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Firm-Level Innovation in Spain: Patterns, Drivers, and Policy Implications

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Firm-Level Innovation in Spain: Patterns, Drivers and Policy Implications*

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ABSTRACT: While Spain's productivity growth has picked up in recent years, a sizable gap with other high-income countries remains. One contributing factor is a large innovation gap vis-à-vis peer countries. Firm-level evidence shows that this gap is particularly pronounced among young firms and widens for higher-quality patents. Innovation is held back by size-dependent regulations, financial constraints, regulatory burdens, and the complexity of the R&D tax credit, which is generous on paper yet has low take-up rate. Quantitative simulations based on endogenous growth model suggest that easing these frictions could raise Spain's long-term total factor productivity growth by over 0.25 percentage points.

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SELECTED ISSUES PAPERS

Firm-Level Innovation in Spain: Patterns, Drivers and Policy Implications

Spain

Prepared by Younghun Shim, Isabel Figueiras (EUR Summer Intern), and Carlo Pizzinelli[1]

[1] The authors would like to thank Romain Duval and participants of the EUR research seminar and Banco de España, Ministerio de Economía, Comercio y Empresa for useful comments and suggestions.

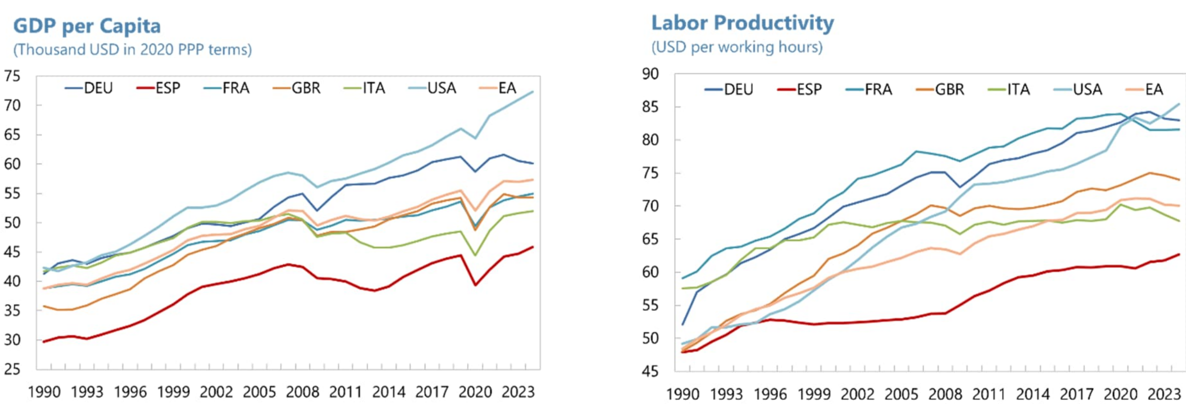
FIRM-LEVEL INNOVATION IN SPAIN: PATTERNS, DRIVERS, AND POLICY IMPLICATIONS[1]

While Spain's productivity growth has picked up in recent years, a sizable gap with other high-income countries remains. One contributing factor, which is the focus of this paper, is a large innovation gap vis-à-vis peer countries. Firm-level evidence shows that this gap is particularly pronounced among young firms and widens further for higher-quality patents. Innovation by Spanish firms is found to be held back by several factors, including size-dependent regulations, financial constraints, and regulatory burdens. These frictions not only reduce the likelihood of innovation but also its payoff in terms of post-innovation firm growth. Another obstacle is the complexity of the R&D tax credit, which is relatively generous on paper compared to other countries yet has a low take-up rate in practice. Simulations of an endogenous growth model with firm-level innovation and creative destruction suggest that easing these frictions, together with streamlining the R&D tax credit, could raise Spain's long-term total factor productivity growth by over a quarter of a percentage point.

A. Introduction

1. Notwithstanding its recent improvement, Spain's productivity growth performance has been weak over the past two decades and a large gap remains with respect to other high-income countries. Figure 1 plots Spain's GDP per capita and labor productivity alongside other high-income countries. Despite some recent catchup, productivity levels remain below the euro area average and are even further behind those of the US. In particular, Spain's labor productivity was roughly comparable to that of the US in 1990, but the gap has widened over time, with Spain's productivity now at about 74 percent of the US level.

Figure 1. GDP per Capita and Labor Productivity of Spain and Other High-Income Countries



Sources: Long Term Productivity Database and IMF staff calculations.

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[1] Prepared by Younghun Shim, Isabel Figueiras (EUR summer intern), and Carlo Pizzinelli.

2. This paper focuses on innovation as a driver of productivity growth. Productivity is determined by various factors, including innovation, foreign technology adoption, technology diffusion across firms, allocative efficiency, and human capital. Among these, this paper focuses on innovation, which is one of the main drivers of long-run productivity growth in high-income countries (Acemoglu and others, 2006). Specifically, it examines the magnitude of the innovation gap, how it varies across firm characteristics such as size and age, and the frictions that hinder innovation in Spain.

3. To study the drivers of, and obstacles to innovation by Spanish firms, empirical analysis is carried out using a firm-level patent dataset. Analyzing innovation requires output-based measures at the micro level; in this paper, patent data are used, as commonly used in the literature. Patent data provide measures of both the quantity and quality of innovation. They are obtained from PATSTAT and merged with firm-level ORBIS data using firm names. Using this dataset, stylized facts are documented on firm-level innovation in Spain relative to other high-income countries. Specifically, the results indicate that Spanish firms innovate less than French and Swedish firms, particularly among young firms. This is consequential for growth, as we also find that younger firms tend to produce higher-quality innovations. In addition, we examine the role of various frictions—including size-dependent regulations, financial frictions, and regulatory burdens—on both the likelihood of innovation and post-innovation firm growth. All three frictions are negatively associated with both the probability of innovation and its quality. Moreover, conditional on innovating, firms grow less when they face frictions.

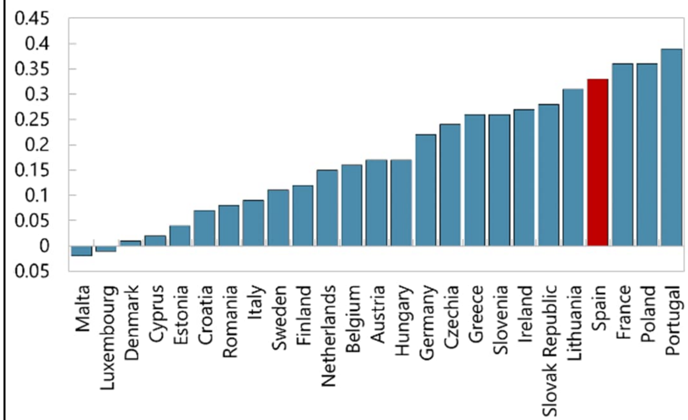
4. To quantify the implications of removing some of the key innovation obstacles for aggregate productivity growth, an endogenous growth model is developed. Building on Klette and Kortum (2004), a general equilibrium framework is constructed in which productivity growth is driven by innovation. In the model, firms invest in R&D to innovate, which raises productivity and expands firm size. We extend the standard framework by incorporating frictions that reduce firms' innovation incentives and, in turn, aggregate growth. The model is calibrated to match the observed micro-level patterns of innovation and firm size in Spain, including those derived from the empirical results.

5. Policy counterfactuals based on the calibrated model point to sizable productivity growth gains from easing the frictions that are holding back innovation and streamlining the R&D tax credit. The counterfactual analysis suggests that addressing all three frictions mentioned above could increase the long-run TFP growth rate by 0.18 percentage points. As for Spain's R&D tax credit, whose complexity lowers take-up, a reform that would streamline the tax credit to raise the take-up rate and thereby the effective subsidy rate could yield an extra productivity growth gain. Specifically, streamlining the program and better targeting it toward young firms could increase the TFP growth rate by a further 0.1 percentage point.

B. Spain's Innovation Policies

6. Spain's R&D tax credit is generous in terms of statutory rates, but its complexity and administrative burden substantially limit actual take-up. R&D expenditure in Spain is eligible for a 25 percent tax credit up to the average expenditure level of the previous two years, and for a higher rate of 42 percent on additional expenditure above that level. OECD data (Figure 2) show that Spain's implied tax subsidy rates on R&D exceed those in most other EU countries. However, AIReF (2020) finds that the actual take-up rate of the R&D tax credit is only around 30 percent. One important contributing factor—highlighted by AIReF—is real and perceived legal and regulatory uncertainty: tax authorities may reject applications after ex-post evaluation if the reported activities are not deemed to qualify as "R&D." Firms, particularly smaller ones, perceive this rejection risk as high. In addition, small and young firms often lack sufficient taxable profits against which to apply the credit, which substantially reduces its effective value since the credit cannot function as a negative tax (AIReF, 2020). Although the Spanish government has introduced a monetization mechanism that allows firms to cash out unused credits in the absence of tax liabilities, this option comes at a cost: the credit is discounted, and firms must satisfy strict continuity of activity and employment requirements. In addition, because this support is received with a lag, it may do little to ease the short-term credit constraints that hold back firms' R&D investment. Finally, the administrative burden associated with documentation, certification, and compliance is widely perceived to be large, further discouraging participation. Together, these features imply that Spain's R&D tax credit is generous on paper but much less accessible in practice, particularly for small and young firms.

Figure 2. Implied Tax Subsidy Rates on R&D Expenditures
(Implied subsidy in $ per $1 of R&D)



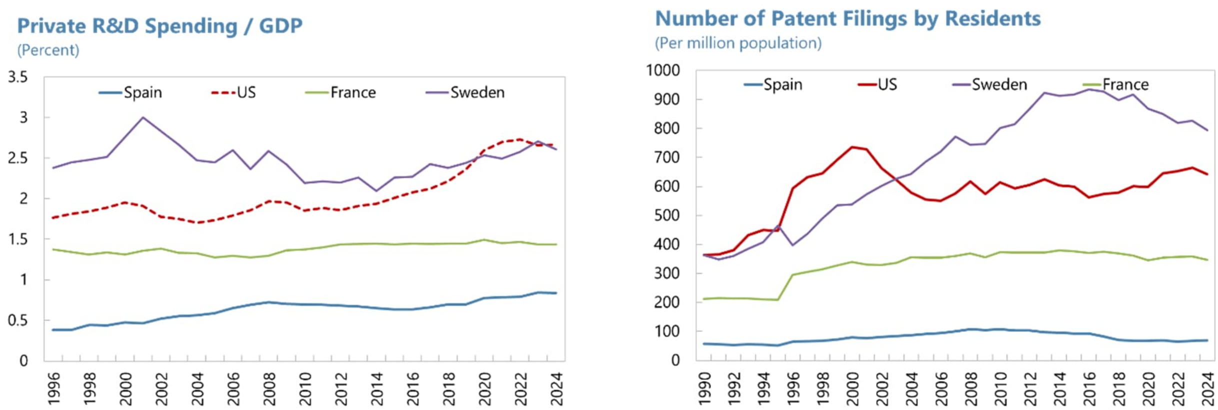
Sources: OECD Innotax

C. Data and Stylized Facts

7. Spain has been lagging behind other advanced economies on both input and output measures of innovation. The left panel of Figure 3 shows that R&D intensity has stagnated since the late 2000s and the gap relative to other advanced economies has remained persistent. The right panel presents an output measure of innovation—the number of patents filed by residents per million population. Spain has been recording substantially fewer patents than other countries, and this gap is even larger than that observed for R&D intensity. Together, these patterns suggest that Spanish firms not only invest less in R&D, but also exhibit lower innovation productivity—since the

patenting gap significantly exceeds the R&D spending gap—compared with firms in other advanced economies.

Figure 3. Innovation in Spain Compared to Other Advanced Economies



Sources: OECD and IMF staff calculations.

Sources: WIPO and IMF staff calculations.

8. Spain's patenting gap vis-à-vis the US is broad-based across sectors and does not mainly reflect Spain's sectoral specialization. The gap is mostly driven by the within-sector margin rather than by differences in sectoral composition, as the results from the following decomposition show:

$$\Delta P = \sum_j (\alpha_j^{US} - \alpha_j^{ES}) P_j^{ES} + \sum_j \alpha_j^{US} (P_j^{US} - P_j^{ES}).$$

where P_j is patents per worker and α_j is the employment share of industry j (2-digit NACE). The first term captures the across-sector (composition) margin, reflecting differences in patenting that arise from variation in industry shares across countries (for example, the higher sectoral share of the tech sector, in which firms have a high propensity to innovate, in the United States compared to Spain). The second term captures the within-sector margin, reflecting differences in patent intensity within given industries. The within-sector margin is found to account for about 70 percent of the total patenting gap between Spain and the US, while the remaining 30 percent is explained by differences in sectoral composition. This implies that Spain's innovation shortfall is driven mainly by weaker innovative performance of firms within the same industries, rather than by a concentration in less innovative sectors.

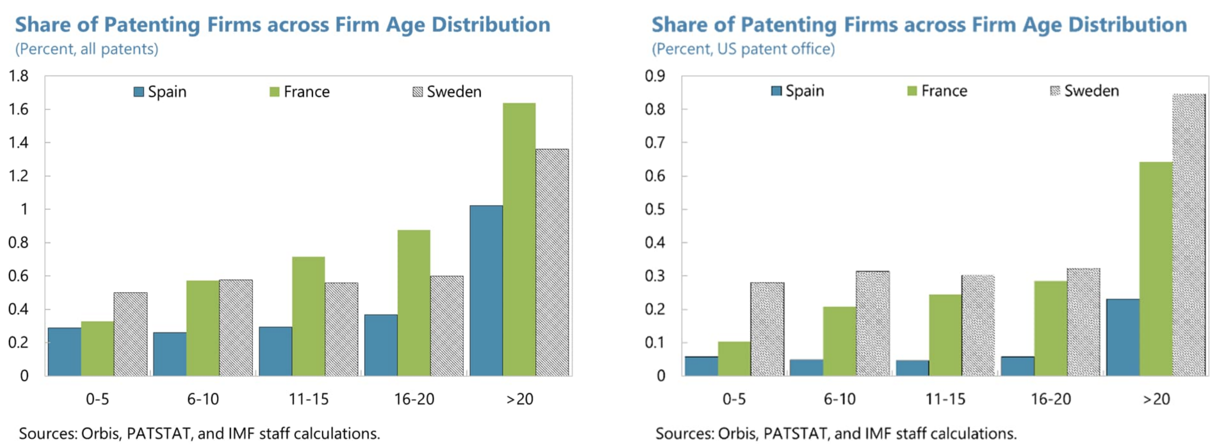
9. In this paper, Orbis data are merged with PATSTAT data to examine firm-level innovation. Firm-level data are obtained from Orbis, which provides data on sales, employment, fixed assets, industry, and location.[2] The analysis focuses on Spain, France, and Sweden, all of which have good coverage in Orbis. These are merged with PATSTAT data, which contains comprehensive patent information from several patent offices, including the European Patent Office, as well as the Spanish, US, and Japanese patent offices. Firm names and locations are used to merge the two

[2] We followed the data cleaning procedure by Díez and others (2021) and Kalemli-Özcan and others (2024).

datasets, following the standardization process of EUIPO (2025). The matching rate for Spanish firms is 87 percent, meaning that 87 percent of all patent applications filed by firms located in Spain are assigned to a harmonized firm ID from Orbis, and thus appear in our final merged sample. The corresponding matching rates for France and Sweden are 78 percent and 85 percent, respectively. These rates are comparable to those in the literature. Details on the data can be found in Annex I.

10. Spanish firms are less likely than French and Swedish firms to file patents, with the gap being larger for younger firms and even more pronounced for high-quality patents. Using the merged Orbis–PATSTAT dataset, firms' innovation probabilities are examined across age groups and countries. Two measures are employed. First, a firm is defined as a patenting firm if it files at least one patent in any patent office (for example, the Spanish Patent Office). Second, to capture higher-quality innovation, we restrict attention to patents filed at the US Patent and Trademark Office (USPTO), which are widely regarded in the literature as a proxy for higher-quality patents. Figure 4 plots the share of patenting firms by firm age, with the left panel showing all patents and the right panel showing only USPTO patents.[3] Across all age groups, Spanish firms exhibit lower patenting rates than their French and Swedish counterparts, and this gap is particularly pronounced for younger firms and for high-quality patents.

Figure 4. Share of Firms that File Patents across Firm Age Distribution



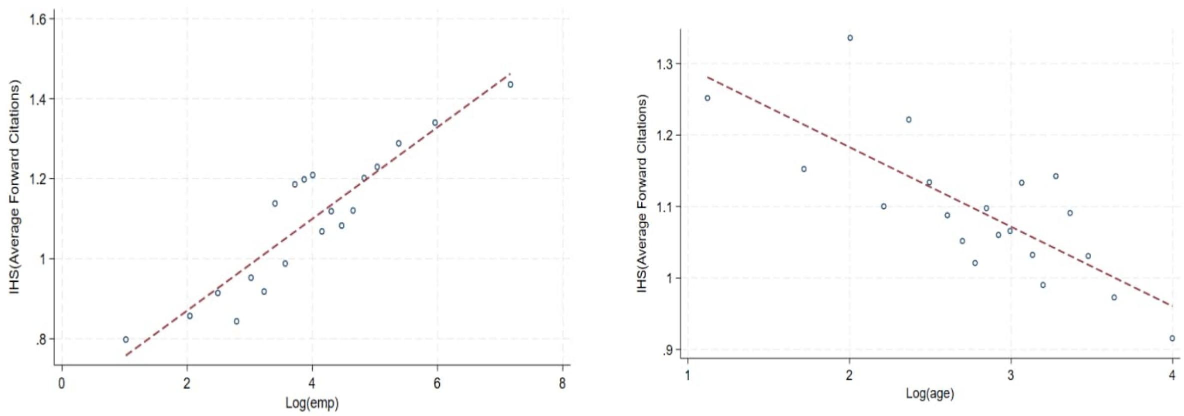
11. The average quality of patents increases with firm size but decreases with firm age, highlighting the importance of large and young firms in driving breakthrough innovation. Following the literature, we measure innovation quality using forward citations—the number of times a patent is cited by subsequent patents—and exclude self-citations in which firms cite their own patents. Firm size is proxied by employment. Figure 5 presents binscatter plots of the inverse hyperbolic sine transformation of forward citations against log employment and log firm age.[4] In

[3] We restrict the sample to the manufacturing sector to improve comparability across the three countries.

[4] The inverse hyperbolic sine (IHS) transformation is defined as $\operatorname{asinh}(x) = \ln\left(x + \sqrt{x^2 + 1}\right)$. It behaves similarly to the natural logarithm for large values of x, while remaining well-defined at zero and for small values.

each specification, we control for the other firm characteristics (age or size), as well as industry and year fixed effects. The left panel shows that, conditional on firm age, smaller firms tend to produce lower-quality innovations. In contrast, the right panel indicates that younger firms are more likely to generate higher-quality innovations. The latter result suggests that policies supporting young firms may be particularly important when designing R&D subsidy programs.

Figure 5. Average Forward Citations across Firm Size and Age



Source: Orbis, PATSTAT, and IMF staff calculations.

12. There is substantial and persistent polarization in innovation outcomes across Spanish firms, with only a small fraction showing the ability to innovate. Only 0.17 percent of firms file a patent when they are young (defined as age five or below). Among firms that innovate when young, 36 percent also innovate at older ages. In contrast, among firms that do not innovate when young, only 0.3 percent file a patent later in life.[5] These patterns point to pronounced heterogeneity in firms' innovative capabilities: most startups appear to be non-innovative, subsistence-type firms, while a small subset exhibits persistent innovative activity (Hurst and Pugsley, 2011; Guntin and Kochen, 2025).

D. Empirical Analysis

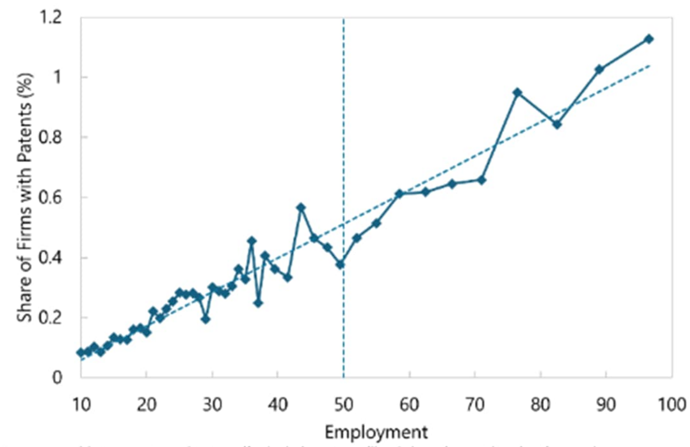
13. Firm-level analysis is carried out to assess the impact of frictions on firm-level innovation. Specifically, three types of frictions are examined: size-dependent labor regulations, financial constraints, and regulatory burdens stemming from regional and sectoral regulations. For each of them, two questions are addressed. First, is firm-level innovation negatively associated with the presence of the friction considered? Second, conditional on a firm innovating, does the friction hinder firm growth following the innovation? To this end, we proceed in two steps. We first regress a patenting indicator on the relevant friction measure to assess whether the friction is negatively correlated with innovation. Second, we regress firm employment growth on the interaction between

[5] Firms in France and Sweden also show similar level of polarization.

the patenting indicator and the friction measure to examine whether firm growth after innovation is dampened by the presence of the friction.

14. The share of patenting Spanish firms significantly declines near the key size-dependent regulation threshold of 50 employees. Spanish firms face significantly more stringent labor regulations once they exceed 50 employees (Almunia and others, 2024).[6] These include, among others, higher layoff costs and the requirement to establish a works council. The literature has found that size-dependent regulations of this type can discourage firm growth, often inducing firms to remain just below the threshold (Garicano and others, 2016). Most directly related to the present paper, Aghion and others (2023) document that similar size-dependent regulations in France reduce firms' incentives to innovate below the size threshold. Figure 6 plots the share of Spanish firms that file any patents by employment size. While the share generally increases with firm size, it also exhibits a noticeable decline around the size-dependent threshold of 50 employees. To assess whether this decline is statistically significant, we estimate the following regression:

Figure 6. Share of Patenting Firms by Employment Level



Sources: Orbis, PATSTAT, and IMF staff calculations. Trendline is based on estimation for employment between 10 to 100.

$$\boldsymbol{Y_{it}} = \boldsymbol{\beta} \cdot \mathbb{1}(\mathbf{45} \leq \boldsymbol{l} \leq \mathbf{49}) + \gamma \cdot \boldsymbol{log}(\boldsymbol{emp_{it}}) + \boldsymbol{\Gamma} \cdot \boldsymbol{X_{it}} + \boldsymbol{\epsilon_{it}}.$$

Three alternative dependent variables $\boldsymbol{Y_{it}}$ are used: i) a dummy variable indicating whether a firm files any patent; ii) the number of patents filed at the Spanish, European, and US patent offices, which captures higher-quality patents since patents filed at multiple offices—particularly those of the US and European patent offices—have typically been considered to be of higher quality in the literature; iii) the inverse hyperbolic sine transformation of the average number of forward citations, which have been used as another typical indicator of higher-quality patents. The vector $\boldsymbol{X_{it}}$ includes control variables such as (4-digit NACE) sector and year fixed effects. Table 1 reports the regression results. The coefficients on the dummy variable for firms with employment levels between 45 and 49 workers are negative across all dependent variables, suggesting that firm-level innovation is negatively correlated with size-dependent regulations.

[6] Almunia and others (2024) point out that another important threshold arises in Spain when a firm's operating revenue exceeds €6 million. On the innovation side, however, we do not find a statistically significant effect associated with this revenue-based threshold.

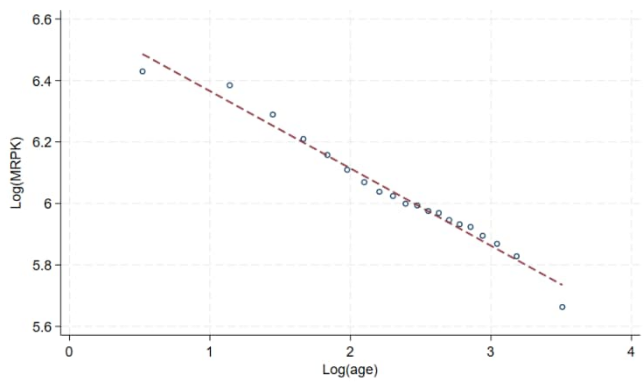
Table 1. Spain: 50-Employee Threshold and Innovation: Firm-Level Regression Results

	Any Patents	Patents filed in ES, EU, US	Average Citations
log(emp)	0.181***	0.039***	0.086***
	(0.001)	(0.001)	(0.008)
45≤ Emp < 50	-0.141***	-0.073***	-0.163*
	(0.019)	(0.008)	(0.089)
Observations	5,049,483	5,049,483	6,496
Mean of dep. var.	0.130	0.022	1.099

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

15. The share of patenting firms also significantly decreases with the magnitude of the financial constraints they face. Following Hsieh and Klenow (2009), we use marginal revenue product of capital (MRPK) as a proxy for the severity of financial constraints. Assuming a Cobb-Douglas production function, MRPK is calculated as below:

Figure 7. Log (MRPK) and Firm Age



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

$$MRPK_i = (1-\alpha)\frac{p_i y_i}{k_i}.$$

Here, firm i's output, y_i, is produced using labor, l_i, and capital, k_i, where a_i denotes firm-specific productivity and α is the output elasticity of labor. The marginal revenue product of capital, $MRPK_i$, is given by revenue per unit of capital, where p_i is the firm-specific output price and $p_i y_i$is the firm's revenue. This measure of MRPK can be directly retrieved from firm balance sheet data. We classify firms as financially constrained if their MRPK exceeds the median within a given sector–year. The underlying intuition is that a higher MRPK signals a large incentive for the firm to expand capital investment which, since not fulfilled, suggests the presence of greater financial constraints compared to other firms. Figure 7 shows a negative correlation between log(MRPK) and log(firm age), conditional on firm sales and sector–year fixed effects, indicating that younger firms are more likely to be financially constrained. Next, for each of the three alternative indicators of firm patenting, the following regression is estimated:

$$Y_{it} = \beta \cdot \mathbb{1}(Constrained) + \gamma \cdot log(emp_{it}) + \Gamma \cdot X_{it} + \epsilon_{it},$$

where, $\boldsymbol{X_{it}}$ includes sector and year fixed effects. Table 2 shows the results. Innovation outcomes—both the probability of patenting and patent quality—are negatively associated with financial constraints.

Table 2. Spain: Innovation with Financial Frictions

	Any Patents	Patents filed in ES, EU, US	Average Citations
log(emp)	0.180***	0.039***	0.084***
	(0.001)	(0.001)	(0.008)
Constrained	-0.087***	-0.021***	-0.144***
	(0.003)	(0.001)	(0.030)
Observations	5,049,483	5,049,483	6,496
Mean of dep. var.	0.130	0.022	1.099

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

16. The probability of filing patents decreases with the intensity of regulatory burdens. Various types of regulatory burdens can hinder firm innovation. Here, we capture the intensity of some region-sector regulations using the number of newly introduced regulations at the region–sector–year level from Mora-Sanguinetti and others (2022, 2024). Specifically, we estimate the following regression:

$$Y_{it} = \beta \cdot \Delta\text{Log (\# of regulations)} + \gamma \cdot log(emp_{it}) + \Gamma \cdot X_{it} + \epsilon_{it},$$

where X_{it} includes sector, year, and region (two-digit NUTS) fixed effects. The regression results reported in Table 3 confirm that increases in the number of regulations are negatively associated with firm-level innovation activity. Although the coefficient on average citations is also negative, it is not statistically significant.

Table 3. Spain: Innovation with Regulatory Burdens

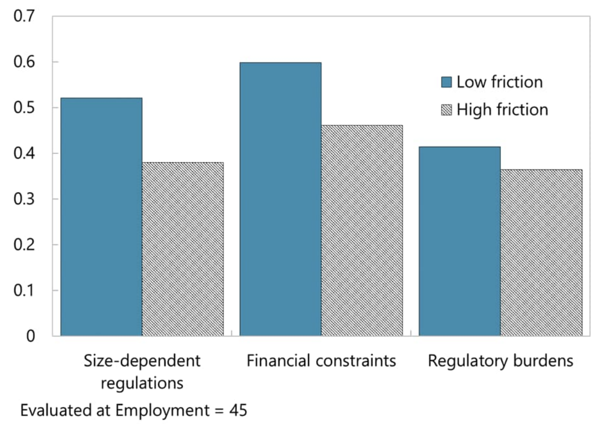
	Any Patents	Patents filed in ES, EU, US	Average Citations
log(emp)	0.130***	0.028***	0.077***
	(0.001)	(0.001)	(0.010)
Δ Log # of regulations	-0.022***	-0.006*	-0.027
	(0.008)	(0.003)	(0.078)
Observations	4,227,020	4,227,020	3,935
Mean of dep. var.	0.094	0.016	1.102

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

17. While caution should be exerted in interpreting non-causal empirical estimates, the analysis points to material impacts of the three frictions on innovation. For each of the three frictions, Figure 8 illustrates the innovation differential by plotting the innovation probability for firms facing low versus high frictions. More constrained firms correspond to those in the top decile of the friction measure considered, while less constrained firms correspond to those in the bottom

decile. For size-dependent regulations, we compare firms with employment between 45 and 49 workers to all other firms. Taken at face value, these implied probabilities suggest that these constraints together might account for about 88 percent of the innovation gap relative to Swedish firms at employment 45 (33 out of 37 percentage points).

Figure 8. Implied Firm-Level Innovation Probabilities for High Versus Low Frictions



18. Conditional on innovating, firms grow less when they face frictions. To examine this hypothesis, we estimate the following regression:

$$\log l_{i,t+5} - \log l_{i,t} = \beta_1 \mathbb{1}(\text{Innovate}) + \beta_2 \mathbb{1}(\text{Friction}) + \beta_3 \mathbb{1}(\text{Innovate}) \times \mathbb{1}(\text{Friction}) + \beta_4 \log l_{i,t} + \epsilon_{i,t}.$$

Here, $l_{j,t}$ is the number of employees of firm i at year t, $\mathbb{1}$(Innovate) is a dummy variable that firms file a patent, and $\mathbb{1}$(Friction) is a dummy variable if firms' friction measure is above the median. In case of employment threshold, it is a dummy variable where employment is between 45 and 50. Our main coefficient of interest is β_3. $\beta_3 < 0$ implies that, conditional on innovating, firms grow less when they face larger frictions. Table 4 reports the results for all three friction measures. For the regulatory burden friction (third column), the variable "Regulated" is a dummy equal to one if the cumulative number of regulations exceeds the within-year median. In all three cases, the coefficient on the interaction term is negative and statistically significant, indicating that post-innovation firm growth is negatively associated with each of the three friction measures.

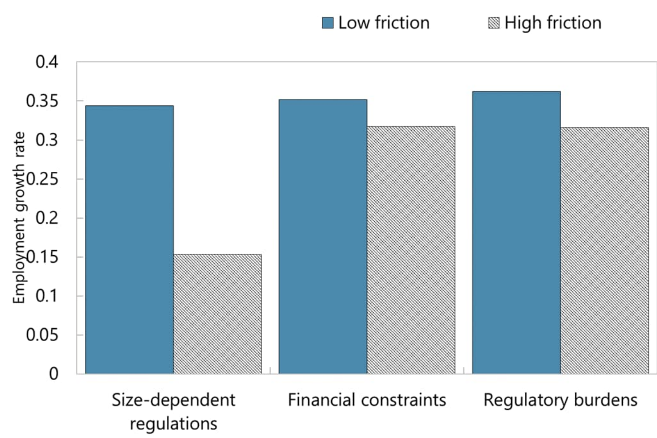
19. The 50-employee regulatory threshold appears to be quantitatively most strongly associated with reduced post-innovation firm growth. Figure 9 plots the employment growth rate differential between firms facing low versus high frictions. The size-dependent regulation captured by the 50-employee threshold appears to be more consequential economically, compared to the other two frictions.

Table 4. Spain: Employment Growth after Patenting and Frictions

	Emp growth	Emp growth	Emp growth
Innovation	0.344***	0.352***	0.362***
	(0.008)	(0.010)	(0.014)
Innovation x 45≤ Emp < 50	-0.191***		
	(0.052)		
Innovation x Constrained		-0.035**	
		(0.017)	
Innovation x Regulated			-0.046**
			(0.022)
Observations	4,705,084	4,705,084	3,940,540

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

Figure 9. Implied Post-Innovation Firm Growth for high versus low Frictions



E. Model

20. To quantify the aggregate growth impact of key frictions and the R&D subsidy program, an endogenous growth model is constructed. The starting point is the framework of Klette and Kortum (2004), who present a continuous-time general equilibrium model of endogenous growth. In this model, firm dynamics are driven by innovation and creative destruction. Firms consist of multiple product lines and invest in R&D to generate innovations that improve product-level productivity by a fixed step. R&D costs, featuring a Poisson arrival rate for innovation x_i, have the following functional form:

$$\boldsymbol{C}(\boldsymbol{x_i}; \boldsymbol{n_i}) = x_i^{\eta} n_i^{1-\eta} Y/\alpha,$$

where n_i is the number of product lines, α is the cost shifter, and Y is the final good in the economy. A successful innovation allows the firm to replace the incumbent producer of a product, increase the productivity of that product line, and add it to its portfolio, while incumbent firms lose existing product lines when rivals innovate. New firms enter the economy by innovating and acquiring an initial product line, and firms exit when all their product lines are displaced. Firm size is therefore determined by the number of product lines operated, generating a stationary firm size distribution, ongoing entry and exit, and aggregate productivity growth driven by firm-level innovation. The production function is linear in labor with heterogeneous productivity, and labor is inelastically supplied by households.

21. We extend the workhorse model by including size-dependent regulations, financial frictions, and regulatory burdens, together with heterogeneous innovation ability across firms. We incorporate size-dependent regulations by assuming that firms incur a fixed cost, $\phi > 0$, when their employment exceeds 50. Next, we extend the R&D cost function to incorporate financial costs and R&D subsidies. Financial frictions are modeled as an additional cost of R&D, $\tau(n_i)$, which decreases with firm-level employment. This can be microfounded if the firms have to borrow to finance R&D and the borrowing cost is larger when the firm is small, in line with empirical evidence. In sum, the R&D cost function with a Poisson arrival rate of innovation, x_i, in our model is

$$\boldsymbol{C(x_i;n_i)} = \left(\boldsymbol{(1-s)}\big(1+\tau(n_i)\big)x_i^{\eta}\, n_i^{(1-\eta)}Y\right)/\alpha,$$

where s is the R&D subsidy rate. Regulatory burdens are incorporated in the entry cost. Specifically, there is a unit mass of potential entrants who choose a Poisson arrival rate of innovation, $\tilde{x}$, with the same R&D cost function. Conditional on a successful innovation, the entrants pay a fixed cost $\delta > 0$ and replace a product line of an incumbent, while improving productivity. Lastly, we assume the step size of innovation—the magnitude of the productivity gain from innovation—can take two values $\lambda \in \{\lambda^H, \lambda^L\}$, where $\lambda^H > \lambda^L$. Following Acemoglu and others (2018), we assume that all firms start with λ^H, and that it transitions to λ^L with Poisson arrival rate κ. Annex II details the full model.

22. In the model, frictions reduce the net return to innovation, thereby suppressing innovation and productivity growth. Firms optimally choose their innovation rate by equating marginal costs and marginal gains from innovation. Accordingly, any factor that lowers the returns to innovation or raises its costs reduces the innovation rate. First, size-dependent regulations lower the return to innovation when firms approach the employment threshold, as expanding through innovation then entails an additional fixed cost. Because the model is dynamic, even smaller firms anticipate the possibility of crossing the threshold in the future and are therefore affected. Next, financial frictions increase the cost of investing in R&D, reducing innovation rates. In particular, smaller firms face tighter financial constraints, leading them to innovate less, all else equal. Regulatory burdens increase entry costs, which disincentivizes potential entrants to innovate. Lastly, high-type firms have larger innovation step sizes and therefore stronger incentives to innovate than low-type ones. However, the wedge between private and social returns increases with step size. This is because social welfare rises linearly with step size through its direct effect on the growth rate, whereas private returns rise concavely as firms' expected profits are discounted by Schumpeterian

forces, with the effective discount rate increasing in step size. Consequently, the optimal R&D subsidy rate is higher for high-type firms (Aghion and Howitt, 1992; Choi and Shim, 2024).

F. Quantitative Exercise

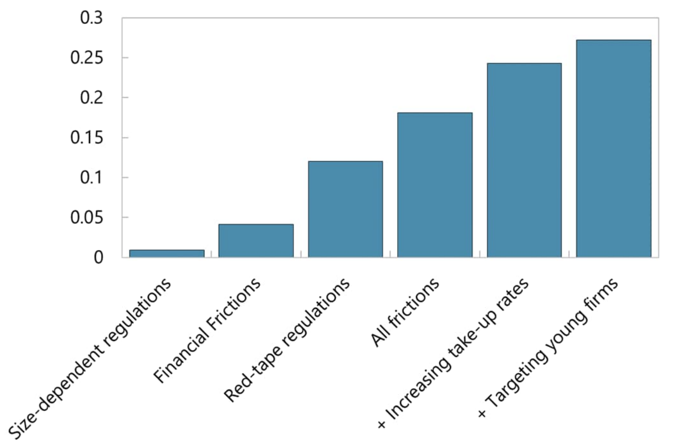
Table 5. Spain: Calibration Results

Parameter	Description	Main target	Model	Data
L	labor supply	Share of firm with emp>50	0.015	0.017
α	Innovation cost shifter	R&D / GDP	0.158	0.149
λ^L	Baseline step size	TFP growth rate	0.71	0.67
ϕ	Size-dependent regulation	Patenting decline at 45<emp<50	-0.44	-0.41
τ	Slope of financial friction	Slope of log(MRPK) over log(emp)	-0.08	-0.08
δ	Regulatory burdens	Entry rate	0.05	0.047
κ	Pr (Low type | High type)	Young vs Old patent quality difference	0.225	0.22
S	R&D subsidy rate	Effective subsidy rate x take up rate	0.1	0.1
η	Convexity of R&D cost	Acemoglu and others (2018)	2	NA

23. The model is calibrated to match key macro and micro moments of the data. We first calibrate a group of parameters by targeting macro moments, following the conventional procedure in the literature. First, α, the innovation cost shifter, is calibrated to match the ratio of R&D to GDP in Spain (1.49 percent). λ^L is calibrated to match the average TFP growth rate between 2015 and 2025 (0.67 percent) and λ^H is assumed to be twice as high as λ^L. Labor supply L is assumed to be fixed and calibrated to match the share of firms with more than 50 employees. Then, micro moments are used to calibrate parameters related to frictions. The cost of size-dependent regulation, ϕ, is calibrated to match the marginal decline in the probability of patenting as firm size increases from 45 to 50 employees obtained in the empirical analysis above. $\tau(n)$ is set to be $-\tau\log(n)$, and τ is calibrated to match the slope of log MRPK with respect to log employment estimated above. δ, the magnitude of regulatory burdens, is calibrated to match the firm entry rate in Spain (4.66 percent). The probability of transition from high to low type is set to match the patent quality difference between young and old firms. The R&D subsidy rate in the baseline is calibrated to be 10 percent, which multiplies the effective subsidy rate (33 percent) with the overall take-up rate (30 percent) estimated by AIReF (2020). Lastly, the R&D cost convexity, η, is set to be 2, following Acemoglu and others (2018). Table 5 summarizes calibration targets and the corresponding model-implied moments, alongside their empirical counterparts.

24. Model simulations of policy counterfactuals suggest that addressing frictions could increase annual productivity growth by about 0.2 percentage points. We conduct several counterfactual exercises and compare outcomes across different steady states. First, we reduce the cost parameters associated with each friction by half, one at a time—size-dependent regulations, financial frictions, and regulatory burdens. Figure 10 reports the long-term productivity growth gains from each counterfactual. The productivity growth increase from addressing size-dependent regulations alone is relatively small because the share of firms close to the employment threshold—and thus directly affected by the regulation—is rather small in the Spanish economy. By contrast, cutting financial frictions and regulatory burdens affects a broader set of firms and therefore generates larger productivity gains. Overall, reducing all three frictions is found to increase the long-term productivity growth rate by 0.18 percentage points.

Figure 10. Long-term TFP Growth Rate Gains from Various Innovation-Enhancing Reforms (Percentage Points)



25. Furthermore, streamlining the R&D tax credit and better targeting it to young firms could increase the productivity growth rate by an additional 0.1 percentage point. An economy is simulated in which the government streamlines the R&D tax credit program, increasing the take-up rate from 30 percent to 60 percent. In the model, this raises the effective R&D subsidy rate from 10 to 20 percent and increases the TFP growth rate by an additional 0.06 percentage points on top of the gains from cutting the three frictions. Finally, we consider a policy that targets young firms rather than all firms. Specifically, the take-up rate is assumed to increase only for firms younger than five years. In this counterfactual, we keep government spending as a share of GDP constant. Relative to the case in which the take-up rate increases for all firms, this targeting rule raises the growth rate by an additional 0.03 percentage points, for a total gain of 0.09 percentage points. This reflects the fact that young firms are more likely to be high-type firms, increasing the returns to R&D subsidies when targeted to these firms. Taken together, all reforms considered in the counterfactual analysis are found to raise the long-term productivity growth rate by 0.27 percentage points.

G. Conclusion and Policy Considerations

26. Addressing key frictions is key to boosting Spain's innovation and long-term productivity growth. On regulatory burdens, the ongoing "Regime 20" initiative—a common

regulatory framework aimed at reducing administrative barriers to doing business across regions—is an important policy initiative that should be pursued and amplified. This top-down approach could be complemented by bottom-up efforts, including broader adoption of open-market laws by individual autonomous communities, which could deliver immediate benefits to participating regions while creating economic and reputational incentives for others to follow. EU-level reforms, such as the EU 28th Regime initiative, could further ease regulatory burdens, thereby incentivizing firms to scale up and innovate. On financial frictions, progress toward the EU's Savings and Investment Union would greatly benefit comparatively more financially-constrained Spanish firms. The new public investment fund *España Crece* could also be helpful if it were to focus on stimulating innovation and were designed to target young and innovative firms rather than smaller, older, less innovative firms. Lastly, size-dependent regulations could be streamlined by smoothing existing regulatory thresholds—particularly the 50-employee threshold, which concentrates multiple regulations, thereby reducing the discontinuities they create.

27. The R&D tax credit could be made more effective by strengthening legal certainty and simplifying access to the refund option, which remains complex and costly to use in practice. AIReF (2020) identifies the costly application process and limited legal certainty as key obstacles to take-up. In particular, if the tax authorities later determine that an expenditure does not qualify as R&D-related, firms may be required to repay the tax benefit they previously claimed. To mitigate this risk, the Ministry of Science issues *ex ante* a Binding Motivated Report (*Informe Motivado Vinculante*, IMV), which is a certification process for firms that submit R&D projects. However, the tax authorities still review the underlying expenditures *ex post,* following which they may downsize the tax benefit. Greater coordination between the Ministry of Science and the tax authorities could strengthen the legal certainty provided by the IMV. Another obstacle, especially for smaller firms, is that many do not yet generate sufficient profits to benefit from a tax deduction. For these firms, a refund option is available, allowing them to receive cash instead of a tax offset. In practice, however, this option is less attractive because of several restrictions that should be eased. Refunds are currently subject to a 20 percent discount, firms must wait at least one year after the expenditure is incurred, and they must maintain at least the same number of R&D workers after receiving the refund. Although these conditions likely help limit abuse, they also weaken innovation; streamlining them could increase take-up, particularly among young and innovative firms.

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Annex I. Data

1. In this paper, we merge ORBIS data with PATSTAT data. Our main sample period spans 2000 to 2019. ORBIS provides firm-level information on sales, employment, fixed assets, industry, and location. The data cover not only large firms but also small and medium-sized enterprises. Kalemli-Ozcan and others (2024) show that Spain has good coverage in ORBIS, accounting for, on average, 82 percent of gross output in the manufacturing sector. To compare Spain with other advanced European countries, we also include France and Sweden, which exhibit similarly high coverage rates of 87 percent and 77 percent, respectively. We follow the data cleaning procedures in Kalemli-Ozcan and others (2024) and Díez and others (2021).

2. PATSTAT contains comprehensive patent information from several patent offices, including the European Patent Office, as well as the Spanish, US, and Japanese patent offices. For each patent, it provides information on assignee names, regions, and citations. Citation data are used to construct forward citations (citations received) as a proxy for patent quality. PATSTAT also reports patent family identifiers for patents that are registered in multiple patent offices.

3. We merge PATSTAT with ORBIS using firm names, following the procedure in EUIPO (2025). A common challenge is that firm names in patent records often contain abbreviations or misspellings, so the same firm may appear under different assignee identifiers. For example, Telefónica may be recorded as “Telefonica” or “Telefonica S.A.”. We therefore first standardize firm names in both PATSTAT and ORBIS and then conduct exact matching. The merge is performed at the subsidiary level: Airbus France and Airbus Spain are treated as distinct firms.

4. The matching rate for Spanish firms is 87 percent, meaning that 87 percent of all patents applied for by firms located in Spain appear in our final merged sample. The corresponding matching rates for France and Sweden are 78 percent and 85 percent, respectively. These rates are comparable to those in the literature. For example, Autor and others (2020) use web-based matching algorithms and obtain a 72 percent matching rate when merging US Patent Office data with Compustat.

Annex II. Model

In this Annex, we describe the full general equilibrium model.

1. Environment

Time is continuous. There is a unit continuum of products indexed by j ∈ [0,1], which are aggregated into a final good using a Cobb–Douglas aggregator:

$$Y = \int_0^1 y_j dj.$$

We normalize the price of the final good to one. A representative household consumes the final good and supplies labor, L, inelastically. At any date, each product is made by a single producer, and the production function is

$$y_j = a_j l_j.$$

As in standard quality ladder models, firms set the price equal to the marginal cost of their competitor, which is lower by a factor λ_i. Given the Cobb-Douglas aggregation, each product generates revenue equal to Y. Profits per product are therefore

$$\pi_i = (1 - 1/\lambda_i)Y,$$

Since all product lines are symmetric in equilibrium, the relevant state variable of the firm is just n, as the firms receive $n\pi_i$ amount of profits and hire nl labor.

In addition, firms face a size-dependent regulation: a deadweight cost ϕY is incurred if employment exceeds 50 workers. Equivalently, firms with more than $\bar{n}$ product lines are subject to this regulation.

2. Innovation

In the model, both incumbents and entrants can innovate. When innovation occurs, it randomly draws a product line and increases the productivity of that product. The innovator becomes the new incumbent on that line, replacing the current incumbent. When the average innovation rate in the economy is m, a firm with n lines loses a product at hazard rate nm.

Firms choose R&D expenditure to determine the Poisson arrival rate x of innovation. Innovation becomes easier as firms accumulate product lines, reflecting knowledge capital from past innovations. Let $\boldsymbol{C(x_i; n_i)}$ denote the flow cost of generating arrival rate $\boldsymbol{x_i}$ for a firm with n_i product lines:

$$\boldsymbol{C(x_i; n_i)} = (\boldsymbol{1 - s})\big(1 + \tau(n_i)\big)x_i^{\eta} n_i^{1-\eta} Y/\alpha,$$

where s is the R&D subsidy rate, $\tau(n_i)$ is financial friction costs, which decreases with n_i, and α is a cost shifter. Entrants face the same R&D cost as incumbents with one product line and additionally pay a fixed entry cost δY.

Firms differ in innovation step size: some firms achieve larger productivity gains than others from a given innovation. Specifically, $\lambda_i \in \{\lambda^H, \lambda^L\}$, with $\lambda^H > \lambda^L > 1$. Entrants are born as high-type firms and transition to low type at a Poisson rate $\kappa > 0$, following Acemoglu and others (2018).

3. Equilibrium

The value function of incumbent firms with n product lines, $q \in \{L, H\}$ type is as below:

$$rV(n,q) - \dot{V}(n,q) = max_x\, n\pi(q)Y - \phi \cdot \mathbb{1}(l \geq 50) - C(x;n) + x\big(V(n+1,q) - V(n,q)\big) - m\big(V(n-1,q) - V(n,q)\big) + \kappa\big(V(n,L) - V(n,q)\big)\ ,$$

where it chooses the innovation rate x to maximize the expected value. By guess and verify, we can define the normalized value function, v, by dividing it by Y, as follows:

$$\begin{aligned} rv(n,q) - \dot{v}(n,q) &= max_x\, n\pi(q) - \phi \cdot \mathbb{1}(l \geq 50) - c(x;n) + x\big(v(n+1,q) - v(n,q)\big) \\ &- m\big(v(n-1,q) - v(n,q)\big) + \kappa\big(v(n,L) - v(n,q)\big), \end{aligned}$$

Where $c(x;n) = \frac{C(x;n)}{Y}$. Then, the innovation rate of the incumbents is

$$x(n,q) = \Big[\big(v(n+1,q) - v(n,q)\big) / \big(\eta(1-s)\big(1+\tau(n)\big)\big)\Big]^{\eta-1} n.$$

Absent frictions, innovation scales linearly with firm size. Subsidies raise innovation, while financial frictions reduce it.

Likewise, the value function of potential entrant is defined as

$$rV^E - \dot{V^E} = \max_x xV(1,H) - C(x;1) - \delta Y,$$

which can be normalized as below:

$$rv^E - \dot{v^E} = \max_x xv(1,H) - c(x;1) - \delta.$$

And the innovation rate of the potential entrant is

$$x^E = \Big[\big(v(1,H)\big) / \big(\eta(1-s)\big(1+\tau(1)\big)\big)\Big]^{\eta-1}.$$

Given the firm distribution $\mu(n,q)$, the aggregate growth rate is

$$g = \int \log(\lambda^H)\, x(n,H) d\mu(n,H) + \int \log(\lambda^L)\, x(n,L) d\mu(n,L) + \log(\lambda^H)\, x^E.$$