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# Competition, product and process innovation: an empirical analysis*

**Carlos D. Santos****

## Abstract

Competition has long been regarded as productivity enhancing. Understanding the mechanism by which competition affects innovation and productivity is therefore an important topic for economic policy. The main contribution of this paper is to disentangle the relationship between competition and two sides of innovation: product and process. I write down a model and discuss the conditions under which we can identify the causal mechanism.
Overall I find that competition, measured by the number of competitors or market shares, has negative effects on product innovation and no effects on process innovation. The explanation is very simple. By shifting demand, competition directly changes the optimality condition for product but not for process innovation. Thus, competition has no direct effects on process innovations or, as a consequence, productivity.

**Keywords:** competition, innovation, R&D, product innovation, process innovation

**JEL Classification:** L11, L60, O30

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# 1 Introduction

The objective in this paper is to analyze the relation between competition and the two sides of innovation: product and process. Figure 1 presents the main evidence. Reported innovations decrease steadily with the increase in the number of competitors. However, as we will see later, the effects disappear for process innovation once we condition on size while they remain for product innovation. This suggests that the relationship between competition and innovation is different when we are considering product and process innovations. Furthermore, larger firms are more likely to do R&D and innovate which is consistent with the existence of large fixed and sunk costs in the R&D process (Santos, 2009). The evidence is easy to rationalize by theory. Changes in competition shift product demand. As such, competition directly affects the optimal choices of product innovation (revenue side) but has no direct effect on process innovation (cost side). Competition measures then satisfy an exclusion restriction in the process innovation equation, arising naturally from economic theory. When productivity is correctly measured, competition has no direct effect on productivity (i.e. conditioning on the whole set of relevant variables). This finding contributes to the recent productivity literature and in particular on how we should think about the effects of competition on productivity. All the effects of competition on productivity are indirect.

I use a dataset of Spanish firms (*Encuesta sobre Estrategias Empresariales*). The main advantage of this dataset is that it contains very detailed information on innovation and market structure together with the usual accounting variables (e.g. sales, capital stock, investment, employment, profits). The large period covered in this panel (1990-2006) allows me to address some of the problems with non-linear panel data models. In particular, to check the robustness of the random and conditional fixed effects models, I use an unconditional fixed effects specification where firm level unobserved heterogeneity is directly estimated. The coefficients are consistently estimated as the time dimension increases.

There are traditionally two main views regarding the effects of competition on innovation. The Schumpeterian view claims that monopolies favor innovation while the opposite view (Arrow, 1962) claims that competition favors innovation. However, it can be shown that both effects can coexist and in some situations one or the other effect might be stronger. For example, Vives (2008) characterizes the effects for a range of competition measures and market structures. Overall, even in a very simple setting, the results change significantly depending on the precise measures of competition and market structure used. This suggests that empirical results are of utmost importance to understand and separate the mechanisms by which competition affects innovation. In this paper two measures of competition are used: number of competitors and market shares. These variables are directly collected in the data.

Using the same dataset I use here, Gonzalez et al (2005) find a positive effect of market share and concentration on R&D decision. Huergo and Jaumandreu (2004) analyze how product and process innovation change with firm's size and age. They find both types of innovation vary considerably across industries and increase with firm size. Cassiman and Martinez-Ros (2007) study the effect of product and process innovation on exports. They curiously find that product innovation rather than process innovation affects firm productivity and exports. A possible explanation for this result is the well know problem of productivity mismeasurement in the absence of firm level price data.

Previous work by Aghion and Grifith (2008) and Aghion et al (2005) finds competition (measured by the Lerner index) has an inverted U effect in innovation (measured by patents). Their study, however, does not look into the microeconomic structure of firm decision processes and specifies an ad-hoc relationship between the variables. In particular, they try to address the endogeneity problems by using policy changes as instruments. This methodology fails to explain the mechanism by which the policy changes affect innovation because the instruments affect market structure in several ways and not only through market structure.[1] The failure of the policy changes to meet an exclusion restriction is a well know problem in the program evaluation literature and one of the reasons for why a more structural approach might be preferred (Heckman, 2008).

The problem that remains with the empirical literature is how to address the fact that market structure and innovation are jointly determined with innovation in equilibrium. In particular, competition variables will depend on industry characteristics and so will innovation. Econometric models suffer from reverse causality and omitted variables that can lead to serious endogeneity problems. In this paper I address these questions by writing down an explicit model about firm level behavior and stating the assumptions about endogenous, exogenous variables and the firms' information set. In particular I am explicit about the assumptions we need to introduce so that we can identify the causal effect. I will assume a timing between states and decisions to avoid the reverse causality and focus on the omitted variables problem. I will then present conditions on the omitted variables such that the effects can be consistently biased.

[1] One example is the use of privatization episodes that lead to a direct change in competition but also firm size. Changes in firm size, and not competition *per se*, can be the responsible for the increase (decrease) in innovations .

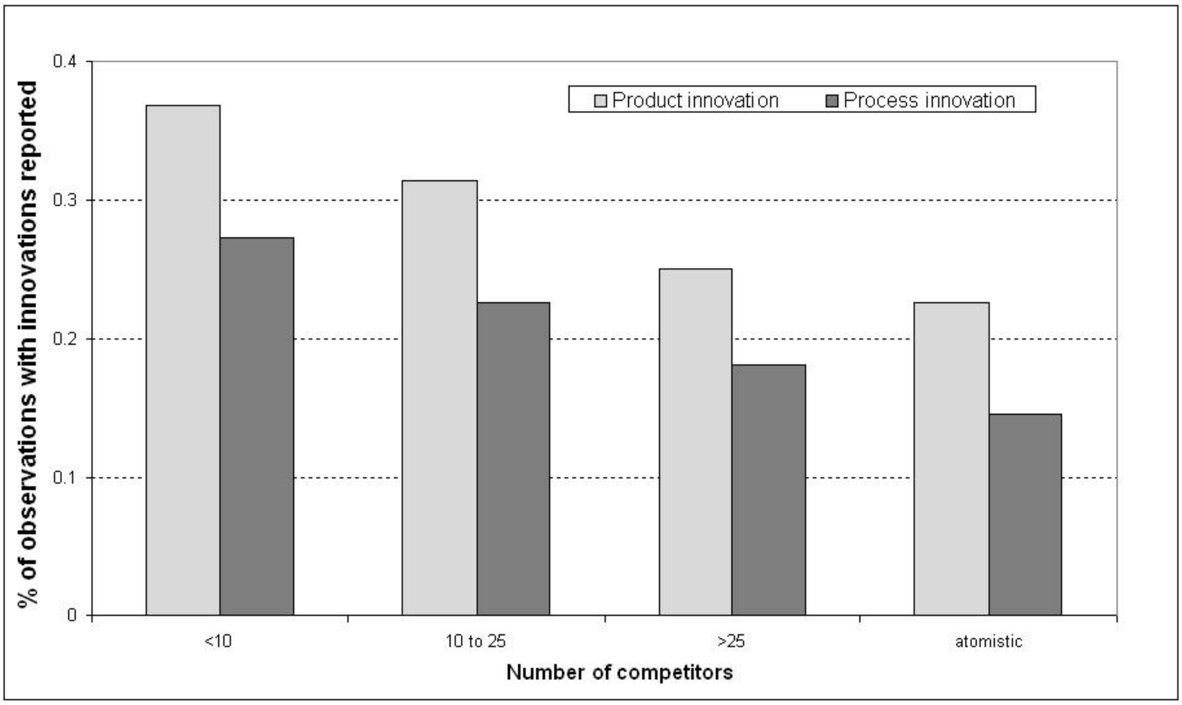


Figure 1: Percentage of firms with innovation by number of competitors

The structure of the paper is as follows. Section two details the empirical strategy and section three discusses the data. Section four contains the results, section five provides a theoretical explanation for the results and finally section six offers some concluding remarks.

# 2 The Model

I will start by specifying the econometric model and introduce the assumptions as they become necessary. There are two sets of variables, outcome variables and state variables. The outcome variables of interest are product and process innovation ($PdI$ and $PcI$), R&D decision and intensity ($rd$ and $RD/Y$). Let the vector of outcome variables be denoted by $Y = \{PdI, PcI, rd, RD/Y\}$. The state variables can be divided into firm level variables ($X$) and market structure variables ($\mu$). We can include here variables like size or productivity. There are also state variables which are observed by the firm but unobserved by the econometrician ($\xi$). These three sets of variables constitute the firm's information set in period $t$, $\Omega_{it} = \{X_{it}, \mu_{it}, \xi_{it}\}$.

The first assumption is about the timing of decisions. Decisions take one period to materialize after firms observe the current state. The role of this assumption is to allow us to abstract from any problems related with reverse causality. We can then write the decisions for firm $i$ in period $t+1$ as follows

$$Y^*_{i,t+1} = f^*(\Omega_{it}) \tag{1}$$

During the rest of the paper I will abstract from how market structure is determined in equilibrium. Provided the agents are playing a dynamic game with a stationary Markov equilibrium, this abstraction is irrelevant for estimation purposes. Optimal decisions in period $t$ are the solution to the dynamic game taking as given the (Markov) equilibrium beliefs. Equation 1 can be seen as the policy function solving the dynamic problem faced by the individual firm

$$\begin{array}{c} \max_{\{Y^*_{is}\}_{s=t+1}^{\infty}} E\left[\sum_{s=t}^{\infty} \beta^{s-t}\pi(\Omega_{is})|\Omega_{it}\right] \\ s.t.\ (\Omega_{i,s+1}) = g(Y_{i,s+1}, \Omega_{is}, \nu_{i,s+1}) \end{array}$$

where $\beta$ is the discount factor, $\nu_{i,s+1}$ is a vector of stochastic variables, $\pi(\Omega_{is})$ are the profits obtained in state $(\Omega_{is})$ and a controlled first order Markov transition is imposed on the state variables. Notice that some of the choice variables can become a state variable in the next period (e.g. $PdI \in X$). I distinguish between firms decision ($Y^*$) and realized outcomes ($Y_{i,t+1} = f(\Omega_{it}, \varepsilon_{i,t+1})$) since some of the outcomes are inherently stochastic. For example, firms decide on innovation but innovation itself is stochastic and subject to random shocks $\varepsilon_{i,t+1}$.

In this setting, omitted variables are the main cause for econometric problems. In particular, any unobserved market level time varying variable is most likely correlated with the market structure, making it impossible to estimate the effect of $\mu$ on $Y$. For example, let $\xi$ represent industry level technological opportunities. When the opportunities are larger, innovation increases. However, technological opportunities also generate entry into the market causing market structure to change. Overall, the underlying technological opportunity can shift both the market structure and innovation and generate spurious correlation between the two variables. Thus, we cannot estimate the policy function 1 because a part of the state space ($\xi$) is unobserved.

I will assume that firms are small relative to the market and abstract from strategic interactions. This assumption is not unrealistic since the average market share is about 12% and more then half of the firms in the sample report a negligible market share. Thus, we can focus on the endogeneity of market structure, i.e. $\mu_{it}$ is not independent from $\xi_{it}$.

## 2.1 Omitted variables

Now I discuss a set of conditions that allow us to address the omitted variables problems. This discussion will guide me in the empirical section for the choice of estimation methods. Our interest is to estimate the policy function

$$Y_{i,t+1} = f(X_{it}, \mu_{it}, \xi_{it}, \varepsilon_{i,t+1}) \tag{2}$$

where by assumption $\varepsilon_{i,t+1}$ is unobserved and independent from any information at period $t$.

a) One trivial solution to the endogeneity problem is when either $\xi_{it}$ does not enter equation 2 or $\xi_{it}$ is independent from $\mu_{it}$. In both of these cases equation 2 can be directly estimated.

b.i) The unobserved component can be factored in the following way $\xi_{it} = \xi_i + \xi_t + \xi'_{it}$. When $\xi'_{it}$ is independent across time and independent from $\mu_{it}$, we have the traditional "fixed effects". In this case we can simply add firm and time dummies to equation 2 and estimate it (see Arellano and Honore (2001)).

b.ii) Alternatively, we can allow dependence between $\xi'_{it}$ and $\mu_{it}$ but maintain independence across time. In this case we can use previous lags, $\mu_{i,t-1}$ as instruments for $\mu_{it}$.

Up to now we have only exploited statistical relations. For example, it is very hard to motivate economically why is $\xi_{it}$ independent across time. I will now exploit the economic structure of the problem.

c) In some cases the independence across time assumption for $\xi'_{it}$ is not plausible. To address the endogeneity problem in those cases we have to impose structure on the unobserved component and the correlation with market structure. Market structure is determined by the unobserved market level characteristics. However, conditional on current (or lagged) characteristics, market structure is independent from future values. For example, $\mu_{it}|\xi_{it}$ is independent from $\xi_{i,t+1}, \xi_{i,t+2}, ...$ or $\mu_{it}|\xi_{i,t-1}$ is independent from $\xi_{it}, \xi_{i,t+1}, ...$ The second case is more plausible for market level variables like the number of firms, since entry and exit take normally one period to materialize. Finally, assume that unobserved characteristics follow a first order Markov process

$$\xi_{i,t+1} = g^{\xi}(\xi_{it}, \nu^{\xi}_{i,t+1}) \tag{3}$$

Such restriction is crucial since we can use lagged values of the dependent variable to "control" for the unobserved component (and in some cases instrument these with further lags). However, such assumption is not testable and has to be maintained. We can write

$$Y_{it} = f(X_{i,t-1}, \mu_{i,t-1}, \xi_{i,t-1}, \varepsilon_{it})$$

if the function $f$ is invertible we get[2]

$$\xi_{i,t-1} = f^{-1}(Y_{it}, X_{i,t-1}, \mu_{i,t-1}, \varepsilon_{it}) \tag{4}$$

Using equations 3 and 4, and replacing in equation 2

$$Y_{i,t+1} = f(X_{it}, \mu_{it}, g^{\xi}(f^{-1}(Y_{it}, X_{i,t-1}, \mu_{i,t-1}, \varepsilon_{it}), \nu^{\xi}_{it}), \varepsilon_{i,t+1}) \tag{5}$$

Since $\mu_{it}|\xi_{i,t-1}$ is independent from $\xi_{it}$, $\mu_{it}$ is independent from $\nu^{\xi}_{it}$ (and from any previous lags). The only problem left to solve is the dependence between $Y_{it}$ and $\varepsilon_{it}$. The solution is easy since we can use lagged values $Y_{i,t-1}$ as instruments for $Y_{it}$. If instead we assume $\mu_{it}|\xi_{it}$ is independent from $\xi_{i,t+1}, \xi_{i,t+2}, ...$, $\mu_{it}$ is correlated with $\nu^{\xi}_{it}$. Thus, equation 5 can no longer be estimated because of this correlation. If shocks to the unobserved component, $\nu^{\xi}_{it}$, are independent across time, lagged values $(\mu_{i,t-1}, \mu_{i,t-2}, ...)$ can be used as instruments for $\mu_{it}$.

d) A final case occurs when there are more than two policy variables. This is useful for the cases where the policies are non-invertible. Let $Y^2$ be a second policy function that depend exactly on the same state variables (i.e. there are no exclusion restrictions)

$$Y^2_{it} = f_2(X_{i,t-1}, \mu_{i,t-1}, \xi_{i,t-1}, \varepsilon^2_{it})$$

If function $f_2$ is invertible we can write

$$\xi_{i,t-1} = f_2^{-1}(Y^2_{it}, X_{i,t-1}, \mu_{i,t-1}, \varepsilon^2_{it})$$

and replace this and equation 3 in equation 2

$$Y_{i,t+1} = f(X_{it}, \mu_{it}, g^{\xi}(f_2^{-1}(Y^2_{it}, X_{i,t-1}, \mu_{i,t-1}, \varepsilon^2_{it}), \nu^{\xi}_{it}), \varepsilon_{i,t+1})$$

As in the previous case $Y^2_{it}$ is correlated with $\varepsilon^2_{it}$ but we can use lagged values as instruments. When $\mu_{it}$ is not independent from $\nu^{\xi}_{it}$ we can also use lagged values as instruments.

[2] Invertibility is obviously violated if the outcome variables are binary. In this case we can use other outcome variables that also depend on market structure like for example total sales or investment.

As we move from a) to d) we impose less restrictions on the model. Estimating the model under the different alternatives will give us an idea about the robustness of the results to the different specifications.

### 2.2 Econometric specification

I study the effects of size, market share and the number of competitors on each firms' individual R&D decisions and innovation outcomes using a linear approximation to equation 2. Firms' decisions are R&D (binary and intensity) and innovation. R&D expenditures are sometimes a poor measure of innovative effort. Furthermore we cannot observe the share of R&D expenditures dedicated to product and process innovation. For such reasons, observing both types of innovation is quite useful in the empirical section.

A natural choice for the information set (state variables) is to include the capital stock, productivity and labor. These variables are quite persistent and subject to adjustment costs so that they naturally become a state of the dynamic problem. Equilibrium variables (market structure) are also states of the dynamic equilibrium. In this case I use both the number of competitors and market shares as the observed measures of market structure. Finally I add individual fixed effects as further states to capture unobserved firm level differences. In principle marginal costs and product quality are also (unobserved) state variables. Costs and quality will be captured in measured productivity and sales. I further add these to the vector of states.

The parameters of interest are the coefficients on market share, number of competitors and size. I allow for a quadratic term on market share to account for possible nonlinearities as found in the previous literature (e.g. Aghion et al, 2005).

**R&D discrete decision** The discrete decision to do R&D is modeled as a standard logit model:

$$rd_{it+1} = \begin{cases} 1 \text{ if } rd^*_{it+1} > 0 \\ 0 \text{ otherwise} \end{cases}$$

where

$$\begin{aligned} rd^*_{it+1} &= \alpha_0^{rd} PdI_{it} + \alpha_1^{rd} PcI_{it} + \alpha_2^{rd} \mu_{it} + \alpha_3^{rd} \mu_{it}^2 + \alpha_4^{rd} N_{it} \\ &\quad + \alpha_5^{rd} y_{it} + \alpha_6^{rd} rd_{it} + \alpha_7^{rd} k_{it} + \alpha_8^{rd} l_{it} + \xi_{it+1}^{rd} \end{aligned} \tag{6}$$

where $\xi_{it+1}^{rd} = \xi_i^{rd} + \xi_{t+1}^{rd} + \xi_{it+1}'^{rd}$ and ${\xi'_{it+1}}^{rd}$ is an i.i.d. logistic error term. $rd$ is a dummy variable taking the value one if R&D is reported and zero otherwise. $PdI$ and $PcI$ are dummy variables for product and process innovations, $\mu$ is market share, $N$ total number of competitors, $y$ is the log of sales, $k$ the log of capital and $l$ the log of employment.

**R&D continuous decision** Conditional on the decision, the R&D intensity (R&D to sales ratio) is

$$\begin{aligned}\left(\frac{R\&D_{it+1}}{Y_{it+1}}|rd_{it+1}=1\right) &= \alpha_0^{RDY}PdI_{it}+\alpha_1^{RDY}PcI_{it}+\alpha_2^{RDY}\mu_{it}+\alpha_3^{RDY}\mu_{it}^2+\alpha_4^{RDY}N_{it} \\ &+\alpha_5^{RDY}y_{it}+\alpha_6^{RDY}rd_{it}+\alpha_7^{RDY}k_{it}+\alpha_8^{RDY}l_{it}+\xi_{it+1}^{RDY}\end{aligned} \tag{7}$$

where $\xi_{it+1}^{RDY}=\xi_i^{RDY}+\xi_{t+1}^{RDY}+\xi_{it+1}^{\prime RDY}$.

**Innovation outcomes** Similarly to R&D, innovations are modeled with standard logit specifications

**Product innovation**

$$PdI_{it+1}=\begin{cases}1 \text{ if } PdI_{it+1}^*>0\\ 0 \text{ otherwise}\end{cases}$$

$$\begin{aligned}PdI_{it+1}^* &= \alpha_0^{pdi}PdI_{it}+\alpha_1^{pdi}PcI_{it}+\alpha_2^{pdi}\mu_{it}+\alpha_3^{pdi}\mu_{it}^2+\alpha_4^{pdi}N_{it} \\ &+\alpha_5^{pdi}y_{it}+\alpha_6^{pdi}rd_{it}+\alpha_7^{pdi}k_{it}+\alpha_8^{pdi}l_{it}+\xi_{it+1}^{pdi}\end{aligned} \tag{8}$$

where $\xi_{it+1}^{pdi}=\xi_i^{pdi}+\xi_{t+1}^{pdi}+\xi_{it+1}^{\prime pdi}$ and $\xi_{it+1}^{\prime pdi}$ is an i.i.d. logistic error term.

**Process innovation**

$$PcI_{it+1}=\begin{cases}1 \text{ if } PcI_{it+1}^*>0\\ 0 \text{ otherwise}\end{cases}$$

$$\begin{aligned}PcI_{it+1}^* &= \alpha_0^{pci}PdI_{it}+\alpha_1^{pci}PcI_{it}+\alpha_2^{pci}\mu_{it}+\alpha_3^{pci}\mu_{it}^2+\alpha_4^{pci}N_{it} \\ &+\alpha_5^{pci}y_{it}+\alpha_6^{pci}rd_{it}+\alpha_7^{pci}k_{it}+\alpha_8^{pci}l_{it}+\xi_{it+1}^{pci}\end{aligned} \tag{9}$$

where $\xi_{it+1}^{pci}=\xi_i^{pci}+\xi_t^{pci}+\ \xi_{it}^{\prime pci}$ and $\xi_{it}^{\prime pci}$ is an i.i.d. logistic error term.

The system of equations is identified by the assumption on the timing of the decisions. In particular it is assumed that all decisions depend on the lagged state of observed variables.

Furthermore, it is assumed that the errors $\{\xi_{it}^{\prime rd}, \xi_{it}^{\prime RDY}, \xi_{it}^{\prime pdi}, \xi_{it}^{\prime pci}\}$ are jointly independent. This allows us to estimate the equations separately.

**Potential econometric problems** There are several problems with panel data limited dependent variable models in short panels (see Arellano and Honoré (2001) for a review). In particular we have:[3]

1. *Strict exogeneity of the regressors*: This assumption is hardly ever met given the structure of the problem. Besides the system structure, which means all variables are endogenously determined, we also have the inclusion of lagged dependent variables (see below). However, the identification problem is less severe when $T$ is large as in our case (Chamberlain, 1985; Honoré and Kyriazidou, 2000).

2. *Incidental parameters (fixed effects)*: This problem arises in short panels because the number of parameters to be estimated increases with the number of observations $N$. As for the previous case, the problem is less severe for large $T$.

3. *Lagged dependent variables*: The existence of lagged dependent variables directly violates the strict exogeneity assumption above. While it is well know how to solve this problem in linear models, the issue is much more complicated in non-linear models where some estimators have been proposed (Honore and Kyriazidou, 2000). However, with a large time-series, we can adopt an unconditional logit to mitigate the problem. For this reason again, large $T$ helps to reduce potential bias in this case. Furthermore, results with and without the lagged dependent variables are presented to evaluate the robustness.

Overall the results reported in the next section are quite robust. The results and their validity is discussed for each specification.

The changes from random effects to the fixed effects specifications are, in most cases, not substantial. This could be due to unobserved heterogeneity already being "controlled" by the set of variables used. For example, the use of lagged dependent variables or second policies as explained in c) and d) above already "control" for potential unobserved heterogeneity. This follows a similar idea explored by Blundell, Griffith and Van Reenen (1999) where pre-sample data was used to "control" for the initial conditions.

[3] Notice that I am interested in the sign and not the magnitude of the coefficients. I am also not interested in distinguishing persistence due to unobserved heterogeneity from "true" state dependence. For this reason we can abstract from problems about identification of the marginal effects.

# 3 Data

The data is part of the ESEE (*Encuesta sobre Estrategias Empresariales*) collected by the *Fundacion Empresa Publica*. The survey collects a variety of variables on R&D, innovation and market structure and has been used by several authors to investigate questions about R&D and Innovation.[4] For this reason, the dataset is particularly attractive for the empirical analysis of the relationship between market structure and innovation. A description of the data and variable construction is contained in the Appendix. It consists of an unbalanced sample of 30,466 observations for 4,094 firms over the period 1990-2006 for the whole manufacturing sector in Spain with an average 1,800 observations per year. On average 35% of the firms report positive R&D expenditures, 30% positive process innovation and 23% positive product innovation. One immediate characteristic is that process innovations are much (40%) more frequent then product innovations. A second characteristic is the decline in innovative output (both product and process) from 2000 until 2003 and the slight recovery in 2004. This is also registered in R&D expenditures which have declined from 1999 until 2002 and recovered afterwards. The steady decline in reported market shares probably signals increased competition in the Spanish industry over this period. Descriptive statistics are presented in Tables 2 and 3.

The variables used are market share ($\mu$); log of sales ($y$), log of capital stock ($k$) and log of labor ($l$); dummies for introduction of product innovation ($PdI$) or process innovation ($PcI$); R&D dummy ($rd$); R&D intensity ($R\&D/Y$) and finally an ordinal variable for the number of competitors ($N$).

# 4 Results

In this section I present the estimates for equations [6] to [9]. Overall, the results suggest quite a robust negative relation between competition (as captured by the number of competitors) and product innovation and no relation between competition and R&D decisions or process innovation.

Regarding market shares, I find robust evidence of an increasing relation between market shares and product innovation but weakly significant for process innovation. The shape of this seems to be an inverted U but we cannot reject the hypothesis of monotonicity (increasing and concave) due to the few observations with very high market shares (i.e. above 50%). I also find evidence of a concave relationship between market shares and the

[4] For example Cassiman and Martinez-Ros (2007), Doraszelski and Jaumandreu (2007), Gonzalez, Jaumadreu and Pazó (2005) and Huergo and Jaumadreu (2004)

R&D discrete decision although the quadratic term is sometimes not significant.[5] Since the results condition for size (sales, capital stock and number of workers) there are reasons to suspect that market shares are capturing a form of market power.

A further fact that emerges is that size (as captured by total sales) is positive and significant for innovation (product and process) and R&D decisions but not for R&D intensity. This can be because R&D decisions are normally subject to large fixed and sunk costs (see for example Santos, 2009). For this reason it is quite common that larger firms are more likely to do R&D (but not necessarily dedicate a larger share to the R&D process) and innovate. The size effect can be unrelated with market power or competition.

For the binary models I use a logit specification[6] both for random and conditional logit fixed effects. I also directly estimate fixed effects (unconditional logit). The sample for fixed effects models is substantially smaller since several observations are lost. For this reason whenever results are similar for both approaches, random effects is preferred. As explained before, lagged dependent variables are important to shed some light on the causality versus correlation problem since together with the assumption on the timing of decisions, it "controls" for missing variables. The econometric problems with using lagged dependent variables have already been discussed and are addressed by the large time dimension.

## 4.1 R&D equations

I separate the R&D decisions into the discrete decision and the choice of intensity. The reason for doing so is because these decisions seem to be partially determined by different factors. In particular, the presence of fixed or sunk costs would be important for the discreteness while particular R&D technology characteristics could be the drivers of the second decision. I have also tried to model both decisions jointly with a tobit specification but the results in the tobit specification are mostly driven by the discrete decision.

### 4.1.1 Discrete R&D decision

The negative correlation between competition and R&D in column (i) of Table 4 disappears once size effects are accounted for in column (iii). Market shares have a positive and concave relation in the random effects estimates of columns (iv) and (v). However, this significance is reduced with the introduction of fixed effects as reported in columns (vi) and (vii). Since the main effects are not significantly altered from the random effects specification in column

[5] This inverted U as found by Aghion et al (2005) is also present when instead of quadratic terms I use dummies for market share classes.

[6] Using a probit model does not change the results.

(v) to the conditional fixed effects of column (vi), the random effects specification in column (v) is preferred. Finally, in column (viii) an unconditional fixed effects logit is estimated. As discussed before, these results are only valid asymptotically in $T$.

The overall picture that emerges from Table 4 is that the discrete R&D decision is not affected by competition. There is also mild evidence of a non-linear market power effect.

#### 4.1.2 R&D intensity

Results for R&D intensity are reported in Table 5 where the sample is restricted to observations with positive R&D. R&D intensity is decreasing with both the number of competitors and market share. However, the results are never statistically significant even though they are quite robust across specifications (random and fixed effects with and without dynamics). Given the lack of good empirical results (and fit) in explaining R&D intensity, it is not surprising that the results are not significant. This is possibly due to individual R&D intensity being mostly determined by unobserved heterogeneity.

### 4.2 Innovation equations

#### 4.2.1 Product innovation

The results for product innovation are presented in Table 6. The number of competitors are negatively related with product innovation while market shares have a positive and concave relationship. There is also a strong size effect (sales). This suggests market power advantages in (product) innovation beyond pure size advantages.

The results are robust to the introduction of fixed effects (conditional and unconditional) in columns (iv) and (v) and dynamics in columns (vii) and (viii). Notice that R&D intensity is always positive and significant so that the relation between competition and innovation is conditional on R&D expenditures. This means that the effects operate either on the split of the R&D expenditures between product and process innovation or on the productivity of R&D expenditures. It could also signal that reported R&D expenditures are a poor measure of innovative performance.

#### 4.2.2 Process innovation

Figure 1 suggests that process innovation shares the same competitive effects as product innovation. Since in the data only 26% of the firms do one single type of innovation (i.e. the remaining either do both or none) we would indeed expect very similar effects. From looking at Table 6 we can conclude that in fact this is not the case. The effect of the number of competitors on process innovation reported in columns (i) and (ii) completely disappears once we condition on size in column (iii). The market share effect is similar to the one for product innovation but it is again not statistically significant. The results hold for the rest of the specifications in columns (iv) to (viii). We can conclude that there is no evidence of any causal effect from competition to process innovation.

The results seem to contradict the predictions by Dasgupta and Stiglitz (1980) and Vives (2008) that an increase in the number of firms leads to a decrease in cost reducing effort. However, in Vives (2008) the predictions are unconditional and operate through the size of the firm. Once size effects are accounted for, there is no effect of competition on process innovation. Thus, the theoretical predictions are perfectly in line with my empirical results. Once we condition for the correct variables (output per firm) the effect disappears. Notice the relevance of this finding for the productivity literature. Competition has no direct effects on process innovation. Since process innovation is normally regarded as productivity enhancing, it means that competition has no direct effects on productivity.

# 5 Rationalizing the evidence

There is a simple explanation for the results. Changes in market structure have an effect on the demand for a firm's product and no effect on the cost structure. If product innovation shifts the demand curve while process innovation shifts the cost curve, changes in competition are expected to have direct effects on product innovation but no direct effects on process innovation . This is because variations in demand change the first order condition for optimal product innovation and leave the first order conditions for process innovation unaltered. To illustrate this, let's define the simplest static model.[7] Firm chooses marginal costs (process innovation), $\omega$, quality (product innovation), $\chi$, and quantity, $q$, to maximize profits.

$$\max_{q,\omega,\chi} \quad \pi = [p(q,\chi,\mu) - c(\omega,q)]q - g(\chi,\omega)$$

$p(.)$ is the inverse demand function, $c(.)$ is the cost function and $g(.)$ is the innovation cost function while $\mu$ represents the competition variables. The first order conditions are

[7] Vives (2008) provides a detailed analysis of several models under different competitive regimes. The results are also valid for a more complete dynamic game. The important assumption is that competition only affects the demand but not the costs of innovation.

$$
\begin{aligned}
p'_\chi(q,\chi,\mu)q - g'_\chi(\chi,c) &= 0 \quad (\chi^*)\\
-c'_\omega(\omega,q)q - g'_c(\chi,c) &= 0 \quad (c^*)\\
p(q,\chi,\mu) - c(\omega,q) + (p'_q(q,\chi,\mu) - c'_q(\omega,q))q &= 0 \quad (q^*)
\end{aligned}
$$

Changes in competition are reflected in movements to the demand curve. They have a direct effect on optimal product innovation while the effect on process innovation is indirect (in this simple case via optimal quantities or product innovation). If we control for quantity and product innovation, competition has no effect on process innovation.

# 6 Conclusion

The aim of this study was to present evidence on the effect of competition on innovation. I have explored variation of these relations across the two types of innovation. The results suggest negative competitive effects on product but not on process innovations. The results are less clear for R&D as we would expect because R&D expenditures might be a poor measure of innovative effort.

When put into perspective, the results are perfectly rationalizable by theory. Competition has a direct effect on product market demand thus, a direct effect on product innovation. Since the optimality conditions for process innovation are not directly influenced by competition, there is no direct effect of competition on process innovation.

Too much emphasis should not be put on the negative effects of competition on product innovation. Most importantly because they are average effects across industries and valid for the population of Spanish manufacturing firms. It is quite likely that the effects are positive for particular industries or different countries. However, the evidence of no effects on process innovation (both in theory and in the data) is quite important for the competition and productivity literature. In particular, the fact that competition effects on cost reducing efforts disappear once we condition on size illustrates the need to be careful when analyzing the role of competition on productivity. Moreover, competition does have indirect effects on process innovation and therefore on productivity, and strong selection effects on **average** productivity.

# A Data Appendix

## A.1 Data and sample construction

**Some notes on the ESEE**: The dataset has been collected by the *Fundacion Empresa Publica* since 1990 for a panel of Spanish manufacturing firms. There has been an effort to avoid attrition in the dataset by bringing back to the sample firms that have dropped reporting for some reason not related with exit. The data is collected using direct interviews with a questionnaire. The sampling procedure includes all manufacturing firms with more then 200 employees. Firms with 10 to 200 employees are randomly sampled by industry and size strata, holding around a 4% of the population. Firms with less than 10 employees are excluded from the survey. The ESEE is representative of Spanish manufacturing firms classified by industrial sectors and size categories and includes exhaustive information at the firm level, especially regarding exporting and innovation activities.

**Representativeness**: The sample is representative of the whole industry and an effort is done to introduce new firms into the sample in order to maintain representativeness.

**Variable construction:**

- Firm level deflators (index) for sales and inputs (materials and services) are constructed using reported variations in prices for sales and inputs. Missing values in the reported price variations are "filled" in two ways. If the missing value is only for one year, an average of the reported price changes in the years immediately before and after is used. If the missing value is for more then one year or a starting or end year industry level value added deflators collected from the OECD/STAN Database for Structural Analysis are used. The deflator indices are therefore time and firm specific.

- Industry and aggregate deflators - Industry deflators (value added and gross fixed capital formation) were collected from OECD/STAN Database for Structural Analysis. Unit labor costs for the whole manufacturing sector were collected from the OECD.

- Capital stock is constructed separately for land, buildings and other fixed assets using the perpetual inventory method

$$K_{it+1}^{j} = (1 - depreciation^{j}) * K_{it}^{j} + I_{it}^{j} \qquad j = land, build, other$$

$$K_{it+1} = K_{it+1}^{land} + K_{it+1}^{build} + K_{it+1}^{other}$$

The depreciation rate used is 2.5% for buildings, 15% for other fixed assets and 0% for land. Deflators for the capital stock were collected from the OECD/STAN Database for

Structural Analysis.

- Value added is equal to deflated sales subtracted from deflated materials and deflated external services expenditures (deflator construction explained above)

$$VA_{it}^{def} = Y_{it}^{def} - M_{it}^{def} - ESE_{it}^{def}$$

- R&D dummy variable takes a value equal to one whenever positive R&D is reported and zero otherwise.

- Other variables used are

| **Variable** | **Unit** |
|---:|---:|
| Family Ownership | Dummy |
| Foreign Ownership | Dummy |
| Production Methods used | Dummy |
| (CAD, Numerical Control, Robotics) | |
| Product Standardization | Dummy |
| Market Share | Percentage |
| Number of Competitors | Ordinal |
| [1 (<10); 2 (11-20); 3(>25); 4(Many)] | |
| Number of Products | Integer |
| Number of Markets | Integer |
| RD Expenditures | Euros |
| Product Innovation | Dummy |
| Process Innovation | Dummy |
| Employees | Integer |
| Long term debt (stock) | Euros |
| Cost of LT debt (stock) | Percentage |
| Long term debt raised (new debt) | Euros |
| Cost of LT debt raised (new debt) | Percentage |
| Equity | Euros |
| RD successfull financing | Dummy |
| Operational Profit | Euros |
| Patents (Spain) | Integer |
| Patents (External) | Integer |
| Capacity Utilization | Percentage |

Table 1: List of variables

The market share variable is constructed using two questions in the survey. Firms are first asked if they have a significant market share. If not a zero is automatically attributed, otherwise firms are asked to report their market share. Due to this, zero reported market shares represent a significant proportion in the data (53%).

The number of competitors is an ordinal variable that takes four possible values. 1 - Less than 10 competitors; 2 - 10 to 25 competitors; 3 - More than 25 competitors; 4 - Atomistic market.

**Cleaning** Original data consists of an unbalanced sample of 31,470 observations for 4,357 firms over the period 1990-2006 for the manufacturing sector in Spain. The firms who only report in 1990 are dropped (248). After cleaning for missing values and firms with inconstant reporting (i.e. firms who leave and re-enter the sample) we are left with an unbalanced panel of 30,466 observations for 4,094 firms.

## A.2 Tables

| Variables | *Mean* | *Standard deviation* | *Min* | *25th percentile* | *Median* | *75th percentile* | *Max* |
|---|---|---|---|---|---|---|---|
| RD dummy | 36% | 48% | 0% | 0% | 0% | 100% | 100% |
| Process Innov | 32% | 47% | 0% | 0% | 0% | 100% | 100% |
| Product Innov | 23% | 42% | 0% | 0% | 0% | 0% | 100% |
| Sales (EUR mio) | 48.40 | 228.00 | 0.01 | 1.07 | 4.53 | 29.30 | 5,940.00 |
| RD intensity | 0.7% | 2.8% | 0.0% | 0.0% | 0.0% | 0.4% | 70.0% |
| Employment | 263 | 816 | 0 | 18 | 47 | 257 | 25,363 |
| Capital Stock (EUR mio) | 21.60 | 92.80 | 0.00 | 0.30 | 1.67 | 13.20 | 3,240.00 |
| Market share | 12% | 19% | 0% | 0% | 0% | 19% | 100% |
| Age | 25 | 22 | 0 | 9 | 19 | 33 | 270 |

Table 2: Descriptive statistics

| Year | *Obs.* | *RD* | *Process Innov* | *Product Innov* | *Conditional RD intensity* | *Inv. rate* | *Sales growth* | *Conditional market share* | *VA growth* |
|---|---|---|---|---|---|---|---|---|---|
| 1990 | 1,834 | 634 | 345 | 301 | 2.74% | . | . | 34 | . |
| 1991 | 1,995 | 727 | 740 | 496 | 2.08% | 15% | 5% | 30 | 5% |
| 1992 | 1,954 | 678 | 671 | 487 | 2.03% | 12% | 3% | 28 | -2% |
| 1993 | 1,831 | 626 | 637 | 440 | 2.24% | 10% | -1% | 28 | 3% |
| 1994 | 1,837 | 645 | 654 | 478 | 2.01% | 9% | 15% | 28 | 21% |
| 1995 | 1,679 | 587 | 580 | 399 | 1.93% | 11% | 15% | 29 | 14% |
| 1996 | 1,706 | 590 | 577 | 402 | 1.92% | 11% | 5% | 27 | 4% |
| 1997 | 1,901 | 660 | 696 | 489 | 1.93% | 11% | 14% | 28 | 10% |
| 1998 | 1,766 | 668 | 676 | 461 | 1.89% | 13% | 11% | 27 | 5% |
| 1999 | 1,741 | 661 | 621 | 442 | 2.10% | 14% | 10% | 25 | 2% |
| 2000 | 1,849 | 693 | 720 | 508 | 2.07% | 14% | 10% | 25 | -1% |
| 2001 | 1,709 | 620 | 570 | 363 | 2.01% | 14% | 6% | 26 | 5% |
| 2002 | 1,704 | 630 | 510 | 375 | 1.73% | 11% | 3% | 26 | -4% |
| 2003 | 1,378 | 490 | 347 | 259 | 1.93% | 10% | 4% | 24 | 4% |
| 2004 | 1,373 | 507 | 380 | 282 | 1.81% | 10% | 7% | 23 | 2% |
| 2005 | 1,869 | 689 | 527 | 358 | 2.18% | 13% | 4% | 23 | 6% |
| 2006 | 1,988 | 689 | 545 | 370 | 2.04% | 11% | 8% | 22 | 10% |

Table 3: Aggregate descriptive statistics, averages per year

| Dependent variable: $rd_{it+1}$ | RE | | | | | | | | | | Conditional FE | | | | Unconditional FE | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (i) | | (ii) | | (iii) | | (iv) | | (v) | | (vi) | | (vii) | | (viii) | |
| | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* |
| Market share$_{it}$ | 1.24 | *0.21**** | 4.44 | *0.52**** | 1.93 | *0.56**** | 1.40 | *0.57*** | 1.11 | *0.46*** | 0.75 | *0.64* | 1.02 | *0.68* | 1.18 | *0.73* |
| Market share$^2_{it}$ | | | -0.46 | *0.06**** | -0.24 | *0.07**** | -0.16 | *0.07*** | -0.11 | *0.06** | -0.08 | *0.08* | -0.11 | *0.09* | -0.10 | *0.10* |
| $N_{it}$ | -0.11 | *0.03**** | -0.08 | *0.03*** | -0.05 | *0.03* | -0.05 | *0.03* | -0.03 | *0.03* | 0.01 | *0.04* | 0.03 | *0.04* | 0.04 | *0.04* |
| $y_{it}$ | | | | | 0.74 | *0.08**** | 0.70 | *0.08**** | 0.32 | *0.05**** | 0.56 | *0.11**** | 0.46 | *0.11**** | 0.51 | *0.12**** |
| $k_{it}$ | | | | | 0.27 | *0.05**** | 0.25 | *0.05**** | 0.09 | *0.03*** | -0.02 | *0.08* | -0.09 | *0.09* | -0.11 | *0.09* |
| $l_{it}$ | | | | | 0.44 | *0.09**** | 0.38 | *0.09**** | 0.17 | *0.06*** | 0.10 | *0.12* | 0.06 | *0.13* | 0.07 | *0.14* |
| $PdI_{it}$ | | | | | | | 1.14 | *0.08**** | 0.69 | *0.07**** | 0.71 | *0.08**** | 0.39 | *0.09**** | 0.44 | *0.09**** |
| $PcI_{it}$ | | | | | | | 0.51 | *0.07**** | 0.22 | *0.06**** | 0.36 | *0.07**** | 0.13 | *0.08* | 0.15 | *0.08** |
| $rd_{it}$ | | | | | | | | | 3.43 | *0.07**** | | | 1.54 | *0.06**** | 1.79 | *0.07**** |
| Time dum. | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Ind. dum. | Yes | | Yes | | Yes | | Yes | | Yes | | No | | No | | No | |
| $R^2$ | | | | | | | | | | | | | | | | |
| Obs | 22,661 | | 22,661 | | 20,122 | | 19,753 | | 19,673 | | 6,884 | | 6,805 | | 6,805 | |
| Firms | 3,428 | | 3,428 | | 3,173 | | 3,143 | | 3,137 | | 740 | | 731 | | 731 | |

Notes: Columns (i) to (v) report random effects logit estimates where the explained variable is R&D dummy. In columns (vi) and (vii)results are reported for a conditional fixed effects logit while in column (viii) fixed effects are directly estimated together with the remaining parameters.
*** significant at 1%, ** significant at 5%, * significant at 10%. Coefficients on market share are scaled by 100 and on market share squares scaled by 1000.

Table 4: R&D dummy logit estimates.

| | (i) | | (ii) | | (iii) | | (iv) | | (v) | | (vi) | | (vii) | | (viii) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | RE | | | | | | | FE | | DPD (GMM) | | DPD (Sys. GMM) | |
| Dependent variable: $R\&D/Y_{it+1}$ | | | | | | | | | | | | | | | | |
| | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* |
| Mkt $\text{sh}_{it} * 10^3$ | -0.05 | *0.02*** | -0.14 | *0.05**** | -0.17 | *0.05**** | -0.18 | *0.05**** | -0.07 | *0.06* | -0.09 | *0.06* | -0.05 | *0.04* | -0.25 | *0.11*** |
| Mkt $\text{sh}_{it}^2 * 10^5$ | | | 0.13 | *0.06*** | 0.24 | *0.07**** | 0.25 | *0.07**** | 0.08 | *0.08* | 0.12 | *0.08* | 0.11 | *0.08* | 0.39 | *0.18*** |
| $N_{it} * 10^3$ | -0.16 | *0.38* | -0.27 | *0.38* | -0.57 | *0.40* | -0.64 | *0.41* | -0.53 | *0.46* | -0.54 | *0.46* | 0.11 | *0.17* | -0.45 | *0.65* |
| $y_{it} * 10^3$ | | | | | -7.16 | *0.85**** | -7.46 | *0.87**** | -6.70 | *1.18**** | -5.93 | *1.19**** | -7.17 | *3.21*** | -6.72 | *3.41*** |
| $k_{it} * 10^3$ | | | | | 0.23 | *0.59* | 0.35 | *0.61* | 1.05 | *0.97* | 0.39 | *0.97* | -0.18 | *1.93* | -2.11 | *3.30* |
| $l_{it} * 10^3$ | | | | | 4.99 | *1.02**** | 5.21 | *1.05**** | 3.61 | *1.43*** | 3.66 | *1.43*** | 1.50 | *2.45* | 12.13 | *6.45** |
| $PdI_{it} * 10^3$ | | | | | | | 2.62 | *0.69**** | 1.93 | *0.73**** | 1.67 | *0.73*** | 1.39 | *0.84* | 3.58 | *1.98** |
| $PcI_{it} * 10^3$ | | | | | | | -0.86 | *0.66* | -0.59 | *0.69* | -0.53 | *0.69* | -0.98 | *0.66* | -1.29 | *1.21* |
| $R\&D/Y_{it}$ | | | | | | | | | | | 0.08 | *0.01**** | 0.08 | *0.09* | 0.17 | *0.09** |
| Time dum. | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Ind. Dum. | Yes | | Yes | | Yes | | Yes | | No | | No | | No | | No | |
| $R^2$ | 9% | | 10% | | 12% | | 12% | | 2% | | 17% | | | | | |
| Nobs | 8,144 | | 8,144 | | 7,152 | | 6,915 | | 6,915 | | 6,866 | | 6,866 | | 6,866 | |
| Nfirm | 1,620 | | 1,620 | | 1,490 | | 1,470 | | 1,470 | | 1,464 | | 1,464 | | 1,464 | |
| AR1 | | | | | | | | | | | | | -2.283 | *0.02* | -2.162 | *0.03* |
| AR2 | | | | | | | | | | | | | 1.1479 | *0.25* | 1.1591 | *0.25* |
| Sargan | | | | | | | | | | | | | 792.72 | *0* | 403.73 | *0* |
| Sargan diff | | | | | | | | | | | | | | | 388.99 | *0.06* |

Notes: Solely observations with positive reported R&D and R&D intensity below 70% are used. Columns (i) to (iv) report random effects estimates where the explained variable is R&D intensity. In columns (v) and (vi) results are reported for a fixed effects model. Dynamic panel data estimates are presented in column (vii) using levels and in column (viii) using a system GMM. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 5: R&D intensity estimates.

| | RE | | | | | | Cond. FE | | Uncond. FE | | RE Sample of FE | | Cond. FE | | Uncond. FE | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (i) | | (ii) | | (iii) | | (iv) | | (v) | | (vi) | | (vii) | | (viii) | |
| Dependent variable: $PdI_{it+1}$ | | | | | | | | | | | | | | | | |
| | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* |
| $PdI_{it}$ | | | | | | | | | | | | | 0.93 | 0.05*** | 1.07 | 0.05*** |
| $PcI_{it}$ | | | 0.78 | 0.05*** | 0.69 | 0.05*** | 0.41 | 0.05*** | 0.47 | 0.06*** | 0.51 | 0.05*** | 0.16 | 0.06** | 0.18 | 0.06*** |
| Mkt $\text{sh}_{it} * 100$ | 0.55 | 0.17*** | 3.17 | 0.41*** | 1.81 | 0.46*** | 1.00 | 0.53* | 1.15 | 0.57** | 0.82 | 0.41* | 0.94 | 0.55* | 1.12 | 0.59* |
| Mkt $\text{sh}^2_{it} * 1000$ | | | -0.39 | 0.05*** | -0.26 | 0.06*** | -0.14 | 0.07** | -0.163 | 0.07** | -0.13 | 0.05** | -0.14 | 0.07* | -0.16 | 0.08** |
| $N_{it}$ | -0.15 | 0.02*** | -0.11 | 0.02*** | -0.10 | 0.03*** | -0.07 | 0.03** | -0.08 | 0.03** | -0.05 | 0.02* | -0.07 | 0.03* | -0.08 | 0.03** |
| $y_{it}$ | | | | | 0.30 | 0.06*** | 0.19 | 0.09** | 0.22 | 0.10** | 0.17 | 0.05*** | 0.16 | 0.09 | 0.18 | 0.10* |
| $k_{it}$ | | | | | -0.03 | 0.04 | -0.17 | 0.07** | -0.19 | 0.07*** | -0.16 | 0.03*** | -0.13 | 0.07* | -0.16 | 0.07** |
| $l_{it}$ | | | | | 0.15 | 0.07** | 0.13 | 0.11 | 0.15 | 0.11 | 0.17 | 0.06*** | 0.10 | 0.11 | 0.12 | 0.12 |
| $R\&D/Y_{it}$ | | | | | 11.28 | 1.35*** | 4.99 | 1.34*** | 5.86 | 1.45*** | 6.77 | 1.17*** | 3.53 | 1.28*** | 4.23 | 1.39*** |
| Nobs | 22,408 | | 22,405 | | 19,770 | | 10,054 | | 10,054 | | 10,066 | | 9,833 | | 9,833 | |
| Nfirm | 3,418 | | 3,418 | | 3,149 | | 1,074 | | 1,074 | | 1,076 | | 1,058 | | 1,058 | |
| Dependent variable: $PcI_{it+1}$ | | | | | | | | | | | | | | | | |
| | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* | Coef. | *s.e.* |
| $PcI_{it}$ | | | | | | | | | | | | | 0.86 | 0.04*** | 1.00 | 0.04*** |
| $PdI_{it}$ | | | 0.85 | 0.04*** | 0.77 | 0.05*** | 0.43 | 0.05*** | 0.00 | 0.06 | 0.65 | 0.05*** | 0.17 | 0.05*** | 0.19 | 0.06*** |
| Mkt $\text{sh}_{it} * 100$ | 0.61 | 0.14*** | 1.92 | 0.34*** | 0.74 | 0.37** | 0.75 | 0.46 | 0.00 | 0.49 | 0.64 | 0.35* | 0.50 | 0.47 | 0.61 | 0.50 |
| Mkt $\text{sh}^2_{it} * 1000$ | | | -0.19 | 0.04*** | -0.08 | 0.05 | -0.1 | 0.06 | -0.117 | 0.06* | -0.06 | 0.04 | -0.06 | 0.06 | -0.07 | 0.06 |
| $N_{it}$ | -0.07 | 0.02*** | -0.05 | 0.02** | 0.00 | 0.02 | 0.02 | 0.02 | 0.00 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 |
| $y_{it}$ | | | | | 0.16 | 0.04*** | 0.15 | 0.07** | 0.00 | 0.08 | 0.13 | 0.04*** | 0.13 | 0.07 | 0.14 | 0.08 |
| $k_{it}$ | | | | | 0.17 | 0.03*** | 0.01 | 0.05 | 0.00 | 0.06 | 0.05 | 0.03 | -0.06 | 0.05 | -0.07 | 0.06 |
| $l_{it}$ | | | | | 0.00 | 0.05 | 0.09 | 0.09 | 0.00 | 0.10 | 0.01 | 0.05 | 0.05 | 0.09 | 0.05 | 0.09 |
| $R\&D/Y_{it}$ | | | | | 3.69 | 1.05*** | 3.23 | 1.28** | 0.00 | 1.38 | 4.05 | 1.08*** | 2.73 | 1.22** | 3.07 | 1.31** |
| Nobs | 22,838 | | 22,380 | | 19,752 | | 13,625 | | 13,503 | | 13,720 | | 13,625 | | 13,503 | |
| Nfirm | 3,444 | | 3,411 | | 3,142 | | 1,462 | | 1,460 | | 1,495 | | 1,462 | | *1,460* | |
| Time dum. | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Ind. dum. | Yes | | Yes | | Yes | | No | | No | | Yes | | No | | No | |

Notes: Columns (i) to (iii) and (vi) report random effects logit estimates where the explained variable is product innovation (top panel) and process innovation (bottom panel). Columns (iv) and (vii) contain results for a conditional fixed effects logit and in columns (v) and (viii) fixed effects are directly estimated with the remaining parameters.
*** significant at 1%, ** significant at 5%, * significant at 10%.

Table 6: Product innovation (top panel) and process innovation (bottom panel) logit estimates.

# References


[1] Arrow, K. (1962): "Economic Welfare and the Allocation of Resources for Invention," NBER Chapters, in: *The Rate and Direction of Inventive Activity: Economic and Social Factors*, 609-626, NBER

[2] Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005): "On Competition and Innovation: An Inverted U Relationship", *Quarterly Journal of Economics*, 120 (2), 701-728

[3] Aghion, P., and R. Griffith (2008): *Competition and Growth: reconciling theory and evidence*, Zeuthen Lectures, MIT Press

[4] Arellano, M., and B. Honoré (2001): "Panel Data Models: Some recent developments", in *Handbook of Econometrics*, vol. 5, ch. 53, ed. by J. Heckman and E. Leamer, Elsevier, 3229–3296.

[5] Blundell, R., Griffith, R. and J. Van Reenen (1999): "Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms, *Review of Economic Studies,* 66 (3), 529-554

[6] Cassiman, B. and Martinez-Ros, E. (2007): "Product Innovation and Exports: Evidence from Spanish Manufacturing", manuscript

[7] Dasgupta, P., and J. Stiglitz (1980): "Industrial Structure and the Nature of Innovative Activity", *Economic Journal*, 90, 266-293

[8] Doraszelski, U., and Jaumandreu, J. (2007): "R&D and productivity: Estimating production functions when productivity is endogenous", manuscript

[9] González, X., Jaumandreu, J. y Pazó, C. (2005): "Barriers to innovation and subsidy effectiveness", *Rand Journal of Economics*, 36

[10] Griffith, R., Huergo, E., Mairesse, J. y B. Peters (2006): "Innovation and productivity across four European countries", *Oxford Review of Economic Policy,* 22(4)

[11] Heckman, J. (2008): "Econometric Causality", *International Statistical Review,* 76(1), 1-27

[12] Honoré, B., and E. Kyriazidou (2000): "Panel data discrete choice models with lagged dependent variables", *Econometrica*, 68 (4), 839-874

[13] Huergo, E., Jaumandreu, J. (2004): “How does probability of innovation change with firm age?”, *Small Business Economics*, 22, 193-207

[14] Santos, C. (2009): "Recovering the Sunk Costs of R&D: The Moulds Industry Case", CEP DP0958

[15] Sutton, J. (1998): *Technology and Market Structure*, MIT Press

[16] Vives, X. (2008): "Innovation and Competitive Pressure", *The Journal of Industrial Economics*, 56(3), 419-469

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