Financial Frictions, Market Power, and Innovation

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Abstract

This paper investigates how financial frictions and market power interact in shaping firms' incentives to innovate. I document stylized facts about innovation using a comprehensive firm-level dataset from Portugal, a country with relatively underdeveloped financial markets. Motivated by the empirical evidence, I augment a general equilibrium framework of heterogeneous producers with imperfect competition and innovative technology. Since innovation is costly, a firm's ability to exercise market power determines how quickly it can overcome financial constraints and engage in innovation. Improving financial markets allows firms to expand and innovate, whereas intensifying competition may come at the cost of lower innovation if borrowing constraints are sufficiently severe. These findings underscore the importance of tailoring a country's competition policy to its level of financial development.

Keywords: E2, E6, D4, O16, O3, L1

JEL codes: innovation, R&D, intangible capital, productivity, markups, market power, financial frictions, financial development, competition policy

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1 Introduction

Key indicators of market power are on the rise across many industries in the U.S. and Europe (De Loecker et al., 2020; De Loecker and Eeckhout, 2018; Akcigit et al., 2021), suggesting that large firms are increasingly dominating their respective markets.[1] Growing concentration concerns policymakers since market power may hinder innovation (Blundell et al., 1999; Aghion et al., 2005), a crucial driver of long-term economic growth. To the extent that rising market power has mostly been observed among large publicly listed firms (De Loecker et al., 2020; Díez et al., 2021), which tend to have better access to external funding (Dinlersoz et al., 2019), an important question is whether and how financial frictions and market power interact in shaping firms' incentives to innovate. This paper aims to fill in that gap. Specifically, I shed light on two key questions. First, how does the economy's competitive structure influence the aggregate level of innovation when firms are financially constrained? Second, what role does a country's financial development play in shaping the impact of competition policies?

In the empirical section, I leverage a large comprehensive firm-level dataset covering the population of non-financial firms operating in Portugal, a country with relatively underdeveloped financial markets. Given its administrative nature, this dataset offers excellent coverage across the entire size distribution, including both private and publicly listed firms. I document several stylized facts about innovation. First, I show that firms with higher market shares in their respective industries are more likely to have workers allocated to R&D and operate using intangible capital. Given that expenses related to R&D activities can be capitalized into intangible assets, the presence of intangible capital and the allocation of part of the workforce to R&D activities suggest that innovation decisions are crucial to understanding how firms grow and maintain their lead position in their respective industries. Second, I estimate firm-level markups by building upon the approaches proposed by Hall (1988), De Loecker and Warzynski (2012), and De Loecker et al. (2020), and show that a

[1] To explain the rise in market power, recent literature has emphasized the role of globalization in creating "winner-takes-all" markets (Autor et al., 2020), excessive regulations erecting barriers for new entrants (Covarrubias et al., 2020), lax antitrust enforcement (Grullon et al., 2019), and various forms of technological change that favored larger scales of operation, namely higher fixed operating costs (Traina, 2018; Ghazi, 2019), information and communication technologies (Calligaris et al., 2018; Bessen, 2020), and the increased importance of intangible capital (Crouzet and Eberly, 2019; De Ridder, 2024) such as patents, software, or proprietary databases.

higher intensity of R&D labor and intangible capital is associated with higher market shares and markups. Third, I exploit the longitudinal nature of the data to identify entry into innovation and show that innovation spells are accompanied by large and persistent increases in both markups and market shares.

Since innovation is an endogenous choice that reflects selection along unobservable characteristics, I develop a quantitative framework that rationalizes the decision to innovate. In particular, I develop a general equilibrium model of heterogeneous producers similar to Buera et al. (2011) and Gopinath et al. (2017) augmented with two key elements: imperfect competition between firms and innovative technology. In the model, firms with different productivity levels and net worth produce differentiated varieties and can choose between operating traditional technology or pursuing innovation. If the firm chooses to innovate, it allocates part of its workforce to R&D activities and incurs fixed operating costs. Since innovation is costly, a firm's ability to exercise market power determines how quickly it can overcome financial constraints and engage in innovation. In this monopolistically competitive setting, the demand elasticity of each firm's variety decreases with its market share, capturing the idea that the firm accrues market power as it grows in size. Once calibrated to fit key moments of the Portuguese data, the model is able to match several important untargeted moments, namely the overall level of innovative activity as well as the elasticity of market shares and markups with respect to R&D labor estimated from the data.

I then use the calibrated model as a quantitative laboratory to examine the aggregate effects of improving a country's financial development and enacting competition policy reforms. Viewed through the quantified model, policies aimed at improving firms' access to external funding raise aggregate output and wages by allowing firms to expand more rapidly and engage in innovation. In contrast, policies that intensify competition result in lower entrepreneurial profits, slower wealth accumulation, and lower innovation. Moreover, when financial markets are underdeveloped, there is a trade-off between competition and innovation. Relaxing competition initially allows firms to accumulate market power, leading to more innovation. However, once competition becomes too low, firms can quickly accumulate market power and charge high markups without having to engage in costly innovation activities. Thus, the incentive to engage in innovation to escape competition dissipates.

This paper is related to a large literature investigating the macroeconomic impact of financial frictions (e.g., Buera et al. (2011), Midrigan and Xu (2014), Moll (2014), Gopinath et al. (2017), Itskhoki and Moll (2019), among others). Similar to these papers, financial frictions in my model limit firms' access to external funds and encourage the accumulation of internal resources for financing investment. However, these papers assume an exogenous distribution of productivity, whereas in my model financial frictions also distort the distribution of productivity by affecting innovation decisions. Most closely related are the works of Buera and Fattal-Jaef (2018) and Ottonello and Winberry (2023) who also study the effect of financial frictions on innovation. However, they abstract from the role of market power, which is a key feature in my model. In the context of heterogeneous markups, the economy's market structure determines the firm's ability to accumulate internal resources and grow out of its borrowing constraints. Thus, market power plays a key role in both investment and innovation decisions in my model.

The rest of the paper is organized as follows. Section 2 describes the dataset. Section 3 presents descriptive evidence regarding the relationship between innovation and market power. Motivated by this evidence, Section 4 develops the model. Section 5 describes the calibration strategy and evaluates the quantitative fit of the model. Section 6 uses the calibrated model to study the effects of policy counterfactuals. Section 7 concludes.

2 Data

2.1 Data Source

The empirical analysis is based on the Central Balance Sheet Database (CBSD) maintained by the Bank of Portugal. The CBSD contains harmonized annual data on firm-level balance sheet and income statement items, as well as other demographic and corporate information, reported under "*Informação Empresarial Simplificada*" (IES or Simplified Corporate Information), a mandatory annual declaration that companies must submit to Portuguese tax authorities to ensure compliance with various regulatory requirements. Given the mandatory nature of the IES filing, the CBSD covers the population of all non-financial corporations in Portugal from 2006 to 2019.

The main variables used in my analysis as defined as follows. Output y_{it} is total

Table 1. Summary Statistics

	avg	sd	p1	p10	p25	p50	p75	p90	p99
output	3,671	48,756	69	157	272	595	1,579	4,583	44,717
materials	2,864	44,061	15	67	145	363	1,096	3,388	34,898
labor	525	3,641	38	60	85	146	311	772	6,369
capital	1,439	39,726	2	10	31	111	385	1,282	14,861
tangible	1,102	26,613	1	9	28	102	356	1,161	12,451
intangible	337	20,126	0	0	0	0	0	17	1,336
employment	27	187	5	5	7	10	19	41	259
non-r&d	10	99	0	0	0	0	8	18	126
r&d	0	5	0	0	0	0	0	0	9

Notes: All financial variables are reported in inflation-adjusted thousands of euros.

turnover (sales of goods and services) plus variation in production and operating subsidies minus indirect taxes. Labor l_{it} is measured by employee expenses. Employment emp_{it} is the total number of employees. Capital k_{it} is the book value of fixed (tangible and intangible) assets. Materials m_{it} is measured as the cost of goods sold and materials consumed, as well as supplies and external services. All financial variables are adjusted for inflation using the GDP deflator (base = 2016).

I limit my sample to private non-financial corporations operating within mainland Portugal. Given the interest in private businesses, I restrict attention to partnerships and limited liability corporations. I also eliminate branches of foreign firms and firms that do not report the district in which the firm is located. To ensure that I only include active and economically meaningful enterprises in the sample, I drop firms with zero employees, as well as those with missing or negative values for book assets or equity. Firms that do not report an industry code are also omitted. These exclusion criteria aim to filter out entities primarily established for accounting, tax, or administrative purposes, as well as very small firms. Finally, I exclude observations related to firms undergoing liquidation or dissolution, thereby focusing on ongoing businesses. The final sample contains 869,705 observations pertaining to 144,166 unique firms, with each firm observed for an average of 6 years.

Table 1 summarizes the main variables. The average firm in the sample has an output of 3.7 million euros, spends 2.9 million euros on materials and 0.5 million euros on labor, has a capital stock of 1.4 million euros, and employs 27 workers.

2.2 Estimation of Markups

A key challenge in obtaining firm-level markups is that marginal costs are not directly observable. To estimate markups, I build upon the production approach pioneered by Hall (1988) and popularized by De Loecker and Warzynski (2012); De Loecker et al. (2020) in various contributions. I relegate most of the technical details to Appendix Appendix A and briefly describe the main steps involved here.

The production approach relies on the cost minimization problem of the firm to recover a measure of the firm's markup that equals the output elasticity of a variable input divided by its cost share in total revenue. Its main advantage is that it allows for inferring the full distribution of markups across firms without imposing any parametric assumptions on consumer demand, the underlying nature of competition, or returns to scale.

Following the literature, I assume a production function with Hicks-neutral productivity that evolves according to a Markov process and employ the estimation methodology described in Levinsohn and Petrin (2003) and Ackerberg et al. (2015) to obtain consistent estimates of the output elasticities in the presence of unobserved productivity shocks and measurement error.

Under the production approach, any variable input can be used to identify markups. A crucial assumption is that within a period, inputs can frictionlessly adjust. I use materials rather than labor costs as the variable input in production, given that Portugal has relatively strict labor regulations and adjusting labor is not expected to be frictionless. Moreover, I consider a composite measure of material inputs comprising the cost of goods and materials as well as supplies and external services.[2]

[2] The choice of variable inputs matters empirically. Raval (2023) finds that markups derived from labor and material inputs behave differently. Given the nature of labor markets in Portugal, the use of labor costs as the flexible input is not appropriate in this setting. Moreover, Traina (2018) claims that estimated markups are likely to reflect management and marketing costs and uses a broader definition of variable costs than De Loecker et al. (2020), which includes sales, general, and administrative (SGA) expenses in addition to the cost of goods sold. Basu (2019) also argues that it is safer to use a more comprehensive input measure that includes some overhead inputs, such as SGA expenses, in deriving markups.

I also depart from the literature in assuming a translog production function rather than a homothetic Cobb-Douglas specification to mitigate some of the drawbacks of estimating markups with revenue data. For example, Ridder et al. (2022) finds that markups estimated using a Cobb-Douglas production function typically capture the average of true markups, but understate their dispersion, arguing for a more flexible translog production function.

These restrictions imply the following expression for the production function:

$$\begin{aligned} y_{it} = {} & \beta^K k_{it} + \beta^L l_{it} + \beta^M m_{it} \\ & + \beta^{KK} k_{it}^2 + \beta^{LL} l_{it}^2 + \beta^{MM} m_{it}^2 \\ & + \beta^{KL} k_{it} l_{it} + \beta^{KM} k_{it} m_{it} + \beta^{LM} l_{it} m_{it} \\ & + \omega_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

where lowercase letters denote logs. The firm's realized output is given by y_{it}, k_{it} is the capital stock, l_{it} is labor costs, m_{it} is intermediate inputs, $\omega_{it} = \ln \Omega_{it}$ denotes idiosyncratic productivity shocks, and ϵ_{it} captures measurement error in output.

I estimate production functions separately for each industry. In order to ensure an industry classification that most closely aligns with the 2-digit industry codes widely used in the literature, I use the broadest level of the NACE codes[3], which comprises 21 categories. Although the production function parameters in the translog function are not time-varying, output elasticities can vary over time due to changes in factor intensity. In a robustness exercise, I also retrieve estimates of markups allowing for the production function coefficients to vary over time as in De Loecker et al. (2020), which captures factor-biased technological change in a parsimonious way.

Given the estimates of the production function coefficients, the output elasticity of material inputs is given by:

$$\hat{\theta}_{it}^M = \hat{\beta}^M + 2\hat{\beta}^{MM} m_{it} + \hat{\beta}^{KM} k_{it} + \hat{\beta}^{LM} l_{it} \tag{2}$$

[3]The NACE (Nomenclature of Economic Activities) is the European classification of business activities, which is similar to the NAICS (North American Industry Classification System), and has a hierarchical structure with 4 levels.

As a result, the estimates for firm-level markups are:

$$\hat{\mu}_{it} = \frac{\hat{\theta}_{it}^{M}}{\alpha_{it}^{M}} \tag{3}$$

where α_{it}^{M} is the share of intermediate inputs in the firm's total sales.

Finally, it is important to note that there is a large literature discussing the validity of estimating markups using the production approach (Flynn et al., 2019; Kirov and Traina, 2021; Ridder et al., 2022; Raval, 2023; Bond et al., 2021; Basu, 2019; Syverson, 2019; Doraszelski and Jaumandreu, 2021). Since the focus of my empirical exercise is to document the variation of markups within and between firms, rather than the overall level of markups, the production estimation is to the best of my knowledge the most appropriate and feasible method.[4]

3 Empirical Analysis

This section explores empirically the relationship between innovation and market power. To proxy for innovation, I use two complementary metrics. First, I use employees engaged in R&D, which provides a direct measure of R&D activities. Employees engaged in R&D include those working in the design, manufacturing, or commercialization of new products.[5] Second, I use the book value of intangible capital. Although costs related to R&D activities are typically recognized as an expense on the income statement, certain R&D expenses related to the development of new products, processes, or software can be capitalized as intangible assets.[6]

[4]For example, Ridder et al. (2022) use an administrative firm-level dataset that includes price data and show that the levels of markups estimated from revenue data are biased, but the estimates are highly correlated with true markups.

[5]According to Portuguese accounting standards, firms must identify employees directly involved in R&D activities. These typically include scientists, engineers, technicians, and other staff involved in studies of design, manufacturing, and commercialization of new products, studies of commercialization or industrial rationalization, etc.

[6]The definition of intangible assets adopted into Portuguese accounting practices aligns with international standards. Intangible assets are defined as identifiable non-monetary assets without physical substance. An asset is considered identifiable if it is separable – that is, capable of being separated and sold, transferred, licensed, rented, or exchanged – either individually or together with a related contract, asset, or liability. Intangible assets include: development costs incurred during the creation of internally generated assets provided they meet recognition criteria (e.g., feasibility, intent to use, and potential to generate future economic benefits); patents, trademarks, and licenses related to intellectual property rights; software, whether purchased or internally developed; goodwill

I begin by documenting that intangible capital and R&D labor are important sources of heterogeneity among firms. Industry leaders (i.e., firms with higher market shares) are much more likely to have intangible assets and workers allocated to R&D activities than their competitors. Moreover, at the intensive margin, higher intangible capital intensity and R&D labor intensity are also associated with higher markups and market shares. Finally, I show that innovation spells are accompanied by large and persistent increases in both markups and market shares.

3.1 Extensive margins of innovation

To examine the prevalence of R&D at the extensive margin, I group firms into bins according to market share in their respective industries and compute the fraction of firms that have workers allocated to R&D activities in each bin. As shown in Panel A of Figure 1, the presence of R&D workers is sparse for firms below the median, but increases rapidly thereafter. For example, less than 1% of manufacturing firms with median market shares have workers allocated to R&D, whereas this number is 3% in the 75th percentile, 10% in the 90th percentile, and 26% in the 99th percentile.

Focusing on the extensive margin of intangible capital, I again rank firms according to their market share and compute the percentage of firms that report positive intangible capital for each bin. Panel B of Figure 1 shows that intangible capital can be found across all firm sizes, but its prevalence increases with market shares. For example, about 30% of manufacturing firms that have median market shares operate using intangible capital, increasing to 42% in the 75th percentile, 62% in the 90th percentile, and 72% in the 99th percentile.

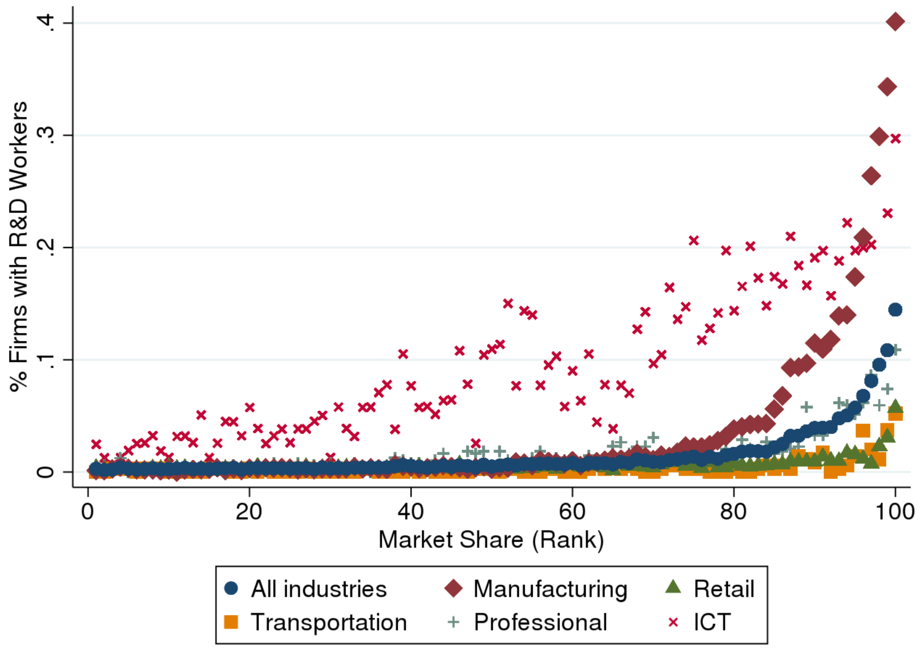
3.2 Intensive margins of innovation

After having investigated the link between firm size and the extensive margins of innovation, I now focus on analyzing outcomes across firms with different innovation intensities. To measure the intensive margin of innovation, I use intangible capital

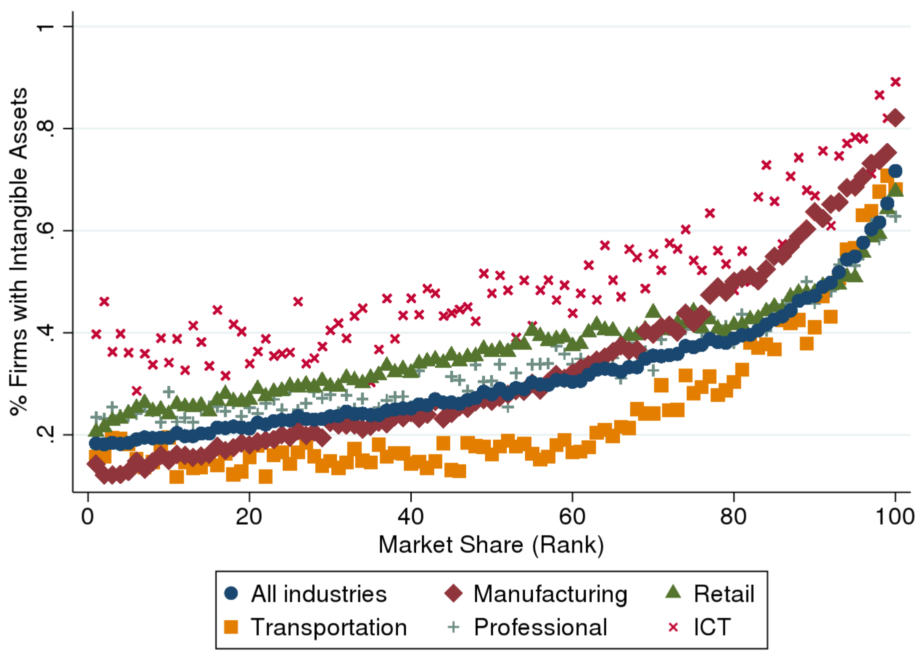
arising from business combinations; franchise rights, concessions, and customer lists when they are acquired. Unfortunately, intangible assets are reported in the Central Balance Sheet Database as a single variable and cannot be purged from other non-R&D components (e.g., goodwill).

Figure 1

Panel A: R&D and Firm Size



Panel B: Intangibles and Firm Size



Notes: The binscatter displays the extensive margins of R&D and Intangible Capital along the size distribution. Firms are ranked according to market share in their respective industries. Each bin groups together firms with similar market shares and displays the fraction of firms with workers allocated to R&D activities in Panel A and the fraction of firms with positive intangible assets in Panel B.

intensity [7] and R&D labor intensity used in production.

In particular, to evaluate the link between innovation and market shares, I run the following regression:

$$\text{Log(Market Share)}_{it} = \beta_0 + \beta_1 X_{it} + \Gamma' Z_{it} + \Omega' W_i + \delta_t + \varepsilon_{it} \tag{4}$$

where X_{it} is a vector containing either the (log) number of R&D workers or (log) book value of intangible capital; Z_{it} is a set of time-varying firm-level controls, namely size (log employment), age, and export status; W_i is a set of time-invariant controls that include either industry or firm fixed effects depending on the specification; and δ_t denotes year fixed effects.

Table 2 shows that higher innovation intensity is associated with higher market shares. In Column (1), which only includes industry and year fixed effects, a 1% increase in the number of workers allocated to R&D activities is associated with 0.5% increase in market share. In Column (2), I introduce firm-level controls, namely size, age, and export status, and the estimated coefficient remains statistically significant and similar in magnitude. Finally, Column (3) introduces firm fixed effects to account for time-invariant unobservable differences across firms. In line with the other coefficients, higher R&D labor intensity is associated with higher market shares, and the relationship remains statistically significant at the 1% level.

Columns (4)-(6) proxy for innovation using intangible capital intensity. Column (4) reports the initial specification with only industry and year fixed effects, showing that a 1% increase in intangible capital is associated with a 0.2% rise in market share. Column (5) introduces a set of firm-level controls and shows that the coefficient of interest remains significant and positive. Finally, Column (6) includes firm fixed effects and thus estimates the relationship from within variation. Again, higher intangible capital intensity correlates with higher market shares, and this relationship is significant at the 1% level.

To evaluate the association between innovation intensity and markups, I estimate the

[7] With the introduction of a new accounting system in 2010, some components that were previously classified as tangible assets were reallocated to intangible assets. The results from this analysis remain robust after restricting the sample to the period after 2010.

regression below:

$$\text{Log(Markup)}_{it} = \beta_0 + \beta_1 X_{it} + \Gamma' Z_{it} + \Omega' W_i + \delta_t + \varepsilon_{it} \tag{5}$$

where the innovation proxies X_{it}, controls Z_{it}, and fixed effects W_i and δ_t are defined as in (4).

The results in Table 3 indicate that higher innovation intensity is also associated with higher markups. Focusing first on R&D labor intensity, Column (1), which includes only industry and year fixed effects, reports that a 10% increase in R&D workers is linked to a 0.2% increase in markups. When considering a full set of controls, as shown in Column (2), as well as firm fixed effects, as displayed in Column (3), the coefficient remains significant and positive.

Finally, Columns (4)-(6) display the relationship between intangible capital intensity and markups. In the simplest specification, shown in Column (4), a 10% increase in intangible capital is associated with a 0.01% increase in markups. The sign and significance of this relationship are robust to the inclusion of firm controls and firm fixed effects, as shown in Columns (5) and (6), respectively.

3.3 Innovation Spells

Next, I exploit the longitudinal nature of my data to identify innovation spells and explore the dynamics of markups and market shares following the allocation of workers to R&D activities. An innovation spell refers to a continuous period of time during which the firm has at least one R&D worker in every consecutive year after previously having none. I show that sustained periods of innovation are followed by large and persistent increases in both markups and market shares.

I define the first year of the innovation spell, denoted $t = 1$, as the year in which the firm hires at least one R&D worker after not having any previously. The duration of the innovation spell is incremented by one in each subsequent year the firm has at least one R&D worker. The year immediately preceding the start of the innovation period, $t = 0$, serves as the reference year for measuring outcome variables, in both

Table 2. R&D, Intangibles, and Market Shares

	Log(Market Share)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(R&D Emp)	0.539***	0.480***	0.107***			
	(0.012)	(0.011)	(0.008)			
Log(Intan Cap)				0.172***	0.160***	0.023***
				(0.001)	(0.001)	(0.001)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	-	Y	Y	-	Y	Y
Firm FE	-	-	Y	-	-	Y
Observations	12,646	12,642	11,280	273,582	273,581	259,264
Adjusted R^2	0.305	0.448	0.975	0.445	0.527	0.970

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. The dependent variable is the firm's (log) market share, with markets defined as the first level of NACE codes (18 industries). Firm controls include size, age, export status. All regressions include industry and year fixed effects. Table B6 provides regression results using a narrower market definition (level 2 CAE - Rev 3 codes).

the pre- and post-innovation periods.

To estimate the evolution of market shares and markups along an innovation spell, I estimate the following regression:

$$y_{it} = \sum_{\tau=-2}^{\tau=5} \mathbb{I}(t=\tau) + \Gamma' Z_{it} + \Omega' W_i + \delta_t + \varepsilon_{it} \tag{6}$$

where y_{it} is the relative firm-level outcome (either the firm's market share or markup). For ease of interpretation, outcomes are expressed in relation to the reference year, i.e., the year preceding the start of the innovation spell. The regression includes a set of time-varying controls Z_{it}, namely size (log employment), age, and export status; a vector of time-invariant characteristics W_i, which include either industry or firm fixed effects depending on the specification; and year fixed effects δ_t.

The estimated trajectories of market shares are plotted in Panel A of Figure 2. Prior to the innovation spell, market shares show no statistically significant differences and remain flat in the previous three years. However, during the innovation spell, market

Table 3. R&D, Intangibles, and Markups

	Log(Markup)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(R&D Emp)	0.022***	0.022***	0.009***			
	(0.005)	(0.002)	(0.003)			
Log(Intan Cap)				0.001***	0.001***	0.002***
				(0.000)	(0.000)	(0.000)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	-	Y	Y	-	Y	Y
Firm FE	-	-	Y	-	-	Y
Observations	12,646	12,642	11,280	273,582	273,581	259,264
Adjusted R^2	0.237	0.239	0.802	0.202	0.205	0.809

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. The dependent variable is the (log) markup estimated following with a translog production function, as explained in subsection 2.2. Firm controls include size, age, export status. All regressions include industry and year fixed effects. Table B7 provides regression results with markups estimated with time-varying input elasticities as in De Loecker et al. (2020).

shares increase on average 6% in the first year and around 30% in the fifth year.

Panel B of Figure 2 displays the estimated trajectories of markups. Markups remain stable before the innovation spell begins, exhibiting no statistically significant differences in the three years leading up to the innovation phase. During the innovation period, markups increase by an average of 1% in the first year and 6% in the fifth year.

To conclude this section, I have shown that innovation is associated with higher market shares and higher markups, both at the extensive and intensive margin. At the extensive margin, the prevalence of R&D labor and intangible capital is higher for firms with higher market shares. In addition, a higher intensity of R&D labor and intangible capital is also associated with higher market shares and markups. Finally, I show that innovation spells are accompanied by large and persistent increases in both markups and market shares. Since innovation is an endogenous decision that reflects the selection of firms along unobservable characteristics, I now turn to a quantitative model that rationalizes the decision to innovate on both margins.

4 Model

In this section, I develop a general equilibrium model featuring heterogeneous producers and dynamic decisions regarding innovation and investment.

In the model, firms are heterogeneous in terms of their productivity and net worth and face a decision to operate with traditional technology or to innovate. If choosing to innovate, firms allocate part of their workforce to R&D activities and incur fixed operating costs. Modeling the firm's decision to innovate as a function of its net worth and productivity captures in a parsimonious way both the financial and operational aspects of innovation that make it dependent on internal funds. First, innovation is often accompanied by various upfront costs, such as research and development, prototyping, and testing. Second, the innovation process is associated with uncertain and distant returns, making it challenging to attract external funding. Third, innovation projects often lack tangible assets that can serve as collateral, making it harder to secure loans or traditional forms of external funding.

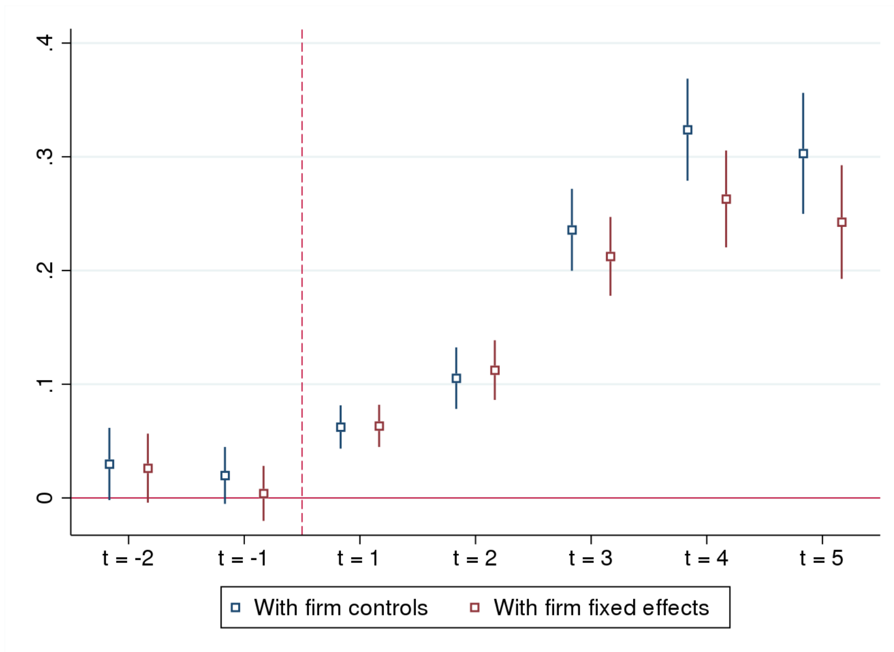
As discussed in the previous section, the fact that R&D activities are associated with higher markups and higher market shares motivates the choice of modeling innovation as a productivity-enhancing process. In the model, firms engaged in R&D activities are more likely to have higher market shares and command higher markups as a result of their products facing lower demand elasticity.

4.1 Setup

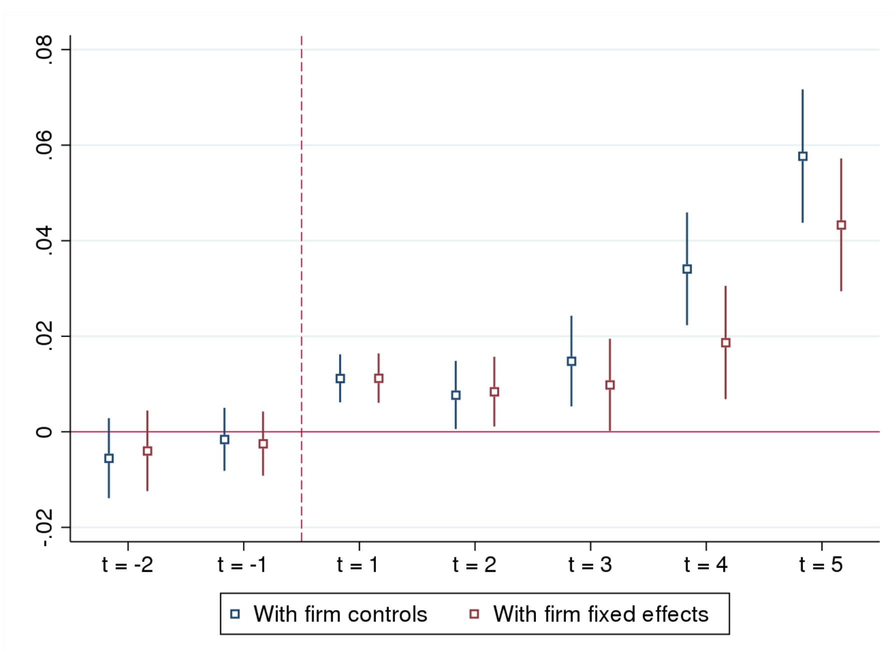
I consider an economy populated by a large number of infinitely lived firms, indexed by $i = 1, \ldots, N$, that produce differentiated varieties. Firms are owned by risk-averse entrepreneurs who can save and borrow in a one-period bond at an exogenous real interest rate r_t. There is a fixed mass $\bar{L}$ of hand-to-mouth workers who supply labor inelastically at a wage rate w_t.

Figure 2

Panel A: Dynamics of Market Shares



Panel B: Dynamics of Markups



Notes: The figure shows the estimated trajectories of market shares (Panel A) and markups (Panel B) before and after an innovation spell. Innovation spells begin at $t = 1$. For ease of interpretation, outcomes are expressed in relation to the reference year $t = 0$ (omitted category), i.e., the year immediately preceding the start of the innovation spell. The corresponding tables are Tables B8 and B9 in Appendix Appendix B. All estimated trajectories are conditional on industry- and year-fixed effects. Firm demographics include size, age, and export status. The vertical lines correspond to 95% confidence intervals.

4.2 Preferences

The firm owner's lifetime utility is given by:

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t u(c_{it}) \tag{7}$$

where β is the discount factor. The utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ is strictly increasing and concave over consumption c_{it}, satisfying the standard Inada conditions, with γ representing the coefficient of relative risk aversion.

4.3 Technology

Firms have a choice between two production technologies: traditional and R&D intensive. Traditional production, denoted by τ, refers to the technology choice that relies solely on labor and capital. In contrast, R&D-intensive production, denoted κ, refers to the technology choice that incorporates R&D alongside labor and capital.

If the firm chooses to operate with traditional technology, it chooses how much capital and labor to hire. If instead the firm chooses to operate the R&D intensive technology, it must also decide how much of its workforce to allocate to R&D activities.

Traditional technology The production function with traditional technology is a Cobb-Douglas, constant returns-to-scale function:

$$y_{it}^{\tau} = \exp(z_{it})\ k_{it}^{\alpha}\ l_{it}^{1-\alpha} \tag{8}$$

where y_{it} denotes physical output, z_{it} is the firm's idiosyncratic productivity, k_{it} is the capital stock, l_{it} is labor, and α is a parameter controlling the elasticity of output to capital.

Given factor prices w_t and r_t, the profit of a firm operating the traditional technology is:

$$\pi_{it}^{\tau} = p_{it}y_{it}^{\tau} - (r_t+\delta)k_{it} - w_t l_{it} \tag{9}$$

where p_{it} is the price of its variety, and δ is the rate of depreciation of capital.

R&D-intensive technology In turn, the production function using R&D-intensive technology is given by:

$$y_{it}^{\kappa} = \exp(z_{it} + \phi(\nu_{it}))\ k_{it}^{\alpha}\ (l_{it} - \nu_{it})^{1-\alpha} \tag{10}$$

where ν_{it} represents the portion of the firm's workforce allocated to R&D activities. Labor allocated to R&D is not available to produce.

Taking the path of r_t and w_t as given, the profit of the R&D-intensive firm is:

$$\pi_{it}^{\kappa} = p_{it}y_{it}^{\kappa} - (r_t + \delta)k_{it} - w_t l_{it} - c_f \tag{11}$$

where c_f denotes fixed operating costs. All labor (including productive and R&D work) is assumed to be remunerated at the same wage rate. The decision to innovate becomes non-convex due to the presence of fixed operating costs, rendering the R&D-intensive technology feasible only if operated above a minimum scale.

The function $\phi(\nu_{it})$ disciplines the relative productivity of R&D work, and therefore the optimal labor allocation is determined by $\phi'(\nu_{it})(l_{it} - \nu_{it}) = 1 - \alpha$. Motivated by Jones (2009) and Bloom et al. (2020), I assume $\phi'(\nu_{it}) > 0$ and $\phi''(\nu_{it}) < 0$, reflecting diminishing returns to innovation. This captures the "burden of knowledge" phenomenon, wherein successive innovation breakthroughs become progressively harder to achieve. Assuming the following functional form:

$$\phi(\nu_{it}) = \xi \log \nu_{it} \tag{12}$$

the firm will optimally choose to allocate a fixed portion of its workforce to R&D work, $\nu_{it}/l_{it} = \xi/(1 - \alpha + \xi)$.

4.4 Market Structure

Each firm i is the sole supplier of a given variety. There is a total number of N_t varieties. A perfectly competitive final good firm produces the homogeneous output good Y_t by assembling all available varieties:

$$\int_0^{N_t} \Upsilon\left(\frac{y_{it}}{Y_t}\right) di = 1 \tag{13}$$

where Υ is the Kimball aggregator, which is strictly increasing and concave, that is, $\Upsilon' > 0$, $\Upsilon'' < 0$, with $\Upsilon(1) = 1$. Following the literature, I adopt the Klenow and Willis (2016) specification for the Kimball aggregator given by:

$$\Upsilon(x) = 1 + (\theta - 1)\exp\left(\frac{1}{\epsilon}\right)\epsilon^{\frac{\theta}{\epsilon}-1}\left(\Gamma\left(\frac{\theta}{\epsilon}, \frac{1}{\epsilon}\right) - \Gamma\left(\frac{\theta}{\epsilon}, \frac{x^{\frac{\epsilon}{\theta}}}{\epsilon}\right)\right) \tag{14}$$

where $x \equiv \frac{y_{it}}{Y_t}$ is the firm's market share and $\Gamma(s, z) \equiv \int_z^\infty t^{s-1}\exp(-t)dt$ is the upper incomplete gamma function.

The final goods producer maximizes profits by choosing quantities y_{it}, taking the prices p_{it} of the differentiated varieties as given:

$$\max_{\{y_{it}\}} Y_t - \int_0^N p_{it} y_{it} di \tag{15}$$

and subject to the Kimball aggregator (13). The solution to this problem gives rise to the following inverse demand function for variety i:

$$p(y_{it}) = \Upsilon'\left(\frac{y_{it}}{Y_t}\right) = \left(\frac{\theta - 1}{\theta}\right)\exp\left(\frac{1 - \left(\frac{y_{it}}{Y_t}\right)^{\frac{\epsilon}{\theta}}}{\epsilon}\right) \tag{16}$$

where the aggregate price level is normalized to one.

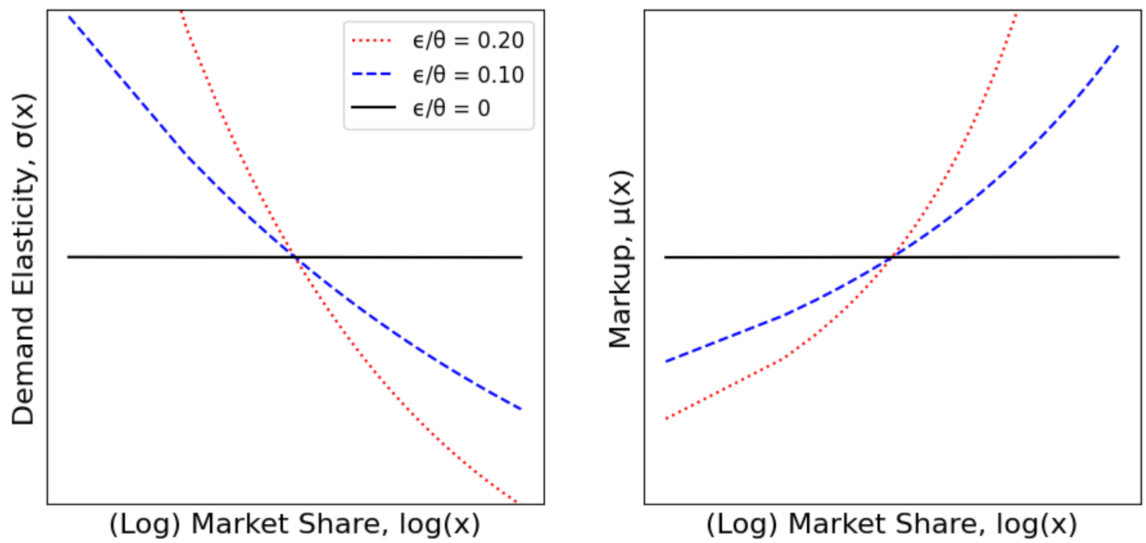
Noting that demand elasticity is given by:

$$\sigma(x) = -\frac{\Upsilon'(x)}{\Upsilon''(x)x} = \theta x^{-\frac{\epsilon}{\theta}} \tag{17}$$

and the superelasticity of demand is $-\frac{d\ln\sigma(x)}{d\ln x} = \frac{\epsilon}{\theta}$, the firm sets its markup according to:

$$\mu(x) = \frac{\sigma(x)}{\sigma(x) - 1} = \frac{\theta}{\theta - x^{\frac{\epsilon}{\theta}}} \tag{18}$$

Figure 3. Market shares, demand elasticity and markups



Under this specification, demand elasticity and markups vary according to the firm's relative output. The left panel of Figure 3 shows that as the firm's market share increases, the elasticity of demand it faces decreases. The rate at which demand elasticity falls with market share is governed by the superelasticity of demand, ϵ/θ. In particular, a higher superelasticity of demand means that the demand elasticity falls at a faster rate. In the limit as $\epsilon \to 0$, demand elasticity is constant. The right panel of Figure 3 shows that markups increase with the firm's relative size, capturing the idea that the firm accumulates market power as it grows in size. The rate at which markups increase with size is again governed by superelasticity. A high superelasticity implies that firms gain market power quickly, leading to faster markup increases. The CES case with constant markups is embedded in the Kimball aggregator when $\epsilon \to 0$.

4.5 Productivity

Productivity z_{it} is stochastic and evolves according to an AR(1) Markov process:

$$z_{it} = \rho z_{it-1} + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma^2) \tag{19}$$

where ρ measures the degree of persistence in productivity, and σ^2 is the variance of stochastic idiosyncratic risk. Thus, firms are subject to idiosyncratic productivity shocks but there is no aggregate uncertainty.

4.6 Financial Markets

Financial markets are incomplete in that borrowing is limited by imperfect enforceability of contracts. As a result, firms can only borrow intra-temporally up to a portion of their capital stock. The borrowing constraint is given by:

$$b_{t+1} \leq \chi k_{t+1} \tag{20}$$

where χ indexes the tightness of the borrowing constraint. If $\chi = 0$, firms operate in a zero credit environment, whereas if $\chi = \infty$, firms become financially unconstrained.

4.7 Recursive Representation of the Firm's Problem

Firm owners choose their consumption c_{it}, next period debt b_{it+1}, and which technology to operate, in every period. Letting $a_{it} = k_{it} - b_{it}$ denote the firm's net worth, and using primes to denote next-period variables, we can rewrite the firm's problem in recursive form as follows:

$$V(a, z) = \max\{V^{\tau}(a, z), V^{\kappa}(a, z)\} \tag{21}$$

where $V^{\tau}(a, z)$ denotes the value function for the traditional firm, and $V^{\kappa}(a, z)$ the value function for the R&D intensive firm.

A firm that operates the traditional technology faces the following problem:

$$V^{\tau}(a,z) = \max_{c,a'}\{u(c) + \beta \mathbb{E} V(a',z')\} \tag{22}$$

$$\text{s.t.:} \quad c + a' = \pi + (1+r)a \tag{23}$$

$$\pi = \max_{k,l}\{py - (r+\delta)k - wl\} \tag{24}$$

$$y = \exp(z)\ k^{\alpha}\ l^{1-\alpha} \tag{25}$$

$$p = \Upsilon'\left(\frac{y}{Y}\right) \tag{26}$$

$$k \leq \lambda a \tag{27}$$

In contrast, a firm that operates the R&D intensive technology solves:

$$V^{\kappa}(a,z) = \max_{c,a'}\{u(c) + \beta \mathbb{E} V(a',z')\} \tag{28}$$

$$\text{s.t.:} \quad c + a' = \pi + (1+r)a \tag{29}$$

$$\pi = \max_{k,l,\nu \leq l}\{py - (r+\delta)k - wl - c_f\} \tag{30}$$

$$y = \exp\left(z + \xi \log \nu\right)\ k^{\alpha}\ (l-\nu)^{1-\alpha} \tag{31}$$

$$p = \Upsilon'\left(\frac{y}{Y}\right) \tag{32}$$

$$k \leq \lambda a \tag{33}$$

where $\lambda = 1/(1-\chi)$.

Note that firm owners face two types of decisions: static input choices and dynamic asset accumulation. Entrepreneurs in the model are constrained and accumulate assets to take advantage of good productivity shocks when they arrive. Both their current profits and the prospect of high profits in the future affect their decisions to accumulate assets in the firm. The economy's competitive structure plays a crucial role in these dynamic decisions because profits are determined by market shares.

4.8 Equilibrium

Let $x = \{a, z\}$ be the state vector for a firm in this economy, and N denote the total number of active firms. A stationary equilibrium is given by value functions $V(x)$,

$V^{\tau}(x)$, and $V^{\kappa}(x)$; optimal policy function for consumption $c(x)$, next period assets $a'(x)$, technology choice $\Lambda(x)$, entrepreneurial capital $k(x)$, labor demand $l(x)$, and variety price $p(x)$; factor prices w and r; aggregates K, L, Y, P, and A; and an invariant distribution $\mu(x)$ of agents over the state variables x such that:

1. Aggregate consistency conditions hold:

$$
\begin{aligned}
A &= \int_{\mathcal{A}\times\mathcal{Z}} a(x)d\mu(x) \qquad & C &= \int_{\mathcal{A}\times\mathcal{Z}} c(x)d\mu(x) \\
L^s &= \bar{L} & L^d &= \int_{\mathcal{A}\times\mathcal{Z}} l(x)d\mu(x) \\
K &= \int_{\mathcal{A}\times\mathcal{Z}} k(x)d\mu(x) & \int_{\mathcal{A}\times\mathcal{Z}} &\Upsilon\left(\frac{y(x)}{Y}\right) d\mu(x) = 1
\end{aligned}
$$

2. The functions $c(x)$, $a'(x)$, $\Lambda(x)$, $k(x)$, $l(x)$, $\nu(x)$, and $p(x)$ solve the maximization problems of the individual firms.

3. The interest rate is constant (small open economy assumption).

4. The labor market clears.

5. The goods market clears.

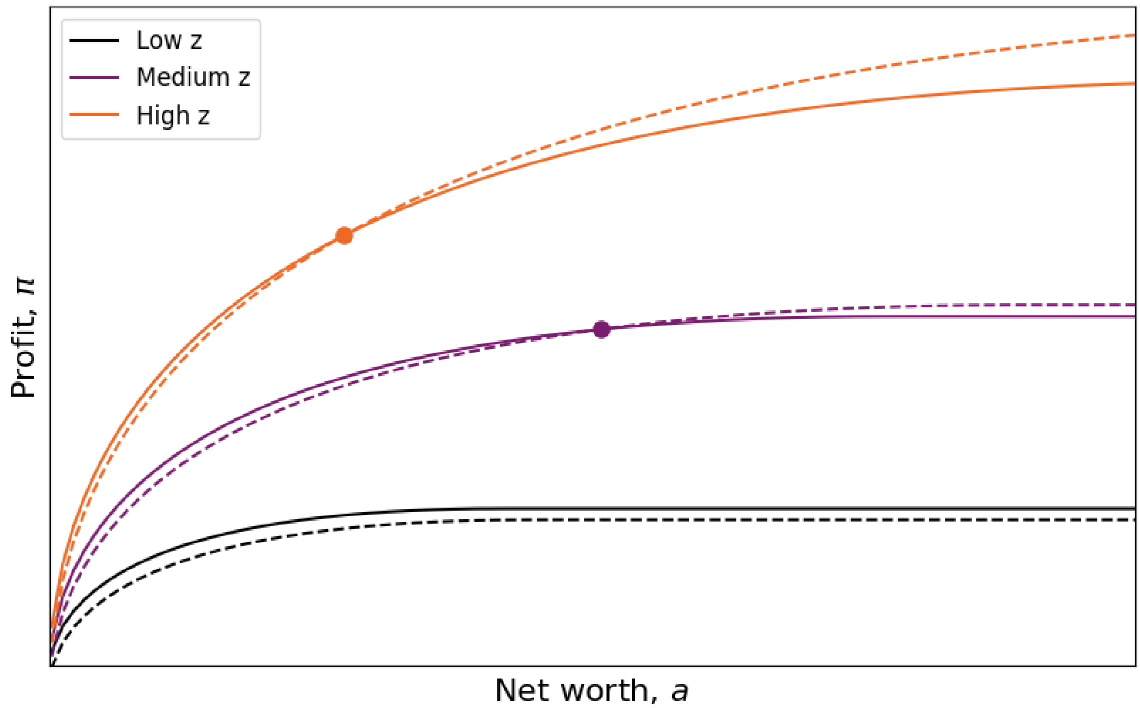
6. The number of active firms is constant.

7. The distribution $\mu(x)$ is the invariant distribution for the economy.

4.9 Decision rules

Figure 4 shows the extensive margin of R&D-intensive technology. For illustration purposes, productivity levels are discretized into three tiers: low, medium, and high productivity. Both productivity and net worth play a key role in determining the adoption of R&D-intensive technology. Highly productive firms adopt R&D-intensive technology at even small scales. For moderately productive firms, the benefits of adopting R&D-intensive technology are only worthwhile once they achieve a certain scale. Finally, the least productive firms will not pursue innovation even at large scales, as the benefits of adopting R&D-intensive technology are low.

Figure 4. Extensive margin of technology choice



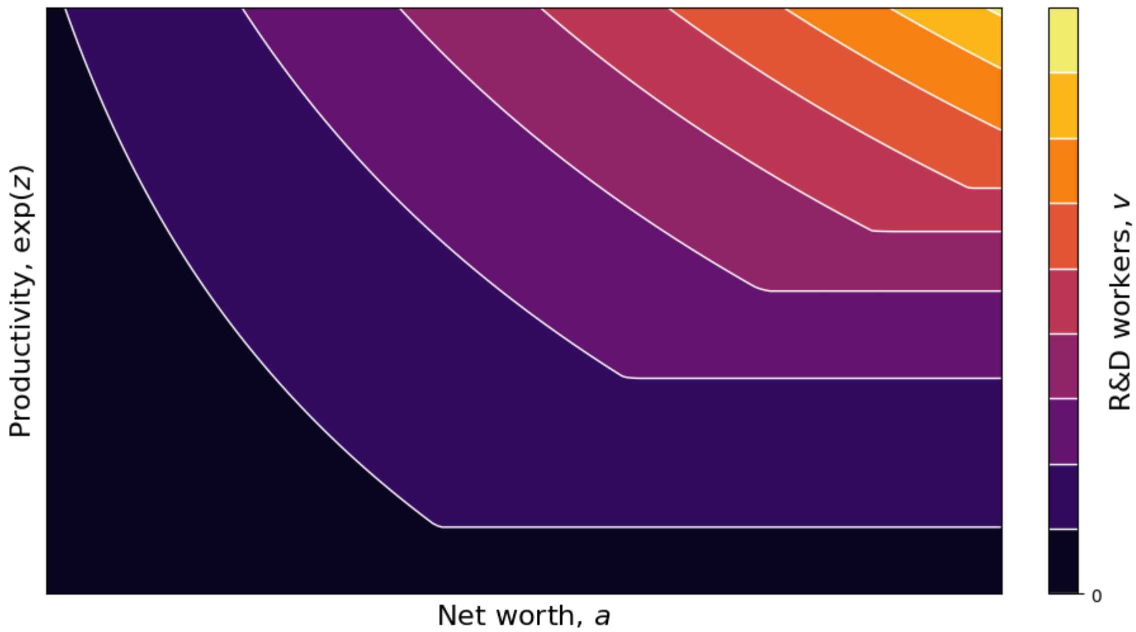
Notes: The plot displays profit functions for traditional and R&D-intensive technology according to productivity and net worth. Solid lines represent profit under traditional technology. Dashed lines represent profit under R&D-intensive technology.

As illustrated in Figure 5, the model also features heterogeneity in R&D intensity across firms. While productivity plays a crucial role in determining the number of workers assigned to R&D activities, these decisions are also significantly influenced by the level of net worth. In particular, high-productivity firms with low net worth will pursue suboptimal levels of R&D activity.

5 Quantitative Analysis

In this section, I present the calibration strategy and discuss the quantitative fit of my framework with respect to targeted moments obtained from the data. I then validate the calibrated model by evaluating its performance in matching key moments from the data that were not targeted during the calibration.

Figure 5. Intensive margin of technology choice



Notes: R&D labor is discretized for visual clarity. In the model, R&D intensity is treated as a continuous variable.

5.1 Calibration

To parameterize the model, I begin by partitioning the parameter space into two groups. As summarized in Table 4, the first group includes predetermined parameters set to standard values obtained from the literature, while the second group is set to match key features of the Portuguese economy.

Externally Calibrated Parameters A period in the model corresponds to a year, the same frequency as the firm-level data. I assign values for five parameters using common values found in the literature. I set the coefficient of relative risk aversion γ to 1.5 as in Cagetti and De Nardi (2006), and the discount factor β to 0.87 as in Gopinath et al. (2017). The capital share α is set to 0.33 and depreciation rate δ to 0.06, both conventional values found in the literature (e.g., Buera and Shin (2013)). The interest rate r is equal to 0.05, which corresponds to the average yield of 10-year government bonds over the sample period. Moreover, the aggregate price level P and labor supply $\bar{L}$ are normalized to unity.

Table 4. Model Calibration

Targeted Moments	Data	Model	Parameter	Value
Exogenously Calibrated				
Risk aversion			γ	1.50
Discount factor			β	0.865
Depreciation rate			δ	0.06
Capital share			α	0.33
Interest rate			r	0.05
Endogenously Calibrated				
Serial Correlation of Output	0.730	0.921	ρ	0.918
Top 10% Employment Share	0.509	0.528	σ	0.340
Avg Debt-to-Equity	0.281	0.263	λ	1.283
Average Markup	1.245	1.324	θ	4.039
P90 Markup	1.765	1.773	ϵ/θ	0.213
Avg Share of R&D Workers	0.072	0.062	ξ	0.044
Relative Scale of R&D firms	8.808	9.887	c_f	0.001

Internally Calibrated Parameters The remaining seven parameters are calibrated to match seven relevant moments in the firm-level data: the serial correlation of output, the top 10% employment share, the average firm debt-to-equity ratio, the average and 90th percentile of the markup distribution, the average share of R&D workers, and the relative scale of R&D firms. Although all model parameters simultaneously impact all target moments, below I provide heuristics for mapping the parameters to the moments.

The first set of calibrated parameters concerns the productivity process. The persistence of the productivity process ρ is set to 0.92 to match the serial correlation of output, which is 0.73 in the data and 0.92 in the model. The volatility of productivity shocks σ is 0.33, as pinned down by the employment share of the top 10% largest firms, which is 0.51 in the data and 0.53 in the model. Using the values for ρ and σ, I discretize the continuous process for the productivity shocks using the method proposed by Rouwenhorst (1995).

The maximum loan-to-value ratio λ is set to 1.28 to target the average debt-to-equity ratio in the firm-level data. The average firm's debt stands at 28% of its net worth, while in the model this figure is 26%.

Under variable markups, the markup distribution is determined not only by the average demand elasticity but also the superelasticity of demand. The average demand elasticity of intermediate producers' output θ is set to 4.04 to match the aggregate markup of Portugal of 1.25. The superelasticity of demand ϵ/θ is set to 0.21 to replicate the 90th percentile of the markup distribution of 1.76.

The last set of parameter concerns the cost and efficiency of R&D activities. The relative efficiency of R&D work ξ is 0.06 to replicate the share of R&D workers found in the data. Among firms engaged in R&D, workers allocated to R&D activities constitute on average 7.2% of the overall workforce. In the model, R&D workers are 6.2% of the typical R&D firm's workforce. Similar to Buera et al. (2011), I capture the large scale of R&D firms by setting the fixed operating costs c_f equal to 0.001. R&D firms hire on average 8.8 times the number of workers of non-R&D firms in the data, whereas this number is 9.8 in the model.

5.2 Validation

Table 5. Model Fit

Untargeted Moments	Data	Model
Share R&D Firms	0.115	0.105
Elasticity of Market Share wrt R&D	0.539	1.588
Elasticity of Markup wrt R&D	0.022	0.620

Table 5 presents moments derived from the firm-level data and the corresponding moments obtained from simulated data using the calibrated model. Although the calibration strategy only targeted the relative scale of R&D firms and the relative efficiency of R&D work, the model is able to predict the share of firms engaged in R&D, which is about 11% both in the model and in the data. The calibrated model can also qualitatively match the elasticities of market shares and markups with respect to R&D activity. In the data, a 1% increase in R&D labor is associated with 0.5% increase in the market share and 0.02% increase in markups (see Table 2-3). Correspondingly, the model predicts that a 1% increase in R&D labor raises the firm's market share by 1.6% and its markup by 0.6%.

6 Policy Counterfactuals

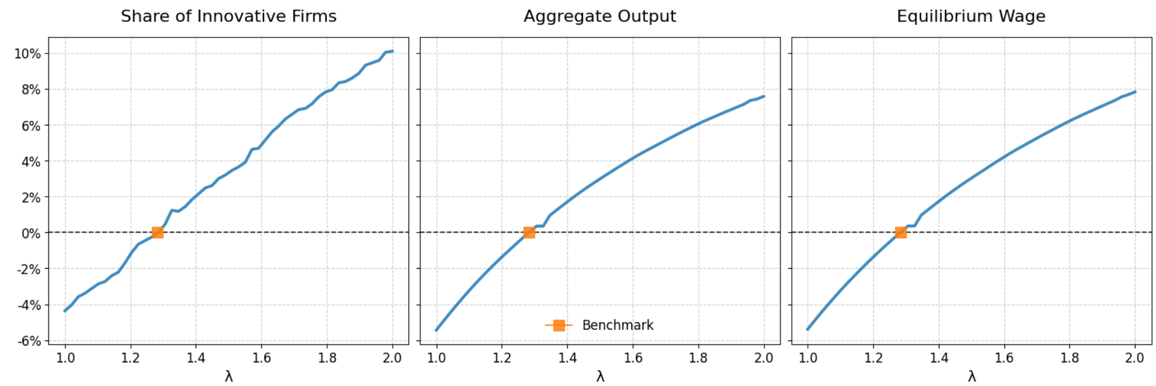
In this section, I study the aggregate and distributional impact of two policy experiments. First, I investigate the impact of financial development policies that alter firms' access to external funding. Next, I examine the effect of competition policy reforms that change the ability of firms to exercise market power. Both exercises are performed in general equilibrium, allowing for the aggregate response of input prices and market shares.

In the model, the tightness of the borrowing constraints and therefore the level of financial development is governed by the parameter λ. To study the aggregate impact policies aimed at improving the level of financial development, I compare the stationary equilibrium of this economy for different levels of λ, while keeping all other parameters unchanged. Policies that improve financial markets can be interpreted as *increases* in λ. As shown in Figure 6, improving firms' access to external funding increases the share of innovative firms by allowing productive firms to expand and grow out of their financial constraints. This increases aggregate output and bids up labor demand, which raises the aggregate wage level.

Next, I investigate the aggregate effects of policies aimed at influencing firms' ability to exercise market power. In the model, the speed at which firms can accumulate market power is governed by the superelasticity of demand ϵ/θ. Increasing the superelasticity of demand determines that firms can quickly gather market power and charge increasingly higher markups as they grow in size. For the purpose of this exercise, I restrict attention to a range of plausible values for ϵ/θ commonly found in the literature, while keeping all other parameters of the model unchanged. I allow for the general equilibrium response of the economy for each of the values considered.

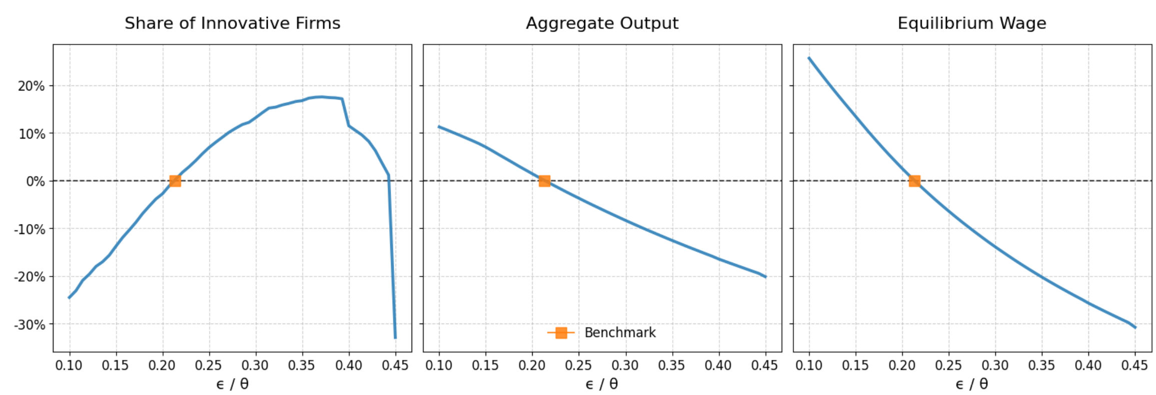
Figure 7 shows the economy's aggregate response to changes in firms' ability to exercise market power. In that sense, policies aimed at curtailing market power can be interpreted as *decreases* in ϵ. There are two important findings worth highlight-

Figure 6. Aggregate Effects of Financial Development



Notes: The share of innovative firms is the number of firms engaged in innovation divided by the overall number of active firms. Values are expressed as percentage deviations from the benchmark calibration.

Figure 7. Aggregate Effects of Competition Policy Reforms



Notes: The share of innovative firms is the number of firms engaged in innovation divided by the overall number of active firms. Values are expressed as percentage deviations from the benchmark calibration.

ing. First, the quantified model predicts that intensifying competition decreases the share of innovative firms in the economy. This is because market power is gained gradually and only a few firms are able to gather sufficient internal funds to invest in innovation when borrowing constraints are binding. Second, the relationship between competition and innovation is non-linear. Starting with low levels of ϵ, representing intense competition between firms, the share of innovative firms in the economy is low. For higher levels of ϵ, as competition becomes less intense, more firms are able to accumulate the necessary funds to innovate, leading to an increase in the share of innovative firms. However, increased market power also has a counteractive effect on a firm's production decision: it reduces the firm's optimal scale of production. Eventually, as competition relaxes even further, firms are able to accumulate market power quickly and charge high markups, reducing the incentive to invest in costly innovation.

7 Conclusion

In this paper, I investigated the aggregate and distributional implications of financial frictions on competition and innovation. Using detailed administrative micro data, I provided descriptive evidence that innovation, as proxied by R&D labor and intangible capital, is associated with higher markups and market shares. Motivated by the empirical evidence, I proposed a dynamic general equilibrium model calibrated to match key facts from the Portuguese data. Viewed through the lens of the quantified model, financial frictions constrain firms' productive capacity, distort innovation decisions, and reduce competition as few firms accumulate enough resources to expand and compete for larger segments of the market. Policies that promote a country's financial development improve aggregate output and wages by allowing firms to expand and engage in innovation. In contrast, policies that intensify competition among firms can come at a cost of lower innovation if borrowing constraints are sufficiently severe. Although this paper focuses on the Portuguese economy, the insights from this paper have broader implications for competition policies for economies with similarly underdeveloped financial markets.

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Appendix A Markup Estimation

In each period t, firm i minimizes the cost of production given the production function:

$$Q_{it} = Q_{it}\left(\Omega_{it}, X_{it}, K_{it}\right) \tag{34}$$

given a set of variable inputs X_{it} and capital K_{it}. Firms are heterogeneous in terms of their productivity Ω_{it} and production technology $Q_{it}(.)$. The only restriction imposed on $Q_{it}(.)$ to derive an expression of the markup is that $Q_{it}(.)$ is continuous and twice differentiable with respect to its arguments. The key assumption is that within one period (a year), variable inputs can adjust frictionlessly, whereas capital is subject to adjustment costs and other frictions.

The Lagrangian function associated with the cost minimization problem is given by:

$$\mathcal{L}\left(X_{it}, K_{it}, \lambda_{it}\right) = P_{it}^{X} X_{it} + r_{it} K_{it} + \lambda_{it}\left(Q_{it} - Q_{it}(X_{it}, K_{it})\right) \tag{35}$$

where P_{it} and r_{it} denote a firm's input prices for variable inputs and capital, respectively.

Taking the first order conditions with respect to the variable inputs results in:

$$\frac{\partial \mathcal{L}}{\partial X_{it}} = P_{it}^{X} - \lambda_{it} \frac{\partial Q_{it}\left(X_{it}, K_{it}\right)}{\partial X_{it}} = 0 \tag{36}$$

which can be rearranged to yield:

$$\frac{\partial Q_{it}\left(X_{it}, K_{it}\right)}{\partial X_{it}} \frac{X_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{X} X_{it}}{Q_{it}} \tag{37}$$

Noting that $\lambda_{it} = \frac{\partial \mathcal{L}}{\partial Q_{it}}$ measures the marginal cost of production and denoting the price of the final good as P_{it}, we can define the markup as:

$$\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}} = \frac{\theta_{it}^{X}}{\alpha_{it}^{X}} \tag{38}$$

where ω_{it}^{X} is the output elasticity of input X_{it} and α_{it}^{X} is that input's expenditure share in total sales ($P_{it} Q_{it}$).

Appendix B Additional Regression Results

Table B6. R&D, Intangibles, and Market Shares – Disaggregated Industry Codes

	Log(Market Share)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(R&D Emp)	0.565***	0.510***	0.094***			
	(0.012)	(0.012)	(0.008)			
Log(Intan Cap)				0.167***	0.155***	0.022***
				(0.001)	(0.001)	(0.001)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	-	Y	Y	-	Y	Y
Firm FE	-	-	Y	-	-	Y
Observations	12,646	12,642	11,280	273,582	273,581	259,264
Adjusted R^2	0.444	0.537	0.975	0.436	0.509	0.969

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. The dependent variable is the firm's (log) market share, with markets defined at the level 2 codes of the CAE Rev 3 (82 categories). Firm controls include size, age, export status. All regressions include industry and year fixed effects.

Table B7. R&D, Intangibles, and Markups – Time-varying Input Elasticities

	Log(Markup)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(R&D Emp)	0.022***	0.022***	0.010***			
	(0.002)	(0.002)	(0.003)			
Log(Intan Cap)				0.001***	0.001***	0.001***
				(0.000)	(0.000)	(0.000)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	-	Y	Y	-	Y	Y
Firm FE	-	-	Y	-	-	Y
Observations	11,882	11,878	10,569	248,685	248,683	234,501
Adjusted R^2	0.283	0.285	0.804	0.223	0.225	0.799

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. The dependent variable is the (log) markup estimated following with a translog production function and time-varying input elasticities as in De Loecker et al. (2020). Firm controls include size, age, export status. All regressions include industry and year fixed effects.

Table B8. R&D Spells and Market Shares

	Rel. Market Share			
	(1)	(2)	(3)	(4)
$t-2$	0.030*	0.026*	0.038	0.068
	(0.016)	(0.015)	(0.005)	(0.052)
$t-1$	0.002	0.004	0.005	0.011
	(0.013)	(0.012)	(0.004)	(0.042)
$t+1$	0.062***	0.063***	0.067**	0.049
	(0.010)	(0.009)	(0.003)	(0.032)
$t+2$	0.105***	0.112***	0.317***	0.255***
	(0.014)	(0.013)	(0.004)	(0.045)
$t+3$	0.236***	0.212***	0.539***	0.447***
	(0.018)	(0.018)	(0.005)	(0.060)
$t+4$	0.324***	0.263***	0.604***	0.426***
	(0.023)	(0.022)	(0.007)	(0.074)
$t+5$	0.303***	0.243***	0.843***	0.562***
	(0.027)	(0.025)	(0.008)	(0.086)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Firm FE	-	Y	-	Y
Observations	9,187	9,803	9,187	9,803
Adjusted R^2	0.346	0.015	0.336	0.055

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table B9. R&D Spells and Markups

	Rel. Markup			
	(1)	(2)	(3)	(4)
$t-2$	-0.006	-0.004	-0.008	-0.010**
	(0.004)	(0.004)	(0.005)	(0.005)
$t-1$	-0.002	-0.002	0.002	0.000
	(0.003)	(0.003)	(0.004)	(0.004)
$t+1$	0.011***	0.011***	0.015***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
$t+2$	0.008**	0.008**	0.015***	0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
$t+3$	0.015***	0.010**	0.022***	0.018***
	(0.005)	(0.005)	(0.005)	(0.006)
$t+4$	0.034***	0.019***	0.044***	0.028***
	(0.006)	(0.006)	(0.007)	(0.007)
$t+5$	0.058***	0.043***	0.061***	0.045***
	(0.007)	(0.007)	(0.008)	(0.008)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Firm FE	-	Y	-	Y
Observations	9,187	9,615	8,976	9,806
Adjusted R^2	0.252	0.027	0.252	0.019

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Appendix C Firm's optimization problem

This section derives the firm's optimal demand for inputs. The choice of inputs is static since the firm observes its productivity prior to choosing inputs.

Noting that demand elasticity is $\sigma(y) = -\frac{p(y)}{p'(y)y}$ and the optimal markup is $\mu(y) = \frac{\sigma(y)}{\sigma(y)-1}$, the traditional firm's optimal input choices satisfy:

$$\frac{p(y^\tau)}{\mu(y^\tau)}\frac{\partial y^\tau}{\partial l} - w = 0 \tag{39}$$

$$\frac{p(y^\tau)}{\mu(y^\tau)}\frac{\partial y^\tau}{\partial k} - (r + \delta + \lambda) = 0 \tag{40}$$

where λ is the multiplier on the borrowing constraint.

Given the traditional firm's production function $y^\tau = \exp(z)k^\alpha l^{1-\alpha}$, we have:

$$\frac{\partial y^\tau}{\partial l} = \frac{(1-\alpha)y^\tau}{l} \tag{41}$$

$$\frac{\partial y^\tau}{\partial k} = \frac{\alpha y^\tau}{k} \tag{42}$$

Thus, the firm's optimal choices of labor and capital are implicitly defined by:

$$l = \left(\frac{1-\alpha}{w}\right)\frac{p(y^\tau)y^\tau}{\mu(y^\tau)} \tag{43}$$

$$k = \left(\frac{\alpha}{r+\delta+\lambda}\right)\frac{p(y^\tau)y^\tau}{\mu(y^\tau)} \tag{44}$$

The R&D firm's input choice is similar to the traditional firm's, with the exception that the firm faces an additional worker allocation choice, and therefore solves:

$$\frac{p(y^\kappa)}{\mu(y^\kappa)}\frac{\partial y^\kappa}{\partial v} = 0 \tag{45}$$

$$\frac{p(y^\kappa)}{\mu(y^\kappa)}\frac{\partial y^\kappa}{\partial l} - w = 0 \tag{46}$$

$$\frac{p(y^\kappa)}{\mu(y^\kappa)}\frac{\partial y^\kappa}{\partial k} - (r + \delta + \lambda) = 0 \tag{47}$$

Given the R&D firm's production function $y^\kappa = \exp(z + \xi \log \nu)\ k^\alpha (l - \nu)^{1-\alpha}$, we obtain:

$$\frac{\partial y^\kappa}{\partial \nu} = \left(\frac{\xi}{\nu}(l - \nu) - (1 - \alpha) \right) \frac{y^\kappa}{l - \nu} \tag{48}$$

$$\frac{\partial y^\kappa}{\partial l} = \frac{(1 - \alpha) y^\kappa}{l - \nu} \tag{49}$$

$$\frac{\partial y^\kappa}{\partial k} = \frac{\alpha y^\kappa}{k} \tag{50}$$

The R&D firm's optimal input choices are therefore implicitly defined by:

$$\nu = \left(\frac{\xi}{1 - \alpha + \xi} \right) l \tag{51}$$

$$l = \left(\frac{1 - \alpha + \xi}{w} \right) \frac{p(y^\kappa) y^\kappa}{\mu(y^\kappa)} \tag{52}$$

$$k = \left(\frac{\alpha}{r + \delta + \lambda} \right) \frac{p(y^\kappa) y^\kappa}{\mu(y^\kappa)} \tag{53}$$

Appendix D Model Solution

The solution of the model is non-standard, as each firm's price and markup depends on its market share, which in turn, is determined by how production is distributed across firms. Moreover, the assumption of a small open economy implies that the interest rate is fixed exogenously, but the labor market clears domestically. Thus, in addition to ensuring consistency in the goods market, the model solution must also satisfy the labor market clearing condition.

The algorithm to compute the solution of the model involves the following steps:

1. Guess aggregate output Y and equilibrium wage rate w.
2. Solve each firm's static optimization problem for a given productivity draw z and initial equity a using a constrained maximization algorithm:
    (a) For the traditional technology, choose capital k and labor l that maximizes profit π^{τ}.
    (b) For the R&D technology, choose capital k, labor l, and R&D ν that maximize profit π^{κ}.
    (c) Choose the technology (either traditional or R&D) that yields the highest profit π.
3. Solve the firm's dynamic optimization problem over a finely discretized grid of productivity draws z and initial equity a using Howard's policy iteration.
4. Given the policy choices, simulate a panel of N firms for T periods using Monte Carlo Simulation.
5. Compute the stationary distribution of agents over individual states.
6. Compute the aggregate variables and check if they satisfy the aggregate consistency conditions.
7. Update guesses for Y and w and return to step 2 if necessary.

I employ discrete space methods over a fine grid rather than relying on function approximation or interpolation over a coarser grid due to the discrete technology choice in the firm's decision problem. While function approximation methods are computationally attractive, they perform poorly when dealing with discrete choices, as they often introduce significant discontinuities in policy functions, making them unsuitable for this problem. To mitigate the computational challenges posed by the curse of dimensionality, I use Google JAX, a Python library optimized for high-performance numerical computations and large-scale machine learning. This approach significantly accelerates computations and achieves the accuracy required to solve the model.

Given the functional form assumed for the Kimball aggregator, no closed-form solution exists for the firm's static optimization problems. I employ Sequential Least Squares Programming to solve for the firm's policy functions, which handles the nonlinearities and constraints in the problem by iteratively approximating the solution through gradient-based optimization.

Although computationally more demanding, I employ Monte Carlo simulation instead of iterating over the density function. Productivity draws follow a Markov process, discretized using the Tauchen method, and individual shock histories are simulated with a random number generator. This approach allows me to compute firm-level moments from the simulated data, which can be directly compared to observed firm-level panel data, ensuring a tight alignment between the model's predictions and the empirical evidence.

Finally, I solve for the general equilibrium conditions using a root-finding algorithm based on Powell's conjugate direction method, a multi-dimensional gradient-free approach that is robust to nonlinearities and corner solutions.