Productivity Dispersion and Misallocation: Industry vs. Market*

Seho Kim
Danmarks Nationalbank

November 2025

Abstract

In the standard approach, misallocation of production inputs is inferred from the dispersion in revenue productivity among firms within the same *industry*. This paper argues that such dispersion is not necessarily a sign of misallocation when it arises from firms operating in different *markets*. Any reallocation of resources across markets raises the utility of consumers in one market but reduces it in another, and thus represents a movement along the Pareto-efficient frontier rather than an improvement in efficiency. Using data from the ready-mixed concrete industry, I quantify the extent to which revenue productivity dispersion across markets can lead to overestimation of misallocation. I find that industry-level measures overstate the degree of misallocation by 27 to 36 percentage points.

JEL Codes: E23, L16, O47

Keywords: Productivity Dispersion; Misallocation; Industry vs. Market; Market Segmentation; Ready-Mixed Concrete.

*This paper was previously circulated under the title "Misallocation and Productivity Dispersion with Locally Segmented Markets." I thank Thomas Drechsel, John Haltiwanger, John Shea, and anonymous referees for their comments and suggestions. E-Mail: econ.seho.kim@gmail.com. Disclaimer: The views expressed in this paper do not reflect the official positions or opinions of Danmarks Nationalbank.

1 Introduction

Differences in aggregate productivity are a key factor in explaining cross-country differences in income per capita. Following the seminal work of Hsieh and Klenow (2009) and Restuccia and Rogerson (2008), a large literature has emphasized that the misallocation of production inputs helps explain cross-country differences in aggregate productivity. Empirically, the degree of misallocation is typically inferred from the dispersion in revenue productivity, or TFPR, among firms within the same industry.

This paper revisits the measurement of misallocation based on two observations. First, to estimate misallocation, researchers must define a relevant group of firms, and the industry is the standard unit for such analysis. Second, misallocation is inherently a normative concept: removing distortions, the sources of misallocation, would raise aggregate productivity and welfare. According to the NAICS 2022 Manual (NAICS (2022)), industries are defined by the similarity of production processes:

> *Economic units that have similar production processes are classified in the same industry, and the lines drawn between industries demarcate, to the extent practicable, differences in production processes.*

Given that misallocation is a normative concept, is it necessarily appropriate to estimate it across producers within the same industry, who merely share similar production processes? Perhaps not, since firms in a single industry may sell their products to different consumers, which makes the notion of misallocation somewhat ambiguous.

In this paper, I argue that markets, defined as groups of firms that sell to the same consumers, rather than industries, should be the relevant unit for measuring misallocation. I develop a simple heterogeneous-firm model with multiple markets within an industry and show that dispersion in TFPR indicates misallocation *within* markets, but dispersion in TFPR *across* markets, even among firms in the same industry, does not necessarily do so. The intuition is that reallocating resources toward more distorted firms within a market constitutes a Pareto improvement, whereas reallocating resources toward firms in markets with higher TFPR merely moves the economy along the Pareto frontier. Reallocating resources across markets simply makes one group of consumers worse off to make another better off, and therefore is not a Pareto improvement.

Based on the theoretical results, I quantify how much the dispersion in TFPR and the degree of misallocation differ between industry- and market-based measures. Defining a market is typically challenging, as data linking producers and consumers are scarce. To address this, I study the ready-mixed concrete industry in Korea, which provides an ideal case study: due to the product's characteristics, the industry exhibits geographic market segmentation (Syverson (2004)), making market boundaries relatively clear.

I first show that TFPR dispersion within an industry can be decomposed into within-market and across-market components. The across-market component accounts for 42% of the total industry-wide dispersion, indicating that substantial TFPR dispersion exists across markets. However, TFPR dispersion across markets could arise mechanically because each market contains a finite number of firms. Thus, the average TFPR in each market may differ across markets simply due to sampling noise, even if the population average TFPR is identical across all markets. To address this concern, I randomly permute the market identifiers of firms to test whether the large across-market component is mechanically driven by finite-sample variation. Although sampling noise indeed accounts for part of the difference—the across-market component of TFPR dispersion in the permuted sample accounts for 24% of the total industry-based measure—an additional 18% (= 42% – 24%) is explained by genuine wedges across markets. These findings remain robust to alternative sample selections and market definitions.

Next, I quantify the difference in the degree of misallocation between the industry- and market-based approaches. In the industry-based approach, the degree of misallocation is 63%, meaning that the dispersion in TFPR reduces aggregate productivity to 63% of its efficient level. In contrast, in the market-based approach, the degree of misallocation is substantially lower, ranging from 27% to 36%, depending on how the market-based measure is constructed. As before, I also compute the market-based misallocation measure using the permuted sample, which ranges from 42% to 44%. Although finite-sample noise indeed contributes to lowering the estimated degree of misallocation, market-specific wedges play a quantitatively significant role as well. These results are robust to alternative samples, market definitions, and assumptions about the elasticity of substitution in demand. Overall, the industry-based approach appears to substantially overestimate the degree of misallocation.

This paper contributes to two strands of the literature. The first is the macro literature on markups and misallocation. Peters (2020) and Edmond et al. (2023) show that dispersion in markups is a source of misallocation and, hence, lowers aggregate productivity. Dhingra and Morrow (2019) study optimal product variety and resource allocation across heterogeneous firms, emphasizing the role of demand elasticities in welfare analysis and the effects of market integration. Baqaee and Farhi (2020) show that depending on the input–output structure, an economy can remain efficient even in the presence of markup dispersion. Bornstein and Peter (2025) show that when firms can extract consumer surplus through nonlinear pricing, dispersion in markups is not necessarily a sign of misallocation, even when consumers share identical preferences. Gupta (2024) emphasizes demand-based markup dispersion: heterogeneity in consumer demand elasticities and assortative matching generate size-dependent markups, and he shows that incomplete pass-through from variable markups within firms reduces the productivity gains from reallocation policies. Relative to this literature, I show that dispersion in TFPR, which includes markups as a component, can also arise from market segmentation and is not necessarily a sign of misallocation. This mechanism is distinct from those emphasized in prior work, such as nonlinear pricing or incomplete pass-through. I further quantify how interpreting TFPR dispersion across markets as distortions leads to substantial overestimation of misallocation. To overcome the lack of data linking consumers and firms, I study the ready-mixed concrete industry, where producers and consumers are linked geographically, allowing markets to be defined more precisely.

Second, this paper also contributes to the broader misallocation literature. Dispersion in TFPR is the standard measure used to quantify the degree of misallocation (Hsieh and Klenow (2009)). However, several studies highlight why dispersion in TFPR may not necessarily indicate misallocation. These explanations include overhead costs (Bartelsman et al. (2013)), adjustment costs (Asker et al. (2014)), measurement error (Bils et al. (2021)), and model misspecification (Haltiwanger et al. (2018)). This paper adds to this literature by showing that market segmentation provides another reason why dispersion in TFPR within an industry may not reflect the degree of misallocation.

The rest of the paper proceeds as follows. Section 2 develops a simple model of heterogeneous firms operating in different markets to show why dispersion in revenue productivity may arise even in the absence of misallocation. Section 3 then quantifies how much revenue productivity dispersion and misallocation decline when using a market-based measure rather than an industry-based one, drawing on data from the ready-mixed concrete industry in Korea. Section 4 concludes.

2 Model

I introduce a simple model to illustrate that dispersion in revenue productivity within an industry is not necessarily a sign of misallocation when it arises across markets. The model extends Hsieh and Klenow (2009) by allowing for multiple markets within a single industry. The economy consists of one industry comprising M markets, indexed by $m \in \{1, \cdots, M\}$. In each market m, there is a representative consumer and a final-good producer, as well as many intermediate-good producers that supply intermediate goods to the final-good producer. I denote the set of intermediate-good producers in market m by Ω_m, and the market in which a firm i operates by $\mathcal{M}(i)$. Thus, for all firms in Ω_m, $\mathcal{M}(i) = m$. The total number of firms in the economy is denoted by N. Production inputs, such as capital and labor, can move freely across markets, and intermediate-good producers operate under monopolistic competition.

2.1 Consumer and final-good producer in each market

I first describe the problem of the final-good producer, followed by that of the consumer. A representative final-good producer in market m has a standard constant elasticity of substitution (CES) production aggregator with a market-specific elasticity of substitution parameter σ_m, capturing potentially different degrees of competition across markets:

$$Y_m = \left(\sum_{i \in \Omega_m} y_i^{\frac{\sigma_m - 1}{\sigma_m}} \right)^{\frac{\sigma_m}{\sigma_m - 1}}, \tag{1}$$

where y_i denotes the output of firm i. Solving the standard profit-maximization problem of the representative final-good producer yields the following demand function for each intermediate-good producer i:

$$\frac{p_i}{P_m} = \left(\frac{y_i}{Y_m} \right)^{-\frac{1}{\sigma_m}}, \tag{2}$$

where p_i is the price charged by firm i, and $P_m = \left(\sum_{i \in \Omega_m} p_i^{1-\sigma_m} \right)^{\frac{1}{1-\sigma_m}}$ is the market-level price index.

A representative consumer in market m consumes final goods using income generated from the endowments of capital and labor, which are supplied to intermediate-good producers, as well as dividends from ownership of those producers. I do not describe the endowments and ownership structure in detail, since under the market-clearing condition each household in market m consumes exactly Y_m in equilibrium. The detailed assumptions about endowments and ownership affect only the price P_m. For this reason, a social planner would focus solely on Y_m, as it represents the exact amount consumed by each household. You can think of this representative consumer as a local construction sector in the context of the ready-mixed concrete industry, which

I use as a case study in the empirical analysis, though the interpretation is more general.

2.2 Intermediate-good producers

Intermediate-good producers operate a constant-returns-to-scale (CRS) production technology that uses capital and labor as inputs. Firm i produces output y_i according to

$$y_i = z_i k_i^{\alpha} l_i^{1-\alpha}, \tag{3}$$

where z_i denotes the productivity of firm i, and k_i and l_i denote its capital and labor inputs, respectively.

I assume that intermediate-good producers are subject to output distortions $\tilde{\tau}_i$. This reduced-form term captures potential sources of misallocation arising from various microeconomic frictions or policy distortions—such as financial or informational frictions, or distortionary taxes. I further assume that $\tilde{\tau}_i$ consists of both market-specific and idiosyncratic components, such that

$$(1 - \tilde{\tau}_i) = (1 - \tau_{\mathcal{M}(i)}) \times (1 - \tau_i), \tag{4}$$

where $\tau_{\mathcal{M}(i)}$ represents a market-wide distortion common to all firms operating in the same market (but potentially varying across markets), while τ_i captures purely idiosyncratic distortions unrelated to market characteristics, i.e., τ_i is orthogonal to $\tau_{\mathcal{M}(i)}$. For example, differences in credit tightness or corporate income tax rates across markets would give rise to $\tau_{\mathcal{M}(i)}$.

Each intermediate-good producer maximizes profit subject to the demand system in Eq. (2) and the production function in Eq. (3):

$$\max_{k_i, l_i}; \pi_i = (1 - \tilde{\tau}_i) p_i y_i - r k_i - w l_i$$
$$\text{s.t. } (2) \text{ and } (3),$$

where r is the price of capital and w is the wage.

Profit maximization yields the standard first-order condition implying that a firm's output price is a fixed markup over its marginal cost:

$$p_i = \frac{\sigma_{\mathcal{M}(i)}}{\sigma_{\mathcal{M}(i)} - 1} \times \frac{1}{1 - \tilde{\tau}_i} \times \frac{1}{z_i} \left(\frac{r}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha}. \tag{5}$$

Revenue productivity, TFPR, is defined as revenue divided by the composite of capital and labor inputs, i.e., $\text{TFPR}_i = p_i y_i / k_i^{\alpha} l_i^{1-\alpha} = p_i z_i$. Combining this definition with Eqs. (4) and (5) gives

$$\begin{aligned} \text{TFPR}_i &= \frac{\sigma_{\mathcal{M}(i)}}{\sigma_{\mathcal{M}(i)} - 1} \times \frac{1}{1 - \tilde{\tau}_i} \times \left(\frac{r}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha} \\ &= \underbrace{\frac{\sigma_{\mathcal{M}(i)}}{\sigma_{\mathcal{M}(i)} - 1} \times \frac{1}{1 - \tau_{\mathcal{M}(i)}}}_{\text{market-wide}} \times \underbrace{\frac{1}{1 - \tau_i}}_{\text{idiosyncratic}} \times \left(\frac{r}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha}. \end{aligned} \tag{6}$$

Intermediate-good producers in this industry can therefore exhibit different levels of TFPR for two reasons. First, even though all firms operate within the same industry, they sell their products in different markets and thus face different market-wide distortions—either through heterogeneous markups $\frac{\sigma_{\mathcal{M}(i)}}{\sigma_{\mathcal{M}(i)}-1}$ or through market-specific distortions $\tau_{\mathcal{M}(i)}$. Second, they may differ in their idiosyncratic distortions τ_i. According to Hsieh and Klenow (2009), any within-industry dispersion in TFPR indicates misallocation. In the next section, I argue that when TFPR dispersion originates from differences in distortions *across* markets, it may not necessarily reflect misallocation.

2.3 Planner's problem

In this economy, I assume that a social planner seeks to attain a Pareto-efficient allocation rather than to maximize aggregate output. This distinction is important when differentiating between industries and markets, as opposed to the traditional industry-based approach that focuses on maximizing industry-level output.

Consider a thought experiment in which an industry consists of two markets, A and B. Suppose firms in market A face less competition and therefore have higher markups, and thus higher TFPR, than firms in market B. Under the conventional industry-based approach, a social planner would reallocate production inputs toward firms in market A to maximize total industry output. As a result, the representative final-good producer in market A becomes better off, while the one in market B becomes worse off. However, due to market segmentation, the increased production in market A cannot be delivered to market B—a feature that is particularly evident in the ready-mixed concrete industry, which I will examine in the empirical section. Such a reallocation therefore raises total industry output but does not constitute a Pareto improvement.

I now formalize this argument and show that a social planner seeks to reduce revenue-productivity dispersion within markets, but not necessarily across markets.

Following the standard Pareto problem formulation (see, e.g., Mas-Colell et al. (1995)), the planner maximizes the aggregate output of a focal market (here, without loss of generality, market 1), subject to the constraint that aggregate outputs in all other markets do not fall below their reference levels and resource constraints.[1]

$$\max_{\{k_i,l_i\}} Y_1 = \left(\sum_{i\in\Omega_1} y_i^{\frac{\sigma_1-1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1-1}}$$

$$s.t.$$

$$Y_m = \left(\sum_{i\in\Omega_m} y_i^{\frac{\sigma_m-1}{\sigma_m}}\right)^{\frac{\sigma_m}{\sigma_m-1}} \geq \bar{Y}_m, \quad m \in \{2,\cdots,M\} \tag{7}$$

$$y_i = z_i k_i^{\alpha} l_i^{1-\alpha}$$

$$\sum_{i=1}^{N} k_i = K \;\; \& \;\; \sum_{i=1}^{N} l_i = L, \tag{8}$$

where $\bar{Y}_m$ the reference levels for market m and K and L are the aggregate capital and labor, which are fixed.

I denote the Lagrange multipliers associated with the constraints (7) as μ_m for each market $m \in \{2,\cdots,M\}$, and λ_K and λ_L for the capital and labor market-clearing conditions (8), respectively. Substituting the output expression $y_i = z_i k_i^{\alpha} l_i^{1-\alpha}$, taking the first-order conditions, and combining them with the demand equation (2) yield

$$\alpha\frac{p_i y_i}{k_i} = \lambda_K \frac{P_m}{\mu_m} \qquad (1-\alpha)\frac{p_i y_i}{l_i} = \lambda_L \frac{P_m}{\mu_m}, \quad m \in \{1,\cdots,M\}, \tag{9}$$

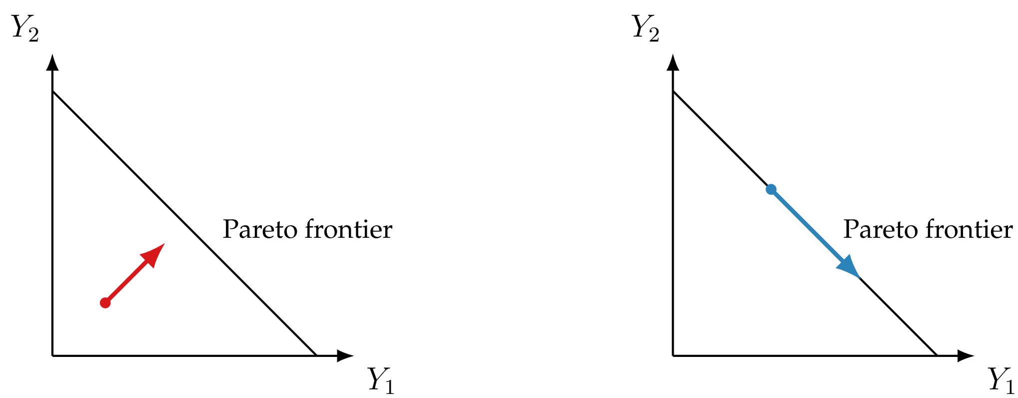
where $\mu_1 = 1$ and $\mu_m = \frac{\lambda_K^{\alpha}\lambda_L^{1-\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}} \times \frac{1}{(\sum_{i\in\Omega_m} z_i^{\sigma_m-1})^{\frac{1}{\sigma_m-1}}}$, $m \in \{2,\cdots,M\}$. Here, μ_m is determined by the supply-side characteristics of market m, such as the number of firms and the productivity distribution of z_i. In contrast, the market-level price index P_m depends on demand conditions as well, which are shaped by the endowments

[1] This is equivalent to the planner's problem for the consumer, since the market-clearing condition implies that consumption is exactly equal to Y_m for the representative consumer in market m.

of capital and labor and by the ownership structure of firms held by the representative consumer in each market. Because demand conditions can vary independently of supply-side factors, P_m/μ_m may not be identical across markets. Hence, the marginal revenue products of capital and labor, $\text{MRPK}_i = \alpha p_i y_i / k_i$ and $\text{MRPL}_i = (1-\alpha) p_i y_i / l_i$, respectively, should be equalized *within* a market but not necessarily *across* markets. Given that $\text{TFPR}_i = p_i y_i / (k_i^{\alpha} l_i^{1-\alpha}) \propto \text{MRPK}_i^{\alpha} \times \text{MRPL}_i^{1-\alpha}$, the TFPR_i should likewise be equalized across firms within a market, but not necessarily across markets.

Proposition 1 *In an economy with an industry that consists of multiple markets, a social planner seeks to equalize the marginal revenue products of capital and labor within each market, but not necessarily across markets.*

Figure 1: Within and across market misallocation



(a) Within market misallocation **(b)** Between market reallocation

Figure 1 illustrates how removing the dispersion in revenue productivity affects the economy in a two-market example. First, when a planner eliminates the dispersion in revenue productivity within markets, the economy moves closer to the Pareto frontier. However, when there is no dispersion in revenue productivity within markets but potentially across markets, a planner's attempt to reallocate resources from the market with a lower revenue product (market 2) to the one with a higher revenue product (market 1) merely shifts the allocation along the Pareto frontier. Hence, it does not generate a Pareto improvement, even though it reduces the dispersion in revenue productivity across markets. Thus, it is important to understand and quantify how much of the industry-wide dispersion in TFPR originates from within- and across-market differences, and hence how much we may overestimate the degree of misallocation.

3 Empirical analysis

Motivated by the theoretical result, this section quantifies how much of the dispersion in revenue productivity can be attributed to the pure within-market component, and hence how much misallocation is overestimated. Defining a market is generally challenging due to the lack of data on firm–customer relationships. To address this, I focus on the ready-mixed concrete industry, where markets can be more clearly defined geographically, as concrete cannot be transported over long distances due to technological constraints (Syverson (2004)).

3.1 Data and the definition of market

The main source of data is the publicly available version of Korean Mining and Manufacturing Survey (KMMS) from 2011 to 2019.[2] This is the Korean counterpart of the Annual Survey of Manufactures in the U.S. The data cover all mining and manufacturing establishments with at least ten employees.[3] The empirical analysis centers on the ready-mixed concrete industry, which is a leading example of an industry where markets are segmented locally. Since producers must deliver ready-mixed concrete before it hardens, markets are necessarily localized (Syverson (2008)).

I estimate a model-consistent TFPR for each establishment i in year t as follows:

$$\log(\text{TFPR}_{it}) = \log(p_{it}y_{it}) - \alpha_t \log(k_{it}) - (1-\alpha_t)\log(l_{it}),$$

where $p_{it}y_{it}$, k_{it}, and l_{it} denote deflated value-added, capital, and the number of workers, respectively. α_t is the average cost share of capital, defined as $\alpha_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\alpha_{it}$, where the establishment-level cost share is $\alpha_{it} = \frac{r_t k_{it}}{r_t k_{it} + w_{it} l_{it}}$, and N_t is the total number of establishments in year t. Here, r_t is the cost of capital, estimated as the ratio of gross surplus to capital stock in the non-metal manufacturing industry, using data from the Bank of Korea, and $w_{it}l_{it}$ is the total wage bill observed in the KMMS.

Note that the interpretation of TFPR depends on how the coefficients on capital and labor are measured. Blackwood et al. (2021) show that when the elasticities of revenue with respect to capital and labor are used, the resulting revenue productivity index captures an establishment's demand or technology fundamentals. In contrast, when cost

[2] The year 2015 is excluded because information on capital is unavailable. In addition, the publicly available version does not contain a longitudinal establishment identifier, so this is not a panel data. However, this is not an issue as I estimate the dispersion of TFPR and misallocation for each year.

[3] I use the terms establishment and plant interchangeably.

shares are used, the measure reflects distortions. Therefore, my TFPR measure captures the degree of distortions rather than the establishment's fundamental productivity.

One of the key tasks is defining markets. According to anecdotal evidence cited in Syverson (2004), "stated maximum ideal delivery distances (for concrete) were between 30- and 45-minutes drive from the plant." Under this principle, I define markets based on the *Si*/*Gun*/*Gu* administrative classification in Korea. Collard-Wexler (2013) defines a U.S. county as the relevant market in the ready-mixed concrete industry, and a *Si*, *Gun*, or *Gu* is the Korean counterpart of a county in the U.S.[4] However, in large cities such as Seoul or Busan, there are multiple *Gu*s, so the county-based market definition can be too granular. As a robustness check, I alternatively define a market such that large *Special Cities*, such as Seoul and Busan, are treated as a single market even if they contain multiple *Gu*s.

Table 1 reports the summary statistics. I collapse and tabulate the original data into three levels of aggregation. The first panel shows the number of firms and markets for each year. The second panel presents the number of firms and the average log(TFPR) in each market and year. Finally, the third panel presents the original establishment-year data, including real value added, capital, the number of workers, and log(TFPR). On average, there are 770 establishments operating in 180 markets, corresponding to roughly four establishments per market. For reference, Collard-Wexler (2013) report an average of 1.86 plants per county in the U.S., indicating that Korean counties include more plants. To minimize potential measurement error when estimating TFPR dispersion in markets with few establishments, I will also exclude all markets with fewer than five firms as a robustness check and verify that the results hold under this restriction.

A notable fact concerns the standard deviation of log(TFPR) in Panels 2 and 3. In Panel 3, the plant-year level, the standard deviation of log(TFPR) is 0.67, while in Panel 2, the market-year level, it is 0.48. This suggests that a substantial portion of the total dispersion in TFPR is driven by variation across markets. Under the theoretical framework, this implies that a large part of the measured misallocation may reflect cross-market differences rather than within-market distortions. In the next section, I formally quantify how much of the overall TFPR dispersion is accounted for by within-versus across-market components, and how this affects the estimated degree of misallocation.

[4]For papers that use the *Si*/*Gun*/*Gu* classification as a county definition in Korea, see Chun et al. (2023) and references therein.

Table 1: Summary statistics

Variable	Mean	SD	P10	P50	P90	N
Panel 1: year sample						
# of firms	773	57	699	777	847	8
# of markets	179	2	174	179	181	8
Panel 2: (market,year) sample						
# of firms per market	4.33	3.22	1.00	3.00	9.00	1428
log(TFPR)	3.62	0.48	3.07	3.59	4.20	1428
Panel 3: (plant,year) sample						
Value added (2020 KRW Mn.)	4411.02	4307.58	1282.30	3072.51	8935.92	6187
Capital (2020 KRW Mn.)	4815.27	8651.42	374.42	2257.95	11741.30	6187
# of workers	24.38	19.83	11.00	18.00	45.00	6187
log(TFPR)	3.61	0.67	2.88	3.59	4.39	6187

Notes: The table presents summary statistics for the ready-mixed concrete industry from the Korean Mining and Manufacturing Survey for 2011–2019, excluding 2015. The first panel shows the number of firms and markets for each year. The second panel presents the number of firms and the average log(TFPR) in each market and year. Finally, the third panel presents the original plant-year data, including real value added, capital, the number of workers, and log(TFPR). For your reference, 1 USD = 1,180.56 KRW was the average exchange rate in 2020.

3.2 TFPR decomposition: within vs. across markets

The sample variance of $\log(\text{TFPR})$, denoted by s_t^2, in a given industry and year t can be decomposed into within-market and across-market components as follows:

$$\begin{aligned} s_t^2 &= \frac{1}{N_t - 1} \sum_{i=1}^{N_t} (\tau_{it} - \bar{\tau}_t)^2 \\ &= \underbrace{\frac{1}{N_t - 1} \sum_{m} \sum_{i \in \Omega_{mt}} (\tau_{it} - \bar{\tau}_{mt})^2}_{\text{within-market}} + \underbrace{\frac{1}{N_t - 1} \sum_{m} N_{mt} (\bar{\tau}_{mt} - \bar{\tau}_t)^2}_{\text{across-market}}, \end{aligned} \tag{10}$$

where $\tau_{it} = \log(\text{TFPR}_{it})$, N_{mt} is the number of plants in market m, $\bar{\tau}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \tau_{it}$ is the industry-wide average of log(TFPR), and $\bar{\tau}_{mt} = \frac{1}{N_{mt}} \sum_{i \in \Omega_{mt}} \tau_{it}$ is the market-specific average.

The goal of this empirical exercise is to statistically quantify how much of the total variance in log(TFPR) is accounted for by the across-market component. However, TFPR dispersion across markets could arise mechanically because each market contains a finite number of firms. Thus, the average TFPR in each market may differ across markets simply due to sampling noise, even if the population average TFPR is identical across all markets. To establish a more meaningful case, I further conduct a counterfactual exercise in which market identifiers are permuted—keeping the number of firms per market fixed but randomly reassigning firms to different markets.[5] Economically, if the across-market dispersion in τ_{it} changes substantially after the permutation, it suggests that there is a sizable place-based component in the wedges. Conversely, if the difference is small, the across-market component likely reflects sampling noise due to the finite number of firms within each market. Lastly, I perform this random permutation 100 times to construct a confidence band around the mean estimates.

Table 2 reports the total dispersion in log(TFPR), the across-market component, and the across-market component based on permuted market identifiers. Panel 1 presents the baseline results, Panel 2 restricts the sample to markets with more than five establishments, and Panel 3 adopts an alternative market definition that treats each *Special City* (e.g., Seoul) as a single market, even when it spans multiple counties. For the baseline sample, I show results for each year as well as the time average, while the latter two panels report only averages for brevity. The patterns are similar when examined year by year.

In the baseline sample, the across-market component accounts on average for 41.6 percent of the total industry-wide dispersion in log(TFPR), ranging from 36.3 to 45.9 percent across years. I compare these estimates with those from the counterfactual exercise that randomly permutes market identifiers while keeping market sizes fixed. Confidence bands at the 1 percent level are constructed from 100 random permutations. Estimates of the across-market component from the original sample that fall outside these bands are marked with *** to indicate statistical significance. On average, the permuted across-market component represents 23.4 percent of total dispersion. Hence, some portion of the observed across-market dispersion in TFPR reflects finite-sample noise. Nevertheless, the original across-market estimates are both statistically and economically distinct from the permuted ones: the original wedges across markets increase dispersion by about 18 percentage points (41.6% – 23.4%).

This pattern persists under alternative sample definitions. When restricting to markets with more than five firms, the original across-market wedges increase dispersion by 18 percentage points (31.3% – 13.1%). Under the coarser market definition aggregating *Special Cities*, the increase is similarly 18 percentage points (38.0% – 20.3%).

Overall, these results indicate that the across-market component accounts for a substantial portion of industry-wide dispersion in log(TFPR). This substantial share cannot

[5] I am grateful to a referee for suggesting this interesting exercise.

be attributed to sampling noise alone, implying the presence of meaningful market-level wedges. Consequently, industry-level measures of misallocation may be overstated, a point I quantify formally in the next section.

Table 2: Productivity dispersion: industry vs. market

	$\sigma^2(\log \text{TFPR})$			Relative to total	
Year	Total	Across	Across (permuted)	Across	Across (permuted)
Panel 1: Baseline					
2011	0.442	0.161***	0.114	0.363***	0.257
			[0.091, 0.148]		[0.207, 0.334]
2012	0.336	0.145***	0.085	0.432***	0.253
			[0.066, 0.106]		[0.196, 0.314]
2013	0.407	0.149***	0.101	0.366***	0.248
			[0.076, 0.123]		[0.188, 0.303]
2014	0.348	0.159***	0.085	0.459***	0.244
			[0.068, 0.102]		[0.196, 0.294]
2016	0.336	0.151***	0.076	0.449***	0.225
			[0.062, 0.095]		[0.183, 0.283]
2017	0.312	0.138***	0.069	0.441***	0.223
			[0.055, 0.086]		[0.175, 0.276]
2018	0.287	0.119***	0.061	0.415***	0.212
			[0.048, 0.079]		[0.168, 0.277]
2019	0.267	0.107***	0.057	0.400***	0.212
			[0.045, 0.072]		[0.170, 0.270]
Avg.	0.342	0.141***	0.081	0.416***	0.234
			[0.064, 0.101]		[0.185, 0.294]
Panel 2: Markets more than 5 firms					
Avg.	0.361	0.112***	0.048	0.313***	0.131
			[0.032, 0.070]		[0.088, 0.192]
Panel 3: Coarser market definition					
Avg.	0.342	0.129***	0.070	0.380***	0.203
			[0.054, 0.090]		[0.157, 0.260]

Notes: This table presents the dispersion in log(TFPR) across all firms in the industry, along with the across-market component based on both the original and the randomly permuted market identifiers. Panel 1 reports the baseline sample. Panel 2 includes only markets with more than five plants. Panel 3 adopts a coarser market definition, treating each *Special City* (e.g., Seoul) as a single market even when it contains multiple counties. The column "Total" reports the industry-wide dispersion in log(TFPR), while "Across" corresponds to the across-market component defined in Eq. (10). Finally, "Across (permuted)" presents the across-market component based on randomly permuted market identifiers, and "Relative to total" shows the ratio of the across-market component to the total. The brackets below the "Across (permuted)" estimates indicate the 1 percent confidence bands, generated from 100 random permutations of market identifiers. *** denotes that the across and across (permuted) estimates are statistically different at the 1 percent level.

3.3 Misallocation: industry- and market-based approach

First, I describe the industry-wide measure of misallocation, which follows Hsieh and Klenow (2009). The industry-wide aggregate TFP is computed as the Solow residual:

$$Z_t = \frac{Y_t}{K_t^{\alpha} L_t^{1-\alpha}},$$

where $Y_t = \left(\sum_{i=1}^{N_t} y_{it}^{\frac{\sigma_t - 1}{\sigma_t}}\right)^{\frac{\sigma_t}{\sigma_t - 1}}$, σ_t is the industry-wide elasticity of substitution, which may vary over time, and K_t and L_t denote aggregate capital and labor, respectively.

In the absence of distortions, the efficient aggregate TFP is computed by

$$Z_t^e = \left(\sum_{i=1}^{N_t} z_{it}^{\sigma_t - 1}\right)^{\frac{1}{\sigma_t - 1}}.$$

Since separate price and quantity data are not available, I follow Hsieh and Klenow (2009) and infer physical productivity z_{it} as

$$z_{it} = \frac{(p_{it} y_{it})^{\frac{\sigma_t}{\sigma_t - 1}}}{k_{it}^{\alpha} l_{it}^{1-\alpha}}.$$

Finally, the degree of industry-wide misallocation, $\mathcal{L}_t$, is defined as

$$\mathcal{L}_t = 1 - \frac{Z_t}{Z_t^e},$$

where a higher value of $\mathcal{L}_t$ indicates that aggregate productivity Z_t deviates further from the efficient benchmark Z_t^e, implying a greater degree of misallocation within the industry.

Turning to the market-based measure of misallocation, I follow a similar approach but compute the degree of misallocation within each market by applying a separate output aggregator for each market. The aggregate TFP in market m is given by

$$Z_{mt} = \frac{Y_{mt}}{K_{mt}^{\alpha} L_{mt}^{1-\alpha}},$$

where $Y_{mt} = \left(\sum_{i \in \Omega_{mt}} y_{it}^{\frac{\sigma_{mt} - 1}{\sigma_{mt}}}\right)^{\frac{\sigma_{mt}}{\sigma_{mt} - 1}}$, σ_{mt} is the market-specific elasticity of substitution, which may vary across years, and K_{mt} and L_{mt} denote total capital and labor in market m in year t. Similarly, in the absence of distortions, the efficient aggregate TFP in market

m is

$$Z_{mt}^e = \left(\sum_{i \in \Omega_{mt}} (z_{it}^m)^{\sigma_{mt}-1} \right)^{\frac{1}{\sigma_{mt}-1}},$$

where $z_{it}^m = \frac{(p_{it}y_{it})^{\frac{\sigma_{mt}}{\sigma_{mt}-1}}}{k_{it}^{\alpha} l_{it}^{1-\alpha}}$.[6]

The degree of misallocation in market m, $\mathcal{L}_{mt}$, is then defined as

$$\mathcal{L}_{mt} = 1 - \frac{Z_{mt}}{Z_{mt}^e}.$$

To aggregate the market-level misallocation index $\mathcal{L}_{mt}$ into a single industry-level measure comparable to $\mathcal{L}_t$, one would ideally specify a social welfare function. However, there is no uniquely correct way to do so. To remain agnostic about welfare weights, I instead compute weighted averages of $\mathcal{L}_{mt}$ using several alternative weighting measures. Thus, the aggregated market-based misallocation index, $\mathcal{L}_t^{\mathcal{M}}$, is given by

$$\mathcal{L}_t^{\mathcal{M}} = \sum_{m=1}^{M_t} \omega_{mt} \mathcal{L}_{mt},$$

where ω_{mt} is the weight satisfying $\sum_{m=1}^{M_t} \omega_{mt} = 1$. Specifically, I consider four weighting schemes: (i) demand-weighted, measured by the operating cost of the local construction sector ($\omega_m = D_m / \sum_{m=1}^{M_t} D_m$); (ii) firm-count weighted ($\omega_{mt} = N_{mt} / \sum_{m=1}^{M_t} N_{mt}$); (iii) revenue-weighted ($\omega_{mt} = \sum_{i \in \Omega_{mt}} p_{it}y_{it} / \sum_{i=1}^{N_t} p_{it}y_{it}$); and (iv) cost-weighted ($\omega_{mt} = \sum_{i \in \Omega_{mt}} (r_t k_{it} + w_{it} l_{it}) / \sum_{i=1}^{N_t} (r_t k_{it} + w_{it} l_{it})$).[7] Note that this approach can be justified by a social welfare function

$$\mathcal{Y} = \sum_m \theta_m Y_m,$$

where θ_m denotes the welfare weight that the planner assigns to market m, for instance due to high construction demand. Holding total capital and labor in each market m in the planner's allocation fixed at their decentralized equilibrium levels,

$$\mathcal{L}_t^{\mathcal{M}} = 1 - \frac{\mathcal{Y}}{\mathcal{Y}^e} = \sum_m \frac{\theta_m Y_m^e}{\sum_m \theta_m Y_m^e} \left(1 - \frac{Y_m}{Y_m^e} \right) = \sum_m \omega_{mt} \mathcal{L}_{mt},$$

where $\mathcal{Y}^e$ is social welfare under the planner's allocation and $Y_m^e = Z_m^e K_m^{\alpha} L_m^{1-\alpha}$. Ac-

[6]When $\sigma_t = \sigma_{mt}$, $z_{it} = z_{it}^m$, but they could be estimated differently when σ_t and σ_{mt} differ. Both the case where σ_t equals σ_{mt} and the case where they do not will be explored.

[7]Operating cost data for the local construction sector are only available for 2015, so there is no time subscript t.

cordingly, the planner weights the degree of misallocation in market m by

$$\omega_{mt} = \frac{\theta_m Y_m^e}{\sum_m \theta_m Y_m^e}.$$

When either construction demand θ_m or efficient productivity Z_m^e is high, where Z_m^e fully describes Y_m^e given fixed K_m and L_m, the misallocation in market m receives a greater weight. I assume that the combination of the demand component θ_m and the supply-side factor Z_m^e will be reflected in the various weighting measures I employ.

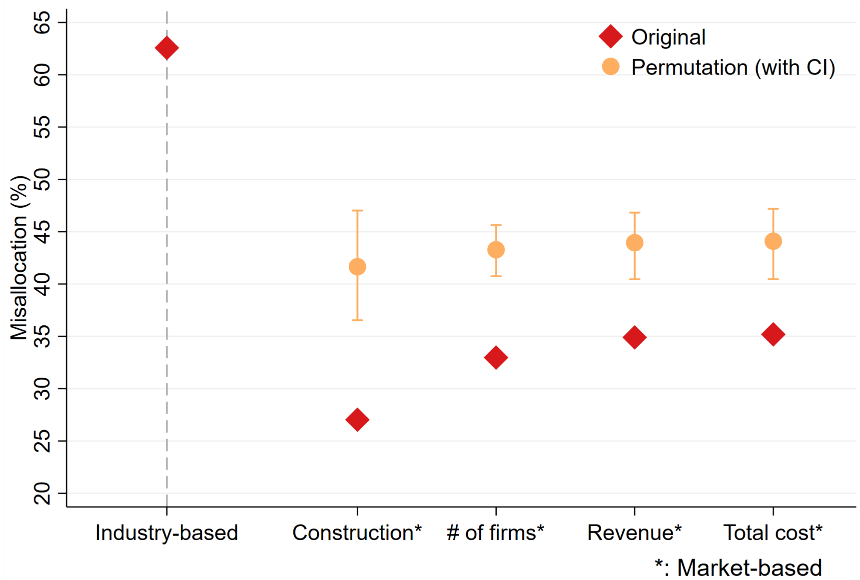
Lastly, in the baseline analysis, I set the elasticity of substitution to $\sigma_t = \sigma_{mt} = 6$, following Foster et al. (2008), who estimate the price elasticity of demand—which corresponds to σ in Eq. (2)—in the ready-mixed concrete industry using U.S. Census data to be approximately -5.93. Robustness checks that allow σ_{mt} to vary across markets are presented below. Lastly, I also randomly permute the market identifiers, as in Section 3.2, to examine whether the decline in the degree of misallocation could be driven by sampling noise arising from the finite number of plants within each market.

Figure 2 presents the baseline results. It plots the industry-wide misallocation measure $\mathcal{L}_t$ and the aggregated market-based misallocation measure $\mathcal{L}_t^{\mathcal{M}}$, each computed with four different weighting measures. Both measures are averaged across years. Each market-based measure is shown alongside its counterpart based on samples with randomly permuted market identifiers.

First, the industry-based misallocation measure shows that in an economy with distortions, aggregate TFP is roughly 60 percent lower than the efficient benchmark where the marginal revenue products of capital and labor are equalized across all firms in the ready-mixed concrete industry. In contrast, the market-based misallocation measures indicate substantially lower degrees of misallocation. Depending on the weighting measure—from construction demand to total-cost-weighted—the degree of misallocation ranges from 27 percent to 35 percent, considerably below the industry-based estimate.

To assess how much of this reduction is mechanically driven by grouping firms into smaller units, I also compute the market-based measure using randomly permuted market identifiers. These results confirm that mechanical effects indeed contribute to the lower misallocation estimates. However, the true market-specific wedges further reduce the degree of misallocation beyond what can be explained by such mechanical effects. The gap between the original and permuted estimates is both statistically and economically significant: the true wedges reduce the degree of misallocation by 9 to 15 percentage points, depending on the weighting measures—an economically substantial effect.

Figure 2: Misallocation: industry vs. market



Notes: This figure presents the industry-wide misallocation measure $\mathcal{L}_t$ and the aggregated market-based misallocation measure $\mathcal{L}_t^{\mathcal{M}}$, each computed using four different weighting measures. The weighting measures—construction demand, number of firms, revenue, and total cost—are used to aggregate $\mathcal{L}_{mt}$. Both measures are averaged across years. Each market-based measure is shown alongside its counterpart based on samples with randomly permuted market identifiers. "Original" refers to estimates from the original sample, while "Permutation" refers to estimates based on samples where market identifiers are randomly permuted. The confidence band corresponds to the top and bottom 1 percent of the distribution, generated from 100 random permutations of market identifiers. Lastly, the analysis assumes $\sigma_t = \sigma_{mt} = 6$.

I conduct several robustness exercises to confirm the main findings. First, as in Section 3.2, I exclude markets with fewer than five firms from the sample to examine whether the results are driven by markets with a small number of plants. Second, I adopt an alternative market definition by aggregating counties within *Special Cities*. Third, instead of applying a uniform elasticity of substitution $\sigma_t = \sigma_{mt} = 6$, I allow for heterogeneous elasticities across markets.

Because separate price and quantity data are unavailable, it is difficult to estimate price elasticities directly for each market. Therefore, I take a simple reduced-form approach that remains economically meaningful. Specifically, I assume that plants are more substitutable when there are more plants per square kilometer in a given market (Syverson (2004)); thus, markets with a higher density of plants should exhibit a higher elasticity of substitution σ_{mt}.

I set the minimum and maximum elasticities of substitution, $\sigma^{\min}$ and $\sigma^{\max}$, by denoting that the market with the lowest plant density has $\sigma^{\min}$ and the market with the highest density has $\sigma^{\max}$. For the remaining markets, I interpolate σ_{mt} by assuming a simple linear relationship in the logarithm of plant density:

$$\sigma_{mt} = \frac{\sigma^{\max} - \sigma^{\min}}{\log(n_{\max,t}) - \log(n_{\min,t})} \times [\log(n_{mt}) - \log(n_{\min,t})] + \sigma^{\min}, \tag{11}$$

where n_{mt} is the number of plants per square kilometer in market m. Using this relationship, I also compute the industry-wide elasticity σ_t by substituting n_t, the total number of plants divided by the total industry area, for n_{mt} in the above equation.

Lastly, I set $\sigma^{\min} = 6$, using the industry-level estimate from Foster et al. (2008) as a lower bound. The underlying intuition is that substitutability among plants within a market should be higher than across the entire industry, since firms within the same market compete more directly. Hence, the industry-level estimate provides a conservative lower bound for market-level elasticities. However, there is no clear empirical basis for $\sigma^{\max}$, so I set it to 2 times $\sigma^{\min}$ and also consider 3 times $\sigma^{\min}$ as an additional robustness check.

Table 3 reports the robustness results. The row labeled "Avg." in Panel 1 corresponds to the same value shown in Figure 2, while the remaining rows in Panel 1 report yearly results.

First, when restricting the sample to markets with more than five plants, the market-based misallocation index remains significantly lower than the industry-based one, although the gap between the original and permuted measures narrows to between 7 and 10 percentage points. Second, using the coarser market definition yields results that are broadly similar to the baseline.

With heterogeneous σ across markets, the industry-based misallocation becomes larger than in the baseline, since the industry-wide elasticity of substitution estimated from Eq. (11) exceeds the baseline value of 6. Also, in this case, both the gap between the industry-based and market-based measures and the gap between the original and permuted market-based measures become more pronounced. For instance, when $\sigma^{\max} = 18$, the market-based measure reduces the degree of misallocation by 42 percentage points (= 73.11%–30.81%), and the difference between the original and permuted measures ranges from 18 to 40 percentage points—substantially larger than in the baseline.

Overall, these results suggest that failing to distinguish between industry and market levels when estimating misallocation can lead to a substantial overestimation of the true degree of misallocation.

Table 3: Misallocation: industry vs. market (robustness)

		Market-based							
		Construction		# of firms		Revenue		Total cost	
Year	Industry-based	Original	Permuted	Original	Permuted	Original	Permuted	Original	Permuted
Panel 1: Baseline									
2011	68.99	29.26***	43.54	36.09***	45.52	38.50***	46.22	40.04***	46.67
			[37.80, 49.25]		[42.67, 48.62]		[41.96, 49.84]		[41.95, 50.80]
2012	64.57	30.06***	41.39	34.83***	42.96	35.84***	43.44	37.28***	43.72
			[36.35, 47.31]		[40.14, 45.17]		[39.76, 46.01]		[39.82, 46.63]
2013	65.81	29.40***	44.00	35.08***	45.79	37.74***	46.60	38.15***	46.79
			[37.44, 49.39]		[42.41, 48.11]		[42.29, 49.64]		[42.57, 50.16]
2014	59.53	28.08***	41.65	30.58***	42.43	32.07***	43.44	32.40***	43.76
			[37.08, 47.06]		[40.17, 44.52]		[40.47, 45.66]		[40.46, 46.32]
2016	64.93	26.67***	44.68	33.42***	46.05	35.65***	46.79	34.72***	46.71
			[37.90, 50.61]		[42.99, 48.70]		[42.94, 50.33]		[42.82, 50.47]
2017	62.02	24.47***	42.14	32.62***	42.96	34.61***	43.74	34.70***	43.69
			[37.69, 46.43]		[40.77, 45.30]		[40.73, 46.49]		[40.51, 46.34]
2018	57.21	24.99***	38.50	30.52***	40.66	32.27***	40.73	31.70***	40.83
			[34.91, 44.28]		[38.85, 42.91]		[37.83, 43.92]		[38.06, 44.15]
2019	57.52	23.34***	37.34	30.66***	39.87	32.52***	40.68	32.53***	40.59
			[33.15, 41.84]		[37.93, 41.82]		[37.72, 42.69]		[37.55, 42.63]
Avg.	62.57	27.03***	41.65	32.98***	43.28	34.90***	43.95	35.19***	44.09
			[36.54, 47.02]		[40.74, 45.64]		[40.46, 46.82]		[40.47, 47.19]
Panel 2: Markets more than 5 firms									
Avg.	64.69	43.06***	50.72	40.64***	50.69	44.04***	50.69	44.01***	50.72
			[48.03, 53.67]		[48.10, 53.29]		[47.86, 53.49]		[47.80, 53.62]
Panel 3: Coarser market definition									
Avg.	62.57	35.72***	45.45	35.22***	45.64	38.83***	46.41	39.05***	46.53
			[41.91, 48.78]		[43.00, 48.08]		[43.13, 49.43]		[43.20, 49.74]
Panel 4: Heterogenous σ_m: $\sigma^{max} = 2 \times 6$									
Avg.	69.41	29.44***	61.63	36.70***	50.15	38.49***	52.23	38.70***	52.42
			[53.62, 67.20]		[46.93, 53.21]		[48.19, 56.25]		[48.38, 56.52]
Panel 5: Heterogenous σ_m: $\sigma^{max} = 3 \times 6$									
Avg.	73.11	30.81***	71.13	38.62***	57.00	40.52***	58.95	40.62***	59.12
			[61.63, 75.64]		[54.09, 60.20]		[54.55, 62.95]		[54.95, 63.19]

Notes: This table presents the degree of misallocation across all firms in the industry, along with market-based misallocation for both the original and randomly permuted market identifiers. The market-level misallocation measures are aggregated using four different weighting schemes: construction demand, number of firms, revenue, and total cost. Panel 1 reports the baseline sample. Panel 2 includes only markets with more than five plants. Panel 3 adopts a coarser market definition, treating each *Special City* (e.g., Seoul) as a single market even when it contains multiple counties. Panels 4 and 5 apply heterogeneous elasticities of substitution across markets, computed using Eq. (11). The column "Industry-based" reports the industry-wide misallocation measure, while "Market-based" corresponds to the aggregated market-level misallocation measures. "Original" refers to estimates based on the original market identifiers, whereas "'Permuted" refers to estimates from samples with randomly permuted identifiers. The brackets below the "Permuted" estimates indicate the 1 percent confidence bands, generated from 100 random permutations of market identifiers. *** denotes that the estimates from the original and permuted samples are statistically different at the 1 percent level.

4 Conclusion

In this paper, I show that distinguishing between industries and markets is crucial for estimating misallocation. Using a canonical model of heterogeneous firms operating across multiple markets, I argue that reallocations toward more distorted firms constitute Pareto improvements when they occur within markets, whereas reallocations across markets move the economy along the Pareto frontier. Bringing this theoretical insight to the ready-mixed concrete industry in Korea, where markets are defined in a relatively straightforward manner, I show that the industry-based misallocation measure is substantially higher than the market-based measure. This difference does not arise mechanically from sampling noise in finite samples but instead reflects genuine wedges across markets.

References

Asker, J., A. Collard-Wexler, and J. De Loecker (2014). Dynamic Inputs and Resource (Mis) Allocation. *Journal of Political Economy 122*(5), 1013–1063.

Baqaee, D. R. and E. Farhi (2020). Productivity and Misallocation in General Equilibrium. *The Quarterly Journal of Economics 135*(1), 105–163.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013). Cross-Country Differences in Productivity: The Role of Allocation and Selection. *American Economic Review 103*(1), 305–34.

Bils, M., P. J. Klenow, and C. Ruane (2021). Misallocation or Mismeasurement? *Journal of Monetary Economics 124*, S39–S56.

Blackwood, G. J., L. S. Foster, C. A. Grim, J. Haltiwanger, and Z. Wolf (2021). Macro and micro dynamics of productivity: From devilish details to insights. *American Economic Journal: Macroeconomics 13*(3), 142–172.

Bornstein, G. and A. Peter (2025). Nonlinear pricing and misallocation. *American Economic Review 115*(11), 3853–3908.

Chun, H., H. H. Joo, J. Kang, and S. H. Kim (2023). Protecting small-scale enterprises: Evidence from the korean ready-mixed concrete industry. *Review of Industrial Organization 63*(1), 73–95.

Collard-Wexler, A. (2013). Demand fluctuations in the ready-mix concrete industry. *Econometrica 81*(3), 1003–1037.

Dhingra, S. and J. Morrow (2019). Monopolistic competition and optimum product diversity under firm heterogeneity. *Journal of Political Economy 127*(1), 196–232.

Edmond, C., V. Midrigan, and D. Y. Xu (2023). How costly are markups? *Journal of Political Economy 131*(7), 1619–1675.

Foster, L., J. Haltiwanger, and C. Syverson (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review 98*(1), 394–425.

Gupta, A. (2024). Demand for Quality, Variable Markups and (Mis)allocation: Evidence from India. Technical report.

Haltiwanger, J., R. Kulick, and C. Syverson (2018). Misallocation Measures: The Distortion that Ate the Residual. Working Paper, National Bureau of Economic Research.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Mas-Colell, A., M. D. Whinston, J. R. Green, et al. (1995). *Microeconomic theory*, Volume 1. Oxford university press New York.

NAICS (2022). North american industry classification system manual.

Peters, M. (2020). Heterogeneous Markups, Growth, and Endogenous Misallocation. *Econometrica 88*(5), 2037–2073.

Restuccia, D. and R. Rogerson (2008). Policy Distortions and Aggregate Productivity with Heterogeneous Establishments. *Review of Economic Dynamics 11*(4), 707–720.

Syverson, C. (2004). Market Structure and Productivity: A Concrete Example. *Journal of Political Economy 112*(6), 1181–1222.

Syverson, C. (2008). Markets: Ready-Mixed Concrete. *Journal of Economic Perspectives 22*(1), 217–234.