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THE PLANT-LEVEL VIEW OF KOREA'S GROWTH MIRACLE AND SLOWDOWN

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The Plant-Level View of Korea's Growth Miracle and Slowdown*

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Abstract

We analyse the evolution of the plant size distribution, static allocative efficiency, and business dynamism of the Korean manufacturing sector during its growth miracle (1967–2000) and the subsequent slowdown since 2000. The average plant size has an inverse-U pattern over time, with a peak in the late 1970s. The measure of static misallocation decreases modestly until 1983 but increases substantially afterwards. These results are at odds with what one may extrapolate from the existing cross-country evidence on the positive relationship between plant size and economic development or the negative one between static misallocation and development. We also find that the growth rate of manufacturing productivity is not systematically correlated with either the level or the rate of change of the average plant size or static misallocation. On the other hand, business dynamism, measured by either churning or responsiveness to shocks, diminished significantly since 2000, coinciding with the decline in the growth rate of manufacturing productivity. Our findings call for more systematic research on how economic performance correlates with establishment/firm size distribution and with static and dynamic allocative efficiency.

Keywords: Size Distribution, Misallocaiton, Business Dynamism
JEL Codes: O14, O47, O53

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1 Introduction

Over the last decade or so, the literature on economic growth and development has delved deeper to understand how macroeconomic performance is determined by what happens at the microeconomic level, both theoretically and empirically. This line of work has shown that the allocation of resources across firms and establishments, both static and dynamic, is an important determinant of aggregate productivity.[1] The empirical support comes from a relatively small number of countries with available data, especially when it comes to dynamic allocation.

We contribute to this literature by analyzing the plant-level data from the Korean manufacturing sector that span a half-century (1967–2019). Korea makes a compelling case for at least two reasons. First, it transformed itself from a poor to a rich country during this period.[2] The real GDP per capita grew more than 13-fold between 1967 and 2000, which translates into an average growth of 8 percent per year, before the growth markedly slowed down since 2000. Second, it has high-quality micro data, some of which were newly digitized. We use administrative data of all manufacturing plants with at least five employees (ten employees since 2007), which have panel dimension since 1982. Although this is admittedly data from but one country, they provide a unique window into how the microeconomy evolved as the macroeconomy traversed the development spectrum. This paper complements the body of knowledge in the literature built on cross-country evidence.

Are there systematic patterns at the plant level behind the Korean economic miracle and the eventual slowdown? We obtain three main results. First, there is no clear relationship between the productivity level of the manufacturing sector and the size distribution of plants. The manufacturing value-added per worker grew almost 18-fold between 1967 and 2020. The average plant size (measured by the number of employees, for all plants with 5 or more employees) grew rapidly between 1968 and 1978, but then fell equally rapidly since 1979, stabilizing in the mid 2000s. This lack of a correlation is quite different from what one may extrapolate from the cross-section of countries that show a positive relationship between economic development and establishment size.[3] Our data also show that the growth rate of manufacturing productivity is not correlated with either the level or the rate of change of

[1]For example, refer to the papers in the January 2013 special issue on misallocation and productivity in the *Review of Economic Dynamics* (Restuccia and Rogerson, 2013). More examples include Brandt, Tombe and Zhu (2013) and Oberfield (2013), which quantify sizable TFP losses due to resource misallocation in China and Chile, respectively.

[2]Its GDP per capita adjusted for purchasing power was 6.9 percent of the US level in 1967, but 64.4 percent of the US level in 2019, according to the Penn World Tables 10.01 (Feenstra, Inklaar and Timmer, 2015).

[3]For example, Bento and Restuccia (2017), Bento and Restuccia (2021), Poschke (2018), and Fattal-Jaef (2022).

the average plant size.

Second, the typical measures of static misallocation (i.e., the dispersion of marginal products within industries) do not necessarily co-move with the productivity of the manufacturing sector. Measured misallocation decreased between 1968 and 1983, albeit modestly. However, its substantial increases during the mid 1980s, and again since the early 2000s, did not come with a corresponding decline in the productivity of the manufacturing sector. This too is at odds with what one may extrapolate from the negative relationship between static misallocation and economic development in the cross-section of countries—for example, the seminal findings of Hsieh and Klenow (2009). Some in the literature have linked the change in productivity to the change in (static) misallocation—for example, Buera and Shin (2013). However, as in the case of plant size, our data show that neither the level nor the rate of change of static misallocation is systematically related with the growth rate of manufacturing productivity.

Finally, using the panel dimension of the data since 1982, we show that dynamism, defined either as labor reallocation across plants or as the correlation between a plant's productivity and its subsequent growth, diminished significantly after 2000, coinciding with the persistent decline in the growth rate of manufacturing productivity in Korea.

Our findings call for more systematic research of the evidence on how economic performance correlates with establishment/firm size distribution and with static and dynamic allocative efficiency, both across countries and over time within countries.

Related Literature This paper contributes to three strands of the literature. First, the establishment/firm size distribution and allocative efficiency have been discussed as important sources of cross-country income differences (e.g., Bento and Restuccia (2017), Bento and Restuccia (2021), Poschke (2018), and Fattal-Jaef (2022) for the establishment/firm size distribution, Hsieh and Klenow (2009) and Hsieh and Klenow (2010) for the allocative efficiency). Overall, establishments are larger, and allocative efficiency is higher in rich countries than in poor countries in the cross-section. With the exception of the United States and a few other Western European countries, time series evidence on the relationship between establishment size and development and the one between misallocation and development is limited. We revisit the case of Korea which experienced a growth miracle and then the eventual slowdown over the last 60 years.

Second, since the early 1980s, the United States has seen a decline in business dynamism, measured by firm entry (Decker, Haltiwanger, Jarmin and Miranda, 2014), the rate of job and worker reallocation (Davis and Haltiwanger, 2014), and responsiveness to shocks (Decker, Haltiwanger, Jarmin and Miranda, 2020). We find that Korea also experienced a similar degree of decline in business dynamism in recent years, suggesting that it may be a global phenomenon. Our documentation of business dynamism in the development context is a unique contribution. There exists little evidence on developing countries in the literature, because few of them offer the panel data required for such calculations.

Lastly, this paper contributes to the literature that studies Korea's growth miracle. Young (1995) emphasized the role of factor accumulation during the East Asian growth experience. Connolly and Yi (2015) study trade reforms. Kim, Lee and Shin (2021) study industrial policy of the 1970s using the same plant-level data, but focus on the divergence between targeted vs. non-targeted industries. This paper studies the development at the plant level during the growth miracle and extends the discussion to the recent slowdown that has received little attention.

2 Background and Data

2.1 Background

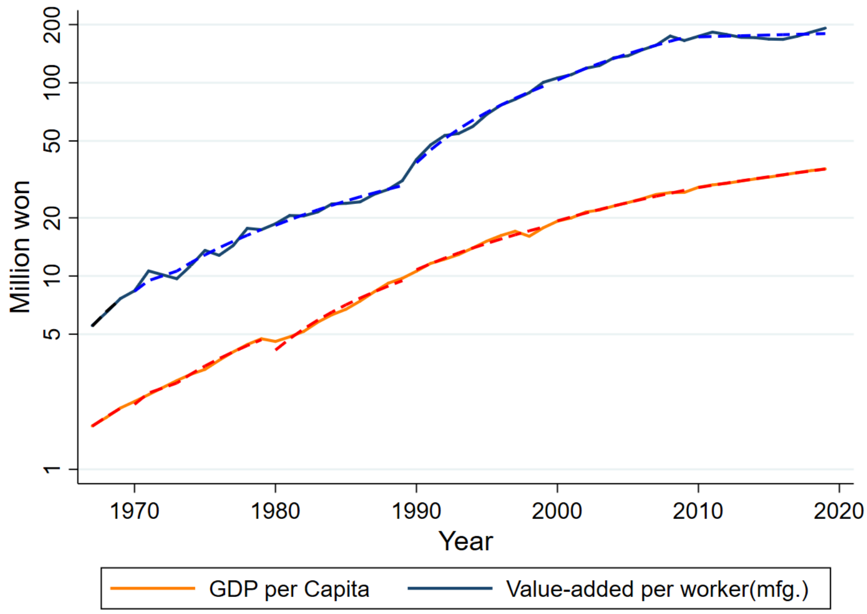
After the Korean War (1950-1953), South Korea underwent a significant transformation from a low-income country to a developed country. Figure 1 shows real GDP per capita and real value-added per worker in manufacturing from 1967 to 2019. The two series show similar trends. Both the aggregate economy and the manufacturing sector in Korea grew rapidly until 1997 but experienced a significant slowdown starting in the early 2000s. The average growth rate of GDP per capita was 8.7% in 1970s, 7.8% in 1980s, 5.3% in 1990s, 3.5% in 2000s, and 2.2% in 2010s. The average growth rate of value-added per worker in manufacturing was 8.4% in 1970s, 5.3% in 1980s, 9.6% in 1990s, 4.6% in 2000s, and 1.0% in 2010s.

2.2 Data

We use Statistics Korea's annual Mining and Manufacturing Survey (MMS) from 1967 to 2019, except for the two missing years of 1970 and 1972.[4] The MMS covers all establishments in the mining and manufacturing sector with at least five employees until 2006 and with at least ten employees from 2007. Plant-level data includes gross output, fixed assets, number of employees, wage bills, intermediate input cost, and geographic location. Prior to 1978, the fixed asset data is available in only one year, 1968. Anonymized plant IDs are available from 1982, which gives the data a panel dimension.

[4]The MMS started in 1967. Even though there were other surveys covering selected mining and manufacturing firms before 1967, plant-level microdata is only available from the MMS.

Figure 1: Korea's Growth Miracle and Slowdown from 1967 to 2019



Notes: The figure shows GDP per capita (orange line) and value-added per worker in manufacturing (blue line). The data comes from the Bank of Korea's national accounts and Statistics Korea's annual Mining and Manufacturing Survey. The dashed lines represent the linear trend for each decade. GDP per capita is deflated by GDP deflator, and value-added per worker is deflated by manufacturing industry deflator, both with 2015 as base year.

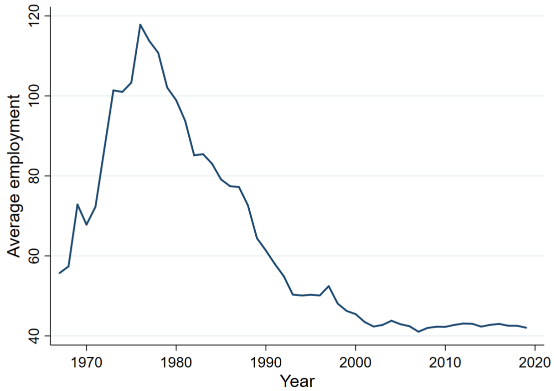
We convert nominal gross output and intermediate input values to real vaules using GDP deflator for manufacturing, with 2015 as base year. Real value added is defined as real gross output minus real intermediate input. Capital stock is the total fixed asset values, including structures, machinery, and transport equipment.

MMS's industrial classification is at the four-digit (before 1970) or five-digit level (since 1970) of the KSIC. During our sample period, the KSIC was revised eight times (Revision 3 in 1970, 4 in 1975, 5 in 1984, 6 in 1991, 7 in 1998, 8 in 2000, 9 in 2007, and 10 in 2017). We constructed a harmonized four-digit industry classification using a crosswalk based on the concordance tables for each revision. We excluded establishments in the mining industry.

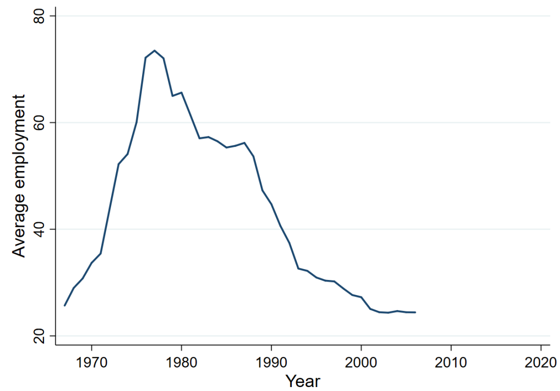
3 Size Distribution and Static Allocative Efficiency

We document the evolution of the plant size distribution and static allocative efficiency across plants from 1967 to 2019.

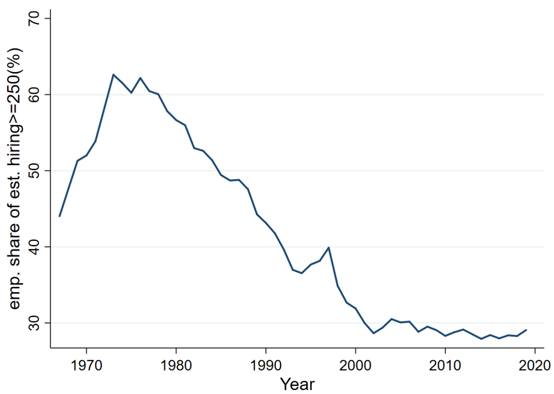
Figure 2: Average Plant Size and Employment Share of Large Plants



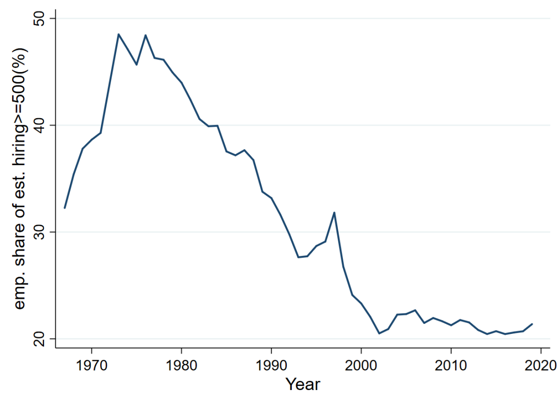
(a) Average Size of Plants w/ 10+



(b) Average Size of Plants w/ 5+



(c) Employment Share of Plants w/ 250+



(d) Employment Share of Plants w/ 500+

Notes: Panel (a) plots the average size (number of employees) of plants hiring at least 10 employees in a given year. Panel (b) plots the average size of plants hiring at least 5 employees, which ends in 2006 because the minimum employment to be in the MMS was raised to 10 in 2007. Panels (c) and (d) plot the employment share of large plants, those hiring at least 250 and 500 persons, respectively.

3.1 Plant Size Distribution

Figure 2 shows the average plant size (number of employees) and the employment share of large plants from 1967 to 2019. Panel (a) shows the average size of plants with at least 10 employees in a given year for the entire sample period. It started at 56, peaked at 118 in the late 1970s, and decreased to around 42 in the early 2000s. Similar increases and decreases are observed in panels (b), (c), and (d), which show the average size of plants with at least 5 employees (series ending in 2006) and the employment shares of plants employing at least 250 and 500 workers, respectively.

The rapid increase in plant size coincides with the period of active industrial policy, through a series of five-year development plans. The first plan (1962-1966) sought to expand the electrical and coal energy industry and establish the basic infrastructure for manufacturing development. The second plan (1967-1971) named heavy and chemical industries as priority areas. However, due to the lack of technological expertise and financial resources, this prioritization was unsuccessful. Major highways were built during the second plan period. The third plan (1972-1976) was a monumental shift toward a "Big Push." President Park stated in January 1973 that "the government is announcing the Heavy and Chemical Industry project. To achieve 10 billion dollars of annual exports by the early 1980s, [...] the government will accelerate the promotion of HCIs such as steel, shipbuilding and petrochemical industries, and thereby increase their exports" (Park, 2005). The industrial policy ended suddenly when Park was assassinated in October 1979. The next regime drastically changed the direction of industrial policy, adopting "stability" and "private sector-led growth" as its slogan (Woo, 1991), embodied in the fifth five-year plan (1982–1986). As an outcome of the stabilization and liberalization, new establishments entered at a faster rate, driving down the average plant size, while the aggregate economy grew steadily.

Employment concentration measured by the employment shares of large plants closely follows the evolution of the average plant size. The only notable exception is a small spike in 1997 in panels (c) and (d), which is attributed to the 1997 Asian Financial Crisis, during which employment concentration temporarily increased because many small and medium-sized plants exited the market.

We can decompose the change in average plant size into two components: within and between industries. Denoting with m_t the average plant size in year t, we write it as a weighted average of industry-level average plant size $m_{i,t}$, with i indexing industries:

$$m_t = \sum_i w_{i,t} m_{i,t} \ , \tag{1}$$

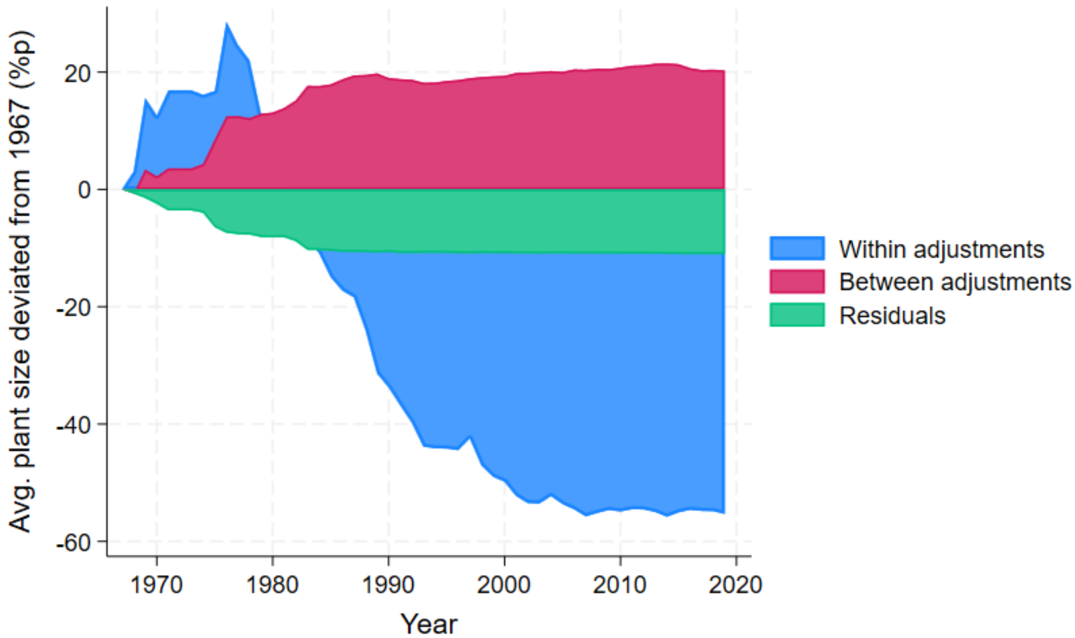
where $w_{i,t}$ is the employment share of industry i in year t. We can write the change in average plant size between year $t-1$ and t, Δm_t, as follows.

$$\Delta m_t = \sum_i w_{i,t-1} \Delta m_{i,t} + \sum_i \Delta w_{i,t} m_{i,t-1} + \sum_i \Delta w_{i,t} \Delta m_{i,t} \tag{2}$$

The first term on the right-hand side is the within-industry change, the second term is the between-industry component, and the last term is the residual or the "cross" term.

Figure 3 shows the decomposition of the cumulative changes in average plant size since 1967, covering all plants with at least 10 workers in a given year. Between 1967 to 2019, the within-industry size change decreased the average plant size by 56 percent, and the

Figure 3: Decomposition of Cumulative Changes in Average Plant Size



Notes: The figure decomposes cumulative changes in average plant size into the within-industry change, the between-industry component, and the cross term, following equation (2).

between-industry component *increased* the average plant size by 20 percent. The positive between-industry component means that the employment share of industries with a larger average plant size tended to increase, but most of the increase took place in the late 1970s, during the heavy and chemical industry promotion. The between-industry component was not important for the evolution of the average plant size since the mid 1980s. The within-industry component contributed to the rise of the average plant size in the 1970s, but reversed its course afterwards, driving the average plant size down in the 1980s and the 1990s. In summary, the upward arc of the inverse-U curve of the average plant size reflected both the plants getting bigger in all industries and employment reallocating to industries that started with larger plants on average. The downward arc after 1980, on the other hand, was nearly exclusively a within-industry phenomenon—that is, plants became smaller in all industries.

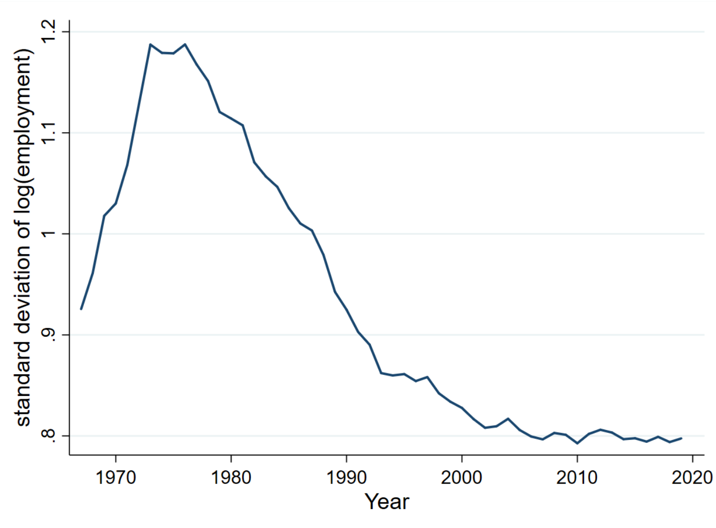
The dispersion of employment across plants can be measured in two different ways. First, panel (a) of Figure 4 shows the evolution of the standard deviation of log employment. It resembles the patterns in Figure 2. Second, panel (b) of Figure 4 is the log-log plot in 1967, 1977, 1987, 1997, and 2006. In a log-log plot, the horizontal axis is the log of the number of employees, and the curve traces the log of the fraction of establishments with at least as many employees as the corresponding number on the horizontal axis. The plot shifted to the right from 1967 to 1977, implying that the entire plant size distribution shifted to the right. Reversing courses, the plot shifted to the left from 1977 to 1987, 1997, and 2006. The decrease of the plant sizes was also broad-based, with the entire size distribution shifting left.

We find that there was no systematic relationship between the average plant size and the productivity level of the Korean manufacturing sector over time. This is a different result from what one may extrapolate from the existing cross-country evidence suggesting that development is associated with systematic changes in the plant/firm size distribution (Bento and Restuccia, 2017; Poschke, 2018; Bento and Restuccia, 2021). Figures 1 and 2 also show that the growth rate of manufacturing productivity is not correlated with either the level or the rate of change of the average plant size. In the light of our findings, we present more evidence on the plant size-development link. One motivation is to see whether the Korean experience is an outlier.

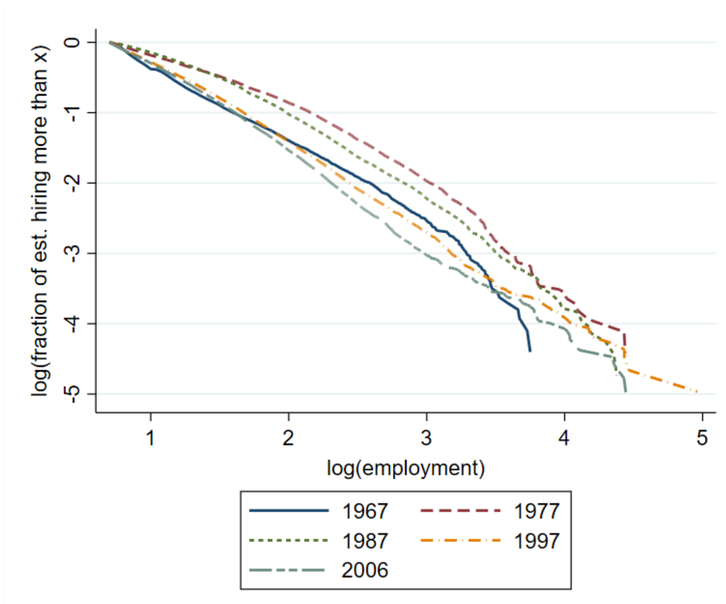
Time-series Evidence from Other Asian Economies The seminal paper by Lucas (1978) showed that the average firm size increased with per-capita income over time in the United States. However, only limited evidence on trends in average firm size is available from other countries. A special issue of *Small Business Economics* in February 2002 (Small Firm Dynamism in East Asia) reports on the evolution of the average plant/firm size over time in several Asian economies. The manufacturing sector in Taiwan showed a similar inverse-U pattern of the average firm size over time. Employment per firm went from 20 in 1981 to 24 in 1986, and to 18 in 1991 (Aw, 2002). A paper on Korea (Nugent and Yhee, 2002) reports that the share of manufacturing employment in large enterprises (at least 300 employees) increased in the 1970s but decreased afterward, consistent with our findings. Similarly, in Japan, the share of manufacturing employment in large enterprises (at least 300 employees) went from 27 percent in 1957 to 31 percent in 1969, and to 26 percent in 1981. However, the share of service employment in large enterprises kept increasing over the same period (Kawai and Urata, 2002). Papers in the same issue also show that the average plant size was stable in Indonesia between 1986 and 1996 (Berry, Rodriguez and Sandee, 2002), increased in Thailand between 1987 and 1996 (Wiboonchutikula, 2002), and increased in the machine tools sector in Malaysia between 1984 and 1994 (Rasiah, 2002). In summary, the evidence on the relationship between plant/firm size and economic development is mixed, but the data from Japan, Korea, and Taiwan exhibit an inverse-U pattern over time.

Cross-sectional Evidence from OECD Countries We use the Structural and Demographic Business Statistics (SDBS) and explore the average plant/firm size over time and

Figure 4: Dispersion of Employment



(a) Standard Deviation of Log Employment



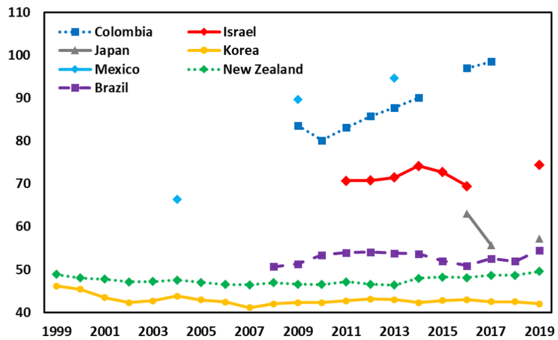
(b) Plant Size Distribution (log-log plot)

Notes: Panel (a) plots the standard deviation of log employment from 1967 to 2019, covering all plants with at least 10 employees in a given year. Panel (b) shows the log of the fraction of establishments larger than or equal to size s on the horizontal axis, where size is the number of employees. Panel (b) covers all plants with at least 5 workers in a given year.

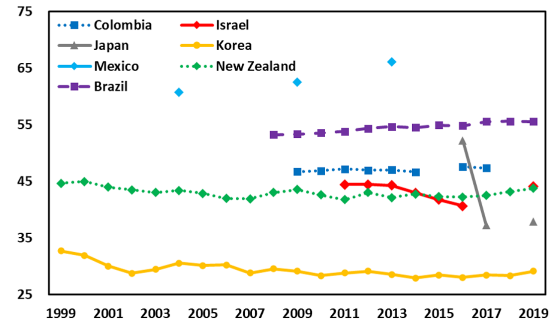
across countries.[5] Panels (a) and (b) of Figure 5 show the average plant size and the em-

[5]In the OECD SDBS database, some non-OECD countries (Brazil, Bulgaria, Croatia, Cyprus, Malta, North Macedonia, Romania, Russia, and Serbia) are also included.

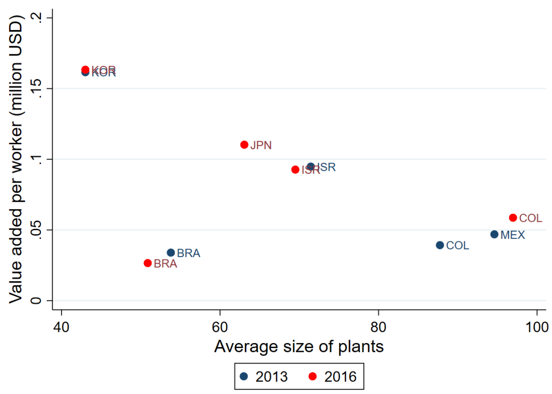
Figure 5: Comparison with OECD Countries



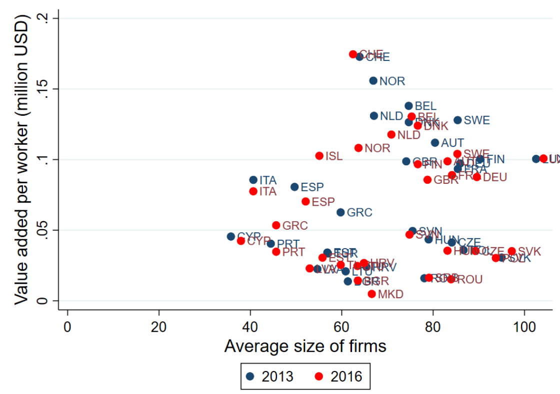
(a) Average Size of Plants w/ 10+



(b) Employment Share of Plants w/ 250+



(c) Plant Size and Labor Productivity



(d) Firm Size and Labor Productivity

Notes: Panels (a), (b), and (c) are for plants, while panel (d) is for firms. Panel (c) utilizes value-added at basic prices, but Panel (d) uses value-added at factor costs. For panels (c) and (d), two years that provide the most complete information, 2013 and 2016, are chosen. Panel (c) has 6 countries, and Panel (d) has 33 countries out of 47 countries in the SDBS database. Linear fitted lines for both panels are statistically insignificant. All data are for establishments or enterprises with at least 10 employees. Appendix A has more details on the data.

ployment share of large (250+) plants in the manufacturing sector over time, for the set of countries with comparable data. See appendix A for data availability. During the last 20 years, both measures of plant size remained stable in the seven countries. Panels (c) and (d) report the correlation between the average plant/firm size and labor productivity, again for the set of countries with comparable data. At least for this set of countries with available data, we find no systematic relationship between the average plant/firm size and the level of productivity, neither over time nor in the cross-section.

An important caveat is that the literature found a positive relationship between the average firm/establishment size and economic development in the cross-section of countries, using data with wider coverage in terms of sectors and/or countries (e.g., Bento and Restuccia, 2017, 2021; Poschke, 2018; Fattal-Jaef, 2022), sometimes covering the universe of establishments including micro-enterprises.

3.2 Static Allocative Efficiency across Plants

One standard measure of static resource misallocation is the dispersion of revenue productivity. Foster, Haltiwanger and Syverson (2008) made a distinction between physical productivity (TFPQ) and revenue productivity (TFPR), and Hsieh and Klenow (2009) showed that—under simple parametric assumptions on market structure (monopolistic competition) and production technology (constant returns to scale)—TFPR dispersion within narrowly-defined industries represents plant-specific distortions and hence resource misallocation.[6] We apply the methodology of Hsieh and Klenow (2009) and express the TFP at the industry level (indexed by s) as follows.

$$TFP_s = \frac{Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}} = \left(\sum_{i=1}^{N_s} \left(A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} , \tag{3}$$

where A_{si} is plant i's TFPQ defined as $Y_{si}/K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}$, $TFPR_{si} = P_{si}A_{si}$ is the TFPR defined as the TFPQ multiplied by its output price, $\overline{TFPR}_s$ is the geometric average of the marginal revenue products of capital and labor, and α_s is the elasticity of output to capital in industry s.

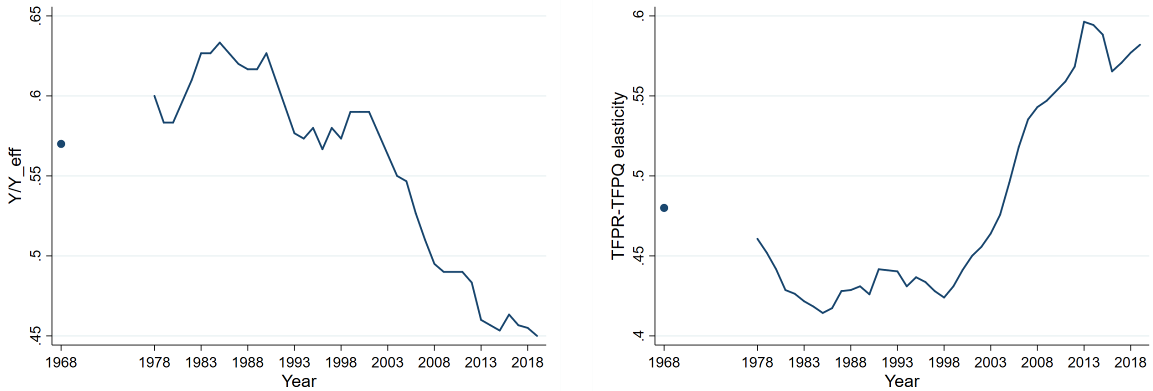
The ratio between the amount of final goods that will be produced with and without idiosyncratic distortions (respectively, Y and Y_{eff}) can be written as:

$$\frac{Y}{Y_{eff}} = \Pi_{s=1}^{S} \left(\sum_{i=1}^{N_s} \left(\frac{A_{si}}{\overline{A}_s} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right)^{\frac{\theta_s}{\sigma-1}} , \tag{4}$$

where θ_s is the value-added share of industry s, and $\overline{A}_s$ is the geometric average of the TFPQ in industry s.

[6] When parametric assumptions are violated or there are measurement errors, dispersion in measured average products need not imply dispersion in true marginal products. Kim, Lee and Shin (2021) calculate the degree of misallocation under constant returns to scale (CRS) and decreasing returns to scale (DRS) technologies and find that results are similar both qualitatively and quantitatively, using the Korean manufacturing data between 1967 and 1987. One way to estimate dispersion in true marginal products in the presence of measurement errors was suggested by Bils, Klenow and Ruane (2021). Their methodology exploits how revenue growth is less sensitive to input growth when plants' average products are overstated by measurement errors. It requires panel dimension in the data, which is only available after 1982 in our case. We applied this methodology to the 1982-2019 sub-period, which is reported in Appendix C.

Figure 6: Allocative Efficiency



(a) Y/Y_{eff} (b) TFPR-TFPQ elasticity

Notes: Panel (a) plots Y/Y_{eff} in equation (4) in 1968 and from 1978 to 2019. Prior to 1978, capital data is available for only one year, 1968. Panel (b) plots the value-added weighted average of elasticities of industry-level TFPR with respect to TFPQ. We report three years moving averages in both panels.

We consider industries at the four-digit level of classification, and Y_{eff} is the output obtained when the TFPR of all establishments within a four-digit industry is equalized. The TFPR may still differ across industries, and we reallocate capital and labor only within industries but not across them. For each year, in each four-digit industry, we drop the top and bottom 1 percent of establishments in terms of TFPR to remove outliers.

The capital rental rate is set to 0.1, and the elasticity of substitution across plant output is set to 3 as in Hsieh and Klenow (2009). We set the elasticity of output to capital for each industry, α_s, to 1 minus its labor share in 2015. The labor share is defined as the ratio of wages paid to value added in each industry. Since the labor shares constructed this way are much lower than the labor share in the national input-output table, we scale up the labor shares by a constant factor, 1.7.

Figure 6 shows the evolution of static resource misallocation from 1968 to 2019. (No numbers are shown for the 1969-77 period, because plant-level capital is not reported during this period.) We make two observations. First, resource misallocation within industries is estimated to be large. As shown in panel (a), Y/Y_{eff} is between 0.45 and 0.64, which implies that a hypothetical equalization of TFPR within industries will increase aggregate manufacturing output by 56 to 122 percent, from the same input. Second, the allocative efficiency in the Korean manufacturing sector improved somewhat between 1968 and 1983, but worsened afterward, especially during the 2000s.[7]

[7] These numbers are similar to what Kim, Oh and Shin (2017) calculated for the 1982–2007 period.

Panel (b) of Figure 6 shows the elasticity of TFPR with respect to TFPQ. The elasticity decreased slightly until 1983 but increased rapidly during the 2000s. A higher elasticity indicates that more productive plants (high TFPQ) are subjected to larger distortions (high TFPR). In this regard, a higher elasticity is another sign of increased misallocation, which means the pattern in panels (a) and (b) are consistent.

The rising allocative efficiency between 1968 and 1983 coincided with fast productivity growth in the manufacturing sector. However, the declining allocative efficiency was not necessarily accompanied by a corresponding decline in the level of manufacturing productivity. At best, one may say that the declining allocative efficiency after 2000 coincided with the decline in the growth rate of manufacturing productivity. However, the evidence does not suggest that static allocative efficiency is systematically correlated with the level or growth rate of manufacturing productivity.

3.3 Robustness Checks and Discussions

We conduct two robustness checks to address potential measurement problems. First, given that MMS only includes establishments hiring at least 5 or 10 employees, our results might be affected by those plants below thresholds, in particular by their "entry" and "exit" around the cutoff. We recalculated the plant size moments and the degrees of static misallocation using a balanced panel of plants between 1982 and 2019. Admittedly, these are very select samples—plants that continuously operated for at least 38 years, constituting only 1.7 percent of all observations in this period. Appendix B reports these results. The balanced panel data also exhibit an inverse-U pattern over time, but the timing is off. The average size of these plants actually increase in the early 1980s, while the overall average falls, because of the entry of many small plants. The plants in the balanced panel become smaller almost discontinuously after the 1997 East Asian financial crisis.

Second, in the presence of measurement errors, the dispersion in average revenue products might not reflect the dispersion in true marginal products. Bils, Klenow and Ruane (2021) suggested a method that leverages how revenue growth is less responsive to input growth, if either the revenue or inputs of plants are overstated by measurement errors. We apply their methodology to the (unbalanced) panel data from 1982 to 2019. Appendix C shows that this correction shifts the level of static allocative efficiency upward, but the decline in allocative efficiency since 2000 stays.

In the context of the existing cross-country evidence that the level of productivity is positively correlated with the average plant size and allocative efficiency, our findings from the Korean manufacturing sector seem puzzling. One hypothesis that can address this discrepancy is that the production technology changed in Korea over time, starting in the mid 1980s. First, the labor movement in the mid 1980s following the democratization of the country may have led firms to invest in more capital-intensive modes of production, driving down plant sizes measured by the number of employees. Second, the opening up of China in the early 1990s prompted many Korean firms to build factories in China to take advantage of the lower labor cost. This may have had a more sustained downward effect on the average plant size of the Korean manufacturing plant, as firms relocated labor-intensive production tasks to their subsidiaries in China.

The framework we are employing to compute static allocative efficiency does not account for changes in the production function over time. Over a long time horizon, this means the production function is misspecified, which may be the reason why the measure of allocative efficiency deteriorated rapidly in the 2000s. More data on firms' multinational activities and outsourcing are needed to test this hypothesis.

4 Dynamism

As discussed above, the MMS data allow us to track individual plants over time from 1982 with anonymized IDs. In this section, we study the change in business dynamism from 1982 to 2019. Our measures of business dynamism are plant-level job creation/destruction (Section 4.1) and plants' responsiveness to productivity shocks (Section 4.2).

4.1 Job Creation and Destruction

We first study the distribution of individual plant size growth, including entry and exit margins. Following Davis, Haltiwanger and Schuh (1998), the employment growth rate of plant i from year t_0 to t_1 is defined as:

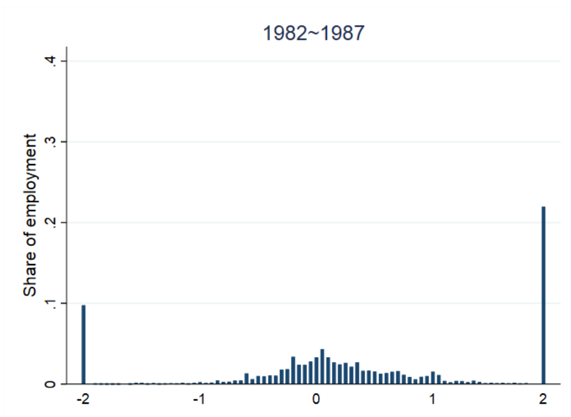
$$g_{i,t_1} = \frac{emp_{i,t_1} - emp_{i,t_0}}{0.5 \times emp_{i,t_1} + 0.5 \times emp_{i,t_0}} \ , \tag{5}$$

where $emp_{i,t}$ is the number of employees of plant i in year t. With this definition, an entry is recorded as +2, and an exit as -2.

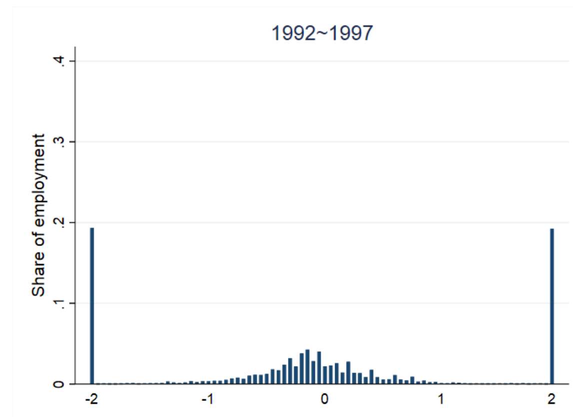
Figure 7 shows the distribution of job creation and destruction for each five-year period.[8] On the horizontal axis, we have employment growth rates, ranging from -2 (exit) to +2 (entry). On the vertical axis, we have the employment share of all plants in each growth bin.

[8] We report four five-year windows: 1982-1987, 1992-1997, 2002-2007, and 2013-2018. In Appendix D, we show all seven five-year windows in our sample period.

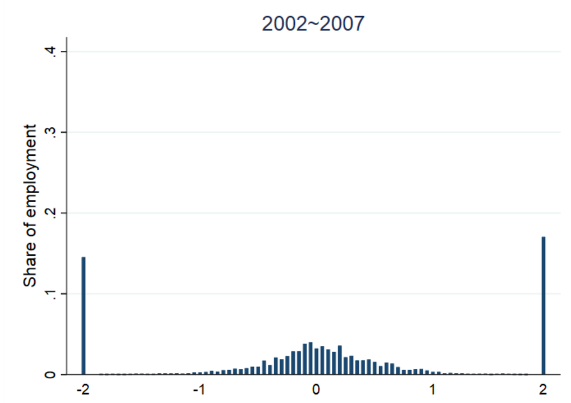
Figure 7: Distribution of Job Creation and Destruction



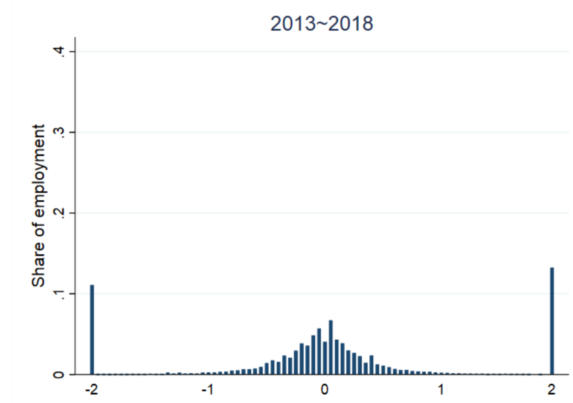
(a) 1982-1987



(b) 1992-1997



(c) 2002-2007



(d) 2013-2018

Notes: In panel (a), employment growth for a plant is defined as the change in plant employment between 1982 and 1987 divided by the plant's average employment in 1982 and 1987. The vertical axis is the employment share of all plants in each growth bin. The other panels are constructed in the same way. Note that entry is +2, and exit is -2.

This way, the plots show the employment-weighted distribution of plant-level growth rates over the given periods.

Comparing across the five-year windows, we find two notable trends. First, job creation by entry (+2) was an important margin of employment reallocation in the earlier periods, but its importance dwindled over the years. The importance of entry explains the falling average plant size since the 1980s, as entrants tend to be smaller than incumbents. Second, job creation and destruction became more concentrated near zero. Under Schumpeterian endogenous growth model as in Garcia-Macia, Hsieh and Klenow (2019), this can be interpreted as the decline in creative destruction by entrants (reflected in entry and exit rates) and by incumbents through new varieties (reflected in large job creations and destructions away from zero). Such a reduction in business dynamism is conspicuous in panels (c) and (d), relative to panels (a) and (b). The diminished dynamism in the 2000s and the 2010s coincides with the productivity slowdown of the Korean manufacturing sector.

4.2 Responsiveness to Productivity

We estimate the responsiveness of plants to shocks following Decker, Haltiwanger, Jarmin and Miranda (2020). Allocative efficiency dictates that more productive plants should expand their production. Under the reasonable assumptions that labor cannot be instantaneously adjusted, and that productivity shocks are persistent, responsiveness is a measure of dynamic allocative efficiency. The regression equation is

$$g_{jt+1} = \beta_0 + \beta_1 a_{jt} + T(a_{jt}, t) + \beta_2 e_{jt} + T(e_{jt}, t) + X'_{jt}\Theta + \epsilon_{jt+1} \ , \tag{6}$$

where g_{jt+1} is the employment growth rate of plant j in equation (5), a_{jt} is log productivity, e_{jt} is log employment, and X_{jt} is other controls, including detailed industry fixed effects, interacted with year effects and plant size bins.

The equation allows productivity responsiveness to vary over time via $T(a_{jt}, t)$. More specifically, we have:

$$\begin{aligned} T(a_{jt}, t) \in \{ & \delta a_{jt} Trend_t, \\ & \lambda_{80s} a_{jt} \mathbb{1}_{t \in [1982,1990)} + \lambda_{90s} a_{jt} \mathbb{1}_{t \in [1990,1999)} \\ & \lambda_{00s} a_{jt} \mathbb{1}_{t \in [2000,2009)} + \lambda_{10s} a_{jt} \mathbb{1}_{t \in [2010,2019)} - \beta_1 a_{jt} \} \ , \end{aligned} \tag{7}$$

where $\mathbb{1}$ is the indicator function. The first element introduces a simple linear trend with coefficient δ. The second element allows the responsiveness coefficient to vary by decade. By subtracting $\beta_1 a_{jt}$, we remove the main effect specified in equation (6), so the decade coefficients can be interpreted in a fully-saturated manner. Similarly, we permit the effects of initial employment to vary over time via $T(e_{jt}, t)$.

An ideal measure of productivity would be technological efficiency, that could be estimated from observable plant-level revenue, input, and price data. Because plant-level price data are not available, we use a revenue-based productivity measure instead. To the extent that plants should respond to demand shocks, using the revenue-based productivity measure is not necessarily a shortcoming, because positive/negative demand shocks will increase/decrease prices, which pushes revenue-based productivity upward/downward. In our baseline results, we use TFPR as our measure of productivity (a_{jt}), as defined in Section

Table 1: Plant-level Responsiveness to Productivity

Dep. var.	Employment growth (1)	(2)	Capital growth (3)	(4)
Productivity (TFPR): β_1	0.0274***		0.2000***	
	(0.0047)		(0.0082)	
Prod $\times$ trend: δ	-0.0003		-0.0038***	
	(0.0002)		(0.0003)	
Prod $\times$ 1980s: λ_{80s}		0.0199***		0.1835***
		(0.0046)		(0.0087)
Prod $\times$ 1990s: λ_{90s}		0.0278***		0.1508***
		(0.0057)		(0.0097)
Prod $\times$ 2000s: λ_{00s}		0.0239***		0.1069***
		(0.0051)		(0.0064)
Prod $\times$ 2010s: λ_{10s}		0.0135***		0.0758***
		(0.0056)		(0.0051)
Observations	$1,297,793$	$1,297,793$	$1,297,793$	$1,297,793$
R-squared	0.1353	0.1356	0.1398	0.1401

Note: Dependent variable is annual employment growth in columns (1)-(2) and annual capital growth in columns (3)-(4). All regressions include controls described in equation (6) and related text. The measure of productivity is TFPR.

3.2, $TFPR_{si} = \dfrac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$. In Appendix E, we report the robustness of our findings using another productivity measure, TFPQ as defined in Section 3.2, $TFPQ_{si} = \dfrac{(P_{si}Y_{si})^{\frac{\sigma}{1-\sigma}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$.

Table 1 reports the regression coefficients. Columns (1) and (2) use annual employment growth as the dependent variable. The first column specifies changing responsiveness with the linear time trend. We estimate a baseline responsiveness coefficient of $\beta_1 = 0.0274$, which is significant, but almost an order of magnitude smaller than what is found in the US data (Decker, Haltiwanger, Jarmin and Miranda, 2020). Column (2) is the result using the fully saturated decade indicators (λ). By decade, the coefficient peaks in the 1990s and then decreases afterwards.

Over the sample period, the average employment of the Korean manufacturing plants decreased (Figure 2), while the average tangible capital stock increased substantially. It is then possible that plants responded to shocks by adjusting capital rather than labor. We estimate the equation by replacing employment growth with capital growth as the dependent variable. Columns (3) and (4) show these results. We observe that tangible capital responded significantly to productivity, much more so than labor. Furthermore, the responsiveness decreased significantly over time, and shows a significant negative time trend in columns (3). By decade, in column (4), we see a monotonic decrease from 0.184 in the 1980s and 0.151 in the 1990s to 0.107 in the 2000s and 0.076 in the 2010s. The declining responsiveness to shocks at the plant level, especially since the 2000s, coincides with the pronounced decline in the growth rate of manufacturing productivity.

Together with the results in Section 4.1, it suggests that business dynamism at the micro-level may be tightly connected to the aggregate productivity growth.

5 Concluding Remarks

We provide a first micro-level view of the evolution of the Korean manufacturing sector during its transformation from a poor economy into a highly-developed, mature economy. We focused on plant size distribution, static allocative efficiency, and business dynamism.

Our finding on the inverse-U pattern of the average plant size over the course of economic development seems inconsistent with the common understanding in the literature, where it is noted that average plant size increases with economic development. Apart from the fact that our result comes from one sector in one country over time, the minimum employment cutoff (of at least five employees) may be a reason for this dissonance. It is possible that the cross-country result is driven by the prevalence of micro-enterprises with no or very few employees in less developed countries. A more systematic review of the evidence on establishment/firm size across countries and over time is needed before we can arrive at a definitive conclusion.

The divergent trends we find between our whole sample and the balanced panel (of plants that continuously operated between 1982 and 2019) suggest that large, productive plants may have a different size-productivity relationship relative to the average plant's. An investigation of this pattern at a more granular level in Korea and other countries may be a promising avenue for future research.

Our second finding is that the evolution of static misallocation is not strongly correlated with either the level or the growth rate of the manufacturing sector's productivity in Korea. This raises the question of how one should compare this measure of misallocation across time periods and/or across countries. To the extent that misspecification may be an issue as we discuss in Section 3.3, one may want to dissect why the misspecification played more and more important roles during the 2000s, in the absence of a corresponding decline in the level of manufacturing sector productivity. It is possible that the decline in the growth rate of manufacturing productivity in the 2000s is connected to the rapid rise of misallocation during this period. However, it is harder to reconcile their magnitudes. Furthermore, the growth rate of manufacturing productivity fell further in the 2010s, while the allocative efficiency changed little during the same period. It may be helpful to develop a framework that connects static allocative efficiency with growth rates, not just with levels.

Our findings on the close (negative) relationship between business dynamism and the growth rate of manufacturing sector productivity suggest that more fruitful research await in this area. More empirical research on business dynamism over time and across countries is needed, subject to the challenge that one needs micro panel data for this purpose. A further missing piece is a micro-founded dynamic model that can rationalize the magnitude and the time trends of the responsiveness. We speculate that adjustment costs, credit constraints, and idiosyncratic risks on the demand side as well as the production side all play a role in such a model.

The next step, which we leave for future research, is to analyze the business dynamism patterns conditioning on plant or firm characteristics. In Korea, large and productive plants tend to belong to large business groups, who dominate the manufacturing sector. Do plants and firms owned by business groups have different dynamism patterns? Is the dynamism of non-business group plants and firms affected by the presence of business group plants and firms in the same sector or market? To answer these questions, one needs to merge MMS with firm ownership data, which is possible for the later periods. Such an analysis will help address the question of the role of business groups in economic growth.

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APPENDIX

A Structural and Demographic Business Statistics (SDBS)

Cross-country data come from OECD SDBS (Structural and Demographic Business Statistics, ISIC Rev.4). It provides information on turnover, value-added, production, operating surplus, employment, labor costs, investment, etc. The data are available at the sector level, and some of them can be broken down into size bins. For Figure 5, data from the manufacturing sector (ISIC 10-33) are used.

For panels (a), (b), and (c) of Figure 5, all of the indicators are calculated for establishments with at least 10 employees. Thus, countries without the number of establishments and those with variables that cannot be categorized into size bins are excluded as noted in Table A.I.

For panels (a) and (b) of Figure 5, the average employment is calculated from the number of establishments and the total employment in establishments with at least 10 employees. The share of employment of the establishments with at least 250 employees is calculated for the countries selected for the average employment, by dividing the number of workers in establishments with at least 250 employees by the total employment in establishments with at least 10 employees.

For panel (c) of Figure 5, real value-added per worker is calculated from deflated value-added at a basic price[9] in USD and the total employment in establishments with at least 10 employees. To deflate value-added in local currency, the manufacturing deflators of each country from OECD national accounts are used. They are then converted into USD using the period-average exchange rate from the IMF International Financial Statistics (IFS).

For panel (d) of Figure 5, firm size is used instead of plant size so that we can utilize data from more countries. Additionally, value-added at factor costs is utilized over value-added at basic prices because the former is available for more countries with the number of firms data (Table A.II).

[9]Value-added at basic prices = value-added at factor costs + production taxes - production subsidies

Table A.I: Sample Selection for Panel (a)-(c) of Figure 5

Countries (47 in total)	Remarks
Columbia, Israel, Japan, Korea, Mexico, Brazil (6 countries)	Included as value-added (VA) at basic prices, total employment, and number of establishments by employment size class are available
New Zealand	Included in Figure 4(a) and (b) but not in (c) as VA at basic prices by employment size is unavailable
Chile, Russia	Excluded as total employment by employment size class is unavailable
Costa Rica	Excluded as VA at basic prices is unavailable
United States	Excluded as VA at basic prices is only available for 2007
Australia, Austria, Belgium, Canada, Czech Rep., Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Rep., Slovenia, Spain, Sweden, Switzerland, Türkiye, United Kingdom, Bulgaria, Croatia, Cyprus, Malta, North Macedonia, Romania, Serbia (36 countries)	Excluded as the number of establishments is unavailable

Table A.II: Sample Selection for Panel (d) of Figure 5

Countries (47 in total)	Remarks
Austria, Belgium, Czech Rep., Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Rep., Slovenia, Spain, Sweden, Switzerland, Türkiye, United Kingdom, Bulgaria, Croatia, Cyprus, North Macedonia, Romania, Serbia (33 countries)	Included as VA at factor costs, total employment, and the number of enterprises by employment size class are available
Australia, Canada, Chile, Colombia, Costa Rica, Israel, Japan, Korea, Mexico, New Zealand, United States, Brazil, Russia (13 countries)	Excluded as VA at factor costs is unavailable
Malta	Excluded as total employment and the number of enterprises by employment size are incomplete

B Results with Balanced Panel of Plants (1982-2019)

Since the MMS includes only those establishments with at least 5 or 10 (from 2007) employees, our results might be affected by the "entry" and "exit" of plants around the size cutoff in the data. To check for the robustness of our findings, we re-draw the figures in the paper only using the balanced panel of plants. As the panel dimension is available from 1982, time interval is restricted to 1982-2019. The total number of observation for the balanced panel is 31,248, encompassing 868 plants annually, a reduction from the 1,823,217 observations in the unbalanced panel.

Figure B.1 shows the average plant size and the employment share of large plants for the balanced panel from 1982 to 2019. The average size actually rises through the mid 1980s, fluctuates during the next 10 years or so, and then almost discontinuously drops after the 1997 East Asian financial crisis. The pattern is another inverse-U, but the timing is different from the one in Figure 2. The divergent trends during the 1980s are easy to explain, because the overall size decline in the 1980s was driven by the entry of smaller plants, which is also corroborated by panels (a) and (b) of Figure 7. It is worth noting that the balanced panel is a highly selected sample, plants continuously operating for at least 38 years. As the figure shows, their average size is three or four times as large as that of the whole sample. While we do not have plant ownership data for this period, but many of these plants in the balanced sample likely belong to big business groups.

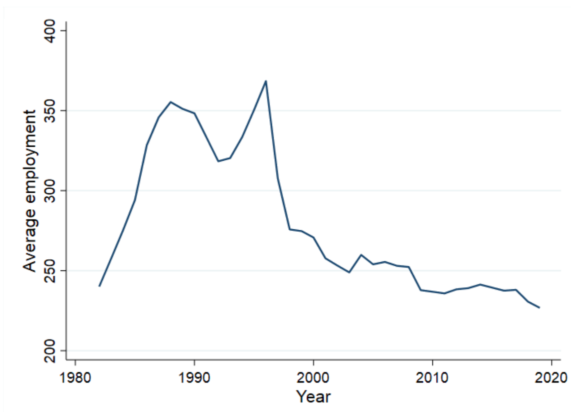
Figure B.2 reports the dispersion of employment and the static allocative efficiency for this balanced panel. When we calculate

$$\frac{Y}{Y_{eff}} = \Pi_{s=1}^{S}\left(\sum_{i=1}^{N_s}\left(\frac{A_{si}}{\overline{A_s}}\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}}$$

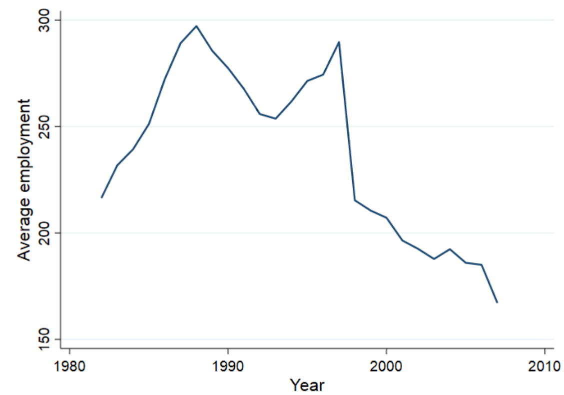
for the balanced panel, $\overline{TFPR_s}$, $\overline{A_s}$, and θ_s are computed for all plants, not just those in the balanced panel. This allows to assess whether the plants in the balanced panel have excessive or insufficient resources.[10] Consistent with Figure 4 and 6, we find decreasing trends in the dispersion and the static allocative efficiency in the balanced panel.

[10]Unlike in Figure 6, the TFPR-TFPQ elasticity for the balanced panel is not reported because the regression coefficients of industries are not well defined due to the small number of plants within each industry. In each year, we have 868 plants across 139 industries in the balanced panel.

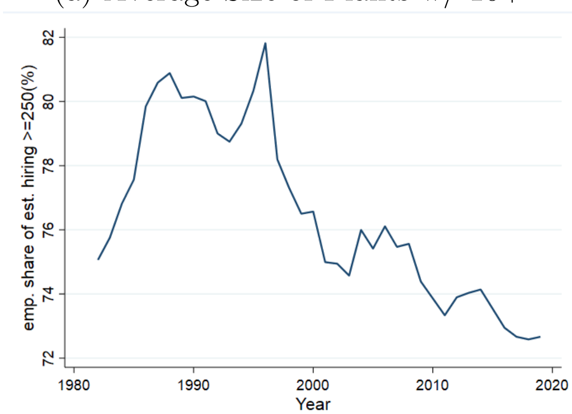
Figure B.1: Average Plant Size and Employment Share of Large Plants in the Balanced Panel



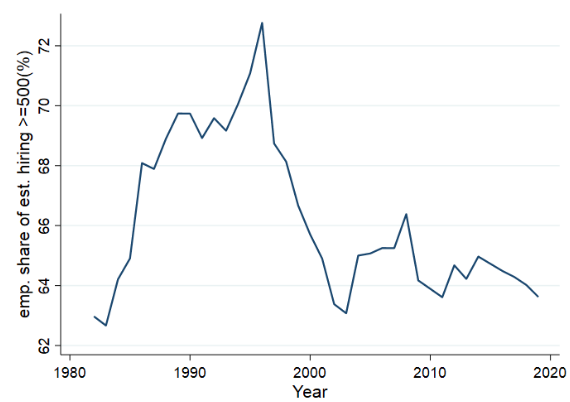
(a) Average Size of Plants w/ 10+



(b) Average Size of Plants w/ 5+



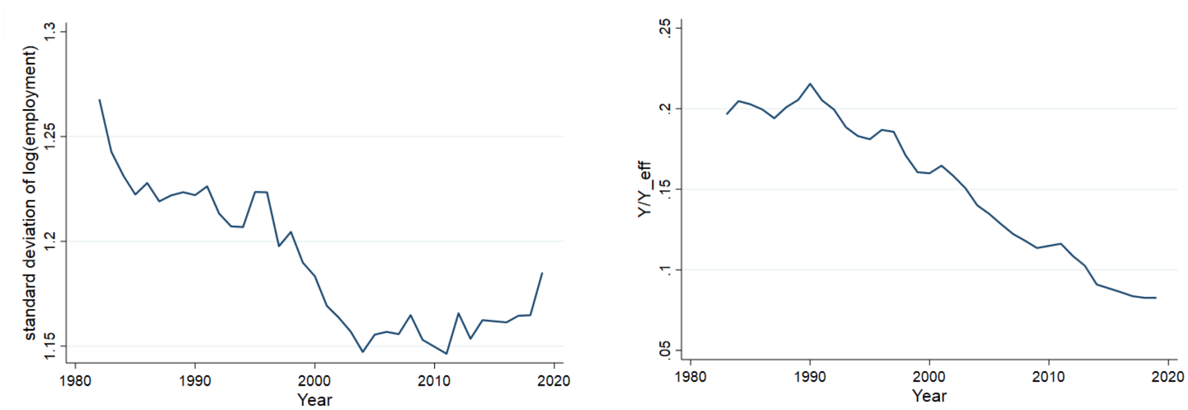
(c) Employment Share of Plants w/ 250+



(d) Employment Share of Plants w/ 500+

Notes: All the details are the same as in Figure 2. Panel (b) uses the balanced panel from 1982 to 2006, covering 1,545 plants annually.

Figure B.2: Dispersion of employment and Allocative Efficiency in the balanced panel



(a) Standard Deviation of Log Employment

(b) Y/Y_{eff}

Notes: Panel (a) and panel (b) are balanced panel versions of panel (a) of Figure 4 and Figure 6 respectively. We report three years moving averages in panel (b).

C Results with Bils, Klenow and Ruane (2021) Methodology

In the presence of measurement errors, the dispersion in average revenue products may not reflect the dispersion in true marginal products. Bils, Klenow and Ruane (2021) suggested a method that builds on the idea that revenue growth is less responsive to input growth if either the revenue or input of plants is overstated by measurement errors. We apply their methodology to our results as a robustness check.

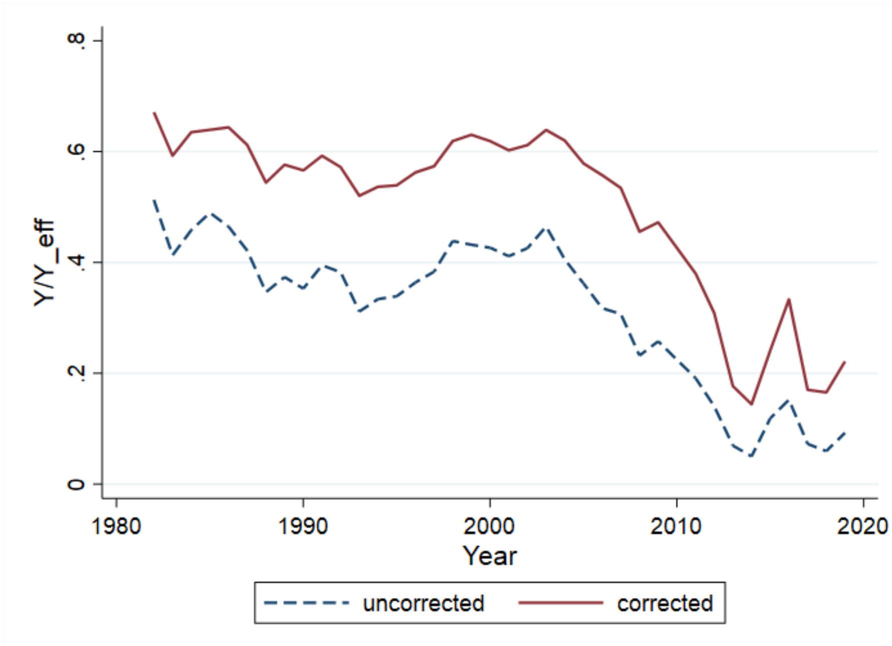
We closely follow their definitions for main variables and their data cleaning procedures. As their methodology exploits the panel dimension of the data, we apply it to the 1982-2019 sub-period. Since some years' data lack overhead costs, bonuses, and benefits, we only include direct costs when calculating intermediates, and only include wages when measuring labor costs.

Unlike Hsieh and Klenow (2009), Bils, Klenow and Ruane (2021) incorporate intermediate inputs X in the production function: $Y_{si} = A_{si}(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s})^{\gamma_s} X_{si}^{1-\gamma_s}$ where $0 < \alpha_s, \gamma_s < 1$. Hence, $TFPR \equiv \dfrac{P_{si}Y_{si}}{(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s})^{\gamma_s} X_{si}^{1-\gamma_s}}$ and $TFPQ \equiv \dfrac{(P_{si}Y_{si})^{\frac{\sigma}{1-\sigma}}}{(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s})^{\gamma_s} X_{si}^{1-\gamma_s}}$. To correct for measurement errors, Bils, Klenow and Ruane (2021) use the elasticity of revenue growth with respect to input growth. After constructing revenue and input growth, each plant is categorized into a decile k based on its Tornqvist $ln(TFPR)$ deviations from the sector-year average. We regress revenue growth on input growth separately for each decile k and get the elasticity $\hat{\beta}_k = \frac{Cov_k(\Delta\hat{R}_i, \Delta\hat{I}_i)}{Var_k(\Delta\hat{I}_i)}$, where $\hat{R}_i$ and $\hat{I}_i$ are measured revenue and inputs of plant i. The corrected measure of misallocation $\hat{\tau}$ is defined as $ln(\hat{\tau}) = ln(TFPR) + ln(\hat{\beta}_k) + \epsilon$.[11]

Figure C.1 illustrates the trends of the static allocative efficiency with and without correction for our (unbalanced) panel. Although the levels are different, the trends are similar, which implies that our results may be robust to measurement errors.

[11] ϵ is distributed lognormal with mean zero and variance $-Cov[ln(TFPR), ln(\hat{\beta}_k)] - Var[ln(\hat{\beta}_k)]$. Bils, Klenow and Ruane (2021) provides the intuition for their approach as follows: *"Absent measurement errors, the elasticity of plant revenue with respect to inputs β should not depend on a plant's level of TFPR. While β will generally be less than one, unless the relative volatility of shocks to firm τ's are correlated with the level of TFPR, then TFPR does not predict β. By contrast, under additive measurement errors, measurement error maps to a lower elasticity β. Therefore, the relation of β to TFPR speaks to the role of measurement error in TFPR dispersion, in turn yielding an expected true distortion τ for a plant, given its TFPR."*

Figure C.1: Static Allocative Efficiency with and without Correction

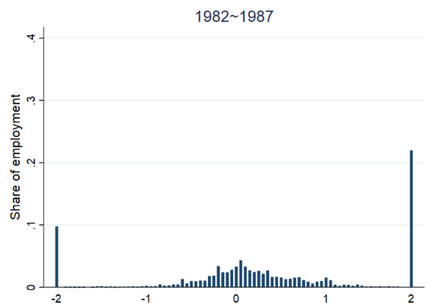


Notes: The uncorrected (dashed line) and corrected (solid line) static allocative efficiency (Y/Y_{eff}) is computed using the method of Bils, Klenow and Ruane (2021). It starts in 1982, because our data has the panel dimension beginning in that year.

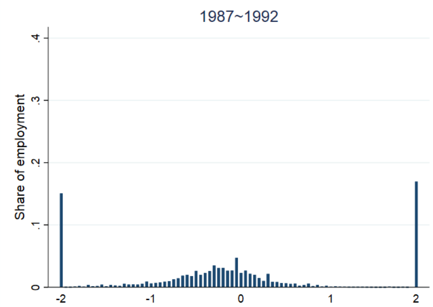
D Distribution of Job Creation and Destruction

In Section 4.1, we report only four 5-year windows: 1982-1987, 1992-1997, 2002-2007, and 2013-2018. Figure D.1 shows all seven 5-year windows during our sample period. The three 5-year windows in the middle (1987-1992, 1997-2002, and 2008-2013) were omitted in Figure 7, because they were similar to their adjacent period figures.

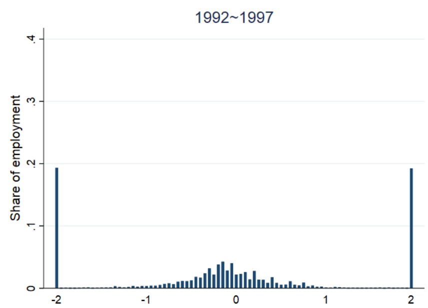
Figure D.1: Distribution of Job Creation and Destruction



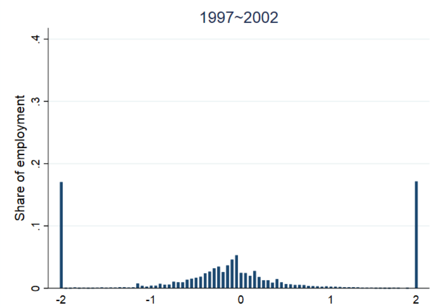
(a) 1982-1987



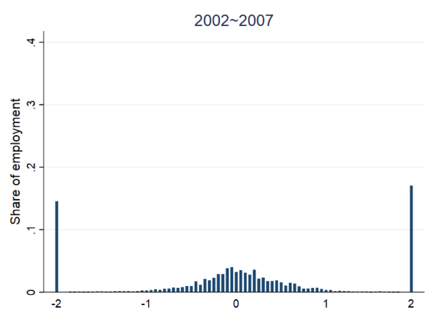
(b) 1987-1992



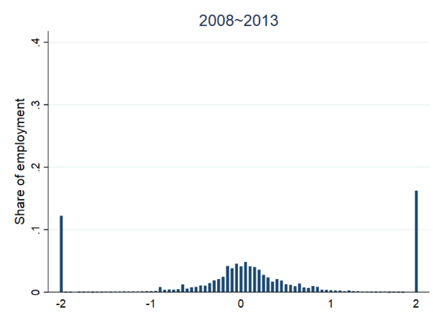
(c) 1992-1997



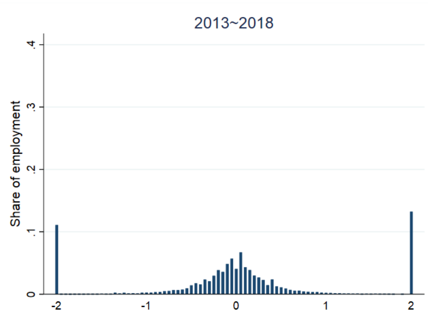
(d) 1997-2002



(e) 2002-2007



(f) 2008-2013



(g) 2013-2018

Notes: Employment growth for a plant is defined as the change in plant employment between, for example, 1982 and 1987 divided by the average of the plant's employment in 1982 and 1987. The vertical axis is the employment share of each growth bin. Entry shows up as +2, and exit as -2.

E Alternative Productivity Measures

In Section 4.2, we use a model-based TFPR ($TFPR_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$) as the measure of productivity. In this section, we use a model-based TFPQ ($TFPQ_{si} = \frac{(P_{si}Y_{si})^{\frac{\sigma}{1-\sigma}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$) as the measure of productivity instead.

Table E.I reports the results from plant-level regressions using the model-based TFPQ. Plant-level employment and capital growth responsiveness with respect to this productivity measure weakened over time from the 1980s to the 2010s, consistent with the result in Table 1.

Table E.I: Plant-level Growth Responsiveness

Dep. var.	Employment growth		Capital growth	
	(1)	(2)	(3)	(4)
Productivity (TFPQ): β_1	0.0418***		0.0963***	
	(0.0037)		(0.0063)	
Prod × trend: δ	-0.0003		-0.0019***	
	(0.0002)		(0.0002)	
Prod × 1980s: λ_{80s}		0.0352***		0.0872***
		(0.0035)		(0.0065)
Prod × 1990s: λ_{90s}		0.0410***		0.0734***
		(0.0042)		(0.0074)
Prod × 2000s: λ_{00s}		0.0363***		0.0541***
		(0.0037)		(0.0044)
Prod × 2010s: λ_{10s}		0.0313***		0.0345***
		(0.0077)		(0.0042)
Observations	1,297,793	1,297,793	1,297,793	1,297,793
R-squared	0.1447	0.1451	0.1226	0.1230

Note: The dependent variable is annual employment growth in columns (1)-(2) and annual capital growth in columns (3)-(4). All regressions include controls as in equation (6) and the description of it in the main text. The measure of productivity is model-based TFPQ.