Distorting Signals: The Role of Short-Selling in Capital Allocation Efficiency*

Jairo Macedo† Paulo Vaz‡

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Abstract

This article investigates the causal impact of financial market constraints on firm-level capital distortions, using the quasi-natural experiment provided by the U.S. *Job and Growth Tax Relief Reconciliation Act (JGTRRA)* of 2003. The JGTRRA introduced differentiated dividend taxation, which generated an exogenous shock to the supply of short selling. Using the framework proposed by Hsieh and Klenow (2009), our analysis reveals that firms exposed to increased speculative pressure experience adverse effects on capital allocation. In particular, the restrictive short-selling environment induced by the JGTRRA led to a 27.3% reduction in capital distortions. We also find that smaller firms are more impacted, indicating that financial frictions exert a differential effect based on firm size. These findings provide novel insights into the role of financial constraints in shaping resource allocation and enhancing firm productivity.

Keywords: Misallocation, Total Factor Productivity, Short selling, Speculations, Efficient Allocation, Corporate Finance

JEL codes: D24, D82, G18, G32, O47

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†Federal University Of Pernambuco, GAPPE/UFPE, jairo.macedo@ufpe.br

‡Federal University Of Pernambuco, GAPPE/UFPE, paulo.vaz@ufpe.br

1 Introduction

In the productivity literature, addressing the question of why some countries are significantly richer than others is a common starting point for researchers. Discussions often begin with such fundamental questions, as understanding and quantifying the causes of these disparities remains a classic challenge in economic theory. After all, differences in productive capacity across countries are profound and represent a central issue in understanding the factors that either constrain or drive economic growth.

Misallocation is a concept that has gained importance as a channel for understanding differences in aggregate productivity between countries, particularly through the analysis of marginal productivities. Banerjee and Duflo (2005) introduced this perspective, highlighting that disparities in marginal productivities play a crucial role in this process. The central idea behind the concept is that factors of production such as capital, labor and land should be allocated in a way that maximizes the aggregate productivity of an economy. However, distortions arising from taxes, subsidies, regulations, or market failures often hinder this efficient allocation. These distortions create imbalances: more efficient producers face restrictions in accessing resources, while less productive ones retain a disproportionate share of inputs.

The literature has made significant progress, especially following key contributions that have brought attention to the topic. Restuccia and Rogerson (2008) suggests that resource misallocation among firms can have substantial effects on aggregate total factor productivity (TFP), using models with heterogeneous firms to highlight these impacts. Building on this field, Hsieh and Klenow (2009) present a seminal analysis that underscores the importance of *misallocation* for productivity dynamics. The authors examined distortions such as taxes and subsidies to estimate productivity differences between China and India, using the United States as a reference point, often regarded as a *benchmark* for efficient resource allocation.

It has also advanced in approaches to understanding the potential sources of *misallocation*, classifying these approaches into direct and indirect methods.[4] The direct approach seeks to measure how specific factors – such as excessive regulation, credit constraints, and specific legislations – directly affect resource allocation. The indirect approach, on the other hand, examines the general effects caused by a combination of various factors, providing an aggregated view of distortions that impact productive efficiency.

This research investigates the causal effects on *misallocation* measures, building on the framework proposed by Hsieh and Klenow (2009). Despite being based on an indirect approach model, this paper focuses on the variables proposed as key elements to analyze the mechanisms of resource misallocation. We examine the causal effects of a financial shock, specifically an exogenous shock to short-selling supply, and its impact

[4]See Restuccia and Rogerson (2013) for a detailed discussion.

on firm productivity and resource allocation distortions. By extending this approach, the study aims to provide deeper insights into the mechanisms through which resource allocation distortions affect economic growth, with a particular focus on firms within the U.S. universe.

Short selling is a relevant practice in financial markets. In this type of operation, investors sell shares they do not own by borrowing them from other investors willing to lend their shares in exchange for a fee, using the equity lending market.[5] This strategy is based on identifying a potential reversal in a stock's trend, from upward to downward, and aiming to profit from the decline.

This study offers three main fields of contributions. First, it adds to the existing literature on productivity, financial frictions, and misallocation (Whited and Zhao (2021), Midrigan and Xu (2014), Greenwood et al. (2013), Cusolito et al. (2024)) by employing the model proposed by Hsieh and Klenow (2009)). The primary focus lies in measuring productivity, capital, and output distortions, offering a detailed analysis of the extent and nature of resource misallocation.

Several studies have examined the relationship between short selling and total factor productivity (TFP), shedding light on the mechanisms through which short selling influences resource allocation and firm efficiency. For instance, Xuewen Kuang and Lin (2024) explores the impact of short selling on enterprise TFP in the context of China's capital market reforms, illustrating how the introduction of short-selling mechanisms improves TFP by fostering technological innovation and enhancing capital allocation efficiency. Another applied example is Uras (2014), which analyzes the dispersion in corporate financial structures to explain the intra-industry allocation efficiency of productive factors.

Second, we examine the regulatory channel through which short selling affects the real economy. While this topic has been widely studied empirically (Grullon et al. (2015)), our approach leverages a quasi-natural experiment: the 2003 *Job and Growth Tax Relief Reconciliation Act* (JGTRRA). This reform constitutes an exogenous shock to the supply of short-selling opportunities, enabling us to identify its causal impact on real economic outcomes.[6] Additionally, recent studies have employed this shock to investigate its effects on mispricing and market performance (see Han et al. (2024), Matta et al. (2025)).

Third, our study builds on the findings of Meng et al. (2020), who investigated the impacts of short selling on firms' financial constraints. The authors demonstrated that short selling can exacerbate these constraints, particularly in firms with higher credit risk or significant information asymmetry. They also found that firms subject to short selling face increased negative media coverage, higher external financing costs, and a reduction in the volume of new external financing. Our study aims to deepen this discussion by examining how these mechanisms influence resource allocation and firm productivity.

[5] For more details on the functioning of this mechanism, see Reed (2013).

[6] See Thornock (2013) for related discussion.

In this paper, we investigate whether short-selling activity negatively impacts the efficient allocation of resources in the short term by restricting access to credit. To assess this, we rely on the misallocation estimates proposed by Hsieh and Klenow (2009). The underlying mechanism is that a high level of short interest signals increased firm risk, making banks and financial institutions more reluctant to extend credit. This credit contraction may, in turn, exacerbate capital misallocation, particularly in firms that rely on external financing for growth and productivity improvements.

Our empirical findings suggest that this restriction led to a 27.3% reduction in capital misallocation, supporting the idea that short-selling constraints can limit excessive speculation and mitigate distortions in capital allocation. These results contribute to the broader discussion on financial frictions and market efficiency, highlighting the role of short-selling regulations in shaping resource distribution across firms. By providing empirical evidence on the unintended consequences of tax-induced financial constraints, this study offers new insights into how regulatory interventions influence firm dynamics and capital allocation efficiency.

To provide a clear and structured analysis, we divide the paper into six main sections. Section 2 discusses the institutional background, presenting the JGTRRA as a quasi-natural experiment affecting short-selling activity and capital misallocation. Section 3 describes the dataset and key variables used in our analysis. Section 4 outlines the research design, detailing our empirical strategy and estimation setup. Section 5 presents the core findings, including the effects of short-selling constraints on capital misallocation, the dynamic impact of JGTRRA over time, and productivity distribution analysis. Finally, Section 6 provides concluding remarks, summarizing the main insights and potential implications of our findings for financial regulation and market efficiency.

2 Institutional Background: JGTRRA as a Shock to Short Selling and Capital Misallocation

This section is divided into two parts. The first introduces our model framework, with a particular emphasis on the key variables driving our analysis. The second provides a detailed discussion on the importance of short-selling activity and the role of our policy intervention as the object of study. In essence, we discuss how the JGTRRA served as an exogenous shock, creating a quasi-natural experiment to analyze the allocation of resources across firms.

2.1 Model Framework

According to the Hsieh and Klenow (2009) model, in an efficient market without firm-level distortions, revenue productivity would be equalized across firms within narrowly defined industries, as capital and labor would naturally flow to their most productive uses. However, observed dispersion in revenue productivity reveals the presence of distortions that hinder the efficient allocation of resources. These distortions lower TFP and constrain total output. As a result, the variance in total revenue productivity (TFPR) across firms within an industry is a key indicator of misallocation.

We follow the canonical model proposed by Hsieh and Klenow (2009), which serves as the foundation for our analysis[7]. Subsequent studies have adapted this model to explore various contexts and applications, including different scenarios and approaches.[8]

It assumes an economy with a single final good Y_t, produced by a representative firm operating in a perfectly competitive market at time t. The representative firm combines the output Y_{st} of S industries using a Cobb-Douglas production function:

$$Y_t = \prod_{s=1}^{S} Y_{st}^{\theta_{st}}, \quad \sum_{s=1}^{S} \theta_{st} = 1, \tag{1}$$

where θ_{st} represents the share of each industry's output in the aggregate production. Cost minimization implies that the share of each sector in the economy is given by:

$$\theta_{st} = \frac{P_{st} \cdot Y_{st}}{P_t \cdot Y_t}. \tag{2}$$

We also derive the price of the final good, assuming the numéraire $P_t = 1$, but formally defined as follows:

[7] The full derivation of this model can be found in Section A.

[8] For adaptations of the model, see Vasconcelos (2017), Oberfield (2013), Chen et al. (2023), Banerjee and Moll (2010), Gondhi (2023), Uras and Wang (2024) and Whited and Zhao (2021).

$$P_t \equiv \prod_{s=1}^{S} \left(\frac{P_{st}}{\theta_{st}} \right)^{\theta_{st}}. \tag{3}$$

For each time t, there are M_s firms, each associated with a sectoral price P_{st} that represents the price of sectoral output Y_{st}:

$$Y_{st} = \left[\sum_{i=1}^{M_{st}} Y_{ist}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

Where Y_{ist} denotes the output of firm i in sector s, and σ represents the elasticity of substitution between the outputs of individual firms. Following the standard in the literature, we set $\sigma = 3$[9]. Solving the profit maximization problem, we derive the following results:

1. The inverse demand equation for each individual variety is:

$$P_{ist}^{\sigma} \cdot Y_{ist} = P_{st}^{\sigma} \cdot Y_{st}. \tag{5}$$

2. The sector price P_{st} is given by:

$$P_{st} = \left(\sum_{i=1}^{M_{st}} P_{ist}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{6}$$

Each differentiated product is defined by the production function, which is given by a Cobb-Douglas function:

$$Y_{ist} = A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s},$$

For firm i in sector s, A_{ist} represents the productivity of , K_{ist} is capital, L_{ist} is labor, and α_s is the capital share parameter specific to sector s.

The model identifies two types of distortions impacting production. Output distortions (τ_{yist}) proportionally affect the marginal products of both capital and labor. These distortions are higher for firms facing restrictions, such as government-imposed size limits or elevated transportation costs, and lower for firms receiving public output subsidies.

[9] We follow Hsieh and Klenow (2009) but there is a discursion on Chirinko (2008)

On the other hand, Capital distortions (τ_{kist}) specifically alter the marginal product of capital relative to labor. Hsieh and Klenow (2009) highlight that these distortions are more pronounced in firms with limited access to credit and less significant for firms that benefit from inexpensive financing, such as those supported by state programs or business groups.

The profit maximization problem for firm i is given by:

$$\Pi_{ist} = (1 - \tau_{yist}) \cdot P_{ist} \cdot Y_{ist} - \omega_t \cdot L_{ist} - (1 + \tau_{kist}) \cdot R_t \cdot K_{ist}$$

where R_t and ω_t represent the costs of capital and wages, respectively. Following the standard in the literature, we set $R_t = 10\%$. Maximizing the firm's profit leads to the standard condition in which its price is a fixed markup over its marginal cost.

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

$$P_{ist} = \frac{\sigma}{\sigma - 1} \cdot \left(\frac{R_t}{\alpha_s}\right)^{\alpha_s} \cdot \left(\frac{\omega_t}{1 - \alpha_s}\right)^{1-\alpha_s} \cdot \frac{(1 + \tau_{kist})^{\alpha_s}}{A_{ist} \cdot (1 - \tau_{yist})}. \tag{7}$$

The allocation of resources across firms is influenced not only by their TFP levels but also by the output and capital distortions. From the first-order conditions, it is evident that the marginal revenues of capital and labor ($MRPK_{ist}$ and $MRPL_{ist}$, respectively) are proportional to the revenue ($P_{si}Y_{si}$) per unit of capital and labor.

The marginal revenue products of labor ($MRPL_{ist}$) and capital ($MRPK_{ist}$) are defined as follows:

$$MRPL_{ist} \triangleq (1 - \alpha_s) \cdot \frac{(\sigma - 1)}{\sigma} \cdot \frac{P_{ist} \cdot Y_{ist}}{L_{ist}} = \frac{\omega_t}{(1 - \tau_{yist})},$$

$$1 - \tau_{yist} = \frac{\sigma}{\sigma - 1} \cdot \frac{\omega_t \cdot L_{ist}}{(1 - \alpha_s) \cdot P_{ist} \cdot Y_{ist}}, \tag{8}$$

$$MRPK_{ist} \triangleq \alpha_s \cdot \frac{(\sigma - 1)}{\sigma} \cdot \frac{P_{ist} \cdot Y_{ist}}{K_{ist}} = R_t \cdot \frac{(1 + \tau_{kist})}{(1 - \tau_{yist})},$$

$$1 + \tau_{kist} = \frac{\alpha_s}{1 - \alpha_s} \cdot \frac{\omega_t \cdot L_{ist}}{R_t \cdot K_{ist}}. \tag{9}$$

Foster et al. (2008) distinguishes between physical productivity, denoted as $TFPQ_{ist}$, and revenue productivity, denoted as $TFPR_{ist}$. In the absence of distortions, more capital and labor should be allocated to plants with higher physical productivity $TFPQ_{ist}$

until their increased output leads to a lower price, equalizing their revenue productivity $TFPR_{ist}$ with that of smaller plants.

We also can get $TFPR_{ist}$ as a proportional to geometric mean of the marginal revenue products of capital and labor:

$$TFPR_{ist} = \frac{\sigma}{\sigma - 1} \cdot \left[\frac{MRPK_{ist}}{\alpha_s}\right]^{\alpha_s} \cdot \left[\frac{MRPL_{ist}}{1 - \alpha_s}\right]^{1-\alpha_s} \tag{10}$$

With some algebraic manipulation, the expression for TFPR can show that, in the absence of distortions, it would be equalized across firms:

$$TFPR_{ist} = \frac{\sigma}{\sigma - 1} \cdot \left[\frac{R_t}{\alpha_s}\right]^{\alpha_s} \cdot \left[\frac{\omega_t}{1 - \alpha_s}\right]^{1-\alpha_s} \cdot \frac{(1 + \tau_{kist})^{\alpha_s}}{1 - \tau_{yist}} \tag{11}$$

To estimate productivity, it is important to note that firms' output Y_{ist} is not directly observable. Therefore, we manipulate the model's equations to derive a feasible expression for productivity A_{ist}:

$$A_{ist} = \kappa_{st} \cdot \frac{(P_{ist} Y_{ist})^{\frac{\sigma}{\sigma-1}}}{K_{ist}^{\alpha_s} L_{ist}^{1-\alpha_s}}. \tag{A19}$$

The scalar $\kappa_{st} = \frac{(P_{st} Y_{st})^{-\frac{1}{\sigma-1}}}{P_{st}}$ is not directly observable. To address this, Hsieh and Klenow (2009) propose setting $\kappa_{st} = 1$, arguing that this assumption does not affect relative productivity comparisons or the estimation of reallocation gains.

After aggregating across all sectors, we obtain a measure of overall misallocation and the potential output gains for the entire economy. The following equation represents the ratio of actual output to the efficient output in a misallocation framework:

$$\frac{Y_t}{Y_t^*} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(\frac{A_{ist}}{\overline{A}_{st}} \cdot \frac{\overline{TFPR}_{st}}{TFPR_{ist}}\right)^{\sigma-1}\right]^{\frac{\theta_{st}}{\sigma-1}}$$

2.2 Speculative Activity Under the JGTRRA Dividend Tax Shock

Understanding the mechanics of short selling is fundamental for understanding the dynamics of the market. In a short sale, an investor initiates a position by borrowing shares—typically incurring a fee—from another investor. If the stock's price subsequently declines, the investor repurchases the shares at a lower cost to close the position, returns the borrowed shares, and retains the difference as profit. Conversely, if the stock price increases, the investor may face substantial losses, as the repurchase cost can exceed the proceeds from the initial sale.

Short selling plays a crucial role in reducing market information asymmetry by enhancing transparency and facilitating the early detection of adverse practices. Fang et al. (2016) and Hirshleifer et al. (2011) demonstrate that short selling can mitigate earnings management, assist in detecting fraud, and improve market efficiency.

Moreover, a substantial body of literature examines the multifaceted effects of short selling, thereby establishing it as a central topic in finance research. Chague et al. (2017), Chen et al. (2022) and Fang et al. (2016) explore various dimensions of short selling and its market implications. In particular, Bessler and Vendrasco (2021) analyzes a short-selling ban enacted in March 2020 during the COVID-19 pandemic, offering valuable insights into the consequences of restricting short-selling activities.

We follow Meng et al. (2020), who concludes that short selling affects firms' financial constraints under certain conditions. As negative information spreads, firms with high short interest face increased financing costs and reduced access to external capital. This effect is particularly pronounced in companies with higher credit risk and greater information asymmetry, reinforcing the negative information hypothesis.

The Job and Growth Tax Relief Reconciliation Act (JGTRRA) of 2003 is a tax law passed by the United States Congress on May 23, 2003, reducing the maximum federal tax rate on qualified dividends from 38.6% to 15%. Auerbach and Hassett (2005) discuss the timing of the approval process, noting that the reduction in dividend taxation had barely been debated before December 2002. Therefore, we do not need to be concerned about anticipatory effects.

We leverage this tax policy shock to examine its impact on short selling, with a particular focus on firms' reactions. Building on the findings of Thornock (2013), we analyze how the JGTRRA dividend tax cut influenced short-selling activity. According to Thornock (2013), dividend taxation affects short selling through the "loan and reimbursement effect," which arises from the different tax treatments of qualified and unqualified dividends. In a typical short sale, the short seller must reimburse the lender for any dividends paid out during the borrowing period. However, these reimbursement payments may not receive the same preferential tax treatment as qualified dividends.

To illustrate the JGTRRA's impact on short selling, we present a numerical example described in Han et al. (2024):

Consider an investor in the *35% marginal tax bracket* holding *100,000 shares* of a company that distributes an annual dividend of *$1.00 per share*. Following the *JGTRRA*, this total dividend of *$100,000* would be taxed at *15%*, resulting in *$15,000* in taxes. However, if the investor lends the shares, the tax liability would increase to *$35,000*, as the ordinary income tax rate applies. This *$20,000 tax differential* represents a significant economic impact.

The JGTRRA dividend tax cut had a profound impact on corporate behavior and financial markets, particularly in the context of capital allocation and short selling activity. One of the key mechanisms through which this reform influenced financial markets was the differential tax treatment of dividends, which introduced distortions in stock lending markets. Similar to the loan and reimbursement effects described by Thornock (2013), short sellers were required to compensate lenders for dividends paid while the stock was on loan. However, these repayments—known as substitute dividends—were taxed as ordinary income, rather than benefiting from the preferential tax rates on qualified dividends. This tax discrepancy likely contributed to shifts in equity lending supply, fluctuations in short interest levels, and changes in overall market liquidity around dividend record dates.

While previous studies have examined the JGTRRA's impact on short selling and financial indicators as in Thornock (2013), Han et al. (2024), Chetty and Saez (2005) and Matta et al. (2025), its broader implications for resource misallocation and capital efficiency remain largely unexplored. By altering investment incentives for both firms and investors, the JGTRRA may have unintentionally disrupted capital allocation, leading to distortions in firm-level investment decisions, reduced productivity, and inefficiencies in overall market dynamics. These gaps in the literature highlight the need for further investigation.

Using data on U.S. manufacturing firms from the Compustat North American Fundamentals Annual database, this study seeks to advance the understanding of how tax policy shocks contribute to capital misallocation and financial market distortions. By examining firm-level responses in both investment and short-selling activities, we aim to shed light on the unintended economic consequences of dividend tax reforms.

In this study, we analyze how the JGTRRA dividend tax cut created a quasi-natural experiment to examine the allocation of resources across firms. Since short selling acts as a mechanism to absorb negative perspectives about firms, companies with higher levels of operations may face greater difficulties in accessing credit markets due to speculation. A restrictive shock to this mechanism, particularly affecting dividend-paying firms, provides a unique setting to assess its consequences.

3 Data

Our main database is *Compustat's North American Fundamentals Annual*, which provides detailed firm-level balance sheet information and serves as an important source for financial analysis. The use of Compustat data can be motivated by several key points as highlighted by Uras and Wang (2024). Compustat offers detailed balance sheet data to identify sources of firm-level inefficiency and quantitative evaluations of misallocation and sectoral productivity. Furthermore, it is particularly suited for analyzing organizational design and technique choice distortions in larger-scale establishments, which are better represented among publicly traded firms covered by this database.

Our baseline sample covers the years *1980 to 2018*. The early 1980s were marked by a series of tax reforms that shaped the taxation of dividends, culminating in the Tax Reform Act of 1986, which eliminated preferential treatment for dividends and fully taxed them under ordinary income rates. This structure remained in place until the JGTRRA of 2003 (Han et al. (2024)). By extending our sample period to begin in 1980, we capture a broader historical context of dividend taxation, including the transition from previous tax regimes to the uniform taxation of dividends under ordinary income rates. This allows us to analyze the effects of dividend taxation over a more extended period while ensuring consistency in the tax environment for the majority of our sample, minimizing potential confounding effects from tax policy changes.[10]

In line with the model's framework, our analysis focuses on firms in the manufacturing sector, identified by Standard Industrial Classification (SIC) codes ranging from 2000 to 3999. We exclude firm-year observations with either missing, equal to zero or negative values for important variables, including total assets (Compustat item *at*), sales (Compustat item *sale*), employees (Compustat item *emp*), and property, plant, and equipment (Compustat item *ppent*). The distribution of the number of firms across industries is shown in Table 1.

To ensure consistency, we restrict the sample to firms reporting financial data in U.S. dollars (Compustat item *curcd*). We drop data with missing values in the dividend variable (Compustat item *dv*). All monetary variables are deflated to constant 2017 values using the annual GDP deflator provided by FRED.

Information on labor expenses is limited in Compustat. Therefore, we construct it as the product of employees (*emp*) and labor costs estimated from the National Bureau of Economic Research and the US Census Bureau's Center for Economic Studies (NBER-CES) Manufacturing Industry Database. To address missing values, a hierarchical approach is employed using SIC codes of three, two, and one digit.

[10]For more details regarding the history of dividend tax rates in the U.S., please refer to `https://www.dividend.com/taxes/a-brief-history-of-dividend-tax-rates/`.

Table 1: **Classification of Manufacturing Industries**

SIC Name	Firms	Industry
Chemicals	1850	2800-2899
Misc. Manufacturing	1496	3800-3999
Electronics	1443	3600-3699
Machinery	1221	3500-3599
Food	500	2000-2099
Transport Equip.	425	3700-3799
Fabricated Metal	327	3400-3499
Primary Metal	277	3300-3399
Printing	264	2700-2799
Plastics	255	3000-3099
Apparel	217	2300-2399
Paper	178	2600-2699
Stone/Concrete	152	3200-3299
Textiles	147	2200-2299
Petroleum	129	2900-2999
Wood	111	2400-2499
Furniture	107	2500-2599
Leather	47	3100-3199
Tobacco	23	2100-2199

Note: Number of firms by manufacturing sector (4-digit SIC). **Source:** Compustat's North American Fundamentals Annual.

3.1 Key variables

The key firm-level variables used for identification and aggregation purposes are constructed as follows:

1. **Labor (L_{ist}):** Labor is measured as the total number of employees reported in Compustat *(emp)* for firm i, sector s, and year t.

2. **Labor Expenses ($\omega_t \cdot L_{ist}$):** Labor expenses are constructed as the product of the total number of employees *(emp)* from Compustat and the aggregate wage per employee (w_t), which is derived from the NBER-CES Manufacturing Industry Database.

3. **Salaries (ω_t):** The average wage per employee is sourced from the NBER-CES Manufacturing Industry Database.

4. **Capital (K_{ist}):** It is calculated using the property, plant, and equipment data items from Compustat *(ppent)*.

5. **Value Added ($P_{ist} \cdot Y_{ist}$):** Following the approach of Gondhi (2023), the key variables for this estimation are the beginning-of-period capital stock (*ppent*), the stock of labor (L_{ist}), and value added. Value added is constructed as the difference between sales (*sale*) and materials. While sales (*sale*) are directly available in Compustat, materials are constructed as total expenses minus labor expenses. Total expenses are calculated as sales (*sale*) minus the sum of operating income after depreciation (*oiadp*) and depreciation (*dp*).

6. **Capital Share (α_s):** The capital share for each firm (α_{ist}) is computed as the fraction of output not allocated to labor costs, weighted by the firm's share of total sectoral output. Specifically, we define:

$$\alpha_{is} = \sum_t \left[\left(1 - \frac{\omega_t \cdot L_{ist}}{P_{ist} \cdot Y_{ist}}\right) \cdot \frac{P_{ist} \cdot Y_{ist}}{\sum_{i \in M_s} P_{ist} \cdot Y_{ist}} \right]$$

where:

- ω_t is the wage rate at time t,
- L_{ist} represents the labor expenses of firm i in sector s at time t,
- $P_{ist} \cdot Y_{ist}$ is the value-added of firm i in sector s at time t,
- $\sum_{i \in M_s} P_{ist} \cdot Y_{ist}$ is the total sectoral value-added, summing over all firms M_s in the sector s.

The aggregate capital share for sector s, denoted as α_s, is then obtained by summing all firms within the sector:

$$\alpha_s = \sum_{i \in M_s} \alpha_{is} = \sum_{i \in M_s} \sum_t \left(1 - \frac{\omega_t \cdot L_{ist}}{P_{ist} \cdot Y_{ist}}\right) \cdot \frac{P_{ist} \cdot Y_{ist}}{\sum_{i \in M_s} P_{ist} \cdot Y_{ist}}$$

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3.2 Data description

We present summary statistics of firms across selected years in Table 2, including the number of firms, value-added, capital, and labor expenses. The data reveal a significant increase in firm-level economic activity over time, with notable growth in value-added and capital. All variables experienced substantial growth throughout the period, indicating a continuous expansion in firms' financial and operational scale. This trend is particularly pronounced after 2000, reflecting broader economic transformations and a marked increase in capital intensity.

Table 2: **Summary Statistics by Year**

Year	**Firms**	**Value-Added**	**Capital**	**Labor Expenses**
1980	2411	96.86	93.44	59.17
1985	2396	159.63	175.41	99.77
1990	2307	265.39	306.15	149.72
1995	2791	336.48	381.29	180.02
2000	2469	568.94	554.04	295.33
2005	2108	986.82	958.19	494.39
2010	1819	1508.12	1592.76	714.09
2015	1535	2101.51	2521.62	1083.91

Note: Summary statistics of firms by year, showing the number of firms, value-added, capital, and labor expenses. All values are in millions. **Source:** Compustat North American Fundamentals Annual.

Table 3 presents descriptive statistics for the distribution of six firm-level variables across firms within the manufacturing industry clusters analyzed in our quantitative study. The data set spans 1980-2018, allowing us to capture the heterogeneity at the firm level over time and examine long-term trends in the dynamics of capital, labor, and productivity.

Table 3: **Summary Statistics of Firm Variables**

Variable	**Max**	**Mean**	**Min**	**Obs**	**SD**
$\ln(K_{ist})$	12.51	3.07	-7.84	85,091	2.84
$\ln(\omega_t \cdot L_{ist})$	11.53	3.34	-5.34	85,091	2.32
$\ln(L_{ist})$	6.78	0.10	-6.91	85,091	2.14
$\ln(P_{ist} \cdot Y_{ist})$	11.95	3.68	-7.85	85,091	2.56
$\ln(TFPR_{ist})$	11.82	2.23	-7.95	85,091	0.82
$\ln(TFPQ_{ist})$	15.36	4.07	-11.48	85,091	1.70

Note: This table presents summary statistics for firm variables, including maximum (Max), mean, minimum (Min), standard deviation (SD), and number of observations (Obs). All values are in natural logarithms. **Source:** Compustat's North American Fundamentals Annual.

Table 4 presents the distribution of $\ln(\tau_{kist})$ across different industry clusters. Some industries exhibit relatively high average values, such as *Leather and Leather Products* and *Apparel and Finished Products*, whereas others, such as *Petroleum Refining* and *Primary Metal Industries*, display much lower means. The standard deviation also differs considerably, with industries like *Leather and Leather Products* and *Tobacco Products* showing relatively low dispersion, while *Petroleum Refining* and *Chemicals and Allied Products* exhibit greater variability.

Finally, we work with an unbalanced panel, allowing for free firm entry while also ensuring that our analysis is not subject to survival bias. Moreover, at the aggregate level, we do not find strong evidence of sectoral heterogeneity.

Table 4: **Distributional Properties of** $\ln(\tau_{kist})$

Industry Cluster	**Mean**	**Std. Dev.**	**Min**	**Max**	**# Obs.**
Electronic and Electrical Equipment	2.472	1.179	-6.864	8.706	15034
Miscellaneous Manufacturing	2.583	1.033	-3.850	8.227	13285
Industrial and Commercial Machinery	2.445	0.949	-4.395	9.209	12044
Chemicals and Allied Products	2.540	1.371	-5.179	11.360	11420
Food and Kindred Products	1.757	1.062	-5.501	7.480	4967
Transportation Equipment	2.030	0.976	-3.977	7.378	4800
Fabricated Metal Products	1.711	0.940	-6.166	5.226	3476
Primary Metal Industries	1.109	1.155	-8.902	7.239	3144
Rubber and Miscellaneous Plastic Products	1.621	0.997	-3.046	4.942	2532
Printing and Publishing	2.188	1.220	-3.986	6.625	2509
Paper and Allied Products	1.078	1.170	-7.122	4.871	2083
Apparel and Finished Products	2.561	1.141	-1.406	11.078	2053
Stone, Clay, Glass, and Concrete	1.153	1.225	-4.627	6.707	1533
Petroleum Refining	0.860	1.299	-5.180	8.595	1443
Textile Mill Products	1.415	0.924	-5.804	5.162	1392
Furniture and Fixtures	1.908	0.796	-2.207	6.438	1300
Lumber and Wood Products	1.252	1.282	-5.286	5.092	1223
Leather and Leather Products	3.013	0.866	0.669	5.988	600
Tobacco Products	2.691	0.709	1.376	4.851	253

Note: This table presents the distributional properties of $\ln(\tau_{kist})$ across different industry clusters. The values represent the mean, standard deviation, minimum, and maximum for each category. The last column shows the number of observations per industry. Less than 1% of observations have missing values due to the log transformation, as the logarithm of zero or negative values does not exist. **Source:** Compustat's North American Fundamentals Annual.

4 Research Design

This section outlines our empirical strategy to evaluate the impact of the JGTRRA on various economic outcomes, including the capital wedge (τ_{kist}). We focus on how the reform differentially affected "treated" firms—particularly those paying dividends—relative to "control" firms that did not pay dividends.

To capture these differential effects over time, we employ a two-way fixed effects (TWFE) model, including both firm and time fixed effects. By leveraging variation in treatment status across firms and over time, this framework allows us to isolate the causal impact of the JGTRRA on economic distortions.

4.1 Empirical Strategy

As defined in Chetty and Saez (2005), dividends can be classified into two types of payouts: regular dividends and special dividends. Regular dividends are periodic and recurrent, typically distributed quarterly, annually, or semiannually, whereas special dividends are one-time, nonrecurring payments that do not necessarily indicate a firm's long-term commitment to distributing earnings.

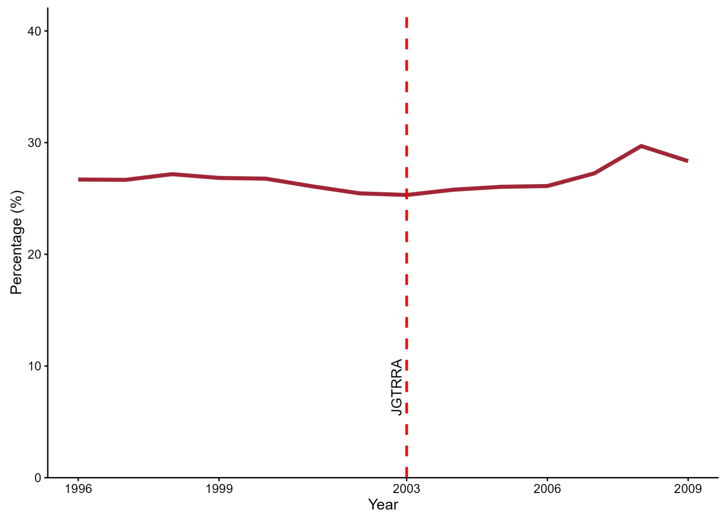

Figure 1: **Dividend-Paying Firms Over Time**

Note: This figure shows the proportion of firms classified as consecutive dividend payers, defined as those paying dividends for at least five consecutive years. The cutoff year of 2003 corresponds to the implementation of the JGTRRA. **Source:** Compustat's North American Fundamentals Annual.

Our treatment group consists of dividend-paying firms, but due to data limitations, where observations are only available at an annual frequency, we cannot rely solely on dividend payments in 2002 to classify firms. This constraint is essential to avoid misclassifying firms that issued special dividends, which are one-time distributions, rather than those that consistently engage in regular dividend payments.

To ensure a more precise classification, we define treated firms as those that paid dividends at least five times between *1980 to 2002*, establishing a baseline for firms with a consistent dividend-paying history. Firms that do not meet this threshold are assigned to the control group, allowing for a structured comparison between companies with a long-term commitment to dividends and those that do not regularly distribute earnings to shareholders.[11]

We can see in Figure 1 that the proportion of firms classified as consecutive dividend payers remained relatively stable before and after the implementation of the JGTRRA in 2003. However, to avoid capturing firms that directly responded to the policy change, we exclude those that started paying dividends after 2003 from our analysis.

Another important concern is how firms might respond to the JGTRRA. Although changes in dividend policies are relatively uncommon, we investigate whether significant adjustments were made in the period surrounding the reform. Figure 2 presents evidence on firm status by dividend payment behavior, based on a balanced panel from 1996 to 2006. It categorizes firms into those that continued paying dividends, stopped paying dividends, or initiated payments after 2003. However, since this was a one-time change, it should not influence the long-term evolution of anomalies. As we can see, there were stable firms that continued paying dividends, as well as those that consistently did not pay dividends. However, to avoid capturing firms that directly responded to the policy change, we exclude those that started paying dividends after 2003 from our analysis.

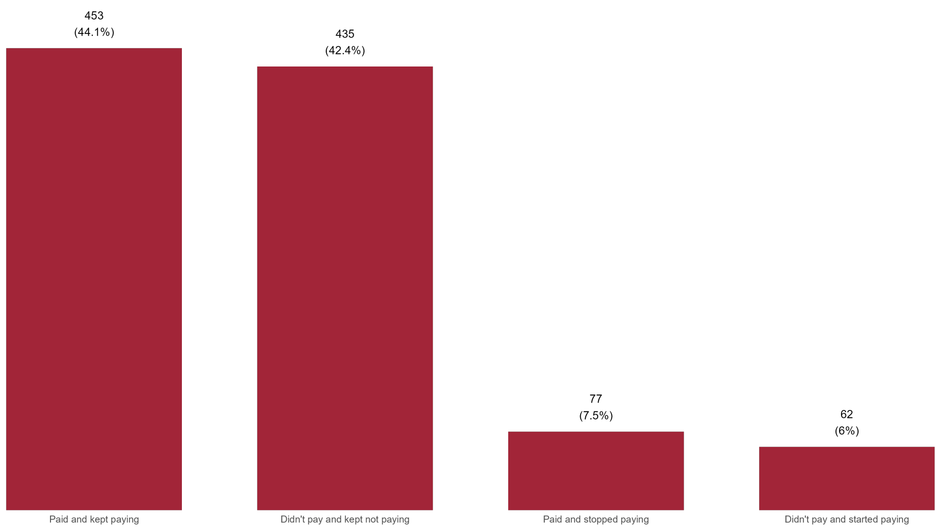

Figure 2: **Firm Status by Dividend Payment Behavior**
Note: Dividend-paying firms are those that paid dividends at least five times. The 2003 cutoff marks the JGTRRA implementation. Categories include firms that continued, stopped, or started paying dividends after 2003. **Source:** Compustat's North American Fundamentals Annual.

[11] DeAngelo and DeAngelo (1990) shows that regular dividends are persistent over time.

After applying the necessary data cleaning procedures, we obtained a final sample of 7778 unique firms. Within this sample, 1656 firms (21.26%) are classified as treated, meaning they consistently paid dividends according to our defined criteria. The remaining 6132 firms (78.74%) form the control group, consisting of firms that did not meet the threshold for consecutive dividend payments. This classification ensures a structured comparison between companies with a long-term commitment to dividends and those without a consistent dividend distribution policy.

4.2 Estimation Setup

Identifying causality in finance and economics is inherently challenging, as randomized controlled trial (RCT) conditions are difficult to achieve in these fields. Therefore, a common approach is to rely on quasi-experimental methods, such as the JGTRRA, to estimate causal effects. As our treated and control groups have been defined, we must verify whether they follow parallel trends. To do so, we estimate the following Dynamic Difference-in-Differences specification:

Here, the variable $Divid_{ist}$ represents the treatment group of dividend-paying firms in year t, categorized as pre- or post-JGTRRA. The indicator variable $\mathbb{I}$ captures each year before and after the policy.

In Equation 12, the baseline is established by taking the year prior to JGTRRA as our reference period, normalizing $\beta_{2002} = 0$. We include firm fixed effects (ϕ_i) and time fixed effects (λ_t) to control for economic shocks affecting corporate tax structures across firms, as well as other temporal shocks influencing effective tax rates.

$$\ln(\tau_{kist}) = \sum_{j \neq 2002} \beta_j \cdot \mathbb{I}(j = t) \cdot Divid_{ist} + \phi_i + \lambda_t + \epsilon_{ist} \tag{12}$$

We expect to observe only non-significant coefficients in the pre-treatment period, meaning that β_j should not be statistically significant before JGTRRA. This would provide evidence that both groups followed similar trends in the outcome variable before the reform took place.

It is important to note that Equation 12 does not represent our causal estimation. Instead, this specification is used to assess the validity of the parallel trends assumption. By estimating the dynamic Difference-in-Differences model, we verify whether the pre-treatment coefficients β_j are statistically indistinguishable from zero, which would indicate that treated and control firms followed similar trends prior to the JGTRRA reform.

In Equation 13, we estimate a two-way fixed effects (TWFE) model to evaluate the causal effect of the JGTRRA on the capital wedge, denoted by τ_{kist}. The model includes firm fixed effects (ϕ_i) to capture time-invariant characteristics at the firm level, and time fixed effects (λ_t) to account for aggregate shocks that affect all firms in a given period. Specifically, the variable $Divid_i$ indicates whether a firm pays dividends, and $JGTRRA_t$ is a binary indicator that equals 1 when $t \geq 2003$, representing the post-JGTRRA period. The coefficient β_1 measures the policy's effect on the capital wedge among dividend-paying firms compared to non-dividend-paying firms.

In addition, following the corporate finance literature and the approaches in Matta et al. (2025) and Xuewen Kuang and Lin (2024), we include a set of lagged firm-level controls, denoted by $\mathbf{X}_{ist-1}$. Specifically, it consists of $\ln(\text{Age}_{i,t-1})$, $\ln(\text{Size}_{i,t-1})$, and $\ln(\text{ROA}_{i,t-1})$. These controls are multiplied by a vector of coefficients Γ. We lag all control variables by one period to mitigate potential endogeneity in the model.

Finally, ϵ_{ist} represents the idiosyncratic error term. This specification follows the methodology recommended by Petersen (2008), ensuring appropriate standard error adjustments for both firm-level and temporal correlations.

$$\ln(\tau_{kist}) = \beta_0 + \beta_1 \Big(JGTRRA_t \cdot Divid_i \Big) + \mathbf{X}_{ist-1}\Gamma + \phi_i + \lambda_t + \epsilon_{ist}, \tag{13}$$

Furthermore, we extend our Differences-in-Differences approach to analyze its impact on additional firm-level variables, allowing for a broader assessment of the JGTRRA's effects beyond the capital wedge.

5 Short Selling Constraints and Capital Misallocation: Results and Analysis

In this section, we present the main findings regarding the impact of the JGTRRA dividend tax cut on capital misallocation and short-selling activity. The overall results suggest that the restriction on short selling led to a reducing capital distortions.

5.1 Effect of Short Selling constrains on Capital Misallocation

Our initial estimates rely on a TWFE approach, as specified in Equation 13. The dependent variable in our setup is $\ln(\tau_{kist})$, which captures distortions in capital allocation across firms. Our treatment group consists of dividend-paying firms, defined as those that paid dividends at least five times between 1980 and 2002, establishing a baseline for firms with a consistent dividend-paying history. The control group consists of firms that either never paid dividends or paid them infrequently before 2003.

To quantify the impact of the JGTRRA dividend tax cut on capital misallocation, we estimate the average treatment effect (ATE) of the policy on $\ln(\tau_{kist})$. Our identification strategy leverages the exogenous nature of the JGTRRA reform, allowing us to compare the evolution of capital distortions between treated and control firms over time.

Our results, presented in Table 5, confirm that dividend-paying firms experienced a significant reduction in capital distortions following the JGTRRA reform. The estimated coefficient on the interaction term $JGTRRA_t \cdot Divid_i$ is negative and statistically significant across different model specifications, indicating that treated firms faced lower capital misallocation relative to the control group.

Table 5: **Effect of Treatment on** $\ln(\tau_{kist})$

	All Firms		**Small Firms**		**Large Firms**	
	(1)	(2)	(3)	(4)	(5)	(6)
$JGTRRA_t \cdot Divid_i$	0.20***	-0.32***	-0.17*	-0.35**	0.21***	-0.19***
	(0.04)	(0.03)	(0.07)	(0.05)	(0.05)	(0.04)
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects:						
Year FE	✓	✓		✓		✓
Firm FE	✓	✓		✓		✓
Fit statistics:						
Observations	76,358	76,358	37,567	37,567	38,791	38,791
R^2	0.16	0.82	0.04	0.79	0.04	0.83
Within R^2	–	0.00	–	0.01	–	0.02

Note: This table presents the results of a TWFE model estimated using equation 13. Columns (1)–(2) use the full sample (*All Firms*), while Columns (3)–(4) restrict the sample to *Small Firms*, and Columns (5)–(6) to *Large Firms*. The dependent variable is $\ln(\tau_{kist})$. Standard errors (in parentheses) are clustered at the firm level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firms are classified as small (large) if their total assets are below (above) the median in a dynamic rule by year.

This effect remains robust even after we modify our measure of aggregate value, acknowledging that such measures likely contain substantial measurement error (Bils et al. (2021)). Following Whited and Zhao (2021), Value Added is computed as the sum of *oibdp* and imputed wages. Our results are consistent with our baseline findings: the restrictive short-selling shock induced by the JGTRRA reduced the capital wedge for dividend-paying firms.

To explore heterogeneity, we build a binary indicator that classifies firms as small if their total assets fall below the annual median (and as large otherwise). Our analysis reveals that smaller firms were more affected by the restrictive speculative shock. This finding suggests that, due to their lower bargaining power and limited access to financing sources, these firms are more vulnerable to adverse market shocks, resulting in greater distortions in capital allocation and investment decisions.

The main result of this interaction is an estimated coefficient indicating that short selling constraints can reduce capital distortion levels by approximately $-27.3\%^{***}$, a significant reduction, using firms from the world's largest financial market. This result[12] suggests that limiting short selling may play a role in improving capital allocation efficiency.

Overall, these findings provide strong empirical evidence that reductions in short selling activity can alleviate capital misallocation, supporting the hypothesis that speculative market behavior can create financial frictions that play a crucial role in shaping firms' efficiency. In particular, firms facing negative market sentiment tend to experience greater financial constraints, as pessimistic expectations can increase the cost of capital and limit investment opportunities.

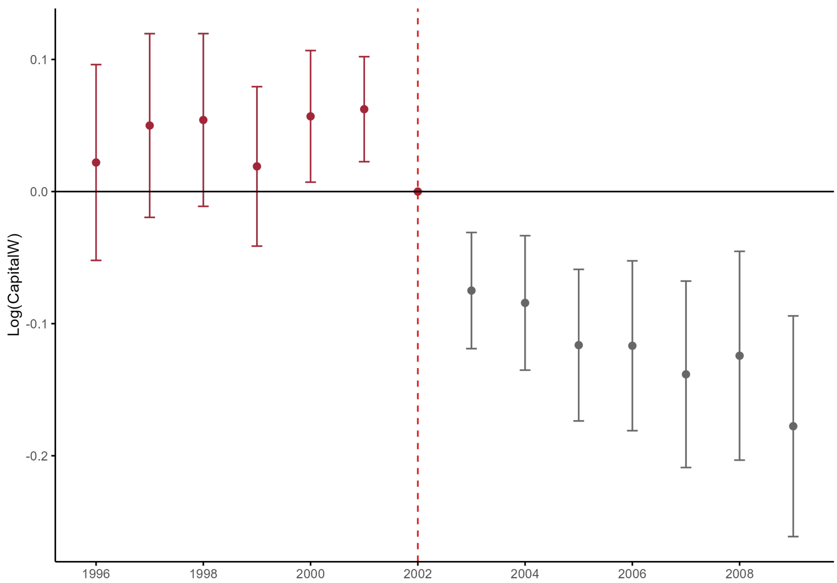

Figure 3: **Leads and Lags:** $\ln(\tau_{kist})$

Note: This figure presents the dynamic effects of the policy change on $\ln(\tau_{kist})$ using Equation 12. The vertical dashed line represents the baseline year, with leads capturing pre-trends and lags showing post-treatment effects. **Source:** Compustat's North American Fundamentals Annual.

[12] Denoting the DiD parameter for the ln specification as β_1, the transformation $\exp(\beta_1) - 1$ yields the precise proportional difference in growth rates.

5.2 The Effect of JGTRRA on Capital Misallocation Over Time

To understand the dynamics of the effect of the short selling constraint reduction on the capital wedge before and after the JGTRRA, we estimate Equation 12. This specification allows us to assess the evolution of capital misallocation over time, identifying potential dynamic effects of the reform. The absence of significant pre-treatment trends reinforces the validity of the DiD strategy, while the evolution of the β_j coefficients in the post-reform period enables us to analyze the persistence of the tax policy's impact on capital allocation efficiency.

The results suggest that before JGTRRA, the estimated coefficients remain close to zero and are not statistically different from it, supporting the parallel trends assumption. However, following the reform, there is a significant and persistent decline in $\ln(\tau_{kist})$ among treated firms, indicating a reduction in capital wedges post-JGTRRA. This pattern is consistent with the hypothesis that the tax cut altered firms' financial conditions, leading to a decrease in capital misallocation.

5.3 Productivity Distributions

A common approach in the misallocation literature is to examine the distribution of productivity measures over time. Foster et al. (2008) emphasizes the importance of studying these distributions to better understand resource allocation dynamics and market efficiency. Figure 4 presents the distribution of TFPQ for selected years: 1997, 2002, and 2008. The distribution of physical productivity is adjusted by sectoral productivity in the absence of distortions, providing a clearer view of underlying efficiency patterns.

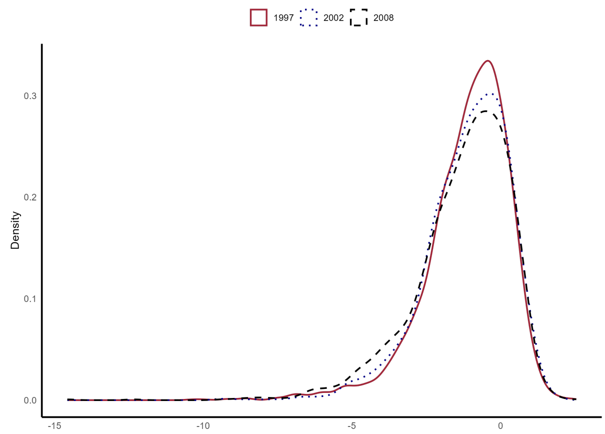

Figure 4: **Distribution of Physical Productivity**

Note: This figure illustrates the distribution of physical productivity across firms for selected years, following the transformation $\ln\left(\frac{A_{ist}\cdot M_{st}^{\frac{1}{\sigma-1}}}{\overline{A}_{st}}\right)$. **Source:** Compustat's North American Fundamentals Annual.

A noticeable feature is the evolution of the left tail of the distribution. In 1997, the left tail is thicker, suggesting that policies or market conditions may have allowed the survival of relatively inefficient firms with lower TFPQ. Over time, this tail becomes thinner in 2002 and even more so in 2008, indicating a decline in the persistence of low-productivity firms. This pattern aligns with market selection mechanisms that gradually improved resource allocation efficiency. Despite these changes in the left tail, the overall shape of the distribution remains relatively stable, with a consistent peak around zero in all periods. The gradual decline in density on the left side suggests that inefficient firms either exited the market or improved their productivity levels over time, reinforcing the role of competitive pressures in firm dynamics.

Table 6: **Dispersion of TFPQ**

	Std Dev			**75 - 25**			**90 - 10**		
Year	Treated	Non-Treated	All	Treated	Non-Treated	All	Treated	Non-Treated	All
1996	0.66	0.82	**0.71**	1.21	1.58	**1.60**	2.41	3.09	**3.10**
1997	0.70	0.84	**0.75**	1.25	1.70	**1.67**	2.45	3.37	**3.26**
1998	0.66	0.81	**0.71**	1.25	1.63	**1.65**	2.37	3.29	**3.23**
1999	0.66	0.83	**0.72**	1.30	1.73	**1.73**	2.53	3.30	**3.29**
2000	0.63	0.76	**0.68**	1.30	1.83	**1.77**	2.55	3.50	**3.36**
2001	0.59	0.73	**0.64**	1.38	1.91	**1.82**	2.47	3.66	**3.48**
2002	0.60	0.75	**0.66**	1.35	1.83	**1.83**	2.58	3.55	**3.40**
2003	0.64	0.75	**0.69**	1.42	1.82	**1.79**	2.65	3.62	**3.38**
2004	0.61	0.70	**0.66**	1.38	1.77	**1.71**	2.48	3.53	**3.29**
2005	0.59	0.67	**0.64**	1.35	1.81	**1.76**	2.48	3.55	**3.32**
2006	0.58	0.65	**0.62**	1.29	1.87	**1.76**	2.56	3.44	**3.34**
2007	0.60	0.68	**0.64**	1.31	1.86	**1.84**	2.60	3.58	**3.47**
2008	0.69	0.72	**0.71**	1.44	2.01	**1.98**	2.67	4.12	**3.83**

Note: Std Dev represents the standard deviation; 75 - 25 denotes the difference between the 75th and 25th percentiles, and 90 - 10 represents the difference between the 90th and 10th percentiles. The adjusted distribution of physical productivity across firms for selected years, following the transformation $\ln\left(\frac{A_{ist}\cdot M_{st}^{\frac{1}{\sigma-1}}}{\overline{A}_{st}}\right)$. **Source:** Compustat North America Fundamentals Annual.

Table 6 illustrates the dispersion of TFPQ, measured using three key statistics: standard deviation (Std Dev) and interquartile ranges. These metrics allow for an assessment of productivity variation among firms over time and the differences between treated and non-treated groups, particularly in the aftermath of the JGTRRA implementation.

The central dispersion, captured by the interquartile range (75-25), exhibits increasing fluctuations throughout the period. However, a key aspect to highlight is that the 90-10 interquartile range remains consistently high, indicating a persistent gap between highly productive firms and those with lower productivity. This pattern suggests that, despite potential improvements in resource allocation over time, structural factors continue to hinder a more pronounced convergence in firm productivity. Additionally, non-treated firms exhibit higher dispersion than treated firms, emphasizing greater heterogeneity within this group.

Furthermore, it is important to emphasize that the gap in dispersion between the two groups remains relatively stable over time, suggesting that dividend-paying firms operate under structurally different conditions compared to non-paying firms. This pattern may reflect differences in credit access, financial constraints, investment strategies, or greater operational stability among firms that regularly distribute dividends.

We also analyze the distribution of Revenue Productivity over time (see Figure 5). The distribution is highly concentrated around zero, with a pronounced and consistent peak across all selected years. Here, TFPR shows less dispersion, suggesting that differences in firms' revenue-generating efficiency are relatively smaller. It is important to note that TFPR is equalized across sectors—since there is no firm-specific component beyond distortions, so the reduced variability is indicative of improved resource allocation at firm level.

The left tail of the distribution remains relatively stable over periods, suggesting that low-revenue productivity firms continue to exist over time. However, slight variations in the density of the peak and the tails might indicate changes in market conditions, pricing power, or competition dynamics. The stability of the distribution suggests that while the revenue-generating capabilities of firms can fluctuate, the overall misallocation in terms of revenue productivity has remained relatively constant during the period analyzed.

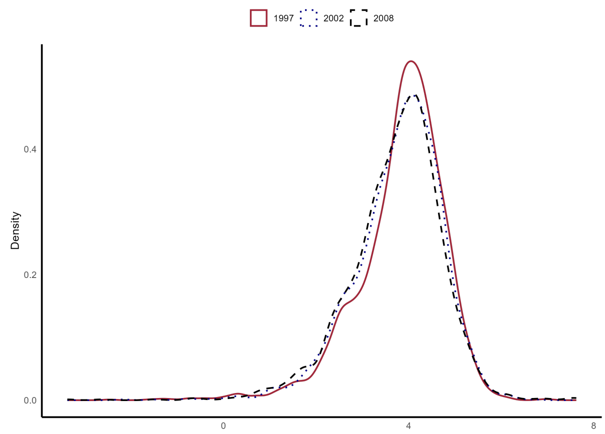

Figure 5: **Distribution of Revenue Productivity**

Note: This figure illustrates the adjusted distribution of revenue productivity across firms for selected years, following the transformation $\ln\left(\frac{TFPR_{ist}}{TFPR_{st}}\right)$. **Source:** Compustat's North American Fundamentals Annual.

Table 7 follows the same structure as previously presented. The statistics remain relatively stable over time. However, it is important to highlight that the 90-10 interquartile range exhibits a growing and significant difference between highly productive firms and those with lower productivity, indicating the persistence of heterogeneity in the market.

In particular, while the control group shows an increase in dispersion measures over time, the treatment group experiences a slight decline. This suggests that the restrictive short-selling shock reduced financial frictions for the treated firms, potentially improving capital allocation and leading to a more homogeneous distribution of productivity within this group. In contrast, the control group, unaffected by the shock, continues to experience increasing dispersion, reinforcing the role of financial frictions in shaping firm heterogeneity.

These findings emphasize the role of market selection mechanisms, capital allocation efficiency, and firm-level constraints in shaping productivity dispersion over time. While some degree of misallocation appears to persist, the long-term trends suggest a dynamic competitive environment where firms continuously adjust to market pressures.

Table 7: **Dispersion of TFPR**

	Std Dev			**75-25**			**90-10**		
Year	Treated	Non-Treated	All	Treated	Non-Treated	All	Treated	Non-Treated	All
1996	0.83	0.80	**0.83**	1.12	1.07	**1.09**	2.09	2.27	**2.20**
1997	0.84	0.81	**0.84**	1.09	1.05	**1.06**	2.13	2.30	**2.24**
1998	0.83	0.78	**0.82**	1.11	1.10	**1.11**	2.13	2.38	**2.26**
1999	0.82	0.80	**0.82**	1.10	1.10	**1.10**	2.12	2.32	**2.25**
2000	0.83	0.80	**0.82**	1.12	1.16	**1.12**	2.09	2.44	**2.29**
2001	0.85	0.82	**0.84**	1.14	1.19	**1.17**	2.16	2.55	**2.36**
2002	0.85	0.77	**0.83**	1.15	1.13	**1.15**	2.16	2.34	**2.27**
2003	0.85	0.79	**0.84**	1.11	1.16	**1.14**	2.14	2.44	**2.30**
2004	0.84	0.87	**0.85**	1.13	1.17	**1.15**	2.09	2.38	**2.26**
2005	0.84	0.91	**0.87**	1.12	1.23	**1.17**	2.10	2.39	**2.29**
2006	0.86	0.90	**0.87**	1.12	1.24	**1.20**	2.08	2.43	**2.28**
2007	0.85	0.90	**0.87**	1.12	1.17	**1.14**	2.08	2.48	**2.33**
2008	0.85	0.92	**0.88**	1.08	1.19	**1.14**	2.07	2.45	**2.35**

scriptsize **Note:** Std Dev represents the standard deviation; 75-25 denotes the interquartile range (difference between the 75th and 25th percentiles), and 90-10 represents the dispersion between the 90th and 10th percentiles. This table presents the adjusted distribution of revenue productivity across firms for selected years, following the transformation $\ln\left(\frac{TFPR_{ist}}{TFPR_{st}}\right)$. **Source:** Compustat North America Fundamentals Annual.

6 Concluding Remarks

This paper examined the impact of short selling constraints on capital misallocation within the framework of Hsieh and Klenow (2009). To investigate this relationship, we leveraged a quasi-natural experiment stemming from the *Job and Growth Tax Relief Reconciliation Act of 2003*.

By utilizing firm-level data from *Compustat's North American Fundamentals Annual* and applying robust econometric techniques, we identified a negative causal relationship between short selling constraints and capital wedges. Our findings highlight the role of taxation and speculative restrictions in shaping corporate financial policies. Specifically, we estimate that short selling constraints reduce capital distortions by approximately 27.3%.

We also find evidence of heterogeneity in the treatment effect. Our results indicate that smaller firms are more impacted by negative speculative shocks. This suggests that short selling constraints not only reduce overall capital distortions but may also improve capital allocation by mitigating the adverse effects of speculation on firms with lower bargaining power and limited financing options.

From a broader perspective, this research makes three key contributions. First, it advances the literature on productivity, financial frictions, and misallocation. Second, it sheds light on the regulatory mechanisms through which short selling affects capital allocation. Third, it builds upon the findings of Meng et al. (2020), who explored the effects of short selling on firms' financial constraints.

Despite the robustness of our results, some limitations remain. Our study relies on observational data, which, while carefully analyzed, is inherently constrained in establishing definitive causality. Additionally, the long-term effects of the JGTRRA remain an open question, requiring further investigation into its sustained impact on firm dynamics and market structures.

Future research could expand on these findings by leveraging higher-frequency data, such as semiannual reports, and incorporating credit line datasets to assess financial constraints through alternative channels. Additionally, new theoretical models could refine our understanding of tax-induced distortions. Comparative analyses with other tax reforms could also provide valuable insights into the generalizability of our findings across different fiscal environments.

In conclusion, this paper underscores the significance of tax policy in shaping corporate investment decisions and overall real market efficiency. The empirical evidence presented offers valuable insights for policymakers, helping them design tax reforms that balance corporate incentives with broader economic efficiency considerations.

References

[1] Auerbach, A. J. and Hassett, K. A. (2005). The 2003 dividend tax cuts and the value of the firm: An event study. Working Paper w11449, National Bureau of Economic Research (NBER).

[2] Banerjee, A. V. and Duflo, E. (2005). Chapter 7 growth theory through the lens of development economics. volume 1 of *Handbook of Economic Growth*, pages 473–552. Elsevier.

[3] Banerjee, A. V. and Moll, B. (2010). Why does misallocation persist? *American Economic Journal: Macroeconomics*, 2(1):189–206.

[4] Bessler, W. and Vendrasco, M. (2021). The 2020 european short-selling ban and the effects on market quality. *Finance Research Letters*, 42:101886.

[5] Bils, M., Klenow, P. J., and Ruane, C. (2021). Misallocation or mismeasurement? *Journal of Monetary Economics*, 124:S39–S56. The Real Interest Rate and the MarginalProduct of Capital in the XXIst CenturyOctober 15-16, 2020.

[6] Chague, F., De-Losso, R., De Genaro, A., and Giovannetti, B. (2017). Well-connected short-sellers pay lower loan fees: A market-wide analysis. *Journal of Financial Economics*, 123(3):646–670.

[7] Chen, C., Restuccia, D., and Santaeulàlia-Llopis, R. (2023). Land misallocation and productivity. *American Economic Journal: Macroeconomics*, 15(2):441–65.

[8] Chen, Y., Da, Z., and Huang, D. (2022). Short selling efficiency. *Journal of Financial Economics*, 145(2, Part B):387–408.

[9] Chetty, R. and Saez, E. (2005). Dividend taxes and corporate behavior: Evidence from the 2003 dividend tax cut*. *The Quarterly Journal of Economics*, 120(3):791–833.

[10] Chirinko, R. S. (2008). : The long and short of it. *Journal of Macroeconomics*, 30(2):671–686. The CES Production Function in the Theory and Empirics of Economic Growth.

[11] Cusolito, A. P., Fattal Jaef, R. N., Mare, D. S., and Singh, A. V. (2024). The Role of Financial (Mis)allocation on Real (Mis)allocation: Firm-level Evidence for European Countries. Policy Research Working Paper Series 10811, The World Bank.

[12] DeAngelo, H. and DeAngelo, L. (1990). Dividend policy and financial distress: An empirical investigation of troubled nyse firms. *The Journal of Finance*, 45(5):1415–1431.

[13] Fang, V. W., Huang, A. H., and Karpoff, J. M. (2016). Short selling and earnings management: A controlled experiment. *The Journal of Finance*, 71(3):1251–1294.

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

[15] Gondhi, N. (2023). Rational inattention, misallocation, and the aggregate economy. *Journal of Monetary Economics*, 136:50–75.

[16] Greenwood, J., Sanchez, J. M., and Wang, C. (2013). Quantifying the impact of financial development on economic development. *Review of Economic Dynamics*, 16(1):194–215. Special issue: Misallocation and Productivity.

[17] Grullon, G., Michenaud, S., and Weston, J. P. (2015). The real effects of short-selling constraints. *The Review of Financial Studies*, 28(6):1737–1767.

[18] Han, Y., Lu, Y. J., Xu, W., and Zhou, G. (2024). Mispricing and anomalies: An exogenous shock to short selling from jgtrra. *Journal of Empirical Finance*, 78:101537.

[19] Hirshleifer, D., Teoh, S. H., and Yu, J. J. (2011). Short arbitrage, return asymmetry, and the accrual anomaly. *The Review of Financial Studies*, 24(7):2429–2461.

[20] Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics*, 124(4):1403–1448.

[21] Matta, R., Rocha, S. H., and Vaz, P. (2025). Short selling and product market competition. *Journal of Banking Finance*, 171:107335.

[22] Meng, Q., Li, X., Chan, K. C., and Gao, S. (2020). Does short selling affect a firm's financial constraints? *Journal of Corporate Finance*, 60:101531.

[23] Midrigan, V. and Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, 104(2):422–58.

[24] Oberfield, E. (2013). Productivity and misallocation during a crisis: Evidence from the chilean crisis of 1982. *Review of Economic Dynamics*, 16(1):100–119. Special issue: Misallocation and Productivity.

[25] Petersen, M. A. (2008). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

[26] Reed, A. V. (2013). Short selling. *Annual Review of Financial Economics*, 5(Volume 5, 2013):245–258.

[27] Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11(4):707–720.

[28] Restuccia, D. and Rogerson, R. (2013). Misallocation and productivity. *Review of Economic Dynamics*, 16(1):1–10. Special issue: Misallocation and Productivity.

[29] Thornock, J. (2013). The effects of dividend taxation on short selling and market quality. *The Accounting Review*, 88(5):1833–1856.

[30] Uras, B. R. (2014). Corporate financial structure, misallocation and total factor productivity. *Journal of Banking Finance*, 39:177–191.

[31] Uras, B. R. and Wang, P. (2024). Misallocation, productivity and development with endogenous production techniques. *Journal of Development Economics*, 167:103251.

[32] Vasconcelos, R. d. S. (2017). Misallocation in the Brazilian Manufacturing Sector. *Brazilian Review of Econometrics*, 37(2).

[33] Whited, T. M. and Zhao, J. (2021). The misallocation of finance. *The Journal of Finance*, 76(5):2359–2407.

[34] Xuewen Kuang, Jing Jiang, C. L. and Lin, H. (2024). Short selling and total-factor productivity: Evidence from a quasi-natural experiment in china. *Emerging Markets Finance and Trade*, 60(10):2111–2125.

A Appendix

Aggregate Price

For each time t, there are S industries, each associated with a sectoral price P_{st}. We aim to find the aggregate price P_t, which is defined as the minimum price required to acquire one unit of the aggregate benefit at time t. This can be formalized as the following minimization problem:

$$C(P_t, Y_t) = \min_{\{Y_{st}\}_{s=1}^{S}} \left\{ \sum_{s=1}^{S} P_{st} \cdot Y_{st} \right\}, \quad \text{subject to:} \quad \overline{Y_t} = \prod_{s=1}^{S} Y_{st}^{\theta_{st}}, \quad \sum_{s=1}^{S} \theta_{st} = 1.$$

The Lagrangian is

$$L_t = \sum_{s=1}^{S} P_{st} \cdot Y_{st} + \lambda_t \left(\overline{Y_t} - \prod_{s=1}^{S} Y_{st}^{\theta_{st}} \right).$$

where λ_t is the Lagrange multiplier. The first-order condition with respect to Y_{st} is given by:

$$\frac{\partial L_t}{\partial Y_{s^*t}} = P_{s^*t} - \lambda_t \cdot \theta_{s^*t} \cdot Y_{s^*t}^{\theta_{s^*t}-1} \cdot \prod_{s=1}^{S-\{s\}} Y_{st}^{\theta_{st}} = 0.$$

By reorganizing terms and applying the given restrictions, we derive:

$$P_{st} = \lambda_t \cdot \theta_{st} \cdot \frac{Y_t}{Y_{st}}. \tag{A1}$$

Taking $P_t = \lambda_t$, it simplifies to:

$$\theta_{st} = \frac{P_{st} \cdot Y_{st}}{P_t \cdot Y_t}. \tag{A2}$$

From $A1$, we take j as the reference sector. Assuming λ_t remains constant across sectors, the relationship can be expressed as:

$$\frac{P_{st} \cdot Y_{st}}{\theta_{st} \cdot Y_t} = \frac{P_{jt} \cdot Y_{jt}}{\theta_{jt} \cdot Y_t} \quad \Rightarrow \quad Y_{st} = \frac{P_{jt}}{P_{st}} \cdot \frac{\theta_{st}}{\theta_{jt}} \cdot Y_{jt}$$

Applying the given restrictions and let sector j be constant in relation to sector s

$$Y_t = \prod_{s=1}^{S} Y_{st}^{\theta_{st}} = \prod_{s=1}^{S} \left(\frac{P_{jt}}{P_{st}} \cdot \frac{\theta_{st}}{\theta_{j,t}} \cdot Y_{jt} \right)^{\theta_{st}} = \left(\frac{P_{jt}}{\theta_{jt}} \cdot Y_{jt} \right)^{\sum_{s=1}^{S} \theta_{st}} \cdot \prod_{s=1}^{S} \left(\frac{\theta_{st}}{P_{st}} \right)^{\theta_{st}}.$$

By aggregating the sectors, we find the numerary price of the final good as a function of the sectoral prices:

$$\frac{P_j}{Y_j} = \theta_j \cdot Y_t \cdot \prod_{s=1}^{S} \left(\frac{P_s}{\theta_s} \right)^{\theta_s} \quad \Rightarrow \quad P_t \equiv \prod_{s=1}^{S} \left(\frac{P_{st}}{\theta_{st}} \right)^{\theta_{st}}. \tag{A3}$$

Sector Price

For each time t, there are M_s firms, each associated with a sectoral price P_{st} and we aim to find it. This can be formalized as the following minimization problem: The cost function is defined as:

$$C(P_{st}, Y_{st}) = \min_{\{Y_{ist}\}_{i=1}^{M_{st}}} \left\{ \sum_{i=1}^{M_{st}} P_{ist} \cdot Y_{ist} \right\}, \quad \text{subject to:} \quad \overline{Y_{st}} = \left[\sum_{i=1}^{M_{st}} Y_{ist}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

The Lagrangian is:

$$L_{st} = \sum_{i=1}^{M_{st}} P_{ist} \cdot Y_{ist} + \lambda_{st} \left(\quad \overline{Y_{st}} - \left[\sum_{i=1}^{M_{st}} Y_{ist}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \right).$$

where λ_{st} is the Lagrange multiplier. The first-order condition with respect to Y_{ist} is given by:

$$\frac{\partial L_{st}}{\partial Y_{ist}} = P_{ist} - \lambda_{st} \cdot \left(\sum_{i=1}^{M_{st}} Y_{ist}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} \cdot Y_{ist}^{\frac{-1}{\sigma}} = 0$$

Reorganizing terms and noting that $\lambda_{st} = P_{st}$, we get the inverse demand equation for each individual variety equal to:

$$P_{ist}^{\sigma} \cdot Y_{ist} = P_{st}^{\sigma} \cdot Y_{st} \quad \Rightarrow \quad Y_{ist} = Y_{st} \cdot \frac{P_{st}^{\sigma}}{P_{ist}^{\sigma}} \tag{A4}$$

Substituting into the constraint gives:

$$Y_{st} = \left[\sum_{i=1}^{M_{st}} \left(Y_{st} \cdot \frac{P_{st}^{\sigma}}{P_{it}^{\sigma}} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} = \left[\sum_{i=1}^{M_{st}} Y_{st}^{\frac{\sigma-1}{\sigma}} \cdot \left(\frac{P_{st}}{P_{ist}} \right)^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}}$$

Simplifying:

$$Y_{st} = \left(Y_{st}^{\frac{\sigma-1}{\sigma}} \cdot P_{st}^{\sigma-1} \cdot \sum_{i=1}^{M_{st}} P_{ist}^{1-\sigma} \right)^{\frac{\sigma}{\sigma-1}} \quad \Rightarrow \quad 1 = P_{st}^{\sigma-1} \cdot \sum_{i=1}^{M_{st}} P_{ist}^{1-\sigma}$$

Thus, the sector price P_{st} is:

$$P_{st} = \left(\sum_{i=1}^{M_{st}} P_{ist}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{A5}$$

Firm's Problem

For each time t, a firm produces output Y_{ist} using labor L_{ist} and capital K_{ist}, subject to a production function. The firm faces prices P_{ist} for its output, a wage w for labor, and a rental rate R for capital. Additionally, there are distortions of capital and product as τ_{yist} and capital τ_{kist} that influence firm decisions.

The firm's objective is to maximize its profits:

$$\max_{Y_{ist},L_{ist},K_{ist}} \Pi_{ist} = (1-\tau_{yist}) \cdot P_{ist} \cdot Y_{ist} - \omega_t \cdot L_{ist} - (1+\tau_{kist}) \cdot R_t \cdot K_{ist}.$$

Using the definitions of $A4$ for P_{ist} and $Y_{ist} = A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}$:

$$\max_{Y_{ist},L_{ist},K_{ist}} \Pi_{ist} = (1-\tau_{yist}) \cdot P_{st} \cdot Y_{st}^{\frac{1}{\sigma}} \cdot \left[A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}\right]^{\frac{\sigma-1}{\sigma}} - \omega_t \cdot L_{ist} - (1+\tau_{kist}) \cdot R_t \cdot K_{ist}.$$

Taking first-order conditions, we get:

$$\frac{\partial \Pi_{ist}}{\partial L_{ist}} = (1-\tau_{yist}) \cdot \frac{\sigma-1}{\sigma} \cdot (1-\alpha_s) \cdot P_{st} \cdot Y_{st}^{\frac{1}{\sigma}} \cdot \left[A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}\right]^{\frac{-1}{\sigma}} \cdot A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{-\alpha_s} = \omega_t \quad (A6)$$

$$\frac{\partial \Pi_{ist}}{\partial L_{ist}} = (1-\tau_{yist}) \cdot \frac{\sigma-1}{\sigma} \cdot (1-\alpha_s) \cdot P_{st} \cdot Y_{st}^{\frac{1}{\sigma}} \cdot Y_{ist}^{\frac{-1}{\sigma}} \cdot \frac{Y_{ist}}{L_{ist}} = \omega_t \quad (A7)$$

$$\frac{\partial \Pi_{ist}}{\partial K_{ist}} = (1-\tau_{yist}) \cdot \frac{\sigma-1}{\sigma} \cdot \alpha_s \cdot P_{st} \cdot Y_{st}^{\frac{1}{\sigma}} \cdot Y_{st}^{\frac{-1}{\sigma}} \cdot \frac{Y_{ist}^{\frac{\sigma-1}{\sigma}}}{K_{ist}} = (1+\tau_{kist}) \cdot R \quad (A8)$$

Dividing both equations, we get the optimal condition:

$$\frac{K_{ist}}{L_{ist}} = \frac{\omega_t}{(1+\tau_{kist}) \cdot R} \cdot \frac{\alpha_s}{1-\alpha_s} \quad (A9)$$

Using the definitions of $A4$ and $A6$:

$$P_{ist} = \frac{\sigma}{\sigma-1} \cdot \left(\frac{R}{\alpha_s}\right)^{\alpha_s} \cdot \left(\frac{\omega_t}{1-\alpha_s}\right)^{1-\alpha_s} \cdot \frac{(1+\tau_{kist})^{\alpha_s}}{A_{ist} \cdot (1-\alpha_s)} \quad (A10)$$

Now, from $A6$ and Y_{ist}:

$$\omega_t \cdot L_{ist} = \frac{\sigma-1}{\sigma} \cdot (1-\tau_{yist}) \cdot (1-\alpha_s) \cdot P_{st} \cdot Y_{st}^{\frac{1}{\sigma}} \cdot \left(A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}\right)^{\frac{\sigma-1}{\sigma}} \quad (A11)$$

Reorganizing terms, where $\mathcal{R}$ encompasses the remaining constant components. We get the following expression:

$$L_{ist} = \mathcal{R} \cdot \frac{A_{ist}^{\sigma-1} \cdot (1-\tau_{yist})^{\sigma}}{(1+\tau_{kist})^{\alpha_s \cdot (\sigma-1)}} \quad \Rightarrow \quad L_{ist} \propto \frac{A_{ist}^{\sigma-1} \cdot (1-\tau_{yist})^{\sigma}}{(1+\tau_{kist})^{\alpha_s \cdot (\sigma-1)}} \quad (A12)$$

Now, using the definition of production function, $A6$ and $A9$, we find:

$$Y_{ist} = \left[\frac{\alpha_s}{1-\alpha_s} \cdot \frac{\omega_t}{R_t}\right]^{\alpha_s} \cdot \mathcal{R} \cdot \frac{A_{ist}^{\sigma} \cdot (1-\tau_{yist})^{\sigma}}{(1+\tau_{kist})^{\alpha_s \cdot \sigma}} \quad \Rightarrow \quad Y_{ist} \propto \cdot \frac{A_{ist}^{\sigma} \cdot (1-\tau_{yist})^{\sigma}}{(1+\tau_{kist})^{\alpha_s \cdot \sigma}} \tag{A13}$$

From $A4$ and $A7$, we find:

$$MRPL_{ist} \triangleq (1-\alpha_s) \cdot \frac{(\sigma-1)}{\sigma} \cdot \frac{P_{ist} \cdot Y_{ist}}{L_{ist}} = \frac{\omega_t}{(1-\tau_{yist})} \tag{A14}$$

$$1-\tau_{yist} = \frac{\sigma}{\sigma-1} \cdot \frac{\omega_t \cdot L_{ist}}{(1-\alpha_s) \cdot P_{ist} \cdot Y_{ist}} \tag{A15}$$

From $A4$ and $A8$, we find:

$$MRPK_{ist} \triangleq \alpha_s \cdot \frac{(\sigma-1)}{\sigma} \cdot \frac{P_{ist} \cdot Y_{ist}}{K_{ist}} = R_t \cdot \frac{(1+\tau_{kist})}{(1-\tau_{yist})} \tag{A16}$$

Using the definition of $1-\tau_{yist}$ on $A16$ we get:

$$1+\tau_{kist} = \frac{\alpha_s}{1-\alpha_s} \cdot \frac{\omega_t \cdot L_{ist}}{R_t \cdot K_{ist}} \tag{A17}$$

The equilibrium allocation of resources across sectors

Now, the aggregate TFP can be found as a function of the misallocation of capital and labor, solving the equilibrium allocations:

$$\text{Let} \quad L_{st} = \sum_{i=1}^{M_{st}} L_{ist}, \quad K_{st} = \sum_{i=1}^{M_{st}} K_{ist}, \quad Y_{ist} = A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}$$

From $A2$ and $A14$:

$$L_{ist} = \frac{1}{MRPL_{ist}} \cdot (1-\alpha_s) \cdot \frac{(\sigma-1)}{\sigma} \cdot \frac{P_{ist} \cdot Y_{ist}}{P_{st} \cdot Y_{st}} \cdot \theta_{st} \cdot P_t \cdot Y_t$$

$$L_{st} = \sum_{i=1}^{M_{st}} L_{ist} = \sum_{i=1}^{M_{st}} \left(\frac{1}{MRPL_{ist}} \cdot \frac{(\sigma-1)}{\sigma} \cdot (1-\alpha_s) \cdot \frac{P_{ist} \cdot Y_{ist}}{P_{st} \cdot Y_{st}} \cdot \theta_{st} \cdot P_t \cdot Y_t\right)$$

$$L_{st} = \frac{(\sigma-1)}{\sigma} \cdot (1-\alpha_s) \cdot \theta_{st} \cdot P_t \cdot Y_t \cdot \sum_{i=1}^{M_{st}} \left(\frac{1}{MRPL_{ist}} \cdot \frac{P_{ist} \cdot Y_{ist}}{P_{st} \cdot Y_{st}}\right) = \frac{(\sigma-1)}{\sigma} \cdot (1-\alpha_s) \cdot \theta_{st} \cdot P_t \cdot Y_t \cdot \frac{1}{\overline{\overline{MRPL_{st}}}}$$

$$\frac{L_{st}}{\left[\frac{1}{\overline{\overline{MRPL_{st}}}} \cdot (1-\alpha_s) \cdot \theta_{st}\right]} = \frac{\sigma-1}{\sigma} \cdot P_t \cdot Y_t, \text{ so we can define this for every sector } s \text{ or } s' \text{ on each time } t$$

$$\frac{L_{st}}{\left[\frac{1}{\overline{MRPL_{st}}}\cdot(1-\alpha_s)\cdot\theta_{st}\right]}=\frac{L_{s't}}{\left[\frac{1}{\overline{MRPL_{s't}}}\cdot(1-\alpha_{s'})\cdot\theta_{s't}\right]}\quad\Rightarrow\quad L_{st}=L_{s't}\cdot\frac{\left[\frac{1}{\overline{MRPL_{st}}}\cdot(1-\alpha_s)\cdot\theta_{st}\right]}{\left[\frac{1}{\overline{MRPL_{s't}}}\cdot(1-\alpha_{s'})\cdot\theta_{s't}\right]}$$

$$\text{Applying labor clean condition}\quad L_{st}\equiv L_t\cdot\frac{\left[\frac{1}{\overline{MRPL_{st}}}\cdot(1-\alpha_s)\cdot\theta_{st}\right]}{\sum_{s'=1}^{S}\left[\frac{1}{\overline{MRPL_{s't}}}\cdot(1-\alpha_{s'})\cdot\theta_{s't}\right]}\tag{A18}$$

From $A2$ and $A16$:

$$K_{ist}=\alpha_s\cdot\frac{(\sigma-1)}{\sigma}\cdot P_{ist}\cdot Y_{ist}\cdot\frac{1}{MRPK_{ist}}\cdot\theta_{st}\cdot P_t\cdot Y_t\cdot\frac{1}{P_{st}\cdot Y_{st}}$$

$$K_{st}=\sum_{i=1}^{M_{st}}K_{ist}=\sum_{i=1}^{M_{st}}\left(\alpha_s\cdot\frac{(\sigma-1)}{\sigma}\cdot P_{ist}\cdot Y_{ist}\cdot\frac{1}{MRPK_{ist}}\cdot\theta_{st}\cdot P_t\cdot Y_t\cdot\frac{1}{P_{st}\cdot Y_{st}}\right)$$

$$K_{st}=\alpha_s\cdot\frac{(\sigma-1)}{\sigma}\cdot\theta_{st}\cdot P_t\cdot Y_t\cdot\sum_{i=1}^{M_{st}}\left(\frac{1}{MRPK_{ist}}\cdot\frac{P_{ist}\cdot Y_{ist}\cdot}{P_{st}\cdot Y_{st}}\right)=\alpha_s\cdot\frac{(\sigma-1)}{\sigma}\cdot\theta_{st}\cdot P_t\cdot Y_t\cdot\frac{1}{\overline{MRPK_{st}}}$$

$K_{st}\cdot\overline{MRPK_{st}}\cdot\frac{1}{\alpha_s\cdot\theta_{st}}=\frac{(\sigma-1)}{\sigma}\cdot P_t\cdot Y_t,$ so we can define this for every sector s or s' on each time t

$$K_{st}\cdot\overline{MRPK_{st}}\cdot\frac{1}{\alpha_s\cdot\theta_{st}}=K_{s't}\cdot\overline{MRPK_{s't}}\cdot\frac{1}{\alpha_{s'}\cdot\theta_{s't}}\quad\Rightarrow\quad K_{st}=K_{s't}\cdot\frac{\frac{1}{\overline{MRPK_{st}}}\cdot\alpha_s\cdot\theta_{st}}{\frac{1}{\overline{MRPK_{s't}}}\cdot\alpha_{s'}\cdot\theta_{s't}}$$

$$\text{Applying capital clean condition}\quad K_{st}\equiv K_t\cdot\frac{\left[\frac{1}{\overline{MRPK_{st}}}\cdot\alpha_s\cdot\theta_{st}\right]}{\sum_{s'=1}^{S}\left[\frac{1}{\overline{MRPK_{s't}}}\cdot\alpha_{s'}\cdot\theta_{s't}\right]}\tag{A19}$$

Productivity

Revenue productivity ($TFPR_{ist}$) is defined as:

$$TFPR_{ist} = P_{ist} \cdot A_{ist} = \frac{P_{ist} \cdot Y_{ist}}{K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}}$$

Physical productivity ($TFPQ_{ist}$) is defined as:

$$TFPQ_{ist} = A_{ist} = \frac{Y_{ist}}{K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}}$$

However, since Y_{ist} is not directly observable, it becomes essential to manipulate the equations further. Using the relationship from $A4$, we derive:

$$Y_{ist}^{\sigma-1} = P_{ist}^{\sigma} \cdot Y_{ist}^{\sigma} \cdot \frac{1}{P_{st}^{\sigma} \cdot Y_{st}}$$

$$A_{ist} \cdot K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s} = P_{ist}^{\frac{\sigma}{\sigma-1}} \cdot Y_{ist}^{\frac{\sigma}{\sigma-1}} \cdot \frac{1}{P_{st}^{\frac{\sigma}{\sigma-1}} \cdot Y_{st}^{\frac{1}{\sigma-1}}}$$

$$A_{ist} = P_{ist}^{\frac{\sigma}{\sigma-1}} \cdot Y_{ist}^{\frac{\sigma}{\sigma-1}} \cdot \frac{1}{P_{st}^{\frac{\sigma}{\sigma-1}} \cdot Y_{st}^{\frac{1}{\sigma-1}}} \cdot \frac{1}{K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}} = \frac{(P_{st}Y_{st})^{-\frac{1}{\sigma-1}}}{P_{st}} \cdot \frac{(P_{ist}Y_{ist})^{\frac{\sigma}{\sigma-1}}}{K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}}$$

$$A_{ist} = \kappa_{st} \cdot \frac{(P_{ist}Y_{ist})^{\frac{\sigma}{\sigma-1}}}{K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}} \tag{A19}$$

The scalar $\kappa_{st} = \frac{(P_{st}Y_{st})^{-\frac{1}{\sigma-1}}}{P_{st}}$ is not directly observable. To solve this, Hsieh and Klenow (2009) propose setting $\kappa_{st} = 1$, arguing that this assumption does not influence relative productivity comparisons or estimates of reallocation gains.

Sectoral Total Factor Productivity

Returning to the definitions of K_{st} and L_{st}:

$$L_{st} = \frac{(\sigma-1)}{\sigma} \cdot (1-\alpha_s) \cdot \theta_{st} \cdot P_t \cdot Y_t \cdot \frac{1}{\overline{\overline{MRPL_{st}}}} \quad \Rightarrow \quad \frac{P_{st} \cdot Y_{st}}{L_{st}} = \overline{MRPL_{st}} \cdot \frac{\sigma}{\sigma-1} \cdot \frac{1}{1-\alpha_s}$$

$$K_{st} = \alpha_s \cdot \frac{(\sigma-1)}{\sigma} \cdot \theta_{st} \cdot P_t \cdot Y_t \cdot \frac{1}{\overline{\overline{MRPK_{st}}}} \quad \Rightarrow \quad \frac{P_{st} \cdot Y_{st}}{K_{st}} = \overline{MRPK_{st}} \cdot \frac{\sigma}{\sigma-1} \cdot \frac{1}{\alpha_s}$$

Let the production of sector s at time t be defined as:

$$Y_{st} = TFP_{st} \cdot K_{st}^{\alpha_s} \cdot L_{st}^{1-\alpha_s}$$

Using mathematical manipulation, the Total Factor Productivity (TFP_{st}) is expressed as:

$$TFP_{st} = \left(\overline{MRPK_{st}} \cdot \frac{\sigma}{\sigma - 1} \cdot \frac{1}{\alpha_s}\right)^{\alpha_s} \cdot \left(\frac{P_{st} \cdot Y_{st}}{L_{st}}\right)^{1-\alpha_s} \cdot \frac{1}{P_{st}}$$

Substituting the expressions for marginal revenue products ($MRPK_s$ and $MRPL_s$):

$$TFP_{st} = \left(\overline{MRPK_{st}} \cdot \frac{\sigma}{\sigma - 1} \cdot \frac{1}{\alpha_s}\right)^{\alpha_s} \cdot \left(\overline{MRPL_{st}} \cdot \frac{\sigma}{\sigma - 1} \cdot \frac{1}{1 - \alpha_s}\right)^{1-\alpha_s} \cdot \frac{1}{P_{st}}$$

Simplifying further, we obtain:

$$TFP_{st} = \frac{\sigma}{\sigma - 1} \cdot \left(\frac{\overline{MRPK_{st}}}{\alpha_s}\right)^{\alpha_s} \cdot \left(\frac{\overline{MRPL_{st}}}{1 - \alpha_s}\right)^{1-\alpha_s} \cdot \frac{1}{P_{st}} = \overline{TFPR_{st}} \cdot \frac{1}{P_{st}} \tag{A20}$$

From $A5$, and using the initial definition of $TFPR_{ist}$:

$$\frac{1}{P_{st}} = \left[\sum_{i=1}^{M_{st}} \left(\frac{1}{P_{ist}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} = \left[\sum_{i=1}^{M_{st}} \left(\frac{A_{ist}}{TFPR_{ist}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$$

Substituting this into $A20$, and assuming $\overline{TFPR_{st}}$ is constant in relation to M_{st}, we obtain:

$$TFP_{st} = \left[\sum_{i=1}^{M_{st}} \left(A_{ist} \cdot \frac{\overline{TFPR_{st}}}{TFPR_{ist}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{A21}$$

We can manipulate the initial definition of $TFPR_{ist}$ and using $A14$ and $A16$:

$$TFPR_{ist} = \frac{P_{ist} \cdot Y_{ist}}{K_{ist}^{\alpha_s} \cdot L_{ist}^{1-\alpha_s}} \cdot \frac{P_{ist}^{\alpha_s} \cdot Y_{ist}^{\alpha_s}}{P_{ist}^{\alpha_s} \cdot Y_{ist}^{\alpha_s}} = \frac{\sigma}{\sigma - 1} \cdot \left[\frac{MRPK_{ist}}{\alpha_s}\right]^{\alpha_s} \cdot \left[\frac{MRPL_{ist}}{1 - \alpha_s}\right]^{1-\alpha_s}$$

$$TFPR_{ist} = \frac{\sigma}{\sigma - 1} \cdot \left[\frac{R_t}{\alpha_s}\right]^{\alpha_s} \cdot \left[\frac{\omega_t}{1 - \alpha_s}\right]^{1-\alpha_s} \cdot \frac{(1 + \tau_{kist})^{\alpha_s}}{1 - \tau_{yist}} \tag{A22}$$

Efficiency Levels

We next calculate the "efficient" output. If marginal products were equalized across plants, meaning that revenue productivity does not vary within the same sector, then from $A21$, industry TFP can be directly compared with actual output levels:

$$\overline{A}_{st} = \overline{TFP_{st}} = \left[\sum_{i=1}^{M_{st}} (A_{ist})^{\sigma-1}\right]^{\frac{1}{\sigma-1}}. \tag{A23}$$

To complete, we use the aggregate production function and the sectoral production function:

$$Y_t = \prod_{s=1}^{S} Y_{st}^{\theta_{st}}, \quad Y_{st} = TFP_{st} \cdot K_{st}^{\alpha_s} \cdot L_{st}^{1-\alpha_s},$$

to derive:

$$Y_t = \prod_{s=1}^{S} \left(TFP_{st} \cdot K_{st}^{\alpha_s} \cdot L_{st}^{1-\alpha_s} \right)^{\theta_{st}} .$$

Finally, for each sector, we calculate the ratio between the observed output Y_t and the efficient output Y_t^*, which is obtained when the $TFPR_{ist}$ of firms is equalized. In this scenario, $\overline{A}_{st} = \overline{TFP_{st}}$, allowing us to measure the degree of misallocation within the industry and estimate the potential output gains when resources are allocated efficiently.

The aggregation of all sectors provides a measure of overall misallocation and the potential output gains for the entire economy.

$$\frac{Y_t}{Y_t^*} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(\frac{A_{ist}}{\overline{A}_{st}} \cdot \frac{\overline{TFPR}_{st}}{TFPR_{ist}} \right)^{\sigma-1} \right]^{\frac{\theta_{st}}{\sigma-1}}$$