The Impact of Regulation on Innovation*

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Abstract

We study the impact of labor regulation on innovation. We exploit the threshold in labor market regulations in France which means that when a firm reaches 50 employees, costs increase substantially. We show theoretically and empirically that the prospect of these regulatory costs discourages firms just below the threshold from innovating (as measured by patent counts). This relationship emerges when looking nonparametrically at patent density around the regulatory threshold and also in a parametric exercise where we examine the heterogeneous response of firms to exogenous market size shocks (from export market growth). On average, firms innovate more when they experience a positive market size shock, but this relationship significantly weakens when a firm is just below the regulatory threshold. Using information on citations we also show suggestive evidence (consistent with our model) that regulation deters *radical* innovation much less than *incremental* innovation. This suggests that with size-dependent regulation, companies innovate less, but if they do try to innovate, they "swing for the fence".

JEL classification: O31, L11, L51, J8, L25
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1 Introduction

There is a considerable literature on the economic impacts of regulations, but relatively few studies on the impact of regulation on technological innovation. Most analyses focus on the static costs (and benefits) of regulation rather than on its dynamic effects. Yet these potential effects on innovation and growth are likely to be much more important in the long-run. Harberger triangles may be small, but rectangles can be very large. Many scholars have been concerned that slower growth in countries with heavy labor regulation, could be due to firms being reluctant to innovate due to the burden of red tape. The slower growth of Southern European countries and parts of Latin America have often be blamed on onerous labor laws (see for example, Gust and Marquez, 2004; Bentolila and Bertola, 1990, Bassanini et al., 2009).

Identifying the innovation effects of labor regulation is very challenging. The OECD, World Bank, IMF and other agencies have developed various indices of the importance of these regulations, based on examination of laws and (sometimes) surveys of managers. These indices are then often included in econometric models and sometimes found to be significant. Unfortunately, these macro indices of labor law are correlated with many other unobservable factors that are hard to convincingly control for.[1] To address this issue we exploit the well-known fact that many of these regulations are size contingent, only kicking in when a firm gets sufficiently large. In particular, the burden of French labor legislation substantially increases when firms employ 50 or more workers. Firms of 50 workers or more must create a works council ("committee d'entreprise") with a minimum budget of 0.3% of total payroll, establish a health and safety committee, appoint a union representative and so on (see Appendix A for a more thorough presentation of size contingent regulations in France). Several authors have found that these regulations have an important effect on the size of firms (Garicano et al., 2016; Gourio and Roys, 2014; Ceci-Renaud and Chevalier, 2011). Unlike the US firm size distribution, for example, in France there is a clear spike in the number of firms that are just below this regulatory threshold.[2]

Existing models that seek to rationalize these patterns have not considered how this regulation could affect innovation, as technology has been assumed exogenous. But when

[1] Furthermore, it may be that the more innovative countries are less likely to adopt such regulations (e.g. Saint-Paul, 2002).

[2] Often, it is hard to see such discontinuities in the size distribution at regulation thresholds (e.g. Hsieh and Olken, 2014).

firms are choosing whether or not to invest in innovation, regulations are also likely to matter. Intuitively, firms may invest less in R&D as there is a very high cost to growing if the firm crosses the regulatory threshold. In the first part of the paper we formalize this intuition using a simple version of the Klette and Kortum (2004) model of growth and firm dynamics, with discrete time and two-period lived individuals and firms. Our model delivers two main predictions. First, a regulatory threshold should discourage innovation mostly for firms below the threshold that are close to the threshold. Second, the discouraging effect of the regulatory threshold on innovation by firms close to the threshold, should be weaker for more important innovations.

We take these predictions to the data. More specifically, we use the discontinuous increase in regulation cost at the regulatory threshold size to test the theory in two ways. First, we investigate non-parametrically how innovation changes with firm size. As expected there is a sharp fall in the fraction of innovative firms just to the left of the regulatory threshold which is suggestive of a chilling effect of the regulation on the desire to grow. Furthermore, this relationship is only visible for lower value patents (as measured by future citations) - there is no visible effect for highly cited patents. The idea is that regulation may deter low quality innovations which have little social value, but if a firm is going to innovate it will try to "strike for the fence" to avoid being only slightly to the right of the threshold. Intuitively, the growth benefits of innovation are less if it brings the firm into the regulatory regime.

Although the descriptive evidence is suggestive, there could be many other reasons why firms are heterogeneous near the regulatory threshold, so we turn to a stronger test using the panel dimension of our data. Specifically, based on the view that an increase in market size should have a robust positive effect on innovation (e.g. Acemoglu and Linn, 2004), we examine the heterogeneous response of firms with different sizes to exogenous demand shocks. We use an shock based measure based on changes in growth in export product markets (HS6 by country) interacted with a firm's initial distribution of exports across export markets (see Hummels et al., 2014; Mayer et al., 2016 and Aghion et al., 2018a). We first show that these positive market size shocks significantly raise innovative activity. We then examine the heterogeneity in firm responsiveness to these export shocks depending on lagged firm size. We show that there is a sharp reduction in firm responsiveness to innovation exactly before the regulatory threshold. Consistent with intuition and our simple model, firms appear reluctant to take advantage of exogenous market growth through innovating when they will be hit by a tsunami of labor regulation.

As noted above, the impact of regulation may be less problematic if the regulation affects only incremental innovations. In our empirical analysis, we uncover evidence that the fall in innovation just before the threshold is strongest for low value patents (as measured by future citations) and not observable for the patents which subsequently receive many citations.

In the rest of the Introduction we turn first to some related literature, then in Section 2 we sketch our theory, our empirical analysis in Section 3 and some concluding remarks in Section 4.

Related literature

Our paper is related to a vast literature examining the effects of regulation (particular labor laws) on economic outcomes. Several recent papers in this literature take structural approaches such as Braguinsky et al. (2011) on Portugal and Garicano et al., 2016 on France. Guner et al. (2006, 2008) also consider a Lucas model with size-contingent regulation. None of these papers allows firms to influence their productivity through innovation choices as we do, however.

One branch of the literature looks at whether labor laws can encourage some kinds of innovation. Acharya et al. (2013a) argue that higher firing costs reduce the risk of firms holding up employees' innovative investments by dismissing them ex post. They find evidence in favor of this using macro time series variation for four OECD countries. Acharya et al. (2013b) also finds positive effects using staggered roll out of employment protection across US states.[3] Griffith and Macartney (2014) use multinational firms patenting activity across subsidiaries located in different countries with various levels of employment protection laws (EPL).[4] Using this cross sectional identification, they find that radical innovation was negatively effected by EPL, but incremental innovation was, if anything, boosted.[5]Relatedly, there are many papers examining the impact of union power (which is affected by labor regulation) on innovation.[6] This literature tends to find that the impact

[3]This is the same empirical variation used by Autor et al. (2007) who actually found falls in TFP and employment.

[4]See also Cette et al. (2016) who document a negative effect of EPL on capital intensity, R&D expenditures and hiring of high skill workers.

[5]Note that this is the opposite of what we find using our within country identification. Labor regulation discourages low value innovation, but has no impact on high value innovation.

[6]See Menezes-Filho et al. (1998) for a survey and evidence. The common view is that the risk of ex post hold-up by unions reduces innovation incentives (Grout, 1984). But if employees need to make sunk investments there could be hold up by firms (this is the intuition of the Acharya et al., 2013a,b papers).

of unions and labor regulation are ambiguous and contingent on the type of innovation (e.g. radical/incremental) and other features of the economic environment (e.g. negative effects are stronger in high labor turnover industries).

Another branch of the literature has documented empirically how distortions can affect aggregate productivity through misallocations of resources away from more productive firms and towards less productive firms. As Restuccia and Rogerson (2008) have argued,[7] these distortions mean that more efficient firms produce too little and employ too few workers. Hsieh and Klenow (2009) show that these misallocations account for a significant proportion of the difference in aggregate productivity between the US, China and India and Bartelsman et al. (2013) confirm this using micro data on OECD countries.[8] One issue with these approaches is that the causes of the random distortions are a bit of a "black box".

We contribute to this literature by introducing an explicit source of distortion, namely the regulatory firm size threshold, and by looking at how this regulation interacts with exogenous export shocks for firms with different size.[9]

The heterogeneous effects of demand shocks on types of innovation is also a theme in the literature of the effects of the business cycle on innovation (Schumpeter, 1939; Shleifer, 1986; Barlevy, 2007; Aghion et al., 2012). Recent work by Manso et al. (2019) suggests that large positive demand shocks (booms) generate more R&D, but this tends to "exploitative" (incremental) rather than "exploratory" (radical) innovation. We find that the impact of regulation following a demand shocks discourages incremental (but not radical) innovation.

Finally, our paper is related to the more general literature using tax "kinks" to identify behavioral parameters (e.g. Saez, 2010; Chetty et al., 2011; Kleven and Waseem, 2013; Kaplow (2013), and Aghion et al., 2019). We contribute to this literature by bringing innovation and patenting into the picture.

[7]See also Parente and Prescott (2000) or Bloom and Van Reenen (2007).

[8]In development economics many scholars have pointed to the "missing middle", i.e. a preponderance of very small firms in poorer countries compared to richer countries (see Banerjee and Duflo, 2005, or Jones, 2011). Besley and Burgess (2000) suggest that heavy labor regulation in India is a reason why the formal manufacturing sector is much smaller in some Indian states compared to others.

[9]See e.g. Bergeaud and Ray (2017) for a discussion. Another issue, is that regulatory distortions in these models typically only have second order effects on welfare if they preserve the size ranking of firms (see Hopenhayn, 2014). If regulations can also affect growth through innovation (as we argue), then they might have first order effects on welfare.

The structure of the paper is as follows. Section 2 develops a simple model of how the amount and importance of innovation can be affected by firm size regulation. Section 3 develops the empirical analysis. Section 4 concludes.

2 Theory

2.1 A simplified Klette-Kortum model

We consider a simple discrete time version of the Schumpeterian growth model with firm dynamics by Klette and Kortum (2004),[10] where individuals live for only two periods. This two-period specification is drawn from Aghion et al. (2018b). In the first period of her life, a firm owner decides how much to invest in R&D. In the second period, she produces and realizes profits and gives birth to an offspring. The offspring inherits the firm at its current size and a new cycle begins.

There is a continuous measure L of production workers, and a mass 1 of intermediate firm owners every period. Each period the final good is produced competitively using a combination of intermediate goods according to the following production function:

$$\ln y = \int_0^1 \ln(y_j) dj$$

where y_j is the quantity produced of intermediate j. Intermediates are produced monopolistically by the innovator who innovated last within that product line j, according to the following linear technology:

$$y_j = A_j l_j$$

where A_j is the product-line-specific labor productivity and l_j is the labor employed for production. This implies that the marginal cost of production in j is simply w/A_j where w is the wage rate in the economy at time t. A firm is defined as a collection of production units (product lines) and expands in product space through successful innovation.

To innovate, a firm i combines its existing knowledge stock that it accumulated over time (n) with its amount of R&D spending (R_i) according to the following Cobb-Douglas production function:

[10] Here we closely follow the presentation of the Klette-Kortum model by Aghion, Akcigit and Howitt (2014).

$$Z_i = \left(\frac{R_i}{\zeta y}\right)^{\frac{1}{\eta}} n^{1-\frac{1}{\eta}},$$

where Z_i is the Poisson innovation flow rate. $\frac{1}{\eta}$ is the elasticity of innovation with respect to scientists and ζ is a scale parameter. This production function generates the following R&D cost of innovation:

$$C(z_i, n) = \zeta n z_i^{\eta} y,$$

where $z_i \equiv Z_i/n$ is simply defined as the innovation intensity of the firm. When a firm is successful in its current R&D investment, it innovates over a random product line $j' \in [0; 1]$. Then, the productivity in line j' increases from A'_j to $A'_j\gamma$. The firm becomes the new monopoly producer in line j' and thereby increases the number of its production lines to $n + 1$. At the same time, each of its n current production lines is subject to the creative destruction x by new entrants and other incumbents: Thus the number of production units of a firm of size n increases to $n + 1$ with flow probability Z_i and decreases to $n - 1$ with flow probability nx. A firm that loses all of its product lines exits the economy.

Because of the Cobb Douglas production function, the final good producer spends the same amount y on each variety j. As a result, final good production function generates a unit elastic demand with respect to each variety: $y_j = y/p_j$. Combined with the fact that firms in a single product line compete a la Bertrand, this implies that a monopolist with marginal cost w/A_j will follow limit pricing by setting its price equal to the marginal cost of the previous innovator $p_j = \gamma w/A_j$.

The resulting equilibrium quantity and profit in product line j are:

$$y_j = \frac{A_j y}{\gamma w} \text{ and } \pi_j = \left(1 - \frac{1}{\gamma}\right) y,$$

and the demand for production worker in each line is given by $\frac{y}{\gamma w}$.

Firm i's employment is then equal to its total manufacturing labor, namely:

$$L_i = \int_{j \in \mathcal{N}_j} \frac{y}{w\gamma} dj = \frac{yn}{w\gamma} = \frac{n}{\omega\gamma},$$

where $\omega = w/y$ is the output-adjusted wage rate, which is invariant on a steady state growth path. Importantly for us, a firm's employment is strictly proportional to its number of lines n.

2.2 Regulatory threshold and innovation

We model the regulation by assuming that a tax on profit must be incurred by firms with labor force exceeding a given threshold $\bar{l}$. We suppose that $\bar{l}$ is sufficiently large that entrants are never affected by this tax.

To the employment threshold $\bar{l}$ corresponds a cutoff number of varieties $\bar{n} = \bar{l}\omega\gamma$ such that if $n > \bar{n}$ profit is taxed at some additional positive marginal rate τ whereas the firm avoids this additional tax if $n \leq \bar{n}$. Because firm owners live only for two periods, they can only expand the number of varieties of the firm by one extra unit during their lifetime. Hence all the firms that have a size $n < \bar{n} - 1$ or $n \geq \bar{n}$ act exactly as if the tax did not exist.[11] For firms that start with $n = \bar{n} - 1$, there is an additional cost to expanding by one extra variety.

The owner of an n-size firm therefore maximizes their expected net present value over z_i, i.e. after dividing up by y:

$$n\pi(n) + nz_i[(n+1)\pi(n+1) - n\pi(n)] + nx[(n-1)\pi(n-1) - n\pi(n)] - \zeta n z_i^{\eta}$$

where $\pi(n) = \left(1 - \frac{1}{\gamma}\right)$ if $n < \bar{n}$ and $\pi(n) = \left(1 - \frac{1}{\gamma}\right)(1-\tau)$ if $n \geq \bar{n}$.

Whenever positive, the optimal innovation intensity is therefore given by:

$$z(n) = \begin{cases} \left(\dfrac{\gamma - 1}{\gamma\zeta\eta}\right)^{\frac{1}{\eta-1}} & \text{if } n < \bar{n} - 1 \\ \left(\dfrac{(\gamma-1)(1-\tau)}{\gamma\zeta\eta}\right)^{\frac{1}{\eta-1}} & \text{if } n \geq \bar{n} \\ \left(\dfrac{(\gamma-1)(1-\tau\bar{n})}{\gamma\zeta\eta}\right)^{\frac{1}{\eta-1}} & \text{if } n = \bar{n} - 1 \end{cases} \tag{I}$$

2.3 Regulatory threshold and firm size distribution

In this subsection, we derive the steady state firm size distribution. Let $\mu(n)$ be the share of firms with n lines. We first have the steady state condition stating that the flow of firms into exit equals the flow of entering firms, namely:

$$\mu(1)x = z_e, \tag{II}$$

[11] The firm that starts at $n = \bar{n}$ can cross the threshold if it is creatively destroyed and looses one line, but this is something that happens endogenously and therefore does not affect z.

where z_e is the innovation intensity of entrants and x is the rate of creative destruction of any line. For all $n > 1$, the steady state condition stating that the flow out of being a size n is equal to the flow into becoming a size n firm, is expressed as :

$$n\mu(n)\left(z(n) + x\right) = \mu(n-1)z(n-1)(n-1) + \mu(n+1)x(n+1)$$

Finally the rate of creative destruction on each line is equal to the rate of creative by an entrant plus the weighted sum of the flow probabilities $z(n)$ of being displaced by an incumbent of size n, namely[12]:

$$x = z_e + \sum_{n=1}^{\infty} \mu(n)nz(n)$$

Finally, by definition:

$$\sum_{n=1}^{\infty} \mu(n) = 1,$$

which provides us with the last equation we need to solve the full model.

2.4 Solving the model

In Appendix C we detail how we solved the model numerically. The unknowns are $\mu(n)$ and $z(n)$ for all values of n as well as x and z_e, and the equations are those derived above. The solution is plotted in Figure 1 for the relation between innovation intensity and employment L which is proportional to n (recall the innovation intensity of a firm with n lines is given by $nz(n)$) and in Figure 2 for the distribution of firm size.

We see that the innovation intensity $z(n)$ decreases sharply with firm size right before the regulatory threshold, but then gets back on an increasing path. As for the steady state firm size distribution, it remains highly skewed, but with an accelerated decrease around the regulatory threshold and a bunching of firms just before the 50 employees threshold, in line with results from Garicano et al. (2016).

2.5 Large versus incremental innovation

We now extend the model by assuming that firms can choose between:

1. Investing in an incremental innovation which augments the firm's size by one additional product line;

[12] Unlike in Klette and Kortum (2004), here innovation intensity $z(i)$ depends on the size of the firm.

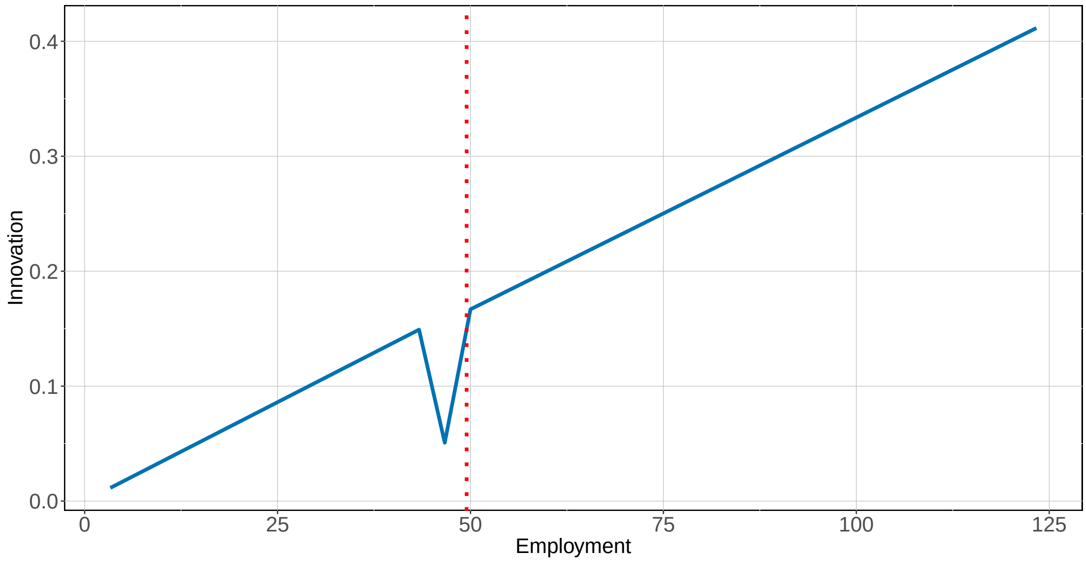


Figure 1: Innovation intensity ($nz(n)$) against employment

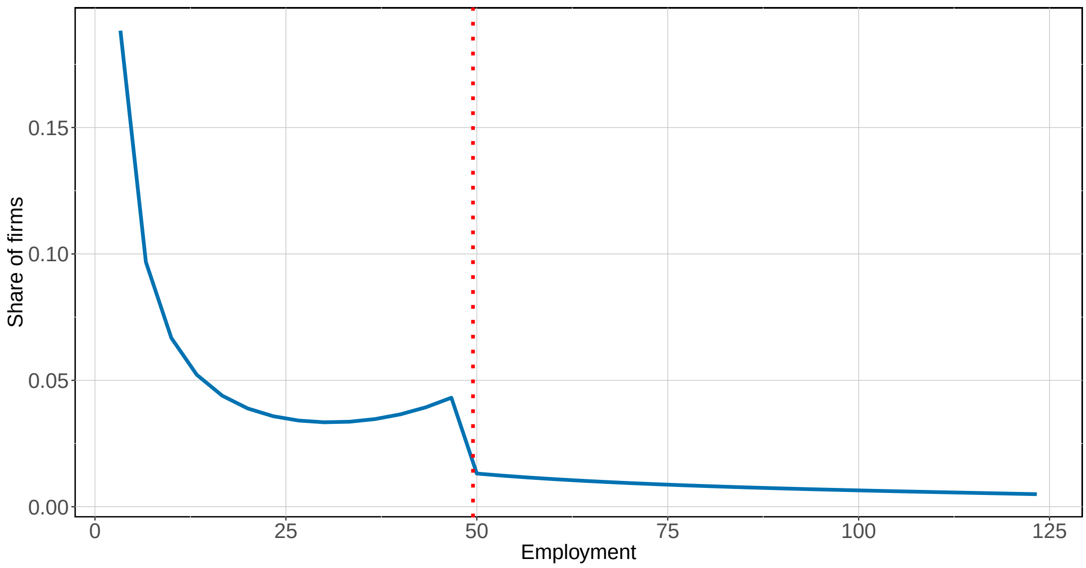


Figure 2: Distribution of firm size ($\mu(n)$) against employment

2. Investing in more radical innovation which is more costly but augments the firm's size by $k > 1$ product lines.

For computational simplicity, we take the overall cost of R&D to be quadratic and equal to $\beta(u+z)^2 n/2 + \alpha u^2 n/2$, where z is the output-adjusted effort invested in incremental R&D and u is the output-adjusted effort invested in radical R&D. The term in β reflects strategic substitutability between the two types of innovation.

We now have four cases depending on the value for n:

1. $n < \bar{n} - k$ in which case the firm is never taxed in period 2
2. $n < \bar{n}$ and $n \geq \bar{n} - k$ in which case the firm is taxed in period 2 only if it successfully innovated with a radical innovation.
3. $n = \bar{n} - 1$ in which case the firm is taxed in period 2 if it innovates, regardless of the type of innovation.
4. $n \leq \bar{n}$ in which case the firm is taxed in period 1 and 2 (except if the firm is at $\bar{n}+1$ but this won't affect the firm's decision)

The firm therefore chooses z and u so as to maximize:

$$\begin{aligned} & n\pi(n) + nz(n)\left((n+1)\pi(n+1) - n\pi(n)\right) + nu(n)\left((n+k)\pi(n+k) - n\pi(n)\right) \quad (1) \\ & + nx\left((n-1)\pi(n-1) - n\pi(n)\right) - (z(n)+u(n))^2 \frac{\beta n}{2} - u(n)^2 \frac{\alpha n}{2} \end{aligned}$$

Thanks to the quadratic cost assumption, the first-order conditions can be conveniently summarized by the linear system:

$$\begin{pmatrix} \beta & \beta \\ \beta & \alpha+\beta \end{pmatrix} \begin{pmatrix} z \\ w \end{pmatrix} = \begin{pmatrix} (n+1)\pi(n+1) - n\pi(n) \\ (n+k)\pi(n+k) - n\pi(n) \end{pmatrix}$$

As long as α and δ are not equal to 0, this linear system solves into:

$$\begin{pmatrix} z \\ w \end{pmatrix} = \frac{1}{\beta\alpha} \begin{pmatrix} \beta+\alpha & -\beta \\ -\beta & \beta \end{pmatrix} \begin{pmatrix} (n+1)\pi(n+1) - n\pi(n) \\ (n+k)\pi(n+k) - n\pi(n) \end{pmatrix}$$

The solutions are presented in Table C1 in Appendix C. The share of radical innovation over total innovation against employment is presented in Figure 3 and the innovation intensity for the two types of innovation is presented in Figure 4. What this latter figure

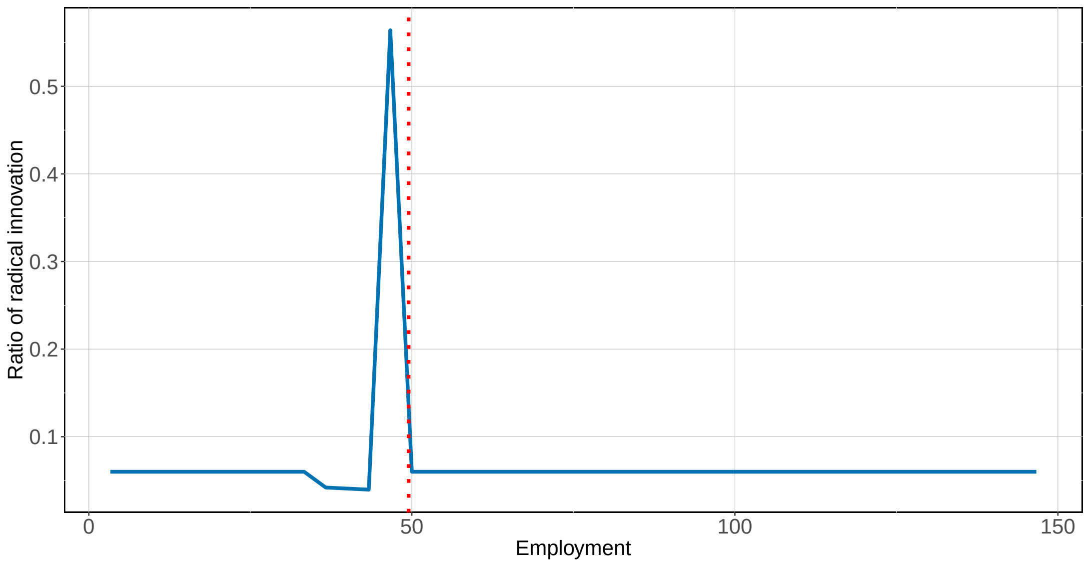


Figure 3: Share of radical innovation over total innovation ($\frac{u(n)}{z(n)+u(n)}$) against employment

strongly suggests is that the discouraging effect of the regulatory threshold on innovation by firms close to the threshold, is weaker for more radical innovations.

In the remaining part of the paper we confront these predictions to the data.

2.6 Predictions

The main predictions from the above model are:

Prediction 1: A regulatory threshold reduces innovation mostly for firms below the threshold but close to the threshold.

Prediction 2: The discouraging effect of the regulatory threshold on innovation by firms close to the threshold, is weaker for more radical innovations.

In the remaining part of the paper we confront these predictions to the data.

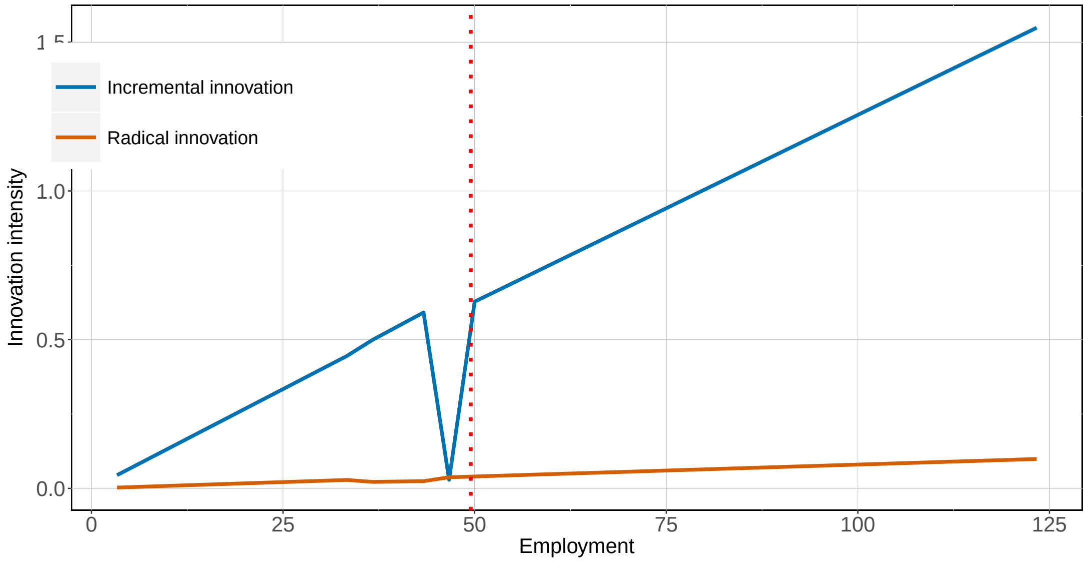


Figure 4: Innovation intensity against employment for radical ($nu(n)$) and incremental ($nz(n)$) innovations against employment

3 Empirical analysis

3.1 Data

Our data comes from the French tax authorities which consistently collect balance sheets of all French firms on a yearly basis from 1994 to 2007 ("FICUS"). We restrict attention to non-government businesses and take patenting information from Lequien et al. (2017). This uses the PATSTAT Spring 2016 database and matches it to FICUS using an algorithm which matches the name of the affiliate (holder of the IP rights) on the patent front page to the firm whose name and address is the closest. The accuracy of the algorithm is weaker for firms that are below 10 employees so we focus on firms with more than 10 employees. Since we are interested in a regulation that affects firms as they pass the 50 employees threshold we further restrict attention to firms below an upper size threshold. Consequently, in our main results we stick to an employment bandwidth of between 10 and 100 employees - i.e. we restrict the main sample to firms with between 10 and 100 workers in 1994 (or the first year they appear in the data).[13] More details about the data source are given in Appendix B.

Our main sample consists of 154,582 distinct firms and 1,439,396 observations. More

[13]We show robustness of the results to changing this bandwidth (see in particular Table D2 in Appendix D). Note that the sample selection allows employment that can be more than 100 employees or lower than 10 employees in some years.

than half of these firms do not innovate, where the term *innovation* refers to firms that have at least one patent over the sample period. We report basic descriptive statistics in Table 1. We can see that on average, firms file on average 0.023 patents per year and, conditional on innovating, 0.44 per year. As is well known, the distribution of innovation is highly skewed with a small number of firms owning a large share of the patents in our sample. However, since we do not include the largest French firms in our data, the skewness is less pronounced than what is documented by Aghion et al. (2018a).

Table 1: Descriptive statistics

Panel A: All firms	Mean	p25	p50	p75	p90	p99
Employment	30	13	21	37	58	152
Sales	5,780	1,031	2,204	5,161	11,387	47,220
Patents	0.023	0	0	0	0	0
Innovative	0.045	0	0	0	0	1
Manufacturing	0.26	0	0	1	1	1

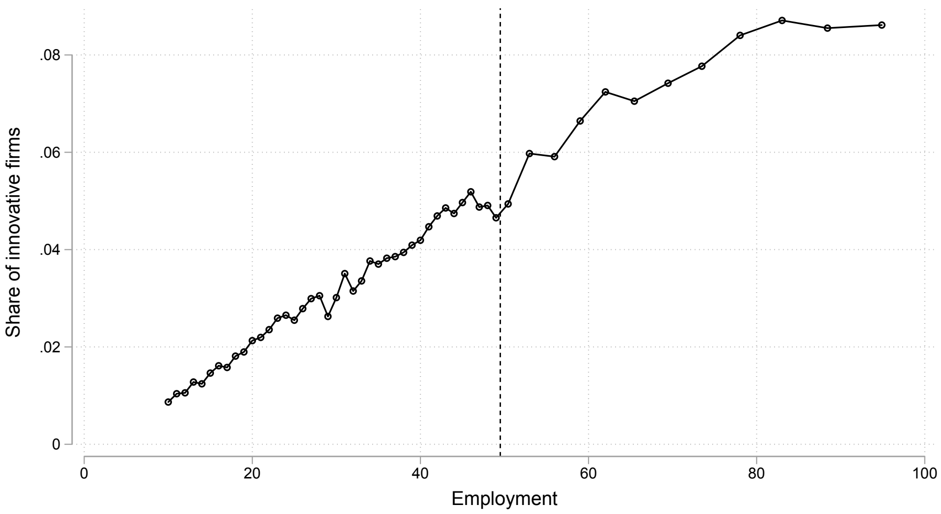
Panel B: Subset of innovative firms	Mean	p25	p50	p75	p90	p99
Employment	46	18	32	53	89	269
Sales	10,167	1,904	4,252	9,000	17,811	89,646
Patents	0.44	0	0	0	1	9
Manufacturing	0.57	0	1	1	1	1

Notes: These are descriptive statistics on our data. Panel A is all firms and Panel B conditions on firms who filed for a patent at least once over the 1994 to 2007 period ("Innovative" firms). We restrict to firms who have between 10 to 100 employees in 1994 (or the the first year they enter the sample). There are 154,582 firms and 1,294,139 observations in Panel A and 4,180 firms and 66,844 observations in Panel B.

3.2 Nonparametric evidence

Figure 5 shows the share of firms with at least one patent in each employment size bin (measured in the current year t) over all our main sample (see Panel A of Table 1). Over the size distribution as a whole, there is an almost linear relation with size: larger firms are increasingly likely to patent (as in Akcigit and Kerr, 2018, for example). However, just before the regulatory threshold at 50 employees there appears to be a discontinuity as the share of innovative firms suddenly decreases. The innovation outcome measure is taken over the whole sample period from 1994 to 2007, but the same is true if we consider

Figure 5: Share of innovative firms at each employment level



Notes: share of firms with at least one priority patent against employment at t. All observations are pooled together. Employment bins have been aggregated so as to include at least 10,000 firms. The sample is based on all firms with initial employment between 10 and 100 (154,582 firms and 1,439,396 observations, see Panel A of Table 1).

different definitions of an innovative firm as reported in Online Appendix Figure D1.

Figure 6 repeats this analysis using the quality of the patent as the measure of innovation output. We measure quality the using the number of future citations. For each patent within a cohort-year of patents we determine whether the patent was in the top 10% of the citation distribution (squares) or in the bottom 90%. The two curves in Figure 5 correspond to the fractions of firms at each employment level respectively with patents in the top 10% cited and with patents in the bottom 90% cited. We clearly see that the drop-off in patents just below the regulatory threshold is barely visible for patents in the top 10% cited. This is consistent with the idea that the regulation discourages low value innovations but not higher value innovation.[14]

3.3 Parametric analysis

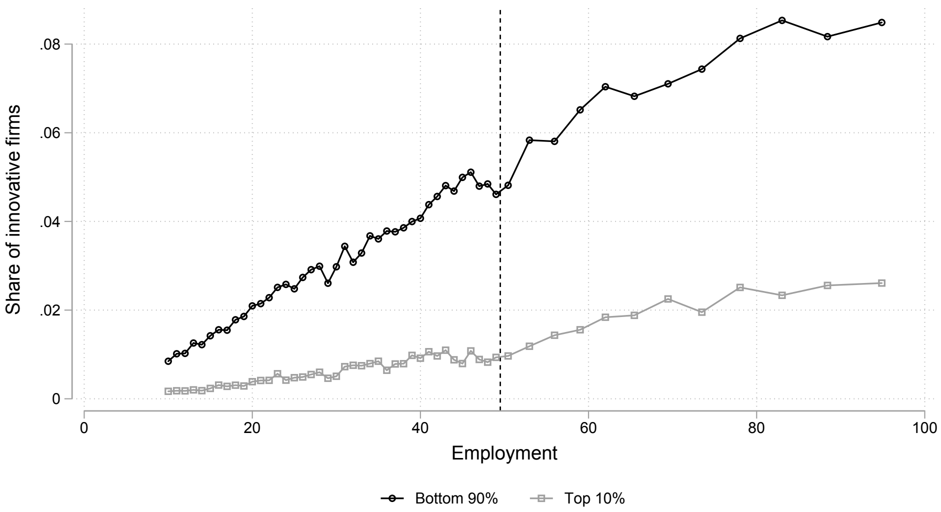
3.3.1 Estimation equation

We now turn to our parametric investigation of how firms respond to market size shocks. More specifically, we estimate the regression equation (2):

$$\tilde{\Delta} Y_{i,t} = \beta L^{\star}_{i,t-2} + \gamma[S_{i,t-2} \times \mathcal{P}(log(L_{i,t-2}))] + \delta[S_{i,t-2} \times L^{\star}_{i,t-2}] + \psi_{s(i,t)} + \tau_t + \varepsilon_{i,t} \quad (2)$$

[14] As with Figure 5, Figure 6 considers the innovation outcome over the whole period of observations. Variations around this can be found in Figure D2 in the Online Appendix D.

Figure 6: Share of innovative firms at each employment level and quality of innovation



Notes: share of firms with at least one priority patent in the top 10% most cited (grey line) and the share of firms with at least one priority patent among the bottom 90% most cited in the year (black line). All observations are pooled together. Employment bins have been aggregated so as to include at least 10,000 firms. The sample is based on all firms with initial employment between 10 and 100 (154,582 firms and 1,439,396 observations, see Panel A of Table 1).

where: $Y_{i,t}$ is a measure of innovation; $L^{\star}_{i,t}$ is a binary variable that takes value 1 if firm i is close to, but below, the regulatory threshold at time t; $S_{i,t-2}$ is an exogenous shock that triggers shifts in innovation; $\psi_{s(i,t)}$ is a set of industry dummies and τ_t is a set of time dummies ($s(i,t)$ denotes the main sector of activity of firm i at time t), $\mathcal{P}(log(L_{i,t-2}))$ is a polynomial in $log(L_{i,t-2})$ and $\varepsilon_{i,t}$ is an error term. We use a two year lag of the shock since there is likely to be some delay between the market opportunity shock, the increase in research effort and the filing of a patent application.Finally, in the LHS of the above regression we use growth rates of Y defined as:[15]

$$\tilde{\Delta} Y_{i,t} = \begin{cases} \frac{Y_t - Y_{t-1}}{Y_t + Y_{t-1}} & \text{if } Y_t + Y_{t-1} > 0 \\ 0 & \text{otherwise} \end{cases}$$

3.3.2 Shocks

To construct the innovation shifters $S_{i,t-2}$, we rely on international trade data to build export demand shocks following Mayer et al. (2016) and Aghion et al. (2018a). The construction of these shocks are explained at length in Aghion et al. (2018a). In a nutshell, we look at how foreign demand for a given product changes over time by measuring

[15]This is essentially the same as in Davis and Haltiwanger (1992) for employment dynamics except that we set the variable equal to zero when a firm does not patent for two periods. Results are robust to considering other types of growth rates (see the last 3 columns of Table D2 in Appendix D).

the change in imports from all countries worldwide but France. We then build a product/destination portfolio for each French firm i, and weight the foreign demands for each product by the relative importance of that product for firm i. More specifically, firm i's export demand shock at date t is defined as:

$$S_{i,t} = \sum_{s,j \in \Omega(i,t_0)} \omega_{i,s,j,t_0} \tilde{\Delta} I_{s,j,t}, \tag{3}$$

where: $\Omega(i, t_0)$ is the set of products and destinations associated with positive export quantities by firm i in the first year t_0 in which we observe that firm in the custom data;[16] ω_{i,s,j,t_0} is the relative importance of product s and destination j for firm i at t_0, defined as firm i's exports of product s to country j divided by total exports of firm i in that year; $I_{s,j,t}$ is country j's demand for product s, defined as the sum of its imports of product s from all countries except France.

3.3.3 Testing the main prediction

To estimate equation (2), we need to make some further restrictions in our use of the dataset. First, shock S is only defined for exporting firms, that is, firms that appear at least once in the customs data from 1994 to 2007. Second, in order to increase the accuracy of our shock measure, we restrict attention to the manufacturing sector. Not only do the most innovative firms belong the manufacturing sector, but these firms are also more likely to take part in the production of the goods they export (see Mayer et al., 2016). Our main regression sample is therefore composed of 21,740 firms and 186,337 observations.

Table 2 presents the results from estimating equation (1), i.e. from regressing the change in patents today on the lagged shock. Column (1) shows, consistently with earlier work, that firms facing a positive exogenous export shock are significantly more likely to increase their patenting activity. A 10% increase in market size increases patents by about 3%. Column (2) includes a control for the lagged level of log(employment) and also its interaction with the shock. The interaction coefficient is positive and significant, indicating that there is a general tendency for larger firms to respond more to the shock than smaller firms. This is what we should expect since both, the market size effect and

[16] French customs data are available from 1994

the competition effect of a positive export shock, are more positive for more productive firms (see Aghion, et. al, 2018). Column (3) generalizes this specification by adding in a quadratic term in lagged employment and its interaction with the shock.

Column (4) of Table 2 returns to the simpler specification of column (1) and includes a dummy a the firm was just below the regulatory threshold (45-49 employees) at $t-2$ and the interaction of this dummy with the shock. Our key coefficient is on this interaction term, and it is clearly negative and significant. This is our main result: innovation in firms just below the threshold is significantly less likely to respond to positive demand opportunities than in firms further away from the threshold. Our interpretation is that when a firm gets near the employment threshold, then it faces a a large "growth tax" due to the regulatory cost of becoming larger than 50 employees. Consequently, such a firm will be more reluctant to invest in innovation in response to this new demand opportunity. That firm might even simply cut its innovative activities altogether to avoid the risk of crossing the threshold.

It might be the case that the negative interaction between the threshold and the shock would be due to some omitted non-linearities. Hence in column (5) we also include lagged employment and its interaction with the shock (as in column (2)). These do have explanatory power, but our key interaction coefficient remains significant and negative and we treat this as our preferred specification. Column (6) adds a quadratic employment term and its interaction following column (3). Our key interaction remains significant and these additional non-linearities are insignificant.

Column (7) of Table 2 shows the results from a tough robustness test where we include a full set of firm dummies. Given that the regression equation is already specified in first differences, this amounts to allowing firm-specific time trends. The key interaction between the market size shock and the threshold dummy remains significant. The data sample underlying Table 2 is limited to manufacturing firms. Column (8) also adds in non-manufacturing firms. The relationship remains negative, although with a smaller coefficient and is less precisely determined. This is likely to be due to the fact that patents are a much more noisy measure of innovation in non-manufacturing firms.

Does the number of patents simply fall simply because firms are less likely to grow and relatively smaller firms do less innovation? Column (9) provides a crude test of this latter hypothesis by including the growth of employment on the right hand side of the regression. This variable is endogenous, of course, yet it is interesting to see, from a purely descriptive viewpoint, that the interaction between the market size shock and the threshold remains significant with a very similar coefficient to that in the baseline regression. This in turn suggests that it is indeed patenting per worker which is reacting negatively to the interaction between the shock and the threshold, in other words this effect on patenting is not simply reflecting changes in firm size.

Finally, we report placebo tests in Table D1 of Appendix D. Specifically, we estimate equation (2) and report coefficient δ as well as confident intervals when $L^{\star}$ has been redefined using different employment intervals. Reassuringly, we find that the only significantly negative effect is our baseline specification, that is when $L^{\star} = 1$ when $L \in [45, 49]$.

Table 2: Main regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Shock_{t-2} \times L^{\star}_{t-2}$				-11.910**	-13.924**	-13.135**	-15.673**	-8.976**	-14.237**
				(5.806)	(5.880)	(5.874)	(6.379)	(4.413)	(5.897)
$L^{\star}_{t-2}$				0.045	0.066	0.066	0.118	0.086	0.124
				(0.138)	(0.147)	(0.146)	(0.229)	(0.086)	(0.150)
$Shock_{t-2}$	2.912**	-8.160*	13.046	3.732***	-9.333*	10.467	-9.077*	-6.914***	-9.812**
	(1.172)	(4.173)	(9.728)	(1.182)	(4.185)	(9.652)	(4.617)	(2.640)	(4.262)
$log(L)_{t-2}$		-0.036	0.012		-0.040	0.008	-0.199**	-0.028	-0.065**
		(0.027)	(0.104)		(0.031)	(0.102)	(0.083)	(0.017)	(0.030)
$Shock_{t-2} \times log(L)_{t-2}$		3.270**	-10.853		3.898***	-9.281	3.857**	2.552***	4.009***
		(1.374)	(7.524)		(1.392)	(7.490)	(1.552)	(0.913)	(1.431)
$log(L)^2_{t-2}$			-0.008			0.156			
			(0.019)			(0.151)			
$Shock_{t-2} \times log(L)^2_{t-2}$			2.182*			2.031			
			(1.291)			(1.287)			
$\Delta log(L)_{t-2}$									0.156
									(0.151)
Fixed Effects									
Sector	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm							✓		
Number Obs.	186,337	186,337	186,337	186,337	186,337	186,337	186,337	377,652	186,337

Notes: This contains OLS estimates of equation (2) on the manufacturing firms in Panel A of Table 1 who have exported at some point 1994-2007. Dependent variable is the Davis and Haltiwanger (1992) growth rate in the number of priority patent applications between $t-1$ and t. Column 1 only considers the direct effect of the shock, taken at $t-2$, column 2 uses a linear interaction with $log(L)$ taken at $t-2$ and column 3 considers a quadratic interaction. Columns 4, 5 and 6 do the same as columns 1, 2 and 3 respectively but also includes an interaction with $L^{\star}$, a dummy variable for having an employment size between 45 and 49 employees at $t-2$. Column 7 replicates column 5 but adds firm fixed effects. Column 8 includes non-manufacturing firms and column 9 also controls for the growth in log(employment) at $t-2$. All models include a 3-digit NACE sector dummies and year dummies. Estimation period is 2007-1997. Standard errors are clustered at the 3-digit NACE sector level. ***, ** and * indicate p-value below 0.01, 0.05 and 0.1 respectively.

3.3.4 Is the negative effect of regulation solely on low quality innovations?

We repeat our preferred specification of column (5) of Table 2 but now distinguish patents of different value using their future citations. Table 3 does this for patents in the top 10%, 15% and 25% of the citation distribution in the first three columns and the patents in the complementary sets in the last three columns (i.e. the bottom 75%, 85% and 90% of the citation distribution). We clearly see that the negative effect of regulation on innovation is only significant for low quality patents in columns (4), (5) and (6). There is no such significant effect for patents in the top decile or quartile of the patent quality distribution (the coefficient on the interaction is even positive in column (2)).[17]

Table 3: Regression results at different quality

Quality	Top 10% **(1)**	Top 15% **(2)**	Top 25% **(3)**	Bottom 75% **(4)**	Bottom 85% **(5)**	Bottom 90% **(6)**
$Shock_{t-2} \times L^{\star}_{t-2}$	-0.825	0.953	-1.661	-15.475**	-12.982*	-16.117**
	(1.340)	(1.983)	(2.928)	(6.540)	(6.714)	(6.487)
$L^{\star}_{t-2}$	-0.051	-0.026	0.001	0.109	0.147	0.119
	(0.047)	(0.074)	(0.088)	(0.135)	(0.138)	(0.144)
$Shock_{t-2}$	-1.857	-3.710	-12.263***	-1.920	-7.715	-8.314*
	(2.059)	(3.222)	(4.614)	(5.156)	(4.929)	(4.588)
$log(L)_{t-2}$	0.015	-0.004	-0.045*	-0.037*	0.002	-0.056**
	(0.019)	(0.025)	(0.026)	(0.020)	(0.016)	(0.026)
$Shock_{t-2} \times log(L)_{t-2}$	0.624	1.198	3.825**	3.156*	1.553	3.414**
	(0.681)	(1.111)	(1.474)	(1.658)	(1.708)	(1.515)
Fixed Effects						
Sector	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Number Obs.	186,337	186,337	186,337	186,337	186,337	186,337

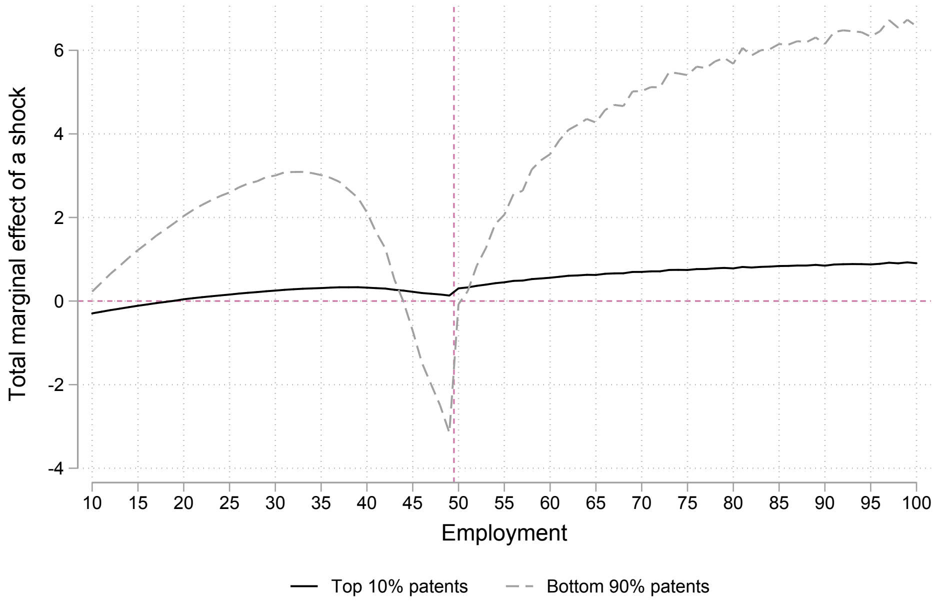
Notes: estimation results of the same model as in column 5 of Table 2. The dependent variable is the Davis and Haltiwanger (1992) growth rate in the number of priority patent applications between $t-1$ and t, restricting to the top 10% most cited in the year (column 1), the top 15% most cited in the year (column 2), the top 25% most cited in the year (column 3), the bottom 85% most cited in the year (column 4), the bottom 75% most cited in the year (column 5) and the bottom 90% most cited in the year (column 6). All models include a 3-digit NACE sector and a year fixed effects. Estimation period: 1997-2007. Standard errors are clustered at the 3-digit NACE sector level. ***, ** and * indicate p-value below 0.01, 0.05 and 0.1 respectively.

To visualize these results, we plot the marginal effect of the demand shock on innovation by the level of firm employment in Figure 7. The dotted grey line is the marginal effect on patents in the bottom 90% of the quality distribution based on column (6) of Table 3. Overall, the impact of the shock is positive and larger for bigger firms. However, when we approach the regulatory threshold at 50, this relationship breaks down and the marginal effect of the shock falls precipitously (and actually becomes negative). The black solid line plots the marginal effect of the demand shock on high quality patents in the top decile of the citation distribution from column (1) of Table 3. This line is also positive for almost all firms and rises with firm size. By contrast, with low value patents, there is no evidence of any sharp downturn just below the regulatory threshold.

In short, there seems to be evidence that the chilling effect of regulation on innovation

[17]We show the diminishing effect of the shock around the threshold for many other quantiles of the patent value distribution in five percentile intervals in Figure D3. This shows a clearly declining pattern.

Figure 7: Total marginal effect of a shock



Notes: marginal effect of a shock at different level of employment, based on the model in column 1 and 6 of Table 3. Marginal effect is calculated on top 10% and bottom 90% most cited patents.

is not an issue for high value patents and is instead confined to lower value patents, consistent with the model we developed in the previous section.

3.4 Robustness and Extensions

We have subjected our results to a large number of robustness tests, some of which are detailed in Appendix C. First, it is possible that the changing relationship between innovation and the market size shock around the threshold is driven by some kind of complex nonlinearities in the innovation-employment relationship, and our quadratic controls are insufficient. To investigate this issue, we allow interactions between the demand shock and different size bins of firms in Table D1. Of all the 14 different size bins, only the interaction of the shock with the size bin just below the threshold (45-49 employees) is significantly different from zero and large in absolute magnitude. Second, our results are robust to the particular way in which we define the upper and lower size cutoffs for our sample. Online Appendix Table C1 reproduces the baseline specification in column (1). Column (2) uses employment at t-2 instead of the initial year to define the sample, column (3) relaxes the upper threshold to include firms of up to 500 employees (instead of 100 employees in the baseline) and column (4) includes all firms below 100 employees (instead of dropping the firms with between zero and 9 workers). Column (5) restricts the sample to firms exporting in 1994 (instead of the restriction that a firm has to export in at least one year over the period 1994-2007). Column (6) includes all the non-exporting firms. The last three columns use three different definitions of the dependent variable instead of our basic Davis-Haltiwanger measure: the log-difference in column (7), the difference in the Inverse Hyperbolic Sign in column (8) and the change in patents normalized on pre-sample patents in column (9). Our results are robust to all these tests.

4 Conclusion

In this paper we have analyzed the impact on innovation of a labor regulation which impacts French firms beyond a predetermined size threshold. More precisely, we have looked at the innovation effect of the French labor market regulations which affects firms beyond 50 employees. We showed both theoretically and empirically that the prospect of these regulatory costs discourages firms just below the threshold from innovating, where innovation is measured by the volume of patent applications. This relationship comes out both, when looking nonparametrically at patent density around the threshold and in a parametric exercise where we examine the heterogeneous response of firms to exogenous market size shocks (from export markets). On average, firms innovate more when they experience a positive shock, but this relationship significantly weakens when a firm is just below the regulatory threshold. Moreover, using information on citations we also showed evidence that the labor regulation deters radical innovation much less than incremental innovation, as also predicted by the theory.

The analysis in this paper can be extended in several interesting directions. A first extension would be to look at the aggregate growth and (dynamic) welfare effects of the labor regulation, and to compare the dynamic welfare effects to the static welfare effects analyzed by Garicano et al. (2016). A second extension would be look at the effects of the labor regulation on firm dynamics (entry, growth and exit). These and other extensions of the analysis in this paper are left for future research.

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ONLINE APPENDICES
NOT INTENDED FOR PUBLICATION

A More Details of some Size-Related Regulations in France

The size-related regulations are defined in four groups of laws. The Code du Travail (labor laws), Code du Commerce (commercial law), Code de la SÃ©curitÃ© Social (social security) and in the Code General des ImpÃŽts (fiscal law). The main bite of the labor (and some accounting) regulations comes when the firm reaches 50 employees. But there are also some other size-related thresholds at other levels. The main other ones comes at 10-11 employees. For this reason we generally trim the analysis below 10 employees to mitigate any bias induced in estimation from these other thresholds. For more details on French regulation see inter alia Abowd and Kramarz (2003) and Kramarz and Michaud (2010), or, more administratively and exhaustively, Moins (2010).

A.1 Main Labor Regulations

The unified and official way of counting employees has been defined since 2004[18] in the Code du Travail,[19] articles L.1111-2 and 3. Exceptions to the 2004 definition are noted in parentheses in our detailed descriptions of all the regulations below. Employment is taken over a reference period which from 2004 was the calender year (January 1st to December 31st). There are precise rules over how to fractionally count part-year workers, part-time workers, trainees, workers on sick leave, etc. (Moins, 2010). For example, say a firm employs 10 full-time workers every day but in the middle of the year all 10 workers quit and are immediately replaced by a different 10 workers. Although in the year as a whole 20 workers have been employed by the firm the standard regulations would mean the firm was counted as 10 employee firm. In this case this would be identical to the concept used

[18]Before that date, the concept of firm size was different across labor regulations.
[19]The text is available at the legifrance website

in our main data FICUS.

Recall that the employment measure in the FICUS data is average headcount number of employees taken on the last day of each quarter in the fiscal year (usually but not always ending on December 31st). All of these regulations strictly apply to the firm level, which is where we have the FICUS data. Some case law has built up, however, which means that a few of them are also applied to the group level.

From 200 employees:

- Obligation to appoint nurses (Code du Travail, article R.4623-51)
- Provision of a place to meet for union representatives (Code du Travail, article R.2142-8)

From 50 employees:

- Monthly reporting of the detail of all labor contracts to the administration (Code du Travail, article D.1221-28)
- Obligation to establish a staff committee ("comitÃ© d'entreprise") with business meeting at least every two months and with minimum budget = 0.3% of total payroll (Code du Travail, article L.2322-1-28, threshold exceeded for 12 months during the last three years)
- Obligation to establish a committee on health, safety and working conditions (CHSC) (Code du Travail, article L.4611-1, threshold exceeded for 12 months during the last three years)
- Appointing a shop steward if demanded by workers (Code du Travail, article L.2143-3, threshold exceeded for 12 consecutive months during the last three years)
- Obligation to establish a profit sharing scheme (Code du Travail, article L.3322-2, threshold exceeded for six months during the accounting year within one year after the year end to reach an agreement)
- Obligation to do a formal "Professional assessment" for each worker older than 45 (Code du Travail, article L.6321-1)

- Higher duties in case of an accident occurring in the workplace (Code de la SÃ©curitÃ© sociale and Code du Travail, article L.1226-10)
- Obligation to use a complex redundancy plan with oversight, approval and monitoring from Ministry of Labor in case of a collective redundancy for 9 or more employees (Code du Travail, articles L.1235-10 to L.1235-12; threshold based on total employment at the date of the redundancy)

From 25 employees:

- Duty to supply a refectory if requested by at least 25 employees (Code du Travail, article L.4228-22)
- Electoral colleges for electing representatives. Increased number of delegates from 25 employees (Code du Travail, article L.2314-9, L.2324-11)

From 20 employees:

- Formal house rules (Code du Travail, articles L.1311-2)
- Contribution to the National Fund for Housing Assistance;
- Increase in the contribution rate for continuing vocational training of 1.05% to 1.60% (Code du Travail, articles L.6331-2 and L.6331-9)
- Compensatory rest of 50% for mandatory overtime beyond 41 hours per week

From 11 employees:

- Obligation to conduct the election of staff representatives (threshold exceeded for 12 consecutive months over the last three years) (Code du Travail, articles L.2312-1)

From 10 employees:

- Monthly payment of social security contributions, instead of a quarterly payment (according to the actual last day of previous quarter);

- Obligation for payment of transport subsidies (Article R.2531-7 and 8 of the General Code local authorities, Code general des collectivitÃ©s territoriales);

- Increase the contribution rate for continuing vocational training of 0.55% to 1.05% (threshold exceeded on average 12 months).

Note that, in additions to these regulations, some of the payroll taxes are related to the number of employees in the firm.

A.2 Accounting rules

The additional requirements depending on the number of employees of entreprises, but also limits on turnover and total assets are as follows (commercial laws, Code du Commerce, articles L.223-35 and fiscal regulations, Code général des Impôts, article 208-III-3):

From 50 employees:

- Loss of the possibility of a simplified presentation of Schedule 2 to the accounts (also if the balance sheet total exceeds 2 million or if the CA exceeds 4 million);

- Requirement for LLCs, the CNS, limited partnerships and legal persons of private law to designate an auditor (also if the balance sheet total exceeds 1.55 million euros or if the CA is more than 3.1 million euros, applicable rules of the current year).

From 10 employees:

- Loss of the possibility of a simplified balance sheet and income statement (also if the CA exceeds 534 000 euro or if the balance sheet total exceeds 267 000 euro, applicable rule in case of exceeding the threshold for two consecutive years).

B Data Appendix

B.1 Patent data

Our first database is PATSTAT Spring 2016's version which contains detailed information about patent applications from every patent office in the world. Among the very rich set of information available, one can retrieve the date of application, the technological class, the name of the patent holder (the *assignee*, often a firm which owns the right of the invention) and the complete list of forward and backward citations.

We use a crosswalk built by Lequien et al. (2017) that associates each patent whose assignee is located in France with the official identifying number (or *SIREN*), which enables us to use most administrative firm level datasets. This matching use supervised learning based on a training sample of manually matched patents from the French patent office (INPI). It has the advantage over other matchings to be specific to French firms and to exploit additional information such as the location of innovative establishments (see Lequien et al., 2017 or Aghion et al., 2018a for more details).[20]

Because we stop our analysis in 2007, we are not affected by the truncation bias toward the end of the sample (Hall et al., 2005) and we consider that our patent information are complete.

In order to be as close to the time of the innovation as possible, we follow the literature and consider the filing year and not the granting year in our study.

Finally, we consider every patent owned by a French firm, regardless of the patent office that granted the patent rights, but we restrict to *priority patents* which correspond to the earliest patents which relate to the same invention. Therefore, if a firm successively fills the same patent in different patent offices, only the first application of this family will be counted.

[20]If the firm shares a patent with another firm, then we only allocate a corresponding share of this patent to the firm.

B.2 Firm-level accounting data

Our second data source provides us with accounting data for French firms from the DGFiP-INSEE, this data source is called `FICUS`. The corresponding data are drawn from compulsory reporting of firms and income statements to fiscal authorities in France. Since every firm needs to report every year to the tax authorities, the coverage of the data is all French firms from 1994 to 2007 with no limiting threshold in terms of firm size or sales. This dataset provides us with information on the turnover, employment, value-added, the four-digit NACE sector the firm belongs to. This corresponds to around 35 million observations.

The manufacturing sector is defined as category C of the first level of the NAF (*Nomenclature d'ActivitÃ©s Françise*), the first two digits of which are common to both NACE (Statistical Classification of Economic Activities in the European Community) and ISIC (International Standard Industrial Classification of All Economic Activities). INSEE provides each firm with a detailed principal activity code (APE) with a top-down approach: it identifies the 1-digit section with the largest value added. Among this section, it identifies the 2-digit division with the largest value-added share, and so on until the most detailed 5-digit APE code (INSEE, 2016). It is therefore possible that another 5-digit code shows a larger value-added share than the APE identified, but one can be sure that the manufacturing firms identified produce a larger value-added in the manufacturing section than in any other 1-digit section, which is precisely what we rely on to select the sample of most of our regressions. The 2-digit NAF sector, which we rely intensively on for our fixed effects, then represents the most important activity among the main section of the firm. Employment each year is measured on average within the year and may therefore be a non-integer number.

B.3 Trade data

Customs data for French firms Detailed data on French exports by product and country of destination for each French firm are provided by the French Customs. These are the same data as in Mayer et al. (2014) but extended to the whole 1994-2012 period. Every firm must report its exports by destination country and by very detailed product (at a level finer than HS6). However administrative simplifications for intra-EU trade have been implemented since the Single Market, so that when a firm annually exports inside the EU less than a given threshold, these intra-EU flows are not reported and therefore not in our dataset. The threshold stood at 250 000 francs in 1993, and has been periodically reevaluated (650 000 francs in 2001, 100 000 euros in 2002, 150 000 euros in 2006). Furthermore flows outside the EU both lower than 1 000 euros in value and 1 000 kg in weight are also excluded until 2009, but this exclusion was deleted in 2010.

Country-product bilateral trade flows CEPII's database `BACI`, based on the UN database `COMTRADE`, provides bilateral trade flows in value and quantity for each pair of countries from 1995 to 2015 at the HS6 product level, which covers more than 5,000 products. To convert HS products into ISIC industries we use a United Nations correspondence table (when 1 HS code corresponds to 2 ISIC codes, we split the HS flow in half into each ISIC code).

C Theoretical Appendix

C.1 Extensions

C.2 Model solver

We solve the model numerically. To do so, we need to discretize the problem and proceed as follows (everything is done at the steady state).

1. There is a finite number N of firms and K of product lines, with $K > N$
2. $\mu(n)$ denotes the number of firms producing in exactly n lines and $z(i)$ its innovation intensity per line (which is taken from equation (I) in the model).
3. All firms produce at least one product, as a result, we must have $\mu(n) = 0$ for all $n \geq K - N$. For all i larger than 1

We therefore have $K - N + 1$ unknowns: $\mu(n)$ for $1 \leq n < K - N$ ($K - N - 1$ unknowns), x and z_e. The corresponding $K - N + 1$ independent equations are given by:

- The law of motion for μ:

$$\mu(n) = \frac{(n-1)\mu(n-1)z(n-1) + \mu(n+1)z(n+1)x}{n(x + z(n))},$$

for all $n \geq 2$ and $n < K - N$, recalling that $\mu(K - N) = 0$

- The definition of μ:

$$\sum_{n=1}^{K-N-1} \mu(n) = N$$

- The definition of x

$$x = z_e + \sum_{n=1}^{K-N-1} z(n) n \mu(n)$$

C.3 Solution radical vs incremental innovation

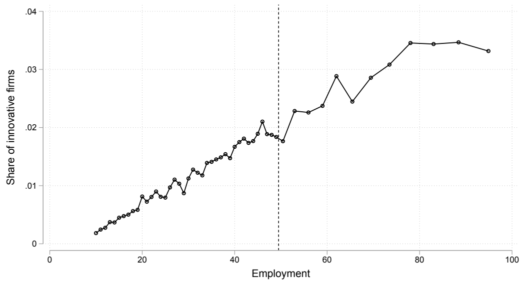
	$z(n)$	$u(n)$
$n < \bar{n} - k$	$\frac{\pi}{\alpha\beta}\left(\alpha - \beta(k-1)\right)$	$\frac{\pi}{\alpha}(k-1)$
$\bar{n} - k \leq n < \bar{n} - 1$	$\frac{\pi}{\alpha\beta}\left(\alpha - \beta(k-1) + \beta\tau(n+k)\right)$	$\frac{\pi}{\alpha}\left((k-1) - \tau(k+n)\right)$
$n = \bar{n} - 1$	$\frac{\pi}{\alpha\beta}\left(\alpha - \beta(k-1) - \beta\tau(\bar{n}-k) - \alpha\tau\bar{n}\right)$	$\frac{\pi}{\alpha}\left((k-1) + \tau(\bar{n}-k)\right)$
$n \geq \bar{n}$	$\frac{\pi}{\alpha\beta}(1-\tau)\left(\alpha - \beta(k-1)\right)$	$\frac{\pi}{\alpha}(1-\tau)(k-1)$
	$u(n) + z(n)$	$\frac{u(n)}{z(n)+u(n)}$
$n < \bar{n} - k$	$\frac{\pi}{\beta}$	$\frac{\beta}{\alpha}(k-1)$
$\bar{n} - k \leq n < \bar{n} - 1$	$\frac{\pi}{\beta}$	$\frac{\beta}{\alpha}(k-1)\left(1 - \frac{\tau(k+n)}{k-1}\right)$
$n = \bar{n} - 1$	$\frac{\pi}{\beta}\left(1 - \tau\bar{n}\right)$	$\frac{\beta}{\alpha}(k-1)\left(1 - \frac{\tau(\bar{n}-k)}{k-1}\right)\frac{1}{1-\tau\bar{n}}$
$n \geq \bar{n}$	$\frac{\pi}{\beta}(1-\tau)$	$\frac{\beta}{\alpha}(k-1)$

Table C1: Solution in the two types of innovation case

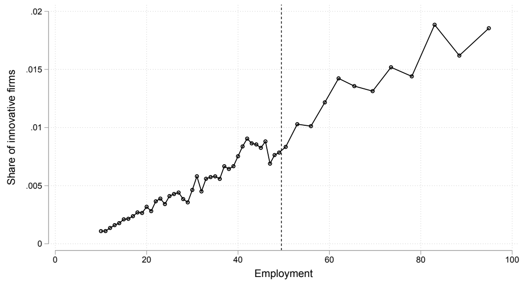
D Additional Empirical Results

Figure D1: Innovative firms at each employment level - robustness

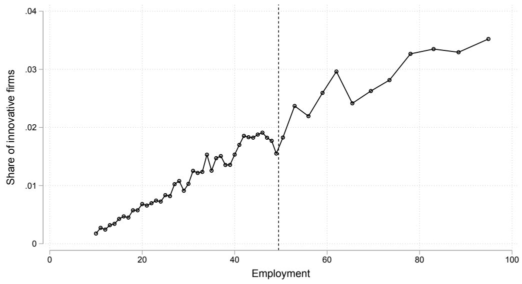
(a) Alternative A



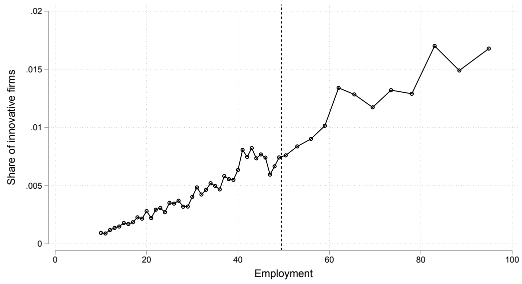
(b) Alternative B



(c) Alternative C



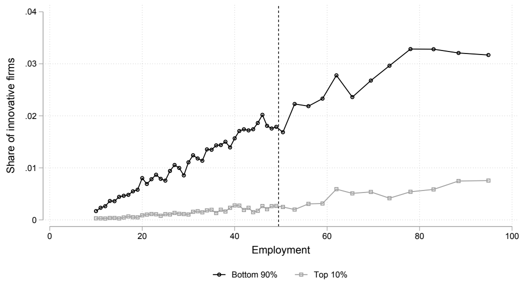
(d) Alternative E



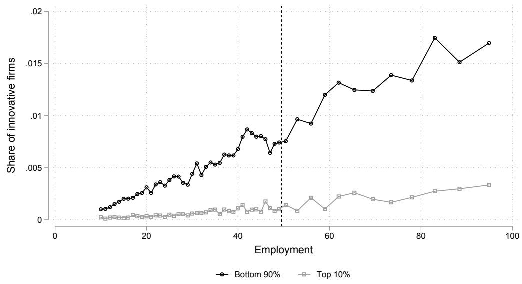
Notes: These Figures replicate Figure 5 using different Y variable. Alternatives A, B, C and D define an innovative firm as a firm having filed a priority patent application between $t-2$ and $t+2$ (A), at t (B), between $t-4$ and t (C). Alternative E uses the logarithm of 1 plus the number of patent application at t.

Figure D2: Innovative firms at each employment level and quality of innovation- robustness

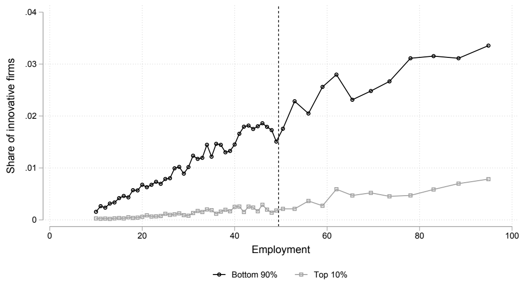
(a) Alternative A



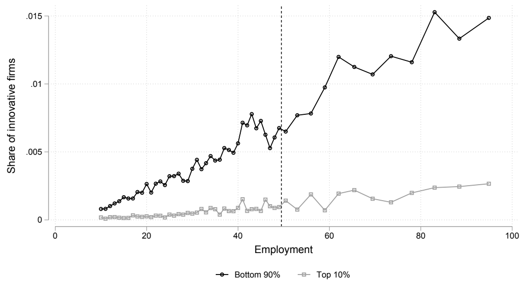
(b) Alternative B



(c) Alternative C

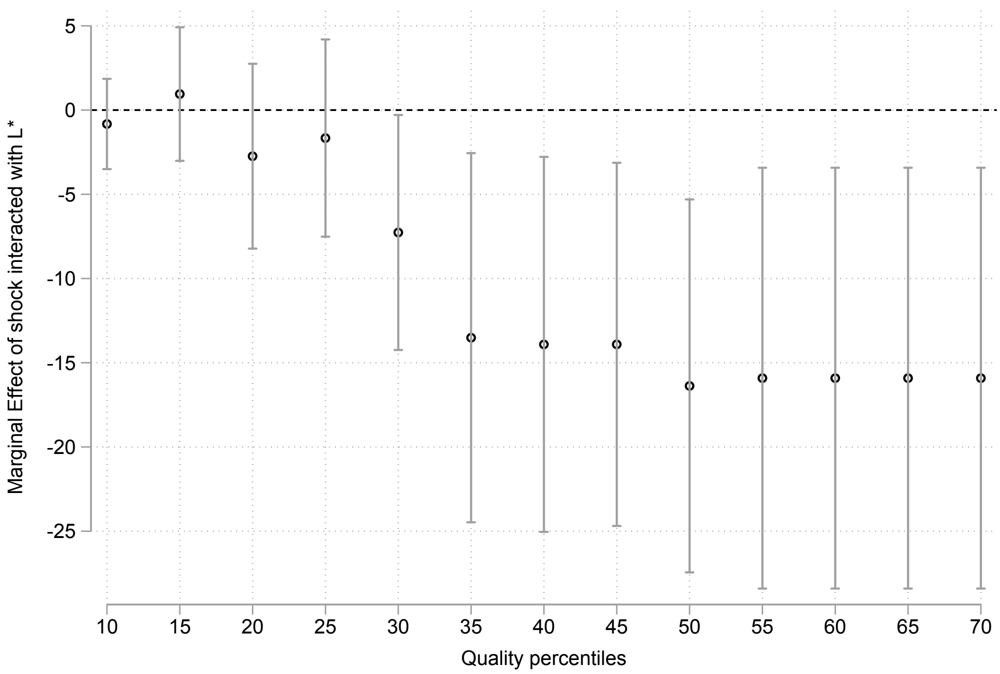


(d) Alternative D



Notes: see Figure D1, the black line consider bottom 90% most cited patent and the grey line the top 10% most cited.

Figure D3: Response to the Demand shock of patents of different quality



Notes: 95% confidence intervals around the estimated coefficient δ in equation (2). Each line corresponds to a separate estimation, where the dependent variable has been redefined by restricting to patents among the x% more cited in the year, with x equal to 10, 15 etc... up to 70. Note that the 65^{th} percentile threshold correspond to 0-citation patent and we include all patents for quality percentiles above 65. The estimated model is the same as in column 5 of Table 2.

Table D1: Placebo tests

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
	10-14	15-19	20-24	25-29	30-34	35-39	40-44	**45-49**	50-54	55-59	60-64	65-69	70-74	75-79
$Shock_{t-2} \times L^{\star}_{t-2}$	-0.304	-1.137	0.183	-7.798	0.631	9.871	5.200	**-13.924****	5.326	8.065	-1.587	44.419**	-23.135	2.426
	(2.479)	(2.384)	(4.548)	(5.942)	(3.867)	(4.207)	(6.130)	**(5.880)**	(11.927)	(12.245)	(9.341)	(20.972)	(26.665)	(20.120)
$L^{\star}_{t-2}$	0.061	-0.048	-0.286	0.168	-0.064	-0.113	0.097	**0.066**	-0.243	-0.094	-0.319	-0.257	0.524	0.436
	(0.059)	(0.050)	(0.079)	(0.109)	(0.112)	(0.149)	(0.112)	**(0.147)**	(0.279)	(0.245)	(0.287)	(0.352)	(0.353)	(0.283)
$Shock_{t-2}$	-8.007*	-7.742*	-8.194**	-7.331*	-8.177**	-8.091*	-7.920*	**-9.333****	-8.380*	-7.704*	-8.224*	-6.162	-9.318**	-8.056*
	(4.687)	(4.295)	(4.103)	(4.310)	(4.120)	(4.207)	(4.265)	**(4.186)**	(4.333)	(4.197)	(4.166)	(4.590)	(4.141)	(4.231)
$log(L)_{t-2}$	- 0.027	-0.041	-0.037	-0.034	-0.035	-0.033	-0.039	**-0.040**	-0.030	-0.033	-0.027	-0.030	-0.050	-0.047
	(0.030)	(0.027)	(0.029)	(0.026)	(0.027)	(0.027)	(0.027)	**(0.031)**	(0.025)	(0.030)	(0.026)	(0.033)	(0.026)	(0.029)
$Shock_{t-2} \times log(L)_{t-2}$	3.232**	3.184**	3.275**	3.208**	3.260**	3.007**	3.076**	**3.899****	3.378**	3.071**	3.297**	2.478	3.716**	3.230**
	(1.478)	(1.383)	(1.356)	(1.383)	(1.395)	(1.418)	(1.421)	**(1.392)**	(1.458)	(1.378)	(1.389)	(1.564)	(1.322)	(1.384)
Fixed Effects														
Sector	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number Obs.	186,337	186,337	186,337	186,337	186,337	186,337	186,337	**186,337**	186,337	186,337	186,337	186,337	186,337	

Notes: These are based on the specification of column 5 of Table 2. The dependent variable is the Davis and Haltiwanger (1992) growth rate in the number of priority patent applications between $t-1$ and t. In each column $L^{\star}$ has been redefined as a dummy variable set to one if employment at $t-2$ is at different levels. These levels are defined as 10-14 (column 1), 15-19 (column 2), 20-24 (column 3) etc... up to 75-79 (the baseline model is therefore in column 8). Innovation is measured by the number of new priority applications. . All models include a 3-digit NACE sector and a year fixed effects. Estimation period: 2007-1997 . Standard errors are clustered at the 3-digit NACE sector level. ***, ** and * indicate p-value below 0.01, 0.05 and 0.1 respectively.

Table D2: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Shock_{t-2} \times L^{\star}_{t-2}$	-13.924**	-19.742**	-10.919*	-17.537**	-19.335**	-13.917**	-10.014**	-12.597**	-19.335**
	(5.880)	(7.802)	(6.641)	(7.048)	(8.676)	(5.865)	(4.753)	(6.088)	(9.358)
$L^{\star}_{t-2}$	0.066	0.054	0.049	0.051	0.054	0.066	0.076	0.100	0.083
	(0.147)	(0.154)	(0.137)	(0.143)	(0.171)	(0.127)	(0.124)	(0.160)	(0.220)
$Shock_{t-2}$	-9.333**	-13.066*	-7.102*	-8.875***	-13.763**	-9.248**	-7.686*	-9.641*	-25.150
	(4.185)	(7.173)	(3.988)	(2.689)	(5.866)	(4.198)	(4.148)	(5.398)	(16.035)
$log(L)_{t-2}$	-0.040	-0.039	-0.020	-0.060*	-0.035	-0.030	-0.024	-0.032	0.033
	(0.031)	(0.038)	(0.018)	(0.032)	(0.036)	(0.024)	(0.026)	(0.034)	(0.063)
$Shock_{t-2} \times log(L)_{t-2}$	3.898***	4.641**	3.309***	3.438***	5.319***	3.869***	3.067**	3.855**	9.171*
	(1.392)	(2.287)	(1.225)	(1.012)	(1.983)	(1.397)	(1.370)	(1.781)	(5.524)
Fixed Effects									
Sector	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number Obs.	186,337	153,270	221,681	249,299	132,016	272,903	186,337	186,337	186,337

Notes: These are based on the specification of column 5 of Table 2. The dependent variable is the Davis and Haltiwanger (1992) growth rate in the number of priority patent applications between $t-1$ and t. Each column considers a different sample. Column (1) replicates our baseline specification. Column 2 includes firms that have a workforce between 10 and 100 employees at $t-2$ (instead of the first year they appear in the sample). Column 3 (resp. 4) includes firms that have a workforce between 10 and 500 (resp. 0 and 100) employees at t_0. Columns 5 and 6 are based on the same sample as column 1 but column 5 restricts to firm that first exported in 1994 (i.e.: $t_0 = 1994$, the earliest year in our dataset) and column 6 extends to non-exporting firms. Columns 7-9 also consider the same sample as column 1 but change the type of growth rate of the dependent variable. Column 7 considers the first difference in $log(1+Y)$, column 8 uses an hyperbolic function $log(Y+\sqrt{1+Y^2})$, also in first difference and column 9 uses the first difference of Y/S_0, where S_0 is the yearly average number of priority patents filed by the firm before t_0 (the first year the firm appears in the database) . All models include a 3-digit NACE sector and a year fixed effects. Estimation period: 2007-1997. Standard errors are clustered at the 3-digit NACE sector level. ***, ** and * indicate p-value below 0.01, 0.05 and 0.1 respectively.