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SUPERSTARS OR SUPERVILLAINS?
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Superstars or Supervillains? Large Firms in the South Korean Growth Miracle
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ABSTRACT

We quantify the contribution of the largest firms to South Korea's economic performance over the period 1972-2011. Using firm-level historical data, we document a novel fact: firm concentration rose substantially during the growth miracle period. To understand whether rising concentration contributed positively or negatively to South Korean real income, we build a quantitative dynamic heterogeneous firm small open economy model. Our framework accommodates a variety of potential causes and consequences of changing firm concentration: productivity, distortions, selection into exporting, scale economies, and oligopolistic and oligopsonistic market power in domestic goods and labor markets. The model is implemented directly on the firm-level data and inverted to recover the drivers of concentration. We find that most of the differential performance of the top firms is attributable to higher productivity growth rather than increasingly favorable distortions. Exceptional performance of the top 3 firms within each sector relative to the average firms contributed 20.8% to the 2011 real GDP and 6.6% to the net present value of welfare over the period 1972-2011. Thus, the largest Korean firms were superstars rather than supervillains.

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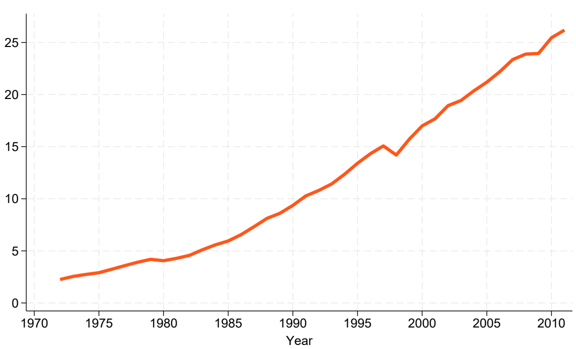
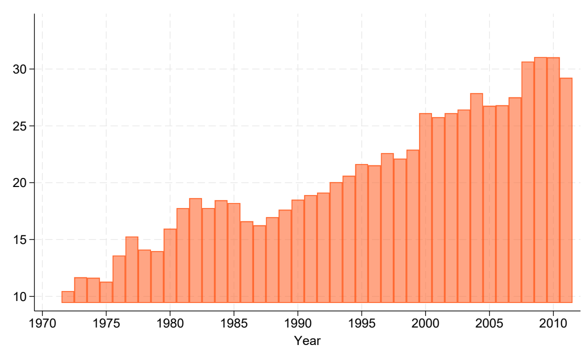
1. Introduction

The rise of "superstar" firms and increased firm concentration have attracted a great deal of recent attention (e.g. Autor et al., 2020; Covarrubias et al., 2020; De Loecker et al., 2020). These trends have been viewed mostly in a negative light, and blamed for rising markups and markdowns and falling labor share. This phenomenon is of course not unprecedented: the rise in industrial concentration during the Gilded Age prompted similar debates and elicited well-known policy responses (e.g. Lamoreaux, 2000, 2019). However, whether concentration is bad for economic performance or welfare depends on both the underlying causes and consequences of increased concentration. For instance, changes in concentration could be driven by productivity growth differentials, changes in distortions, or selection of large firms into exporting. Markups and markdowns would correspondingly be affected by these trends. All of these forces are not mutually exclusive, and disentangling the drivers of firm concentration is important for understanding the impact of large firms on the macroeconomy.

Figure 1: Real GDP Per Capita and Firm Concentration in South Korea



A. Real GDP per capita (thousands 2010 USD)



B. Mfg. Concentration Ratio of the Top-3 (%)

Notes. Panel A plots the real GDP per capita in thousands 2010 US dollars. Panel B plots the sales shares of the top 3 firms in each manufacturing sector in the total manufacturing gross output.

This paper studies the role of large firms in the long-run economic performance of South Korea between the 1970s and the 2010s. This setting is of particular interest for 2 reasons. First, it is the growth miracle period (Lucas, 1993). The left panel of Figure 1 displays the well-known rapid growth in South Korea. Between 1972 and 2011, the real GDP per capita increased nearly 12-fold (a 6.5% average annual growth rate over 40 years). And second, South Korea is famous for the presence of very large firms. While this fact is familiar in levels (see, e.g. di Giovanni and Levchenko, 2012), the right panel of Figure 1 displays the changes in firm concentration over this period. It plots the share of the top 3 firms in each manufacturing sector in total manufacturing gross output. The top-3 share increased from 10.1% to 28.5% between 1972 and 2011. This long-run trend in the South Korean firm concentration has not to our knowledge been previously documented in the literature. Thus, superficially at least, it appears that the rising concentration had not held back the growth miracle.

However, to fully understand the role of concentration in South Korea's macroeconomy, we must quantify the forces that produced this trend.

Our theoretical contribution is to develop a quantifiable model of individual firms' role in concentration and real income. We set up a general equilibrium dynamic multi-sector heterogeneous-firm small open economy framework, in which the firm size distribution is jointly determined by (i) heterogeneous productivity à la Melitz (2003); (ii) heterogeneous idiosyncratic labor and capital distortions à la Restuccia and Rogerson (2008) and Hsieh and Klenow (2009); (iii) heterogeneous exporting à la Melitz (2003); (iv) oligopoly in domestic goods markets à la Atkeson and Burstein (2008); (v) oligopsony labor markets à la Berger et al. (2022); and (vi) non-constant returns to scale at the firm level. All of these features interact with each other and shape firm concentration.

To guide quantification, we state 4 analytical results. First, we derive aggregations of micro-level productivities, distortions, and foreign market access into sector-level production functions, TFPs, and markups, that generalize existing results in the literature to our richer setting. Second, we develop an additive decomposition of the top-3 concentration ratio into the components capturing differential top-3 firms' productivity, foreign market access, entry and exit into the top 3, and sectoral reallocation. These two propositions set up the theory-consistent targets for the measurement and quantification exercises. Third, we state a proposition that connects sectoral concentration and sectoral TFP. It shows that concentration-increasing shocks to firm productivity, distortions, or export demand can either raise or lower sectoral TFP. Sectoral TFP falls with concentration when the firms that grow in size were initially sufficiently distorted, and vice versa. Thus, the shocks that produced the observed increase in South Korean concentration have an *ex ante* theoretically ambiguous impact on aggregate productivity, real GDP, and welfare. It is ultimately a quantitative question. Finally, we develop a mapping between unobservable firm primitives and observable firm market shares. This result shows we can recover from the data the key candidate structural determinants of firm concentration – productivity, distortions, and export market access – which in turn enable quantification.

Our quantitative contribution is to provide a joint account of the micro (changing concentration) and the macro (real GDP and welfare) economic performance in South Korea. The quantification employs a novel panel firm-level dataset spanning 40 years, 1972-2011. Importantly, our model is implemented directly on firm-level data, so that actual firms in South Korea correspond to firms in the model. We invert the model to recover firm-level productivity, distortions, and foreign demand from data on domestic and export sales shares, wage bill shares, and capital shares. Productivity and distortions are identified jointly by comparing the domestic sales, wage bill, and capital shares, after accounting for exports. Intuitively, higher productivity makes a firm larger on all dimensions, increasing both sales and factor usage symmetrically. By contrast, a distortion changes a firm's factor share relative to its sales share. In our setting this mapping is made more complicated by heterogeneous exporting, non-constant returns to scale, and variable price markups and wage markdowns. Thus, the inversion also requires information on export shares, recovers the export demand shifters, and accounts for non-constant returns to scale and variable markups/downs in a theory-consistent way. When fed back into the model, the shocks reproduce both firm-level (sectoral sales, export, and factor usage shares) and aggregate (GDP, sectoral output, exports, and imports) objects in the data. We disentangle the contributions of each of these shocks to South Korean concentration and macro outcomes over this period.

Our results can be summarized as follows. The top-3 firms experienced substantially higher TFP growth over this period. While they were 2.3 times more productive than other firms in 1972, they were 8.8 times more productive in 2011. They also experienced a faster increase in foreign demand. By contrast, the top-3's relative labor and capital distortions fluctuated widely over this period but exhibited no long-run trend. The decomposition of the change in concentration shows that about 58% of the total increase from 1972 to 2011 is accounted for by sectoral reallocation – sectors with larger firms growing faster than sectors with smaller firms. The remaining 42% is driven by within-sector increases in the top-3 firm shares. Of that, about half is due to the churning of the set of the top-3 firms, indicating quite a bit of dynamism at the top of the firm size distribution over this period.

We next quantify the contribution of the top-3 firms to South Korean real GDP and welfare and assess the strength of the individual underlying forces. We compare the observed baseline economy to an alternative in which the top-3 firms instead exhibited the average sectoral growth rates of productivity, distortions, and export market access. Had the top-3 firms not experienced differential shocks, the top-3 concentration ratio change would have been one-fifth of that in the data, but 2011 real GDP would have been 20.8% lower, and the net present value of welfare over 1972-2011 would have been 6.6% lower. Most of the total effect is due to the top-3 firms productivity. Without the differential productivity growth of the top-3 firms, 2011 real GDP would have been 18.1% lower, and the NPV of welfare would have been 4.9% lower. Differential foreign market access and distortions had a more modest GDP and welfare impact. The positive impacts of the top firms come despite the fact that higher concentration led to higher markups and markdowns. Indeed, notwithstanding the observed increase in concentration, aggregate markups and wage markdowns rose quite modestly in the baseline economy, and barely changed in the counterfactuals.

Our framework also allows us to quantify the contributions of individual firms to real GDP and welfare over this period. We begin by computing the impact of South Korea's two largest firms, Samsung Electronics and Hyundai Motors. Had Samsung Electronics' and Hyundai Motors' shocks evolved at the same rate as the regular firms', real 2011 GDP would have been 7.0% and 0.7% lower, and welfare 1.2% and 0.9% lower, respectively. Thus, even a single large firm can exert a noticeable influence on the aggregate long-run outcomes.

We next compute the contribution of each of the top-3 firms' shocks to both concentration and real GDP. This exercise connects the quantification to the theoretical result that a firm-level shock that raises concentration can either increase or decrease sectoral TFP, depending on the initial conditions. For a large majority of top-3 firms, idiosyncratic shocks contributed positively to both concentration and real GDP, echoing the aggregate results that the top-3 firms were a positive force. It appears that in South Korea, most – though not all – top firms were indeed superstars rather than supervillains.

Related literature. A compact characterization of our analysis is that we perform growth (and concentration) accounting, but with firm-level shocks. As such, we build primarily on two strands of the literature. The first is growth accounting (see among many others, Solow, 1956; Domar, 1961; Hulten, 1978; Lucas, 1988; Mankiw et al., 1992; Klenow and Rodríguez-Clare, 1997; Barro, 1999; Hall and Jones, 1999; Fernald and Neiman, 2011; Gourinchas and Jeanne, 2013; Baqaee and Farhi, 2019a; Baqaee et al., 2025), and in particular the work on the Asian growth experience (e.g. Young, 1995; Hsieh, 2002; Song et al., 2011; Chang and Hornstein, 2015; Ohanian et al., 2018; Han and Lee, 2020; Fan et al., 2023). With the partial exception of Alviarez et al. (2023b), the growth accounting literature has not quantified the role of individual firms in aggregate long-run real income.

The second is the literature on the aggregate implications of microeconomic shocks (see among many others, Gabaix, 2011; Acemoglu et al., 2012; di Giovanni and Levchenko, 2012; di Giovanni et al., 2014, 2018, 2024; Carvalho and Gabaix, 2013; Atalay, 2017; Cravino and Levchenko, 2017; Huneeus, 2018; Baqaee and Farhi, 2019b, 2020; Carvalho and Grassi, 2019; Huo et al., 2025). Most of this research program has focused on the impact of individual firms on shock transmission and business cycle fluctuations. By contrast, this paper turns attention to the role of individual firms in long-run economic performance.

Our focus on concentration is inspired by the recent active research program on this topic (e.g. Autor et al., 2020; Covarrubias et al., 2020; De Loecker et al., 2020; Rossi-Hansberg et al., 2021; Hsieh and Rossi-Hansberg, 2023; Kwon et al., 2024; Firooz et al., 2025; Ma et al., 2025). While most research in this area has focused on the US and developed countries, we turn attention to a relatively underexplored setting: South Korea's growth miracle. Lee and Shin (2024) document a number of stylized facts about average plant size, misallocation, and business dynamism in South Korea over this period. We provide a full-fledged model-based quantification of the sources of rising firm concentration and its consequences for real GDP and welfare.

Our modeling and quantification build on a number of research programs that would be impractical to review comprehensively here: (i) large firms (e.g. Atkeson and Burstein, 2008; Eaton et al., 2012; Amiti et al., 2014, 2019; Freund and Pierola, 2015; Gaubert and Itskhoki, 2021); (ii) misallocation (e.g Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Banerjee and Moll, 2010; Buera et al., 2013; Buera and Shin, 2013; Moll, 2014; Hsieh et al., 2019; Itskhoki and Moll, 2019; Peters, 2020; Ruzic and Ho, 2023); (iii) markups and markdowns (Edmond et al., 2015, 2023; De Loecker and Eeckhout, 2018; Díez et al., 2021; Berger et al., 2022; Deb et al., 2022, 2024; Yeh et al., 2022; Afrouzi et al., 2023; Alviarez et al., 2023a; Felix, 2023; Azkarate-Askasua and Zerecero, 2024; Burstein et al., 2025; Pellegrino, 2025; De Ridder et al., 2026); and (iv) firm dynamics (e.g. Foster et al., 2001; Akcigit et al., 2021; Kehrig and Vincent, 2021; Sterk et al., 2021; Akcigit and Ates, 2023; Asturias et al., 2023; Eslava et al., 2024).

The rest of this paper is organized as follows. Section 2 builds the quantitative framework and states the analytical results that guide the quantification. Section 3 discusses the calibration strategy and the data, and Section 4 presents the quantitative results. Section 5 concludes. The Appendix collects the details of theory, data, and quantification, as well as results of additional exercises.

2. Theoretical Framework

2.1 Setup

The world is divided into Home and Foreign, corresponding to South Korea and the rest of the world. Home is a small open economy that takes Foreign's demands and export prices as exogenously given. Time is discrete and indexed by $t \in \{0, \ldots, \infty\}$. There is a continuum of sectors, indexed by $i, j \in [0, 1]$. In each manufacturing sector $\mathcal{J}^M \subset [0, 1]$, there is a finite number of heterogeneous firms and one fringe firm, indexed by $f \in \mathcal{F}_{jt} = \{1, \ldots, F_{jt} - 1, \tilde{f}_j\}$, where $\mathcal{F}_{jt}$ is the set of sector j firms present at time t, F_{jt} is their number ($F_{jt} = |\mathcal{F}_{jt}|$), and $\tilde{f}_j$ denotes the fringe firm. Heterogeneous firms have oligopolistic and oligopsonistic market power in domestic goods and labor markets, whereas fringe firms act as monopolistic competitors.[1] The remainder of the economy is composed of the commodity and service sectors $\mathcal{J}_{\text{NM}} = [0, 1]/\mathcal{J}_{\text{M}}$, where there are only fringe firms. Firm entry and export status are exogenous, with $\mathcal{F}^F_{jt} \subset \mathcal{F}_{jt}$ denoting the set of sector j exporters at time t.

Households. A representative household supplies labor and owns the country's capital stock and all the firms. It has perfect foresight and maximizes the present discounted value of utility given by GHH preferences (Greenwood et al., 1988):

$$\begin{aligned}
&\max_{\{C_t, L_t\}} \sum_{t=0}^{\infty} \beta^t U\left(C_t - \bar{\psi}_t \frac{L_t^{1+\frac{1}{\psi}}}{1 + \frac{1}{\psi}}\right) \\
&s.t. \\
&P_t(C_t + I_t) = W_t L_t + \varrho_t K_t + \Pi_t + T_t + \mathcal{D}_t \quad \forall t,
\end{aligned}$$

where β is the discount rate, C_t and I_t are consumption and investment whose price is P_t, L_t is the composite labor earning the wage index W_t, K_t and ϱ_t are the capital stock and the rental price of capital, Π_t is aggregate profits, T_t is the lump sum transfer from the government, and $\mathcal{D}_t$ is a transfer from abroad (trade deficit).

A household chooses investment I_t to accumulate capital, which evolves according to:

$$K_{t+1} = (1 - \delta)K_t + \Xi_t I_t, \tag{2.1}$$

where δ is the depreciation rate and Ξ_t is the investment-specific technology shock (Greenwood et al., 1988), that captures technological changes in the production of new capital (e.g., improvements in

[1] Fringe firms can be interpreted as a continuum of atomistic homogeneous firms, whose mass is normalized to one.

computing power or robotization), with higher values increasing capital stock accumulation. Utility maximization leads to the following Euler equation:

$$U'_t = \beta \frac{\Xi_t}{\Xi_{t+1}} U'_{t+1} \left(\frac{\Xi_{t+1} \varrho_{t+1}}{P_{t+1}} + (1-\delta) \right). \tag{2.2}$$

Capital accumulation is the only source of dynamics in this model. Conditional on the capital stock, within-period allocations are static. Therefore, in describing the within-period allocations below, we omit time subscripts in order to streamline notation.

The household provides differentiated workers to firms and sectors, with the composite labor L taking a CES form with two nests (Berger et al., 2022):

$$L = \left(\int_0^1 L_j^{\frac{\theta+1}{\theta}} \mathrm{d}j \right)^{\frac{\theta}{\theta+1}}, \qquad L_j = \left(F_j^{\frac{1}{\eta}} \sum_{f \in \mathcal{F}_j} l_{fj}^{\frac{\eta+1}{\eta}} \right)^{\frac{\eta}{\eta+1}}, \tag{2.3}$$

where L_j is sectoral employment and l_{fj} is employment in firm f. This formulation allows for imperfect substitution of workers both within and across sectors, with the elasticities of substitution η and θ subsequently shaping firms' labor market power. Guided by existing evidence, we assume that jobs within sectors are more substitutable than jobs across sectors, $\eta > \theta$. The sectoral labor aggregate is normalized by the number of firms to neutralize the love-of-variety effects. The aggregate and sectoral wage indices are:

$$W = \left(\int_0^1 W_j^{1+\theta} \mathrm{d}j \right)^{\frac{1}{1+\theta}} \qquad \text{and} \qquad W_j = \left(\frac{1}{F_j} \sum_{f \in \mathcal{F}_j} w_{fj}^{1+\eta} \right)^{\frac{1}{1+\eta}},$$

where w_{fj} is wage paid by firm f. The aggregate labor supply is given by

$$L = \left(\frac{1}{\bar{\psi}} \frac{W}{P} \right)^{\psi}. \tag{2.4}$$

Sectors. An aggregating firm within each sector j combines the output of individual firms into a sectoral Home good Y_j^H that is sold at price P_j^H:

$$Y_j^H = \left[F_j^{-\frac{1}{\sigma}} \sum_{f \in \mathcal{F}_j} (y_{fj}^H)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad \text{and} \quad P_j^H = \left[\frac{1}{F_j} \sum_{f \in \mathcal{F}_j} (p_{fj}^H)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \tag{2.5}$$

where y_{fj}^H is the quantity of firm f output demanded in domestic markets, p_{fj}^H is firm f's domestic price, and σ is the elasticity of substitution across firms within a sector. Note that the Home sector j output is also normalized by the number of firms to neutralize the love-for-variety effects.[2]

[2]CES aggregators with substitution elasticities above 1 have the well-known property that the aggregate increases in the number of units (here, firms). We neutralize this effect with the eye towards the quantitative implementation. In our data, the number of firms rises substantially over time. Without un-doing love-for-variety, the quantitative model would

The home bundle Y_j^H is combined with the foreign Y_j^F into a sectoral aggregate Y_j:

$$Y_j = \left[(Y_j^H)^{\frac{\rho-1}{\rho}} + (Y_j^F)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \quad \text{and} \quad P_j = \left[(P_j^H)^{1-\rho} + (P_j^F)^{1-\rho} \right]^{\frac{1}{1-\rho}},$$

where ρ is the elasticity of substitution between Home and Foreign goods, P_j^F is the price of Y_j^F that is exogenous from Home's perspective, and P_j is the price of Y_j. The shares of imports and domestically-produced goods in total sector j expenditure are $\lambda_j^F = (P_j^F/P_j)^{1-\rho}$ and $\lambda_j^H = 1 - \lambda_j^F$, respectively.

The sectoral aggregate has two uses: consumption/investment for households and intermediate inputs for firms. Perfectly competitive producers use constant-returns-to-scale Cobb-Douglas technologies to produce C at price P (and same for I):

$$C = \exp\left(\int_0^1 \alpha_j \ln Y_j^C \mathrm{d}j \right) \quad \text{and} \quad P = \exp\left(\int_0^1 \alpha_j \ln\big(P_j/\alpha_j\big) \mathrm{d}j \right) \text{ where } \int_0^1 \alpha_j \mathrm{d}j = 1,$$

and to produce intermediate inputs M_i used by sector i at price P_i^M:

$$M_i = \exp\left(\int_0^1 \gamma_i^j \ln Y_{j,i}^M \mathrm{d}j \right) \quad \text{and} \quad P_i^M = \exp\left(\int_0^1 \gamma_i^j \ln\Big(P_j/\gamma_i^j\Big) \mathrm{d}j \right) \text{ where } \int_0^1 \gamma_i^j \mathrm{d}j = 1, \quad \forall i \in [0,1].$$

Parameters α_i and γ_i^j are the Cobb-Douglas cost shares, and Y_j^C and $Y_{j,i}^M$ are sector j outputs demanded by final consumption and for intermediate use by sector i, respectively.

Firms. Each heterogeneous firm produces a unique variety using labor l_{fj}, capital k_{fj}, and intermediate inputs m_{fj}, with exogenous productivity a_{fj}:

$$y_{fj} = a_{fj} l_{fj}^{\gamma_j^L} k_{fj}^{\gamma_j^K} m_{fj}^{\gamma_j^M}, \qquad \gamma_j^L + \gamma_j^K + \gamma_j^M = \gamma_j.$$

Production is subject to returns to scale γ_j, with γ_j^L, γ_j^K, and γ_j^M denoting elasticities of output with respect to factor and intermediate inputs. Each firm faces downward-sloping CES demands:

$$y_{fj}^H = \frac{1}{F_j} (p_{fj}^H)^{-\sigma} (P_j^H)^{\sigma-\rho} P_j^{\rho-1} E_j, \qquad y_{fj}^F = (p_{fj}^F)^{-\sigma} D_{fj}, \tag{2.6}$$

where E_j is the total sector j domestic expenditure that the firm takes as given. Firms are potentially oligopolistic in the domestic goods market: they internalize the impact of their own price p_{fj}^H on P_j^H and P_j. Export demand y_{fj}^F is a function of the export price p_{fj}^F and a firm-specific exogenous foreign

interpret the increasing number of firms as increasing real output. However, our quantification will target data on sectoral real output and price indices, and national statistical agencies do not incorporate love-for-variety when they construct these objects. To make the model consistent with the targets for quantification, our sectoral aggregates are also set up not to exhibit love-for-variety. Section 4.4 and Appendix Table B13 report the results without neutralizing love-for-variety, and show that the main conclusions of the counterfactual exercises are unchanged.

demand shifter D_{fj}, that includes any iceberg trade costs. For non-exporters, $D_{fj} = 0$. We assume that South Korean firms are monopolistically competitive in the foreign market. Firms allocate their output to domestic and foreign markets subject to the following resource constraint:

$$y_{fj} = y_{fj}^H + y_{fj}^F. \tag{2.7}$$

Each firm faces an upward-sloping labor supply curve, potentially allowing it to exercise two forms of labor market power:

$$l_{fj} = \frac{1}{F_j} w_{fj}^{\eta} W_j^{\theta-\eta} W^{-\theta} L. \tag{2.8}$$

By internalizing how its labor demand affects the wage w_{fj}, a firm can exercise monopsonistically competitive power. Additionally, by internalizing how its labor demand affects the sectoral wage W_j, a firm can exercise oligopsony power. All firms take the aggregate wage index W as given.

Firms maximize their profits:

$$\pi_{fj} = \max_{\{y_{fj}^H, y_{fj}^F, l_{fj}, k_{fj}, m_{fj}\}} \left\{ p_{fj}^H y_{fj}^H + p_{fj}^F y_{fj}^F - (1+\tau_{fj}^L) w_{fj} l_{fj} - (1+\tau_{fj}^K) \varrho k_{fj} - P_j^M m_{fj} \right\},$$

subject to the resource constraint (2.7) and demand and labor supply functions (2.6) and (2.8). In hiring labor and capital firms potentially face exogenous distortions, τ_{fj}^L and τ_{fj}^K, which are interpreted as taxes or subsidies to labor and capital inputs. The rental rate of capital ϱ is common across all firms.

The domestic goods and labor market structure is Cournot. Firms set quantities to maximize their own profits, taking as given foreign quantity supplied Y_j^F, and the vectors of domestic quantities supplied $\mathbf{y}_{-fj}^H$, and of labor employed $\mathbf{l}_{-fj}$, by all the other firms in the sector.

Profit maximization implies that the marginal revenues should equal the marginal costs of labor, as implied by the first-order condition with respect to l_{fj}:

$$p_{fj}^H \left(1 - \frac{1}{\varepsilon_{fj}}\right) \frac{\partial y_{fj}}{\partial l_{fj}} = p_{fj}^F \left(1 - \frac{1}{\sigma}\right) \frac{\partial y_{fj}}{\partial l_{fj}} = (1+\tau_{fj}^L)\left(1 + \frac{1}{\varepsilon_{fj}^L}\right) w_{fj}, \tag{2.9}$$

where ε_{fj} is the elasticity of domestic demand and ε_{fj}^L is the elasticity of labor supply. Both of these are firm-specific, since firms can exercise market power in both domestic product and labor markets. The first two terms in (2.9) are the marginal revenue products of labor in the domestic and foreign markets; the third term is the marginal cost of labor.

In turn, the two elasticities can be written as functions of exogenous model parameters and endogenous shares:

$$\varepsilon_{fj} = -\left(\left. \frac{\partial \ln p_{fj}^H}{\partial \ln y_{fj}^H} \right|_{\mathbf{y}_{-fj}^H, Y_j^F} \right)^{-1} = \left[\frac{1}{\sigma} + \left(\frac{1}{\rho} - \frac{1}{\sigma}\right) s_{fj}^H + \left(1 - \frac{1}{\rho}\right) \lambda_j^H s_{fj}^H \right]^{-1} \tag{2.10}$$

and

$$\varepsilon_{fj}^{L} = \left(\frac{\partial \ln w_{fj}}{\partial \ln l_{fj}} \bigg|_{\mathbf{l}_{-fj}} \right)^{-1} = \left[\frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta} \right) s_{fj}^{L} \right]^{-1}, \tag{2.11}$$

where s_{fj}^{H} is the share of firm f in the total sector j firms' domestic revenue, and s_{fj}^{L} is the share of firm f in the sector j wage bill. Expressed as functions of these elasticities, domestic (μ_{fj}^{H}) and exporting (μ_{fj}^{F}) markups and wage markdowns μ_{fj}^{L} are:

$$\mu_{fj}^{H} = \frac{\varepsilon_{fj}}{\varepsilon_{fj} - 1}, \qquad \mu_{fj}^{F} = \frac{\sigma}{\sigma - 1}, \qquad \mu_{fj}^{L} = \frac{\varepsilon_{fj}^{L} + 1}{\varepsilon_{fj}^{L}}. \tag{2.12}$$

Firms with larger domestic sales shares s_{fj}^{H} face more inelastic demand and charge higher domestic markups over marginal cost. This size-elasticity correlation is mediated by foreign competition (as in, e.g. Edmond et al., 2015): when foreign competition is greater—captured by a lower λ_{j}^{H}—all firms face more elastic demand and all markups are lower. Moreover, firms with a larger sectoral wage bill share s_{fj}^{L} face more inelastic labor supply and impose higher wage markdowns. Note that the export markup μ_{fj}^{F} is common across firms, consistent with our assumption that these firms are globally small and monopolistically competitive in foreign markets.[3] The fringe firms face the same demand and labor supply functions. However, because they do not exert oligopolistic and oligopsonistic power, they charge constant markups and markdowns as in the standard monopolistically competitive models: $\mu_{\tilde{f}j}^{H} = \sigma/(\sigma - 1)$ and $\mu_{\tilde{f}j}^{L} = (\eta + 1)/\eta$.

The firm's unit cost function is:

$$c_{fj} = \left[\frac{y_{fj}^{1-\gamma_j}}{a_{fj}} \left(\frac{\mu_{fj}^{L}(1 + \tau_{fj}^{L}) w_{fj}}{\gamma_{j}^{L}} \right)^{\gamma_{j}^{L}} \left(\frac{(1 + \tau_{fj}^{K})\varrho}{\gamma_{j}^{K}} \right)^{\gamma_{j}^{K}} \left(\frac{P_{j}^{M}}{\gamma_{j}^{M}} \right)^{\gamma_{j}^{M}} \right]^{\frac{1}{\gamma_j}}. \tag{2.13}$$

Marginal cost is decreasing in productivity and increasing in different input distortions. When returns to scale γ_j differ from 1, marginal cost varies with the scale of production. The markups are applied to this marginal cost.

To summarize, each firm is characterized by 4 primitive shocks: a_{fj}, τ_{fj}^{L}, τ_{fj}^{K}, D_{fj}. These shocks together with supply and demand features (such as variable returns to scale) and endogenous decisions (such as pricing) affect both the firm size distribution and the macro outcomes. Appendix A states the market clearing conditions and defines the equilibrium in this economy.

Road map. The main goal of the paper is to develop a unified framework for macro (growth) and micro (concentration) accounting and implement it on firm-level data. With that goal in mind, the

[3] In spite of its rapid growth, South Korea is still a small economy when measured against the world market. In 2011, imports from South Korea on average accounted for 3% of total absorption in manufacturing sectors in foreign destinations (source: World Input-Output Database). This average sectoral share is of course an upper bound on firm-level sales shares. By contrast, the share of domestically produced goods in South Korea's manufacturing absorption in 2011 was 77%, highlighting the disparity in South Korean firms' potential market power in domestic vs. export destinations.

rest of the section goes through 4 results. The first is aggregation: we derive the macro objects relevant for growth accounting, and relate them to the potentially observable firm-level data and (yet) unobservable shocks to be recovered. Second, we develop a decomposition of the concentration ratio into additive components, implementable using the same micro data and shocks. This proposition allows us to determine the drivers of the change in concentration in Figure 1. Thus, the first two results define the theoretically-consistent objects for growth and concentration accounting, and set targets for the subsequent measurement. The third proposition shows that in a distorted economy, concentration and aggregate productivity have an ambiguous relationship: a micro shock that increases concentration could either raise or lower aggregate TFP. This theoretical ambiguity naturally highlights the need for measurement and quantification. The fourth proposition paves the way to quantification by establishing that the required micro primitives – the 4 firm-level shocks – can be recovered from observed data on market shares.

2.2 Aggregation and National Accounting

We begin with a proposition relating sectoral and aggregate objects of interest—output, productivity, markups—to firm primitives. To start, define the sectoral producer price index (PPI) as:

$$PPI_j = \left(\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\tilde{p}_{fj}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \qquad \text{with} \qquad \tilde{p}_{fj} = p^H_{fj}\frac{y^H_{fj}}{y_{fj}} + p^F_{fj}\frac{y^F_{fj}}{y_{fj}}, \tag{2.14}$$

where $\tilde{p}_{fj}$ is the firm-level quantity-weighted average of domestic and export prices. The reason behind this definition is that a first-order expansion of (2.14) approximates the total-sales-weighted average of firm-level prices, and thus mimics the PPI constructed by the national statistical agencies. The functional form of PPI_j can be viewed as a modification of the closed-economy CES welfare-relevant price index. Note that in an open economy PPI_j is not the welfare-relevant price index as it does not include foreign import prices and includes some export prices.[4] Denote total firm revenue $r_{fj} = r^H_{fj} + r^F_{fj}$ as the sum of revenues in domestic and foreign markets: $r^e_{fj} = p^e_{fj}y^e_{fj}$ for $e \in \{H, F\}$. Next define the real gross sectoral output as the nominal gross revenue $R_j \equiv \sum_{f\in\mathcal{F}_j} r_{fj}$ deflated by the PPI:

$$Y^r_j = \frac{R_j}{PPI_j}.$$

These definitions allow us to derive useful analytical aggregation formulas. We characterize two notions of productivity at both the firm and the sectoral level: the productivity for generating physical output—denoted by a_{fj} and A_j—and the productivity for generating revenue—denoted by $tfpr_{fj}$

[4] In the closed-economy case, achieved by letting $D_{fj} \to 0\ \forall f$ and $P^F_j \to \infty$, it converges to the welfare-relevant ideal price index: $PPI_j \to P_j$.

and $TFPR_j$:

$$a_{fj} = \frac{y_{fj}}{l_{fj}^{\gamma_j^L} k_{fj}^{\gamma_j^K} m_{fj}^{\gamma_j^M}}, \quad A_j = \frac{Y_j^r}{L_j^{\gamma_j^L} K_j^{\gamma_j^K} M_j^{\gamma_j^M}}, \quad tfpr_{fj} = \frac{r_{fj}}{l_{fj}^{\gamma_j^L} k_{fj}^{\gamma_j^K} m_{fj}^{\gamma_j^M}}, \quad TFPR_j = \frac{R_j}{L_j^{\gamma_j^L} K_j^{\gamma_j^K} M_j^{\gamma_j^M}},$$

where $L_j = \left(F_j^{\frac{1}{\eta}} \sum_{f \in \mathcal{F}_j} l_{fj}^{\frac{\eta+1}{\eta}}\right)^{\frac{\eta}{\eta+1}}$, $K_j = \sum_{f \in \mathcal{F}_j} k_{fj}$, and $M_j = \sum_{f \in \mathcal{F}_j} m_{fj}$ represent sectoral aggregates of labor, capital, and material inputs. From these expressions, our notion of the sectoral production function $Y_j^r = A_j L_j^{\gamma_j^L} K_j^{\gamma_j^K} M_j^{\gamma_j^M}$ holds by definition.

In defining sectoral markups and markdowns we rely on the notion that revenue shares of flexible inputs are characterized by a ratio of output elasticities, markups and markdowns (see De Loecker and Warzynski, 2012; Yeh et al., 2022). Based on this property, we can back out sectoral markups $\mathcal{M}_j$ and markdowns $\mathcal{M}_j^L$ by comparing sectoral factor shares to output elasticities γ_j^M and γ_j^L (Yeh et al., 2022; Edmond et al., 2023):

$$\mathcal{M}_j = \gamma_j^M \left(\frac{P_j^M M_j}{R_j}\right)^{-1} \quad \text{and} \quad \mathcal{M}_j \mathcal{M}_j^L = \gamma_j^L \left(\frac{(1+\tau_j^L) W_j L_j}{R_j}\right)^{-1}, \tag{2.15}$$

where $W_j L_j = \sum_{f \in \mathcal{F}_j} w_{fj} l_{fj}$ and the sectoral labor distortion is a wage-bill-weighted average of firm-level distortions: $(1+\tau_j^L) = \sum_{f \in \mathcal{F}_j} s_{fj}^L (1+\tau_{fj}^L)$. The sectoral markup $\mathcal{M}_j$ is the wedge between the sectoral output elasticity of a flexible input—materials—and its revenue share. The sectoral markdown $\mathcal{M}_j^L$ is the part of the wedge between the sectoral output elasticity of labor inputs and the labor shares that is not accounted for by the sectoral markup and the sectoral labor distortion.

Proposition 2.1 now states the formulas for sectoral real output, productivity, markups, markdowns as functions of firm-level primitives, markups, markdowns, and observable shares.

Proposition 2.1. ***(Aggregation)***
(i) Real gross output of each sector can be expressed in terms of a sectoral production function:

$$Y_j^r = A_j L_j^{\gamma_j^L} K_j^{\gamma_j^K} M_j^{\gamma_j^K} \quad \text{with} \quad A_j = \left[\frac{1}{F_j} \sum_{f \in \mathcal{F}_j} \left(a_{fj} \frac{TFPR_j}{tfpr_{fj}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}, \tag{2.16}$$

where the ratio of relative revenue productivities $TFPR_j / tfpr_{fj}$ reflects within-sector variation in firms' total sectoral revenue shares $s_{fj} = \frac{r_{fj}}{R_j}$ and in firm marginal revenue products:

$$\frac{TFPR_j}{tfpr_{fj}} = s_{fj}^{\gamma_j - 1} \left(\frac{\widetilde{MRPL}_j}{\widetilde{mrpl}_{fj}}\right)^{\gamma_j^L} \left(\frac{\widetilde{MRPK}_j}{\widetilde{mrpk}_{fj}}\right)^{\gamma_j^K} \left(\frac{\widetilde{MRPM}_j}{\widetilde{mrpm}_{fj}}\right)^{\gamma_j^M},$$

where $\widetilde{mrpv}_{fj}$, $v \in \{l, k, m\}$ are markup-adjusted marginal revenue products, and $\widetilde{MRPV}_j$, $V \in \{L, K, M\}$

are their sectoral aggregations. Their functional forms are stated in equations (A.4) and (A.5).

(ii) The sectoral markup $\mathcal{M}_j$ and markdown $\mathcal{M}_j^L$ can be expressed as weighted averages of firm-level markups $\tilde{\mu}_{fj}$ and markdowns μ_{fj}^L:

$$\mathcal{M}_j = \left(\sum_{f \in \mathcal{F}_j} \tilde{\mu}_{fj}^{-1} s_{fj} \right)^{-1} \qquad \textit{and} \qquad \mathcal{M}_j^L = \frac{\left(\sum_{f \in \mathcal{F}_j} (\tilde{\mu}_{fj} \mu_{fj}^L)^{-1} s_{fj} \right)^{-1}}{\left(\sum_{f \in \mathcal{F}_j} \tilde{\mu}_{fj}^{-1} s_{fj} \right)^{-1}}, \tag{2.17}$$

where $\tilde{\mu}_{fj}$ is the within-firm average of domestic and foreign markups:

$$\tilde{\mu}_{fj} = \mu_{fj}^H \frac{y_{fj}^H}{y_{fj}} + \mu_{fj}^F \frac{y_{fj}^F}{y_{fj}}.$$

Proof. See Appendix A. □

The aggregation results in Proposition 2.1 are open-economy generalizations of existing aggregation results. For instance, the expressions for sectoral productivity in part (i) generalize those in Hsieh and Klenow (2009) and Ruzic and Ho (2023) to the open economy case, as they feature the total sales shares s_{fj} and the markups $\tilde{\mu}_{fj}$ that average across domestic and export destinations. The definition of the sectoral markup $\mathcal{M}_j$ in part (ii) is similar to the aggregation in Edmond et al. (2015) and Edmond et al. (2023), with the difference being the use of $\tilde{\mu}_{fj}$, the within-firm average of domestic and foreign markups. Similarly, the result that the product of the sectoral markup $\mathcal{M}_j$ and markdown $\mathcal{M}_j^L$ can be expressed as the sales-weighted harmonic weighted average of the product of μ_{fj}^L and $\tilde{\mu}_{fj}$ parallels the closed-economy case in Yeh et al. (2022).[5]

National accounts and aggregate productivity. From now onwards we reinsert the time index t. National accounting conventions define aggregate real GDP at year t as output evaluated at base prices (prices at the base year $t-1$) minus real inputs also evaluated at the base year input prices:

$$Y_t^r = \int_0^1 (PPI_{j,t-1} Y_{jt}^r - P_{j,t-1}^M M_{jt}) \mathrm{d}j. \tag{2.18}$$

The change in real GDP between $t-1$ and t is then:

$$\hat{Y}_t^r = \int_0^1 \Omega_{j,t-1} (\hat{Y}_{jt}^r - S_{j,t-1}^M \hat{M}_{jt}) \mathrm{d}j,$$

[5] We nest the closed economy case by letting $D_{fj} \to 0 \; \forall f, j$ and $P_j^F \to \infty \; \forall j$. The expressions for sectoral markups and markdowns in (2.17) would in that case be identical to those in Yeh et al. (2022) and Edmond et al. (2023). Edmond et al. (2015) also studies the open economy setup. However, our expression for the sectoral markup differs slightly from theirs: our within-firm markup $\tilde{\mu}_{fj}$ is quantity-weighted while theirs is revenue-weighted, with the difference arising from the way we define PPI_j and Y_j^r.

where the "hat" denotes time-series changes, $S^M_{j,t-1} = \frac{P^M_{j,t-1} M_{j,t-1}}{R_{j,t-1}}$ are the shares of material expenditures in nominal gross output, and $\Omega_{j,t-1} = \frac{R_{j,t-1}}{Y^r_{t-1}}$ is the Domar weight.[6] Aggregate productivity A_t is then a Domar aggregation of sectoral productivities (Hulten, 1978):

$$A_t = \int_0^1 \Omega_{j,t-1} A_{jt} \mathrm{d}j. \tag{2.19}$$

We define the aggregate markup $\mathcal{M}_t$ and markdown $\mathcal{M}^L_t$ as sales-weighted averages of their sectoral counterparts:

$$\mathcal{M}_t = \left(\int_0^1 \mathcal{M}_{jt}^{-1} S_{j,t-1} \mathrm{d}j \right)^{-1}, \qquad \mathcal{M}^L_t = \frac{\left(\int_0^1 (\mathcal{M}_{jt} \mathcal{M}^L_{jt})^{-1} S_{j,t-1} \mathrm{d}j \right)^{-1}}{\left(\int_0^1 \mathcal{M}_{jt}^{-1} S_{j,t-1} \mathrm{d}j \right)^{-1}}, \tag{2.20}$$

where $S_{j,t-1} = \frac{R_{j,t-1}}{\int_0^1 R_{i,t-1} \mathrm{d}i}$ are sectoral revenue shares.

2.3 Concentration Ratio Decomposition

With a view to explaining the change in concentration in Figure 1 through firm primitives, we now state a proposition that decomposes concentration into its firm-level determinants. The objects of the proposition are the sales share of the top 3 firms within a sector CR^3_{jt}, and the manufacturing-wide sales concentration ratio for the top-3 firms CR^3_t:

$$CR^3_{jt} = \frac{\sum_{f \in \mathcal{F}^3_{jt}} r_{fjt}}{\sum_{f \in \mathcal{F}_{jt}} r_{fjt}} \qquad \text{and} \qquad CR^3_t = \frac{\sum_{j \in \mathcal{J}_M} \sum_{f \in \mathcal{F}^3_{jt}} r_{fjt}}{\sum_{j \in \mathcal{J}_M} \sum_{f \in \mathcal{F}_{jt}} r_{fjt}},$$

where $\mathcal{F}^3_{jt}$ is the set of top 3 firms in sector j at time t. We state the proposition for the top-3 firm share, but there is nothing specific about 3: it could as easily be stated for any set of top firms.

A firm's role in concentration growth will be captured by two terms: productivity-cum-domestic distortions $\tilde{a}_{fjt}$ and export demand ϕ_{fjt}. The first term, $\tilde{a}_{fjt}$, combines a firm's Hicks-neutral productivity a_{fjt} and the relative marginal revenue products of the firm's inputs:

$$\tilde{a}_{fjt} = a_{fjt} \left(\frac{\widetilde{MRPL}_{jt}}{\widetilde{mrpl}_{fjt}} \right)^{\gamma^L_j} \left(\frac{\widetilde{MRPK}_{jt}}{\widetilde{mrpk}_{fjt}} \right)^{\gamma^K_j} \left(\frac{\widetilde{MRPM}_{jt}}{\widetilde{mrpm}_{fjt}} \right)^{\gamma^M_j}.$$

The marginal revenue product ratios summarize the product and factor market distortions across firms in a sector. Within-sector concentration is shaped by a firm's $\tilde{a}_{fjt}$ relative to the sectoral average $\tilde{A}_{jt} = (F_{jt})^{\frac{1}{\sigma-1}} A_{jt}$, defined as sectoral productivity A_{jt} adjusted for the number of firms F_{jt}.

[6] See, e.g. Burstein and Cravino (2015), Huo et al. (2023), and di Giovanni et al. (2024).

The export demand term ϕ_{fjt} takes the value of 1 for non-exporting firms; otherwise it reflects two distinct channels through which firm-specific participation in international trade shapes sectoral concentration:

$$\phi_{fjt} = \frac{(\tilde{D}^{MA}_{fjt})^{\frac{\sigma}{\sigma-1}-\gamma_j}}{(\tilde{D}^{RTS}_{fjt})^{1-\gamma_j}}.$$

In turn, $\tilde{D}^{MA}_{fjt}$ captures the importance of export market access for firm size and $\tilde{D}^{RTS}_{fjt}$ captures the extent to which export demand can change marginal costs through returns-to-scale:

$$\tilde{D}^{MA}_{fjt} = \left(\frac{\tilde{\mu}_{fjt}}{\mu^H_{fjt}}\right)^{\sigma-1} + \left(\frac{\tilde{\mu}_{fjt}}{\mu^F_{fjt}}\right)^{\sigma-1} \tilde{D}_{fjt}, \qquad \text{and} \qquad \tilde{D}^{RTS}_{fjt} = \left(\frac{\tilde{\mu}_{fjt}}{\mu^H_{fjt}}\right)^{\sigma} + \left(\frac{\tilde{\mu}_{fjt}}{\mu^F_{fjt}}\right)^{\sigma} \tilde{D}_{fjt}.$$

The importance of each channel reflects firm-specific demand from the rest of the world, $\tilde{D}_{fjt} = \frac{D_{fjt}}{\frac{1}{F_j}(P^H_j)^{\sigma-\rho}P^{\rho-1}_j E_j}$, and the firm's differential market power domestically and abroad $\tilde{\mu}_{fjt}/\mu^F_{fjt}$. Within-sector concentration is shaped by a firm's ϕ_{fjt} compared to the sectoral average Φ_{jt}:

$$\Phi_{jt} = \left(\sum_{f\in\mathcal{F}_{jt}} s_{fjt}\phi^{1-\sigma}_{fjt}\right)^{\frac{1}{1-\sigma}}.$$

Proposition 2.2. ***(Concentration Ratio)***
(i) Changes in sectoral concentration CR^3_{jt} between $t-p$ and t can be decomposed as:

$$\ln\frac{CR^3_{jt}}{CR^3_{j,t-p}} = \underbrace{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}\left[\sum_{f\in\mathcal{F}^{3,cont}_{j,t,t-p}} \omega_{fjt,t-p}\left(\ln\frac{\tilde{a}_{fjt}/\tilde{A}_{jt}}{\tilde{a}_{fj,t-p}/\tilde{A}_{j,t-p}} + \ln\frac{\phi_{fjt}/\Phi_{jt}}{\phi_{fj,t-p}/\Phi_{j,t-p}}\right)\right]}_{\textit{Continuing top-3 firms}} \underbrace{-\ln\frac{S^{3,cont}_{jt}}{S^{3,cont}_{j,t-p}}}_{Entry/exit}, \tag{2.21}$$

where the weights $\omega_{fjt,t-p}$ are in (A.14), and $S^{3,cont}_{j,t-p}$ and $S^{3,cont}_{jt}$ are the sales shares of the set of firms that are in the top 3 in both t and $t-p$ in total top-3 sales at $t-p$ and t, respectively, as in (A.15).

(ii) Changes in aggregate concentration CR_t^3 between $t-p$ and t can be approximated as follows:

$$\begin{aligned}\ln\frac{CR_t^3}{CR_{t-p}^3} &\approx \sum_{j\in\mathcal{J}_M}\omega_{j,t-p}^3\left(\ln\frac{CR_{jt}^3}{CR_{j,t-p}^3}+\ln\frac{S_{jt}}{S_{j,t-p}}\right)\\ &= \underbrace{\sum_{j\in\mathcal{J}_M}\omega_{j,t-p}^3\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}\left(\sum_{f\in\mathcal{F}_{jt,t-p}^{3,cont}}\omega_{fjt,t-p}\left(\ln\frac{\tilde{a}_{fjt}/\tilde{A}_{jt}}{\tilde{a}_{fj,t-p}/\tilde{A}_{j,t-p}}+\ln\frac{\phi_{fjt}/\Phi_{jt}}{\phi_{fj,t-p}/\Phi_{j,t-p}}\right)\right)}_{\text{Continuing top 3 firms}}\\ &\quad -\underbrace{\sum_{j\in\mathcal{J}_M}\omega_{j,t-p}^3\ln\frac{S_{jt}^{3,cont}}{S_{j,t-p}^{3,cont}}}_{\text{Entry/exit}}+\underbrace{\sum_{j\in\mathcal{J}_M}\omega_{j,t-p}^3\ln\frac{S_{jt}}{S_{j,t-p}}}_{\text{Sectoral reallocation}},\end{aligned} \tag{2.22}$$

where $\omega_{j,t-p}^3$ is the share of the top-3 firms in sector j in the combined sales of all top-3 firms from all sectors, as in (A.16).

Proof. See Appendix A. □

Equation (2.21) decomposes the change in concentration into components due to continuing top-3 firms and to the turnover among the top-3 firms. In turn, the continuing top-3 firms contribute to changing concentration either through differential growth in $\tilde{a}_{fjt}/\tilde{A}_{jt}$—encompassing both productivity and distortions—or through differential access to exporting, ϕ_{fjt}/Φ_{jt}. At the same time, between any two periods $t-p$ and t the set of top-3 firms might change. The "entry/exit" term captures the impact of turnover in the top 3 on concentration by comparing the market shares of the firms entering vs. exiting the top 3 between $t-p$ and t, in a manner similar to the Feenstra (1994) correction for entry and exit of new product varieties. When the new entrants into the top 3 are, for instance, more productive than the exiters from the top 3, then this turnover term contributes positively to the rise in concentration.

As we aggregate the within-sector changes up to manufacturing-wide concentration in equation (2.22), the decomposition additionally features a sectoral reallocation term. It captures the changes in the aggregate CR_t^3 due to changes in sectoral shares either towards or away from sectors with the largest firms economywide. The intersectoral reallocation between periods $t-p$ and t could be due, for instance, to differential productivity trends across sectors, or to sector-level shifts in the household, producer, or foreign demand.

2.4 Concentration and Aggregate Productivity

This section uses a simplified version of the model to state a proposition connecting sectoral concentration and productivity. In particular, it states conditions under which an increase in concentration following a shock to firm productivity, distortions, or export demand is accompanied by an increase or a decrease in sectoral TFP A_{jt}.

Proposition 2.3. ***(Concentration and Productivity)***
When firms (a) are monopolistically competitive in product markets, (b) competitively hire labor ($\eta \rightarrow \infty$), and (c) face export demand that scales with domestic demand ($\tilde{D}_{fjt}$ constant at the firm level), then:

(i) higher productivity a_{fjt} increases a firm's market share s_{fjt} but lowers sectoral productivity A_{jt} if:

$$\underbrace{\sum_{V\in\{K,L,M\}} \frac{\gamma_j^V}{\gamma_j} \frac{\widetilde{MRPV}_{jt}}{\widetilde{mrpv}_{fjt}}}_{\text{Firm's relative subsidy}} \geq \frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1 + \frac{(\phi_{fjt}/\Phi_{jt})^{1-\sigma} - 1}{\sigma}\right);$$

(ii) higher subsidy $\frac{1}{(1+\tau_{fjt}^V)}$, $V = K, L$, increases a firm's market share s_{fjt} but lowers sectoral productivity A_{jt} if:

$$\underbrace{\sum_{V\in\{K,L,M\}} \frac{\gamma_j^V}{\gamma_j} \frac{\widetilde{MRPV}_{jt}}{\widetilde{mrpv}_{fjt}}}_{\text{Firm's relative subsidy}} \geq \frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1 + \frac{(\phi_{fjt}/\Phi_{jt})^{1-\sigma} - 1}{\sigma}\right) - \left(\frac{\frac{\sigma}{\sigma-1}}{\gamma_j} - 1\right)\frac{\widetilde{MRPV}_{jt}}{\widetilde{mrpv}_{fjt}};$$

(iii) higher export demand $\tilde{D}_{fjt}$ increases a firm's market share s_{fjt} but lowers sectoral productivity A_{jt} if:

$$\underbrace{\sum_{V\in\{K,L,M\}} \frac{\gamma_j^V}{\gamma_j} \frac{\widetilde{MRPV}_{jt}}{\widetilde{mrpv}_{fjt}}}_{\text{Firm's relative subsidy}} \geq 1 + \frac{\gamma_j - 1}{\gamma_j}\left(\left(\frac{\Phi_{jt}}{\phi_{fjt}}\right)^{\sigma-1} - 1\right).$$

Reversing the inequalities in (i)-(iii) defines the conditions under which higher a_{fjt}, $\frac{1}{(1+\tau_{fjt}^V)}$, and $\tilde{D}_{fjt}$ instead simultaneously increase a firm's market share s_{fjt} and raise sectoral productivity A_{jt}.

Proof. See Appendix A. □

The proposition says that following a shock to a_{fjt}, τ_{fjt}^L, τ_{fjt}^K, or $\tilde{D}_{fjt}$ that increases a top firm f's sectoral sales share (and by extension the sector's concentration), A_{jt} can go up or down depending on parameter values. Essentially, A_{jt} falls if the firm receiving a positive shock is sufficiently subsidized to start with (meaning, it faces sufficiently low τ_{fjt}^L and τ_{fjt}^K).

Perhaps most surprisingly, Proposition 2.3(i) shows that in a distorted world, a firm's productivity growth can reduce sectoral TFP. Sectoral TFP reflects both the productivity of firms and the (mis)allocation of resources across all firms. An increase in productivity of a firm that is already too big—i.e. whose inputs are highly subsidized relative to the other firms in the sector—exacerbates misallocation. Sectoral TFP falls when the direct effect of the firm's own higher productivity is more than offset by the worsened misallocation of inputs across all firms in the sector.

To build intuition, imagine a sector in which only one firm's inputs are subsidized while all other firms receive no subsidies. What matters for the misallocation of resources is each firm's subsidy relative to the (weighted) average of all firms' subsidies. Hence, while in absolute terms most firms receive neither a subsidy nor a tax, in a relative sense most firms are taxed. This dispersion—whereby one firm is relatively subsidized and all others are relatively taxed—leads to misallocation that lowers sectoral TFP. If the subsidized firm becomes more productive, it grows in size and increases the weighted average subsidy of the whole sector. As a result of higher productivity growth by a single firm, all other firms are now *relatively* more taxed. There is consequently more dispersion in these distortions, increasing misallocation and putting downward pressure on sectoral TFP.

Our proposition shows that there is a threshold level of the firm's initial relative input distortions above which the misallocation effect dominates the firm productivity effect. This threshold is lower and easier to surpass for a more prominent exporter ($\phi_{fjt} > \Phi_{jt}$), meaning that productivity growth by a heavily subsidized exporter is more likely to be TFP-reducing.

Proposition 2.3(ii) highlights a similar result when the increase in firm size is driven by a subsidy. If the firm is already sufficiently subsidized relative to its competitors in the sector, then a further subsidy can exacerbate the misallocation of inputs and reduce sectoral TFP. The threshold above which sectoral TFP falls with a higher subsidy is lower and easier to satisfy for a more prominent exporter ($\phi_{fjt} > \Phi_{jt}$). Also, note that it must be the case that $\frac{\sigma}{\sigma-1} \geq \gamma_j$, in order for the firm's second order condition to be satisfied. Thus the threshold for a sectoral TFP decline is easier to satisfy for the subsidy shock compared to the productivity shock in Proposition 2.3(i). In other words, there is an intermediate level of initial distortions under which a higher firm subsidy would lower sectoral TFP while a higher firm productivity would increase sectoral TFP. However, there is a high enough initial subsidy under which both a higher subsidy and higher productivity would lower sectoral TFP while increasing the firm's market share.

Lastly, Proposition 2.3(iii) shows that an increase in export demand can similarly benefit a firm's own market share but with an ambiguous impact on sectoral TFP. When a heavily subsidized firm receives an export demand shock, hiring more inputs to satisfy this new export demand could potentially misallocate inputs in the economy in a way that lowers sectoral TFP. The subsidy threshold for generating this misallocation depends both on the returns to scale and on the firm's current export status. When returns to scale are constant $\gamma_j = 1$, a positive export demand shock to a firm receiving a relative subsidy would lower sectoral TFP regardless of the firm's current export demand ϕ_{fjt}. If returns to scale are somewhat decreasing, as will be the case for many sectors in our estimation below, then the threshold for a reduction would be higher for a currently prominent exporter and lower for a non-exporter, and the opposite is true when returns are increasing.

Proposition 2.3 highlights that there is no simple one-to-one relationship between concentration and sectoral productivity: increases in concentration can coincide with either higher or lower TFP. Furthermore, different shocks feature different thresholds for when the relationship flips from positive to negative.[7] It is then ultimately an empirical and quantitative question whether the forces behind the rise in concentration contributed positively or negatively to real income and welfare. To make progress, we must jointly measure the firm-level shocks.

2.5 Recovering Shocks from Observables

We now state a proposition that provides a tight mapping between the unobservable firm primitives $(a_{fjt}, \tau^L_{fjt}, \tau^K_{fjt}, D_{fjt})$ and data. The observed shares of firm f in domestic sales, wage bills, capital, and exports are:

$$s^H_{fjt} = \frac{r^H_{fjt}}{\sum_{g\in\mathcal{F}_{jt}} r^H_{gjt}}, \quad s^L_{fjt} = \frac{w_{fjt} l_{fj}}{\sum_{g\in\mathcal{F}_{jt}} w_{gjt} l_{gjt}}, \quad s^K_{fjt} = \frac{k_{fjt}}{\sum_{g\in\mathcal{F}_{jt}} k_{gjt}}, \quad s^F_{fjt} = \frac{r^F_{fjt}}{\sum_{g\in\mathcal{F}^F_{jt}} r^F_{gjt}}.$$

Proposition 2.4. ***(Market Shares)*** *For each sector, given sectoral domestic shares $\{\lambda^H_{jt}\}_{j\in\mathcal{J}_M}$ and firm revenues in domestic and foreign markets $\{r^H_{fjt}, r^F_{fjt}\}$, the shares $\{s^H_{fjt}, s^L_{fjt}, s^K_{fjt}, s^F_{fjt}\}_{f\in\mathcal{F}_{jt}}$ satisfy the following system of $4\times|\mathcal{F}_{jt}|$ equations:*

$$s^H_{fjt} = \frac{\left(a_{fjt}^{-\frac{1}{\gamma_j}} \mu^H_{fjt} \left(\mu^L_{fjt}(1+\tau^L_{fjt})(s^L_{fjt})^{\frac{1}{\eta+1}}\right)^{\frac{\gamma^L_j}{\gamma_j}} (1+\tau^K_{fjt})^{\frac{\gamma^K_j}{\gamma_j}} (\Lambda^H_{fjt})^{\frac{\gamma_j-1}{\gamma_j}}\right)^{-\frac{\gamma_j}{\frac{\sigma}{\sigma-1}-\gamma_j}}}{\sum_{g\in\mathcal{F}_{jt}} \left(a_{gjt}^{-\frac{1}{\gamma_j}} \mu^H_{gjt} \left(\mu^L_{gjt}(1+\tau^L_{gjt})(s^L_{gjt})^{\frac{1}{\eta+1}}\right)^{\frac{\gamma^L_j}{\gamma_j}} (1+\tau^K_{gjt})^{\frac{\gamma^K_j}{\gamma_j}} (\Lambda^H_{gjt})^{\frac{\gamma_j-1}{\gamma_j}}\right)^{-\frac{\gamma_j}{\frac{\sigma}{\sigma-1}-\gamma_j}}}, \tag{2.23}$$

$$s^L_{fjt} = \frac{s^H_{fjt}(\Lambda^H_{fjt})^{-1}\left(\mu^H_{fjt}(1+\tau^L_{fjt})\mu^L_{fj}\right)^{-1}}{\sum_{g\in\mathcal{F}_j} s^H_{gj}(\Lambda^H_{gj})^{-1}\left(\mu^H_{gjt}(1+\tau^L_{gjt})\mu^L_{gjt}\right)^{-1}}, \tag{2.24}$$

$$s^K_{fjt} = \frac{s^H_{fjt}(\Lambda^H_{fjt})^{-1}\left(\mu^H_{fjt}(1+\tau^K_{fjt})\right)^{-1}}{\sum_{g\in\mathcal{F}_{jt}} s^H_{gjt}(\Lambda^H_{gjt})^{-1}\left(\mu^H_{gjt}(1+\tau^K_{gjt})\right)^{-1}}, \tag{2.25}$$

$$s^F_{fjt} = \frac{s^H_{fjt}(\mu^F_{fjt}/\mu^H_{fjt})^{1-\sigma} D_{fjt}}{\sum_{g\in\mathcal{F}^F_{jt}} s^H_{gjt}(\mu^F_{gjt}/\mu^H_{gjt})^{1-\sigma} D_{gjt}}, \tag{2.26}$$

where the markups μ^H_{fjt}, μ^F_{fjt}, and μ^L_{fjt} are given by (2.12) *and*

$$\Lambda^H_{fjt} = \frac{r^H_{fjt}/\mu^H_{fjt}}{r^H_{fjt}/\mu^H_{fjt} + r^F_{fjt}/\mu^F_{fjt}} = \frac{y^H_{fjt}}{y_{fjt}}.$$

[7] The core intuition from the proposition—that growth by relatively more subsidized firms can decrease TFP—likely generalizes to endogenous distortions such as oligopolistic markups μ^H_{fj} and oligopsonistic markdowns μ^L_{fj}. Market power distorts firm size by driving a wedge between the value of the marginal product and the marginal cost. In particular, firms with high markups behave as if they face a tax on expansion and are therefore inefficiently too small. By contrast, firms with relatively low markups behave as if they face implicit subsidies to expansion and are inefficiently too large, hiring too many inputs relative to the efficient allocation. The concern is therefore that growth by sufficiently low-markup firms could be privately beneficial but socially costly, since it expands firms that are already too large relative to their fundamentals.

For each j and t, given data on s^H_{fjt}, s^L_{fjt}, s^K_{fjt}, s^F_{fjt}, and Λ^H_{fjt} there exists a unique (up to a scalar normalization) set of firm primitives $\{a_{fjt}, 1+\tau^L_{fjt}, 1+\tau^K_{fjt}, D_{fjt}\}$ that satisfies the above system of equations.[8]

Proof. See Appendix A. □

The key implication of Proposition 2.4 is that recovering firm-level shocks only requires solving the system of nonlinear equations (2.23)–(2.26). This result delivers substantial computational convenience, since each of the shares in (2.23)–(2.26) depends only on other shares and the shocks of firms in the same sector and year, allowing us to solve the system separately for each sector-year; we do not have to solve the full model to recover the shocks. Solving the full model can be computationally costly because it requires finding the Nash equilibrium with many firms and sectors jointly. This approach to inferring primitives from observed shares is similar to Hsieh and Klenow (2009), Berger et al. (2022), and Deb et al. (2024).

Proposition 2.4 highlights the drivers of the cross-sectional dispersion in the different market shares. Appendix A.3 builds intuition for the identification of the shocks by going through a sequence of simpler models that clarify step by step how each share informs the inference of each shock, and how each successive model complication modifies the shock recovery. Here we summarize the intuition briefly. Domestic sales shares (2.23) help recover firm productivity a_{fj}. However, to do that we must take into account that domestic sales shares also reflect price markups μ^H_{fj}, wage markdowns μ^L_{fj}, and factor-market distortions τ^L_{fj} and τ^K_{fj}. Moreover, under non-constant returns to scale, firm-specific export demand also shapes domestic market shares through Λ^H_{fj}, the ratio of quantity demanded by the domestic market relative to the firm's total output. For instance, under decreasing returns, a higher foreign demand drives up a firm's marginal cost for all production, increasing its domestic price and decreasing its domestic market share relative to an otherwise identical firm that only serves the domestic market.

Similarly, ratios of factor payment and sales shares help identify factor distortions and firm-specific foreign demand. For instance, if there were no distortions in hiring labor and capital, there would be a one-to-one mapping between the domestic sales shares in equation (2.23) and the labor or capital shares in (2.24) and (2.25). Using the same intuition as Hsieh and Klenow (2009), we can then recover the factor distortions faced by a firm as deviations from this one-to-one mapping. Furthermore, we can identify firm-specific foreign demand from the export shares in (2.26). Conditioning on other primitives, we would deduce that a firm with a higher export share faces a higher foreign demand.[9]

We next combine Proposition 2.4 with micro data on South Korea to perform our quantification of the role of individual firms in South Korea's economic performance.

[8] Any two possible solutions $\{a_{fjt}, 1+\tau^L_{fjt}, 1+\tau^K_{fjt}, D_{fjt}\}$ and $\{a'_{fjt}, 1+\tau'^L_{fjt}, 1+\tau'^K_{fjt}, D'_{fjt}\}$ differ only by a primitive-specific positive multiplicative constant $c^x_{jt} > 0$: $x_{fjt} = c^x_{jt} x'_{fjt}$, $x \in \{a, 1+\tau^L, 1+\tau^K, D\}$.

[9] Our model nests important benchmarks such as Melitz (2003) and Hsieh and Klenow (2009). Without market power, distortions, and differential foreign demand, higher domestic sales shares would reflect only differences in productivity, as in Melitz (2003). When we eliminate exporting ($\Lambda^H_{fjt} = 1, \forall f$) and restrict firms to monopolistic competition and perfectly competitive labor markets, we obtain the Hsieh and Klenow (2009) formulas for identifying labor and capital distortions.

3. Data and Model Implementation

This section provides an overview of our firm-level and sectoral data for South Korea, and describes the calibration and estimation of the parameters and shocks. Appendix B elaborates in detail on both the underlying data and the calibration/estimation procedures.

3.1 Data

Our analysis utilizes a novel firm-level panel dataset covering the period from 1972 through 2011. Firm balance sheet data from 1972 to 1982 come from digitizing the historical Annual Reports of Korean Companies published by the Korea Productivity Center. Data for the 1982-2011 period come from KIS-VALUE, which covers firms with assets above 3 billion Korean Won, for whom reporting balance sheet data has been mandatory since the introduction of the 1981 Act on External Audit of Joint-Stock Corporations.[10] We merge these two datasets based on firm names. We treat each firm within a business group (chaebol) as a separate entity. While there have been a number of mergers and acquisitions over this period, in the overwhelming majority of cases the merged/acquired firms continue to be present as separate entities in the dataset. See Section 4.4 for a comprehensive discussion of mergers.

To ensure the comparability of the two datasets across time, we impose the KIS-VALUE inclusion criterion on the data from the earlier period. That is, while the 1972-1982 data have broader coverage, we include in the firm-level analysis only those firms that would have been required to report their balance sheets had the 1981 Act on External Audit been in force prior to 1982. The resulting dataset comprises of 23,464 unique firms, with the number of firm-year observations increasing from 731 in 1972 to 18,761 in 2011 (Appendix Figure B1).

The dataset has information on sales, exports, fixed assets, employment, wage bill, and firm age. However, wage bill data are only available after 1983, so we use the wage bill data only for the estimation of the production functions, but not for the quantitative exercises.[11] While our firm-level data cover most of South Korea's economic activity, to capture the entire economy we complement the firm-level data with sector-level data from KLEMS and the IO tables from the Bank of Korea. Both the sectoral and the firm-level datasets use the ISIC sectoral classification, making the merge straightforward. The sectoral data cover imports, exports, gross output, producer price indices (PPI), capital, and employment. Our final data set consists of 19 sectors, of which 11 are manufacturing and have firm-level information (Appendix Table B1). While there have been revisions to the ISIC classification over time, it remained stable at the relatively aggregated 1-digit level used in our analysis.

[10]The threshold is roughly 2.3 mln 2023 USD. The data structure of KIS-VALUE is similar to Compustat. However, unlike Compustat, it covers medium-sized firms that are not publicly traded.

[11]We can still carry out the analysis starting in 1972 because we have employment data. The wage bill share s^L_{fjt} can be expressed in terms of only labor: $s^L_{fjt} = l^{(\eta+1)/\eta}_{fjt} / \sum_{g \in \mathcal{F}_j} l^{(\eta+1)/\eta}_{gjt}$.

Concentration ratios. Figure 1 displays the concentration ratio of the top 3 firms within each sector, defined as the sum of these firms' sales divided by the total manufacturing gross output. Additionally, Appendix Figure B2 reports concentration ratios for alternative variables, including domestic sales, exports, fixed assets, and employment. Over time, both domestic sales and export concentration ratios increased, with a more pronounced increase in export concentration. Concentration in employment and fixed assets also increased, although the magnitudes were smaller compared to the increase in the sales concentration ratio. Appendix Figure B3 plots the concentration ratios of the top 1, top 5, and top 10 firms in each sector. Appendix Figure B4 reports the top 3 and top 100 concentration ratios and the Herfindahl index, computed on all manufacturing firms, regardless of sector. The trend increase in concentration is equally evident for these alternative measures.

Persistence of top-3 status. Panel A of Figure B5 plots the hazard rate of remaining in the top 3 at year $t + h$, $h = 1, \ldots, 38$, conditional on being in the top 3 in year t: $\Pr\left[f \in \mathcal{F}^3_{jt+h} | f \in \mathcal{F}^3_{jt}\right]$. The top-3 status is persistent, with 91% top-3 firms at t remaining in the top 3 at $t + 1$. The probability of remaining in the top 3 38 years later is above 45%. Panels B and C of Figure B5 depict the heterogeneity in the 1-year hazard rate across time and sectors. There is some sectoral and time variation, but it is limited. Section 4.1 presents a theoretically-consistent treatment of the impact of turnover in the top 3 on the concentration ratio, based on Proposition 2.2.

3.2 Structural Parameters

The model calibration proceeds in 3 steps. First, we externally calibrate a number of parameters, that our data do not allow us to estimate. Second, we estimate and take directly from the Korean data a number of production function and preference parameters. Third, given these parameters, we invert the model to recover the shocks experienced by the Korean firms over the sample period. Table 1 presents the summary of the calibration, with 3 panels corresponding to each calibration step.

Externally calibrated parameters. We externally calibrate the elasticity of substitution between firms σ to 5, which aligns with the existing estimates of 4 from Broda and Weinstein (2006), 5.8 from De Loecker et al. (2021), and 7 from Burstein et al. (2025). We set the elasticity of substitution between Home and Foreign composites ρ to 2 (Boehm et al., 2023). We take these from the literature because—as in most firm-level data sets—we observe firms' sales but not their prices and quantities separately. Below we check the sensitivity of the results to these parameter values.

We set the across-firm labor supply elasticity η to 4, the preferred value in Card et al. (2018). We set the across-sector labor supply elasticity θ to 1.89 following Deb et al. (2022) who estimate the elasticity across sectors in the US using state-level variation in corporate income tax rates.[12] We set the Frisch

[12]Our choices for the values of η and θ are based on the studies that employed exogenous variation at the US state or commuting zone levels. We view these settings to be suitable for application to South Korea, a small country comparable in geographic size to the state of Indiana, whose population grew from 35 million at the beginning of the sample to 50 million at the end, on average roughly 1.5 times the population of California over this period. The value of $\eta = 4$ is also broadly consistent with estimates from other recent contributions. Deb et al. (2022) estimate the across-firm labor supply elasticity

Table 1: Calibration

Param.	Value	Description	Moment	Source
	Elasticities (externally calibrated)			
σ	5	Elast. subst. firms		Literature
ρ	2	Elast. subst. Home vs. Foreign		Boehm et al. (2023)
η	4	Labor supp. elast. firms		Card et al. (2018)
θ	1.89	Labor supp. elast. sectors		Deb et al. (2022)
ψ	0.5	Agg. labor supp. elast.		Chetty et al. (2013)
ζ	0	Govt. revenue waste		
β	0.97	Discount rate		
	Production and Consumption (estimated or data)			
γ_j^L	0.12–0.46, avg. 0.22	Prod. fcn. labor share	eq. (B.1)	Own estimate
γ_j^K	0.07–0.24, avg. 0.14	Prod. fcn. capital share	eq. (B.1)	Own estimate
γ_j^M	0.41–0.65, avg. 0.57	Prod. fcn. material share	eq. (B.1)	Own estimate
γ_j^i	0–0.75	Intermediate input shares	IO tables	IO tables
α_j	0–0.26	Consumption share	IO tables	IO tables
δ	0.08	Capital depreciation rate		KLEMS
	Shocks (model inversion)			
a_{fjt}		Productivity	Dom. sales sh., eq. (2.23)	Data
D_{fjt}		Foreign demand	Export sh., eq. (2.26)	Data
$1+\tau_{fjt}^L$		Labor distortion	Emp. sh, eq. (2.24)	Data
$1+\tau_{fjt}^K$		Capital distortion	Cap. sh., eq. (2.25)	Data
P_{jt}^F		Import price shock	Import shares	Data
Ξ_t		Invest. productivity	Capital stock	Data
$\bar{\psi}_t$		Labor supp. pref. shock	Working hours per worker	Data

Notes. This table presents the summary of the calibration.

aggregate labor supply elasticity ψ to 0.5, a value advocated by Chetty et al. (2013). We set $\zeta = 0$ implying that there is no loss of resources due to distortions beyond their misallocation effects (see equation A.1). Section 4.4 and Appendix Table B13 assess the sensitivity of the quantitative results to the values of all of these parameters. Finally, assume that the period utility is log: $U(\cdot) = \ln(\cdot)$, and the annual discount rate is $\beta = 0.97$.

Parameters estimated or taken from data. We estimate the firm-level production function parameters γ_j^L, γ_j^K, and γ_j^M for each sector. Appendix B.2 lays out the procedure in detail. We derive an estimable regression model by combining the production function with the demand curve faced by the firm (see, e.g. De Loecker, 2011). Our estimation approach is internally consistent with the model, in particular it recognizes that firms charge variable markups. Appendix Table B2 reports the estimation results. The mean of the returns to scale γ_j is 0.93.[13] The mean of the labor share in

of 3.1 in the US; Lamadon et al. (2022) 4.6 in the US; Kroft et al. (2025) 4 in the US construction industry; Dhyne et al. (2025) 3.5 in Belgium; and Huneeus et al. (2022) the range of 3–6 in Chile.

[13] This value is in line with the existing estimates in the literature. For example, Basu and Fernald (1997) estimate the returns to scale around 1.1–1.3 using the US sectoral data; Gao and Kehrig (2021) around 0.9–1.0 for manufacturing firms in

primary factor costs in manufacturing $\gamma_j^L/(\gamma_j^L+\gamma_j^K)$ is 0.5.

We use the Bank of Korea input-output tables to obtain the final consumption shares α_j and the input-output shares of material inputs γ_j^i. We allow both α_j and γ_j^i to vary across years to capture structural change. For commodity and service sectors in which firm-level data are not available, we use the averages of γ_j^L, γ_j^K, and γ_j^M across manufacturing sectors. We set $\delta = 0.08$, which is the unweighted average value for the depreciation rate in Korean KLEMS.

3.3 Inverting the Model to Recover Shocks

To back out the firm-level and aggregate shocks, we proceed in two steps. In our quantification, each firm observed in the data is an object in the model, and the shock recovery procedure is performed year by year. The first step of the calibration identifies each firm's productivity, distortions and foreign demands relative to fringe firms. Using data on domestic sales, employment, capital, and export shares, we solve for $\{a_{fjt}, D_{fjt}, 1+\tau^L_{fjt}, 1+\tau^K_{fjt}\}_{j\in\mathcal{F}_{jt}}$ for each sector and year using (2.23)-(2.26) as detailed in Section 2.5 and Appendix A.3. This step only relies on the cross-section of shares, and thus can be done sector-year by sector-year.

In the second step—given these identified shocks relative to fringe firms—we pin down fringe firms' productivity, foreign demands, and distortions $\{a_{\tilde{f}jt}, D_{\tilde{f}jt}, 1+\tau^K_{\tilde{f}jt}, 1+\tau^L_{\tilde{f}jt}\}_{j\in[0,1]}$, the sectoral foreign import price shocks $\{P^F_{jt}\}_{j\in[0,1]}$, the aggregate preference shock to the disutility of labor $\bar{\psi}_t$, and investment productivity shocks Ξ_t. Unlike the previous step, we have to solve for the full dynamics of the model to back out these remaining shocks, assuming that the economy reaches the steady state after a sufficiently long period. We calibrate fringe firms' productivity by fitting relative sectoral PPI changes and aggregate real GDP growth. We use changes in PPI (relative to a reference sector) to pin down each sector's fringe firms' productivity changes relative to the reference sector. We then pin down the reference sector fringe firms' productivity using aggregate real GDP growth. We calibrate fringe firms' foreign demand by fitting aggregate exports. The sectoral import price shocks are identified by sectoral import shares λ^F_{jt}. The labor supply shifts $\bar{\psi}_t$ are pinned down by the evolution of efficiency-adjusted labor supply in South Korea. Labor supply in efficiency units is the product of human-capital adjusted labor force and hours per worker.[14] We select $\bar{\psi}_t$ such that L_t in (2.4) matches these data in each year. To pin down fringe firms' distortions, we set $1+\tau^L_{\tilde{f}jt}$ and $1+\tau^K_{\tilde{f}jt}$ to satisfy $\sum_{f\in\mathcal{F}_{jt}} s_{fjt}(1/(1+\tau^L_{fjt})\tilde{\mu}_{fjt}\mu^L_{fjt}) = 1$ and $\sum_{f\in\mathcal{F}_{jt}} s_{fjt}(1/(1+\tau^K_{fjt})\tilde{\mu}_{fjt} = 1$, respectively. By doing so, we set the sectoral capital income share $\sum_{f\in\mathcal{F}_j} \varrho k_{fjt}/R_{jt}$ equal to γ_j^K, and the sectoral labor income share $\sum_{f\in\mathcal{F}_{jt}} w_{fjt} l_{fjt}/R_{jt}$ to γ_j^L. We truncate the top and bottom 1.5% for $1+\tau^L_{fjt}$ and $1+\tau^K_{fjt}$. Then, we take the 5-year rolling moving averages for the recovered firm-level shocks.

Investment shocks are pinned down by the evolution of the aggregate capital stock. We set Ξ_t such that the Euler equation holds in every period while matching the capital stock in the data in

the US Census; Eslava et al. (2024) around 0.9–1.2 using the Colombian plant data; and Huo et al. (2023) around 1.05–1.17 for manufacturing sectors using the KLEMS data.

[14] We obtain data on human capital stock per capita from Lee and Lee (2016) and hours per worker from Korean KLEMS.

each year. We do not have firm-level information in commodity and service sectors, so we assume homogeneous fringe firms in these sectors and their shocks are matched to the sectoral data. The trade deficits $\mathcal{D}_t$ are exogenous and taken directly from the data, as standard in the trade literature.

All in all, when all the shocks are fed back into the model, it matches both micro-level objects (firm sales, export, and factor payment shares), and macro-level objects (sectoral output, imports, exports, capital stock, population adjusted by human capital, and real GDP). Appendix B.3 describes the procedure in detail.

External validation and the role of industrial policy. Appendix B.4 explores in detail the recovered shocks and connects them to salient features of South Korea's economic history over this period. First, it externally validates the shocks by showing that they are significantly correlated with directly observed proxies for productivity-enhancing investments, capital subsidies, financial constraints, and external demand. Second, it delves more deeply into South Korea's large scale industrial policies of the 1970s. We document that indeed industrial policies were more likely to benefit large firms. We then quantify how much of the South Korea's concentration and GDP changes can be attributed to these industrial policies.

4. Quantitative Results

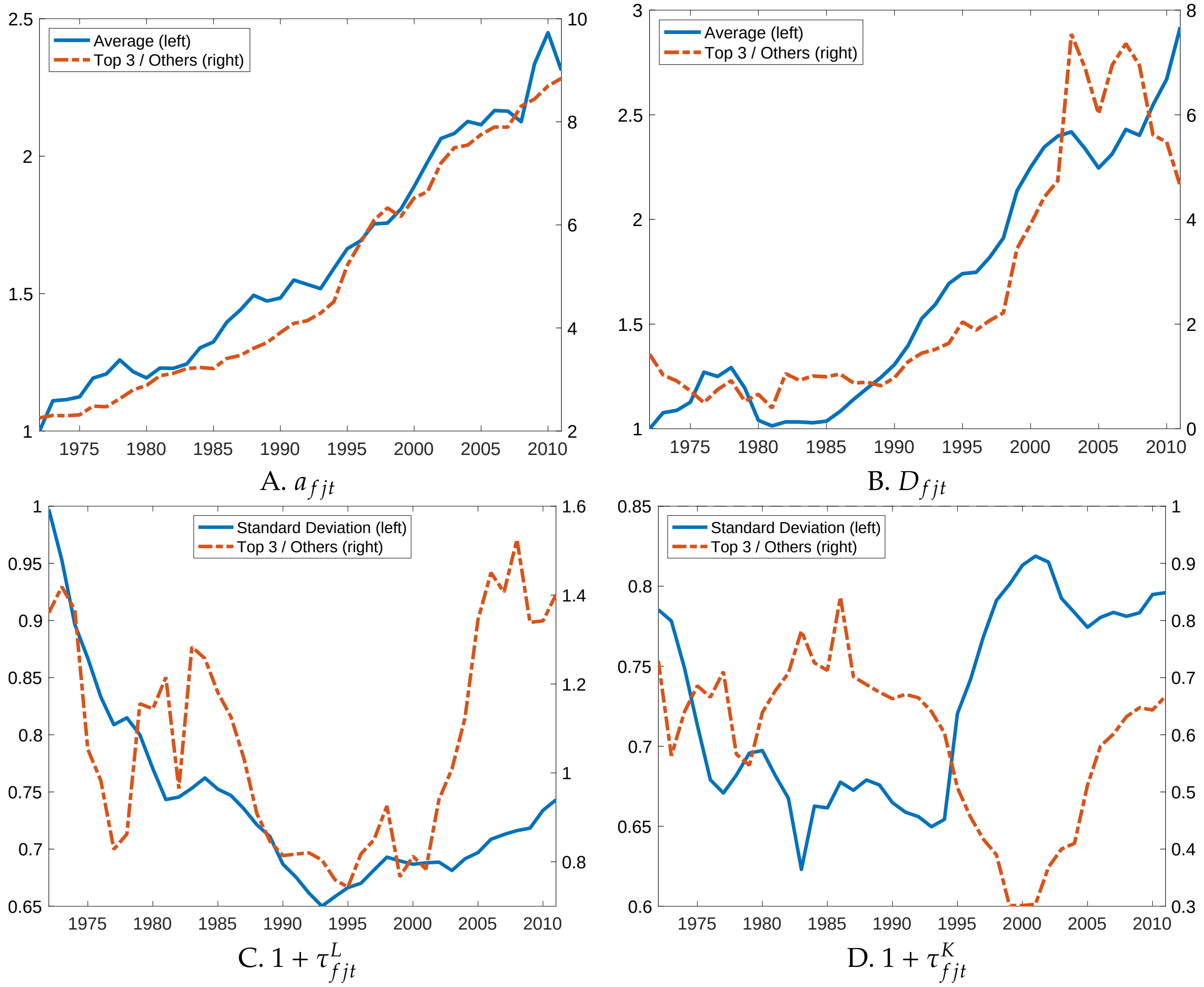
4.1 Trends in Shocks, Productivity, and Markups

The solid blue lines in Figure 2 display the trends in the 4 shocks since the 1970s. Panel A illustrates the rapid increase in the manufacturing sector productivity. Average productivity is normalized to 1 in 1972. During the sample period, the sales-weighted average manufacturing productivity more than doubled.[15] Panel B plots the export-weighted average of foreign demand. Its evolution tracks closely the global demand conditions and the real exchange rate movements. Notably, foreign demand dropped in the late 1970s due to the global recession induced by the oil crisis. During the mid-1980s, a depreciated real exchange rate and low oil prices drove an increase in foreign demand. Around 1997, foreign demand surged as the real exchange rate depreciated in the midst of the Asian financial crisis.

Panels C and D report the dispersions in log labor and capital distortions, a widely used measure of the degree of resource misallocation (e.g. Hsieh and Klenow, 2009). We compute standard deviations of firm-level log distortions within sectors and then take sales-weighted averages of these standard deviations across sectors. The dispersion in labor distortions exhibited a declining trend from the 1970s to the early 1990s, before reversing somewhat. The dispersion in capital distortions initially decreased until the mid 1990s but saw a peak around the 1997-1998 Asian financial crisis. This is in

[15] Choi and Shim (2022, 2025) document that these productivity increases were driven by both the adoption of foreign advanced technologies and innovation.

Figure 2: Shocks



Notes. Panels A and B plot, for productivity and foreign demand shocks, respectively, the sales-weighted average of all firms (solid blue) and the unweighted average for top-3 firms divided by that of other firms (red dashed). Sales-weighted averages of both productivity and foreign demand shocks are normalized to 1 in 1972. Panels C and D plot for the labor and capital distortions, respectively, the standard deviation (solid blue) and the unweighted average of for top-3 firms divided by that of other firms (red dashed). All results are computed within manufacturing sectors and then aggregated by taking the sales-weighted averages across sectors.

line with financial frictions being exacerbated during the crisis (e.g. Midrigan and Xu, 2014). Since then, it has remained elevated, hovering around the levels seen in the early 1970s.

The red dashed lines in Figure 2 plot the evolution of shocks for the top 3 largest firms in each sector relative to the rest. We calculate the unweighted average of shocks of the top 3 firms, divide it by the unweighted average of shocks of all other firms in the same sector, and then take the sales-weighted average of these ratios across sectors.[16] We allow for the set of the top 3 firms to vary across years.

[16] Specifically, we calculate $\sum_{j\in\mathcal{J}_M} S_{jt} \frac{\sum_{f\in\mathcal{F}^3_{jt}} X_{fjt}}{\sum_{f\in\mathcal{F}_{jt}} X_{fjt}}$, for $X_{fjt} \in \{a_{fjt}, D_{fjt}, 1+\tau^L_{fjt}, 1+\tau^K_{fjt}\}$. One might be concerned that as more firms enter the dataset over time, the comparison group for the top-3 firms has on average less and less productive

Panel A shows that the top 3 firms experienced faster productivity growth. In 1972, their average productivity was 2.3 times higher than that of the other firms; by 2011, it had surged to 8.8 times higher. The top 3 firms' foreign demands—plotted in panel B—remained stable and similar to those of the other firms until the early 1990s. However, in the mid-1990s, their foreign demands sharply increased and remained elevated since. At their 2007 peak, they were 7.5 times higher than those of other firms. Panels C and D display the top 3 firms' relative labor and capital distortions. In the 1970s, there were drops in both relative distortions, meaning that the top 3 firms were progressively more "favored." These drops were potentially due to the Heavy and Chemical (HCI) Drive, a large-scale industrial policy that subsidized the heavy manufacturing firms (Choi and Levchenko, 2025; Kim et al., 2021). However, that trend reversed after the HCI Drive ended in 1979. The top 3 firms' relative distortions fell again from the 1980s to about 2000, and increased from the early 2000s until the end of the sample period. Overall, there is no long-run net change in the top 3 firms' relative distortions between 1970 and 2010.[17]

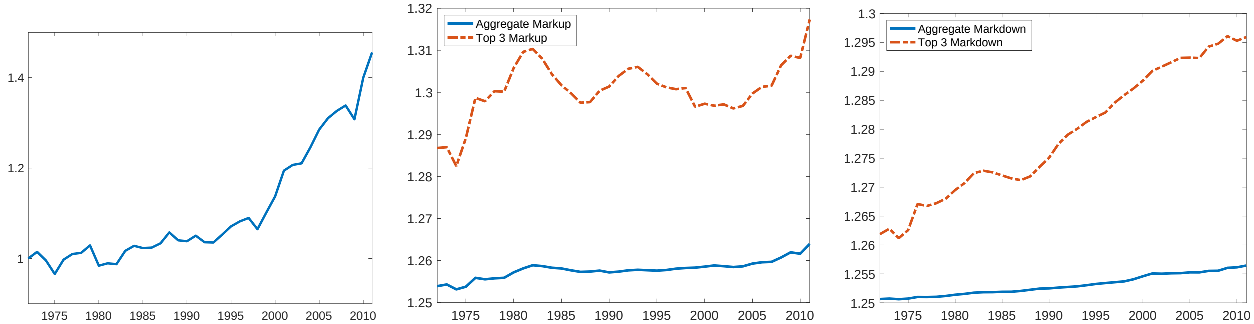
The blue lines in Figure 3 plot the aggregate productivity, markup, and markdown (equations 2.19 and 2.20) for the whole economy, including the non-manufacturing sectors. Note that the weights and expressions are based on the theoretical aggregation (Proposition 2.1). The aggregate productivity increased around 50%. However, despite the increased concentration, the aggregate markup and markdown increased by only 4% (from 25.4% to 26.4%). The red dashed lines plot the top 3 firms' markup and markdown. The top 3 firms' markups and markdowns are higher than the aggregate throughout, and increased by more than the aggregate, but the change is still modest at 12% (from 28.7% to 31.8%).

Appendix B.5 presents three additional exercises on markups. First, we show the trends in the firms' markups in the domestic market, and assess the role of import competition in the markup trends. The small increase in aggregate markups is not due to the fact that large firms charge lower markups on exports, and their exports rose in this period. It is also not due to changes in import competition over this period. Rather, it appears that the increase in the top firms' markups was modest, and when averaged with all the firms in the sector yields an even smaller change in aggregate markups. Second, we adopt a complementary approach and infer markups from cost shares as in De Loecker and Warzynski (2012) and De Loecker et al. (2020). This alternative method shows no increase in aggregate markups over the sample period. Third, we quantify the welfare effects of variable markups by comparing the baseline model to alternatives in which markups and/or markdowns are fixed to the Dixit-Stiglitz values. Existence of variable markups and markdowns reduced the net present value

firms in it, leading to a mechanical increase in the relative productivity of the top 3. However, if anything the size threshold for inclusion in the dataset actually rose gradually over time, from assets of 2.3mln 2023 USD in 1980-1989 to 7.7mln 2023 USD in 2009-2011. Note also that Figure 2 is illustrative and does not enter directly into the quantitative results. Our counterfactual exercises adjust explicitly for the changing composition of the firm sample, as described in Section 4.3.

[17] Appendix Figure B12 correlates the relative labor and capital wedges to firm size across the firm size distribution. All in all, larger firms face relatively higher labor wedges throughout out time period. There is no consistent pattern for capital wedges: larger firms face on average lower capital wedges from mid-1970s to mid-1980s, and again in the latter half of the 1990s, but the correlation flips to modestly positive in the other subperiods.

Figure 3: Aggregate Productivity, Markup, and Markdown



A. Aggregate productivity A_t B. Aggregate markup $\mathcal{M}_t$ C. Aggregate markdown $\mathcal{M}_t^L$

Notes. The solid blue lines plot the aggregate productivity, markup, and markdown defined in equations (2.19) and (2.20) (left scale). Red dashed lines in Panels B and C plot the markup and markdown of only top-3 firms (right scale).

of welfare by about 1.3% over this period, relative to the alternative of Dixit-Stiglitz markups.

4.2 Concentration Ratio Decomposition

Table 2 decomposes the observed increase in the aggregate top-3 concentration ratio into the three components following Proposition 2.2(ii) (equation 2.22): relative improvement of firms that were continuously in the top 3, entry and exit margins, and sectoral reallocation.[18] Over the entire 40-year period, 58% of the increase in concentration (9.67 out of 16.55) was driven by the reallocation towards sectors with the largest firms. The remaining 42% (6.88 out of 16.55) is split essentially 50/50 between the better performance by the continuing top 3 firms, and by the extensive margin of new firms entering the top 3.

The long run hides some interesting heterogeneity across periods. Almost half of the cross-sectoral reallocation component (4.58 out of 9.67) came in the first decade on the sample, the period of large-scale industrial policy and dramatic transformation of South Korea into a heavy manufacturing powerhouse. The sectoral reallocation force weakened by the 2000s. The 1970s was also the period responsible for the majority of the churning in and out of the top 3 (3.94 out of the total of 3.69). In fact, in the 1970s the continuing top-3 firms underperformed, contributing negatively to the rise in concentration.

For the rest of the period structural change and new entry into the top 3 become less important. Instead, the continuing top-3 firms enjoy a productivity growth advantage, and an expansion in the relative foreign market access in the 1990s.

[18]The changes in the aggregate top-3 concentration ratio in Table 2 do not exactly match Figure 1 because we truncate some outliers and take the 5-year rolling averages. Due to approximation errors, we apply the decomposition year-to-year and sum each component over years within each sub-period. Specifically, between $t-p$ and t, we apply the decomposition to $\ln \frac{CR_\tau^3}{CR_{\tau-1}^3}$ between $\tau-1$ and τ, and then sum each component from $t+1-p$ to t as $\ln \frac{CR_t^3}{CR_{t-p}^3} = \sum_{\tau=t+1-p}^{t} \ln \frac{CR_\tau^3}{CR_{\tau-1}^3}$.

Table 2: Decomposition of the Aggregate Top-3 Concentration Ratio

Period	1972–1982	1982–1992	1992–2002	2002–2011	1972–2011
△ Agg. Top-3 CR (pp)	4.26	2.82	7.20	2.27	16.55
Within-sector component	−0.31	1.34	4.17	1.87	6.88
Cont. Top 3 – Productivity	−4.64	2.86	1.58	2.73	1.89
Cont. Top 3 – Exports	0.39	−0.85	2.91	−1.16	1.31
Entry & exit	3.94	−0.67	−0.32	0.31	3.69
Across-sector component	4.58	1.48	3.03	0.40	9.67

Notes. This table presents the decomposition results of the aggregate top-3 concentration ratio based on equation (2.22). All units are percentage points.

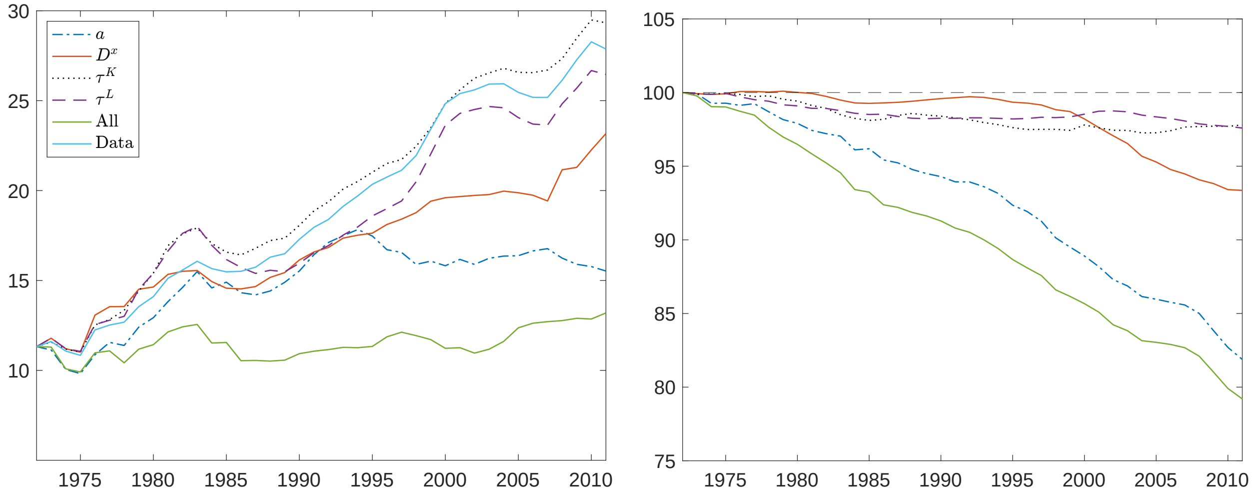
4.3 Contribution of Large Firms to Concentration and Real Income

We next examine the quantitative importance of the differential microeconomic shocks faced by the largest firms for aggregate growth, market concentration, and welfare. We compare the baseline economy with a series of counterfactual economies in which we set various shocks of the top-3 firms to the unweighted average shocks in their sector, while other firms' shocks remain the same as the baseline. This exercise can be viewed as removing the top-3 firms "granular residual" (Gabaix, 2011). It is motivated by Figure 2, which showed that the top firms experienced systematically different shocks than other firms.

The spirit of the counterfactual exercise is to ask, what would the economy have looked like had the top-3 firms' productivity, market access, and distortions grown at the same rate as the "typical" firm in the sector? Defining "typical" is not completely straightforward in our dataset, which exhibits a great deal of firm entry over this period. Younger firms are known to grow faster than older ones, and the top-3 firms tend to be older on average. To address this compositional effect, we adopt the procedure detailed in Appendix B.6 to calculate the "typical" firm average to apply to the top-3 firms in the counterfactuals. In a nutshell, it sets the top 3 counterfactual growth rates to the average growth rates of similarly aged firms in the same sector. These counterfactuals generally result in smaller top-3 firms. For instance, in the productivity counterfactual, the average productivity of the top-3 firms is 36% lower by 2011, leading to a significant decline in their sales.

Figure 4 presents the quantitative results. Panel A displays results for the top 3 concentration ratio. The light blue solid line displays the concentration ratio in the data. In the data the concentration ratio rose from 11.3% in 1972 to 27.9% in 2011, a 147% increase. The solid green line shows what would happen if all 4 shocks to the top-3 firms were replaced with the corresponding unweighted averages. In this case, the top 3 concentration ratio would have increased only to 13.2% in 2011 – a 17% increase. Thus, in this counterfactual the growth in the concentration ratio is 8.6 times smaller than in the data.

Figure 4: The Impact of the Top-3 Micro Shocks



A. Top 3 Mfg. Concentration Ratio (%) B. Real GDP Relative to Data (%)

Notes. This figure displays the top-3 concentration ratios (Panel A) and real GDP per capita (B), under the counterfactual sequences of the top-3 firms' shocks defined in equation (B.14).

The rest of the lines display concentration for one shock at a time. Productivity shocks (dashed-dotted blue line) had the most significant impact on firm concentration, with the elimination of the top-3 productivity shocks reducing the concentration ratio to 15.5% in 2011. The foreign demand shock had the second largest impact, bringing the concentration ratio down to 23.2% in 2011. In contrast, labor and capital distortions had more limited impacts on concentration.

Panel B shows the real GDP per capita in the counterfactuals relative to that of the baseline. Replacing the top-3 shocks with the averages would have led to a 20.8% lower real GDP per capita by 2011. The productivity shock emerges as the primary driver, with other shocks playing a more restrained role. It is noteworthy that foreign demand shocks significantly contribute to explaining the concentration ratio, while their impact on real GDP is much smaller. This discrepancy comes from general equilibrium effects. The reduction in export demand by the top-3 firms results in lower wages, stimulating production by other firms. The decreased production due to lower foreign demand shocks from the top-3 firms is largely offset by the increased production from other firms.

Appendix Figure B13 displays the theoretically-consistent counterfactual aggregate productivity, markups, and markdowns from Proposition 2.1. Substituting the top-3 shocks with the averages would reduce the aggregate productivity by 10.0%. However, its impacts on the markup and the markdown are essentially negligible, resulting in only about a 0.7% and 0.3% decrease, respectively. Shutting down the top-3 foreign demand increases the markup but decreases the markdown. Higher foreign demand induces the top-3 firms to charge lower markup on average due to a constant markup in the foreign market. Nevertheless, higher foreign demand also increases their demand for labor, which in turn lead to higher employment shares and higher markdown. These results echo the finding

Table 3: Welfare Effects of the Top-3 Micro Shocks

Shocks	All shocks	Productivity a_{fjt}	Foreign demand D^f_{fjt}	Labor distortions $1+\tau^L_{fjt}$	Capital distortions $1+\tau^K_{fjt}$
	(1)	(2)	(3)	(4)	(5)
	Panel A. Top 3 firms within sectors				
$\triangle$ Welfare (%)	−6.60	−4.90	−0.76	−0.80	−0.58
	Panel B. Samsung Electronics				
$\triangle$ Welfare (%)	−1.21	−0.90	−0.57	−0.10	−0.36
	Panel C. Hyundai Motors				
$\triangle$ Welfare (%)	−0.86	−0.55	−0.24	0.06	0.12

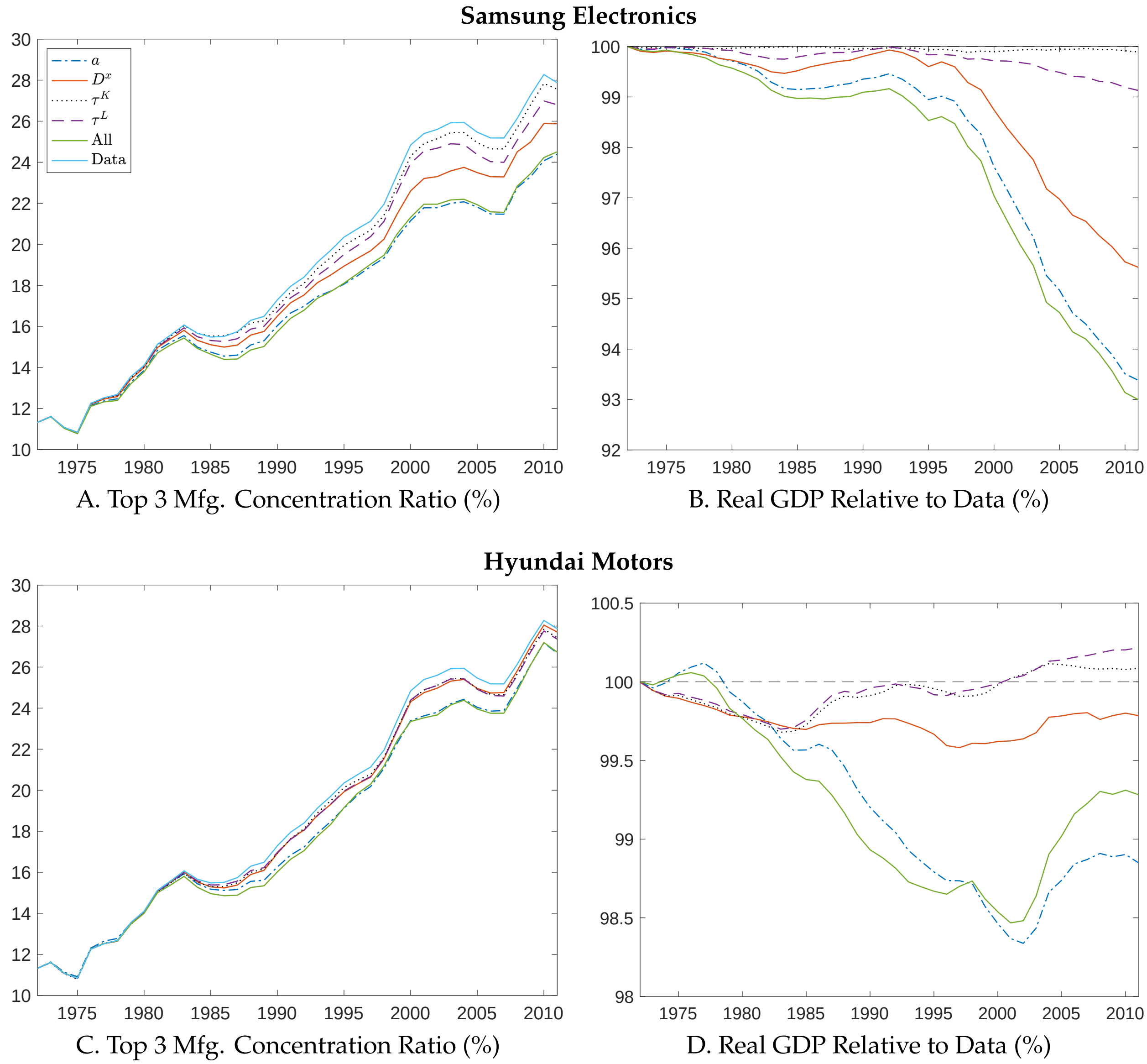
Notes. Panels A, B, and C report the welfare effects when we replace sequences of shocks of all the top-3 firms, Samsung Electronics only, and Hyundai Motors only, respectively, with the counterfactual sequences of shocks defined in equation (B.14).

in Figure 3 that in spite of the large increase in concentration, the aggregate markup and markdown changes over this 40-year period have been quite small.

Table 3 reports the welfare effects in these counterfactuals. Welfare is measured in consumption equivalent variation. We compute χ that equates the discounted welfare of the baseline to that of the counterfactual: $\sum_{t=1972}^{2011} \beta^{t-1972} U((1+\chi)C_t, L_t) = \sum_{t=1972}^{2011} \beta^{t-1972} U(C^c_t, L^c_t)$, where C^c_t and L^c_t are the counterfactual consumption and labor supply. Replacing all of the top-3 firms' shocks with the averages would have decreased welfare by 6.60%. Consistent with the findings for the concentration ratio and real GDP, productivity had the largest welfare effects, decreasing welfare by 4.90%. Top-3 foreign demand (−0.76%) and labor (−0.80%) and capital (−0.58%) distortions had quantitatively similar effects. If we replace the top-3's growth in distortions with the unweighted average, their $1+\tau^L_{fjt}$ and $1+\tau^K_{fjt}$ rise, making the top-3 firms face higher costs of labor and capital and therefore decreasing welfare.

The observed concentration ratio decomposition in Table 2 found that the majority of the change in concentration is due to sectoral reallocation. Superficially, it may then appear that most of the changes in concentration are driven by macro shocks, such as structural change or evolving nature of the IO linkages, rather than micro shocks to firms. However, this is not the case: Figure 4 shows that micro shocks to the top-3 firms are responsible for four-fifths of the observed concentration increase. Thus, the micro shocks to the top-3 firms also lead to sectoral reallocation. To illustrate this, we applied the concentration ratio decomposition from Proposition 2.2 to the counterfactual concentration in which all top-3 firms' shocks are set to sectoral averages (the green line in Figure 4). The sectoral reallocation term in the counterfactual concentration ratio decomposition is 2.96. Thus, the micro shocks to the top firms are responsible for 6.71 (= 9.67 − 2.96) percentage points of the contribution of sectoral

Figure 5: The Impact of Shocks to Samsung Electronics and Hyundai Motors



Notes. This figure displays the top-3 concentration ratios (Panels A and C) and real GDP per capita (B and D), when we replace the sequences of shocks to Samsung Electronics (top half) or Hyundai Motors (bottom half) with the counterfactual sequences of shocks defined in equation (B.14).

reallocation to the change in CR^3. Examining the sectoral reallocation term in (2.22) clarifies how this can happen. Even conditional on a given set of changes in sectoral shares $\ln(S_{jt}/S_{j,t-p})$, if the sectors that grow in size have smaller top-3 firms (lower $\omega^3_{j,t-p}$), the sectoral reallocation term will get closer to zero. In addition, in the counterfactual, there is also less sectoral reallocation towards industries with the largest firms.

Individual firms. The counterfactual exercise above shows that the micro shocks experienced by the top-3 firms had macroeconomic implications. We now push this finding further and examine how individual large firms contributed to the aggregate economy. First, we present results on South Korea's two largest firms, Samsung Electronics and Hyundai Motors. In 2011, they accounted for 7.1% and 2.5% of total manufacturing gross output, respectively. As in the top-3 counterfactual exercise above, we replace each of these two firms' shocks with the sectoral unweighted averages.

Panels A and B of Figure 5 report the results for Samsung Electronics. Restricting Samsung Electronics' productivity in this way would have reduced concentration. Without Samsung's differential shocks, the top 3 firms' concentration ratio would have been 3.4 percentage points lower in 2011. While concentration would have declined, the real GDP in 2011 would have been 7.0% lower relative to the baseline (Panel B), and welfare would have been 1.21% lower (Table 3). Thus, Samsung Electronics alone is responsible for 34% of the GDP and 18% of the welfare impact of the differential trends of the set of the top-3 firms.

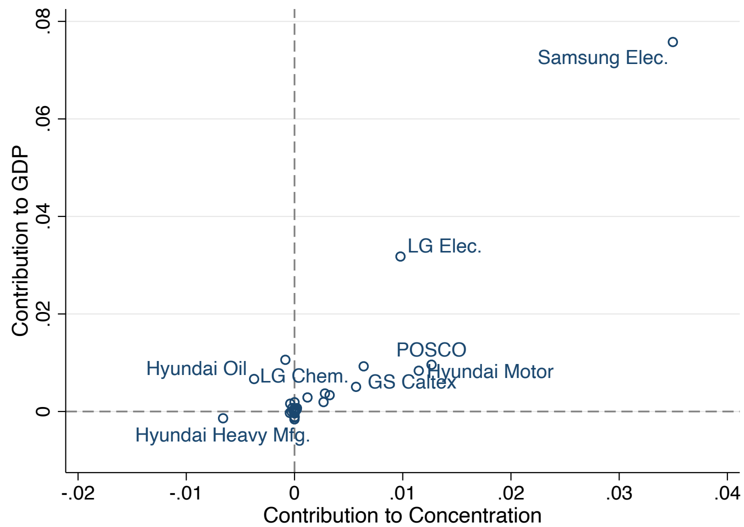
Panels C and D of Figure 5 report the same results for Hyundai Motors. Overall, the effects are smaller, reflecting Hyundai's smaller size compared to Samsung. At the peak of its impact around 2000, removing Hyundai's relatively favorable shocks would have decreased real GDP by about 1.5%. The Hyundai Motors positive GDP impact partly reversed after 2000. This is due to its relatively poor productivity performance in the 2000s, and to the relatively unfavorable distortions it faced in that period. Setting Hyundai Motors' distortions to the average level would have actually raised South Korean GDP slightly in the 2000s. Panel C of Table 3 reports that over the whole period, however, the NPV of South Korean welfare would have been 0.86% lower had Hyundai grown like a "typical" firm. Appendix Figure B14 displays the theoretically-consistent aggregate productivity, markups, and markdowns from Proposition 2.1 for the Samsung Electronics and Hyundai Motors counterfactuals.

We next expand the exercise to all the top-3 firms. For each top-3 firm, we replace the growth rate of its four shocks with the sectoral averages. The goal here is to document differences among the top-3 firms in how much each contributed to both concentration and real GDP. In particular, we want to speak to Proposition 2.3 which shows that any of the 4 shocks that increases concentration can either raise or lower sectoral productivity, depending on parameter values. Figure 6 presents a scatterplot of each firm's contribution to concentration on the x-axis against its contribution to real GDP on the y-axis. Firms in the first quadrant are what we would call superstars – "super" because they outperformed other firms (thus increasing concentration) and "stars" because they contributed positively to real GDP. Both Samsung Electronics and Hyundai Motor are found in this quadrant. Firms in the fourth quadrant would be supervillains – as they outperformed other firms, they also lowered GDP. In practice, there is no such firm clearly visible in the figure.

The other quadrants are harder to label. Shocks to Hyundai Oil contributed positively to GDP, but at the same time they meant that these firms underperformed relative to others, and thus contributed to reducing concentration. We might call them "underachieving stars." Hyundai Heavy Manufacturing is located in the third quadrant – top-3 firms whose shocks reduced both concentration and real GDP.

Most firms by either number or total sales are in the first quadrant, echoing the results for all the

Figure 6: The Impact of Micro Shocks for Each Top-3 Firm



Notes. This figure plots the results from the all shocks' counterfactual to each of the top-3 firms individually. The x-axis shows the top-3 concentration ratio in the baseline minus that in the counterfactual, and the y-axis shows log difference in real GDP in the baseline relative to the counterfactual. We include firms that were top-3 firms for at least 10 years.

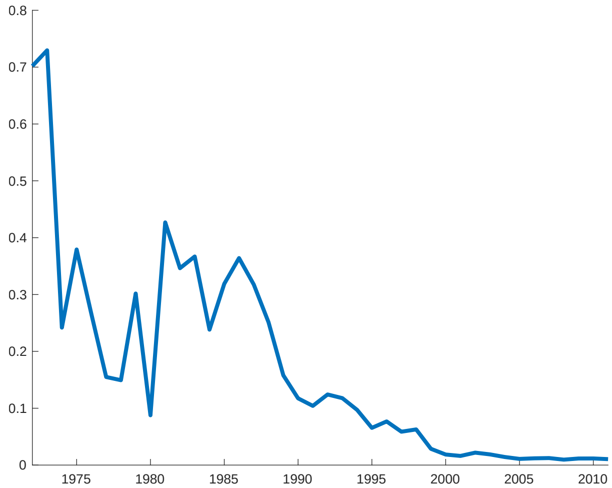
top-3 firms combined in Figure 4 and Table 3. Firms in the first quadrant (superstars) account for 21% of aggregate sales in 2010, compared to 4% in the second quadrant (underachieving stars), 3% in the third quadrant, and 0.1% in the fourth quadrant (supervillains).

When would the top-3 firms be supervillains? The preponderance of superstar firms—and the relative paucity of villains—in Figures 4 and 6 and Table 3 is not a pre-ordained outcome of our procedure. Proposition 2.3 shows that the impact of concentration-increasing shocks on aggregate productivity is ambiguous, and that productivity is more likely to fall when concentration rises due to changing distortions. Thus, ex ante the observed increase in concentration could have been welfare-reducing, especially if it were driven by distortions. We now show which aspect of the data falsifies the hypothesis that large firms are supervillains.

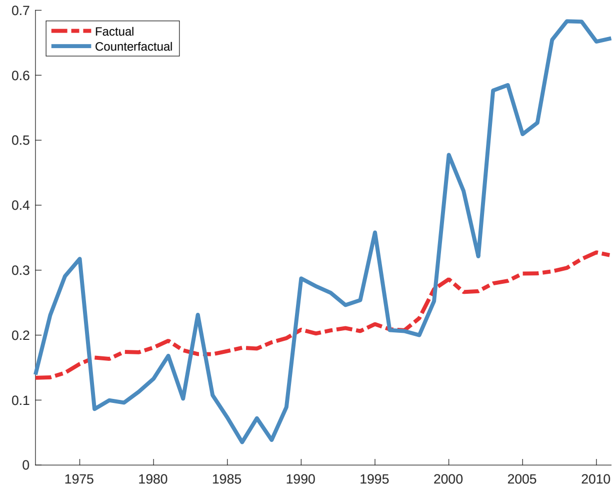
To that end, we present scenarios that match the observed changes in concentration purely with changes in input distortions. First, we set the capital distortions to match the evolution of the domestic sales shares using equation (2.23), but do not match the capital shares. Second, we set the labor distortions to match the evolution in the domestic sales shares but not the wage bill shares. In both scenarios, we fix the relative productivity of each firm to the factual productivity in the initial year. These scenarios answer the question: what would the economy have looked like if the relative productivities of all the firms remained the same, and instead the increase in concentration was entirely driven by changes in distortions over time?

Panels A and C of Figure 7 plot the distortions faced by the top-3 firms relative to the other firms required to rationalize the increase in sales concentration observed in the data. The top-3

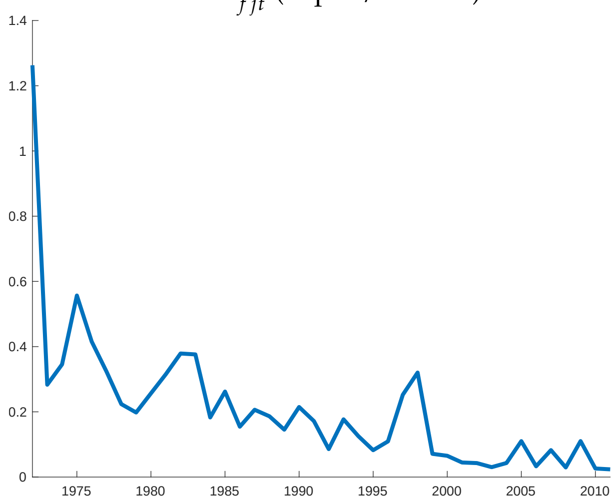
Figure 7: Top-3 Distortions and Factor Shares, Distortion-Only Scenarios



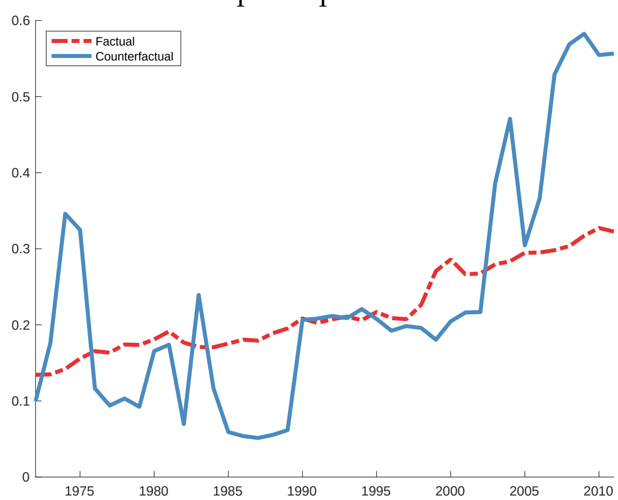
A. $1 + \tau^K_{fjt}$ (Top-3 / Others)



B. Top-3 Capital Share



C. $1 + \tau^L_{fjt}$ (Top-3 / Others)



D. Top-3 Wage Bill Share

Notes. Panel A plots the unweighted average $1 + \tau^K_{fjt}$ of the top-3 firms divided by that of other firms when we pick $1 + \tau^K_{fjt}$ to match the evolution of sales shares. Panel B displays the capital shares of the top-3 firms in these counterfactuals and the data. Panel C plots the unweighted average $1 + \tau^L_{fjt}$ of the top-3 firms divided by that of other firms when we pick $1 + \tau^L_{fjt}$ to match the evolution of sales shares. Panel D displays the wage bill shares of top-3 firms in these counterfactuals and the data.

firms' relative distortions required to match the change in sales concentration are lower (i.e. greater subsidies), and exhibit much stronger downward trends compared to those recovered in the baseline (Figure 2). Table 4 quantifies the impacts of top-3 firms on South Korean real GDP and welfare in each of the two distortion-driven exercises, a counterpart of our baseline analysis in Figure 4 and Table 3. In contrast to our baseline results, both real GDP and welfare are *higher* in the counterfactuals where the top-3 firms' relative distortions are kept at their initial values. In other words, when concentration is driven purely by ever-exacerbating distortions, the increase in concentration is indeed GDP- and welfare-reducing. In this world, the top-3 firms as a group would be clearly labeled supervillains.

Panels B and D of Figure 7 display the feature of the data that falsifies this view of South Korean

Table 4: Counterfactual Real GDP and Welfare when Engineering the Observed Rise in Concentration Purely Through Distortions

Counterfactual vs. Factual Shocks					
Capital Distortions			Labor Distortions		
△ CR in 2011 (pp)	△ Real GDP per capita in 2011 (%)	△ Welfare (%)	△ CR in 2011 (pp)	△ Real GDP per capita in 2011 (%)	△ Welfare (%)
(1)	(2)	(3)	(4)	(5)	(6)
−16.46	279.18	6.21	−22.37	101.40	2.54

Notes. This table reports the real GDP and welfare effects when we replace sequences of shocks of all the top-3 firms with the counterfactual sequences of shocks defined in equation (B.14), in the model implementation that uses only capital and labor distortions to match the evolution of sales shares.

concentration. They plot the actual factor shares of the top-3 firms (dashed lines) and the factor shares predicted by this model scenario (solid lines). The plots show that these scenarios badly miss on the top-3 firms' shares of the wage bill (s^L_{fjt}) and capital (s^K_{fjt}). Increasing sales concentration purely through τ^L_{fjt} and τ^K_{fjt} requires very high subsidies on these firms' factor usage, implying that they employ 65% the labor and capital in the economy by 2011. In the data, the corresponding figures are around 30%. This discrepancy is to be expected: engineering the increase in top-3 sales shares with distortions requires subsidizing these firms' factor usage at a very high rate. In turn, these subsidies imply that the top firms utilize more and more of the factors. This implication is of course at odds with the data, where the increase in the top-3 factor shares s^L_{fjt} and s^K_{fjt} is roughly commensurate with their change in sales shares.

Are the top-3 firms too big or too small?. Our main results find that faster productivity growth by the top-3 firms contributed positively to GDP and welfare. A distinct question is whether the top firms are too big or too small relative to a case without misallocation across firms, conditional on that productivity. All else equal, they would be inefficiently small either because they face relatively higher exogenous distortions ($\tau^V_{fjk} >> 0$, $V = L, K$ for these firms) or because they endogenously reduce their scale to take advantage of their market power. The top firms would be inefficiently large if they face relatively lower distortions ($\tau^V_{fjk} << 0$). To address this question, we contrast the baseline economy with one in which these two forces are muted. In particular, we construct a hypothetical economy in which there is no misallocation (no dispersion in τ^K_{fjt} and τ^L_{fjt}) and in which all firms are monopolistically competitive. Thus, comparing the baseline to this alternative economy reveals whether the top-3 firms are too small or too big relative to the case without misallocation.[19] Panel A

[19] We know that when there is no markup dispersion across firms, the monopolistically competitive economy is efficient if labor and capital are supplied inelastically (Bilbiie et al., 2019; Dhingra and Morrow, 2019). In our case, because labor and capital supplies are elastic, the economy is not efficient even if there is no misallocation. Nonetheless, when misallocation is absent the social planner would not change the *relative* size of firms within a sector, compared to the market equilibrium.

of Figure B15 presents the scatterplot of the top-3 firms' observed sectoral sales shares on the x-axis against their sectoral sales shares in the no-misallocation economy in 2011. A firm below the 45-degree line is inefficiently big, above that line, inefficiently small. We see a mixed bag, with roughly similar numbers of firms too big and too small. Panel B of Figure B15 plots the concentration ratio in the data and the concentration ratio in the no-misallocation economy. For more than half of the sample period, concentration is actually higher in the no-misallocation economy relative to the data. This means that historically, as a group the top-3 firms were inefficiently small, though the difference flipped and became minor in the last 15 years or so. All in all, these results imply that the forces that make the top firms inefficiently small—tax-like distortions and exercises of market power—are quantitatively more important than the differential distortions that may make these firms too big.[20]

4.4 Alternative Scenarios and Sensitivity

The role of endogenous capital accumulation. One margin of response of the economy to the top-3 productivity and distortion shocks is capital accumulation. Making the top-3 firms like the "typical" firms in the counterfactual lowers their productivity, reducing the marginal product of capital and therefore the equilibrium capital stock. Capital accumulation is thus an amplification mechanism for the changes in aggregate productivity engineered in the counterfactual. To assess the contribution of endogenous capital accumulation, Panel B of Appendix Table B13 reports the results for a model in which the capital stock is exogenously fixed to its observed values in every year, and thus does not react to productivity changes in the counterfactual. Without endogenous capital response, the real GDP in 2011 is 15.0% lower in the all-shocks counterfactual, and 13.8% lower in the productivity-only counterfactual. The corresponding baseline model GDP changes are −20.8% and −18.1%. Thus, capital accumulation contributes about one-fourth of the total counterfactual real GDP change.

Mergers and acquisitions. Top-3 firm growth through mergers could pose two potential challenges to our exercise and our interpretation of the microdata. First, if in a merger the acquirer absorbs the target (becomes a single accounting entity), acquirer sales would show a discrete jump, even if nothing fundamental changed in the economy. The jump in sales would be interpreted by our shock recovery procedure as an increase in the acquirer's productivity, since productivity is largely backed out from the firm sales share (see eq. 2.23).

We analyzed a comprehensive merger dataset assembled by Center for Economic Catch-up (2007), covering 771 mergers in the Korean manufacturing sector over 1978-2005. Among these, 541 acquirers and 160 target firms could be matched to our firm balance sheet dataset. (The number of matched target firms is lower because they tend to be smaller.) Of these 160 matched acquisition targets, only 6 resulted in the disappearance of the target from the firm-level balance sheet dataset. In none of these

[20] The implied large no-misallocation top-3 share from the early 1980s to the early 1990s is due to just 2 firms, Kolon (Textiles) and Korea Pilot (Manufacturing, n.e.c.), for whom very large wedges are inferred in this period. Some of these excessive wedges could be due to measurement error. Removing these 2 firms eliminates the bulge, and makes the no-misallocation top-3 share much closer, though still above, the data in this period.

6 instances was the acquirer a top-3 firm. In the remaining 154 instances, the target continued to be present as a separate firm in the data, even though its ownership structure had changed. Thus, in the large majority of cases, there would be no mechanical jump in the acquirer's sales from absorbing the balance sheet of the target.

The second concern is "killer acquisitions" (Cunningham et al., 2021). These occur when following a merger, the acquirer deliberately depresses the productivity of the target in order to reduce head-to-head competition between the target's and the acquirer's products. This would be a problem for us because increased concentration would be accompanied by reduced productivity outside of the top-3, an effect we would miss in our counterfactuals. However, killer acquisitions are unlikely to be a major force in our setting quantitatively. The killer motive is less relevant when the acquirer and the target are in different sectors, which is often the case in our data. Among the 771 South Korean mergers, the target and acquirer are in different 1-digit sectors 39% of the time, in different 2-digit sectors 48% of the time, and in different 3-digit sectors 91% of the time.[21] Additionally, even in a sample of purely within-industry acquisitions (US pharmaceuticals), Cunningham et al. (2021) find that only $5.3 - 7.4\%$ fall in the "killer" category. As the target and acquirer are rarely in the same 3-digit sector, head-to-head product market competition between the target and the acquirer is unlikely to be intense in most observed mergers in our data.

Nonetheless, since target firms continue to be present in our data following acquisitions, we examine directly what happens to their productivity and find no noticeable change after the merger. Appendix B.7 details both the underlying data and the difference-in-differences estimation that compares acquisition targets to counterparts that (have not yet but) will subsequently be part of a merger, in the style of Cengiz et al. (2019). Figure B11 displays the evolution of the target firms' productivity before and after a merger. It shows no economically or statistically significant negative impact of acquisition on the target firm's productivity. This finding is not surprising in light of the discussion above, which argued that *a priori*, the "killer acquisitions" are unlikely to predominate in Korean manufacturing.

Simulating responses by other firms. The main counterfactual above changes the top-3 firms' shocks, while keeping other firms' shocks as they were in the data. The spirit of the exercise is that of development accounting: we compute how different real GDP and welfare would be in the absence of these firms' exceptional performance. These numbers should be interpreted as the top-3 firms' contribution to aggregate real GDP and welfare. Given a plethora of possible effects on other firms productivity that go in potentially opposite directions, the main analysis adopts a neutral approach and changes only the top-3 firms' shocks.

Having said that, we now perform 4 exercises that simulate other firms' responses to the counterfactual growth of the top-3 firms. First, in our main counterfactual the top-3 firms become smaller. This increases the profits of the rest of the (potential) firms in the sector, and thus may elicit new

[21] To fix ideas, there are a total of 11 1-digit manufacturing sectors, listed in Table B1, and 232 3-digit sectors.

Table 5: Alternative Assumptions on Non-top-3 Firms

(1)	(2)	(3)	(4)	(5)	(6)
		Counterfactual vs. Factual Shocks			
All shocks			Productivity shocks		
△ CR in 2011 (pp)	△ Real GDP per capita in 2011 (%)	△ Welfare (%)	△ CR in 2011 (pp)	△ Real GDP per capita in 2011 (%)	△ Welfare (%)
Panel A. Baseline					
−14.68	−20.80	−6.60	−12.35	−18.12	−4.90
Panel B. Free entry					
−14.17	−18.34	−5.10	−11.51	−15.04	−3.31
Panel C. Constant sectoral productivity					
−16.67	−7.26	−0.92	−14.75	−5.97	−0.10
Panel D. Productivity spillovers: Structural (Choi and Shim, 2025)					
−15.25	−23.19	−7.60	−12.87	−20.74	−5.92
Panel E. Productivity spillovers: Reduced-form empirical					
−14.50	−22.48	−5.91	−12.09	−19.73	−4.35

Notes. This table reports the change in the top-3 concentration ratio, real GDP, and welfare from counterfactuals under different assumptions on other firms' response, described in Section 4.4.

firms to enter or existing firms to upgrade productivity (e.g. Lileeva and Trefler, 2010; Bustos, 2011). To take this force into account, we increase fringe firms' productivity to keep the unweighted average firm profit at the sector-year level the same as in the baseline. This essentially simulates the free entry condition: as profits increase, new firms will enter until these additional profits have been dissipated.[22] Panel B of Table 5 displays the results for both the 4-shock counterfactual (left), and the productivity counterfactual (right). Predictably, the fall in real GDP and welfare is now smaller, as the other firms' increased productivity partly offsets the lower productivity of the top-3, but the net effect goes in the same direction.

Second, an extreme version of this type of exercise is to keep sectoral TFP constant in the counterfactual. That is, as we reduce the top-3 firms' productivity, we raise all firms' productivity such that A_{jt} remains the same. (It is not clear what economic mechanism would give rise to this constancy, however.) Panel C in Table 5 displays the results. Both real GDP and welfare are still lower in this counterfactual despite constant aggregate productivity. This is because the top-3 firms also have the greatest foreign market access. Reallocating productivity away from them and towards the rest of the firms in the sector weakens the correlation between productivity and foreign market access, thereby lowering demand for factors of production and intermediate inputs.

The above scenarios simulate a positive productivity/entry response by non-top-3 firms to reduced

[22]Since the mass of fringe firms vs. their productivity is indeterminate, increasing their productivity is isomorphic in its impact on prices and welfare to increasing their mass. Thus, this scenario encompasses both entry (higher mass of fringe firms) and productivity upgrading. Note that the fringe firms charge Dixit-Stiglitz markups. Modeling instead entry of large firms with higher markups would produce a strictly lower welfare impact of new entry.

top-3 productivity. However, there are also mechanisms, such as spillovers, imitation, or agglomeration forces, that would instead reduce non-top-3 firms' productivity when the top 3 become less productive. This is especially relevant for the top-3 firms, as they are the leaders in their sectors, and thus it would be reasonable to expect that other firms would learn from them (see, e.g. Greenstone et al., 2010, Chen and Xu, 2023 for empirical evidence, and Perla and Tonetti, 2014 for a theory of the less productive firms learning from the leading firms). The third scenario incorporates productivity spillovers from top-3 firms to other firms based on the structural estimates in Choi and Shim (2025). Appendix B.8 details the procedure. Panel D of Table 5 shows that real GDP and welfare would be even lower than in the main counterfactual, since in this scenario non-top-3 firms' productivity also falls.

Finally, the fourth scenario adopts a data-driven approach to calibrating the non-top-3 reaction to the top-3 firms' productivity. Appendix B.8 reports the results of estimating in a reduced-form way the spillovers from the top-3 firms' productivity to other firms' productivity. In particular, we regress log firm productivity on the lagged average log productivity of the top-3 firms (i) in the same sector; (ii) in the upstream sectors; (iii) in the downstream sectors. The latter is potentially important because based on some survey evidence, monopsony power by the top firms has been claimed to stifle innovation among their suppliers (Park, 2020). The results in Table B12 of Appendix B.8 show that firm productivity is positively correlated with lagged top-3 productivity in the same sector. This echoes the structural and identified estimates of Choi and Shim (2025), that also show positive productivity spillovers. Top-3 productivity in either upstream or downstream sectors does not have a significant effect on firm productivity. These results suggest that on net, top-3 firm productivity has if anything a positive net productivity effect on other firms. While there may be some anecdotal evidence of negative impacts, it appears that the positive channels outweigh the negative ones.

Panel E of Table 5 reports the results of a scenario in which as we change the top-3 productivity, other firms' productivity changes according to the coefficients reported in Table B12. In this counterfactual scenario, the impact of the top-3 firms' productivity on GDP and welfare is comparable to that in the main analysis.

Alternative parameter values. Appendix Table B13 assesses the sensitivity of the main quantitative results to alternative parameter values. For each alternative parameterization, we reestimate production function parameters and recalibrate the shocks to exactly fit the baseline scenario to the data. First, instead of the baseline $\sigma = 5$, Panel C uses sector-specific elasticities from Broda and Weinstein (2006) and estimates production function parameters based on these alternative values. The sector-specific σ_j's and the resulting production function estimates are reported in Appendix Table B2. We find larger GDP and welfare effects because some sectors that include large firms, such as Electronics, had lower σ_j, making large firms less substitutable with others. Panels D through H consider both lower and higher values of σ, ρ, η, θ, and ψ. Panel I tries alternative tax revenue waste parameters ζ. Panel J implements a model with constant returns to scale in each sector. Panel K allows for love-of-variety. Specifically, we remove the adjustment by $1/F_j$ in the labor and product aggregators (2.3) and (2.5). Panel L presents results based on production-function estimates obtained using either exporters only or non-exporters only. Lastly, Panel M conducts counterfactuals with different numbers of large firms, replacing top-4 or top-10 shocks with the averages. The results remain robust to all of these alternative parameterizations.

5. Conclusion

We document a novel fact about South Korea's growth miracle period: a dramatic increase in manufacturing firm concentration. To understand the driving forces and the macro consequences this trend, we build a quantitative dynamic small open economy heterogeneous firm model in which firms have oligopolistic and oligopsonistic market power in domestic goods and labor markets, and are subject to idiosyncratic distortions and foreign demand. The model allows us to disentangle the factors that drove the increase in concentration. We find roles for between- and within-sector reallocation, and for productivity and market access in the overall concentration increase. Our counterfactual exercises show that productivity growth of a few large firms had a sizable impact on real GDP and firm concentration. Our findings highlight the importance of large firms' contributions to economic growth. They also show that an increase in concentration need not be a symptom of economic malaise. Indeed, in South Korea the rise of large firms has been a positive phenomenon: it was driven by productivity growth but accompanied by only a limited increase in markups and markdowns.

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ONLINE APPENDIX

(NOT FOR PUBLICATION)

A. Proofs and Derivations

A.1 Equilibrium

Market clearing conditions. Goods market clearing implies

$$\sum_{f\in\mathcal{F}_{jt}} r^H_{fjt} = \lambda^H_{jt}\left[\alpha_j(W_tL_t + \varrho_tK_t + \Pi_t + T_t + \mathcal{D}_t) + \int_0^1 \gamma_i^{\mathrm{M}}\gamma_i^j\Big(\sum_{f\in\mathcal{F}_{it}}\sum_{e\in\{H,F\}}(\mu^e_{fit})^{-1}r^e_{fit}\Big)\mathrm{d}i\right],$$

where $\Pi_t = \int_0^1 \big(\sum_{f\in\mathcal{F}_{it}}\pi_{fit}\big)\mathrm{d}i$. The labor and capital market clearing conditions are

$$L_t = \int_0^1 \sum_{f\in\mathcal{F}_{it}} l_{fit}\mathrm{d}i \qquad \text{and} \qquad K_t = \int_0^1 \sum_{f\in\mathcal{F}_{it}} k_{fit}\mathrm{d}i.$$

The government budget is balanced:

$$T_t = (1-\zeta)\int_0^1\left(\sum_{f\in\mathcal{F}_{it}}\tau^L_{fit}w_{fit}l_{fit} + \tau^K_{fit}\varrho_tk_{fit}\right)\mathrm{d}i, \tag{A.1}$$

where $\zeta\in[0,1]$ is a parameter that governs how much resources are wasted due to distortions. Market clearing conditions imply balanced trade given the exogenous deficit.

We formally define an equilibrium as follows.

Definition 1. *An equilibrium is a set of prices* $\{p^H_{fjt}, p^F_{fjt}, w_{fjt}\}^{t\in\{0,\dots,\infty\}}_{f\in\mathcal{F}_{jt},j\in[0,1]}$, $\{P^H_{jt}, P_{jt}, P^M_{jt}\}_{j\in[0,1]}$, ϱ_t, P_t, *and goods and factor allocations* $\{y^H_{fjt}, y^F_{fjt}, l_{fjt}, k_{fjt}, m_{fjt}\}^{t\in\{0,\dots,\infty\}}_{f\in\mathcal{F}_{jt},j\in[0,1]}$, $\{C_t, I_t, Y^H_{jt}, Y^F_{jt}, Y_{jt}, Y^M_{j,it}, Y^C_{jt}\}^{t\in\{0,\dots,\infty\}}_{i,j\in[0,1]}$ *such that*

- *(Static equilibrium) For each period, (i) households choose labor supplies to maximize utility; (ii) firms maximize profits; (iii) all goods and factor markets clear; (iv) the government budget is balanced inclusive of the exogenous deficit; and (v) trade is balanced.*
- *(Dynamic equilibrium) (i) households choose a path of consumption and investment to maximize utility; and (ii) capital stock accumulates according to households' optimal investment.*

A.2 Derivations and Proofs

Derivation of equation (2.9). The Lagrangian for the profit maximization problem is

$$\max_{y^H_{fj},y^F_{fj},l_{fj},k_{fj},m_{fj}} p^H_{fj}y^H_{fj} + p^F_{fj}y^F_{fj} - (1+\tau^L_{fj})w_{fj}l_{fj} - (1+\tau^K_{fj})\varrho k_{fj} - P^M_j m_{fj} + \lambda(y_{fj} - y^H_{fj} - y^F_{fj}),$$

where λ is the Lagrangian multiplier of the resource constraint. Taking the first-order conditions with respect to y^H_{fj}, y^F_{fj}, and l_{fj},

$$p^H_{fj} + y^H_{fj}\frac{\partial p^H_{fj}}{\partial y^H_{fj}} = p^H_{fj}\Big(1 + \frac{\partial \ln p^H_{fj}}{\partial \ln y^H_{fj}}\Big) = \lambda, \qquad p^F_{fj} + y^F_{fj}\frac{\partial p^F_{fj}}{\partial y^F_{fj}} = p^F_{fj}\Big(1 + \frac{\partial \ln p^F_{fj}}{\partial \ln y^F_{fj}}\Big) = \lambda,$$

$$\lambda\frac{\partial y_{fj}}{\partial l_{fj}} = (1+\tau^L_{fj})\Big(w_{fj} + \frac{\partial w_{fj}}{\partial l_{fj}}l_{fj}\Big) = (1+\tau^L_{fj})w_{fj}\Big(1 + \frac{\partial \ln w_{fj}}{\partial \ln l_{fj}}\Big),$$

where $-\frac{\partial \ln p^H_{fj}}{\partial \ln y^H_{fj}} = -\varepsilon(s^H_{fj}, \lambda^H_j)^{-1}$ and $-\frac{\partial \ln p^F_{fj}}{\partial \ln y^F_{fj}} = -\frac{1}{\sigma}$, and $\frac{\partial \ln w_{fj}}{\partial \ln l_{fj}} = \varepsilon^L(s^L_{fj})$. Combining the above three first-order conditions gives the expression in equation (2.9).

Derivation of equation (2.10). We show that ε_{fj} can be written in terms of domestic sales and import shares. The inverse demand function is expressed as $p^H_{fj} = F_j^{-\frac{1}{\sigma}}(y^H_{fj})^{-\frac{1}{\sigma}}(Y^H_j)^{\frac{1}{\sigma}-\frac{1}{\rho}}(Y_j)^{\frac{1}{\rho}-1}E_j$. From this, we can derive that

$$\varepsilon^{-1}_{fj} = -\frac{\partial \ln p^H_{fj}}{\partial \ln y^H_{fj}} = \frac{1}{\sigma} + \Big(\frac{1}{\rho} - \frac{1}{\sigma}\Big)\frac{\partial \ln Y^H_j}{\partial \ln y^H_{fj}} + \Big(1 - \frac{1}{\rho}\Big)\frac{\partial \ln Y_j}{\partial \ln y^H_{fj}}. \tag{A.2}$$

Note that $\frac{\partial \ln Y^H_j}{\partial \ln y^H_{fj}} = s^H_{fj}$ and that $\frac{\partial \ln Y_j}{\partial \ln y^H_{fj}} = \underbrace{\frac{\partial \ln Y_j}{\partial \ln Y^H_j}}_{=\lambda^H_j}\underbrace{\frac{\partial \ln Y^H_j}{\partial \ln y^H_{fj}}}_{=s^H_{fj}}$. Substituting these two expressions into equation (A.2) gives

$$\varepsilon^{-1}_{fj} = \frac{1}{\sigma} + \Big(\frac{1}{\rho} - \frac{1}{\sigma}\Big)s^H_{fj} + \Big(1 - \frac{1}{\rho}\Big)\lambda^H_j s^H_{fj}.$$

Note that if firms take Y_j as given, $\varepsilon^{-1}_{fj} = \frac{1}{\sigma} + \Big(\frac{1}{\rho} - \frac{1}{\sigma}\Big)s^H_{fj}$. In a closed economy, $\lambda^H_j = 1$ and therefore $\varepsilon^{-1}_{fj} = \frac{1}{\sigma} + \Big(\frac{1}{\rho} - \frac{1}{\sigma}\Big)s^H_{fj}$. If $\sigma = \rho$, $\varepsilon^{-1}_{fj} = \frac{1}{\sigma} + \Big(1 - \frac{1}{\sigma}\Big)\lambda^H_j s^H_{fj}$ holds.

Derivation of equation (2.11). The inverse labor supply function can be written as

$$w_{fj} = F_j^{\frac{1}{\eta}} l_{fj}^{\frac{1}{\eta}} L_j^{\frac{1}{\theta}-\frac{1}{\eta}} W,$$

where firms internalize l_{fj} and L_j and take W as given. From this inverse labor supply function, we can derive that

$$(\varepsilon^L_{fj})^{-1} = \frac{\partial \ln w_{fj}}{\partial \ln l_{fj}} = \frac{1}{\eta} + \Big(\frac{1}{\theta} - \frac{1}{\eta}\Big)\underbrace{\frac{\partial \ln L_j}{\partial \ln l_{fj}}}_{=s^L_{fj}}.$$

Marginal revenue products and prices. The first-order conditions show that the firm trades off the marginal revenue product of any input in each market against the marginal cost of that input. For each $e \in \{H, F\}$:

$$\begin{aligned} mrpl_{fj} &:= \frac{\gamma_j^L p_{fj}^e y_{fj}}{\mu_{fj}^e l_{fj}} = \mu_{fj}^L (1+\tau_{fj}^L) w_{fj}, \\ mrpk_{fj} &:= \frac{\gamma_j^K p_{fj}^e y_{fj}}{\mu_{fj}^e k_{fj}} = (1+\tau_{fj}^K)\varrho, \\ mrpm_{fj} &:= \frac{\gamma_j^M p_{fj}^e y_{fj}}{\mu_{fj}^e m_{fj}} = P_j^M. \end{aligned} \tag{A.3}$$

The markup-adjusted marginal revenue products appearing in Proposition 2.1 are:

$$\begin{aligned} \widetilde{mrpl}_{fj} &= \tilde{\mu}_{fj} \frac{\gamma_j^L p_{fj}^e y_{fj}}{\mu_{fj}^e l_{fj}} = \tilde{\mu}_{fj} \mu_{fj}^L (1+\tau_{fj}^L) w_{fj}, \\ \widetilde{mrpk}_{fj} &= \tilde{\mu}_{fj} \frac{\gamma_j^K p_{fj}^e y_{fj}}{\mu_{fj}^e k_{fj}} = \tilde{\mu}_{fj} (1+\tau_{fj}^K)\varrho, \\ \widetilde{mrpm}_{fj} &= \tilde{\mu}_{fj} \frac{\gamma_j^M p_{fj}^e y_{fj}}{\mu_{fj}^e m_{fj}} = \tilde{\mu}_{fj} P_j^M. \end{aligned} \tag{A.4}$$

The sectoral counterparts of these marginal products appearing in Proposition 2.1 are:

$$\widetilde{MRPL}_j = \left[F_j^{\frac{1}{\eta}} \sum_{f \in \mathcal{F}_j} \left(s_{fj} \frac{1}{\widetilde{mrpl}_{fj}} \right)^{\frac{\eta+1}{\eta}} \right]^{-\frac{\eta}{\eta+1}}, \; \widetilde{MRPK}_j = \left[\sum_{f \in \mathcal{F}_j} s_{fj} \frac{1}{\widetilde{mrpk}_{fj}} \right]^{-1}$$
$$\text{and} \qquad \widetilde{MRPM}_j = \left[\sum_{f \in \mathcal{F}_j} s_{fj} \frac{1}{\widetilde{mrpm}_{fj}} \right]^{-1}. \tag{A.5}$$

To solve for price, using equation (A.3), we obtain

$$l_{fj} = \frac{\gamma_j^L p_{fj}^e y_{fj}}{\mu_{fj}^e \mu_{fj}^L (1+\tau_{fj}^L) w_{fj}}, \quad k_{fj} = \frac{\gamma_j^K p_{fj}^e y_{fj}}{\mu_{fj}^e R (1+\tau_{fj}^K)}, \quad m_{fj} = \frac{\gamma_j^M p_{fj}^e y_{fj}}{P_j^M \mu_{fj}^e},$$

for $e \in \{H, F\}$. Substituting the above expressions into production function $y_{fj} = a_{fj} l_{fj}^{\gamma_j^L} k_{fj}^{\gamma_j^K} m_{fj}^{\gamma_j^M}$, we obtain

$$y_{fj} = a_{fj} (\mu_{fj}^e)^{-\gamma_j} (p_{fj}^e y_{fj})^{\gamma_j} \left(\mu_{fj}^L (1+\tau_{fj}^L) \right)^{-\gamma_j^L} (1+\tau_{fj}^K)^{-\gamma_j^K} \left(\frac{w_{fj}}{\gamma_j^L} \right)^{-\gamma_j^L} \left(\frac{R}{\gamma_j^K} \right)^{-\gamma_j^K} \left(\frac{P_j^M}{\gamma_j^M} \right)^{-\gamma_j^M}.$$

Rearranging the above expression, we obtain

$$
\begin{aligned}
p^e_{fj} &= \mu^e_{fj}\Big[\frac{y_{fj}^{1-\gamma_j}}{a_{fj}}\Big(\frac{mrpl_{fj}}{\gamma^L_j}\Big)^{\gamma^L_j}\Big(\frac{mrpk_{fj}}{\gamma^K_j}\Big)^{\gamma^K_j}\Big(\frac{mrpm_{fj}}{\gamma^M_j}\Big)^{\gamma^M_j}\Big]^{\frac{1}{\gamma_j}} \qquad \text{(A.6)}\\
&= \mu^e_{fj}\big(\mu^L_{fj}(1+\tau^L_{fj})\big)^{\frac{\gamma^L_j}{\gamma_j}}(1+\tau^K_{fj})^{\frac{\gamma^K_j}{\gamma_j}}c_{fj}a_{fj}^{-1/\gamma_j} \qquad\qquad e \in \{H, F\}.
\end{aligned}
$$

Proof of Proposition 2.1(i). We first show that $A_j = \Big[\sum_{f\in\mathcal{F}_j} F_j^{-1}\Big(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\Big)^{\sigma-1}\Big]^{\frac{1}{\sigma-1}}$ holds. By definition, because $R_j = \mathrm{PPI}_j \times Y^r_j$, $TFPR_j = \mathrm{PPI}_j \times A_j$ holds. Similarly, at firm-level, because $r_{fj} = \tilde{p}_{fj}y_{fj}$, $tfpr_{fj} = \tilde{p}_{fj}a_{fj}$ also holds. From these relationships,

$$
A_j = TFPR_j(\mathrm{PPI}_j)^{-1} = TFPR_j\Big(\sum_{f\in\mathcal{F}_j} F_j^{-1}\tilde{p}_{fj}^{1-\sigma}\Big)^{\frac{-1}{1-\sigma}} = \Big(\sum_{f\in\mathcal{F}_j} F_j^{-1}\Big(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\Big)^{\sigma-1}\Big)^{\frac{1}{\sigma-1}},
$$

where the second equality comes from the fact that $\tilde{p}_{fj} = tfpr_{fj}/a_{fj}$.

Next, we turn our focus on $tfpr_{fj}$. From the FOC with respect to labor, we obtain that

$$
(\gamma^L_j)^{-1}\mu^H_{fj}\mu^L_{fj}(1+\tau^L_{fj})w_{fj}l_{fj} = p^H_{fj}y_{fj} = \frac{p^H_{fj}y^H_{fj}}{p^H_{fj}y^H_{fj}+p^F_{fj}y^F_{fj}}\frac{y_{fj}}{y^H_{fj}}r_{fj}.
$$

Using equation (A.13), we can re-express as $l_{fj} = \gamma^L_j\frac{r_{fj}}{\tilde{\mu}_{fj}\mu^L_{fj}(1+\tau^L_{fj})w_{fj}}$. Using the fact that $\frac{w_{fj}}{W_j} = (s^L_{fj})^{\frac{1}{\eta+1}}$,

$$
l_{fj} = \gamma^L_j\frac{r_{fj}}{\tilde{\mu}_{fj}\mu^L_{fj}(1+\tau^L_{fj})(s^L_{fj})^{\frac{1}{\eta+1}}W_j}. \qquad \text{(A.7)}
$$

Similarly for other inputs, we obtain the following relationships

$$
k_{fj} = \gamma^K_j\frac{r_{fj}}{\tilde{\mu}_{fj}(1+\tau^K_{fj})\varrho} \qquad \text{and} \qquad m_{fj} = \gamma^M_j\frac{r_{fj}}{\tilde{\mu}_{fj}P^M_j}. \qquad \text{(A.8)}
$$

Substituting the above three expressions into the definition of $tfpr_{fj} = \frac{r_{fj}}{l_{fj}^{\gamma^L_j}k_{fj}^{\gamma^K_j}m_{fj}^{\gamma^M_j}}$, we obtain that

$$
\begin{aligned}
tfpr_{fj} = r_{fj}^{1-\gamma_j}\Big((\tilde{\mu}_{fj}(1+\tau^L_{fj})\mu^L_{fj}(s^L_{fj})^{\frac{1}{\eta+1}}\Big)^{\gamma^L_j}\Big((\tilde{\mu}_{fj}(1+\tau^K_{fj})\Big)^{\gamma^K_j}\Big(\tilde{\mu}_{fj}\Big)^{\gamma^M_j}& \\
\times (W_j/\gamma^L_j)^{\gamma^L_j}(\varrho/\gamma^K_j)^{\gamma^K_j}(P^M_j/\gamma^M_j)^{\gamma^M_j}.& \qquad \text{(A.9)}
\end{aligned}
$$

Lastly, we turn our focus on $TFPR_j$. From equation (A.7) and $L_j = (F_j^{\frac{1}{\eta}} \sum_{f\in\mathcal{F}_j} l_{fj}^{\frac{\eta+1}{\eta}})^{\frac{\eta}{\eta+1}}$,

$$\begin{aligned} L_j &= \gamma_j^L \Bigg(F_j^{\frac{1}{\eta}} \sum_{f\in\mathcal{F}_j} \Big(r_{fj} (\tilde{\mu}_{fj} \mu_{fj}^L (1+\tau_{fj}^L)(s_{fj}^L)^{\frac{1}{\eta+1}} W_j)^{-1} \Big)^{\frac{\eta+1}{\eta}} \Bigg)^{\frac{\eta}{\eta+1}} \\ &= \gamma_j^L \Bigg(F_j^{\frac{1}{\eta}} \sum_{f\in\mathcal{F}_j} \Big(s_{fj} (\tilde{\mu}_{fj} \mu_{fj}^L (1+\tau_{fj}^L)(s_{fj}^L)^{\frac{1}{\eta+1}} W_j)^{-1} \Big)^{\frac{\eta+1}{\eta}} \Bigg)^{\frac{\eta}{\eta+1}} R_j, \end{aligned} \tag{A.10}$$

where the second equality comes from that $s_{fj} = r_{fj}/R_j$. Similarly, we can obtain

$$K_j = \gamma_j^K \Bigg(\sum_{f\in\mathcal{F}_j} s_{fj} (\tilde{\mu}_{fj}(1+\tau_{fj}^K) R_j^K)^{-1} \Bigg) R_j \tag{A.11}$$

and

$$M_j = \gamma_j^M \Bigg(\sum_{f\in\mathcal{F}_j} s_{fj} (\tilde{\mu}_{fj} P_j^M)^{-1} \Bigg) R_j \tag{A.12}$$

Substituting equations (A.10), (A.11), and (A.12) into $TFPR_j = \frac{R_j}{L_j^{\gamma_j^L} K_j^{\gamma_j^K} M_j^{\gamma_j^M}}$, we obtain

$$\begin{aligned} TFPR_j = R_j^{1-\gamma_j} &\Bigg[F_j^{\frac{1}{\eta}} \sum_{f\in\mathcal{F}_j} \Big(s_{fj} \big(\tilde{\mu}_{fj}(1+\tau_{fj}^L)\mu_{fj}^L (s_{fj}^L)^{\frac{1}{\eta+1}} \big)^{-1} \Big)^{\frac{\eta+1}{\eta}} \Bigg]^{-\gamma_j^L \frac{\eta}{\eta+1}} \\ &\times \Bigg[\sum_{f\in\mathcal{F}_j} s_{fj} \Big(\tilde{\mu}_{fj}(1+\tau_{fj}^K) \Big)^{-1} \Bigg]^{-\gamma_j^K} \Bigg[\sum_{f\in\mathcal{F}_j} s_{fj} \Big(\tilde{\mu}_{fj} \Big)^{-1} \Bigg]^{-\gamma_j^M} \times (W_j/\gamma_j^L)^{\gamma_j^L} (\varrho/\gamma_j^K)^{\gamma_j^K} (P_j^M/\gamma_j^M)^{\gamma_j^M}, \end{aligned}$$

which can be expressed as

$$TFPR_j = R_j^{1-\gamma_j} \widetilde{MRPL}_j^{\gamma_j^L} \widetilde{MRPK}_j^{\gamma_j^K} \widetilde{MRPM}_j^{\gamma_j^M}.$$

□

Proof of Proposition 2.1(ii). We first derive the expression for the aggregate markup $\mathcal{M}_j$. From the FOC with respect to material inputs (equation A.3),

$$P_j^M m_{fj} = (\mu_{fj}^H)^{-1} \gamma_j^M p_{fj}^H y_{fj} = (\mu_{fj}^H)^{-1} \gamma_j^M \frac{y_{fj}}{y_{fj}^H} \times \frac{p_{fj}^H y_{fj}^H}{p_{fj}^H y_{fj}^H + p_{fj}^F y_{fj}^F} \times \underbrace{(p_{fj}^H y_{fj}^H + p_{fj}^F y_{fj}^F)}_{=r_{fj}} = \gamma_j^M (\tilde{\mu}_{fj})^{-1} r_{fj},$$

where the second equality comes from the fact that

$$\mu_{fj}^H \frac{y_{fj}^H}{y_{fj}} \left(\frac{p_{fj}^H y_{fj}^H}{p_{fj}^H y_{fj}^H + p_{fj}^F y_{fj}^F} \right)^{-1} = \mu_{fj}^H \frac{y_{fj}^H}{y_{fj}} \left(\frac{\mu_{fj}^H \frac{y_{fj}^H}{y_{fj}}}{\mu_{fj}^H \frac{y_{fj}^H}{y_{fj}} + \mu_{fj}^F \frac{y_{fj}^F}{y_{fj}}} \right)^{-1} = \mu_{fj}^H \frac{y_{fj}^H}{y_{fj}} + \mu_{fj}^F \frac{y_{fj}^F}{y_{fj}} = \tilde{\mu}_{fj}. \tag{A.13}$$

From the above expressions, we obtain that

$$P_j^M M_j = \sum_{f \in \mathcal{F}_j} P_j^M m_{fj} = \gamma_j^M \Bigg(\sum_{f \in \mathcal{F}_j} (\tilde{\mu}_{fj})^{-1} \frac{r_{fj}}{R_j} \Bigg) R_j = \gamma_j^M \Bigg(\sum_{f \in \mathcal{F}_j} (\tilde{\mu}_{fj})^{-1} s_{fj} \Bigg) R_j,$$

Plugging in the above expression into equation (2.15), we obtain that $\mathcal{M}_j = (\sum_{f \in \mathcal{F}_j} \tilde{\mu}_{fj}^{-1} s_{fj})^{-1}$.

We now turn our focus on the expression for sectoral markdown $\mathcal{M}_j^L$. From the FOC with respect to labor,

$$(1 + \tau_{fj}^L) w_{fj} l_{fj} = (\mu_{fj} \mu_{fj}^L)^{-1} \gamma_j^L p_{fj}^H y_{fj} = (\tilde{\mu}_{fj} \mu_{fj}^L)^{-1} \gamma_j^L r_{fj} = (\tilde{\mu}_{fj} \mu_{fj}^L)^{-1} \gamma_j^L s_{fj} R_j,$$

where the second equality holds due to equation (A.13) and the third equality comes from the fact that $s_{fj} = r_{fj}/R_j$. Summing both sides across firms,

$$\sum_{f \in \mathcal{F}_j} (1 + \tau_{fj}^L) w_{fj} l_{fj} = \Bigg(\sum_{f \in \mathcal{F}_j} (1 + \tau_{fj}^L) s_{fj}^L \Bigg) W_j L_j = \gamma_j^L \Bigg(\sum_{f \in \mathcal{F}_j} (\tilde{\mu}_{fj} \mu_{fj}^L)^{-1} s_{fj} \Bigg) R_j,$$

where the equality comes from that $\sum_{f \in \mathcal{F}_j} w_{fj} l_{fj} = W_j L_j$. Plugging the above expression into the definition of the aggregate markdown (equation 2.15), we obtain the desired results. $\square$

Weights definitions for Proposition 2.2. The weights $\omega_{fjt,t-p}$ are defined as

$$\omega_{fjt,t-p} = \frac{\frac{s_{fjt}^{3,cont} - s_{fj,t-p}^{3,cont}}{\ln s_{fjt}^{3,cont} - \ln s_{fj,t-p}^{3,cont}}}{\sum_{g \in \mathcal{F}_{jt,t-p}^{3,cont}} \frac{s_{gjt}^{3,cont} - s_{gj,t-p}^{3,cont}}{\ln s_{gjt}^{3,cont} - \ln s_{gj,t-p}^{3,cont}}}, \quad \text{where} \quad s_{fj\tilde{t}}^{3,cont} = \frac{r_{fj\tilde{t}}}{\sum_{g \in \mathcal{F}_{jt,t-p}^{3,cont}} r_{gj\tilde{t}}}, \quad \tilde{t} \in \{t-p, t\}. \tag{A.14}$$

The $S_{j,t-p}^{3,cont}$ and $S_{jt}^{3,cont}$ are defined to be the sales shares of the set of firms $\mathcal{F}_{j,t,t-p}^{3,cont} = \mathcal{F}_{jt}^{3,cont} \cap \mathcal{F}_{j,t-p}^{3,cont}$ that are in the top 3 in both t and $t-p$:

$$S_{j,t-p}^{3,cont} = \frac{\sum_{f \in \mathcal{F}_{j,t,t-p}^{3,cont}} r_{fj,t-p}}{\sum_{f \in \mathcal{F}_{j,t-p}^{3}} r_{fj,t-p}} \quad \text{and} \quad S_{jt}^{3,cont} = \frac{\sum_{f \in \mathcal{F}_{j,t,t-p}^{3,cont}} r_{fjt}}{\sum_{f \in \mathcal{F}_{jt}^{3}} r_{fjt}}. \tag{A.15}$$

The weight $\omega_{j,t-p}^3$ is defined as:

$$\omega_{j,t-p}^3 = \frac{\sum_{f \in \mathcal{F}_{j,t-p}^3} r_{fj,t-p}}{\sum_{i \in \mathcal{J}_M} \sum_{f \in \mathcal{F}_{i,t-p}^3} r_{fi,t-p}}. \tag{A.16}$$

Proof of Proposition 2.2(i). First, we show that $s_{fj} = \frac{(\tilde{a}_{fj}\phi_{fj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}}{\sum_{g\in\mathcal{F}_j}(\tilde{a}_{gj}\phi_{gj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}}$ holds. We omit the subscript t for notational convenience and introduce it when necessary. Note that

$$r_{fj} = p^H_{fj}y^H_{fj} + p^F_{fj}y^F_{fj} = (p^H_{fj})^{1-\sigma}(P^H_j)^{\sigma-\rho}P^{\rho-1}_j E_j + (p^F_{fj})^{1-\sigma}D_{fj} \propto (p^H_{fj})^{1-\sigma} + (p^F_{fj})^{1-\sigma}\tilde{D}_{fj},$$

where $\tilde{D}_{fj} = D_{fj}/(P^H_j)^{\sigma-\rho}P^{\rho-1}_j E_j$ is firm-specific foreign demand relative to domestic demand. Note that domestic demand $(P^H_j)^{\sigma-\rho}P^{\rho-1}_j E_j$ is common across firms.

Using equation (A.6) and the fact that p^H_{fj} and p^F_{fj} only differ in μ^H_{fj} and μ^F_{fj}, we obtain

$$r_{fj} \propto \left(a_{fj}^{-\frac{1}{\gamma_j}}\,\widetilde{mrpl}_{fj}^{\frac{\gamma^L_j}{\gamma_j}}\,\widetilde{mrpk}_{fj}^{\frac{\gamma^K_j}{\gamma_j}}\,\widetilde{mrpm}_{fj}^{\frac{\gamma^M_j}{\gamma_j}}\,y_{fj}^{\frac{1-\gamma_j}{\gamma_j}}\right)^{1-\sigma}\tilde{D}^{MA}_{fj}. \tag{A.17}$$

Note that y_{fj} can be expressed as $y_{fj} = (p^H_{fj})^{-\sigma}(P^H_j)^{\sigma-\rho}P^{\rho}_j E_j + (p^F_{fj})^{-\sigma}D_{fj}$ and we can obtain that

$$\begin{aligned} y_{fj} &\propto \left(a_{fj}^{-\frac{1}{\gamma_j}}\,\widetilde{mrpl}_{fj}^{\frac{\gamma^L_j}{\gamma_j}}\,\widetilde{mrpk}_{fj}^{\frac{\gamma^K_j}{\gamma_j}}\,\widetilde{mrpm}_{fj}^{\frac{\gamma^M_j}{\gamma_j}}\,y_{fj}^{\frac{1-\gamma_j}{\gamma_j}}\right)^{-\sigma}\tilde{D}^{RTS}_{fj} \\ &\Leftrightarrow y_{fj}^{\frac{\gamma_j(1-\sigma)+\sigma}{\gamma_j}} \propto \left(a_{fj}^{-\frac{1}{\gamma_j}}\,\widetilde{mrpl}_{fj}^{\frac{\gamma^L_j}{\gamma_j}}\,\widetilde{mrpk}_{fj}^{\frac{\gamma^K_j}{\gamma_j}}\,\widetilde{mrpm}_{fj}^{\frac{\gamma^M_j}{\gamma_j}}\right)^{-\sigma}\tilde{D}^{RTS}_{fj}. \end{aligned} \tag{A.18}$$

Substituting equation (A.18) into equation (A.17), we obtain that

$$r_{fj} \propto \left(a_{fj}\widetilde{mrpl}_{fj}^{-\gamma^L_j}\,\widetilde{mrpk}_{fj}^{-\gamma^K_j}\,\widetilde{mrpm}_{fj}^{-\gamma^M_j}\right)^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}\phi_{fj}^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}} \propto (\tilde{a}_{fj}\phi_{fj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}.$$

Note that the second relationship holds due to the fact that $\widetilde{MRPL}_j$, $\widetilde{MRPK}_j$, and $\widetilde{MRPM}_j$ are common across firms within sectors. From the above expression, we can express firm sales shares as

$$s_{fj} = \frac{(\tilde{a}_{fj}\phi_{fj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}}{\sum_{g\in\mathcal{F}_j}(\tilde{a}_{gj}\phi_{gj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}} = \frac{(\tilde{a}_{fj}\phi_{fj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}}{\Omega_j}, \tag{A.19}$$

where Ω_j denote the sector-wide denominator.

In the next step, we show that $\Omega_j = (A_j\Phi_j)^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}$.

$$
\begin{aligned}
s_{fj} = (\tilde{a}_{fj}\phi_{fj})^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}\Omega_j^{-1} &\Rightarrow s_{fj} = \Big(\frac{\tilde{a}_{fj}}{s_{fj}^{1-\gamma_j}}\phi_{fj}\Big)^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}} s_{fj}^{\frac{1-\gamma_j}{\frac{\sigma}{\sigma-1}-\gamma_j}}\Omega_j^{-1} \\
&\Rightarrow s_{fj}^{\frac{1}{\sigma-1}} = \left(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\right)\phi_{fj}\Omega_j^{-(\frac{\sigma}{\sigma-1}-\gamma_j)} \\
&\Rightarrow \left(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\right)^{\sigma-1} = s_{fj}\phi_{fj}^{1-\sigma}\Omega_j^{(\frac{\sigma}{\sigma-1}-\gamma_j)(\sigma-1)}.
\end{aligned}
$$

Summing over both sides across firms,

$$
\begin{aligned}
\sum_{f\in\mathcal{F}_{jt}}\left(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\right)^{\sigma-1} &= \sum_{f\in\mathcal{F}_{jt}} s_{fj}\phi_{fj}^{1-\sigma}\Omega_j^{(\frac{\sigma}{\sigma-1}-\gamma_j)(\sigma-1)} \\
&\Rightarrow \underbrace{\left[\sum_{f\in\mathcal{F}_{jt}}\left(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}}_{=\tilde{A}_j} = \underbrace{\left(\sum_{f\in\mathcal{F}_{jt}} s_{fj}\phi_{fj}^{1-\sigma}\right)^{\frac{1}{\sigma-1}}}_{=\Phi_j^{-1}}\Omega_j^{(\frac{\sigma}{\sigma-1}-\gamma_j)},
\end{aligned}
$$

which gives $\Omega_j^{(\frac{\sigma}{\sigma-1}-\gamma_j)} = \tilde{A}_j\Phi_j$.

Now, we introduce the subscript t to denote for year t. Substituting $\Omega_{jt}^{(\frac{\sigma}{\sigma-1}-\gamma_j)} = \tilde{A}_{jt}\Phi_{jt}$ into equation (A.19), taking logs, and differencing between $t-p$ and t, we obtain that

$$
\ln\frac{s_{fjt}}{s_{fj,t-p}} = \frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}\Big(\ln\frac{\tilde{a}_{fjt}/\tilde{A}_{jt}}{\tilde{a}_{fj,t-p}/\tilde{A}_{j,t-p}} + \ln\frac{\phi_{fjt}/\Phi_{jt}}{\phi_{fj,t-p}/\Phi_{j,t-p}}\Big). \tag{A.20}
$$

Note that s_{fjt} and $s_{fj,t-p}$ can be re-expressed as

$$
s_{fjt} = \frac{r_{fjt}}{\sum_{g\in\mathcal{F}^{3,cont}_{jt,t-p}} r_{gjt}}\frac{\sum_{f\in\mathcal{F}^{3,cont}_{jt,t-p}} r_{fjt}}{\sum_{g\in\mathcal{F}^{3}_{jt}} r_{gjt}}\frac{\sum_{f\in\mathcal{F}^{3}_{jt}} r_{fjt}}{\sum_{g\in\mathcal{F}_{jt}} r_{gjt}} = s^{3,cont}_{fjt}S^{3,cont}_{jt}S^{3}_{jt}. \tag{A.21}
$$

$$
s_{fj,t-p} = \frac{r_{fj,t-p}}{\sum_{g\in\mathcal{F}^{3,cont}_{jt,t-p}} r_{gj,t-p}}\frac{\sum_{f\in\mathcal{F}^{3,cont}_{jt,t-p}} r_{fj,t-p}}{\sum_{g\in\mathcal{F}^{3}_{j,t-p}} r_{gj,t-p}}\frac{\sum_{f\in\mathcal{F}^{3}_{j,t-p}} r_{fj,t-p}}{\sum_{g\in\mathcal{F}_{j,t-p}} r_{gj,t-p}} = s^{3,cont}_{fj,t-p}S^{3,cont}_{j,t-p}S^{3}_{j,t-p}. \tag{A.22}
$$

Define

$$
\omega_{fjt,t-p} = \frac{\frac{s^{3,cont}_{fjt}-s^{3,cont}_{fj,t-p}}{\ln s^{3,cont}_{fjt}-\ln s^{3,cont}_{fj,t-p}}}{\sum_{g\in\mathcal{F}^{3,cont}_{jt,t-p}}\frac{s^{3,cont}_{gjt}-s^{3,cont}_{gj,t-p}}{\ln s^{3,cont}_{gjt}-\ln s^{3,cont}_{gj,t-p}}}.
$$

We sum across continuing top-3 firms of both sides of equation (A.20) using the weights:

$$\sum_{f\in\mathcal{F}^{3,cont}_{jt,t-p}} \omega_{fjt,t-p} \ln \frac{s_{fjt}}{s_{fj,t-p}} = \frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j} \sum_{f\in\mathcal{F}^{3,cont}_{jt,t-p}} \left(\ln \frac{\tilde{a}_{fjt}/\tilde{A}_{jt}}{\tilde{a}_{fj,t-p}/\tilde{A}_{j,t-p}} + \ln \frac{\phi_{fjt}/\Phi_{jt}}{\phi_{fj,t-p}/\Phi_{j,t-p}} \right). \tag{A.23}$$

Note that the left hand side can be expressed as

$$\sum_{f\in\mathcal{F}^{3,cont}_{jt,t-p}} \omega_{fjt,t-p} \ln \frac{s_{fjt}}{s_{fj,t-p}} = \underbrace{\sum_{f\in\mathcal{F}^{3,cont}_{jt,t-p}} \omega_{fjt,t-p} \ln \frac{s^{3,cont}_{fjt}}{s^{3,cont}_{fj,t-p}}}_{=0} + \ln \frac{S^{3,cont}_{jt} S^{3}_{jt}}{S^{3,cont}_{j,t-p} S^{3}_{j,t-p}} \tag{A.24}$$

Combining equations (A.23) and (A.24), we can obtain the desired result. □

Proof of Proposition 2.2(ii). $CR^3_t = \frac{\sum_{j\in\mathcal{J}_M}\sum_{f\in\mathcal{F}^3_{fjt}} r_{fjt}}{\sum_{j\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_{fjt}} r_{fjt}}$ can be written as $CR^3_t = \sum_{j\in\mathcal{J}_M} CR^3_{jt} S_{jt}$. From this,

$$\frac{CR^3_t}{CR^3_{t-p}} = \sum_{j\in\mathcal{J}_M} \omega^3_{j,t-p} \frac{CR^3_{jt}}{CR^3_{j,t-p}} \frac{S_{jt}}{S_{j,t-p}}.$$

Log approximating the above equation, we obtain that

$$\ln \frac{CR^3_t}{CR^3_{t-p}} \approx \sum_{j\in\mathcal{J}_M} \omega^3_{j,t-p} \left(\ln \frac{CR^3_{jt}}{CR^3_{j,t-p}} + \ln \frac{S_{jt}}{S_{j,t-p}} \right).$$

Substituting equation (2.21) into the above expression gives equation (2.22). □

Proof of Proposition 2.3. For analytical tractability, we impose three assumptions: (i) firms are monopolistically competitive in the goods markets, so that markups are constant; (ii) factor markets are perfectly competitive ($\eta \to \infty$), and (iii) firm export demand scales with domestic demand: $D_{fj} = d_{fj} \times D^H_j$, where $D^H_j \equiv \frac{1}{F_j}(P^H_j)^{\sigma-\rho}(P_j)^{\sigma-1}E_j$ is Home market size and d_{fj} is an exogenous shifter that makes firm f's export demand constant proportionally to D^H_j. Below we explain the implications of the third assumption. We drop the time subscripts in the proof as it creates no confusion.

Firm sales shares can be expressed as

$$s_{fj} = \frac{\hat{a}_{fj}\hat{\phi}_{fj}}{\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}}, \quad \hat{a}_{fj} = \left(a_{fj} \widetilde{mrpl}_{fj}^{-\gamma^L_j} \widetilde{mrpk}_{fj}^{-\gamma^K_j} \widetilde{mrpm}_{fj}^{-\gamma^M_j} \right)^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}, \quad \hat{\phi}_{fj} = \phi_{fj}^{\frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j}}. \tag{A.25}$$

Totally differentiating $\hat{a}_{fj}$ and $\hat{\phi}_{fj}$ in equation (A.25),

$$d\ln \hat{a}_{fj} = \frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j} \left(d\ln a_{fj} - \sum_{v\in\{l,k,m\}} \gamma^v_j \widetilde{mrpv}_{fj} \right), \quad d\ln \hat{\phi}_{fj} = \frac{1}{\frac{\sigma}{\sigma-1}-\gamma_j} d\ln \phi_{fj}. \tag{A.26}$$

Note that under constant markups and markdowns due to monopolistic competition in product markets and perfect competition in factor markets,

$$d\ln\widetilde{mrpl}_{fj} = d\ln\left(1+\tau^L_{fj}\right), \quad d\ln\widetilde{mrpk}_{fj} = d\ln\left(1+\tau^K_{fj}\right), \quad d\ln\widetilde{mrpm}_{fj} = 1. \tag{A.27}$$

Aggregate productivity can be expressed as

$$\begin{aligned}
A_j &= \left[\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\left(a_{fj}\frac{TFPR_j}{tfpr_{fj}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \\
&= \left[\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\left(a_{fj}s_{fj}^{\gamma_j-1}\widetilde{mrpl}_{fj}^{-\gamma_j^L}\widetilde{mrpk}_{fj}^{-\gamma_j^K}\widetilde{mrpm}_{fj}^{-\gamma_j^M}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}\widetilde{MRPL}_j^{\gamma_j^L}\widetilde{MRPK}_j^{\gamma_j^K}\widetilde{MRPM}_j^{\gamma_j^M} \\
&= \left[\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\left(\hat{a}_{fj}^{\frac{\sigma}{\sigma-1}-\gamma_j}s_{fj}^{\gamma_j-1}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}\widetilde{MRPL}_j^{\gamma_j^L}\widetilde{MRPK}_j^{\gamma_j^K}\widetilde{MRPM}_j^{\gamma_j^M} \\
&= \left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\right)^{1-\gamma_j}\left(\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\hat{\phi}_{fj}^{(\sigma-1)(\gamma_j-1)}\hat{a}_{fj}\right)^{\frac{1}{\sigma-1}}\widetilde{MRPL}_j^{\gamma_j^L}\widetilde{MRPK}_j^{\gamma_j^K}\widetilde{MRPM}_j^{\gamma_j^M} \\
&= \left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\right)\left(\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\phi_{fj}^{(\sigma-1)(1-\gamma_j)}\hat{a}_{fj}\right)^{\frac{1}{\sigma-1}} \\
&\qquad\times\left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\frac{1}{\widetilde{mrpl}_{fj}}\right)^{-\gamma_j^L}\left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\frac{1}{\widetilde{mrpk}_{fj}}\right)^{-\gamma_j^K}\left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\frac{1}{\widetilde{mrpm}_{fj}}\right)^{-\gamma_j^M},
\end{aligned} \tag{A.28}$$

where the third and fourth lines come from the definition of $\hat{a}_{fj}$ and the relationship between s_{fj} and $\hat{a}_{fj}$ in equation (A.25), respectively. The fifth line comes from equation (A.25) and the fact that under perfect competition in factor markets,

$$\widetilde{MRPV}_j = \left(\sum_{f\in\mathcal{F}_j}s_{fj}\frac{1}{\widetilde{mrpv}_{fj}}\right)^{-1}, \qquad V\in\{L,K,M\}.$$

We examine each term in equation (A.28). First, totally differentiating $\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}$,

$$d\ln\left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\right) = \sum_{f\in\mathcal{F}_j}s_{fj}(d\ln\hat{a}_{fj}+d\ln\hat{\phi}_{fj}). \tag{A.29}$$

Totally differentiating $(\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\hat{\phi}_{fj}^{(\sigma-1)(\gamma_j-1)}\hat{a}_{fj})^{\frac{1}{\sigma-1}}$,

$$\begin{aligned}
d\ln\left(\frac{1}{F_j}\sum_{f\in\mathcal{F}_j}\hat{\phi}_{fj}^{(\sigma-1)(\gamma_j-1)}\hat{a}_{fj}\right)^{\frac{1}{\sigma-1}} &= \sum_{f\in\mathcal{F}_j}\frac{\hat{\phi}_{fj}^{(\sigma-1)(\gamma_j-1)}\hat{a}_{fj}}{\sum_{g\in\mathcal{F}_j}\hat{\phi}_{gj}^{(\sigma-1)(\gamma_j-1)}\hat{a}_{gj}}\left(\frac{1}{\sigma-1}d\ln\hat{a}_{fj}+(\gamma_j-1)d\ln\hat{\phi}_{fj}\right) \\
= \sum_{f\in\mathcal{F}_j}s_{fj}\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}\left(\frac{1}{\sigma-1}d\ln\hat{a}_{fj}+(\gamma_j-1)d\ln\hat{\phi}_{fj}\right),
\end{aligned} \tag{A.30}$$

where the second line comes from dividing both numerator and denominator by $\sum_{g'\in\mathcal{F}_j}\hat{a}_{g'j}\hat{\phi}_{g'j}$ and the definition of $\hat{\phi}_{fj}$ in equation (A.25) and Φ_j. Totally differentiating $(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\frac{1}{\widetilde{mrpv}_{fj}})$,

$$
\begin{aligned}
d\ln\left(\sum_{f\in\mathcal{F}_j}\hat{a}_{fj}\hat{\phi}_{fj}\frac{1}{\widetilde{mrpv}_{fj}}\right) &= \sum_{f\in\mathcal{F}_j}\frac{\hat{a}_{fj}\hat{\phi}_{fj}/\widetilde{mrpv}_{fj}}{\sum_{g\in\mathcal{F}_j}\hat{a}_{gj}\hat{\phi}_{gj}/\widetilde{mrpv}_{gj}}\Big(d\ln\hat{a}_{fj}+d\ln\hat{\phi}_{fj}-d\ln\widetilde{mrpv}_{fj}\Big) \\
&= \sum_{f\in\mathcal{F}_j}s_{fj}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Big(d\ln\hat{a}_{fj}+d\ln\hat{\phi}_{fj}-d\ln\widetilde{mrpv}_{fj}\Big),
\end{aligned}
\tag{A.31}
$$

where the second line comes from equation (A.25) and the definition of $\widetilde{MRPV}_j$.

Combining equations (A.29), (A.30), and (A.31),

$$
\begin{aligned}
d\ln A_j = \sum_{f\in\mathcal{F}_j}\gamma_j s_{fj}\Bigg\{&\Bigg[\frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1+\frac{\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}-1}{\sigma}\right)^{1-\sigma}-\sum_{V\in\{L,K,M\}}\frac{\gamma_j^V}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg]d\ln\hat{a}_{fj} \\
&+\Bigg[1+\frac{\gamma_j-1}{\gamma_j}\left(1-\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}\right)-\sum_{V\in\{L,K,M\}}\frac{\gamma_j^V}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg]d\ln\hat{\phi}_{fj} \\
&-\sum_{V\in\{L,K,M\}}\frac{\gamma_j^V}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}d\ln\widetilde{mrpv}_{fj}\Bigg\}.
\end{aligned}
$$

Combining the above equation with (A.25) and (A.27),

$$
\begin{aligned}
d\ln A_j = \sum_{f\in\mathcal{F}_j}\frac{\gamma_j s_{fj}}{\frac{\sigma}{\sigma-1}-\gamma_j}\Bigg\{&\Bigg[\frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1+\frac{\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}-1}{\sigma}\right)-\sum_{V\in\{L,K,M\}}\frac{\gamma_j^V}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg]d\ln a_{fj} \\
&+\Bigg[1+\frac{\gamma_j-1}{\gamma_j}\left(1-\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}\right)-\sum_{V\in\{L,K,M\}}\frac{\gamma_j^X}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg]d\ln\phi_{fj} \\
+\sum_{V\in\{L,K\}}\gamma_j^V\Bigg[\frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1+\frac{\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}-1}{\sigma}\right)&-\left(\frac{\frac{\sigma}{\sigma-1}-1}{\gamma_j}-1\right)\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg)-\sum_{V'\in\{L,K\}}\frac{\gamma_j^{V'}}{\gamma_j}\frac{\widetilde{MRPV'}_j}{\widetilde{mrpv}_{fj}}\Bigg)\Bigg]d\ln\left(1+\tau_{fj}^V\right)\Bigg\}.
\end{aligned}
\tag{A.32}
$$

Note that under monopolistic competition,

$$
\phi_{fj}=(1+\tilde{D}_{fj})^{\frac{1}{\sigma-1}},\qquad \tilde{D}_{fj}=\frac{D_{fj}}{(P_j^H)^{\sigma-\rho}P_j^{\rho-1}E_j}.
$$

Under the third assumption that firm export demand scales with Home market size $D_{fj}=d_{fj}\times D_j^H$, $\tilde{D}_{fj}=d_{fj}$ and $d\ln\tilde{D}_{fj}=d\ln d_{fj}$. Under this assumption, price indices and expenditure do not enter the expression for $\tilde{D}_{fj}$. The assumption simplifies the analysis because each firm's own shocks to primitives do not affect the others' ϕ_{fj}. Substituting $d\ln\phi_{fj} = d\ln\tilde{D}_{fj}$ into equation (A.32), we obtain that

$$
\begin{aligned}
d\ln A_j = \sum_{f\in\mathcal{F}_j} \frac{\gamma_j s_{fj}}{\frac{\sigma}{\sigma-1}-\gamma_j} \Bigg\{ & \Bigg[\frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1+\frac{\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}-1}{\sigma}\right) - \sum_{V\in\{L,K,M\}} \frac{\gamma_j^V}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg] d\ln a_{fj} \\
& + \Bigg[1+\frac{\gamma_j-1}{\gamma_j}\left(1-\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}\right) - \sum_{V\in\{L,K,M\}} \frac{\gamma_j^V}{\gamma_j}\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\Bigg] d\ln\tilde{D}_{fj} \\
+ \sum_{V\in\{L,K\}} \gamma_j^V \Bigg[\frac{\frac{\sigma}{\sigma-1}}{\gamma_j}\left(1+\frac{\left(\frac{\phi_{fj}}{\Phi_j}\right)^{1-\sigma}-1}{\sigma}\right) & - \left(\left(\frac{\frac{\sigma}{\sigma-1}-1}{\gamma_j}-1\right)\frac{\widetilde{MRPV}_j}{\widetilde{mrpv}_{fj}}\right) - \sum_{V'\in\{L,K\}} \frac{\gamma_j^{V'}}{\gamma_j}\frac{\widetilde{MRPV'}_j}{\widetilde{mrpv}_{fj}}\Bigg)\Bigg] d\ln\left(1+\tau_{fj}^V\right)\Bigg\},
\end{aligned}
$$

which gives the desired results. □

Proof of Proposition 2.4. The proof has two parts. The first derives the share formulas. The second proves existence and uniqueness, up to a rescaling, of the primitive shocks recovered from observed shares.

Shares. The shares are all within a period, thus the proof drops the t subscripts to streamline notation. Because price differences in domestic and export markets come from variation in market power, a share of quantities produced for domestic to total quantities produced can be written as

$$
\Lambda_{fj}^H = \frac{y_{fj}^H}{y_{fj}} = \frac{y_{fj}^H}{y_{fj}^H + y_{fj}^F} = \frac{r_{fj}^H/p_{fj}^H}{r_{fj}^H/p_{fj}^H + r_{fj}^F/p_{fj}^F} = \frac{r_{fj}^H/\mu_{fj}^H}{r_{fj}^H/\mu_{fj}^H + r_{fj}^F/\mu_{fj}^F},
$$

where a_{fj} and c_{fj} are canceled out in the last equality. Using the above expression, total quantity produced can be expressed as

$$
y_{fj} = (\Lambda_{fj}^H)^{-1} y_{fj}^H = (1-\Lambda_{fj}^H)^{-1} y_{fj}^F. \tag{A.33}
$$

We first derive a formula in equation (2.23). Using that $y_{fj}^H = \frac{1}{F_j}(p_{fj}^H)^{-\sigma}(P_j^H)^{\sigma-\rho}P_j^{\rho-1}E_j$ and equation (A.33), we can rewrite equation (A.6) as

$$
p_{fj}^H = \left(\mu_{fj}^H\left(\mu_{fj}^L(1+\tau_{fj}^L)\right)^{\frac{\gamma_j^L}{\gamma_j}} (1+\tau_{fj}^K)^{\frac{\gamma_j^K}{\gamma_j}} \left(\frac{w_{fj}}{W_j}\right)^{\frac{\gamma_j^L}{\gamma_j}} (\Lambda_{fj}^H)^{\frac{\gamma_j-1}{\gamma_j}} a_{fj}^{-\frac{1}{\gamma_j}} B_j W_j^{\frac{\gamma_j^L}{\gamma_j}}\right)^{\frac{\gamma_j}{(1-\sigma)\gamma_j+\sigma}}, \tag{A.34}
$$

where B_j is a collection of ϱ, F_j, P_j^M, P_j^H, P_j, E_j, and the Cobb-Douglas production parameters common across firms within sectors. From the CES property, we can obtain that

$$
\frac{w_{fj}}{W_j} = F_j^{\frac{1}{\eta}}\left(\frac{l_{fj}}{L_j}\right)^{\frac{1}{\eta}} \quad\Rightarrow\quad s_{fj}^L = \frac{w_{fj}l_{fj}}{W_jL_j} = F_j^{\frac{1}{\eta}}\left(\frac{l_{fj}}{L_j}\right)^{\frac{\eta+1}{\eta}} \quad\Rightarrow\quad \frac{w_{fj}}{W_j} = (F_j s_{fj}^L)^{\frac{1}{\eta+1}}.
$$

Substituting the above expression into equation (A.34),

$$(p_{fj}^H)^{1-\sigma} \propto \left(\mu_{fj}^H\big(\mu_{fj}^L(1+\tau_{fj}^L)\big)^{\frac{\gamma_j^L}{\gamma_j}}(1+\tau_{fj}^K)^{\frac{\gamma_j^K}{\gamma_j}}(s_{fj}^L)^{\frac{\gamma_j^L}{\gamma_j(\eta+1)}}a_{fj}^{-\frac{1}{\gamma_j}}(\Lambda_{fj}^H)^{\frac{\gamma_j-1}{\gamma_j}}\right)^{-\frac{\gamma_j}{\frac{\sigma}{\sigma-1}-\gamma_j}}. \tag{A.35}$$

Domestic sales shares are

$$s_{fj}^H = \frac{p_{fj}^H y_{fj}^H}{\sum_{g\in\mathcal{F}_j} p_{gj}^H y_{gj}^H} = \frac{\frac{1}{F_j}(p_{fj}^H)^{1-\sigma}(P_j^H)^{\sigma-\rho}P_j^{\rho-1}E_j}{\sum_{g\in\mathcal{F}_j}\frac{1}{F_j}(p_{gj}^H)^{1-\sigma}(P_j^H)^{\sigma-\rho}P_j^{\rho-1}E_j} = \frac{(p_{fj}^H)^{1-\sigma}}{\sum_{g\in\mathcal{F}_j}(p_{gj}^H)^{1-\sigma}}.$$

Substituting equation (A.35) into the above expression gives (2.23).

Second, we derive the expression for the wage bill shares in equation (2.24). Substituting $y_{fj} = (\Lambda_{fj}^H)^{-1}y_{fj}^H$ into the FOC with respect to labor $w_{fj}l_{fj} = (\mu_{fj}^H\mu_{fj}^L(1+\tau_{fj}^L))^{-1}\gamma_j^L p_{fj}^H y_{fj}$ gives

$$w_{fj}l_{fj} = \left(\mu_{fj}^H\mu_{fj}^L(1+\tau_{fj}^L)\Lambda_{fj}^H\right)^{-1}\gamma_j^L p_{fj}^H y_{fj}^H = \left(\mu_{fj}^H\mu_{fj}^L(1+\tau_{fj}^L)\right)^{-1}(\Lambda_{fj}^H)^{-1}\gamma_j^L s_{fj}^H\Big(\sum_{g\in\mathcal{F}_j} p_{gj}^H y_{gj}^H\Big),$$

where the last equality comes from dividing and multiplying $\sum_{g\in\mathcal{F}_j} p_{gj}^H y_{gj}^H$. Substituting the above expression into wage bill shares $s_{fj}^L = \frac{w_{fj}l_{fj}}{\sum_{g\in\mathcal{F}_j} w_{gj}l_{gj}}$ gives (2.24), because $\sum_{g\in\mathcal{F}_j} p_{gj}^H y_{gj}^H$ is canceled out in the numerator and the denominator of the wage bill shares.

Third, we derive the expression for the capital shares in equation (2.25). We proceed similarly to the wage bill shares. Substituting $k_{fj} = (\mu_{fj}^H(1+\tau_{fj}^K))^{-1}\varrho^{-1}\gamma_j^K p_{fj}^H y_{fj}$ from the first-order conditions and $y_{fj} = (\Lambda_{fj}^H)^{-1}y_{fj}^H$ into capital shares and dividing both numerator and the denominator by $\sum_{g\in\mathcal{F}_j} p_{gj}^H y_{gj}^H$ give the desired result.

Fourth, using equation (A.6) and that $r_{fj}^F = (p_{fj}^F)^{1-\sigma}D_{fj}$ and $r_{fj}^H = (p_{fj}^H)^{1-\sigma}\frac{1}{F_j}(P_j^H)^{\sigma-\rho}P_j^{\rho-1}E_j$, we obtain that $s_{fj}^F \propto (\mu_{fj}^F/\mu_{fj}^H)^{1-\sigma}s_{fj}^H D_{fj}$ because domestic demand and total exports and gross output are common across firms, which gives (2.26).

Existence and uniqueness. Now we prove the existence and uniqueness of firm-specific primitives that satisfy the system of equations (2.23)-(2.26). We begin with $1+\tau_{fj}^L$ in equation (2.24). Define $\mathcal{A}_{fj} = s_{fj}^H(\Lambda_{fj}^H)^{-1}(\mu_{fj}^H\mu_{fj}^L)^{-1}$ and $x_{fj} = (1+\tau_{fj}^L)^{-1}$. Then (2.24) can be re-written as $x_{fj} = \frac{s_{fj}^L}{\mathcal{A}_{fj}}\sum_g \mathcal{A}_{gj}x_{gj}$. Let $\mathbf{x}_j = (x_{fj})_{f\in\mathcal{F}_j}$ denote the $|\mathcal{F}_j|$-dimensional vector of unknowns, and define the matrix $\mathbf{B}_j$ with entries $(\mathbf{B}_j)_{fg} = \frac{s_{fj}^L}{\mathcal{A}_{fj}}\mathcal{A}_{gj}$. In matrix notation, the system (2.24) becomes $\mathbf{x}_j = \mathbf{B}_j\,\mathbf{x}_j$.

The matrix $\mathbf{B}_j$ is strictly positive by construction. The vector $\mathbf{x}_j$ is strictly positive. To see this, note that all employment shares in (2.24) are strictly positive and finite, $s_{fjt}^L > 0\ \forall f$. Thus, $(1+\tau_{fj}^L)^{-1}$ cannot be zero or have different signs across f. A $(1+\tau_{fj}^L)^{-1} = 0$ (infinite labor wedge) contradicts all strictly positive employment shares. If $(1+\tau_{fj}^L)^{-1}$ is positive for some firms but negative for some others, some firms' s_{fjt}^L will take negative values, which is also contradictory. Therefore, all firms' $(1+\tau_{fj}^L)^{-1}$ should have the same sign. Without loss of generality, we assume that $(1+\tau_{fj}^L)^{-1}$ are all strictly positive, because we can always multiply both the numerator and denominator of (2.24) by -1.

Because $\mathbf{B}_j > 0$, by the Perron-Frobenius theorem (Horn and Johnson, 2012, ch. 8) there exists a positive eigenvalue (the Perron root $\rho(\mathbf{B}_j)$) with an associated unique (up to a scalar) strictly positive eigenvector. This eigenvector is the unique eigenvector with all non-negative entries, and $\rho(\mathbf{B}_j)$ is the only eigenvalue associated with a non-negative eigenvector. Since $\mathbf{B}_j\mathbf{x}_j = \mathbf{x}_j$, the only way these conditions are satisfied is if the Perron root is $\rho(\mathbf{B}_j) = 1$, and the associated unique positive eigenvector is $\mathbf{x}_j$. This establishes existence and uniqueness (up to a rescaling) of $1 + \tau^L_{fj}$.

Because capital distortions (2.25) have the same functional form as labor distortions (2.24), we can apply the same steps to prove that $1 + \tau^K_{fj}$ are also uniquely identified, up to a rescaling. Although foreign demand D_{fj} from equation (2.26) has the same structure, one issue arises due to non-exporters with $s^F_{fj} = 0$. For these non-exporters, we assign $D_{fj} = 0$ and apply the same steps only to the subset of firms with strictly positive s^F_{fj}. Finally, for productivity a_{fj} in (2.23), once we recover labor and capital distortions, we can plug these into (2.23) and apply the same steps. □

A.3 Inferring Four Firm-Specific Shocks from Four Market Shares

This appendix develops the intuition behind the model inversion and the recovery of four firm-level shocks from four firm-level market shares. We build up by starting with the simplest model and adding features until arriving at the full model. In particular, we consider five versions with progressively more features:

1. **Closed** economy with constant returns to scale, homogeneous inputs, and no firm-specific exogenous distortions or firm-specific market power: productivity a_{fj} is the only source of firm heterogeneity and can be recovered from domestic revenue shares s^H_{fj}.

2. **1.** + **open economy**: productivity a_{fj} and export demand D_{fj} are the two sources of firm heterogeneity and can be recovered from domestic and export revenue shares s^H_{fj} and s^F_{fj}.

3. **2.** + **exogenous firm-specific labor and capital distortions**: productivity a_{fj}, export demand D_{fj}, labor distortions $1 + \tau^L_{fj}$, and capital distortions $1 + \tau^K_{fj}$ can be recovered from domestic, export, labor, and capital expenditure shares s^H_{fj}, s^F_{fj}, s^L_{fj}, and s^K_{fj}.

4. **3.** + **non-constant returns to scale** and **heterogeneous labor** with upward-sloping firm-specific labor supply: demand in one market (domestic or export) affects marginal cost in both markets, intertwining the identification of productivity and export demand.

5. (Full Model) **4.** + **firm-specific market power** in goods and labor markets: firm-specific markups and markdowns make the inference of all four shocks depend jointly on all four market shares.

A.3.1 Closed economy with constant returns to scale, homogeneous inputs, and no firm-specific distortions: a_{fj}

In a closed economy with constant returns to scale, homogeneous inputs, and no firm-specific distortions (either endogenous ones such as market power μ or exogenous ones such as τ), productivity is the only driver of firm heterogeneity. In this case, the market-share equations (2.23)–(2.26) collapse to the following system:

$$
\begin{aligned}
s^H_{fj} &= \frac{a^{\sigma-1}_{fj}}{\sum_{g\in\mathcal{F}_j} a^{\sigma-1}_{gj}}, \\
s^L_{fj} &= s^H_{fj}, \\
s^K_{fj} &= s^H_{fj}, \\
s^F_{fj} &= 0.
\end{aligned}
$$

In this model, domestic revenue shares s^H_{fj} are monotonic in productivity alone, so data on these shares are sufficient to invert the model and recover firm productivity a_{fj}, up to a reference firm. In particular, for any 2 firms f and f', the ratio of productivities is a simple transformation of the ratio of shares: $\frac{a_{fj}}{a_{f'j}} = \left(\frac{s^H_{fj}}{s^H_{f'j}}\right)^{\frac{1}{\sigma-1}}$. Since inputs are homogeneous and there are no firm-specific distortions, input-expenditure shares and revenue shares coincide: $s^H_{fj} = s^L_{fj} = s^K_{fj}$. Finally, since the economy is closed, no firm exports, so $s^F_{fj} = 0$.

A.3.2 Open economy with constant returns to scale, homogeneous inputs and no firm-specific distortions: a_{fj} and D_{fj}

To account for firm-specific differences in observed exports s^F_{fj}, we now open the economy and allow for two sources of firm heterogeneity: productivity a_{fj} and export demand D_{fj}. Recall that s_{fj} denotes a firm's overall revenue share:

$$
s_{fj} = \frac{r_{fj}}{R_j} = \frac{s^H_{fj} R^H_j + s^F_{fj} R^F_j}{R_j},
$$

where R^H_j and R^F_j are sector-wide domestic and export revenues, respectively. With constant returns to scale, homogeneous inputs, and no firm-specific distortions (either endogenous ones such as market power μ or exogenous ones such as τ), the market-share equations (2.23)–(2.26) collapse to the following system:

$$
\begin{aligned}
s^H_{fj} &= \frac{a^{\sigma-1}_{fj}}{\sum_{g\in\mathcal{F}_j} a^{\sigma-1}_{gj}}, \\
s^L_{fj} &= s_{fj}, \\
s^K_{fj} &= s_{fj}, \\
s^F_{fj} &= \frac{s^H_{fj} D_{fj}}{\sum_{g\in\mathcal{F}^F_j} s^H_{gj} D_{gj}}.
\end{aligned}
$$

In this model, domestic revenue shares s^H_{fj} are again monotonically increasing in productivity alone, so data on s^H_{fj} are sufficient to invert that set of equations and recover firm productivity a_{fj}. Matching export shares s^F_{fj}, however, requires an additional set of firm-level parameters D_{fj}. For any two exporters f and f', the ratio of export demands can be recovered from comparing domestic and export shares: $D_{fj}/D_{f'j} = \frac{s^F_{fj}/s^H_{fj}}{s^F_{f'j}/s^H_{f'j}}$. For non-exporters, setting $D_{fj} = 0$ ensures the model matches the data. Higher-productivity firms naturally export more, so D_{fj} is inferred from departures of export-market shared from domestic-market shares. In particular, a firm whose export share exceeds its domestic sales share ($s^F_{fj} > s^H_{fj}$) is inferred to have an export demand shifter greater than the weighted sectoral average: $D_{fj} > \sum_{g \in \mathcal{F}^F_j} s^H_{gj} D_{gj}$. At the same time, in this model a firm's labor s^L_{fj} and capital s^K_{fj} expenditure shares remain fully pinned down by the firm's overall revenue share s_{fj}, which is itself determined by productivity a_{fj} and export demand D_{fj}.

A.3.3 Open economy with constant returns to scale, homogeneous inputs and no firm-specific market power: a_{fj}, D_{fj}, $1 + \tau^L_{fj}$, and $1 + \tau^K_{fj}$

To account for firm-specific differences in labor expenditures s^L_{fj} and capital expenditures s^K_{fj}, we additionally allow for firm-specific distortions τ^L_{fj} and τ^K_{fj}. With constant returns to scale, homogeneous inputs, and no firm-specific market power, the market-share equations (2.23)–(2.26) collapse to the following system:

$$\begin{aligned}
s^H_{fj} &= \frac{\left(a^{-1}_{fj}(1+\tau^L_{fj})^{\gamma^L_j}(1+\tau^K_{fj})^{\gamma^K_j}\right)^{1-\sigma}}{\sum_{g \in \mathcal{F}_j}\left(a^{-1}_{gj}(1+\tau^L_{gj})^{\gamma^L_j}(1+\tau^K_{gj})^{\gamma^K_j}\right)^{1-\sigma}} \\
s^L_{fj} &= \frac{s_{fj}(1+\tau^L_{fj})^{-1}}{\sum_{g \in \mathcal{F}_j} s_{gj}(1+\tau^L_{gj})^{-1}}, \\
s^K_{fj} &= \frac{s_{fj}(1+\tau^K_{fj})^{-1}}{\sum_{g \in \mathcal{F}_j} s_{gj}(1+\tau^K_{gj})^{-1}}, \\
s^F_{fj} &= \frac{s^H_{fj} D_{fj}}{\sum_{g \in \mathcal{F}^F_j} s^H_{gj} D_{gj}}.
\end{aligned}$$

In this model, the input distortions τ^L_{fj} and τ^K_{fj} capture the extent to which a firm's input expenditure shares differ from its overall revenue share. For any two firms f and f', the relative distortion can be recovered as a ratio of wage bill shares relative to the sales shares: $\left(\frac{1+\tau^L_{fj}}{1+\tau^L_{f'j}}\right)^{-1} = \frac{s^L_{fj}/s_{fj}}{s^L_{f'j}/s_{f'j}}$. Thus, a firm whose share of sectoral labor expenditures exceeds its share of sectoral revenue ($s^L_{fj} > s_{fj}$) is inferred to face a distortion that acts as a lower tax/higher subsidy to its labor hiring relative to the sectoral harmonic average: $(1+\tau^L_{fj}) < [\sum_{g \in \mathcal{F}_j} s_{gj}(1+\tau^L_{gj})^{-1}]^{-1}$, and vice versa. The same discussion applies to capital shares and distortions. Conditional on τ^L_{fj} and τ^K_{fj}, domestic revenue shares s^H_{fj} still pin down relative productivity a_{fj}. Matching export shares s^F_{fj} then requires export-demand shocks D_{fj}, as above.

A.3.4 Open economy with non-constant returns to scale, heterogeneous labor and no firm-specific market power

The steps above build up to a procedure that uses 4 shares to infer the 4 shocks present in our full model. From this point forward there are no additional shocks. We now introduce two model elements that create interactions between productivity and export demand in our shock inversion procedure: (i) non-constant returns to scale ($\gamma_j \neq 1$), and (ii) firm-specific upward-sloping labor supply curves as in (2.3)/(2.8). Both elements add realism (and additional structure) without introducing new firm-specific parameters, but will necessitate additional data. First, non-constant returns to scale create stronger interactions between domestic and export markets: demand in one market now changes the firm's scale and therefore its marginal cost of serving both markets. The extent of these spillovers across markets is captured by Λ^H_{fj}, the ratio of the quantity demanded in the domestic market y^H_{fj} to the firm's total quantity demanded across both markets y_{fj}:[23]

$$\Lambda^H_{fj} = \frac{y^H_{fj}}{y_{fj}} = \frac{s^H_{fj} R^H_j}{s_{fj} R_j}.$$

Second, upward-sloping labor supply implies that larger firms must pay higher wages, $\frac{w_{fj}}{W_j} = \left(s^L_{fj}\right)^{\frac{1}{\eta+1}}$, once again linking demand in one market to the marginal cost of serving both markets. With potentially non-constant returns to scale captured by γ_j, upward-sloping labor supply governed by η, and no firm-specific market power, the market-share equations (2.23)–(2.26) become:

$$\begin{aligned}
s^H_{fj} &= \frac{\left(a_{fj}^{-\frac{1}{\gamma_j}} \left((1+\tau^L_{fj})(s^L_{fj})^{\frac{1}{1+\eta}}\right)^{\frac{\gamma^L_j}{\gamma_j}} (1+\tau^K_{fj})^{\frac{\gamma^K_j}{\gamma_j}} (\Lambda^H_{fj})^{\frac{\gamma_j - 1}{\gamma_j}}\right)^{-\frac{\gamma_j}{\frac{\sigma}{\sigma-1}-\gamma_j}}}{\sum_{g\in\mathcal{F}_j} \left(a_{gj}^{-\frac{1}{\gamma_j}} \left((1+\tau^L_{gj})(s^L_{fj})^{\frac{1}{1+\eta}}\right)^{\frac{\gamma^L_j}{\gamma_j}} (1+\tau^K_{gj})^{\frac{\gamma^K_j}{\gamma_j}} (\Lambda^H_{gj})^{\frac{\gamma_j - 1}{\gamma_j}}\right)^{-\frac{\gamma_j}{\frac{\sigma}{\sigma-1}-\gamma_j}}} \\
s^L_{fj} &= \frac{s_{fj}(1+\tau^L_{fj})^{-1}}{\sum_{g\in\mathcal{F}_j} s_{gj}(1+\tau^L_{gj})^{-1}}, \\
s^K_{fj} &= \frac{s_{fj}(1+\tau^K_{fj})^{-1}}{\sum_{g\in\mathcal{F}_j} s_{gj}(1+\tau^K_{gj})^{-1}}, \\
s^F_{fj} &= \frac{s^H_{fj} D_{fj}}{\sum_{g\in\mathcal{F}^F_j} s^H_{gj} D_{gj}}.
\end{aligned}$$

In the earlier models, export demand did not enter the expression for domestic revenue shares s^H_{fj}. Now, both non-constant returns to scale and upward-sloping labor supply create interactions in the inference of productivity a_{fj} and export demand D_{fj} from domestic revenue shares s^H_{fj} and

[23] Note that Λ^H_{fj} can only be written as the second equality when markups are constant across firms and markets, the maintained assumption in this subsection. The general form for Λ^H_{fj} is in the statement of Proposition 2.4.

export shares s^F_{fj}. For instance, when returns to scale are decreasing ($\gamma_j < 1$), a positive export-demand shock reduces Λ^H_{fj}, raising the marginal cost of serving the domestic market. The same export-demand shock also increases the firm's scale of employment, raising its marginal cost as the firm must pay a higher wage. This force is captured in the s^H_{fj} equation by a higher labor-expenditure share s^L_{fj}. These two new channels now cause export demand D_{fj} to interact with productivity a_{fj} in determining the domestic market share s^H_{fj}. As a result, inferring productivity from domestic sales shares now requires both the wage bill share s^L_{fj}, and the additional piece of information in Λ^H_{fj}, that can also be taken from data. The recovery of distortions τ^V_{fj}, $V = L, K$ remains unchanged: differences between input-expenditure shares and revenue shares identify the distortions.

A.3.5 (Full Model) Open economy with non-constant returns to scale, heterogeneous labor and firm-specific market power

By additionally allowing for firm-specific market power in domestic output (μ^H_{fj}) and labor (μ^L_{fj}) markets, the inference of all four shocks (productivity a_{fj}, export demand D_{fj}, distortions τ^L_{fj} and τ^K_{fj}) is interlinked with all four market shares s^H_{fj}, s^F_{fj}, s^L_{fj}, and s^K_{fj}.

In this full version of the model, the markups and markdowns are firm-specific and can be characterized with sector-level parameters and firm-level market shares of domestic revenue s^H_{fj} and labor expenditures s^L_{fj} as in (2.10)-(2.12). The market shares are then given by (2.23)-(2.26). In the full model, the presence of firm-specific markups and markdowns implies that distortions and market power jointly shape the relationship between input-expenditure shares and revenue shares. In the previous subsection, differences between a firm's input-expenditure shares and its overall revenue share directly identified the distortions τ^L_{fj} and τ^K_{fj}. Once firm-specific markdowns μ^L_{fj} and markups μ^H_{fj} are introduced, however, these wedges enter the input-demand conditions alongside the distortions. As a result, observed deviations of labor and capital expenditure shares from revenue shares now reflect the joint influence of distortions and market power. The latter must be taken into account via the markup/down expressions (2.10)-(2.12) when recovering τ^L_{fj} and τ^K_{fj}.

Firm-specific markups also affect the inference of productivity from domestic revenue shares. In earlier sections, domestic revenue shares has a simple relationship with productivity, conditional on the other wedges. In the full model the domestic markup μ^H_{fj} enters the expression for the domestic revenue share s^H_{fj} together with productivity and distortions. Because the markup depends on the firm's domestic market share, variation in s^H_{fj} now in addition reflects endogenous variation in market power. Consequently, the recovery of productivity from domestic revenue shares must account for the firm variability in markups.

Finally, firm-specific markups also affect the mapping between domestic and export revenue shares. In the simpler models above, export shares differed from domestic shares solely because of export-demand shocks D_{fj}. In the full model export revenue shares can in addition diverge from domestic revenue shares due to different markups charged in the two markets, $(\mu^F_{fj}/\mu^H_{fj})^{1-\sigma}$. Since domestic markups depend on domestic market shares, the relationship between export shares and domestic shares now reflects both export demand and endogenous market power. As a result, the inference of export-demand shocks must account for the interaction between export demand, domestic markups, and the other wedges that shape firm size.

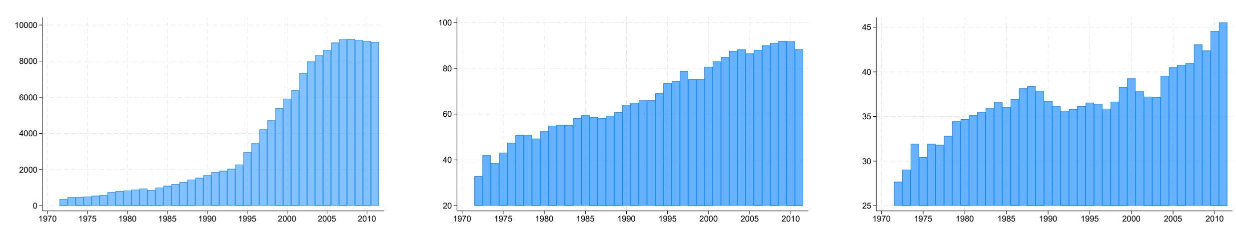
Taken together, these mechanisms imply that all four shocks—productivity a_{fj}, export demand D_{fj}, and the distortions $1 + \tau^L_{fj}$ and $1 + \tau^K_{fj}$—are jointly inferred from the four market shares s^H_{fj}, s^F_{fj}, s^L_{fj}, and s^K_{fj}. Relative to the previous subsections, the full model therefore introduces an additional layer of interdependence: market power affects the mapping from shocks to market shares, while market shares themselves determine the markups and markdowns that enter this mapping.

B. Data and Quantification

B.1 Data

This section describes how we constructed our main dataset from three main data sources. First, firm-level data for 1972 to 1981 are collected from the historical Annual Report of Korean Companies published by the Korea Productivity Center. The data are digitized from paper documents. The data for 1982 to 2011 come from KIS-VALUE. The coverage of the data from the Annual Report of Korean Companies is larger than that of KIS-VALUE. Therefore, we use the criterion for inclusion in KIS-VALUE, namely an asset threshold of roughly 2.3 million 2023 USD. Firms with assets below this threshold in the Annual Report of Korean Companies are excluded. We merge these two firm-level datasets based on firm names, years of starting operation, and firms' historical records available on their websites. For observations with missing sales in the Annual Report of Korean Companies, we impute sales based on assets. For firms with missing export information, we impute exports using the geometric average of observed export values immediately before and after the missing observation. The number of unique firms is 23,464. The total number of firm-year observations is 323,514. Finally, firm-level data are merged to the sectoral data obtained from KLEMS and IO tables from Bank of Korea based on firms' industry affiliations. Panel A of Figure B1 reports the yearly number of observations. Panel B reports the combined sales of the firms in the firm-level data relative to total manufacturing gross output. The coverage of our firm-level data improves over time. Panel C reports the share of manufacturing sector in overall gross output. The manufacturing share keeps increasing over time in our sample period. The sectoral classification is listed in Table B1.

Figure B1: Firm Coverage



A. The Number of Mfg. Firms per Year

B. Shares of the Firms' Sales to Mfg. Gross Output

C. Mfg. Sectors' Shares (%) of Gross Output

Notes. Panel A reports the number of firm observations for each year. Panel B reports the combined sales of all firms in the dataset as a ratio to manufacturing gross output. Panel C reports the manufacturing sector's share of gross output to total gross output.

One issue is business groups, known as chaebols, that own multiple firms. We treat each firm within a chaebol group as an independent entity. There were three special cases in which existing corporations were closed, and new corporations were formed as big business groups changed their ownership structure by establishing new holding companies. In such cases, we match these existing and new corporations. These cases include LG Electronics in 2002, LG Chemicals in 2002, and SK

Innovation in 2007. These instances were identified by tracking historical records of big business groups.

Figure B2: Robustness. The Top-3 Concentration Ratio. Alternative Variables.

A. Domestic sales

B. Exports

C. Employment

D. Fixed assets

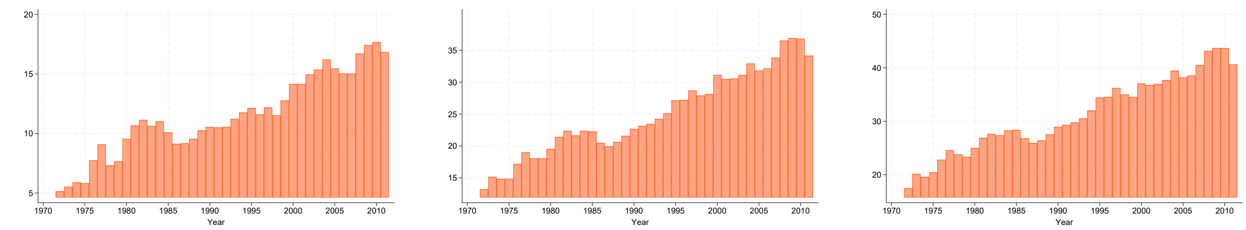
Notes. This figure plots shares of the sum of the top-3 manufacturing firms' domestic sales, exports, employment, and fixed assets across sectors to the total manufacturing gross output net of exports, exports, employment, and fixed assets, respectively. The sectoral data come from KLEMS and IO tables.

Table B1: Sector Classification

Aggregated Industry	Industry
Petrochemicals*	Coke oven products (231), Refined petroleum products (232)
Chemicals, and rubber and plastic products*	Basic chemicals (241), Other chemical products (242) Man-made fibres (243) except for pharmaceuticals and medicine chemicals (2423) Rubber products (251), Plastic products (252)
Pharmaceuticals*	pharmaceuticals and medicine chemicals (2423)
Electronics*	Office, accounting, & computing machinery (30) Electrical machinery and apparatus n.e.c. (31) Ratio, television and communication equipment and apparatus (32) Medical, precision, and optical instruments, watches and clocks (33)
Metals*	Basic metals (27), Fabricated metals (28)
Machinery, and transportation equipment*	Machinery and equipment n.e.c. (29) Motor vehicles, trailers and semi trailers (34) Manufacture of other transport equipment (35)
Food*	Food products and beverages (15), Tobacco products (16)
Textiles, Apparel, and Leather*	Textiles (17), Apparel (18) Leather, luggage, handbags, saddlery, harness, and footwear (19)
Manufacturing n.e.c.*	Manufacturing n.e.c. (369)
Wood*	Wood and of products, cork (20), Paper and paper products (21) Publishing and printing (22), Furniture (361)
Other nonmetallic mineral products*	Glass and glass products (261), On-metallic mineral products n.e.c. (269)
Commodity	Agriculture, hunting, and forestry (A), Fishing (B)
Mining	Mining and quarrying (C)
Construction	Construction (F)
Utility	Electricity, gas and water supply (E)
Retail	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods (G)
Transportation	Land transport; transport via pipelines (60) Water transport (61), Air transport (62), Supporting and auxiliary transport activities; activities of travel agencies (63)
Business service	Post and telecommunications (64), Financial intermediation (J) Real estates, renting, and business activities (K)
Other service	Public administration and defence; compulsory social security (L) Education (M), Health and social work (N) Other community, social and personal service activities (O) Activities of private households as employers and undifferentiated production activities of private households (P) Extra-territorial organizations and bodies (Q)

Notes. * denotes manufacturing sectors. The numbers in parentheses are ISIC Rev 3.1 codes.

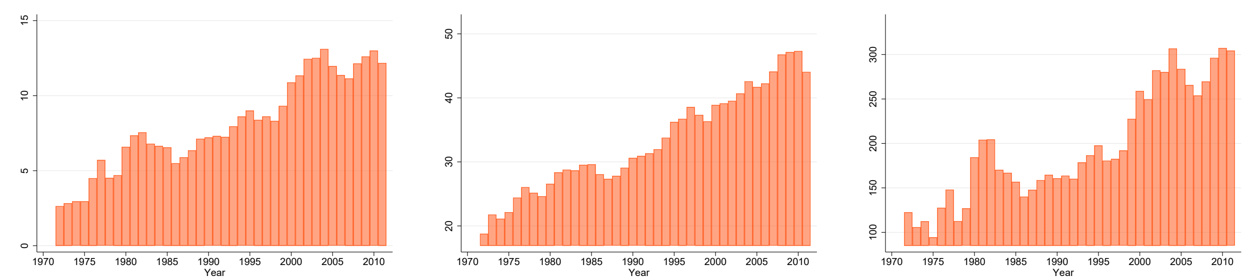
Figure B3: Robustness. Concentration Ratio. Alternative Sets of Top Firms.



A. Top 1 B. Top 5 C. Top 10

Notes. This figure plots shares of the sum of the top 1, 5, and 10 manufacturing firms' sales to the total manufacturing gross output. The sectoral data come from KLEMS and IO tables.

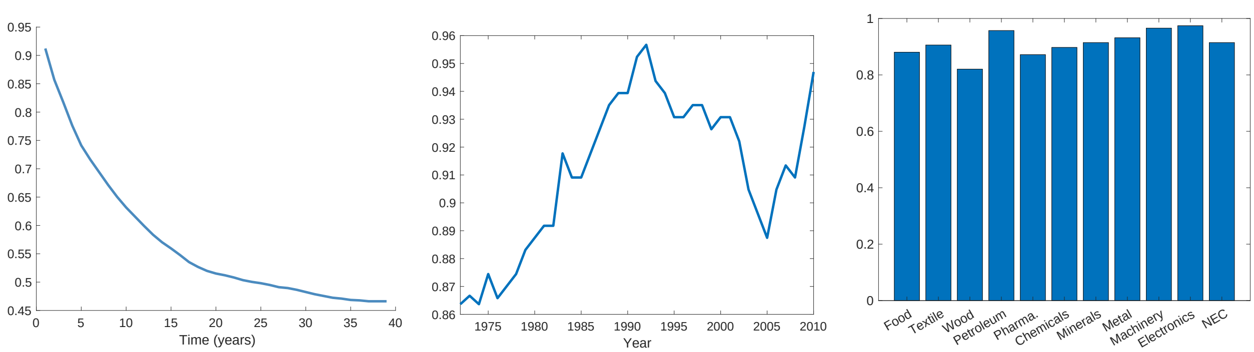
Figure B4: Robustness. Alternative Concentration Indices. Whole Manufacturing.



A. Top 3 B. Top 100 C. HHI

Notes. Panels A and B plot shares of the sum of the top 3 and 100 firms' sales to the total manufacturing gross output, respectively. The selection of top firms is based on the entire manufacturing sector. Panel C reports the Herfindahl-Hirschman Index for all observations in the firm-level data.

Figure B5: Persistence of Top-3 Status



A. Hazard rate B. By year C. By sector

Notes. Panel A displays the share of top-3 firms that remained in the top 3 h years later: $\Pr\left[f \in \mathcal{F}^3_{jt+h} | f \in \mathcal{F}^3_{jt}\right]$ on the y-axis against h on the x-axis. Panels B and C show the share of firms that remained in the top three after one year, $\Pr\left[f \in \mathcal{F}^3_{jt+1} | f \in \mathcal{F}^3_{jt}\right]$, with Panel B presenting trends over calendar years t and Panel C showing variation across sectors j.

B.2 Production Function Estimation

We combine the production function and firm demand (2.6) to derive an estimable equation. Using the fact that $p^H_{fjt} = (y^H_{fjt}/Y^H_{jt})^{-\frac{1}{\sigma}} P^H_{jt}$, we obtain the following expression for domestic revenue:

$$r^H_{fjt} = (y^H_{fjt})^{\frac{\sigma-1}{\sigma}} (Y^H_{jt})^{\frac{1}{\sigma}} P^H_{jt} = (\Lambda^H_{fjt})^{\frac{\sigma-1}{\sigma}} y_{fjt}^{\frac{\sigma-1}{\sigma}} (Y^H_{jt})^{\frac{1}{\sigma}} P^H_{jt},$$

where the second equality comes from that $\Lambda^H_{fjt} = y^H_{fjt}/y_{fjt}$. For non-exporters, $\Lambda^H_{fjt} = 1$. Combining the above expression with the production function and taking logs, we obtain that

$$\ln \frac{r^H_{fjt}}{P^H_{jt}} = \gamma^L_j \frac{\sigma-1}{\sigma} \ln l_{fjt} + \gamma^K_j \frac{\sigma-1}{\sigma} \ln k_{fjt} + \gamma^M_j \frac{\sigma-1}{\sigma} \ln m_{fjt} + \frac{\sigma-1}{\sigma} \ln \Lambda^H_{fjt} + \frac{1}{\sigma} \ln Y^H_{jt} + \frac{\sigma-1}{\sigma} \ln a_{fjt},$$

which leads to the following expression for domestic revenue deflated by the sectoral price index:

$$\ln \frac{r^H_{fjt}}{P^H_{jt}} = \beta^M_j \ln m_{fjt} + \beta^L_j \ln l_{fjt} + \beta^K_j \ln k_{fjt} + \frac{1}{\sigma} \ln Y^H_{jt} + \frac{\sigma-1}{\sigma} \ln \Lambda^H_{fjt} + \frac{\sigma-1}{\sigma} \ln a_{fjt} + \ln u_{fjt}. \tag{B.1}$$

The estimating equation relates deflated firm sales to production inputs (m_{fjt}, l_{fjt}, and k_{fjt}), domestic output share Λ_{fjt}, firm productivity a_{fjt} and industry size Y^H_{jt} through a series of revenue elasticities β.[24] We also allow for measurement error u_{fjt}. The revenue elasticities on the production inputs are a combination of demand and production parameters, $\beta^v_j = \frac{\sigma-1}{\sigma}\gamma^v_j$ for $v \in \{L, K, M\}$. Using the calibrated σ and the revenue elasticities β^v_j, we can back out the production parameters γ^L_j, γ^K_j, and γ^M_j, whose sum γ_j constitutes the returns to scale.

The dependent variable is log nominal domestic sales deflated by sectoral PPIs, k_{fjt} is fixed assets deflated by the investment deflators, and m_{fjt} is constructed by deflating expenditures on material inputs, $P^M_{jt} m_{fjt}$, by input deflators. We construct the input deflators using sectoral PPIs and intermediate input shares from the IO tables. We measure Y^H_{jt} by the real gross output obtained from KLEMS. Because material expenditures are available only after 1983 from KIS-VALUE, we restrict the estimation sample to observations after 1983. Due to the small number of observations in the petrochemical sector, we combine firms in petrochemical and chemical sectors when estimating the production function parameters.

Our estimation proceeds in two steps. We closely follow Ruzic and Ho (2023) who proceed in these two steps to recover the revenue elasticities. In the first step, we pin down the revenue elasticity of material inputs. From the FOC with respect to material inputs, $\frac{p^H_{fj}}{\mu^H_{fj}} = \frac{p^F_{fj}}{\mu^F_{fj}}$, and equation (2.10) we obtain:

$$\gamma^M_j = \frac{P^M_{jt} m_{fjt}}{r^H_{fjt}/\mu^H_{fjt} + r^F_{fjt}/\mu^F_{fjt}}.$$

Summing over both sides across firms and taking the average yields the following relationship for

[24] For non-exporters, Λ^H_{fjt} disappears in the estimating equation.

each sector:

$$\hat{\beta}_j^M = \frac{\sigma-1}{\sigma}\frac{1}{N}\sum_t \sum_{f\in\mathcal{F}_{jt}} \frac{P_{jt}^M m_{fjt}}{r_{fjt}^H/\mu_{fjt}^H + r_{fjt}^F/\mu_{fjt}^F}. \tag{B.2}$$

Given the calibrated values of σ and ρ, μ_{fjt}^H and μ_{fjt}^F can be computed from the data using the domestic sales shares and the expenditure share on domestic inputs (equations 2.10 and 2.12). In addition to reducing the set of parameters to be estimated, this first step is one way of dealing with the identification challenges to control-function approaches of estimating (gross output) production functions, using firms' first-order conditions, which have been highlighted by Ackerberg et al. (2015), Gandhi et al. (2020), and Bond et al. (2021). In short, flexibly chosen variable inputs—as materials are often assumed to be—cannot generally be expected both to proxy for productivity through the control function and be used to estimate the revenue elasticity with respect to themselves.

For the second estimation step, we net out material inputs from the initial expression in equation (B.1). Then we estimate the following modified estimating equation:

$$\ln\frac{r_{fjt}^H}{P_{jt}^H} - \hat{\beta}_j^M \ln m_{fjt} = \beta_j^L \ln l_{fjt} + \beta_j^K \ln k_{fjt} + \frac{1}{\sigma}\ln Y_{jt}^H + \frac{\sigma-1}{\sigma}\ln\Lambda_{fjt}^H + \frac{\sigma-1}{\sigma}\ln a_{fjt} + \ln u_{fjt}. \tag{B.3}$$

OLS estimates of (B.3) suffer from an endogeneity problem arising from the fact that firms make input decisions after observing productivity, which is unobservable to researchers. To deal with the endogeneity issue, we estimate (B.3) using the control function approach (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). We assume that productivity follows the following flexible first-order Markov process: $\ln a_{fjt} = \iota_0 + \iota_1 \ln a_{fj,t-1} + \xi_{fjt}$, where ξ_{fjt} is an innovation to productivity. Following the literature, we also assume that firms can adjust their variable inputs—labor and materials—after observing a_{fjt}, but that the capital stock cannot be adjusted contemporaneously.

Using the timing of input choices, we can invert productivity as a function of material inputs conditional on markups, markdowns, and aggregate demand in both markets (Doraszelski and Jaumandreu, 2021; De Ridder et al., 2026). Because markups and markdowns are functions of s_{fjt}^H, λ_{jt}^H, and s_{fjt}^L, it is sufficient to invert productivity conditional on these observable shares:

$$\ln a_{fjt} = m^{-1}(\ln m_{fjt}, \ln k_{fjt}, \ln l_{fjt}, s_{fjt}^H, \lambda_{jt}^H, s_{fjt}^L, \Lambda_{jt}^H, \ln Y_{jt}^H).$$

Following Ackerberg et al. (2015), we first purge out measurement errors by nonparametrically estimating the following function:

$$\ln\frac{r_{fjt}^H}{P_{jt}^H} - \hat{\beta}_j^M \ln m_{fjt} = h(\ln l_{fjt}, \ln k_{fjt}, \ln m_{fjt}, s_{fjt}^H, \lambda_{jt}^H, s_{fjt}^L, \Lambda_{jt}^H, \ln Y_{jt}^H) + u_{fjt}$$

and obtaining the estimated fit $\hat{h}$. Then, the parameters $\boldsymbol{\kappa} = (\beta_j^L, \beta_j^K, \iota_0, \iota_1)$ are identified by the following moment conditions based on the timing structure:

$$\mathbb{E}_t[\mathbf{Z}_{fjt}\xi_{fjt}(\boldsymbol{\kappa})] = 0,$$

where $\mathbf{Z}_{fjt} = [\ln k_{fj,t-1}, \ln l_{fj,t-1}, \ln m_{fj,t-1}, 1, \ln a_{fj,t-1}]'$ is a set of instrumental variables. For a given guess of $\boldsymbol{\kappa}$ and calibrated values of the elasticities, we obtain $\ln a_{fjt}$ as

$$\ln a_{fjt} = \frac{\sigma}{\sigma - 1}\left(\hat{h} - \frac{\sigma - 1}{\sigma}\Lambda_{fjt} - \frac{1}{\sigma}\ln Y_{jt}^{H} - \beta_j^L \ln l_{fjt} - \beta_j^K \ln k_{fjt}\right)$$

and calculate $\xi_{fjt}(\boldsymbol{\kappa})$ as the residual of the Markov process: $\xi_{fjt}(\boldsymbol{\kappa}) = \ln a_{fjt} - \iota_0 - \iota_1 \ln a_{fj,t-1}$.

We impose a constraint on the parameter space that guarantees the second order condition of firm profit maximization problem: $\frac{\sigma}{\sigma-1} - \gamma_j \geq 0$. Once we obtain β_j^L, β_j^K, and β_j^M sector-by-sector, we can obtain γ_j^L, γ_j^K, and γ_j^M by multiplying the estimated coefficients by $\frac{\sigma}{\sigma-1}$.

We compute standard errors using bootstrap methods. To address potential serial correlation in firm-level error terms, we employ a nonparametric block bootstrap method with replacement across firms, in which the parameters are estimated in two steps for each bootstrapped sample. We perform 100 replications.

Table B2 reports the estimation results. The parameters are precisely estimated. We also conduct sensitivity analysis for the estimates. We consider alternative samples including only exporters and non-exporters, an alternative IV, $\mathbf{Z}_{fjt} = [\ln k_{fj,t-1}, \ln l_{fj,t-1}, 1, \ln a_{fj,t-1}]'$, and an alternative Markov-process with third-order polynomials, $\ln a_{fjt} = \sum_{p=0}^{3} \iota_p (\ln a_{fj,t-1})^p$.[25] The estimates remain stable (Table B3).

[25] An IV for the alternative process is $\mathbf{Z}_{fjt} = [\ln k_{fj,t-1}, \ln l_{fj,t-1}, \ln m_{fj,t-1}, 1, \ln a_{fj,t-1}, (\ln a_{fj,t-1})^2, (\ln a_{fj,t-1})^3]$.

Table B2: Calibrated Values of Elasticity of Substitution and Estimates of Production Function Parameters

	Baseline. $\sigma = 5$, $\rho = 2$					Robustness. σ_j BW (2006), $\rho = 2$				
	σ	γ_j^L	γ_j^K	γ_j^M	γ_j	σ_j	γ_j^L	γ_j^K	γ_j^M	γ_j
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Food, Beverage, & Tobacco	5	0.10***	0.19***	0.64***	0.92***	4.73	0.10***	0.21***	0.65***	0.96***
		(0.00)	(0.01)	(0.01)	(0.02)		(0.00)	(0.01)	(0.01)	(0.02)
Textile, Apparel, & Leather	5	0.38***	0.20***	0.53***	1.11***	5.12	0.38***	0.20***	0.53***	1.10***
		(0.03)	(0.01)	(0.01)	(0.02)		(0.01)	(0.00)	(0.01)	(0.00)
Wood	5	0.12***	0.18***	0.57***	0.87***	6.29	0.12***	0.23***	0.55***	0.90***
		(0.01)	(0.00)	(0.01)	(0.00)		(0.01)	(0.00)	(0.01)	(0.00)
Pharmaceuticals	5	0.23***	0.19***	0.43***	0.85***	1.77	0.39***	0.35***	0.79***	1.53***
		(0.01)	(0.00)	(0.01)	(0.01)		(0.00)	(0.00)	(0.01)	(0.01)
Chemicals, Plastics, & Rubber (Petrochemical)	5	0.08***	0.11***	0.64***	0.83***	4.01	0.14***	0.14***	0.68***	0.96***
		(0.00)	(0.01)	(0.01)	(0.02)		(0.01)	(0.01)	(0.00)	(0.02)
Non-metallic minerals	5	0.41***	0.11***	0.55***	1.07***	2.00	0.72***	0.14***	0.88***	1.74***
		(0.02)	(0.00)	(0.01)	(0.01)		(0.02)	(0.00)	(0.00)	(0.01)
Metal	5	0.13***	0.12***	0.66***	0.90***	5.14	0.14***	0.12***	0.65***	0.91***
		(0.01)	(0.00)	(0.00)	(0.01)		(0.01)	(0.00)	(0.00)	(0.01)
Machinery, & Trans. equip.	5	0.12***	0.14***	0.59***	0.85***	5.28	0.15***	0.15***	0.58***	0.88***
		(0.01)	(0.00)	(0.00)	(0.01)		(0.01)	(0.00)	(0.00)	(0.02)
Electronics	5	0.16***	0.12***	0.61***	0.89***	4.44	0.14***	0.15***	0.63***	0.92***
		(0.00)	(0.01)	(0.00)	(0.00)		(0.01)	(0.01)	(0.00)	(0.00)
Mfg. nec	5	0.26***	0.22***	0.47***	0.94***	2.74	0.30***	0.45***	0.59***	1.34***
		(0.03)	(0.03)	(0.02)	(0.01)		(0.02)	(0.01)	(0.01)	(0.00)
Mfg. average	5	0.19	0.15	0.58	0.91	4.14	0.25	0.21	0.66	1.11

Notes. This table reports the calibrated values of the elasticity of substitution and the Cobb-Douglas production function parameters for each manufacturing sector. Standard errors clustered at the firm-level are in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. We calculate standard errors using a nonparametric block bootstrap method with replacement across firms, in which the parameters are estimated in two steps for each bootstrapped sample. We perform 100 replications. In columns 6-10, we take the estimates of σ from Broda and Weinstein (2006). $\gamma_j = \gamma_j^L + \gamma_j^K + \gamma_j^M$.

Table B3: Sensitivity Analysis. Production Function Parameters

	γ_j^L	γ_j^K	γ_j^M	γ_j	$\frac{\gamma_j^L}{\gamma_j^L+\gamma_j^K}$
	(1)	(2)	(3)	(4)	(5)
Panel A. Baseline Estimates					
Mean	0.20	0.19	0.58	0.96	0.50
Median	0.13	0.15	0.59	0.93	0.50
SD	0.13	0.11	0.07	0.09	0.18
Min	0.10	0.07	0.43	0.88	0.20
Max	0.49	0.47	0.66	1.11	0.87
Panel B. Only Non-exporters					
Mean	0.21	0.14	0.57	0.92	0.58
Median	0.17	0.15	0.59	0.92	0.57
SD	0.10	0.05	0.08	0.09	0.14
Min	0.12	0.07	0.41	0.82	0.33
Max	0.46	0.24	0.65	1.12	0.84
Panel C. Only Exporters					
Mean	0.17	0.18	0.57	0.92	0.44
Median	0.12	0.16	0.59	0.91	0.40
SD	0.18	0.08	0.08	0.14	0.17
Min	0.06	0.06	0.44	0.62	0.25
Max	0.69	0.32	0.66	1.20	0.90
Panel D. $\mathbf{Z}_{fjt} = [\ln k_{fj,t-1}, \ln l_{fj,t-1}, 1, \ln a_{fj,t-1}]'$					
Mean	0.19	0.15	0.58	0.91	0.52
Median	0.13	0.14	0.59	0.89	0.52
SD	0.12	0.04	0.07	0.09	0.13
Min	0.08	0.11	0.43	0.83	0.34
Max	0.41	0.22	0.66	1.11	0.79
Panel E. $\ln a_{fjt} = \sum_{p=0}^{3} \iota_p (\ln a_{fj,t-1})^p$					
Mean	0.22	0.10	0.58	0.89	0.64
Median	0.19	0.07	0.59	0.82	0.67
SD	0.14	0.05	0.07	0.18	0.16
Min	0.06	0.06	0.43	0.60	0.40
Max	0.42	0.19	0.66	1.14	0.85

Notes. This table report results of the sensitivity analysis of the production function parameters. Panel A reports the summary statistics of the baseline estimates. Panels B, C, D, and E report the summary statistics of the estimates based on the alternative samples including only non-exporters and exporters, the alternative IV, $\mathbf{Z}_{fjt} = [\ln k_{fj,t-1}, \ln l_{fj,t-1}, 1, \ln a_{fj,t-1}]'$, and the alternative Markov process with third-order polynomials, $\ln a_{fjt} = \sum_{p=0}^{3} \iota_p (\ln a_{fj,t-1})^p$, respectively.

B.3 Recovering the Shocks

Data inputs.

- Sales, exports, employment, and fixed assets of manufacturing firms, $\forall f \in \mathcal{F}_{jt}/\{\tilde{f}\}$, $\forall j \in [0, J_m]$, where $\mathcal{F}_{jt}/\{\tilde{f}\}$ is the set of sector j firms observed in the firm-level data in year t;
- Sectoral gross output, exports, and import shares, PPI, $j \in [0, 1]$;
- Aggregate real GDP growth, working hours per worker, human capital adjusted population growth.

Structural parameters.

- Production function $\{\gamma_j^L, \gamma_j^K, \gamma_j^M\}_{j\in[0,1]}$;
- Cobb-Douglas shares of intermediate inputs $\{\gamma_i^j\}_{i,j\in[0,1]}$;
- Elasticities of substitution σ and ρ;
- Labor supply elasticities, η, θ, and ψ.

Recovering relative productivity and distortions. Using sales and exports data, we calculate fringe firms' domestic sales and exports as residuals: $r^H_{\tilde{f}jt} = R^{H,\text{Agg}}_{jt} - \sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} r^H_{fjt}$, and $r^F_{\tilde{f}jt} = R^{F,\text{Agg}}_{jt} - \sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} r^F_{fjt}$. $R^{H,\text{Agg}}_{jt}$ and $R^{F,\text{Agg}}_{jt}$ are sectoral domestic sales and exports from KLEMS and IO tables. r^H_{fjt} and r^F_{fjt} are firm-level domestic sales and exports from the firm-level data. From these constructed fringe firms' $r^H_{\tilde{f}jt}$ and $r^F_{\tilde{f}jt}$, we can compute the markup-adjusted revenue share $\Lambda^H_{\tilde{f}jt}$.

Then, using these fringe firms' domestic sales and exports, we construct sales shares as $s^H_{fjt} = \frac{r^H_{fjt}}{\sum_{g\in\mathcal{F}_{jt}} r^H_{gjt}}$ and $s^F_{fjt} = \frac{r^F_{fjt}}{\sum_{g\in\mathcal{F}^F_{jt}} r^F_{fjt}}$. Given $\{s^H_{fjt}, s^F_{fjt}\}$ and the structural parameters, we calculate fringe firms' distortions and labor and capital inputs in a model-consistent way. We assume that fringe firms' distortions are the average of those of the firms present in the data. We proceed with the following algorithm for each sector and year.

<u>Step 1.</u> Guess $\{\tau^L_{fjt}, \tau^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$, where $\tau^L_{\tilde{f}jt} = \tau^K_{\tilde{f}jt} = 0$.

<u>Step 2.</u>

- Make a guess on $l_{\tilde{f}jt}$ and compute $\{s^L_{fjt}\}_{f\in\mathcal{F}_{jt}}$ and $\{\mu^L_{fjt}\}_{f\in\mathcal{F}_{jt}}$.
- Using the first-order conditions (equation A.3) and the inverse labor supply function $w_{fjt} = F_{jt}^{\frac{1}{\eta}} l_{fjt}^{\frac{1}{\eta}} L_{jt}^{\frac{1}{\theta}-\frac{1}{\eta}} W_t$, we obtain that

$$\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \gamma_j^L r^H_{fjt}/\Lambda^H_{fjt} = \Big(\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \mu^H_{fjt}\mu^L_{fjt}(1+\tau^L_{fjt}) l_{fjt}^{\frac{\eta+1}{\eta}}\Big) F_{jt}^{\frac{1}{\eta}} L_{jt}^{\frac{1}{\theta}-\frac{1}{\eta}} W_t,$$

which gives

$$F_{jt}^{\frac{1}{\eta}} L_{jt}^{\frac{1}{\theta}-\frac{1}{\eta}} W_t = \underbrace{\frac{\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \gamma_j^L r^H_{fjt}/\Lambda^H_{fjt}}{\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \mu^H_{fjt}\mu^L_{fjt}(1+\tau^L_{fjt}) l_{fjt}^{\frac{\eta+1}{\eta}}}}_{\text{Data and guess}},$$

where the right hand side can be measured using the guessed $\{\tau^L_{fjt}\}_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}}$ and employment from the data.

- Using the measured $L_{jt}^{\frac{1}{\theta}-\frac{1}{\eta}} W_t$ and fringe firms' first-order conditions, we can obtain that

$$l_{\tilde{f}jt} = \left(\frac{\gamma^L_j r^H_{\tilde{f}jt}/\Lambda^H_{\tilde{f}jt}}{\frac{\sigma}{\sigma-1}\frac{\eta+1}{\eta}(1+\tau^L_{\tilde{f}jt})F_{jt}^{\frac{1}{\eta}} L_{jt}^{\frac{1}{\theta}-\frac{1}{\eta}} W_t} \right)^{\frac{\eta}{\eta+1}}.$$

- Using the obtained $l_{\tilde{f}jt}$, compute the new $\{s^L_{fjt}\}_{f\in\mathcal{F}_{jt}}$ and compare with the previous $\{s^L_{fjt}\}_{f\in\mathcal{F}_{jt}}$.
- Iterate until $\{s^L_{fjt}\}_{f\in\mathcal{F}_{jt}}$ is consistent with fringe firms' first-order conditions and the initial guess of $\{\tau^L_{fjt}\}_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}}$.

Step 3.

- Make a guess of $k_{\tilde{f}jt}$ and compute $\{s^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$.
- Using the first-order conditions (equation A.3), we obtain that

$$\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \gamma^K_j r^H_{fjt}/\Lambda^H_{fjt} = \sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \mu^H_{fjt}(1+\tau^K_{fjt})Rk_{fjt},$$

which gives

$$\varrho = \frac{\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \gamma^K_{jt} r^H_{fjt}/\Lambda^H_{fjt}}{\sum_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}} \mu^H_{fjt}(1+\tau^K_{fjt})k_{fjt}},$$

where the right hand side can be measured using the guessed $\{\tau^K_{fjt}\}_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}}$ and fixed assets from the data.

- Using the measured ϱ and fringe firms' first-order conditions, we can obtain that

$$k_{\tilde{f}jt} = \left(\frac{\gamma^K_j r^H_{\tilde{f}jt}/\Lambda^H_{\tilde{f}jt}}{\frac{\sigma}{\sigma-1}(1+\tau^K_{\tilde{f}jt})\varrho} \right).$$

- Using the obtained $k_{\tilde{f}jt}$, compute the new $\{s^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$ and compare with the previous $\{s^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$.
- Iterate until $\{s^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$ is consistent with fringe firms' first-order conditions and the guess of $\{\tau^K_{fjt}\}_{f\in\mathcal{F}_{jt}/\{\tilde{f}\}}$.

Step 4. Using fringe firms' labor and capital inputs calculated in the previous steps, we construct $\{s^L_{fjt}, s^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$.

Step 5. Using $\{s^H_{fjt}, s^F_{fjt}, s^L_{fjt}, s^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$ and $\{\Lambda^H_{fjt}\}_{f\in\mathcal{F}_{jt}}$, solve the system of equations (2.23), (2.24), (2.25), and (2.26) and obtain $\{a_{fjt}, \tau^L_{fjt}, \tau^K_{fjt}, D_{fjt}\}_{f\in\mathcal{F}_{jt}}$ that is normalized relative to fringe firms. For non-exporters, set $D_{fjt} = 0$.

Step 6. Compare obtained $\{\tau^L_{fjt}, \tau^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$ in the previous step to the initial guess.

Step 7. Iterate until $\{\tau^L_{fjt}, \tau^K_{fjt}\}_{f\in\mathcal{F}_{jt}}$ converge.

Step 8. Set $1+\tau^L_{\tilde{f}jt}$ and $1+\tau^K_{\tilde{f}jt}$ to satisfy $\sum_{f\in\mathcal{F}_{jt}} s_{fjt}\frac{1}{(1+\tau^L_{fjt})\tilde{\mu}_{fjt}\mu^L_{fjt}} = 1$ and $\sum_{f\in\mathcal{F}_{jt}} s_{fjt}\frac{1}{(1+\tau^K_{fjt})\tilde{\mu}_{fjt}} = 1$, respectively.

Recovering the remaining shocks. We now describe the procedure to back out the remaining shocks: $\Xi_t, \bar{\psi}_t$ and $\{P^F_{jt}, a_{\tilde{f}jt}, D_{\tilde{f}jt}\}_{j\in[0,1]}$. We solve the full model and proceed with the following algorithm in two layers: inner and outer loops.

Outer loop:

1. Make a guess $\{\Xi_t\}$ while normalizing $\Xi_{t\geq 2011} = \Xi^* = 1$, where the superscript * denotes the steady state values.
2. Using Ξ^*, we compute K^*
3. Assuming the economy converges in $t=T$, Make a guess of $\{K_t\}_{t=1}^{t=T}$ and solve the model using the inner loop to get $\{C_t\}$.
4. Update $\{K_t\}_{t=1}^{t=T}$ using Euler Equation (2.2).
5. Update $\{\Xi_t\}_{t<2011}$ until $\{K_t\}_{t\leq 2011}$ converges to the data.

Inner loop:

1. Make a guess for the shocks: $\bar{\psi}^{(0)}_t$ and $\{P^{F,(0)}_{jt}, D^{(0)}_{\tilde{f}jt}, a^{(0)}_{\tilde{f}jt}\}_{j\in[0,1]}$
2. Based on the guess, compute firms' productivity and foreign demand shocks as $a^{(0)}_{fjt} = a^{(0)}_{\tilde{f}jt}\times\dot{A}_{fjt}$ and $D^{(0)}_{fjt} = D^{(0)}_{\tilde{f}jt}\times\dot{D}_{fjt}$ for all firms and sectors, where $\dot{A}_{fjt}$ and $\dot{D}_{fjt}$ are the backed out productivity and foreign demands relative to the fringe firm within sectors, as described above.
3. Feed the firm-level shocks $\{a^{(0)}_{fjt}, D^{(0)}_{fjt}, \tau^L_{fjt}, \tau^K_{fjt}\}_{f\in\mathcal{F}_{jt}, j\in[0,1]}$, $\{P^{F,(0)}_{jt}\}_{j\in[0,1]}$, and $\bar{\psi}^{(0)}_t$ and solve the model. Note that distortions are backed out in the procedure above.
4. Update $\{P^{F,(0)}_{jt}\}_{j\in[0,1]}$ until the import shares of the model fit the data
5. Update $\{D^{(0)}_{\tilde{f}jt}\}_{j\in[0,1]}$ until the sectoral exports of the model fit the data
6. Update $\{a_{\tilde{f}jt}\}_{j\in[0,1]}$ until the sectoral gross outputs of the model fit the data
7. Update fringe firm's productivity relative to that of the reference sector j_0, $\{a_{\tilde{f}jt}/a_{\tilde{f}j_0t}\}_{j\in[0,1]}$, by fitting PPI_{jt}/PPI_{j_0t}. We assume $PPI_{j_0t} = 1$ for all t.
8. Update fringe firm's productivity of the reference sector $a_{\tilde{f}j_0t}/a_{\tilde{f}j_0t_0}$ by fitting the aggregate real GDP growth, where t_0 denotes the initial year of our data. We normalize $a_{\tilde{f}j_0t_0}$ to one.
9. Update $\bar{\psi}_t$ by fitting working hours per worker in the model (equation 2.4) to the data counterpart.

B.4 External Validation/Industrial Policies/Historical Narratives

This subsection merges our recovered shocks with a battery of additional firm- and sector-level data to perform 3 exercises. First, we show that our firm-level shocks—estimated using only four firm-specific market shares as detailed by Proposition 2.4—line up well with external data and historical narratives on industrial policy, technology transfers, the financial crisis, and international trade. This step externally validates our inferred shocks by correlating them to various observables.

Second, we establish that during the activist industrial policy period of the 1970s, larger firms were more likely to be treated with industrial policies. This correlation hints that industrial policies potentially contributed to the increase in concentration in the South Korean economy.

Third, we turn to the question of whether industrial policies contributed to the increase in South Korean manufacturing concentration and GDP growth, by projecting the recovered shocks on industrial policies and quantifying the impact of only the component of the firm-level shocks attributable to those industrial policies.

B.4.1 External Validation: Relating Recovered Shocks to Observables

We present a three-part historical narrative. From 1973 to 1979 South Korea implemented its large-scale industrial policy: the Heavy and Chemical Industry (HCI) Drive. In 1998 economic growth was briefly, yet starkly, interrupted by the Asian Financial Crisis. Lastly we relate the firms' export demand to an independent measure of international trade shocks throughout the period.

Industrial policies. We begin by identifying firm-level data sources on industrial policy treatment at the firm level. First, during the HCI Drive (1973-1979), one of the most important subsidy instruments was the allocation of foreign credit. Due to balance of payments problems, the government tightly regulated domestic firms' US dollar borrowing from foreign financial institutions. The government selectively allowed certain firms to borrow in US dollars, while providing guarantees. These guarantees allowed specific Korean firms to borrow at significantly lower interest rates. We obtain the firm-level credit data from Choi and Levchenko (2025) and merge them into our main firm dataset. We expect that firms receiving the subsidized credit would primarily experience a reduction in their capital wedge relative to the non-subsidized firms.

Also, as part of industrial policy, the government heavily promoted the adoption of foreign technology through subsidized credits, which has been shown to be an important source of Korean productivity growth in the 1970s and 1980s (Choi and Shim, 2022, 2025). We thus obtain data on individual firms' foreign technology adoption contracts from Choi and Shim (2022). We expect that foreign technology adoption will primarily appear in increased productivity. Third, during this period the Korea Trade-Investment Promotion Agency (KOTRA) facilitated Korean firms' access to export markets by encouraging participation in international trade fairs and by matching foreign buyers with Korean firms at these events (Barteska and Lee, 2025). To capture this export-promotion activity, we re-collect the KOTRA fair participation data from archival sources, and use the number of times a firm participated in trade fairs as a covariate.

To correlate recovered shocks to these observable policies, we estimate the following distributed lag model:

$$\ln X_{fjt} = \sum_{\tau=0}^{10} \beta_1^\tau \text{CumTech}_{fj,t-\tau} + \sum_{\tau=0}^{10} \beta_2^\tau \text{Ihs}(\text{Credit}_{fj,t-\tau}) + \sum_{\tau=0}^{10} \beta_3^\tau \text{Ihs}(\text{Trade Fair}_{fj,t-\tau}) + \delta_f + \delta_{jt} + \varepsilon_{fjt},$$
$$X_{fjt} \in \{a_{fjt}, 1+\tau^K_{fjt}, 1+\tau^L_{fjt}, D_{fjt}\}, \quad \text{(B.4)}$$

where $\text{CumTech}_{fj,t-\tau}$ denotes the cumulative number of technology adoption contracts up to year $t-\tau$; $\text{Ihs}(\text{Credit}_{fj,t-\tau})$ is the inverse hyperbolic sine transformation of foreign credit allocated to the firm; and $\text{Ihs}(\text{TradeFair}_{fj,t-\tau})$ is the inverse hyperbolic sine of the number of trade fairs the firm participated in. All three variables are standardized. All specifications include firm and sector-year fixed effects (δ_f and δ_{jt}) and are estimated over the pre-crisis period (1972–1995). Standard errors are clustered at the firm level.

Table B4 reports the estimation results. Rather than presenting the full set of distributed-lag coefficients, we report long-run effects, defined as the effect of a permanent one-unit increase in each regressor: $\sum_{\tau=0}^{10} \hat{\beta}_k^\tau$ for $k = 1, 2, 3$. As expected, recovered productivity a_{fjt} is positively correlated with technology adoption and firms receiving foreign credit subsidies experienced lower capital distortions. While participation in trade fairs is not meaningfully correlated with export demand shocks D_{fjt}, it is positively associated with productivity, potentially reflecting learning-by-exporting mechanisms.

Table B4: External Validation of Shocks. Industrial Policy. Distributed Lag Model

Dep. Var.	(1) $\ln a_{fjt}$	(2) $\ln 1+\tau^K_{fjt}$	(3) $\ln 1+\tau^L_{fjt}$	(4) $\ln D_{fjt}$
CumTech_{fjt}	0.04**	0.07	−0.02	0.03
	(0.02)	(0.05)	(0.04)	(0.09)
$\text{Ihs}(\text{Credit}_{fjt})$	0.01	−0.06***	0.00	0.01
	(0.01)	(0.02)	(0.03)	(0.05)
$\text{Ihs}(\text{Trade Fair}_{fjt})$	0.05***	0.02	−0.01	0.05
	(0.02)	(0.02)	(0.02)	(0.07)
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
N	25,052	25,052	25,052	11,145

Notes. This table reports long-run effects, defined as the effect of a permanent one-unit increase in each regressor, $\sum_{\tau=0}^{10} \hat{\beta}_k^\tau$ for $k = 1, 2, 3$, in equation (B.4). Standard errors clustered at the firm level are in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. All three explanatory variables are standardized. All specifications include controls for firm and sector-year fixed effects.

To further probe the reach of the 1970s industrial policies, we exploit the fact that industrial policy during this period targeted not only specific sectors but also specific regions. Choi and Levchenko (2025) discuss and justify this identification strategy at length. Here, we project the recovered firm shocks on binary indicators for industrial policy treatment. The treatment is defined as being located in the region and sector targeted by industrial policy. This specification is essentially the reduced-form of the IV strategy in Choi and Levchenko (2025). The tradeoff with respect to equation (B.4) above is that (B.4) uses observed firm-level industrial policies as the covariates, thus the variation in recovered shocks is related variation in policies at the firm level. However, to the extent that the policy package was broader than the observed policies we have access to, the reduced-form specification below can potentially pick it up as it casts a wider net.

We estimate the following event-study specification:

$$\begin{aligned} X_{fnjt} = \sum_{\tau=-1}^{22} \beta_\tau^L \left(\mathbb{1}[\text{Treated}_{fnj,72}^{\text{large}}] \times \mathcal{T}_{\tau=t-1973} \right) \\ + \sum_{\tau=-1}^{22} \beta_\tau^S \left(\mathbb{1}[\text{Treated}_{fnj,72}^{\text{small}}] \times \mathcal{T}_{\tau=t-1973} \right) + \delta_{nj} + \delta_{nt} + \delta_{jt} + \varepsilon_{fnjt}, \\ X_{fnjt} \in \{a_{fjt}, 1+\tau_{fjt}^K, 1+\tau_{fjt}^L, D_{fjt}\}, \end{aligned} \tag{B.5}$$

where f denotes firm, n region, j sector, and t year. The binary indicators $\mathbb{1}[\text{Treated}_{fnj,72}^{\text{large}}]$ and $\mathbb{1}[\text{Treated}_{fnj,72}^{\text{small}}]$ reflect whether firm f was located in the treated region-sector nj. We further differentiate between the treatment effect on large vs. small firms. Firm size is based on sales in 1972, one year prior to the implementation of the policy, rendering these indicators predetermined.[26] We normalize β_{-1}^L and β_{-1}^S to zero. $\mathcal{T}_{\tau=t-1973}$ is an indicator for event time relative to the 1973 start of the policy. The fixed effects δ_{nj}, δ_{nt}, and δ_{jt} absorb region-sector, region-year, and sector-year unobservables, respectively. Standard errors are clustered at the region level.

This specification identifies the effects of region-sector-level policy exposure by comparing firms in targeted region-sectors to those in non-targeted ones, while allowing for heterogeneous effects by initial firm size. Although the policy was implemented between 1973 and 1979, its effects may persist beyond the policy period. In particular, productivity effects may arise through learning-by-doing, as studied by Choi and Levchenko (2025). Contemporaneous policy effects are captured by coefficients for event times during the implementation period ($0 \leq \tau \leq 6$), while longer-run effects are reflected in post-policy coefficients ($\tau \geq 7$).

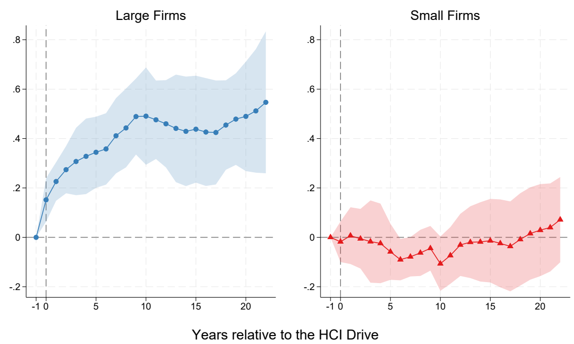
We also estimate average effects by means of the following specification:

$$\begin{aligned} X_{fnjt} = \beta_{\text{short}}^L \left(\mathbb{1}[\text{Treated}_{fnjt_0}^{\text{large}}] \times \mathcal{T}_{73\leq t\leq 79} \right) + \beta_{\text{long}}^L \left(\mathbb{1}[\text{Treated}_{fnjt_0}^{\text{large}}] \times \mathcal{T}_{80\leq t\leq 95} \right) \\ + \beta_{\text{short}}^S \left(\mathbb{1}[\text{Treated}_{fnjt_0}^{\text{short}}] \times \mathcal{T}_{73\leq t\leq 79} \right) + \beta_{\text{long}}^S \left(\mathbb{1}[\text{Treated}_{fnjt_0}^{\text{short}}] \times \mathcal{T}_{80\leq t\leq 95} \right) + \delta_{nj} + \delta_{nt} + \delta_{jt} + \varepsilon_{fnjt}, \end{aligned} \tag{B.6}$$

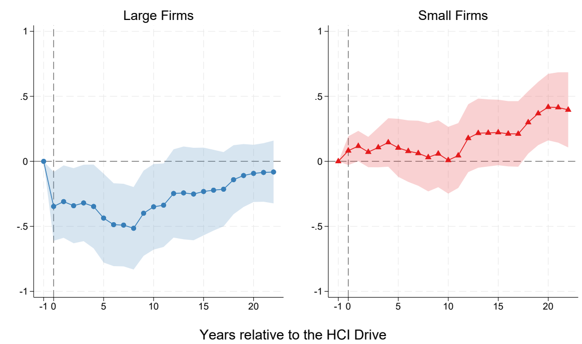
where $\mathcal{T}_{73\leq t\leq 79}$ and $\mathcal{T}_{80\leq t\leq 95}$ are indicators for the policy and post-policy periods, respectively. The coefficients β_{short}^L and β_{short}^S capture heterogeneous short-run effects by initial firm size, while β_{long}^L and β_{long}^S capture heterogeneous long-run effects.

[26] We choose a size cutoff of 91.5 percentile, which maximizes the adjusted R^2.

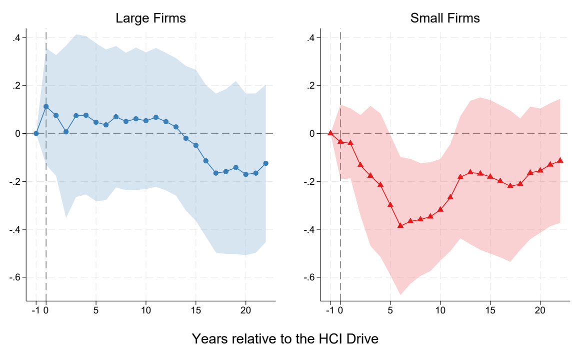
Figure B6: External Validation of Shocks. HCI Drive. Large vs. Small Firms. Event Study



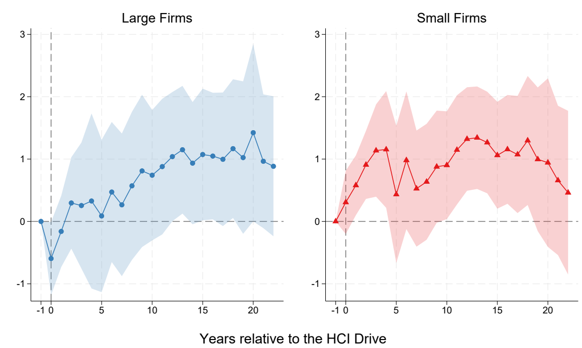
A. $\ln a_{fjt}$



B. $\ln 1 + \tau^K_{fjt}$



C. $\ln 1 + \tau^L_{fjt}$



D. $\ln D_{fjt}$

Notes. This figure displays the estimates of equation (B.5). The 90% confidence intervals based on standard errors clustered at the region level are displayed. In Panels A, B, C, and D, the dependent variables are log productivity, capital distortions, labor distortions, and export demand shocks, respectively. All specifications include region-sector, region-year, and sector-year fixed effects.

Figure B6 and Table B5 present the results. Being in the treated region-sectors was associated with both short- and long-run increases in firm productivity. However, these gains are confined to the initially large firms; we find no statistically significant productivity improvements for small firms. During the policy period, capital distortions decline among large firms, while distortions for small firms tend to increase over time, though small firms' average effects are statistically insignificant. This divergent pattern is consistent with resource misallocation during the HCI period, as documented by Kim et al. (2021). We find no material effects on labor distortions. Finally, the policy increased export demand similarly for both small and large firms, with coefficients more precisely estimated for smaller firms. Broadly, these patterns are consistent with the distributed-lag results in Table B4, which show that technology adoption is positively correlated with productivity and that foreign credit allocation is associated with reductions in capital distortions, reflecting the fact that large firms were more likely to receive subsidized credit and adopt foreign technologies (as shown formally in the next subsection).

Overall, these results show that our recovered wedges can be successfully tied to the observed industrial policy variation during the 1970s.

Table B5: External Validation of Shocks. HCI Drive. Large vs. Small Firms. Average Effects

Dep. Var.	$\ln a_{fjt}$ (1)	$\ln 1+\tau^K_{fjt}$ (2)	$\ln 1+\tau^L_{fjt}$ (3)	$\ln D_{fjt}$ (4)
β^L_{short}	0.28***	−0.37**	0.06	0.10
	(0.06)	(0.16)	(0.17)	(0.51)
β^L_{long}	0.46***	−0.25	−0.05	0.91
	(0.11)	(0.15)	(0.18)	(0.58)
β^S_{short}	−0.03	0.10	−0.18	0.78**
	(0.07)	(0.08)	(0.13)	(0.36)
β^S_{long}	−0.02	0.21	−0.22	0.96**
	(0.08)	(0.14)	(0.14)	(0.42)
Region-sector FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
N	8978	8978	8978	6170

Notes. This table reports the estimates of equation (B.6). Standard errors clustered at the region level are in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Asian Financial Crisis. Figure 2 documents that our estimated capital distortions fluctuated widely during the Asian Financial Crisis, between its onset in 1998 and South Korea's full repayment of the IMF loan in 2001. The macroeconomics literature on financial crises documents that more financially constrained firms are more susceptible to the deterioration in the financial conditions during crisis episodes (e.g. Gertler et al., 2007; Kim et al., 2015). We therefore relate firm-level capital and labor distortions to the severity of firm financial constraints, proxied by the pre-crisis debt-to-asset ratios. We expect firms with higher debt-to-asset ratios to experience larger increases in these distortions during the crisis.

We run the following long-difference model:

$$d\ln X_{fj} = \beta\frac{\text{Debt}_{fj}}{\text{Assets}_{fj}} + \delta_j + \varepsilon_{fj}, \qquad X_{fj}\in\{1+\tau^K_{fj}, 1+\tau^L_{fj}, a_{fj}, D_{fj}\}, \tag{B.7}$$

where on the left-hand side is the log-difference in the inferred shock over the crisis period 1997-2001, and δ_j denotes sector fixed effects. Our key variable of interest is $\frac{\text{Debt}_{fj}}{\text{Assets}_{fj}}$, computed as the average of the pre-crisis (1996-1997) debt-to-asset ratio.

The left panel of Table B6 reports the results. As expected, the debt-to-asset ratio is significantly correlated only with capital and labor distortions, but not with other shocks. To reinforce the role of the crisis, as a placebo exercise the right panel of the table uses the log-change in the shocks during the pre-crisis period (1990-1994) as the dependent variable. Outside of the crisis, there is no relationship between the debt-to-asset ratio and changes in distortions.

Export demand shocks. Finally, we relate the foreign demand wedges to an external correlate of foreign demand for South Korean products. For this purpose, we use the exports of Taiwan, an open

Table B6: External Validation of Shocks. Asian Financial Crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample period	Crisis: 1997-2001				Pre-crisis: 1990-1994			
Dep. Var.	$\Delta \ln 1+\tau^K_{fj}$	$\Delta \ln 1+\tau^L_{fj}$	$\Delta \ln a_{fj}$	$\Delta \ln D_{fj}$	$\Delta \ln 1+\tau^K_{fj}$	$\Delta \ln 1+\tau^L_{fj}$	$\Delta \ln a_{fj}$	$\Delta \ln D_{fj}$
$\frac{\text{Debt}_{fj}}{\text{Assets}_{fj}}$	0.27***	0.21**	0.10	−0.15	0.07	0.08	−0.01	0.02
	(0.06)	(0.10)	(0.07)	(0.19)	(0.07)	(0.06)	(0.04)	(0.22)
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
N	3617	3617	3617	787	1534	1534	1534	650

Notes. This table reports the estimates of equation (B.7). Robust standard errors are in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

economy with a similar industrial composition to South Korea. Taiwanese exports should be a good proxy the foreign demand for South Korean exports, without being contaminated with the South Korean supply shocks. We would expect the Taiwanese exports to be primarily correlated with the recovered export demand shocks.

Specifically, we construct the sectoral export demand shocks as follows:

$$\Delta\text{Export shock}_{jt} = \frac{\text{Export}^{\text{TWN}}_{jt}}{\text{Gross Output}_{j,t-1}} - \frac{\text{Export}^{\text{TWN}}_{j,t-1}}{\text{Gross Output}_{j,t-2}}, \tag{B.8}$$

where $\text{Export}^{\text{TWN}}$ is exports from Taiwan to the world (excluding to South Korea) and Gross Output_{jt} is sector j's gross output in South Korea. We use lagged rather than contemporaneous gross output.

We then examine whether our recovered firm-level shocks correlate with these proxies for global demand using the following regression specification:

$$\Delta \ln X_{fjt} = \beta \Delta\text{Export shock}_{jt} + \delta_t + \varepsilon_{fjt}, \qquad X_{fjt} \in \{a_{fjt}, 1+\tau^K_{fjt}, 1+\tau^L_{fjt}, D_{fjt}\}, \tag{B.9}$$

where δ_t are year fixed effects. Because our regressor of interest varies at the sector-year level, standard errors are clustered at the sector level. One potential concern with these standard errors is the small number of clusters (11), so we also report the p-values obtained via wild bootstrap.

Table B7 reports the results. As expected, the proxy for global demand constructed from Taiwanese trade data is significantly positively correlated with export demand, but not with other shocks.

B.4.2 Did Industrial Policies Favor Large Firms?

We now establish whether large firms were disproportionately targeted by the 1970s' industrial policies. Table B8 reports regression coefficients of firm-level policy treatment on log total sales $\ln(r_{fjt})$. For all three, it is indeed the case that firm size was correlated with the likelihood of treatment. The coefficients on firm size barely change in size or significance when adding sector-year fixed effects. Since the expositional focus of the paper is on the top 3 firms in each sector, Table B9

Table B7: External Validation of Shocks. Export Demand Shocks

Dep. Var.	$\Delta \ln a_{fjt}$ (1)	$\Delta \ln 1 + \tau^K_{fjt}$ (2)	$\Delta \ln 1 + \tau^L_{fjt}$ (3)	$\Delta \ln D_{fjt}$ (4)
ΔExport shock$_{jt}$	0.07	−0.05	−0.04	0.35***
	(0.08)	(0.06)	(0.08)	(0.11)
	[0.88]	[0.50]	[0.67]	[0.03]
Year FE	✓	✓	✓	✓
N	130250	130250	130250	31471

Notes. This table reports the estimates of equation (B.9). Robust standard errors clustered at the sector level are in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Wild bootstrapped p-values are reported in brackets.

reports summary statistics for firm-level treatment with industrial policies by top-3 status. It is clear that the top-3 firms were more likely to be treated with industrial policy: while 24% of top-3 firm-year instances recorded technology adoption contracts, only 6% of non top-3 observations did. The mean amount of subsidized credit received by top-3 firms was more than 10 times larger than by non-top-3 firms. Similarly, the number of trade fairs attended per year was 0.21 for a top-3 firm vs. 0.06 for a non-top-3 firm. Columns 9 and 10 report the t-statistics and p-values for the difference between the top-3 and non-top-3 means. For all 3 industrial policies, treatment rates of the top-3 firms were highly statistically different. However, even within the top-3 set, the treatment was rather sparse. For all three policies for which we have information, the median top-3 firm-year observation was not treated.

Table B8: Correlation between Firm Size and Industrial Policy-Related Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$\mathbb{1}$[Tech. Adopt$_{fjt}$ > 0]		Ihs(Credit$_{fjt}$)		Ihs(Trade fair$_{fjt}$)	
$\ln(r_{fjt})$	0.04***	0.05***	0.44***	0.45***	0.05***	0.05***
	(0.00)	(0.01)	(0.06)	(0.07)	(0.01)	(0.01)
Sector-year FE		✓		✓		✓
N	7,169	7,169	7,169	7,169	7,169	7,169

Notes. This table reports the results of regressing the industrial policy-related outcomes on firm size, measured by log total revenue $\ln(r_{fjt})$. $\mathbb{1}$[Tech. Adopt$_{fjt}$ > 0] is an indicator for the adoption of foreign technologies. Ihs(Credit$_{fjt}$) denotes the inverse hyperbolic sine of government credit received. Ihs(Trade fair$_{fjt}$) denotes the inverse hyperbolic sine of the inverse hyperbolic sine of the number of times the firm participated in trade fairs. t-statistics test the null hypothesis that the means of the top-3 and non-top-3 groups are equal, with corresponding p-values reported in brackets. The sample period is 1972-1982.

B.4.3 Concentration and GDP Growth Attributable to Industrial Policies

We now quantify the extent to which industrial policy affected firm concentration and growth.[27] We construct two counterfactual shock series using estimates from the distributed lag model (B.4) and the

[27] This is inspired by the exercise in Section of 6 of Bau and Matray (2023).

Table B9: Summary Statistics of Industrial Policy Variables, Top 3 vs. Non-top 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Top 3				Not top 3				(Col. 1 - Col. 5)	
	Mean	Med.	SD	Obs.	Mean	Med.	SD	Obs.	t-stat.	p-val
$\mathbb{1}[\text{Tech. Adopt}_{fjt} > 0]$	0.24	0	0.43	1,028	0.06	0	0.24	6,141	42.38	[0.00]
Ihs(Credit$_{fjt}$)	2.17	0	5.93	1,028	0.21	0	1.89	6,141	32.61	[0.00]
Ihs(Trade fair$_{fjt}$)	0.21	0	0.60	1,028	0.06	0	0.29	6,141	10.33	[0.00]

Notes. This table reports descriptive statistics of the industrial policy-related outcomes. $\mathbb{1}[\text{Tech. Adopt}_{fjt} > 0]$ is an indicator for the adoption of foreign technologies. Ihs(Credit$_{fjt}$) denotes the inverse hyperbolic sine of government credit received. Ihs(Trade fair$_{fjt}$) denotes the inverse hyperbolic sine of the number of trade-fair participation. t-statistics test the null hypothesis that the means of the top-3 and non-top-3 groups are equal, with corresponding p-values reported in brackets. The estimation sample period is 1972-1982.

reduced form (B.6). First, we construct alternative shock series that purge the component accounted for by observable policies using estimates from the distributed lag model in Table B4:

$$\ln X^c_{fjt} = \ln X_{fjt} - \sum_{\tau=0}^{10} \hat{\beta}_1^{\tau} \mathbb{1}[\text{Cum. Tech}_{fj,t-\tau} > 0] - \sum_{\tau=0}^{10} \hat{\beta}_2^{\tau} \text{Ihs}(\text{Credit}_{fj,t-\tau}) - \sum_{\tau=0}^{10} \hat{\beta}_3^{\tau} \text{Ihs}(\text{Trade Fair}_{fj,t-\tau}), \qquad X_{fjt} \in \{a_{fjt}, 1+\tau^K_{fjt}, 1+\tau^L_{fjt}, D_{fjt}\}, \quad \text{(B.10)}$$

This counterfactual shock series isolates the component of each shock that is not predicted by observed industrial policy variables. We construct these alternative series only for shocks that exhibit statistically significant coefficients at the 10% level.

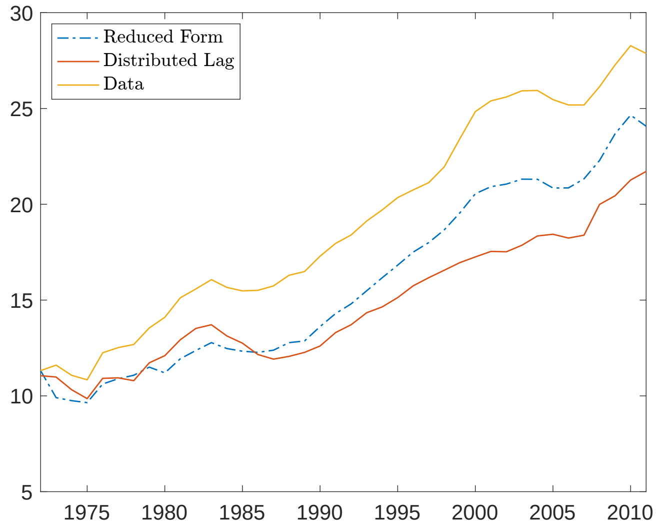
Second, based on the average region-sector reduced-form treatment effects in Table B5, we construct alternative shock series that remove the estimated short- and long-run effects of the industrial policy:

$$\ln X^c_{fjt} = \ln X_{fjt} - \hat{\beta}^S_{\text{long}} \left(\mathbb{1}[\text{Treated}^{\text{large}}_{fnjt_0}] \times \mathcal{T}_{73 \le t \le 79} \right) - \hat{\beta}^L_{\text{long}} \left(\mathbb{1}[\text{Treated}^{\text{large}}_{fnjt_0}] \times \mathcal{T}_{80 \le t \le 95} \right) - \hat{\beta}^S_{\text{short}} \left(\mathbb{1}[\text{Treated}^{\text{short}}_{fnjt_0}] \times \mathcal{T}_{73 \le t \le 79} \right) - \hat{\beta}^S_{\text{long}} \left(\mathbb{1}[\text{Treated}^{\text{short}}_{fnjt_0}] \times \mathcal{T}_{80 \le t \le 95} \right). \quad \text{(B.11)}$$

For both counterfactual series, we apply these adjustments only to firms that were already operating prior to the implementation of the policy. For the post-1995 period, we extrapolate the counterfactual shocks using the growth rates observed in the baseline shock series, as the estimated policy effects are available only up to 1995.

We then feed these alternative shock series into the model and evaluate their implications for the concentration ratio, aggregate GDP in 2011, and welfare. Figure B7 plots the concentration ratios absent these industrial policies. Without industrial policies concentration would have increased somewhat less: while in the data the top-3 firm sales share is about 28% in 2011, without industrial policies it would be 22-24%. Thus, industrial policies contributed modestly to the increase in concen-

Figure B7: Firm Concentration and Industrial policy



Notes. This figure reports the counterfactual CR3 under alternative shock series calculated from equations (B.10) and (B.11).

Table B10: Firm Concentration and Industrial policy

	CR3	GDP	Welfare
Distributed Lag	−6.33	−11.89	−4.38
Reduced Form	−3.80	−6.43	−4.15

Notes. This table reports the counterfactual results under alternative shock series calculated from equations (B.10) and (B.11).

tration. Table B10 reports the 2011 real GDP and the NPV of welfare changes had industrial policy not happened, GDP would be 6-12% lower, and cumulative welfare about 4% lower.

Note that the numbers in Figure B7 and Table B10 are not nested with those reported for the top-3 counterfactuals in the main text, Figure 4 and Table 3. Those figures pertain to all the shocks affecting the top-3 firms specifically. In this appendix, we consider only components of the shocks attributable to industrial policy, but affecting firms well beyond the top-3. Thus, the numbers in Table B10 are not, e.g., the fraction of the values in Figure 4/Table 3 that are attributable to industrial policy.

B.5 More on Markups

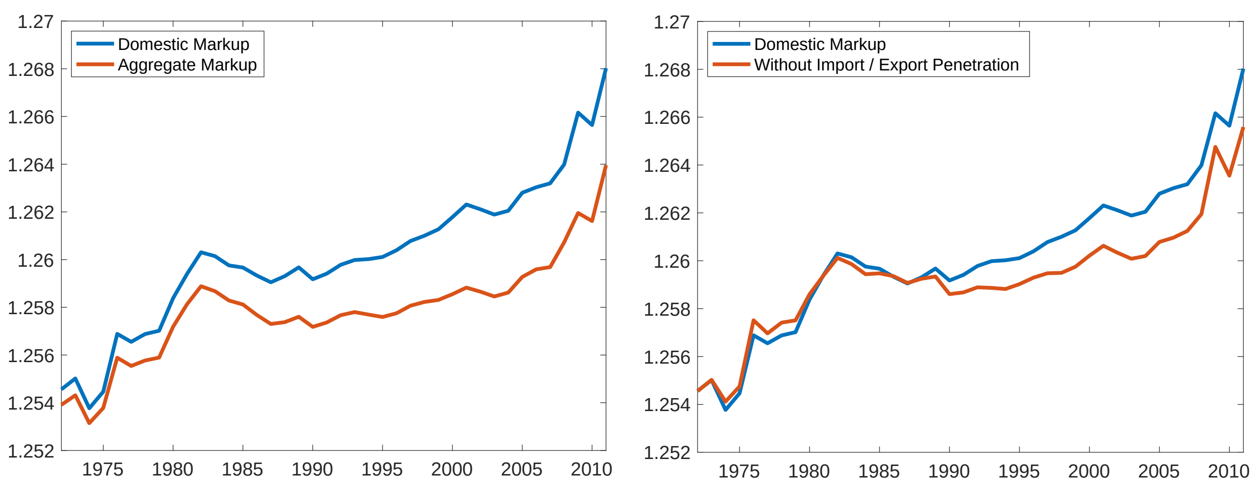
Alternative markup scenarios. Panel A of Figure B8 plots the aggregate markup using only markups in the domestic market as defined below:

$$\mathcal{M}^H_{jt} = \left(\sum_{f \in \mathcal{F}_{jt}} (\mu^H_{fjt})^{-1} s^H_{fjt} \right)^{-1} \quad \text{and} \quad \mathcal{M}^H_t = \left(\int_0^1 \frac{1}{\mathcal{M}^H_{jt}} S_{j,t-1} \mathrm{d}j \right)^{-1}. \tag{B.12}$$

Since our model assumes that the markup in domestic market is always larger than in export market, this domestic markup is larger than the aggregate markup. Panel A shows that the domestic markup also increases faster than the aggregate markup, but the difference is minor.

Panel B of Figure B8 plots the domestic markup when we fix the sectoral import and export shares to those of the initial year. It is intended to answer the question of how much changes in import competition affected the domestic markups. Panel B shows that the domestic markup with constant import penetration is not larger than in the baseline case. This is because import shares did not necessarily increase over time in all sectors: some sectors had the higher import shares in the initial year compared to later years, leading to the higher import shares in the counterfactuals, not lower ones. Therefore, the aggregate domestic markup is lower in this counterfactual, not higher.

Figure B8: Domestic Markups



A. Aggregate markup $\mathcal{M}_t$ and Domestic markup $\mathcal{M}^H_t$

B. Domestic markup $\mathcal{M}^H_t$ with constant import/export penetration

Notes. Panel A plots the aggregate markup and domestic markup $\mathcal{M}^H_t$ defined in equation (B.12). Panel B plots the baseline domestic markup along with a counterfactual domestic markup when we fix sectoral import and export shares at the initial year.

Markup estimation based on the production function approach. We next estimate markups following the production function approach in De Loecker and Warzynski (2012). As in De Loecker et al. (2020), we consider the following functional form:

$$\ln r_{fjt} = \theta^n_{jt} \ln n_{fjt} + \theta^k_{jt} \ln k_{fjt} + \ln a_{fjt} + \varepsilon_{fjt}, \tag{B.13}$$

where r_{fjt} denotes sales, k_{fjt} capital, a_{fjt} productivity, and ε_{fjt} measurement error. Total variable costs n_{fjt} are the sum of the wage bill and material input expenditures, similar to the variable Cost of Goods Sold (COGS) in US Compustat, deflated by input price deflators. We assume that $\ln a_{fjt}$ follows a first-order Markov process: $\ln a_{fjt} = g(\ln a_{fj,t-1}) + \xi_{fjt}$, where ξ_{fjt} denotes innovations in productivity.

To account for potential technological changes over time and across sectors, we allow θ^n_{jt} and θ^k_{jt} to be sector-specific and time-varying. We estimate equation (B.13) on 5-year rolling windows for each sector. We focus on the sample period 1985-2011 because the total variable costs n_{fjt} are not reported reliably before 1985.

We proceed in three steps. In the first step, given that productivity is an invertible function of the inputs: $\ln a_{fjt} = h(\ln n_{fjt}, \ln k_{fjt})$, we rewrite the production function as

$$\ln r_{fjt} = \theta^n_{jt} \ln n_{fjt} + \theta^k_{jt} \ln k_{fjt} + h(\ln n_{fjt}, \ln k_{fjt}) + \varepsilon_{fjt} = \mathcal{H}(\ln n_{fjt}, \ln k_{fjt}) + \varepsilon_{fjt}.$$

We approximate $\mathcal{H}(\ln n_{fjt}, \ln k_{fjt})$ using third-order polynomials of $\ln n_{fjt}$ and $\ln k_{fjt}$. We then regress $\ln r_{fjt}$ on these polynomial terms and obtain predicted values, which removes measurement errors from $\ln r_{fjt}$.

In the second step, we estimate θ^n_{jt} and θ^k_{jt} using the following moment conditions:

$$\mathbb{E}[\mathbf{Z}_{fjt}\xi_{fjt}] = 0, \qquad \mathbf{Z}_{fjt} = (\ln k_{fjt}, \ln n_{fj,t-1})',$$

where ξ_{fjt} is obtained as residuals from regressing $\ln a_{fjt}$ on third-order polynomials of $\ln a_{fj,t-1}$ for a given guess of θ^n_{jt} and θ^k_{jt}.

Finally, firms' cost minimization implies that the markup can be expressed as the elasticity of output to variable input θ^n_{jt} and the revenue share of the variable input:

$$\mu_{fjt} = \theta^n_{jt} \frac{P^n_{jt} n_{fjt}}{r_{fjt}/\exp(\varepsilon_{fjt})},$$

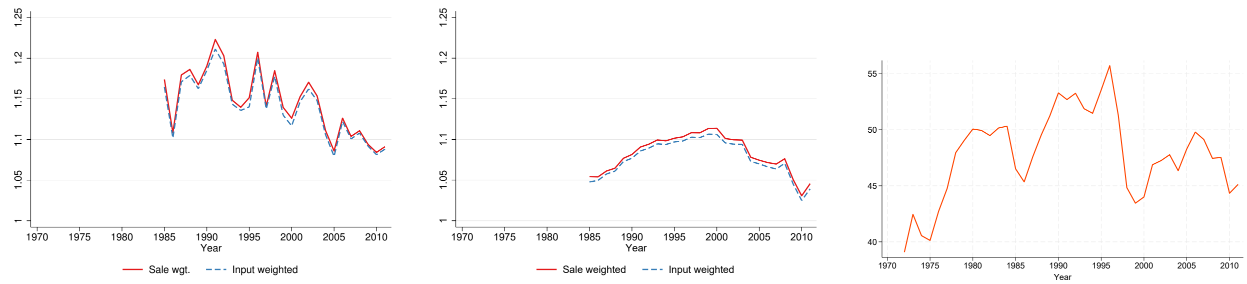
where P^n_{jt} is the price of n_{fjt}. When calculating the revenue share, we correct for measurement errors by adjusting by $\exp(\varepsilon_{fjt})$. We compute the aggregate markups by averaging across firms using firm-specific weights ω_{fjt}:

$$\mu_t = \sum_f \omega_{fjt}\mu_{fjt}.$$

We consider two sets of weights: sales and variable input expenditures (De Loecker et al., 2020; Edmond et al., 2023).

Panel A of Figure B9 displays the aggregate markups based on the two sets of weights. Despite the observed increase in concentration, we find no evidence of increasing aggregate markups over

Figure B9: Aggregate Markups and the Labor Share



A. Time-varying output elasticity

B. Time-invariant output elasticity

C. Labor share in manufacturing

Notes. Panels A and B illustrate the aggregate markup estimated using the production function approach, based on time-varying and time-invariant estimates of the output elasticities θ^n_{jt} and θ^k_{jt} in equation (B.13), respectively. Panel C displays the aggregate manufacturing labor share, defined as the ratio of total the wage bill to total value added across all manufacturing sectors.

this period, and the weighting is inconsequential for this conclusion. Panel B instead assumes that the output elasticities θ^n_{jt} and θ^k_{jt} are time-invariant, and estimates them using the whole time series. While the resulting aggregate markup levels are lower than those in Panel A, this alternative approach also does not show a noticeable increase over this period.

As a sanity check on these results, Panel C of Figure B9 plots the labor share, defined as the ratio of the total wage bill to total value added across all manufacturing sectors. Rising aggregate markups have been proposed as one potential mechanism for the declining aggregate labor share (e.g. Autor et al., 2020; Kehrig and Vincent, 2021). If increased concentration raised aggregate markups, this could have led to a decline in the labor share. The figure illustrates that if anything, the labor share in manufacturing rose over this period, consistent with our finding of little to no increase in aggregate markups.

While the aggregate markups derived from market shares in our baseline model show a very modest positive trend, the evolution of markups based on the production function approach follows a U-shape since 1985. It is common to find conflicting trends in markups inferred from market shares vs. the production function approach. For instance, Afrouzi et al. (2023) observe a negative correlation between Atkeson-Burstein markups and those estimated via the production function approach. Moreover, even when using the production function approach, Raval (2023) finds that markups estimated using labor inputs are negatively correlated with those estimated using material inputs, and exhibit divergent trends. What is important for us in this robustness exercise is that the production function approach confirms that there has not been a notable increase in aggregate markups in this period in South Korea.

Panels A and B exhibit different markup trends compared to those found by De Loecker and Eeckhout (2018) using data from South Korean publicly traded firms in Compustat Global. However, other work has found that markup estimation via the production function approach can be sensitive to the measurement of variable inputs (e.g. Traina, 2018), and the sample composition (e.g. Díez et al., 2021). In particular, Díez et al. (2021) expand the sample beyond the publicly listed firms by using the ORBIS data. They find that the patterns observed in De Loecker and Eeckhout (2018) among listed firms are significantly mitigated in a broader dataset. The Díez et al. (2021) dataset aligns more closely with our sample, which also includes non-listed firms.

Market structure. We next examine the welfare costs of oligopolistic and oligopsonistic market power. To do this, we compare the welfare in the baseline model to an alternative model with monopolistic and monopsonistic competition, in which the large firms' markups and markdowns are the same as the other firms'. In this alternative model, we maintain all the baseline firm-level shocks. Thus, comparing welfare levels in the baseline vs. the alternative reveals the welfare costs of higher markups/markdowns by the large firms.

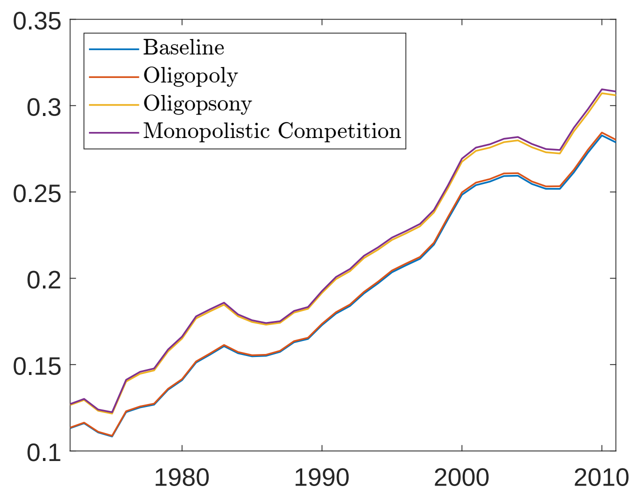
Table B11 reports the differences in welfare compared to the baseline under three alternative market structures. Without oligopolistic market power, welfare increases by around 1.32%, while the removal of oligopsonistic market power has negligible welfare impacts. The combined welfare impact of oligopolistic and oligopsonistic behavior is therefore about 1.3%. Appendix Figure B10 reports the accompanying concentration ratios. Interestingly, the concentration ratio is actually about 3 percentage points higher under monopolistic competition in goods markets. This is because compared to monopolistic competition, under oligopoly the largest firms charge higher prices and produce less, leading to lower revenues and lower concentration.

Table B11: Counterfactual: Welfare Effects of Market Structure

Goods market Labor market	Oligopoly Monopsonistic compet.	Monopolistic compet. Oligopsony	Monopolistic compet. Monopsonistic compet.
	(1)	(2)	(3)
$\triangle$ Welfare (%)	0.06	1.32	1.28

Notes. This table reports the percentage differences in welfare in the alternative monopolistic/monopsonistic competition models relative to the baseline.

Figure B10: The Top-3 Concentration Ratio, Alternative Market Structures



Notes. This figure plots concentration ratios of the top-3 firms under alternative market structures.

B.6 Constructing the Counterfactual Growth Rates of the Top-3 Firms

Denote the unweighted average DHS growth rate (Davis et al., 1998) of a variable among a subset of firms as:

$$\widehat{X}_{jt}^{a} = \sum_{f \in \mathcal{F}_{jt}^{a} \cap \mathcal{F}_{jt}^{cont,nz}} \underbrace{\frac{X_{fjt} - X_{fj,t-1}}{2(X_{fjt} + X_{fj,t-1})}}_{=\widehat{X}_{fjt}},$$

for $X_{fjt} \in \{a_{fjt}, D_{fjt}, 1+\tau_{fjt}^{L}, 1+\tau_{fjt}^{K}\}$. $\mathcal{F}_{jt}^{a}$ is the set of sector j firms of age bin a. When computing the unweighted average, we restrict the set of firms to satisfy two conditions denoted by $\mathcal{F}_{jt}^{cont,nz} := \{f | t_f^{\text{entry}} < t, X_{fj,t-1} \neq 0, X_{fjt} \neq 0\}$, where t_f^{entry} is firm f's entry year.[28] We impose the two conditions: (i) firms consecutively operated in $t-1$ and t ($t_f^{\text{entry}} < t$) and (ii) their values of X_{fjt} were non-zero in $t-1$ and t ($X_{fj,t-1} \neq 0$, $X_{fjt} \neq 0$). The latter condition only applies to foreign demand shocks, because $\{a_{fjt}, 1+\tau_{fjt}^{L}, 1+\tau_{fjt}^{K}\}$ are almost surely non-zero for operating firms. This condition implies that when computing the average growth for foreign demand shocks, we restrict the set of firms to be exporters consecutively in $t-1$ and t ($D_{fj,t-1} > 0$, $D_{fjt} > 0$). We compute the unweighted average within age bins to account for the fact that young firms exhibit different growth patterns compared to older firms (e.g., Decker et al., 2014, 2016), and that shock processes may differ depending on firm age (e.g., Luttmer, 2007; Arkolakis, 2016; Sterk et al., 2021).

Using these computed unweighted averages, for the top-3 firm f in sector j of age bin a, we construct sequences of the counterfactual shocks:

$$X_{fjt}^{c} = \begin{cases} X_{fjt} & \text{if} \quad f \notin \mathcal{F}_{jt}^{cont,nz} \\ (1+\widehat{X}_{jt}^{a}) X_{fj,t-1}^{c} & \text{if} \quad f \in \mathcal{F}_{jt}^{cont,nz} \cap \mathcal{F}_{jt}^{3} \\ (1+\widehat{X}_{fjt}) X_{fj,t-1}^{c} & \text{if} \quad f \in \mathcal{F}_{jt}^{cont,nz} \cap (\mathcal{F}_{jt}/\mathcal{F}_{jt}^{3}). \end{cases} \tag{B.14}$$

The first line means that we assign the factual values of shocks to firms entering the top 3 in t or to firms that have zero values of X_{fjt} in either $t-1$ or t ($f \notin \mathcal{F}_{jt}^{cont,nz}$). For example, we apply the factual values of foreign demand shocks in levels in t when a firm starts exporting in t regardless of its top-3 status. The second line implies that for the top-3 firms ($f \in \mathcal{F}_{jt}^{3}$), we apply the unweighted average $\widehat{X}_{jt}^{a}$. By applying $(1+\widehat{X}_{jt}^{a})X_{fj,t-1}^{c}$, we make the top-3 firms grow at the same rate as the other firms within the same sector and age bin. The exercises that feed the counterfactual shocks to these top-3 firms can be viewed as removing the "granular residual" studied in Gabaix (2011).[29] The third line says that for firms that are not in the top-3 group in t ($f \in \mathcal{F}_{jt}/\mathcal{F}_{jt}^{3}$), we apply the factual growth rate $\widehat{X}_{fjt}$.

[28] Note that firms that exit in t are dropped when calculating the average growth rates.

[29] According to Gabaix (2011), the granular residual of the top 3 firms within sectors is defined as $\sum_{f \in \mathcal{F}_{jt}^{3}} \frac{r_{fjt}}{GDP_t}(\widehat{X}_{fjt} - \widehat{X}_{jt}^{a})$. In the counterfactuals, because we are replacing $\widehat{X}_{fjt}$ with $\widehat{X}_{jt}^{a}$, we are removing the top-3 firm granular residual.

B.7 Mergers and Acquisitions

Data. M&A information comes from the dataset constructed by Center for Economic Catch-up (2007), which digitized M&A records from the Maekyung Company Yearbook for years of 1978-1999 and the Data Analysis, Retrieval and Transfer System run by the Financial Supervisory Service – a government agency responsible for overseeing and regulating the financial industry – for 2000-2005. These datasets encompass all types of M&A activities between corporate entities in South Korea, including firms that are smaller than the threshold for inclusion in our main dataset. The acquisitions recorded in these datasets cover various forms of corporate takeovers, including asset, share, stake, and control acquisitions, as well as the acquisition of goodwill.

There were 771 M&A's in which both acquirer and target firms are in manufacturing. The median sales of acquirers and target firms, conditional on being matched to our main dataset, were \$95 million and \$86 million 2015 USD, respectively.

Target productivity: difference-in-differences results. We examine how targets' productivity evolves following an M&A event. The difficulty lies in constructing an appropriate set of control firms, as M&A are endogenous decisions made by firms. We acknowledge that estimating causal effects of M&A activities is challenging, and this is not the goal of the paper. Nonetheless, subject to caveats related to causal identification, the results below are informative on how productivity evolved around M&A events.

The treatment group is the target firms. We construct control groups for each target in two steps following Cengiz et al. (2019). In the first step, we pick a set of firms that become targets later but have not yet been acquired. Because these firms eventually become acquired, they may be systematically different from firms that were never a target of an acquisition. This restriction of the control group helps make the control group more similar to the treatment group, attenuating endogeneity concerns. In the second step, for each treated firm, we pick one control firm that is most similar in terms of log sales, log fixed assets, log employment, inverse hyperbolic sine transformation of exports, and their 3-year growth before the event occurs, with replacement. Firms' similarity is measured by Mahalanobis distance.

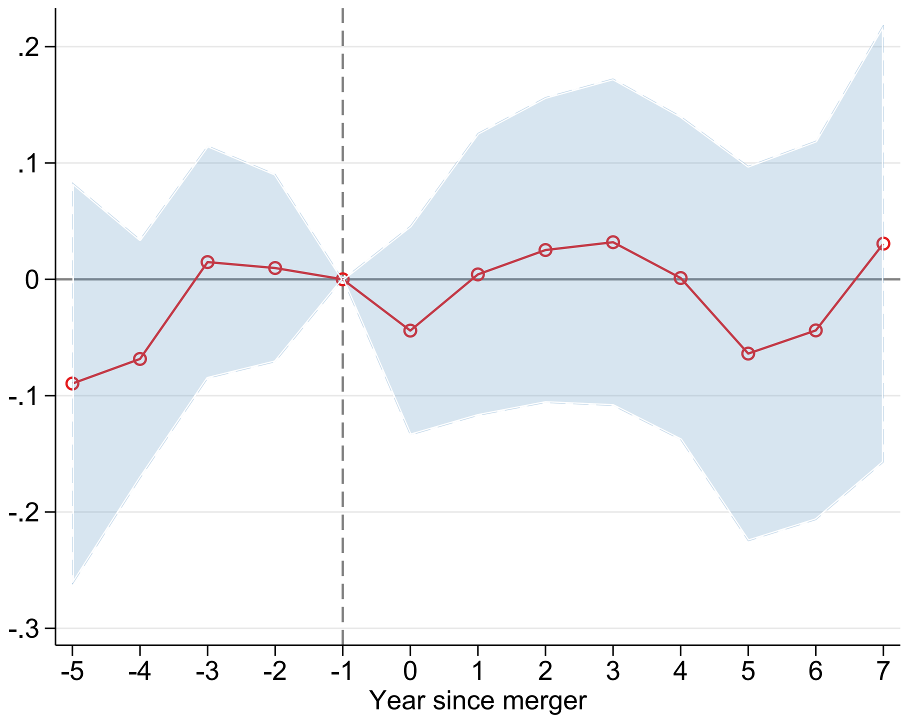
The matching process results in 115 pairs for the event of being a target firm. Using these pairs, we estimate the following event study specification:

$$\ln a_{fmt} = \sum_{\tau=-5}^{7} \beta^{\tau} \left(D_{mt}^{\tau} \times \mathbb{1}[\text{Treat}_{fm}] \right) + \delta_{fm} + \delta_{mt} + \varepsilon_{fmt}, \tag{B.15}$$

where f denotes firm, m matched pair, and t calendar years. D_{fmt}^{τ} are event time variables for pair m and $\mathbb{1}[\text{Treat}_{fm}]$ is a dummy for treatment status. The dependent variable is firms' productivity backed out from our model. The specification includes firm-pair and pair-year fixed effects δ_{fm} and δ_{mt}, and standard errors are two-way clustered at the pair and firm levels.

We drop control firms once they engage in M&A activities. For example, if a control firm becomes a target firm four years after the event, we only keep pairs up to three years after the event. Therefore, our control groups are uncontaminated by subsequent acquisitions. Due to the inclusion of firm-pair

Figure B11: Event Study. The Effect of an Acquisition on Productivity of Targets



Notes. This figure reports the event study coefficients from estimating equation (B.15). The dependent variable is firms' productivity backed out from our model. In Panels A and B, the events are being target firms and being acquirers, respectively. β^{-1} is normalized to zero. The 95% confidence intervals, based on standard errors two-way clustered at the pair and firm levels, are reported.

and pair-year fixed effects, the coefficients of interest β^{τ} are identified only based on the comparison between treated firms and clean controls. Therefore, our event study specification does not suffer from the issues raised by the recent staggered diff-in-diff literature (see, e.g. Roth et al., 2023).

Figure B11 reports the results. We find that target firms did not experience economically or statistically significant changes in productivity around the event.

B.8 Spillovers to Non-Top-3 Firms

B.8.1 Structural Evidence

We assume that productivity of non-top-3 firms consists of exogenous and spillover components:

$$a_{fjt} = \tilde{a}_{fjt} \times \exp\left(\upsilon \frac{\sum_{f' \in \mathcal{F}_{njt}^{t3}} a_{f'jt}^{\sigma-1}}{\sum_{f' \in \mathcal{F}_{njt}} a_{f'jt}^{\sigma-1}} \right),$$

where $\tilde{a}_{fjt}$ denotes the exogenous component, $\mathcal{F}_{njt}^{t3}$ a set of the top-3 firms in region n and sector j, and $\mathcal{F}_{njt}$ a set of all firms in region n and sector j.

Choi and Shim (2025) provide causal evidence on the local spillover effects of foreign technology adoption on local firms' sales or revenue TFP. Using the IV strategy, they estimate a semi-elasticity of shares of firms that adopted modern foreign technology of around 2.5. Given that the large firms were more active in adopting technologies, we use the proxy for local shares of adopting firms as $\frac{\sum_{f' \in \mathcal{F}_{njt}^{t3}} a_{f'jt}^{\sigma-1}}{\sum_{f' \in \mathcal{F}_{njt}} a_{f'jt}^{\sigma-1}}$, which can be interpreted as the top-3 firms' sales shares within region n and sector j. We supplement our analysis with additional information on firms' locations of production to compute the spillover terms. Based on Choi and Shim (2025)'s estimates and assumed values for σ, we set $\upsilon = 0.63$. We restrict the spillover effects to non-top-3 firms, excluding fringe firms, so our spillover exercise can be viewed as a lower bound of the total spillover effects.

B.8.2 Reduced-Form Evidence

To examine how top 3 firms' productivity shocks affect other firms' shocks, we consider the following regression model:

$$\ln a_{fjt} = \rho \ln a_{fj,t-1} + \gamma_1 \widetilde{\ln a_{fj,t-1}}^{\text{h},3} + \gamma_2 \widetilde{\ln a_{fj,t-1}}^{\text{u},3} + \gamma_3 \widetilde{\ln a_{fj,t-1}}^{\text{d},3} + \delta_j + \delta_t + \varepsilon_{fjt}, \tag{B.16}$$

where δ_j and δ_t are sector and year fixed effects. All specifications control for the own lagged productivity $\ln a_{fj,t-1}$. Standard errors are clustered at the sector level. Due to the small number of clusters (11), we also report wild bootstrapped p-values.

We relate firm f's productivity to the productivity growth of the top-3 firms in its own sector, the the productivity growth of the top-3 firms immediately upstream and downstream from it. Specifically, the own-sector ("horizontal") the sales-weighted average of the top-3 firms' productivity shocks is constructed as:[30]

$$\widetilde{\ln a_{fj,t-1}}^{h,3} = \sum_{g \in \mathcal{F}_{j,t-1}^{3}/\{f\}} \frac{\text{Sale}_{gj,t-1}}{\sum_{g' \in \mathcal{F}_{j,t-1}^{3}/\{f\}} \text{Sale}_{g'j,t-1}} \times \ln a_{gj,t-1}.$$

The upstream and the downstream top-3 productivity growth are constructed as the weighted av-

[30] If firm f was in the top 3 at $t-1$, we exclude firm f when computing this variable and take the weighted average of the remaining two firms.

erages of upstream or downstream sectors' top-3 shocks, where weights are based on cost or sales shares:

$$\widetilde{\ln a_{fj,t-1}}^{\mathrm{u},3} = \sum_{k\in\mathcal{J}^{\mathrm{M}}} \frac{\mathrm{Cost}^k_{j,73}}{\mathrm{Cost}_{j,73}} \times \widetilde{\ln a_{fk,t-1}}^{\mathrm{h},3}, \qquad \widetilde{\ln a_{fj,t-1}}^{\mathrm{d},3} = \sum_{k\in\mathcal{J}^{\mathrm{M}}} \frac{\mathrm{Sales}^k_{j,73}}{\mathrm{Sales}_{j,73}} \times \widetilde{\ln a_{fk,t-1}}^{\mathrm{h},3}.$$

The sectoral weights of the upstream and downstream top-3 shocks are computed using the 1973 input-output table and are fixed across years.

Columns 1-2 of Table B12 report the results. Column 1 includes only horizontal top 3 shocks, while column 2 additionally includes both downstream and upstream top 3 shocks. The horizontal top 3 shocks show significant positive coefficients, and their values remain stable even when controlling for the other upstream and downstream shocks in column 2. These reduced-form patterns confirm the more thorough and well-identified results of Choi and Shim (2025), who also show that the productivity spillovers from the top-3 firms on other firms are positive. The coefficients of upstream and downstream top 3 shocks are insignificant, suggesting that to the extent the survey evidence (Park, 2020) documents important mechanisms, there may be others that act in the opposite direction, rendering the net effect ambiguous.

Searching for additional covariates. Given the lack of strong guidance on the exact functional forms and spillovers governing the data, we also consider a more data-driven approach based on LASSO with flexible controls (e.g. Bartelme et al., 2024; Choi and Levchenko, 2025). We search for important controls using the following LASSO procedure:

$$\begin{aligned}\ln a_{fjt} = {} & \rho \ln a_{fj,t-1} + \gamma_1 \widetilde{\ln a_{fj,t-1}}^{\mathrm{h},3} + \gamma_2 \widetilde{\ln a_{fj,t-1}}^{\mathrm{u},3} + \gamma_3 \widetilde{\ln a_{fj,t-1}}^{\mathrm{d},3} \\ & + \underbrace{\sum_{\substack{X\in\{\ln\tau^L,\\ \ln\tau^K, \mathrm{Ihs}\, D^x\}}} \beta_1^X X_{fj,t-1} + \sum_{\substack{Q\in\{\text{horiz},\\ \text{up,down}\}}} \sum_{\substack{X\in\{\ln\tau^L,\\ \ln\tau^K, \mathrm{Ihs}\, D^x\}}} \beta_2^X \widetilde{X_{fj,t-1}}^{Q,3}}_{=\textbf{1st poly}} + \textbf{2nd poly}'\boldsymbol{\alpha} + \delta_j + \delta_t + \varepsilon_{fjt}, \end{aligned} \quad \text{(B.17)}$$

where **2nd poly** refers to the second-order polynomials of **1st poly**. We then regress productivity shocks on the selected variables.

We follow the approach developed by Belloni et al. (2014). Own lagged and horizontal top 3 productivity shocks are always included, with sector and year fixed effects partialled out. Depending on the specifications, we also consider always including upstream and downstream top 3 productivity shocks. When only horizontal top 3 productivity shocks are included, we also include own lagged labor and capital distortions, export demand shocks, and the horizontal top 3 shocks to the capital and labor distortions and export demand. When horizontal, upstream, and downstream top 3 productivity shocks are all included, we also include the corresponding top 3 shocks for other distortions. The methodology is based on post-double-selection, meaning that the final set of controls is the union of all the variables selected as relevant controls for the dependent variable and any of the always-included independent variables.

Table B12: Firm Productivity and Productivity of Top-3 Firms

Dep. Var.	$\ln a_{fjt}$			
	OLS		LASSO	
	(1)	(2)	(3)	(4)
$\ln a_{fj,t-1}$	0.85***	0.85***	0.91***	0.90***
	(0.01)	(0.01)	(0.01)	(0.00)
	[0.000]	[0.000]	[0.000]	[0.000]
$\widetilde{\ln a_{fj,t-1}}^{h,3}$	0.04***	0.05***	0.04***	0.05***
	(0.01)	(0.02)	(0.01)	(0.02)
	[0.005]	[0.215]	[0.005]	[0.187]
$\widetilde{\ln a_{fj,t-1}}^{u,3}$		0.07		0.06
		(0.09)		(0.08)
		[0.272]		[0.010]
$\widetilde{\ln a_{fj,t-1}}^{d,3}$		−0.13*		−0.16***
		(0.07)		(0.02)
		[0.445]		[0.034]
Addl. LASSO-selected ctrl.			✓	✓
N	129,907	129,907	129,907	129,907

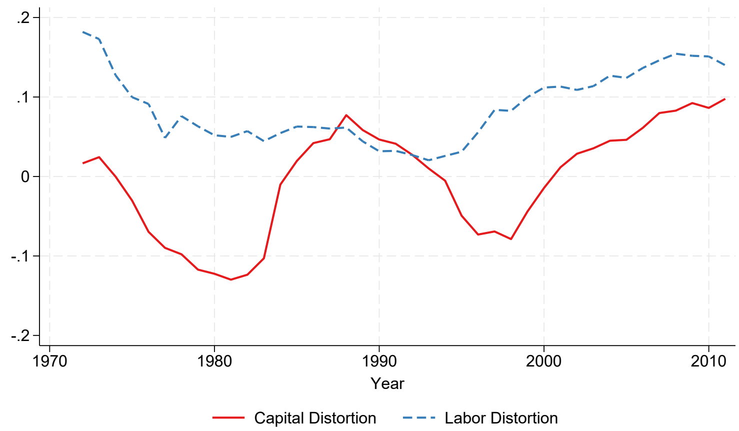
Notes. This table reports the estimates of equation (B.16). Standard errors, clustered at the sector level, are in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Wild bootstrapped p-values are reported in brackets. In columns 3 and 4, we select variables using LASSO based on the methodology developed by Belloni et al. (2014). In columns 3 and 4, LASSO-selected variables are included. To preserve space, in both columns, we report only own lagged productivity shocks and the top 3 productivity shocks.

Columns 3 and 4 of Table B12 report the results. Searching for additional important controls has a limited impact on the estimated coefficients of interest. Similar to OLS, the own-sector top-3 productivity is positively correlated with firm productivity, while the upstream and downstream top-3 productivity does not exhibit a significant conditional correlation with firm productivity.

All in all, these results support the notion that productivity improvements of the top 3 firms had positive impacts on the remaining firms, rather than negative effects (e.g., killer acquisitions, or suppressing innovations of competitors). Moreover, productivity improvements of upstream and downstream top 3 firms were unlikely to significantly influence the evolution of productivity in other sector firms, as evidenced by the imprecisely estimated coefficients.

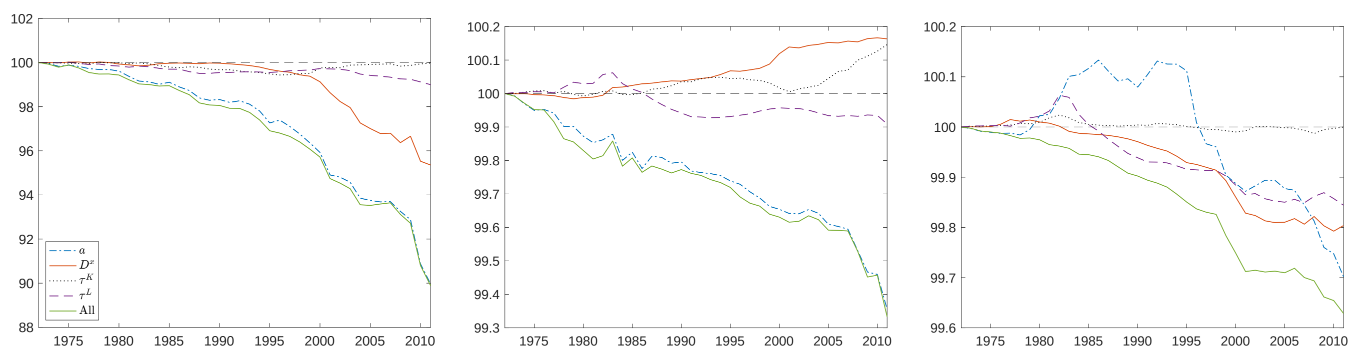
B.9 Additional Tables and Figures

Figure B12: Correlation between Distortions and Firm Size over Time



Notes. This figure plots time-varying coefficients obtained from regressions of log capital and labor distortions on log sales: $\ln\left(1+\tau^{V}_{fjt}\right) = \beta_t \ln r_{fjt} + \delta_j + \varepsilon_{fjt}$, for $V = L, K$.

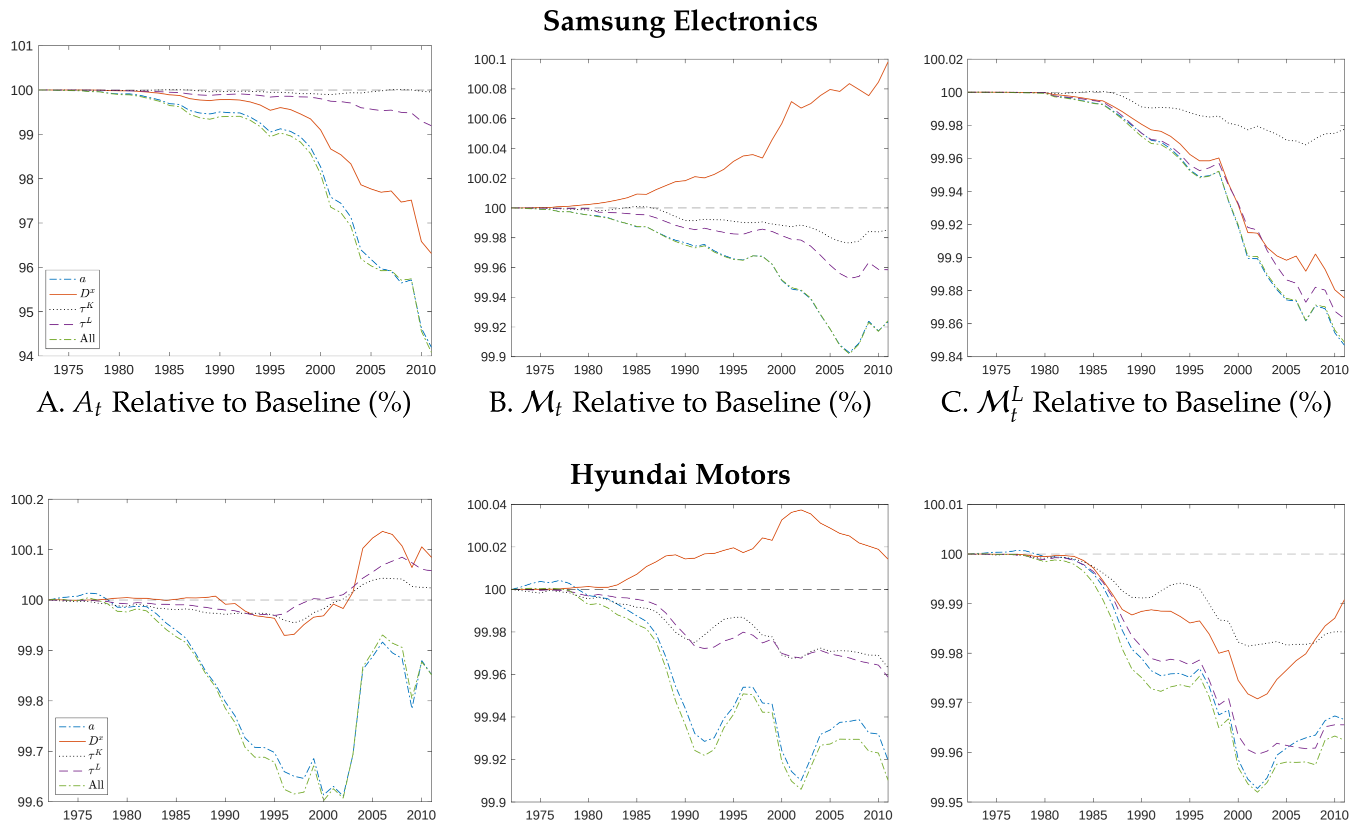
Figure B13: The Impact of the Top-3 Micro Shocks: Productivity, Markups, and Markdowns



A. A_t Relative to Baseline (%) B. $\mathcal{M}_t$ Relative to Baseline (%) C. $\mathcal{M}^L_t$ Relative to Baseline (%)

Notes. This figure illustrates counterfactual aggregate productivity (Panel A), markup (B), and markdown (C) relative to the baseline, under the counterfactual sequences of the top-3 firms' shocks defined in equation (B.14).

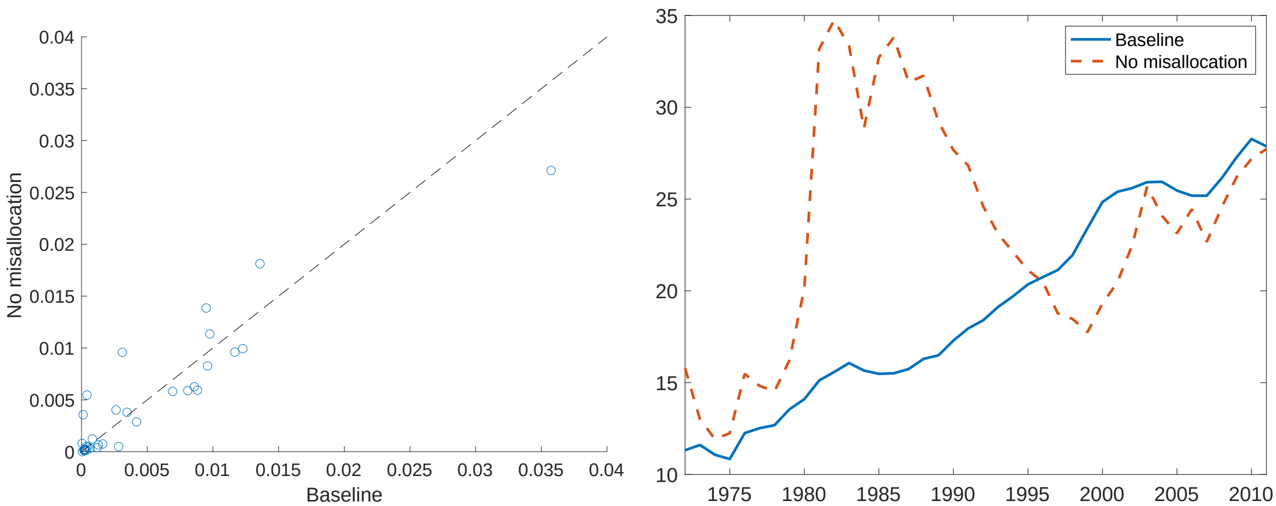
Figure B14: The Impact of Shocks to Samsung Electronics and Hyundai Motors: Productivity, Markups, and Markdowns



A. A_t Relative to Baseline (%)
B. $\mathcal{M}_t$ Relative to Baseline (%)
C. $\mathcal{M}^L_t$ Relative to Baseline (%)
D. A_t Relative to Baseline (%)
E. $\mathcal{M}_t$ Relative to Baseline (%)
F. $\mathcal{M}^L_t$ Relative to Baseline (%)

Notes. This figure illustrates counterfactual aggregate productivity (Panels A and D), markup (B and E), and markdown (C and F) relative to the baseline, under the counterfactual sequences of the shocks to Samsung Electronics (top half) or Hyundai Motors (bottom half) defined in equation (B.14).

Figure B15: Market Share of Top-3 Firms in the No-misallocation shares vs. Baseline



A. Top-3 Market Share B. CR3 ratio (%)

Notes. Panel A plots the top-3 firms' sales shares in 2011. The x-axis is the baseline economy and the y-axis is a hypothetical economy with no dispersion in $1 + \tau^K_{ijt}$ and $1 + \tau^L_{ijt}$, and where all firms are monopolistically competitive. Panel B displays the top-3 concentration ratio in the baseline and counterfactual no-misallocation share economy.

Table B13: Robustness. The Top-3 Micro Shocks. Alternative Parameterizations

	Counterfactual vs. Factual Shocks					
	All shocks			Productivity shocks		
	△ CR in 2011 (pp)	△ Real GDP per capita in 2011 (%)	△ Welfare (%)	△ CR in 2011 (pp)	△ Real GDP per capita in 2011 (%)	△ Welfare (%)
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Baseline					
	−14.68	−20.80	−6.60	−12.35	−18.12	−4.90
	Panel B. Exogenous capital					
	−14.69	−14.97	−4.17	−12.35	−13.77	−2.97
	Panel C. Sector-specific σ_j (Broda and Weinstein, 2006)					
	−14.61	−29.38	−8.82	−12.31	−25.27	−6.12
	Panel D. σ					
$\sigma = 7$	−14.91	−18.04	−5.45	−12.68	−15.13	−3.46
$\sigma = 3$	−14.17	−27.63	−9.10	−11.69	−24.70	−6.99
	Panel E. ρ					
$\rho = 2.5$	−14.46	−20.14	−6.15	−12.00	−17.42	−4.19
$\rho = 1.5$	−15.12	−21.98	−7.18	−13.08	−19.16	−5.45
	Panel F. η					
$\eta = 3$	−14.74	−20.31	−6.60	−12.56	−18.42	−5.03
$\eta = 6$	−14.68	−20.80	−6.60	−12.35	−18.12	−4.90
	Panel G.θ					
$\theta = 1.5$	−14.69	−20.86	−6.71	−12.37	−18.15	−5.05
$\theta = 2.5$	−14.67	−20.78	−6.56	−12.33	−18.13	−4.88
	Panel H. ψ					
$\psi = 0$	−14.69	−18.31	−6.57	−12.36	−15.80	−4.30
$\psi = 1$	−14.68	−23.47	−6.73	−12.35	−20.25	−4.82
	Panel I. ζ					
$\zeta = 0.5$	−14.68	−20.80	−6.77	−12.35	−18.04	−4.75
$\zeta = 1$	−14.68	−20.78	−6.82	−12.35	−17.95	−4.40
	Panel J. Constant returns to scale $\gamma_j = 1, \forall j$					
	−13.93	−20.35	−6.05	−9.78	−16.03	−3.91
	Panel K. Allowing for love-of-variety					
	−13.95	−19.42	−5.88	−10.65	−15.91	−3.97
	Panel L. Production Function Estimation					
Only Non-exporters	−14.80	−20.41	−6.28	−12.33	−17.96	−4.78
Only Exporters	−14.86	−20.69	−6.70	−12.56	−17.74	−4.85
	Panel M. The number of top firms					
Top-4 firms	−16.55	−21.94	−6.83	−13.93	−19.05	−4.65
Top-10 firms	−17.39	−25.15	−7.72	−13.47	−20.04	−4.56

Notes. This table reports the sensitivity analysis of the top-3 shock counterfactuals under alternative sets of parameters.