Financial Development, Competition, and Productivity

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Abstract

I study how financial development promotes competition. I extend the model of Atkeson and Burstein (2008) to include dynamic capital accumulation and financial frictions. Capital market imperfections interact with endogenous misallocation from market power and variable markups. Calibrating the model with data from Chilean manufacturing firms, I show that improved access to external finance reduces industry concentration and both the level and dispersion of markups. These effects explain over half of the total productivity gains from financial development and are especially pronounced in financially underdeveloped economies. Models that ignore markup variation thus underestimate the benefits of improving capital markets.

Keywords: Market Power, Markups, Financial Development, Financial Frictions, Misallocation

JEL: D43, E44, L13, L60, O41, O47

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1 Introduction

Can improvements in a country's financial sector promote competition? A large body of literature (e.g., Amaral and Quintin (2010); Buera et al. (2011); Midrigan and Xu (2014)) has examined the effects of financial development on aggregate productivity and output. However, these studies abstract from strategic pricing interactions among firms – interactions that generate heterogeneous markups and distortions in product markets. Financial frictions are known to increase the dispersion of firm size (Buera et al., 2011; Bento and Ranasinghe, 2025), potentially leading to greater market power among a small set of dominant firms. This suggests that competitive forces may play a crucial role in shaping the aggregate effects of financial development. This paper investigates the importance of this channel.

Existing studies emphasize two main channels through which financial development affects productivity and output: distortions to the return on capital, which lead to dispersion in the marginal revenue product of capital (MRPK), and firm entry. This paper contributes by highlighting a third, previously overlooked mechanism: competition. For instance, if financial frictions prevent small, young firms from growing or entering the market, large firms can exploit their position and charge higher markups. This, in turn, amplifies distortions in product markets. Conversely, if frictions disproportionately affect large firms, their market power may decline, reducing both markups and their dispersion and fostering competition.

Another contribution of this paper is to provide a framework that connects frictions in capital markets to competitive forces and product-market distortions.[1] The model integrates the strategic competition elements from Atkeson and Burstein (2008), which generate endogenous markups, with a producer dynamics structure in the tradition of the heterogeneous-firms literature (see, e.g., Khan and Thomas (2013); Mehrotra and Sergeyev (2021)). I calibrate it using detailed panel data on Chilean manufacturing firms, covering all establishments with ten or more employees from 1979 to 1996. Following the existing literature (e.g. Buera et al. (2011), Buera and Shin (2013), Midrigan and Xu (2014)) I assume that the degree of financial development is captured by the collateral requirements firms face when accessing credit. I then study counterfactual economies in which these requirements vary. In financially underdeveloped environments, firms rely heavily on self-financing, as borrowing is limited by high collateral demands imposed by financial intermediaries, while in financially developed economies intermediaries are more willing to lend against limited collateral.

Consistent with previous research, I find that improving financial markets can generate substantial macroeconomic gains: output and total factor productivity are approximately 70% and 50% lower in financial autarky than in a frictionless economy. In addition, the competitive impact of financial development is highly non-linear: in economies with already well-developed financial

[1] I use the terms output distortion and product-market distortion interchangeably to refer to wedges that affect the marginal product of capital and labor equally (Hsieh and Klenow, 2009). In contrast to Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), these distortions arise endogenously in my framework through markups generated by imperfect competition.

markets, further reductions in frictions have little influence on competition or the distribution of markups. In these settings, most distortions stem from the direct effect of frictions on the marginal revenue product of capital (MRPK). By contrast, in financially underdeveloped economies, easing financial constraints strengthens competition, lowering both the level and dispersion of markups, and amplifying gains in aggregate productivity.

In the model, firms are heterogeneous in both idiosyncratic productivity and net worth, and they compete in quantities within their industry. In equilibrium, more productive firms face a lower price elasticity of demand and consequently charge higher markups. In other words, the model predicts that larger firms possess greater market power, consistent with prior empirical evidence (Edmond et al. (2015), Atkin et al. (2015), De Loecker et al. (2016)) and theoretical work (Atkeson and Burstein (2008), Melitz and Ottaviano (2008)). At the end of each period, firms accumulate profits as net worth, which serves as collateral and gradually relaxes their borrowing constraints (Buera, 2009; Moll, 2014). Additionally, entry is endogenous and subject to fixed operating costs, which vary across sectors and influence market concentration by determining how many firms operate in each industry.

To examine the role of competition, I begin by evaluating the impact of financial development on the distribution of markups. I consider three counterfactual economies: the benchmark calibration, which displays a moderately high level of financial development, as indicated by an external-finance-to-GDP ratio of 0.74; a financially repressed economy, with a total borrowing-to-GDP ratio equal to that of India (0.30); and an economy without financial frictions. While the distribution of markups in the benchmark and frictionless economies is similar, the "India scenario" exhibits much greater markup dispersion, higher average markups, and significantly more concentrated industries.

What do these results imply for losses due to misallocation? To answer this question, I develop a novel decomposition that separates the labor productivity losses from misallocation into two components: a direct effect, stemming from frictions that distort firms' capital-labor ratios (and thus their MRPK), and an indirect effect, operating through product-market misallocation.[2] In the benchmark economy, the direct effect accounts for roughly 12% of productivity losses, while the indirect effect, arising from markup dispersion, accounts for about 10%, a value similar to that in the frictionless case.[3] In the "India scenario", however, the contrast is stark: while direct losses from MRPK dispersion rise to around 20%, indirect losses due to product-market misallocation rise to approximately 50%. The findings suggest that, in financially repressed economies, easing frictions not only improves capital allocation directly but also boosts productivity by strengthening competition.

Although financial development can have large indirect effects through competition, these impacts are not uniform across industries. In particular, sectors without entry costs exhibit little

[2] This decomposition is static in nature, holding entry decisions and firm net worth fixed.

[3] Edmond et al. (2023) estimate that losses from market power in the U.S. are close to 2%, whereas Baqaee and Farhi (2017) report a value of 20% (for 1997-2015). Using Taiwanese manufacturing data (2000-2004), Edmond et al. (2015) find losses of around 9%, similar to those in my benchmark calibration.

change in their markup distribution, meaning that the competitive gains from financial development are concentrated in high fixed-cost sectors. Therefore, accounting for entry barriers is essential to fully capture the aggregate impact of financial development – not only through their effect on firm entry, as emphasized by Buera et al. (2011) and Midrigan and Xu (2014), but also through their role in shaping product-market competition.

Would a model with constant markups understate the benefits of financial development? The results discussed so far strongly suggest the answer is yes. To reinforce this conclusion, I repeat the exercises above using an observationally equivalent version of the model that preserves all features of the baseline except for one key difference: it abstracts from markup dispersion. As expected, the constant-markup model predicts substantially smaller gains from financial development, especially in terms of total factor productivity.

Related Literature. An extensive body of research, with prominent early examples being Hsieh and Klenow (2009), Restuccia and Rogerson (2008), and Bartelsman et al. (2013), finds that firm-level distortions substantially reduce aggregate productivity through misallocation of resources. One important source of such distortions is the quality of financial institutions, as studied by Buera et al. (2011), Buera and Shin (2013), and Midrigan and Xu (2014), among others.[4] I follow this literature by explicitly modeling the source of distortions in capital markets as stemming from financial constraints.[5] However, existing work abstracts from the potential competitive effects of improving financial markets, assuming either perfect competition or constant markups. My work is the first to examine the interaction between financial frictions and competitive forces, with particular emphasis on the role of markups.

Later, yet contemporaneous works are Armada (2024) and Li et al. (2025), both of which use Kimball (1995) demand systems to examine the effects of financial market imperfections on productivity and output. Beyond differences in the modeling framework, a key distinction between my approach and theirs is that they abstract from sectoral heterogeneity in entry costs – a feature that, as in Buera et al. (2011) and Midrigan and Xu (2014), plays a central role in driving my results.

I also connect to a literature that employs the framework pioneered by Atkeson and Burstein (2008) to study competition and/or the sources and consequences of variable markups. Using this framework, Edmond et al. (2015) studies the (pro-) competitive effects of international trade; Auer and Schoenle (2016) and Amiti et al. (2019) examine the exchange rate pass-through; Mongey (2021) and Wang and Werning (2022) study monetary non-neutrality; Smitkova (2024) studies how superstar firms' profits affect international capital flows; Burstein et al. (2025) studies the cyclicality of markups. I draw from and contribute to this literature methodologically by proposing a dynamic, closed-economy extension of the oligopolistic competition model they employ, incorporating elements from the framework in Mehrotra and Sergeyev (2021).

This paper is closely related to Peters (2013), who studies how reducing entry barriers fosters

[4]See also Greenwood et al. (2013), Moll (2014), and Blaum (2022).

[5]Liang (2023) shows how considering variable markups can greatly affect the model predictions of eliminating other types of distortions, without taking a stand on the source of those distortions.

competition, whereas I focus on how financial market imperfections distort both firm entry and firm size. I also connect to Altomonte et al. (2017), who study how financial frictions affect firm pricing in a monopolistic competition framework à la Melitz and Ottaviano (2008). Unlike their approach, I focus on structural financial changes and compute the general equilibrium response of the markup distribution. Closely related is also Galle (2019), who studies how the effects of changing competition depend on the presence of financial frictions, while I focus on how changes in financial frictions indirectly affect markups, output, and productivity. Another related paper is Soares and Meinen (2022), who empirically assess the impact of firm-level credit supply shocks on markups. My study, instead, considers the general equilibrium impact of financial frictions that potentially affect all firms.

Finally, this paper also contributes to a broader debate on the origins of low productivity in the developing world, which is often attributed to limited competition (De Loecker et al., 2016). Related work includes Godfrey (2008), Aghion et al. (2008), among others. The analysis presented here suggests that underdeveloped financial markets are a key factor behind the lack of competition observed in many developing countries.

The remainder of this paper is structured as follows: in Section 2, I provide a simple model illustrating how output market misallocation interacts with input market frictions. In Section 3, I introduce the quantitative model, Section 4 explains the dataset and the calibration procedure, Section 5 presents the results, and Section 6 concludes.

2 Price Setting under Input Constraints - A Simple Framework

This section illustrates how input constraints determine price setting behavior, and, through this mechanism, influence aggregate economic activity. To do so, I present a standard Cournot competition model with two firms differing in productivity and may face input constraints.

Consider a partial-equilibrium economy, which can be interpreted as a small industry within a larger economy, where firms have negligible influence on input prices. Two firms produce a homogeneous good using a single input, denoted by k, whose price is r. Technology exhibits constant returns to scale, and firms are identical in all respects except productivity.

The quantity of output produced by firm i is:

$$q_i = A_i f(k) = A_i k$$

Without loss of generality, I assume that $A_1 \geq A_2$.

The demand for the homogeneous good is isoelastic. Let $P(Q)$ denote the inverse demand function:

$$P(q_1 + q_2) = P(Q) = Q^{-\frac{1}{\sigma}},$$

where $\sigma > 1$ is the price-elasticity of demand.

In this simple framework, the equilibrium is achieved when each firm maximizes profits given the other firm's decisions. The maximization problem is:

$$\max_{k_i, q_i} P(q_i + q_{-i})q_i - rk_i,$$

where r denotes the price of inputs, and firms are subject to the available technology $q_i = A_i k$.

To illustrate the producers' price setting behavior in this framework, I first consider the case where there are no constraints to input usage. Here, the equilibrium is obtained by solving the second equality of the following expression:

$$P(q_1^* + q_2^*) = \left(\frac{r}{A_1}\right)\left(1 - \frac{s_1^*}{\sigma}\right)^{-1} = \left(\frac{r}{A_2}\right)\left(1 - \frac{s_2^*}{\sigma}\right)^{-1}, \tag{1}$$

where $s_i^* \equiv \frac{q_i^*}{q_i^* + q_{-i}^*}$ denotes the market share of firm i, so $s_1^* + s_2^* = 1$.

In equilibrium, firms must set the same price as they produce the same good. Firm i's markup is given by:

$$\mu_i^* = \frac{P(Q)}{r/A_i} = \frac{1}{1 - \frac{s_i^*}{\sigma}} \tag{2}$$

The expression above shows that the larger the market share of firm i, the more its demand elasticity resembles that of a monopoly, and thus the larger is this firm's market power and markup. In particular, as s_i approaches 1, the producer behaves as a monopoly and its markup approaches $\frac{\sigma}{\sigma-1}$. On the other hand, as s_i approaches zero, the firm behaves as if it were atomistic in a competitive market, and the price equals the marginal cost ($\mu \to 1$).

These insights carry over to the quantitative model presented in Section 3: large firms display more market power. This is because, in equilibrium, they face a lower elasticity of demand, represented by the inverse of $\frac{s_i^*}{\sigma}$. Intuitively, large producers understand they have relatively more control over the aggregate demand Q, which they internalize in their pricing decisions.

I now introduce the possibility that firms are constrained in their input choice. Consider the following simple constraint:

$$k_i \leq \bar{k}_i \implies q_i \leq A_i \bar{k}_i \equiv \bar{q}_i$$

Here, the input constraint takes the form of a hard quantity limit – an extreme case, since firms cannot reallocate resources across inputs when only one is available. Nevertheless, the underlying intuition naturally extends to settings with multiple inputs, as developed in the next section.

Initially, I consider a constraint affecting firm 2, the least productive producer. In equilibrium, we have:

$$\mu_2 = \left(\frac{1}{1 - \frac{s_2}{\sigma}}\right) + \frac{\lambda}{r/A_2}\left(\frac{1}{1 - \frac{s_2}{\sigma}}\right) \tag{3}$$

Here, $\lambda > 0$ is the Lagrange multiplier associated with the constraint. Intuitively, the constraint influences the pricing behavior of firm 2 in two opposing ways. On one hand, it creates an incentive to raise the markup by reducing output, thereby relaxing the constraint. This mechanism is given by the second term in the expression above. On the other hand, since $\bar{q}_2 \leq q_2$ by construction, the constraint lowers the market share of firm 2 ($s_2 < s_2^*$), which tends to reduce its markup. As a result, the overall effect on pricing is, a priori, ambiguous. To assess the net impact, one must consider the response of firm 1, whose markup is given by:

$$\mu_1 = \frac{1}{1 - \frac{s_1}{\sigma}} = \frac{1}{1 - \frac{s_1^*}{\sigma}} \geq \mu_1^*$$

The inequality is due to the fact that, in equilibrium, $\frac{ds_1}{d\bar{q}_2} < 0$, and since $q_2^* > \bar{q}_2$ by construction, it follows that $s_1 > s_1^*$.[6] In other words, the market share of firm 1 increases as the constraint on firm 2 tightens. The intuition is straightforward: when one firm is constrained, the other takes advantage, expands, and consequently gains market power.

Note that the equilibrium price is higher as a result of firm one charging higher markups, which can be seen from the second equality of expression (2). Consequently, firm 2 also charges higher markups, as its marginal cost remains constant. These conclusions can be seen in the left panel of Figure 1, which plots each firm's equilibrium markups and their sales-weighted average, as a function $\frac{\bar{q}_2}{q_2^*}$, so that $\frac{\bar{q}_2}{q_2^*} = 1$ represents the equilibrium without frictions.

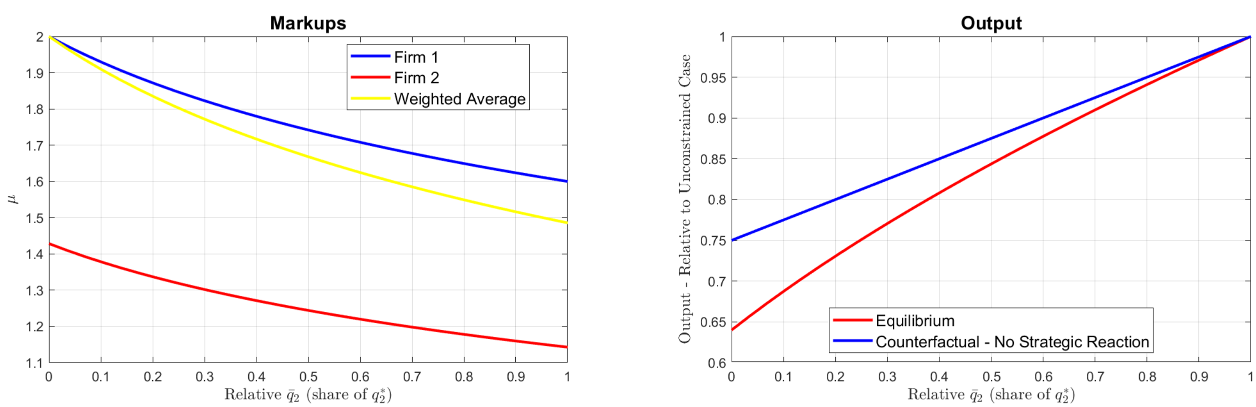

Figure 1: Price and Output Reactions to Constraining Firm 2

Notes: This figure plots equilibrium outcomes as a function of the constraint on input use by firm 2, expressed as a fraction of its unconstrained optimum ($\frac{\bar{q}_2}{q_2^*}$). The left panel displays markups for firm 1 (blue), firm 2 (red), and their sales-weighted average (yellow). The right panel shows total equilibrium output (red) and a counterfactual where q_1 is held fixed (blue). Parameters are $A_1 = 1.4$, $A_2 = 1$, $\sigma = 2$, and $r = 1$.

The red line in the right panel of Figure 1 shows the equilibrium level of total output (Q), which declines as firm 2 becomes increasingly constrained. The blue line, by contrast, represents a counterfactual in which the output of firm 1 (q_1) is held fixed. This isolates the direct effect of the

[6] In Appendix Section B, I show the conditions under which $\frac{ds_1}{d\bar{q}_2} < 0$. This condition is satisfied in all my simulations, including when I consider the case of constraining the more productive firm.

constraint on total output, abstracting from any strategic response by firm 1. The fact that the blue line lies above the red line indicates that firm 1 reduces its output when firm 2 shrinks. In other words, the constraint not only reduces output directly but also indirectly, through the strategic reaction of firm 1.

The dynamics illustrated in Figure 1 are the main focus of this paper. The ultimate goal is to assess the importance of this channel of competition in shaping welfare-relevant aggregates, such as total factor productivity and output.

Figure 2 presents the results of the same exercise, but this time firm 1 faces the constraint. The left panel shows that markups increase as the constraint tightens, following a similar pattern to the previous case. However, the right panel reveals a key difference: equilibrium output is now higher than in the counterfactual where firm 2 does not adjust in response to firm 1 being constrained. This is because firm 1 initially holds substantial market power, and limiting its output increases competition. As firm 2 grows, it faces a less elastic demand and responds by raising its output even further, partially offsetting the impact of the constraint on firm 1.

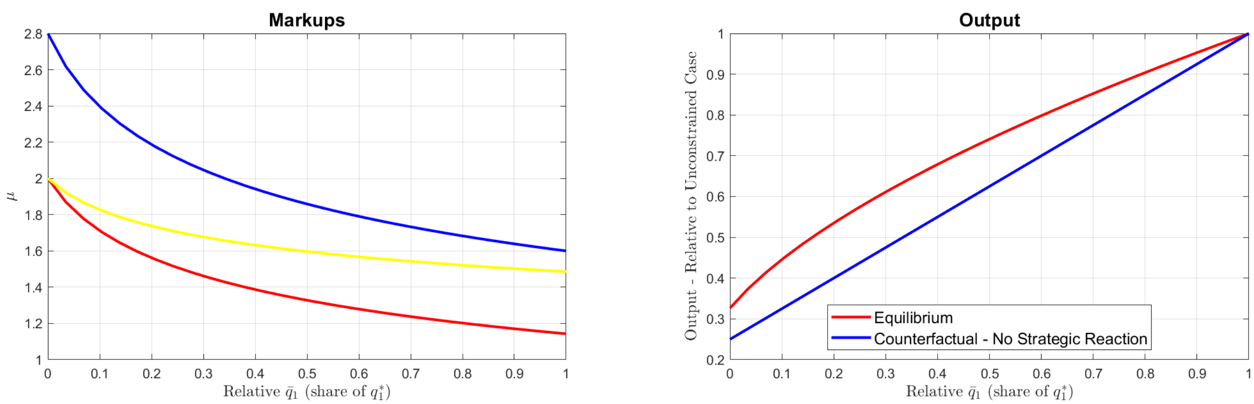

Figure 2: Price and Output Reactions to Constraining Firm 1

Notes: This figure shows the effect of tightening the input constraint on firm 1, expressed as $\bar{q}_1/q_1^*$, on total factor productivity (left panel) and output (right panel). The red lines plot equilibrium outcomes under endogenous markups. The blue lines represent a counterfactual scenario in which q_2 remains fixed at its unconstrained level. Parameters are the same as in Figure 1: $A_1 = 1.4$, $A_2 = 1$, $\sigma = 2$, and $r = 1$.

Taken together, the two figures highlight that the effect of financial constraints on competition is ambiguous. As shown in Figure 1, constraints can reduce competition when they limit the less productive firm, while Figure 2 illustrates that they can instead promote competition when the more productive firm is constrained. Whether the constraint falls on the more or less productive firm is ultimately an empirical question. In practice, studies typically find that financial constraints disproportionately affect smaller, less productive firms (see Buera et al. (2011)) – a pattern I also observe in Chilean data.

The remainder of the paper quantifies how the mechanisms discussed in this section affect misallocation and output across economies with varying levels of financial development – captured by the severity of financial constraints. Although the quantitative framework is more elaborate, the core intuitions remain: more efficient firms have larger market shares, exert greater market power, and charge higher markups. In addition, constraints on one firm trigger strategic pricing responses from others, altering markups and the demand for inputs, thereby affecting allocative efficiency and total output.

3 Quantitative Model

Time is discrete and infinite. There are three types of agents, households, firms, and financial intermediaries, and two factors of production, capital and labor. Each firm produces a differentiated good.

Preferences. Representative households face a consumption-savings decision, supply their unit endowment of labor to the firms inelastically, and can lend their assets to competitive intermediaries. Their objective function is:

$$\max_{c_t, a^h_{t+1}} \sum_{t=0}^{\infty} \beta^t u(c_t) \tag{4}$$

subject to:

$$P_t(c_t + a^h_{t+1}) = w_t + (1 + r_t)P_t a^h_t + P_t d_t,$$

where β is the discount rate, c_t denotes consumption at time t, a^h_t denotes asset holdings, w_t denotes the wage, r_t denotes the interest rate, d_t denotes real payouts from firms, and P_t denotes the price of the consumption good, which can be transformed one to one in the capital good.

Technology. The productive sector extends the standard framework of Atkeson and Burstein (2008) to an environment in which firms hire both capital and labor, but face constraints on capital. A representative competitive firm produces the final good Q_t using a continuum of differentiated sectoral inputs $Q_t(s)$:

$$Q_t = \left[\int_{s\in[0,1]} Q_t(s)^{\frac{\theta-1}{\theta}} ds \right]^{\frac{\theta}{\theta-1}}$$

Here, s refers to sectors and $\theta > 1$ is the elasticity of substitution across sectoral goods. Each sector consists of a large but finite number of intermediate good firms indexed by i. The sectoral good is then produced according to the following technology:

$$Q_t(s) = \left[\sum_{i=1}^{N} q_{it}(s)^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}}, \tag{5}$$

Here, N denotes the number of potential firms per sector, and γ is the within-sector elasticity of substitution. Following Atkeson and Burstein (2008) and Edmond et al. (2015), I assume each sector has the same number of potential producers. The finite number of firms captures the idea of scarce entrepreneurial talent.

I assume that $\gamma > \theta$, implying that goods are *more* substitutable within sectors than across sectors. The relative magnitudes of γ and θ will play an important role in determining markup dispersion and, thus, the level of misallocation in this economy.

Heterogeneous Firms. Intermediate good producers differ in their productivity, denoted by $z_{it}(s)$, their fixed production costs, which vary by sector, and their net worth, given by $a_{it}(s)$. As in e.g. Khan and Thomas (2013), in every period, they face a probability ν of exiting the market, in which case accumulated net worth is paid to the representative consumer. The firm then gets replaced by a new company, which receives startup funds a_0.

Each period, a firm that enters the market pays a fixed cost $F(s)$ in units of capital, as in Blaum (2022). It then competes oligopolistically within its sector, as in Atkeson and Burstein (2008). This decision is represented by the binary variable $x_{it}(s)$. Specifically, firms engage in Cournot competition, recognizing that their output decisions affect sectoral aggregate supply $Q_t(s)$.

Their production technology is given by the following function:

$$q_{it}(s) = z_{it}(s) k_{it}(s)^{\alpha} l_{it}(s)^{1-\alpha}, \tag{6}$$

where $k_{it}(s)$ and $l_{it}(s)$ denote capital and labor inputs, respectively, and $\alpha \in (0, 1)$.

Per-period nominal profits are given by:

$$\pi_{it}(s) = x_{it}(s) \left\{ p_{it}(s) q_{it}(s) - (r_t + \delta) P_t k_{it}(s) - w_t l_{it}(s) - (r_t + \delta) P_t F(s) \right\} \tag{7}$$

In expression (7), w_t denotes wages, r_t denotes the interest rate, δ is depreciation, P_t denotes the price of the final good, and $p_{it}(s)$ is the price of the good produced by firm i in sector s.

The formulation of the firms' dynamic problem follows that of Mehrotra and Sergeyev (2021). Let $\Lambda_{t,t+i}$ denote households' discount factor from time t to time $t+i$. The firms' problem, displayed below, implies that their goal is to maximize their terminal net worth:[7]

$$\max_{\substack{k_{it}(s) \geq 0,\, l_{it}(s) \geq 0 \\ x_{it}(s) \in \{0,1\},\, p_{it}(s)}} \mathbb{E}_t \sum_{i=1}^{\infty} \nu (1-\nu)^{i+1} \Lambda_{t,t+1+i} a_{i,t+1}(s)$$

subject to the production function and the expressions below:

[7] Similar formulations, in which the firm never finds it optimal to pay dividends whenever it is constrained or there is a non-zero probability of being constrained in the future, are adopted in the literature (see e.g. Khan and Thomas (2013), Ottonello and Winberry (2020))

$$a_{i(t+1)}(s) = (1 + r_t)a_{it}(s) + \frac{\pi_{it}(s)}{P_t} \tag{8}$$

$$p_{it}(s) = p(\{q_{jt}\}_{j=1}^{N}, Q_t) \tag{9}$$

$$k_{it}(s) + F(s) \leq \lambda a_{it}(s) \tag{10}$$

Expression 8 represents the firms' budget constraint represented in real terms. This formulation implies that firms' objective is to maximize profits – selecting inputs, prices, and entry choice – on a period-by-period basis, as a static problem, which greatly simplifies my analysis.

Expression (9) represents the inverse demand function. Because the number of firms competing in sector s is finite, firm i will react strategically to production decisions of firms $j \neq i$. In fact, the relevant state variable for a given firm involves the joint distribution of individual productivities and net worth within the firm's sector. I will return to the firms' pricing problem later in this section.

Expression (10) captures a standard financial constraint. In line with the heterogeneous firm literature (see, for example, Khan and Thomas (2013) and Moll (2014)), I assume the presence of a representative financial intermediary that borrows at the risk-free interest rate r_t and lends to firms, breaking even in equilibrium. To safeguard its lending, the intermediary imposes a collateral requirement: firms may not borrow more than a multiple $\lambda \geq 1$ of their current real asset holdings.[8]

This constraint can be interpreted as arising from a limited enforcement problem. Suppose that, at the end of the period, a firm chooses to default on its obligations to financial intermediaries. In that case, the lenders retain the posted collateral, and financial institutions in the economy impose a punishment that allows them to recover a fraction $1 - \frac{1}{\lambda}$ of the firm's capital stock $k_{it}(s)$. As a result, default is not optimal unless the firm attempts to borrow more than $\lambda a_{it}(s)$ – a condition that does not hold in equilibrium.

My definition of financial development follows Buera et al. (2011), and is captured by the parameter λ. In particular, lower values of λ reflect weaker enforcement of loan contracts, and thus imply tighter collateral requirements. In the extreme case where $\lambda = 1$, the economy is in financial autarky – firms are unable to borrow. Conversely, as $\lambda \to \infty$, no collateral is required.

Pricing. In every period, a representative sector-goods producer purchases intermediates at prices $p_{it}(s)$, aggregates them using a CES aggregator (Expression (5)), and sells an amount $Q_t(s)$ at prices $P_t(s)$ to the final goods producer. Their problem is given by:

$$\max_{Q_t(s)} \left\{ P_t Q_t - \int_{s \in [0,1]} \left[\sum_{i=1}^{N} p_{it}(s) q_{it}(s) \right] ds \right\} \tag{11}$$

[8] The constraint is expressed in real terms.

The first-order condition yields the following inverse demand function:[9]

$$p_{it}(s) = q_{it}(s)^{-\frac{1}{\gamma}} Q_t(s)^{\left(\frac{1}{\gamma}-\frac{1}{\theta}\right)} Q_t^{\frac{1}{\theta}} P_t^{-\frac{1}{\theta}} \tag{12}$$

I also define the sector s price index as

$$P_t(s) = \left[\sum_{i=1}^{N} x_{it}(s) p_{it}(s)^{1-\gamma} \right]^{\frac{1}{1-\gamma}},$$

The solution to this problem determines the prices that firms charge, which take the form of a markup over marginal cost:

$$p_{it}(s) = \mu_{it}(s) mc_{it}(s) \tag{13}$$

In Appendix C, I show how the marginal costs depend on whether firms are constrained or not.

For both constrained and unconstrained firms, the markup is given by:

$$\mu_{it}(s) = \left(\frac{\epsilon(\omega_{it}(s))}{\epsilon(\omega_{it}(s)) - 1} \right), \tag{14}$$

where $\omega_{it}(s) = \frac{p_{it}(s)q_{it}(s)}{\sum_{j=1}^{N} p_{jt}(s)q_{jt}(s)}$ is the revenue market share of firm i in sector s. In particular $\epsilon(\omega_{it}(s))$ represents the demand elasticity the producer faces, given by:

$$\epsilon(\omega_{it}(s)) = \left[\frac{1}{\gamma}(1-\omega_{it}(s)) + \frac{1}{\theta}\omega_{it}(s) \right]^{-1}, \tag{15}$$

The expression above, similar to equation (2) in Section 2, is a weighted harmonic mean of γ and θ. It shows that larger firms face lower demand elasticities and therefore charge higher markups. As a firm's market share approaches one ($\omega_{it}(s) \to 1$), its demand elasticity converges to θ, reflecting limited competition within its sector and stronger substitution across sectors. In contrast, smaller firms ($\omega_{it}(s) \to 0$) face intense competition within their own sector, leading to a higher elasticity of demand – closer to γ.

Rearranging expression (14), we link markups and market shares:

$$\frac{1}{\mu_{it}(s)} = \frac{\gamma - 1}{\gamma} - \left(\frac{1}{\theta} - \frac{1}{\gamma} \right) \omega_{it}(s) \tag{16}$$

Expression (16) does not make it immediately clear that financial constraints (λ) affect firm-level markups. However, as discussed in Section 2, this expression reflects an equilibrium condition in which the market share $\omega_{it}(s)$ is endogenously determined as a function of marginal costs– and, thus, depends on whether, and how strongly, a producer is financially constrained.

[9]To obtain expression 12, I also use the first-order conditions from final goods' producer problem. For brevity, I omit the details, which are available in Atkeson and Burstein (2008).

In Appendix C, I revisit the illustrative exercise from Section 2 using the full quantitative model and show that the same mechanism –where financial frictions reallocate market share and amplify markups – remains active.

Equilibrium. I am interested in studying steady state equilibria in this framework. In that case, consumption (and all aggregates) are constant over time. Also, the Euler Equation pins down the interest rate $r = \frac{1}{\beta} - 1$. Throughout the remainder of this paper, I assume labor to be the numéraire, setting $w_t = 1$.

Dropping time subscripts, the market clearing condition for labor is:

$$\int_{s\in[0,1]} \sum_{i=1}^{N} l_{it}(s)ds = 1 \tag{17}$$

Aggregate capital employed in production is given by:

$$K = \int_{s\in[0,1]} \sum_{i=1}^{N} k_i(s)ds \tag{18}$$

The aggregate resource constraint is:

$$c_t + \delta K + \int_{s\in[0,1]} \sum_{i=1}^{N} x_i(s)F(s)ds = Q$$

Aggregate payouts to households from firm exit are given by:

$$d_t = \int_{s\in[0,1]} \left[\sum_{i=1}^{N} \mathbb{I}(exit)a_i(s) \right] ds,$$

where $\mathbb{I}$ denotes the indicator function. In the case of exit, the firm is replaced by a new one with a new productivity draw and an initial level of assets a_0.

The definition of a steady state equilibrium follows standard practice: firms and households optimize subject to their respective constraints. Importantly, intermediate goods producers do not take output prices as given.

In this model, the law of large numbers does not hold within each sector. As a result, the joint distribution of firm-level productivity and net worth, along with sectoral output, evolves over time. Stationarity is instead defined at the level of final goods: aggregate production remains constant, and the joint distribution of sector-level variables, such as production, prices, capital, and labor, is time-invariant. Appendix Section C.4 provides further details on the computation of the stationary equilibrium.

3.1 Decomposing Productivity Losses

I now examine how markups and financial frictions interact to shape productivity in the model. In particular, I distinguish between the direct effects of financial development – through input market misallocation – and its indirect effects via changes in markup dispersion. I then show how the aggregate markup (to be defined shortly), together with total factor productivity (TFP), determines the demand for capital in the frictionless benchmark and, ultimately, influences aggregate output. For simplicity, I omit time subscripts throughout the analysis.

I begin by defining a sector-level labor productivity:

$$A(s) \equiv Q(s)/L(s), \tag{19}$$

where $L(s)$ is the total labor employed in sector s. This measure will later facilitate an intuitive decomposition of the sources of misallocation in the economy.

Following the methodology proposed by Hall (1988), I define the sector-level markup as:

$$\mu(s) = (1-\alpha)\frac{P(s)Q(s)}{wL(s)}, \tag{20}$$

where $1-\alpha$ is the elasticity of production with respect to labor, the flexible input in this framework. We can re-write equation (33), using equation (19):

$$\mu(s) = (1-\alpha)\frac{P(s)Q(s)}{wL(s)} = (1-\alpha)\frac{P(s)}{w/A(s)} \tag{21}$$

Intuitively, the equation above states that the sector markup depends on the labor elasticity and on the ratio of the sectoral price and a measure of the sector level unit cost, which depends on its productivity $A(s)$. In addition, we can re-write expression (19):

$$A(s) = Q(s)\left[\sum_{i=1}^{N} x_i(s) l_i(s)\right]^{-1} \tag{22}$$

and substitute the individual producers' production function:

$$A(s) = Q(s)\left[\sum_{i=1}^{N} x_i(s)\frac{q_i(s)}{z_i(s)}\left(\frac{k_i(s)}{l_i(s)}\right)^{-\alpha}\right]^{-1} \tag{23}$$

Turning our attention to individual producers, re-write the production function:

$$q_i(s) = z_i(s)k_i(s)^{\alpha}l_i(s)^{1-\alpha} = z_i(s)\left(\frac{k_i(s)}{l_i(s)}\right)^{\alpha} l_i(s) \equiv \bar{z}_i(s)l_i(s) \tag{24}$$

Equation (24) rewrites the production function to highlight two distinct components. The first is the reframed productivity term, $\bar{z}_i(s)$, which depends not only on the exogenous productivity

$z_i(s)$ but also on the firm's *capital-labor mix*. Recall that in the absence of financial frictions, the capital-labor ratio is uniform across producers. However, capital-constrained firms underutilize capital relative to labor, which depresses $\bar{z}_i(s)$.

The second component, $l_i(s)$, captures the *scale* of the firm. Conditional on $\bar{z}_i(s)$, scale is inversely related to markup: a higher markup implies a smaller scale of operation, while a lower markup is associated with a larger scale.

I now combine expressions (24) (23), and (21), and use the fact that $\mu_i(s) = (1-\alpha)\cdot\frac{p_i(s)q_i(s)}{wl_i(s)} = (1-\alpha)\frac{p_i(s)}{\frac{w}{\bar{z}_i(s)}}$ to obtain:[10]

$$\mu(s) = \left[\sum_{i=1}^{N} x_i(s)\omega_i(s)\frac{1}{\mu_i(s)}\right]^{-1} \tag{25}$$

Equation (25), extending the result from Edmond et al. (2015) to a setup with capital and labor, shows that the sector markup is a weighted harmonic average of the firm-level markups.

In equilibrium, for participating firms $\omega_i(s) = \left(\frac{p_i(s)}{P(s)}\right)^{1-\gamma}$. This implies:

$$\mu(s) = \left[\sum_{i=1}^{N} x_i(s)\left(\frac{p_i(s)}{P(s)}\right)^{1-\gamma}\frac{1}{\mu_i(s)}\right]^{-1}$$

Recall that $\frac{1}{\bar{z}_i(s)p_i(s)}\frac{w}{1-\alpha} = \frac{1}{\mu_i(s)}$, while $\frac{1}{A(s)P(s)}\frac{w}{1-\alpha} = \frac{1}{\mu(s)}$. Using these, we obtain:

$$A(s) = \left\{\sum_{i=1}^{N} x_i(s)\left(\frac{\mu_i(s)}{\mu(s)}\right)^{-\gamma}\bar{z}_i^{\gamma-1}\right\}^{\frac{1}{\gamma-1}} \tag{26}$$

Equation (26) shows that sector-level productivity is shaped by three key components. The first term, $x_i(s)$, captures the *extensive margin* – whether a firm is actively producing in the sector. The second term reflects *markup dispersion*: heterogeneity in firm-level markups leads to misallocation and reduces aggregate productivity. The third term, $\bar{z}_i(s)^{\gamma-1}$, incorporates both *exogenous firm-level productivity* and distortions in the capital-labor ratio due to financial frictions.

Analogously to expressions 33 and 26, the *aggregate* markup and aggregate (labor) productivity can be represented respectively by:

$$\mu = (1-\alpha)\frac{PQ}{wL} = \left(\int_0^1 \frac{1}{\mu(s)}ds\right)^{-1}, \tag{27}$$

and

$$A = \frac{Q}{L} = \left(\int_0^1 A(s)^{\theta-1}\right)^{\frac{1}{\theta-1}} \tag{28}$$

In the results section, I employ the above formulas to understand the role of each misallocation component (markup dispersion and capital-labor ratio dispersion) in causing efficiency losses.

[10] See Appendix C for details.

From equation (28), the Total Factor Productivity can be recovered:

$$TFP = \frac{A}{\left(\frac{K}{L}\right)^{\alpha}}, \tag{29}$$

where $L = 1$ represents the aggregate labor employed in the economy.

I now consider a hypothetical representative firm and represent its markup as the ratio of revenues to input expenditures, weighted by the capital share:

$$\mu = \alpha \frac{PQ}{(r+\delta)K}$$

setting $L = 1$, we can re-write:

$$\mu = \frac{\alpha}{r+\delta} \times TFP \times K^{\alpha-1}, \tag{30}$$

Isolating K and plugging in the (hypothetical) aggregate production function we obtain:

$$Q = TFP^{\frac{1}{1-\alpha}} \cdot \left(\frac{\alpha}{\mu(r+\delta)}\right)^{\frac{\alpha}{1-\alpha}} \tag{31}$$

Equation 31 shows how the aggregate markup and output are linked for this hypothetical representative firm. Conditional on aggregate TFP – which itself is determined by the allocation of inputs – a higher markup implies lower aggregate capital, which in turn reduces output. Thus, financial constraints can (i) affect the allocation of resources and (ii) affect total input usage. Taken together, these two effects determine their impact on output.

4 Calibration

Dataset. I now provide a brief overview of the Chilean firm-level panel dataset, which has been employed in several contexts, including international trade (Pavcnik (2002)) and production function estimation (Levinsohn and Petrin (2003),Gandhi et al. (2011)). The data comes from the Chilean National Institute of Statistics. The panel extends from 1979 to 1996 and covers the universe of manufacturing plants with 10 or more employees[11]. As over 90% of firms are single plants, throughout this paper I treat plants as individual producers. The final dataset contains 10,927 unique plants, with an average of 4,788 unique plants in each year.

I use information on gross revenue output, value added, the wage bill, and corresponding deflators. Capital measures are avoided due to the lack of information on intangible assets. Value added is calculated as gross output minus the total (deflated) cost of intermediate inputs. The wage bill is constructed as a weighted average of blue- and white-collar compensation, using each group's share of total plant employment as weights.[12] When computing dynamic moments such

[11] Figure A1 in Appendix A shows that, during this period, manufacturing in represented around 20% of the Chilean Gross Domestic Product.

[12] I am grateful to Salvador Navarro for providing access to the Chilean dataset and for his assistance in computing

as firm growth I detrend variables by removing average annual growth across firms. Sales growth and market share calculations exclude exports.

The finest sector classification available in these data displays 89 industries, using the four-digit ISIC classification. Examples are "Manufacture of Engines and Turbines", "Manufacture of Bakery Products", "Manufacture of Textiles", or "Wine Industries". Producer market shares are computed within these industries using gross output (domestic sales). Finally, I compute industry-level moments (for instance, within-sector concentration) using sector-year observations, which is consistent with the model notion of stationarity.

In the data, there is large across-industry variation in market concentration. The median Herfindahl-Hirschman Index (HH) is 0.16, while the mean is 0.23 and the standard deviation is 0.22. That is, there are many sectors that display low concentration, but a considerable amount of very concentrated sectors. The same heterogeneity is observed in the number of firms by industry - the median, mean, and standard deviation of the number of firms is respectively 23, 55, and 105. Therefore, there is a large number of sectors with only a few firms, and a considerable amount with a very large number of firms. I interpret this fact as differences in the fixed costs of operating in each sector, and parametrize the distribution of F_s to match the heterogeneity in the number of firms.

Calibration. I use standard values in the literature for three parameters. I set α, the capital elasticity of output, to 0.33, the depreciation rate δ to 0.06, and the discount factor β to 0.9635, targeting a real interest rate of roughly 4%.

I assume that idiosyncratic productivity consists of two components. The first is a permanent component, denoted by $\psi_i(s)$, which is time-invariant and follows a Pareto distribution with shape parameter η and scale normalized to one. The second is a transitory component, $\xi_{it}(s)$, whose logarithm follows an AR(1) process:

$$\log(\xi_{it}(s)) = \rho \log(\xi_{i,t-1}(s)) + \epsilon_{it}(s),$$

where $\epsilon_{it}(s) \sim \mathcal{N}(0, \sigma^2)$.

A firm's productivity is then given by the product of the two components:

$$z_{it}(s) = \psi_i(s) \cdot \xi_{it}(s).$$

I assume that fixed costs can take one of three possible values, $F_s \in \{0, F_l, F_h\}$, each occurring with equal probability. I set N, the potential number of firms per sector, to 134 in order to match the average number of operating firms within the top tercile of the empirical distribution of firms per sector. In these industries, all potential producers are active, which justifies setting $N = 134$ directly. The values of F_l and F_h are then chosen jointly with nine additional parameters, as described below.

value added and wage bill measures.

I calibrate 11 parameters by targeting 11 empirical moments, using moment-matching procedure These parameters include the fixed cost values F_l and F_h; the across- and within-sector elasticities of substitution, θ and γ; the parameters governing the idiosyncratic productivity process, η, ρ, and σ; the exogenous exit probability ν; the collateral constraint parameter λ; and the initial asset level a_0. Although these parameters are jointly identified within the calibration procedure, I next provide an intuitive discussion of how each moment is primarily influenced by one or more of these parameters.

The elasticity of substitution parameters, γ and θ, jointly discipline the mean and the dispersion of markups in this economy. The model structure delivers a linear relationship between producer market share and labor share (both connected to markups), even in the presence of frictions. In particular, I posit:

$$\frac{wl_{it}(s)}{p_{it}(s)q_{it}(s)} = a + b\omega_{it}(s) \tag{32}$$

Here, the larger is a firm's market share $\omega_{it}(s)$, the lower will be its labor share ($b < 0$), which translates into higher markups. Following Edmond et al. (2015), to capture the relationship between labor and market shares, I match the coefficient b in a data regression analogous to the expression above (including industry fixed effects, both in the data and in the model), which equals -0.354.

To assess the overall level of markups in this economy, linked to θ, I target the aggregate labor share (or, equivalently, one minus the sum of profits and capital shares) obtained from the Penn World Table (averaged over 1979 to 1996), which equals 47%.

The fixed cost parameters, as mentioned, discipline the number of firms and thus the industries' market concentration. Sectors where fixed costs are high will have on average fewer firms. Following this logic, I choose F_l and F_h to match the average number of participants on the second and first terciles, respectively 6.2 and 24.2.

The right panels of Figure 3 compare the distribution of firm counts in the data with that generated by the benchmark calibration. The model closely matches the distribution in the first and second terciles but fails to capture the relatively low mass of sectors with 45 to 120 firms observed in the data. Due to the calibration strategy, this mass is absorbed by sectors with zero fixed costs. Additionally, while the model's distribution of Herfindahl-Hirschman (HH) indices provides a reasonable fit, it slightly understates the prevalence of highly concentrated sectors (left panels of Figure 3).

I identify the parameters governing firm productivity dynamics as follows. The Pareto shape parameter η is chosen, following Buera et al. (2011), to match the top 10% revenue share in the data (76%). The persistence and volatility parameters, ρ and σ, are selected to match the mean squared error and the revenue autocorrelation coefficient ρ_{rev} from the following regression:

$$\Delta \log \left(rev_{it}(s)\right) = \rho_{rev} \Delta \log rev_{i,(t-1)}(s) + \epsilon_{it}(s),$$

where $rev_{it}(s) = p_{it}(s)q_{it}(s)$ represents firm revenue and Δ represents time differences. Taking

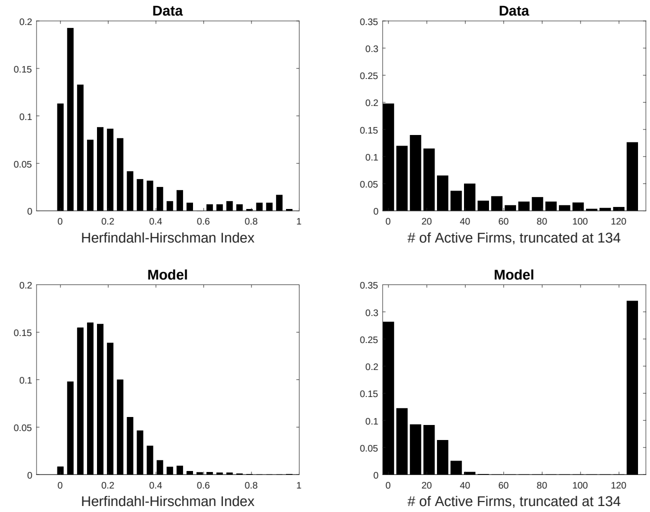

Figure 3: Model Performance - Distribution of Number of Producers

Notes: This figure compares model-implied distributions of market concentration and firm counts with their empirical counterparts from the Chilean manufacturing data. The left panels show the distribution of Herfindahl-Hirschman (HH) indices across sectors.

differences eliminates firm-specific fixed effects, particularly the permanent productivity component captured by the Pareto distribution.

I set ν to match the exit rate of firms younger than three years (12.8%). While exit is partly governed by this exogenous parameter, it also reflects the endogenous entry margin, which is influenced by transitory shocks.

I set λ to match the ratio of aggregate borrowing to GDP, which averages 0.74 between 1989 (the start of the series) and 1996, according to the Global Financial Database. The initial asset level a_0 is then chosen to match the average growth of producers over their first three years, which is 82.4% in the data (or roughly 22% yearly growth).

Table 1 summarizes the calibration procedure and shows that the model closely replicates all targeted moments. Table 2 reports additional, untargeted moments and compares them to their model counterparts. The model successfully reproduces the central moments of the market concentration (HH) distribution but slightly understates its right tail – suggesting that, if anything, it underestimates the degree of concentration in the data. Interestingly, the model overstates the mean and median of maximum market shares. For the overall market share distribution, the model performs well in matching the mean, standard deviation, and quantiles, but slightly understates the median, again indicating a conservative estimate of concentration. Lastly, the model accounts for the fact that exit rates decrease with firm age, but overstates exit rates for older firms.[13]

[13]Using data on listed firms, De Loecker and Eeckhout (2018) report that the sales-weighted average markup in Chile post-1980 ranges from 1.40 to 1.60 (see Figure A.4 in their paper). My benchmark calibration yields a value of 1.40. Given that listed firms tend to have greater market power than non-listed ones, I interpret this as a good fit.

Table 1: Calibration Output: Model and Data

Parameter	Targeted Moment	Model	Data	Source
$\gamma = 7.44$	Regression of Labor Share on Market Share.	-0.536	-0.534	Chilean Data
$\theta = 1.07$	Profit+Capital Share (1990)	57%	53%	CEPAL
$\eta = 3.63$	Top 10% Revenue Share	80%	76%	Chilean Data
$N = 134$	$\mathbb{E}(N_s \mid N > N_s^{66.7})$	134	134	Chilean Data
$F_l = 3.29$	$\mathbb{E}(N_s \mid N_s^{33.3} < N \leq N_s^{66.7})$	23.8	24.2	Chilean Data
$F_h = 25.9$	$\mathbb{E}(N_s \mid N \leq N_s^{33.3})$	6.3	6.2	Chilean Data
$\lambda = 4.7$	External Finance to GDP	0.74	0.74	GFDD
$\rho = 0.38$	FE AR(1) of Revenues ρ	-0.22	-0.22	Chilean Data
$\sigma = 0.072$	FE AR(1) MSE	0.35	0.36	Chilean Data
$\nu = 0.087$	Exit Rate if Young Firms	14.4%	12.8%	Chilean Data
$a_0 = 2.06$	Growth of Young Firms	83.4%	82.4%	Chilean Data

Notes: This table reports the values of calibrated parameters and the corresponding empirical moments used as targets. Data sources include Chilean manufacturing microdata (1979-1996), national income accounts from CEPAL, and the Global Financial Development Database (GFDD).

Market Power in the Benchmark Calibration. Before turning to the counterfactual exercises, I briefly discuss key features of the benchmark economy, focusing on markups and firm concentration. Figure 4 displays the equilibrium distribution of markups and its relationship with market concentration. Panel A shows the producer-level markup distribution by sector type. Panel A shows the markup distribution by sector type. I group sectors into two categories: "low entry cost" sectors ($F_s = 0$) and "high entry cost" sectors ($F_s > 0$), since sectors with F_l and F_h exhibit similar patterns in both concentration and their response to frictions (as discussed in the results section). The markup distribution is tight in low entry cost sectors but highly dispersed in high entry cost sectors. This heterogeneity in markup dispersion translates into distinct patterns of market concentration, shown in Panel B. Sectors with high entry costs are, on average, more concentrated, though low entry cost sectors also display substantial variation.

The bottom panels explore the relationship between markups and market concentration. Panel C plots sector-level markups – measured as the sales-weighted average of firm markups – against the HH index. Markups increase with concentration, particularly when the index exceeds 0.4. Panel D confirms this pattern at the firm level, showing that producer markups also rise with the concentration of their respective industries.

Panel D also reveals that higher concentration levels are associated with greater markup dispersion, which is linked to productivity losses. At very high HH index values, the markup distribution becomes bimodal: a few dominant firms charge high markups while competing with a fringe of smaller producers setting low markups.

Table 2: Concentration and Dynamic Facts - Baseline Calibration

Moment Description	Data	Model	**Moment Description**	Data	Model
Within Sector Concentration			*Exit Rates By Firm Age (%)*		
Mean HH-index	0.23	0.21	Age ages 0-2	12.8	14.4
Median HH-index	0.16	0.19	Ages 3-5	8.6	9.5
SD in HH-index	0.22	0.11	Ages 5-10	7.2	8.9
p25 HH-index	0.07	0.12	Ages 11+	3.8	8.4
p75 HH-index	0.29	0.26			
p95 HH-index	0.77	0.41			
Mean Top Market Share(%)	17	34			
Median Top Market Share (%)	13	32			
Distribution of Market Shares			*Firm-Size Distribution*		
Mean Market Share (%)	1.81	1.91	Top 10% Wages Share	0.67	0.76
Median Market Share(%)	0.21	0.11	Top 10% Revenue Share	0.79	0.80
SD in Market Share(%)	6.17	5.95	Top 1% Wages Share	0.24	0.16
p25 Market Share(%)	0.07	0.03	Top 1% Revenue Share	0.43	0.23
p75 Market Share(%)	0.99	0.82			
p95 Market Share(%)	7.94	10.79			

Notes: This table compares moments obtained from the Chilean firm-level dataset with those in the model. The only moments directly targeted in the calibration are the exit rate of firms aged 0-2 and the top 10% revenue share. The other statistics are untargeted.

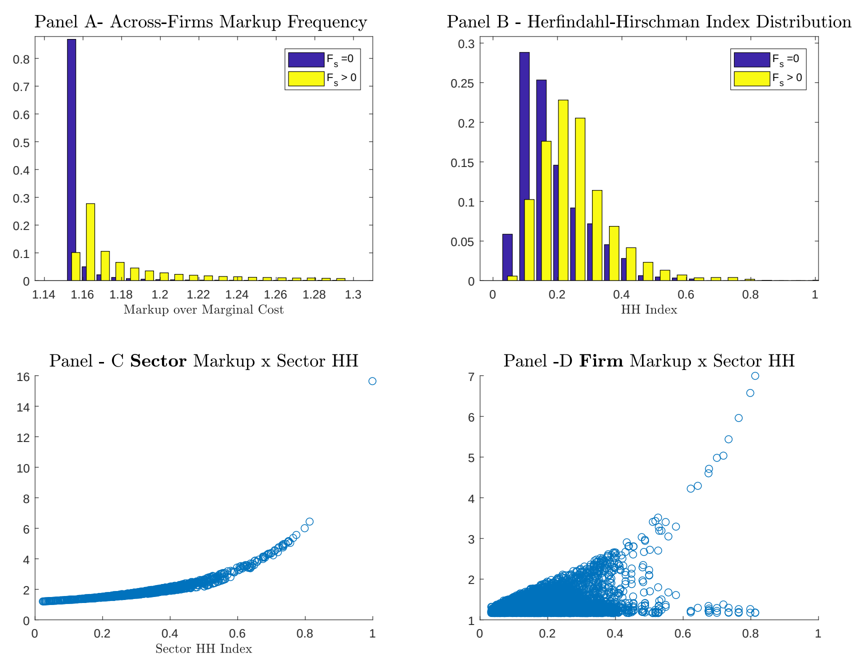

Figure 4: Markups and Market Concentration - Baseline Calibration

Notes: Panel A plots the distributions of firm-level markups in each sector type; Panel B plots the distribution of HH indices by sector type; Panel C plots the sector II index against its (aggregate) markup; and Panel D plots firm-level markups against their sector-level HH index.

5 Financial Constraints, Markup Dispersion, and Productivity Losses

Armed with the calibrated model, I now address the main questions of this paper: how do financial constraints affect markup dispersion and, in turn, competition and its associated losses? I divide the analysis in three parts. First, I study how markups react to counterfactual levels of frictions. I then decompose the losses due to financial market imperfections into the direct effect – on input markets – and the indirect effect – on markups – at various levels of capital market development (λ). Finally, I investigate the effect of financial development on the aggregate markup, and how changes in markups translate into variations in aggregate output.

5.1 How Does Financial Development Affect Markups?

Table 3 summarizes key moments of the markup distribution across three counterfactual economies, each differing in the degree of financial development. The first economy simulates a severely underdeveloped financial system by setting the collateral constraint parameter, λ, to generate an aggregate borrowing-to-output ratio of 0.3 – comparable to that of India in 1995, the final year of my dataset.[14] The second economy corresponds to the benchmark calibration, which matches Chile's average credit-to-GDP ratio of 0.76. The third economy sets $\lambda \to \infty$, eliminating frictions in capital markets. In addition to markup statistics, the table also reports the distribution of Herfindahl-Hirschman indices across sectors in each case.

Panel A shows that, across all three economies, the producer-level markup distribution is highly concentrated near the lowest admissible value, $\frac{\gamma}{\gamma-1} = 1.155$. Financial frictions primarily affect the upper tail of the distribution. Notably, in the "India" scenario, the 95th percentile of the markup distribution remains below its Chilean counterpart, even though the average markup is higher. As a result, dispersion – measured by the standard deviation of log markups – is greater in the low-finance scenario, but changes little between the benchmark and the frictionless economy. The firm-level markup patterns in Panel A are driven by shifts in the firm size distribution caused by financial frictions. When frictions are severe, the distribution becomes highly skewed, with a large mass of very small firms that, as a result, charge low markups.

Turning to sector-level markups, Panel B shows that tighter financial frictions lead to higher average markups and a more fat-tailed distribution. In the most constrained scenario ("India"), frictions are strong enough to induce the emergence of monopolies: over 10% of sectors exhibit markups consistent with monopolistic behavior, i.e., $\mu = \frac{\theta}{\theta-1} = 15.62$.

Panel C confirms that stronger financial frictions reduce competition. In the frictionless case, the average HH index is 0.18, while under the "India" scenario it rises to 0.39 – indicating a substantial increase in concentration.

In sum, tighter financial frictions raise both the average level and dispersion of markups – at both the firm and sector levels. In the next subsection, I examine how these shifts affect produc-

[14] I refer to this case as the "India" scenario, though only the financial constraint parameter λ is adjusted; all other features of the economy remain unchanged.

Table 3: Markup Dispersion and Concentration in Three Counterfactual Economies

Panel A - Across-firms Markup Distribution	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p50	1.16	1.16	1.16
p90	1.18	1.20	1.20
p95	1.25	1.28	1.27
p99.5	2.77	1.87	1.78
Mean markups	1.23	1.18	1.18
SD(log)	0.16	0.07	0.06
Panel B - Across-sector Markup Distribution	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p50	1.58	1.42	1.38
p75	2.35	1.82	1.72
p90	15.62	2.04	1.92
p95	15.62	3.97	4.03
Mean Sector-Level Markups	3.80	1.51	1.47
Sales-Weighted Average Markup	1.73	1.51	1.47
SD(log)	0.85	0.18	0.17
Panel C- Distribution of HH Concentration Index	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p25	0.14	0.12	0.12
p50	0.25	0.19	0.16
p75	0.52	0.26	0.23
p95	1.00	0.41	0.37
Mean	0.38	0.21	0.18
Standard Deviation	0.31	0.11	0.10

Notes: This table shows statistics of markups and industry concentration in three counterfactual economies with varying degrees of financial development: a financially constrained setting calibrated to match the external-finance-to-GDP of India in 1995, the benchmark economy calibrated to Chile, and a frictionless economy. Panel A shows statistics of firm-level markups; Panel B repeats the analysis for sector-level markups; and Panel C displays industry-concentration statistics.

tivity and aggregate output. I now turn my attention to the heterogeneous impacts on markups across sectors. I classify sectors into two groups: those with zero entry-cost ($F_s = 0$), and those high entry cost ($F_s > 0$).

Table 4 shows that, in industries without fixed costs, financial frictions have minimal impacts: firm-level markups remain stable, and sector-level markups, dispersion, and concentration show little change.

The pattern shifts in sectors with positive entry costs ($F_s > 0$). In these, frictions strongly affect the markup distribution: both firm- and sector-level markups are high and dispersed under the"India" scenario, substantially lower and less dispersed in the benchmark economy, and even more so in the frictionless case. As shown in Panel C, this reflects greater industry-level concentration under tighter frictions.

A key mechanism behind this result is entry. Table 6 shows that, in high entry-cost sectors ($F_s > 0$), the average number of operating firms is just 10.7 under the "India" scenario, but nearly doubles in the frictionless case. Moreover, while the share of constrained firms is small in zero fixed-cost sectors in all economies – explaining the limited impact of financial frictions there – it is much higher in positive-fixed-cost sectors: 44.1% in the "India" case and around one-third even in the benchmark. These figures highlight the substantial competitive gains that can be achieved by relaxing financial constraints in these industries, as shown in Table 5.

To conclude the analysis, Figure 5 illustrates how selected statistics of the markup distribution

Table 4: Markup Dispersion and Concentration in Zero Fixed Cost Industries

Panel A - Across-firms Markup Distribution	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p50	1.16	1.16	1.16
p95	1.18	1.18	1.18
p99.5	1.51	1.52	1.53
Mean Markups	1.17	1.17	1.17
SD(log)	0.04	0.04	0.04
Panel B - Across-sector Markup Distribution	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p50	1.33	1.34	1.35
p75	1.48	1.89	1.89
p95	1.89	2.95	2.88
Mean Sector-Level Markup	1.42	1.42	1.43
Weighted Average Markup	1.39	1.40	1.41
SD(log)	0.15	0.15	0.15
Panel C- Distribution of HH Concentration Index	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p25	0.08	0.09	0.10
p75	0.21	0.21	0.22
p95	0.36	0.36	0.36
Mean	0.16	0.16	0.17
Standard Deviation	0.10	0.10	0.10

Notes: This table shows statistics of markups and industry concentration in **zero-fixed-cost sectors** in three counterfactual economies with varying degrees of financial development: a financially constrained setting calibrated to match the external-finance-to-GDP of India in 1995, the benchmark economy calibrated to Chile, and a frictionless economy. Panel A shows statistics of firm-level markups; Panel B repeats the analysis for sector-level markups; and Panel C displays industry-concentration statistics.

evolve across different levels of financial development. Note that the x-axis reports the *recovery rate* $(1 - \frac{1}{\lambda})$, such that higher values (toward the right) correspond to weaker financial frictions.

The top-left panel illustrates how the aggregate markup evolves with financial development.[15] The key takeaway is straightforward: financial development reduces the aggregate markup – primarily through its effect on sectors with high fixed costs, where markups respond more strongly to changes in financial frictions.

The bottom-left panel shows how moments of the *firm-level* markup distribution are affected. Regardless of the degree of financial frictions, the average markup consistently lies above the 75th percentile, reflecting the strong right skewness of the distribution. The median remains close to the minimum feasible markup, $\frac{\gamma}{\gamma-1}$. This panel also reveals that lower recovery rates *stretch* the markup distribution – raising its upper percentiles and compressing the lower ones. This pattern stems from the way financial market imperfections distort the firm-size distribution.

The top-right panel shifts the focus to sector-level markups, using the same statistical moments as in the bottom-left panel. Under high recovery rates, their dispersion remains relatively stable, as indicated by the narrow and nearly constant interquartile range (dotted lines). In contrast, when financial frictions become severe (i.e., the recovery rate falls below 0.6, or $\lambda = 2.5$), this range expands considerably. This increase in dispersion reflects the amplified heterogeneity in sectoral outcomes under tighter financial constraints.

[15] I employ a version of equation (27) (second equality) to obtain aggregate markups conditional on sector types, re-weighting by the adequate measure of sectors

Table 5: Markup Dispersion and Concentration - $F_s > 0$

Panel A- Across-firms Markup Distribution	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p50	1.18	1.18	1.18
p95	2.11	1.58	1.48
p99.5	15.62	2.41	2.15
Mean Markups	1.55	1.25	1.23
SD(log)	0.38	0.12	0.11
Panel - B Across-sector Markup Distribution	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p50	1.75	1.45	1.39
p75	2.49	2.13	1.95
p95	15.62	4.34	4.65
Mean Sector-Level Markup	4.26	1.55	1.49
Sales-Weighted Average Markup	4.00	1.55	1.50
SD(log)	0.87	0.19	0.18
Panel C - Distribution of HH Concentration Index	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
p25	0.19	0.15	0.12
p75	0.54	0.27	0.23
p95	1.00	0.43	0.38
Mean	0.44	0.22	0.19
Standard Deviation)	0.30	0.11	0.10

Notes: This table shows statistics of markups and industry concentration in **positive-fixed-cost sectors** in three counterfactual economies with varying degrees of financial development: a financially constrained setting calibrated to match the external-finance-to-GDP of India in 1995, the benchmark economy calibrated to Chile, and a frictionless economy. Panel A shows statistics of firm-level markups; Panel B repeats the analysis for sector-level markups; and Panel C displays industry-concentration statistics.

Table 6: Heterogeneous Impacts of Financial Frictions

	"India" ($\lambda = 1.85$)	Benchmark ($\lambda = 4.7$)	Frictionless
Mean Number of Operating Firms - $F_s = 0$	134.0	134.0	134.0
Mean Number of Operating Firms - $F_s > 0$	10.7	14.8	17.8
(%) of Constrained Firms - $F_s = 0$	7.9	3.1	0.0
(%) of Constrained Firms - $F_s > 0$	44.1	32.6	0

Notes: The table reports, for each sector type, the average number of active firms and the share of firms operating under binding financial constraints in three counterfactual economies with varying degrees of financial development: a financially constrained setting calibrated to match the external-finance-to-GDP of India in 1995, the benchmark economy calibrated to Chile, and a frictionless economy.

Finally, the bottom-right panel plots the *standard deviation of log markups* at the sector level. In line with the top-right panel, this measure of dispersion remains relatively stable under high levels of financial development but rises sharply as the recovery rate declines. Moreover, consistent with the patterns in Tables 4 and 5, the increase in markup dispersion is largely driven by sectors with positive fixed costs, where financial constraints bind more frequently and distort competition more severely.

In sum, this section yields two main takeaways. First, the markup distribution remains relatively stable between the benchmark calibration and the frictionless economy, but changes dramatically under the "India" scenario. This suggests that dysfunctional financial markets can significantly distort markups, but the relationship is highly non-linear, with effects becoming disproportionately stronger as financial frictions become extremely severe. Second, the impact of

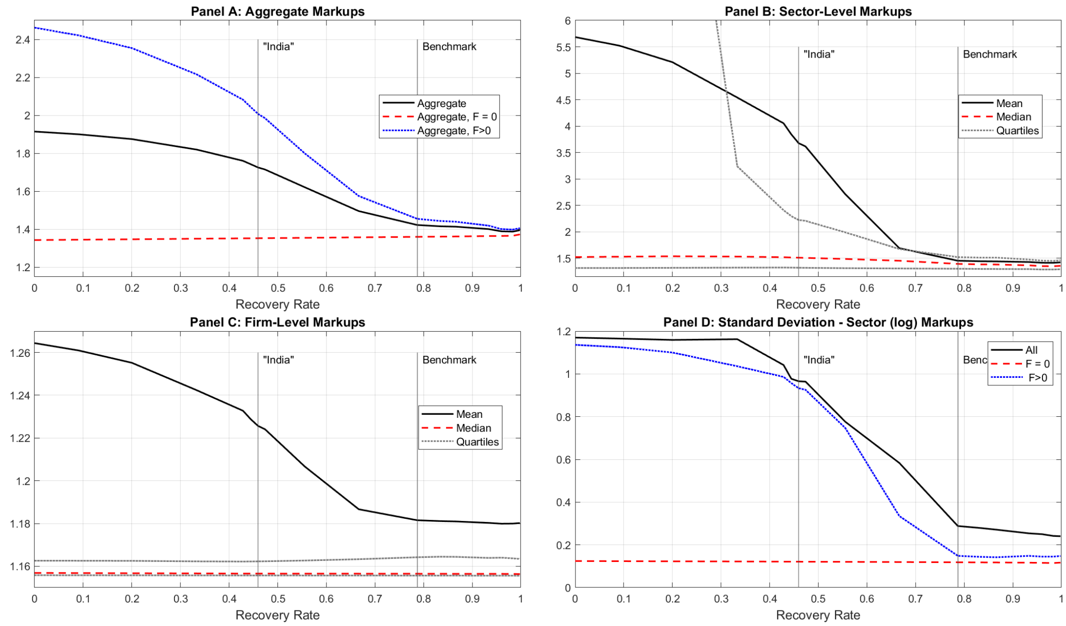

Figure 5: Distribution of Markups and Financial Market Development

Notes: Notes: Panel A plots the aggregate markup as a function of the recovery rate $1 - \frac{1}{\lambda}$. Panel B displays the mean, median, and the interquartile range of the sector-level markup distribution; Panel C repeats Panel B with firm-level markups; and Panel D reports the standard deviation of log sector-level markups as financial development varies.

these distortions is concentrated in sectors with high fixed costs – industries where competition is already limited. In contrast, sectors characterized by a large number of operating firms are largely unaffected by financial frictions in terms of their contribution to changes in the markup distribution.

I now turn to the implications of these markup shifts for aggregate productivity and output.

5.2 Direct and Indirect Effects of Financial Markets Development

I begin by examining the aggregate effects of financial development. Figure 6 displays steady-state output and total factor productivity (TFP) across different levels of the recovery rate.[16] Because labor supply is inelastic, aggregate output coincides with the (labor) productivity measure defined in equation 28 – a relationship that does not hold at the industry level due to labor reallocation across sectors. As expected, both output and TFP reach their maximum values in the frictionless case, where they are normalized to one.

Quantitatively, financial frictions lead to a reduction in output of up to 72% when comparing the frictionless case ($\lambda \to \infty$) to financial autarky ($\lambda = 1$). These losses are substantially larger than those estimated by Buera et al. (2011), who report a decline of about 52% (see their Figure 3), and by Midrigan and Xu (2014), who estimate a drop of roughly 38% (based on their Table 4, output). For total factor productivity, my estimated decline reaches up to 50 percent. This is,

[16] TPF is computed based on a hypothetical representative firm whose production function is $Y = TFP \times K^{\alpha} L^{1-\alpha}$, where Y represents total production.

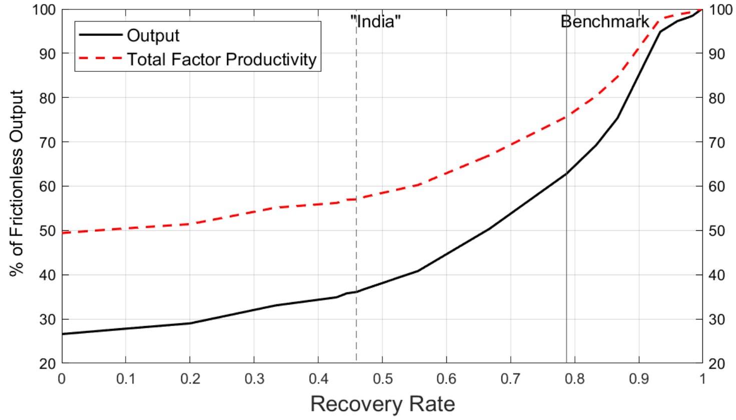

Figure 6: Financial Development, Output, and TFP

Notes: The figure plots output and TFP for economies with different degrees of the recovery rate, i.e. $1 - \frac{1}{\lambda}$. These statistics are normalized to one in the frictionless economy. The dashed and solid vertical lines respectively represent the "India scenario" and the benchmark calibration levels of the recovery rate.

again, substantially larger than TFP losses reported in Buera et al. (2011) (36%) and Midrigan and Xu (2014) (roughly 23%). The stark differences suggest a critical role for competition – absent from those frameworks – in amplifying the aggregate costs of financial underdevelopment.

To further examine the role of competition, I now turn to a decomposition of the effects of changes in λ into two distinct channels: the direct impact on input markets and the indirect impact operating through competition. Recall that sector-level labor productivity can be expressed as:

$$A(s) = \left\{ \sum_{i=1}^{N} x_i(s) \left(\frac{\mu_i(s)}{\mu(s)} \right)^{-\gamma} \bar{z}_i^{\gamma-1} \right\}^{\frac{1}{\gamma-1}},$$

and its economy-wide counterpart is:

$$A = \left(\int_0^1 A(s)^{\theta-1} \right)^{\frac{1}{\theta-1}}.$$

Using these formulas, I conduct the following counterfactual exercise for a given economy (i.e., for a given value of λ). First, I isolate the role of markup dispersion by setting $\mu_(s) = \mu$, the economy-wide aggregate markup, and recomputing productivity A. Changes in this measure, relative to the benchmark equilibrium, measure (misallocation) losses due to markup dispersion.

Second, I isolate the direct input channel by shutting down capital-labor ratio dispersion. Specifically, I set all $\bar{z}_i$ values to correspond to the ones that would obtain if firms selected their unconstrained level of capital-labor ratio. The resulting change in aggregate productivity reflects the direct effect of financial frictions on firms' input choices.

Finally, I eliminate both markup and capital-labor ratio dispersion to assess the total productivity loss attributable to financial frictions. This exercise resembles that of Hsieh and Klenow

([2009](#)), who investigate the losses due to dispersion in wedges in output and input markets. The distinction is that these distortions are endogenous in my framework. In all cases, I keep firm net worth $a_{it}(s)$ and the pool of participant firms unchanged and recompute the (static) counterfactual equilibrium. I later evaluate the role of dynamics by comparing the predictions from the benchmark model with a similar model that ignores firm competition.

Figure 7 presents the results. The x-axis shows the recovery rate, while the y-axis reports the change in aggregate productivity for each counterfactual economy relative to the corresponding equilibrium productivity (at that level of the recovery rate).

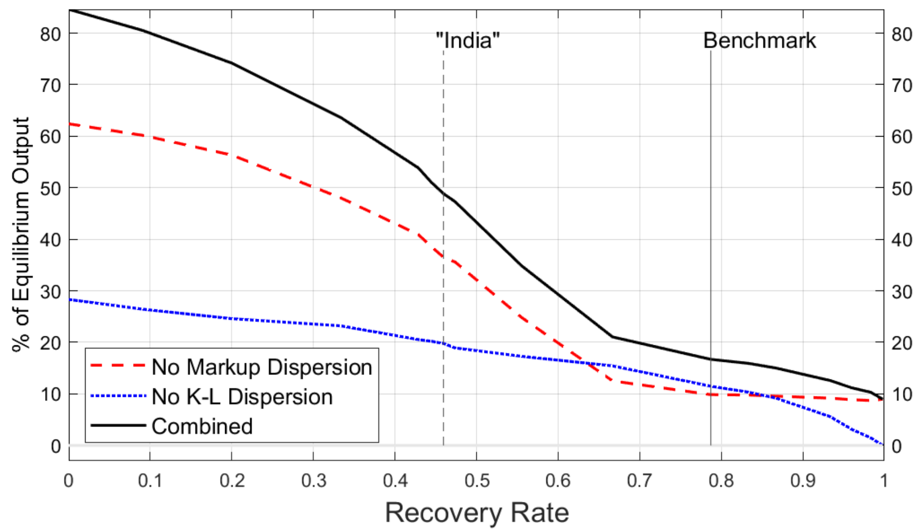

Figure 7: Decomposition of Misallocation Sources

Notes: The figure plots the decomposition of productivity losses for economies with different degrees of the recovery rate, i.e. $1 - \frac{1}{\lambda}$. See text for further details on how those are computed. The dashed and solid vertical lines respectively represent the "India scenario" and the benchmark calibration levels of the recovery rate.

At the rightmost end of the plot, the frictionless economy, capital-labor ratio dispersion is nonexistent. Thus, its removal has no effect on aggregate productivity, as indicated by the blue line approaching zero on the y-axis. However, even in this situation there are losses due to markup dispersion. I find those to be roughly 9% in the frictionless economy, substantially larger than those found by Edmond et al. (2023) for the United States.[17]

As we move to the left, losses due to capital-labor dispersion begin to increase, while those from markup dispersion initially remain relatively stable. For the benchmark economy, with a recovery rate close to 0.8, misallocation from capital-labor dispersion is slightly below 20%, while that due to markup dispersion is slightly above 10%, virtually the same as in the frictionless scenario. In the benchmark economy, eliminating both sources of dispersion would increase productivity by around 25% . The reason the combined efficiency losses are smaller than the sum of the

[17]The framework in Edmond et al. (2023) features monopolistic competition and a Kimball (1995) demand aggregator. Their paper features no financial frictions.

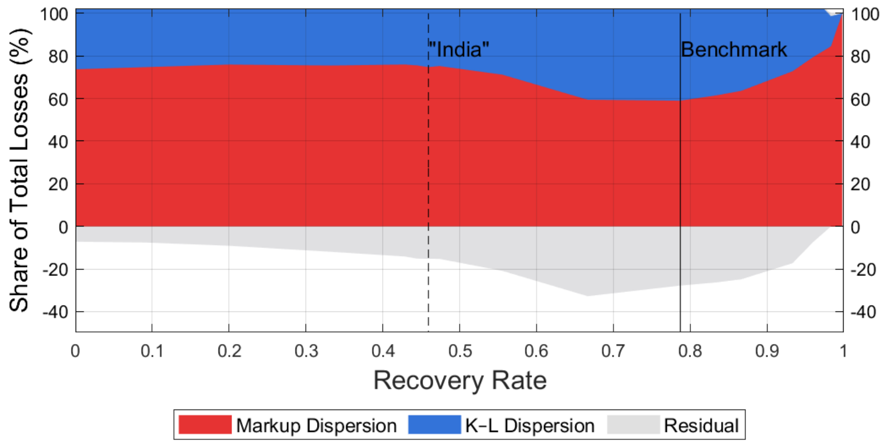

Figure 8: Decomposition of Productivity Losses

Notes: The figure plots the share of productivity losses for economies with different degrees of the recovery rate, i.e. $1 - \frac{1}{\lambda}$, attributable to each component of the decomposition. See text for further details on how those are computed. The dashed and solid vertical lines respectively represent the "India scenario" and the benchmark calibration levels of the recovery rate.

individual losses is the positive covariance between the implied changes in $\bar{z}_i(s)$ and $\mu_i(s)$.[18] Intuitively, eliminating markup dispersion reallocates labor away from small firms, which are also the main beneficiaries of eliminating capital-labor dispersion.

In the "India" scenario, the indirect losses due to markup dispersion rise to approximately 38%. This reflects a substantial increase of nearly 29 percentage points relative to the frictionless economy, where such losses are only 9%. Notably, these additional losses exceed those associated with capital-labor dispersion, which remain at around 20% under the "India" scenario. In total, efficiency losses amount to roughly 50%, with the majority stemming from the indirect, pro-competitive effects of financial frictions. These findings underscore the importance of accounting not only for the direct distortions introduced by financial frictions, but also for their indirect impact on market structure and competition. Figure 8 concludes by displaying the share of losses attributable to each type of dispersion for different degrees of financial development.

In the frictionless case, all efficiency losses are due to markup dispersion. As financial frictions increase, the share of losses attributable to capital-labor misallocation rises steadily, peaking at around 35% near the benchmark recovery rate. However, under very severe financial constraints, the contribution of markup dispersion increases again, reflecting the more pronounced reduction in competition caused by financial frictions.

Figures 7 and 8 help reconcile the quantitative predictions in this paper with those the previous literature. In my framework, financial frictions trigger markup dispersion, leading to large output and productivity losses shown in Figure 6. However, I have shown that a large proportion of those losses are due to competitive effects, suggesting that ignoring those would lead to smaller losses, quantitatively closer to those Buera et al. (2011) and Midrigan and Xu (2014). We will return to

[18]In other words, the covariance between the terms $\bar{z}^{\gamma-1}$ and $\left(\frac{\mu_i(s)}{\mu(s)}\right)^{-\gamma}$ is negative.

examine this possibility in the last part of this paper, after we investigate the heterogeneous effects on different sectors.

Across-Industry Heterogeneity. To complete the analysis, I examine how losses vary across industries, distinguishing between sectors with zero and positive fixed costs. Focusing first on sectors with zero fixed costs, Figure 9 (analogous to Figure 7) shows that misallocation due to markup dispersion remains largely constant across levels of financial development, at around 10%. As we have seen, in the absence of entry costs, the distribution of markups is relatively insensitive to financial frictions, as zero entry costs ensure a large number of producers and, consequently, a high degree of competition. Note that the losses due to K-L dispersion in these industries are also relatively muted, reflecting the small percentage of constrained firms (see Table 6).

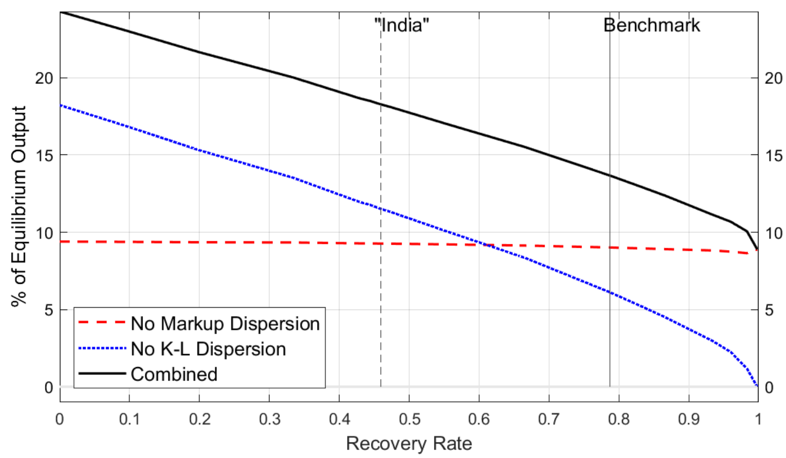

Figure 9: Decomposition of Productivity Losses- $F = 0$

Notes: The figure plots the decomposition of productivity losses **in zero-fixed-cost sectors** for economies with different degrees of the recovery rate, i.e. $1 - \frac{1}{\lambda}$. See text for further details on how those are computed. The dashed and solid vertical lines respectively represent the "India scenario" and the benchmark calibration levels of the recovery rate.

Efficiency losses due to frictions, either direct or indirect, are concentrated in the positive fixed cost sectors. Note from the difference in the y-axis scales between Figures 9 and 10 that the losses on the latter are larger, both for markup and for capital-labor ratio dispersion. Again, the losses due to the former are important particularly in highly dysfunctional financial markets. These results are consistent with those Buera et al. (2011), who emphasize the importance of high-fixed-costs sectors.

In sum, this section has shown that financial frictions distort market structure by weakening competition, thereby reducing aggregate productivity and output. These effects are especially pronounced in financially underdeveloped economies. In other words, improving financial markets has pro-competitive effects that operate through reallocation and markups. What remains to be explored is the role of economy-wide *markup levels*, to which we now turn.

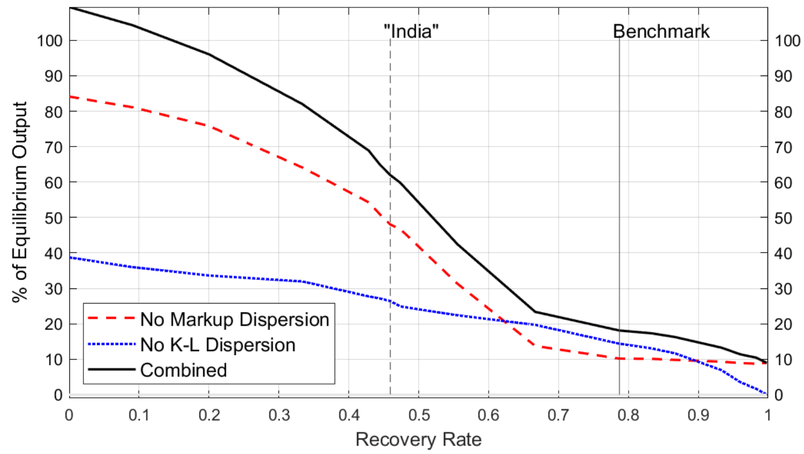

Figure 10: Decomposition of Productivity Losses - $F > 0$

Notes: The figure plots the decomposition of productivity losses **in positive-fixed-cost sectors** for economies with different degrees of the recovery rate, i.e. $1 - \frac{1}{\lambda}$. See text for further details on how those are computed. The dashed and solid vertical lines respectively represent the "India scenario" and the benchmark calibration levels of the recovery rate.

Aggregate Markup, Capital, and Output. Figure 6 shows that financial development has a stronger impact on output than on total factor productivity. Given that labor supply is inelastic, this gap is driven by differences in capital accumulation. I now turn to a more detailed examination of this mechanism.

Equilibrium aggregate capital responds to financial market development through three interconnected channels: changes along the intensive and extensive margins of capital use, and changes in the markups charged by producers. Markup levels affect firms' input choices directly, but they also influence entry decisions by altering profitability. As a result, the overall effect of markups on aggregate capital is ambiguous in equilibrium.

To assess the contribution of changes in markup *levels* to capital accumulation and output, I conduct a simple decomposition based on equations (30) and (31). In a frictionless economy with a hypothetical representative producer, these expressions illustrate how the aggregate markup influences aggregate capital and, in turn, output, holding total factor productivity constant.

I then ask: what would aggregate output be if the frictionless economy instead exhibited the higher aggregate markups associated with financially constrained ones? Take, for example, the aggregate markup under the "India" scenario, 1.73, compared to 1.40 in the frictionless case. By substituting this value of μ into expression (31), we find that output would be 10.1% lower. The red line in Figure 11 answers this question across a range of recovery rates, showing the output loss that would result from holding TFP constant and varying only the aggregate markup.

Figure 11 shows that while changes in the aggregate markup resulting from financial market imperfections have a meaningful effect on output, they account for only a limited portion of the overall decline. For example, in the "India" scenario, where total output falls by 64% due to financial frictions, the increase in the aggregate markup explains just under one-sixth of that drop.

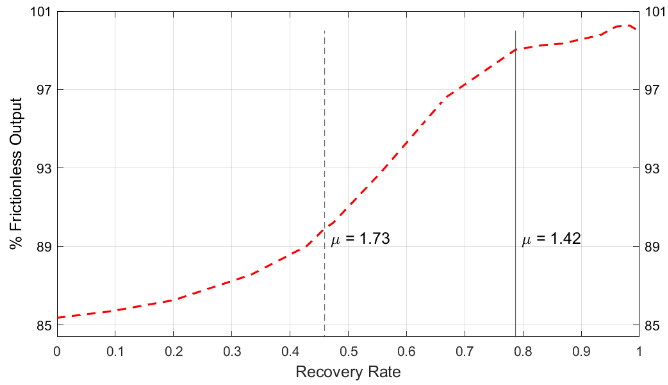

Figure 11: Aggregate Markup and Output

Notes: The figure displays the hypothetical output that would obtain holding TFP fixed and altering the aggregate markup, which in turn affects aggregate capital. See text for further details. The dashed and solid vertical lines respectively represent the "India scenario" and the benchmark calibration levels of the recovery rate.

5.3 A Comparison Between Models

To further highlight the pro-competitive effects of financial development, I now compare my results with those obtained from a version of the model that abstracts from oligopolistic competition and therefore features constant markups.[19] Specifically, we consider a framework in which firms behave as if they are atomistic. That is, they do not internalize the impact of their production decisions on sectoral output or on the behavior of other firms.

We calibrate this version of the model to match all the targets listed in Table 1, with the exception of the correlation between the labor and market shares. In this alternative framework, we impose $\gamma = \theta$, which implies that the estimated coefficient b in the regression analogous to expression (32) is zero when using model-generated data. The resulting calibration outcomes are reported in Table D1 in Appendix D.

Figure 12 illustrates that the version with constant markups predicts substantially smaller losses in both output and total factor productivity (TFP) compared to the benchmark setting.[20] Under the "India" scenario, output falls to roughly 35% of the frictionless level in the benchmark, while in the version without oligopolistic competition it remains above 50%. The corresponding figures for TFP are 57% and 80%, respectively. These findings reinforce the importance of accounting for competitive forces when assessing the gains from financial development.

[19] One could label this alternative model as "observationally equivalent" to the benchmark model of Section 3, in the sense that it replicates the same empirical targets, except for those related to markup heterogeneity.

[20] Note that the losses reported here differ from those in Figure 7, as the latter are based on a static environment and use an alternative definition of productivity.

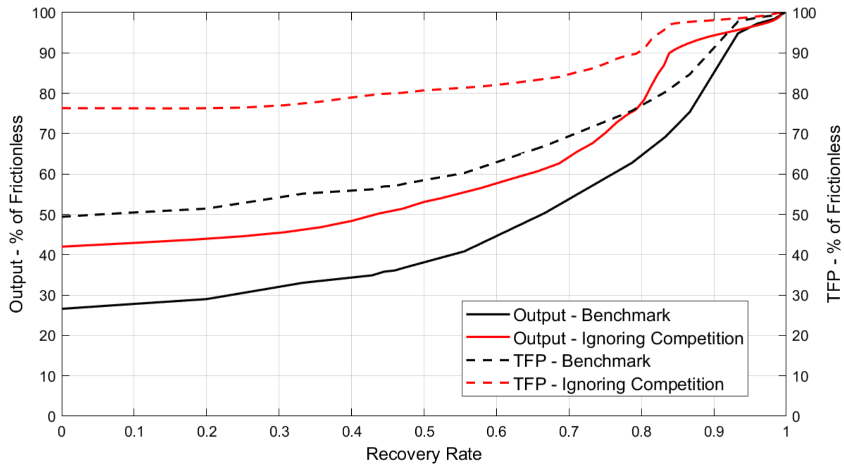

Figure 12: Comparison Between Models - Output and TFP

Notes: The figure plots output (left axis) and TFP (right axis) for economies with different degrees of the recovery rate, i.e. $1 - \frac{1}{\lambda}$, in the benchmark model (black) and in a model with constant markups (red). These statistics are normalized to one in the frictionless economy.

6 Conclusion

This paper investigates the competitive effects of financial development. I develop a dynamic extension of Atkeson and Burstein (2008) in which producers face collateral constraints. Financial frictions distort the allocation of capital, preventing constrained firms from scaling up and, through strategic pricing, reshape the distribution of markups. Constrained firms shrink, easing competitive pressure, while unconstrained rivals wield greater market power and raise markups.

I show that the total effect of financial frictions can be split into a direct impact on capital-labor ratios and an indirect effect via markups. For the quantitative analysis, I calibrate the model to Chilean manufacturing data and solve for equilibrium outcomes under varying degrees of financial constraints severity, which serve as a proxy for financial development. I evaluate impacts on productivity, output, and market structure.

I find that financial development reduces both the level and dispersion of markups, especially in economies facing severe financial constraints. Moreover, the productivity losses from the indirect impact of financial frictions operating through reduced competitive pressure are particularly pronounced in financially underdeveloped environments. In fact, in such settings, the indirect effect on markups can exceed the direct impact of distortions.

In all, this paper offers two main conclusions. First, improving capital markets fosters competition. Second, quantitative models studying the impact of financial frictions that assume either perfect competition or constant markups overlook a powerful mechanism: the competitive channel.

My insights shed light on the underlying forces behind the apparent lack of competition in many developing economies. More broadly, they offer guidance to policymakers seeking to understand the sources of misallocation and their interactions, and, ultimately, how to design more effective policies to foster competition and promote economic development.

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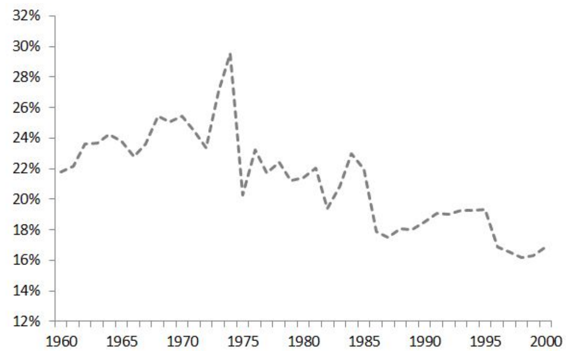
Supplemental Appendix

A Additional Figures - Data

Figure A1 shows the evolution of the share of manufacturing in Chilean GDP over time.

Figure A1: Value Added in Manufacturing in Chile (% of GDP)



Source: World Bank.

B Simple Model - Additional Details

B.1 How does s_i changes if firm j is constrained?

Consider the equilibrium condition:

$$P(q_1 + q_2) = (q_1 + q_2)^{-\frac{1}{\sigma}} - \frac{w}{A_1 \left(1 - \sigma \cdot \frac{q_1}{q_1+q_2}\right)}$$

And define the implicit function F as:

$$F(q_1, q_2) \equiv (q_1 + q_2)^{-\frac{1}{\sigma}} - \frac{w}{A_1 \left(1 - \sigma \cdot \frac{q_1}{q_1+q_2}\right)} = 0$$

We want to compute $\frac{dq_1}{dq_2}$ using the Implicit Function Theorem:

$$\frac{dq_1}{dq_2} = -\frac{\frac{\partial F}{\partial q_2}}{\frac{\partial F}{\partial q_1}}$$

Let $S = q_1 + q_2$, and $s = \frac{q_1}{q_1+q_2}$. Then:

$$F(q_1, q_2) = Q^{-\frac{1}{\sigma}} - \frac{w}{A_1(1-\sigma s)}$$

Step 1: Partial derivative with respect to q_1:

$$\frac{\partial F}{\partial q_1} = -\frac{1}{\sigma} Q^{-\frac{1}{\sigma}-1} - \frac{w}{A_1} \cdot \frac{d}{dq_1} \left(\frac{1}{1-\sigma s_1} \right)$$
$$= -\frac{1}{\sigma}(q_1+q_2)^{-\frac{1}{\sigma}-1} - \frac{w}{A_1} \cdot \frac{\sigma \cdot \frac{q_2}{(q_1+q_2)^2}}{(1-\sigma s_1)^2}$$

Step 2: Partial derivative with respect to q_2:

$$\frac{\partial F}{\partial q_2} = -\frac{1}{\sigma}(q_1+q_2)^{-\frac{1}{\sigma}-1} + \frac{w}{A_1} \cdot \frac{\sigma \cdot \frac{q_1}{(q_1+q_2)^2}}{(1-\sigma s_1)^2}$$

Step 3: Implicit derivative

$$\frac{dq_1}{dq_2} = -\frac{\frac{\partial F}{\partial q_2}}{\frac{\partial F}{\partial q_1}}$$

$$= \frac{\frac{1}{\sigma}(q_1+q_2)^{-\frac{1}{\sigma}-1} - \frac{w\sigma q_1}{A_1(q_1+q_2)^2(1-\sigma s_1)^2}}{\frac{1}{\sigma}(q_1+q_2)^{-\frac{1}{\sigma}-1} + \frac{w\sigma q_2}{A_1(q_1+q_2)^2(1-\sigma s_1)^2}}$$

This can be simplified a bit further to:

$$\frac{dq_1}{dq_2} = \frac{1 - \frac{w\sigma^2 q_1 S^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2}}{1 + \frac{w\sigma^2 q_2 S^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2}}$$

What we want is the total derivative

$$\frac{ds_1}{dq_2} = \frac{q_1' q_2 - q_1}{(q_1+q_2)^2} = \frac{q_2 \cdot \frac{dq_1}{dq_2} - q_1}{Q^2}.$$

Substituting the expression for $\frac{dq_1}{dq_2}$, we get:

$$\frac{ds_1}{dq_2} = \frac{q_2 \cdot \left(\frac{1 - \frac{w\sigma^2 q_1 S^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s)^2}}{1 + \frac{w\sigma^2 q_2 S^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s)^2}} \right) - q_1}{S^2}$$

Let:

$$N \equiv 1 - \frac{w\sigma^2 q_1 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s)^2} \qquad D \equiv 1 + \frac{w\sigma^2 q_2 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s)^2}$$

Then the total derivative of $s_1 = \frac{q_1}{Q}$ with respect to q_2 is:

$$\frac{ds_1}{dq_2} = \frac{q_2 \cdot \frac{N}{D} - q_1}{Q^2} = \frac{Nq_2 - Dq_1}{DQ^2}$$

This expresses $\dfrac{ds_1}{dq_2}$ fully in terms of q_1, q_2, Q, s, and the model parameters.

To sign the expression above, it suffices to sign the numerator, as the denominator is clearly *positive*.

$$\begin{aligned} Nq_2 - Dq_1 &= \left(1 - \frac{w\sigma^2 q_1 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2}\right) q_2 - \left(1 + \frac{w\sigma^2 q_2 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2}\right) q_1 \\ &= q_2 - \frac{w\sigma^2 q_1 q_2 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2} - q_1 - \frac{w\sigma^2 q_1 q_2 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2} \\ &= (q_2 - q_1) - \frac{2w\sigma^2 q_1 q_2 Q^{\frac{1}{\sigma}-1}}{A_1(1-\sigma s_1)^2} \end{aligned}$$

The condition above ensures that a decrease in the production of firm 2 due to the constraint makes firm 1 increase its market share.

C Model - Additional Details

C.1 Marginal Costs

A firm's marginal cost $mc_{it}(s)$ depends on whether it is credit constrained. Unconstrained firms choose their optimal capital-labor mix through cost minimization, resulting in the following unit cost:

$$c_{unc}(q; r_t, w_t, P_t) = \frac{1}{z_{it}(s)} \kappa (P_t(r_t + \delta))^\alpha w_t^{1-\alpha} q,$$

where $\kappa = \alpha^{-\alpha}(1-\alpha)^{\alpha-1}$ is a constant. Thus the marginal cost of the unconstrained firm is invariant to output and equals $\frac{1}{z_{it}(s)}\kappa(P_t(r_t+\delta))^{\alpha}(w_t)^{1-\alpha}$.

On the other hand, the marginal cost of constrained firms is:

$$mc_{it}^{con}(s) = \left[\frac{1}{1-\alpha} w \lambda^{\frac{1}{\alpha-1}} \left(\frac{q_{it}(s)}{P_t a_{it}(s)}\right)^{\frac{\alpha}{1-\alpha}}\right]$$

As $\frac{\alpha}{1-\alpha} > 0$, the constrained firm's marginal cost is increasing in q, which plays an important role in markup setting.

C.2 Frictions and Pricing Revisited.

I now revisit the exercise performed in section 2 to show that the intuition extends to the quantitative model. Assume there is a single sector with four firms, no fixed costs, fixed labor but elastic capital supply (r is constant). I then introduce capital constraints tailored to bind only for the three least productive firms and evaluate the (one-period) Cournot equilibrium. Firm **four** is the only unconstrained one.

Figure C1 illustrates the exercise. The x-axis now represents the *recovery rate* $1-\frac{1}{\lambda}$. When frictions are harsher, firms one, two, and three must reduce their production, which in turns leads to a reduction in their market share. Firm four in turn seizes the opportunity to charge higher markups, increasing the sales-weighted average markup of this sector. Markup dispersion also increases dramatically. These movements can be seen in the left panels of figure C1.

The blue lines in the right panels show how frictions affect output and TFP. The red line is constructed by computing an equilibrium in the presence of credit constraints but markups are fixed at $\bar{\mu} = \frac{\gamma}{\gamma-1}$, the "atomistic case". Note that the vertical distance between the red and the blue lines measures the total losses due to market power - in other words, it measures what would be the gains experimented by this economy if all firms were to behave "atomistically". Frictions harm the economy in either case, but the impact is *larger* when firms act strategically. In particular, the vertical distance between the red and the blue lines increase as constraints gets tighter (moving towards the left), indicating that the reduction in competition seen in the left panels feeds back into even larger losses.

C.3 Derivation of Expression 25

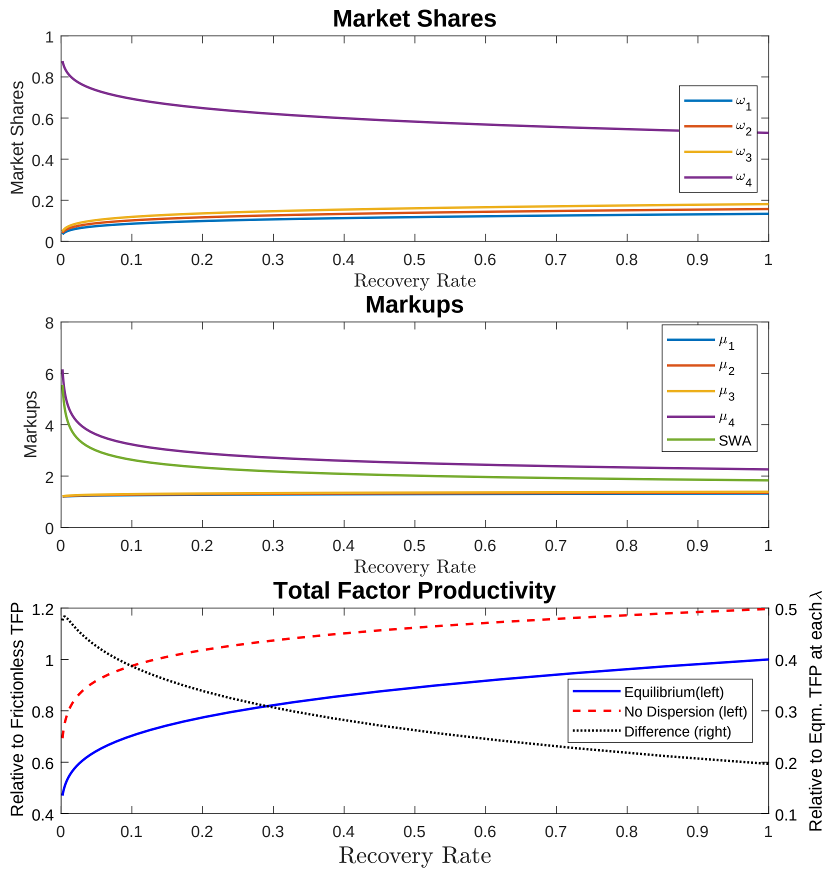
We begin with the definition of the sector-level markup, following Hall (1988):

$$\mu(s) = (1-\alpha) \cdot \frac{P(s)Q(s)}{wL(s)}. \tag{33}$$

Using the definition of sector-level labor productivity,

$$A(s) = \frac{Q(s)}{L(s)} \Rightarrow L(s) = \frac{Q(s)}{A(s)},$$

Figure C1: Quantitative Model - Illustrative Example



Note: The x-axis corresponds to the recovery rate $1 - \frac{1}{\lambda}$. In this exercise, firm 4 has enough collateral to self-fund, while the other producers require external funds, and thus are effectively affected by a change in λ. SWA stands for sales-weighted average.

we substitute into equation (33) to obtain:

$$\mu(s) = (1 - \alpha) \cdot \frac{P(s)A(s)}{w}. \tag{34}$$

We now express $A(s)$ in terms of firm-level production. Individual producers follow a Cobb-Douglas production function:

$$q_i(s) = z_i(s) \left(\frac{k_i(s)}{l_i(s)} \right)^{\alpha} l_i(s) = \bar{z}_i(s) \cdot l_i(s) \Rightarrow l_i(s) = \frac{q_i(s)}{\bar{z}_i(s)}. \tag{35}$$

Then, total labor in the sector is:

$$L(s) = \sum_i x_i(s) \cdot l_i(s) = \sum_i x_i(s) \cdot \frac{q_i(s)}{\bar{z}_i(s)},$$

which implies:

$$A(s) = \frac{Q(s)}{L(s)} = \left[\sum_i x_i(s) \cdot \frac{q_i(s)}{Q(s)} \cdot \frac{1}{\bar{z}_i(s)}\right]^{-1} = \left[\sum_i x_i(s) \cdot \omega_i^q(s) \cdot \frac{1}{\bar{z}_i(s)}\right]^{-1}, \tag{36}$$

where $\omega_i^q(s) = \frac{q_i(s)}{Q(s)}$ is the output quantity share.

Next, we express $\bar{z}_i(s)$ in terms of firm-level markups. From the definition of the firm-level markup:

$$\begin{aligned}
&\mu_i(s) = (1-\alpha) \cdot \frac{p_i(s) q_i(s)}{w l_i(s)} = (1-\alpha) \cdot \frac{p_i(s)}{w/\bar{z}_i(s)} \Rightarrow \\
&\frac{1}{\bar{z}_i(s)} = \frac{(1-\alpha)}{w} \cdot p_i(s) \cdot \frac{1}{\mu_i(s)}.
\end{aligned} \tag{37}$$

Substituting (37) into (36), we obtain:

$$\begin{aligned}
A(s) &= \left[\sum_i x_i(s) \cdot \omega_i^q(s) \cdot \frac{(1-\alpha)}{w} \cdot p_i(s) \cdot \frac{1}{\mu_i(s)}\right]^{-1} \\
&= \frac{w}{1-\alpha} \cdot \left[\sum_i x_i(s) \cdot \omega_i^q(s) \cdot p_i(s) \cdot \frac{1}{\mu_i(s)}\right]^{-1}
\end{aligned}$$

Plugging this into (34):

$$\mu(s) = (1-\alpha) \cdot \frac{P(s)}{w/A(s)} = \frac{P(s)}{\left[\sum_i x_i(s) \cdot \omega_i^q(s) \cdot p_i(s) \cdot \frac{1}{\mu_i(s)}\right]}.$$

We now express $\omega_i^q(s) \cdot p_i(s)$ in terms of revenue shares. By definition:

$$\omega_i(s) = \frac{p_i(s) q_i(s)}{P(s) Q(s)} \Rightarrow \omega_i^q(s) \cdot p_i(s) = P(s) \cdot \omega_i(s).$$

Substituting into the expression for $\mu(s)$:

$$\mu(s) = \frac{P(s)}{\sum_i x_i(s) \cdot P(s) \cdot \omega_i(s) \cdot \frac{1}{\mu_i(s)}} = \left[\sum_i x_i(s) \cdot \omega_i(s) \cdot \frac{1}{\mu_i(s)}\right]^{-1}.$$

$$\mu(s) = \left[\sum_{i=1}^N x_i(s) \cdot \omega_i(s) \cdot \frac{1}{\mu_i(s)}\right]^{-1}. \tag{38}$$

C.4 Computational Details

To compute statistics related to the steady-state equilibrium in the economy, I employ an algorithm combining those of Edmond et al. (2015) and of Mehrotra and Sergeyev (2021). The moments are computed using a simulation-based method, selecting a large number of *sectors* and simulating the economy over a long period. In practice, I simulate 350 sectors over 120 periods (years). I compute aggregate statistics based on averages over the last 20 periods of the simulation.

The algorithm is the following:

1. Initialize the economy's distribution of firm net worth. In practice, I select all firms' net worth to be initially large, so that no firms are initially constrained.

2. Compute the (static) Cournot equilibrium in each sector, following a slightly modified version of the algorithm in Edmond et al. (2015). The algorithm jointly iterates market shares, individual production levels, entry and constrained statuses, and aggregate production. The latter is set to ensure clearing in the labor market, and indirectly pins down the price level P_t (or, alternatively, real wages $\frac{1}{P_t}$).

3. Collect firm profits and compute the distribution of firms' net worth in the next period.

4. Repeat steps 1-3 until the economy's aggregates (aggregate net worth, aggregate production) become stable.

D Results - Additional Details

D.1 Calibration in the Economy without Oligopolostic Competition

Table D1 below display the calibration of the counterfactual economy where markups are fixed. Note that the first moment, capturing how markups vary with market share, is not enforced, while the remaining 10 targets are reasonably matched.

Table D1: Calibration Output: Model and Data - Constant Markups

Parameter	Targeted Moment	Model	Data	Source
$\gamma = 7.44$	Regression of Labor Share on Market Share.	-0.00	-0.534	Chilean Data
$\theta = 1.07$	Profit+Capital Share (1990)	0.50	53%	CEPAL
$\eta = 3.63$	Top 10% Revenue Share	71%	76%	Chilean Data
$N = 134$	$\mathbb{E}(N_s \| N > N_s^{66.7})$	134	134	Chilean Data
$F_l = 3.29$	$\mathbb{E}(N_s \| N_s^{33.3} < N \leq N_s^{66.7})$	22.0	24.2	Chilean Data
$F_h = 25.9$	$\mathbb{E}(N_s \| N \leq N_s^{33.3})$	5.4	6.2	Chilean Data
$\lambda = 4.7$	External Finance to GDP	0.60	0.74	GFDD
$\rho = 0.38$	FE AR(1) of Revenues ρ	-0.21	-0.22	Chilean Data
$\sigma = 0.072$	FE AR(1) MSE	0.32	0.36	Chilean Data
$\nu = 0.087$	Exit Rate if Young Firms	16%	12.8%	Chilean Data
$a_0 = 2.06$	Growth of Young Firms	88%	82.4%	Chilean Data

Notes: This table reports the values of calibrated parameters and the corresponding empirical moments used as targets **for the model with constant markups**. The model moments (column 3) are the result of a simulated method of moments estimation procedure. Data sources include Chilean manufacturing microdata (1979-1996), national income accounts from CEPAL, and the Global Financial Development Database (GFDD).