Table PL90 : PL Aggregate Productivity and Its Decomposition
- Average in the 1990s by Industry.

SIC	Industry Name	PL APG	Technical Efficiency	Reallo -cation	Net-Entry
9	Foods	1.45	1.52	-0.42	0.35
10	Beverages and tabacco	0.74	3.54	-2.40	-0.40
11	Textile products	-2.53	-0.67	-1.13	-0.73
12	Wearing apparel and other textile products	-1.49	0.78	-1.57	-0.71
13	Timber and wooden products	-1.30	0.04	-0.87	-0.47
14	Furniture and fixtures	-3.32	-0.92	-1.70	-0.70
15	Pulp and Paper products	-0.22	1.08	-1.22	-0.08
16	Printing	0.76	0.75	-0.17	0.18
17	Chemical products	1.97	2.34	-0.32	-0.05
18	Petroleum and coal products	1.33	1.95	-0.33	-0.29
19	Plastic products	0.99	1.60	-0.56	-0.05
20	Rubber products	0.09	0.84	-0.77	0.03
21	Leather and miscellaneous leather products	-3.61	-0.85	-1.51	-1.24
22	Ceramic, stone and clay products	-0.48	1.04	-1.19	-0.33
23	Iron and steel	-1.03	0.29	-1.17	-0.14
24	Non-ferrous metals	0.37	1.27	-0.87	-0.04
25	Metal products	0.33	1.25	-0.88	-0.04
26	General machinery	-0.15	0.73	-0.72	-0.17
27	Other electrical machinery and apparatus n.e.c.	1.53	2.43	-0.47	-0.43
28	Electronic computing equipment and communication equipment	7.20	9.98	-2.76	-0.02
29	Semiconductor devices and electronic components	12.83	12.05	0.24	0.54
30	Transportation equipment	0.19	1.04	-0.99	0.14
31	Precision instruments	1.47	3.02	-0.77	-0.79
32	Miscellaneous manufacturing products	2.44	3.79	-0.87	-0.47
41	Publishing	-1.90	-1.80	-0.64	0.54

All values are the averages in the 1990s. Industry is defined by 2-digit SIC code.

Table RE80 : Decomposition of Reallocation Effect
- Average in the 1980s by Industry.

SIC	Industry Name	Reallo -cation	Decomposition Labor	Capital	Materials
9	Foods	0.50	-0.20	0.15	0.55
10	Beverages and tabacco	0.09	-1.08	0.08	1.08
11	Textile products	-0.53	-0.41	-0.25	0.13
12	Wearing apparel and other textile products	0.52	0.08	-0.13	0.57
13	Timber and wooden products	-0.69	-0.27	-0.25	-0.16
14	Furniture and fixtures	0.75	0.21	-0.07	0.61
15	Pulp and Paper products	-1.45	0.05	-0.56	-0.94
16	Printing	0.15	0.83	-0.46	-0.22
17	Chemical products	0.44	-0.20	-0.17	0.81
18	Petroleum and coal products	-0.18	-2.27	0.20	1.89
19	Plastic products	0.45	0.96	-0.58	0.07
20	Rubber products	0.09	0.23	-0.44	0.30
21	Leather and miscellaneous leather products	0.21	-0.01	0.12	0.11
22	Ceramic, stone and clay products	-0.06	-0.25	-0.22	0.41
23	Iron and steel	-1.54	-0.64	-0.48	-0.42
24	Non-ferrous metals	-2.40	-0.22	-0.45	-1.73
25	Metal products	0.25	0.36	-0.22	0.11
26	General machinery	0.07	0.18	-0.06	-0.05
27	Other electrical machinery and apparatus n.e.c.	0.41	0.48	-0.23	0.16
28	Electronic computing equipment and communication equipment	1.13	0.45	0.22	0.46
29	Semiconductor devices and electronic components	4.35	0.47	-0.96	4.84
30	Transportation equipment	-3.39	0.53	-0.27	-3.65
31	Precision instruments	0.11	-0.09	-0.37	0.57
32	Miscellaneous manufacturing products	0.48	0.23	-0.01	0.25
41	Publishing	2.41	0.30	-0.13	2.24

All values are the averages in the 1980s. Industry is defined by 2-digit SIC code.

Table RE90 : Decomposition of Reallocation Effect
- Average in the 1990s by Industry.

SIC	Industry Name	Reallo-cation	Decomposition		
			Labor	Capital	Materials
9	Foods	-0.42	-0.35	-0.01	-0.05
10	Beverages and tabacco	-2.40	-1.27	-0.06	-1.07
11	Textile products	-1.13	-1.04	-0.10	0.01
12	Wearing apparel and other textile products	-1.57	-1.00	-0.09	-0.47
13	Timber and wooden products	-0.87	-0.83	-0.15	0.11
14	Furniture and fixtures	-1.70	-0.71	-0.11	-0.87
15	Pulp and Paper products	-1.22	-0.97	-0.36	0.11
16	Printing	-0.17	-0.02	-0.20	0.05
17	Chemical products	-0.32	-0.32	-0.13	0.13
18	Petroleum and coal products	-0.33	-0.69	-0.18	0.55
19	Plastic products	-0.56	-0.33	-0.15	-0.07
20	Rubber products	-0.77	-0.27	-0.19	-0.32
21	Leather and miscellaneous leather products	-1.51	-0.96	-0.13	-0.42
22	Ceramic, stone and clay products	-1.19	-0.45	-0.14	-0.60
23	Iron and steel	-1.17	-1.39	-0.32	0.54
24	Non-ferrous metals	-0.87	-0.60	-0.52	0.25
25	Metal products	-0.88	-0.55	-0.10	-0.23
26	General machinery	-0.72	-0.33	0.03	-0.42
27	Other electrical machinery and apparatus n.e.c.	-0.47	-0.70	-0.13	0.35
28	Electronic computing equipment and communication equipment	-2.76	-1.16	0.00	-1.60
29	Semiconductor devices and electronic components	0.24	-0.21	-0.55	1.01
30	Transportation equipment	-0.99	-1.19	-0.16	0.36
31	Precision instruments	-0.77	-0.51	-0.09	-0.17
32	Miscellaneous manufacturing products	-0.87	-0.48	0.15	-0.54
41	Publishing	-0.64	-0.33	-0.20	-0.11

All values are the averages in the 1990s. Industry is defined by 2-digit SIC code.

B.6 Further Decomposition of Reallocation Effect

Table LH: Labor Reallocation Effect - Decomposition by Margin and Input Growth.

		Positive Margin $\varepsilon_L - s_{iL} \geq 0$	Negative Margin $\varepsilon_L - s_{iL} < 0$
$d \ln L_i \geq 0$	80s	1.55	-0.07
	90s	1.03	-0.05
$d \ln L_i < 0$	80s	-1.55	0.08
	90s	-1.73	0.11

Table K: Capital Reallocation Effect - Decomposition by Margin and Input Growth.

		Positive Margin $\varepsilon_K - s_{iK} \geq 0$	Negative Margin $\varepsilon_K - s_{iK} < 0$
$d \ln K_i \geq 0$	80s	0.30	-0.75
	90s	0.21	-0.68
$d \ln K_i < 0$	80s	-0.15	0.41
	90s	-0.16	0.48

Table M: Intermediate Material Reallocation Effect - Decomposition by Margin and Input Growth.

		Positive Margin $\varepsilon_M - s_{iM} \geq 0$	Negative Margin $\varepsilon_M - s_{iM} < 0$
$d \ln M_i \geq 0$	80s	2.67	-1.93
	90s	2.15	-1.13
$d \ln M_i < 0$	80s	-1.80	1.06
	90s	-2.22	1.14

Each cell shows reallocation effect aggregated over subgroups defined according to whether the plant increased or decreased their input and whether the plant's margin was positive or negative. Rows of 80s and 90s respectively correspond to the averages during the 1980s and the 1990s. The sum of the four values in all cells for each decade is respectively equal to the average reallocation effect in the 1980s and the 1990s: 0.02 and -0.66 for labor, -0.20 and -0.14 for capital, and 0.00 and -0.05 for intermediate material.