Innovation, Competition, and Incentives: Evidence from Uruguayan firms.

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Abstract

Using a sample of manufacturing firms in Uruguay, this paper studies the effect of product market competition on innovative activities, labor practices and the provision of incentives within firms. Our estimates show that a higher level of market competition: (i) decreases innovative expenditures, (ii) increases the number of innovations per dollar spent on innovative activities, and (iii) leads firms to implement incentive payment schemes based on employee performance. These results suggest that, in developing economies, firms react to a higher level of market competition by providing incentives that ultimately lead to significant increases in the productivity of their innovative outlays. (JEL: L6, L10, L12, O3.)

Keywords: Competition, Innovation, Innovative Productivity, Incentives.

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1 Introduction

How does product market competition affect the rate of innovation? There is a relatively large and still growing literature that deals with this policy question from an empirical perspective.

Following the well-known ideas of Schumpeter (1942), Scherer (1967) was one of the first to study the relationship between patenting activities and competition using cross-sectional data of Fortune 500 companies in the US. Since then much effort has been devoted to uncovering the relationship between competition and innovation. Nickell (1996), based on the analysis of 670 UK firms, and Blundell et al. (1999), using data for US companies, find that competition positively affects innovation. Aghion et al. (2005), using a panel of 311 UK manufacturing firms, showed the existence of an inverted-U shape relationship between patenting activity and competition. However, Correa and Ornaghi (2014) cast doubts on this result. Using data for US manufacturing firms, they find that competition increases innovation and productivity growth.[1]

This literature focuses on the existing relationship between competition and innovation in developed economies. There is however scant empirical evidence (discussed below) on the interplay between competition and innovation in developing countries. This article contributes to filling this gap by examining the interaction between competition and innovative activities using a panel of manufacturing firms in Uruguay. Our goal is to measure how the implicit incentives provided by product market competition affect innovative outcomes, the productivity of the innovation process and the organization of working practices inside firms.

In emerging economies, a significant part of innovative activities is directed to adapting technologies that are usually embodied in capital goods. Much less effort is devoted to searching for novel and patentable discoveries. Uruguay is not an exception: Just 2.1% of all manufacturing firms in our sample reported to have applied for a patent in Uruguay or abroad during the time period 2007–2009. We thus naturally rely on innovation surveys (designed to capture the broader range of innovative activities) to construct several indexes of innovative outcomes and expenditures.

Our results come in three groups. First, we examine, as most of the empirical literature does, the effect of competition on innovative outcomes and innovative expenditures. Second, we explore the causal effect of competition on the productivity of innovative expenditures. Third, we study the relationship between competition, labor practices and incentive payments within firms.

On the one hand, our estimates are not conclusive with respect to the influence of competition on innovative outcomes; i.e., the number of successful innovations implemented by firms. On the other hand, our findings are unambiguous when we consider the input side of innovative activities. In this case, competition has a clearly negative and statistically

[1] Boldrin et al. (2011) and Hashmi (2013) obtain similar results.

significant effect on innovative expenditures.

These findings pave the way for our key results. First, we show that competition has a positive and statistically significant effect on the number of innovations per dollar spent on innovative activities. Put differently, higher levels of competition positively affect the productivity of the innovative process. Moreover, its impact is important: increasing competition in one standard deviation increases productivity between 1 and 2.9 standard deviations depending on the econometric specification. Second and finally, our results are inconclusive with respect to the effect of competition on firms' job practices. Neither monitoring activities nor job design arrangements are responsive to changes in competition intensity. However, we do find that higher competition levels lead firms to introduce incentive payment schemes based on employee performance.

We interpret our results as follows. When exposed to higher competition intensity, firms react not only by cutting innovative expenditures but also, and more importantly, by significantly increasing the productivity of these outlays. Moreover, the results suggest that, perhaps, behind the significant increase in productivity lies the implementation, within firms, of incentive payment schemes.

The Place in the Literature

Our article relates to a number of strands in the literature. First, a decent number of papers examine the relationship between innovation and product market competition in developing economies. Teshima (2008), for instance, studies the effect that trade liberalization policies had on innovation in Mexico during the period 2000–2003. The author shows that, as a response to lower tariffs, due to the NAFTA agreement, firms increased their innovative outlays for decreasing production costs rather than for creating new products. Carlin et al. (2004), using survey data for manufacturing firms in 24 developing countries, find that competition positively affects innovative outcomes when the number of competitors jumps from one to, at least, four or five. Gorodnichenko et al. (2010), using data from 27 transition economies, also provide evidence of a positive effect of foreign competition on innovative outcomes.

Although related, none of these articles study the effect of competition on innovative productivity and incentive payment schemes. Our results, differently from theirs, highlight that competition increases the productivity of the innovative process by potentially affecting the 'production function' through which firms innovate; i.e. by affecting innovative outlays and introducing incentive schemes.

Second, there is an interesting literature that explores the connections between foreign competition, total factor productivity, and technology upgrading. Notable examples are Amiti and Konings (2007) for Indonesia, Bustos (2011) for Argentina, Fernandes (2007) for Colombia, and Ferreira and Rossi (2003) for Brazil. Shortly said, all these articles find a robust positive impact of trade reforms on plant productivity. Our work complements theirs by showing that competition generates important productivity gains in the innovative process itself.

Third, extensive literature studies the connections between competition and incentives. A complete discussion of these articles is beyond the scope of this paper. On the theory side, Raith (2003) and Schmidt (1997) are the most relevant for our work. Raith (2003) studies how managerial incentives depend on the intensity of competition. The author concludes that a higher level of product market competition leads firms to provide stronger incentives to their managers. Schmidt (1997) shows that, though the effect of competition on managerial effort is ambiguous, there are natural scenarios in which more competition reduces managerial slack.

On the empirical side, Cuñat and Guadalupe (2005) study how competition affects (explicit) payment packages that firms offer to their executives and workers. Using a sample of UK firms, they find that higher levels of competition make compensation payments more sensitive to a firm performance. Bloom and Van Reenen (2007) using survey data for firms in developed economies, find that management practices improve when the intensity of product market competition becomes higher. Bloom et al. (2012) find, for transition economies that competition is correlated with better managerial skills.[2] Our results are in line with the findings of this literature. Indeed, our data, although limited, suggest that competition may lead to higher managerial efforts through the introduction of incentive payment schemes.

The rest of the paper is organized as follows. In Section 2 we provide a description of the data. Section 3 presents the econometric model and the identification strategy. Sections 4 and 5 show the results of the estimation. Section 6 concludes. Figures and tables are collected in the Appendix.

2 Data and Measurement issues

In this section, we present our competition and innovation indexes (interchangeable, indicators or variables) and describe the data which we use in our estimations.

Measuring Innovation

Our indicators of innovative activities are constructed using the information provided by the Survey of Innovation Activities. This survey, which is carried out by the National Agency of Research and Innovation (ANII) in Uruguay, records self-reported information about innovation within firms along regular time intervals of three-years long each. The target population is firms with more than five employees and the sample has a panel data structure.

We use four consecutive time periods (the first one being 2004–2006) and consider only

[2] For a good review of this literature, see Van Reenen (2011).

manufacturing firms with a positive number of employees and sales.[3] Our final sample has 3,336 observations. Figure 1 depicts the size distribution of firms according to the number of employees. The figure illustrates that the majority of firms are relatively small. Precisely, 50% of them have fewer than 35 employees while the largest 5% has more than 400 employees. We use the information provided by the survey to measure:

Innovative Outcomes: The survey classifies innovations into four categories: (i) product innovations –i.e., selling a new or improved product, (ii) process innovations –i.e., adoption of new or improved processes to reduce costs, (iii) organizational innovations –i.e., changes in the organizational design of the firm, and: (iv) marketing innovations –i.e., adoption of new commercialization methods.

We then construct four binary indicators of innovative outcomes. First, a variable called 'technological innovations' that indicates if a firm has introduced an innovation belonging to either category (i) or (ii). Second, a variable named as 'non-technological innovations' that records if a firm has introduced an innovation belonging to either one of the two remaining categories. Third, a variable designated as 'any innovation' that indicates if a firm has introduced an innovation belonging to *any* category. Finally, a variable called 'any new innovation' that indicates if any type of implemented innovation is perceived by the innovating firm as *novel* for either one domestic or international markets.

For developing countries, these measures of innovation are much more suitable than others like patent counts. The reason is that most of the innovative activities in Latin American countries are directed to adopting (adapting) technologies that are embodied in capital goods rather than pursuing novel patentable discoveries. Our data confirm this feature since, for instance, just 2.1% of the firms in our sample applied for a patent in Uruguay or abroad in the time interval 2007–2009.

Table 1 provides some descriptive statistics. Observe that, along the four-time intervals, 43% of the firms introduced an innovation but just 21% of them reported to have introduced 'any new innovation'. Besides, the majority of innovations have a technological nature since 38% of the firms reported the introduction of a technological improvement while 20% percent of them said that their innovations were directed to organizational and marketing improvements.

Innovative Expenditures: The survey also reports the monetary budget that firms allocate to innovative activities. In particular, it distinguishes between three different kind of expenditures: (i) R&D expenditures –i.e., money used to accumulate knowledge about products and processes, (ii) capital expenditures –i.e., money devoted to acquire capital goods, and (iii) other expenditures –i.e., money allocated to the acquisition of technology transfer, industrial design, etc.

We construct then three variables of innovative efforts. In particular, we focus our attention on the ratio over sales of (i) R&D expenditures, (ii) R&D plus capital expenditures, and:

[3] Our sample does not include manufacturing sectors with less than four firms because in this case the competition index cannot be accurately computed.

(iii) total innovative expenditures. Table 1 reports some descriptive statistics for these variables. Similarly, Figure 2 illustrates the distribution of the ratio (with respect to sales) of total innovative expenditures. The (average) ratio of R&D expenditures amounts to 0.21%, the ratio of R&D plus capital expenditures is roughly 1.41%, while the ratio of total innovative expenditures is equal to 1.75%. Besides, 50% of the firms in our sample spend, on total, less than 1.51% of their sales on innovative expenditures and only 10% of them allocate overall more than 10% of its sales in innovative expenditures. These statistics show that most of the relatively small innovative budget is allocated to the acquisition of capital goods. Thus, instead of only using, as it is usually done in the literature, R&D expenditures, we also take into account the amount of money that is spent on acquiring capital goods.

Productivity: To measure the (average) productivity of the innovative process, we construct three different indexes. These variables are just ratios of (different types of) innovative outcomes with respect to *total* innovative expenditures (in millions of Uruguayan pesos of 2010).[4] To avoid working with a selected sample of firms with positive expenditures, we compute these variables at the industry level (disaggregated at the three-digit ISIC codes). The productivity index for industry k at time period t is

$$p_{kt} = \frac{\text{innovative outcome}_{kt}}{\text{aggregate expenditure}_{kt}}.$$

The entries in the numerator of p_{kt} are: (i) the number of firms that have introduced at least one (of any type) innovation; i.e., the number of innovators in the industry, (ii) the number of *any type* of innovations in the industry, and: (iii) the number of *any type* of *new* innovations in the industry.[5]

Table 1 provides descriptive statistics of our productivity measures and Figure 3 illustrates the distribution of productivity for any type of innovation. Observe, for instance, that the average productivity index is 0.26. There are, at least, two different interpretations of this number. The first, and perhaps more natural is that an expenditure of approximately 50.000 dollars produces 0.26 innovations on average across industries.[6] In other words, the cost of getting one innovation of *any type* is around 192.000 dollars for the average industry. The second interpretation suggests that by spending 50.000 dollars, the average industry gets an innovation with probability 0.26. The average productivity is, however, larger than the median since 50% of the industries displays productivity roughly smaller than 0.09. Of course, when the value of the indexes goes up, productivity increases since

[4] Because innovative outcomes correspond to a three-year period and innovative expenditures correspond to the last year of the period, we multiply innovative expenditures by three to approximate the total expenditure in the three-year period.

[5] For each category (process, product, organizational or marketing innovation), the Survey of Innovation Activities records if a firm has innovated (i.e., if it has implemented at least one innovation) independently of the number of innovations that the firm could have implemented. We thus approximate the number of innovations by simply adding the number of categories in which the firm has indeed innovated.

[6] 50.000 dollars $\simeq$ 1.000.000 Uruguayan pesos in the year 2010.

the same number of outcomes are generated by spending less money.

Measuring Competition

To construct our indicator of (product market) competition, we use the Survey of Economic Activity from year 2003 to year 2012.[7] Following Aghion et al. (2005), we use, as an index of competition, the Lerner or the price-cost margin index. More precisely, the competition index for industry k at time period t is given by

$$c_{kt} = 1 - m_{kt},$$

where:

$$m_{ikt} = \frac{\text{gross output}_{ikt} - \text{intermediate consumption}_{ikt} - \text{wage expenses}_{ikt}}{\text{gross ouput}_{ikt}}.$$

is the price-cost margin at time period t for firm i in industry k, and:

$$w_{ikt} = \frac{\text{gross output}_{ikt}}{\sum_{i\in k} \text{gross ouput}_{ikt}}$$

is the share of gross output at time period t for firm i in industry k. Observe that $0 \leq c_{kt} \leq 1$ and that when $c_{kt} = 1$, industry k is perfectly competitive at time period t. Of course, the intensity of competition increases monotonically as c_{kt} goes from zero to one.

Table 1 provides some descriptive statistics for the competition variable and Figure 4 illustrates its distribution. Its mean is 0.82 and its standard deviation is equal to 0.09. These numerical values are in line with those reported by Correa and Ornaghi (2014) and Hashmi (2013) for the US.

3 Econometric Model and Empirical Strategy

We study the effect of competition on innovation by estimating the following equation

$$y_{ikt} = \beta\, c_{k(t-1)} + \gamma' x_{ikt} + \eta_i + \eta_t + \epsilon_{ikt}, \tag{1}$$

where y_{ikt} is the innovative variable (i.e., outcomes, expenditures, productivity, etc.) of firm i in industry k at time period t, $c_{k(t-1)}$ is the index of competition in industry k at time period $t-1$, x_{ikt} is a vector of controls at the firm level, η_i is a firm fixed effect, η_t is a time fixed effect, and ϵ_{ikt} is a time-varying unobservable variable that affects the innovation of firm i in industry k at time period t.

[7] This survey is yearly administered by the National Bureau of Statistics.

Empirical Strategy

It is well known that estimating the causal effect of competition on innovation faces several obstacles. Three are the main threats to identification. First, the potential existence, at the firm level, of unobserved characteristics that are correlated with both innovative outcomes and competition. If this were the case, the existing correlation between competition and innovation could obey to the mere presence of these unobserved characteristics rather than to a causal effect from competition to innovation. We attack this problem by including, in our regressions, firm fixed effects. In this way, we control for any firm time-invariant unobservable variable that may lead to a spurious relationship between innovation and competition.

Second, both innovative outcomes and competition are usually correlated with the phase of the business cycle. Along expansionary cycles, firms have usually more incentives to introduce innovations due to the larger market demand. However, a higher market demand usually makes profitable the entry of new firms to the industry. Our estimates would then show a positive correlation between innovative outcomes and competition even if there were no causal relationship between them. To deal with this problem, we include, in our regressions, time fixed effects. In this manner, we control for common trends that may affect both competition and innovative outcomes across industries.

The third and most challenging threat to identification is the mutually endogenous nature of innovative outcomes and competition. The key concern is the possibility of reverse causality running from innovation to competition. When a firm adopts a successful innovation, it usually gets a higher market share *and* also increases its price-cost margin. These two simultaneous effects, by affecting our competition variable, would undermine the credibility of our estimates.

We address this threat by following two complementary avenues. First, instead of using our contemporaneous measure of competition, we lag our, otherwise unaffected, competition variable by one year. This differential timing between the indexes of competition and innovative outcomes decreases the likelihood of capturing the correlation between our variables due to the reverse causality problem discussed above. Second, we instrument the level of competition in the industry by using a measure of import penetration from China (henceforth, import penetration.)

Instrumenting Competition: We measure import penetration from China using statistical information from The United Nations International Trade Statistics Database.[8] Our index of import penetration for industry k at time period t is:

$$\frac{\text{imports from China}_{kt}}{\text{domestic production}_{kt} + \text{total imports}_{kt} - \text{total exports}_{kt}}.$$

This variable measures the proportion of total domestic consumption that is served

[8]Other authors, most notably Aghion et al. (2005) and Correa and Ornaghi (2014), also instrument competition using import penetration.

by Chinese imports. Table 1 provides some descriptive statistics for this index. More important for the validity of our results, table 2 allows us to make two arguments. First, it seems clear that import penetration is far from being a homogeneous process across industries and time periods. Indeed, the table shows that not only import penetration has increased over time but also its remarkably differential impact across industries. Specially affected industries are textiles (industry 17), apparel (18), television and communication equipment (32), bicycles and motorcycles (35), and games and toys (36) as shown in table 2. Second, changes in import penetration are clearly exogenous to the performance of domestic innovative activities. Indeed they are part of the broader trend that has China as one of the leading actors in international markets. At the risk of being repetitive, there are no obvious connections, other than competition, between import penetration and domestic innovative activities. Put differently, we believe that our instrument provides exogenous variation in the intensity of competition at both industry level and time.

To examine the relevance of our instrument, we estimate a first stage model. Table 3 reports the regression results between import penetration and competition. The model includes firm and time fixed effects, and standard errors are clustered at the industry level. The results show that the effect of import penetration on competition is positive and statistically significant. Moreover, the effect is quantitatively large since an increase in 10 percentage points in import penetration (around 1 standard deviation) increases our competition index in 0.022 (around 0.24 standard deviations). For testing the relevance of our instrument, we compute a (cluster) robust F-statistic. The robust F-statistic is equal to 12.7 and it is above the critical values computed in Stock and Yogo (2005) for testing the presence of weak instruments.

4 Competition and Innovation

4.1 Outcomes and Expenditures

Table 4 reports the estimated effect of competition on our different variables of innovative output (outcomes). Competition has no statistically significant effect on any one of them. If any, although point estimates are not precise, the results suggest that competition decreases the probability of innovating no matter the category to which an innovation belongs to. The results are however different when, instead of outcomes, one considers innovative expenditures.

Table 5 reports the estimated effect of competition on different measures of innovative expenditures. The results show that competition has a clearly negative and statistically significant effect on the ratio over sales of both 'R&D plus capital acquisition expenditures' and 'total innovative expenditures.' We do not find however any evidence that competition affects the ratio over sales of 'R&D expenditures'; i.e., expenditures on R&D without taking into account expenditures on capital goods.

As one can deduce, the effect of competition on (the ratio over sales of) total innovative expenditures is mainly driven by the (average) firm's policy of cutting the budget allocated for acquiring capital goods. This should not be surprising since expenditures in emerging countries come from adopting and adapting technologies embodied in capital goods. Uruguay is not an exception as capital expenditures represent around 70% of total innovative expenditures.

Ultimately, the results say that an increase in competition decreases the amount of innovative expenditures *per unit* of sales. One, however, cannot infer from them whether this effect obeys to changes in either sales, innovative expenditures or even both. Table 6 sheds light on this issue. It shows that, at least, part of the decrease in the corresponding ratios (when competition increases) is explained by a substantial drop in the budget allocated to innovative activities.

Overall, these results suggest that, as a consequence of a higher competition level, the (average) firm becomes internally more productive in managing its innovative process. We examine this matter below.

4.2 Productivity of the Innovative Process

Table 7 reports the estimated effect of competition on the productivity of the innovative process. The findings are conclusive. Competition has a positive and statistically significant effect on any of our productivity indexes. Besides, the impact of competition is quantitatively important: an increase in one standard deviation in the competition index increases the productivity of the innovative process between 1 and 2.9 standard deviations depending on the econometric specification. The comparison of the OLS and IV estimates, suggests a negative bias in OLS which is consistent with the presence of reverse causality from innovation to competition or a attenuation bias due to measurement error in the competition index. Let us discuss these results more carefully.

For concreteness, we focus our attention on the ratio (over total innovative expenditures) of the number of any type of innovations; i.e., the second column of table 7. There are several complementary ways of exploring the efficiency effects of a higher competition level. For all of them, we assume that the competition index increases in one standard deviation. To get an idea of the magnitude of this shock, it suffices to say that after being exposed to this competitive change, the average industry passes to rank between the 10% of the most competitive ones. In qualitative terms, the average industry is exposed to a 'large' competitive shock.

Being said that, recall, from our discussion in section 2, that, in an average industry, a total innovative expenditure of approximately 50.000 dollars results in 0.26 innovations. Then, when competition increases, the same total innovative expenditure results in 1.29 innovations; that is, a higher competition level increases (average) productivity by a factor close to 4.9. Alternatively put, the cost of obtaining an innovation decreases roughly from 192.000 dollars to 38.000 dollars. Admittedly, this large effect is at least partially driven by the lack of precision of our point estimates. However, the *lower bound* of these costs savings is also significant. Taking a 95% confidence interval, when competition increases in one standard deviation, spending 50.000 dollars results in at least 0.57 innovations instead of 0.26; i.e., an increase in the average productivity index by a factor of 2.2. In monetary terms, the cost of one innovation decreases at least from 192.000 dollars to 87.000 dollars; i.e., a cost-saving close to 45%.

The conclusions are almost the same when productivity is, for instance, measured by the ratio (over total innovative expenditures) of the number of any 'new' innovations. Similarly, Table 8 presents the estimated effect of competition on productivity when one classifies innovations either as technological or non-technological ones. As can be seen, the results are also robust to this alternative specification. In summary, although the results should be cautiously taken, the lower bound of productivity gains due to a higher level of competition are significant: an increase in one standard deviation in competition implies that the median industry increases its productivity by a factor of 4. What are the mechanisms through which competition increases productivity?

5 Competition, Labor Practices and Explicit Incentives

Recent literature has shown that higher competition levels are correlated with better management practices.[9] An important example is Bloom et al. (2015). The authors show (using data for English public hospitals) that higher competition levels lead to better management quality and hospital performance. We believe that, in our case, competition affects productivity through changes in both labor practices and incentives within firms. To put differently, the causality we have in mind is the following: an increase in competition leads to better labor practices and the introduction of incentives payment schemes which, in turn, increase the productivity of the innovative process.

To test these ideas, we first create two variables that capture introductions or changes in labor practices within firms.[10] Precisely, we group labor practices into the following two categories: (i) 'job design', and: (ii) 'monitoring.' In the job design group, we include survey questions that measure changes in working responsibilities, job duties, team working practices and redesign of the hierarchical structure of the firm. The monitoring category contains questions that capture changes in peer monitoring activities and communication channels. Secondly, we construct a third binary variable that we call '(explicit) incentives' that indicates if firms have introduced payment schemes based on the performance of their employees.[11] Table 1 reports some descriptive statistics for these variables. The table shows that 21% of the firms base their payment schemes on employee performance, 28% of the companies use monitoring practices and 26% of them have delineated job designs.[12]

[9] For a review of the literature, see Van Reenen (2011).

[10] The data for this section comes from the Survey of Innovation Activities.

[11] Appendix C describe the construction of labor and explicit incentives variables with more detail.

[12] The smaller number of observations of these variables in comparison to the others is because these

Third, we run an OLS regression between competition and each variable controlling for firm and time fixed effects, and firm's controls. Unfortunately, we cannot instrument competition because the data about labor practices and incentives were not available in the first time period (2004–2006) of the survey. Missing that information, we cannot reject the hypothesis that our instrument is not relevant.

The main challenge to identification is, as previously discussed, the possibility of reverse causality running from changes in labor practices (incentives) at the firm level to changes in competition at the industry level. A firm, by improving labor practices, might increase its price-cost margin which, in turn, would negatively affect the measure of competition. This problem should have a minor (if any) effect on our estimates because of the ensuing reasons. First, the competition variable uses price-cost margins for *all* firms in an industry. Thus the correlation between labor practices and price-cost margins at the firm level should have minor effects at the industry level. Second, we use the Survey of Innovation Activities to measure labor practices–incentives but the Survey of Economic Activity to measure competition. The different sources of information should alleviate the problem since firms in these data sets are *not* all the same. Third, we use the competition variable with a time lag of one period. This different timing should also mitigate concerns about reverse causality. Lastly, even if reverse causality were present in the data, the negative correlation between better labor practices (incentives) and competition should cause a negative bias in the estimates. In other words, the estimates should be considered as lower bounds to the causal effect of competition on labor practices and incentives.

Table 9 reports the estimated effect of competition on labor practices and incentives. As can be seen, competition has no statistically significant effect on labor practices. In other words, an increase in competition does not lead firms to introduce monitoring practices or change their job design. The results are significantly different when, instead of labor practices, one considers incentive schemes. The results show that competition has a clearly positive and statistically significant effect on the introduction of incentive schemes.

Moreover, the impact of competition is not negligible: an increase of one standard deviation in competition means that around 3% of the firms start introducing new incentive-based compensation packages. Table 10 presents the estimated effect of competition on labor practices and incentives but instead of using binary variables for the latter, we follow Bloom and Van Reenen (2007) and Bloom et al. (2012) and compute z-scores for labor practice and incentive variables. The results just confirm the findings showing that the effect of competition on these variables is robust.[13]

questions were first introduced in the period 2007–2009.

[13]See Bloom et al. (2012) for a detailed description of the methodology for computing z-scores.

6 Discussion and Conclusions

In developing countries, like Uruguay, intellectual property rights, and patents, in particular, play little (if any) role as incentive tools for the creation of new products and technologies. In these countries, innovative outcomes, like processes and product improvements, are mostly a by-product of the adaptation of existing market technologies. Thus the long-standing debate concerning appropriability and spillovers losses its intuitive appeal.

In that environment, the firms in our sample reacted to higher levels of product market competition through changes along several dimensions. On the one hand, they substantially diminished the budget allocated to the acquisition of capital goods. Any sensible interpretation of this result should suggest that a higher level of product market competition decreases the marginal profitability of adapting existing market technologies. Notwithstanding that, we do not find any evidence that higher levels of product market competition affect innovative outcomes.

On the other hand, we found that firms responded to higher levels of product market competition by achieving significant productivity gains in their innovative process. Suggestively, a higher level of product market competition also guided firms to provide incentive payments schemes for their employees. We believe that this sort of complementary between explicit incentives at the interior of firms and implicit incentives at the market level might be at the heart of the drastic productivity gains. Further research efforts should be directed to get a better knowledge of the productive process that transforms innovative inputs into innovations. A detailed understanding of the inner workings of the innovative process is fertile territory for future empirical research.

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Appendix A: Tables

Table 1: Descriptive statistics

Variables	Mean	S.D.	Obs.
Competition index	0.82	0.09	3,336
Import penetration from China	0.07	0.10	3,336
Innovative outcomes			
Technological innovation	0.38	0.49	3,336
Non-technological innovation	0.20	0.40	3,336
Any innovation	0.43	0.50	3,336
Any *new* innovation	0.21	0.41	3,336
Innovative expenditures (in % of sales)			
R&D expenditures	0.21	1.41	3,335
R&D plus capital expenditures	1.41	8.52	3,335
Total innovative expenditures	1.75	8.92	3,335
Productivity of the innovative process on:			
N. of innovators	0.16	0.54	3,309
N. of innovations	0.26	0.62	3,309
N. of *new* innovations	0.08	0.12	3,309
Management practices			
Job design	0.26	0.30	2,539
Monitoring	0.28	0.39	2,539
Incentives	0.21	0.41	2,539
Firm's characteristics			
Firm's age	27	21	3,313
N. of employees	90	177	3,336
Holding company dummy	0.15	0.36	3,335

Source: Survey of Innovation Activities 2004–2006, 2007–2009, 2010–2012 and 2013–2015 for innovation variables, management practices and firm's characteristics, Survey of Economic Activity 2003–2012 for the competition index, and UN Comtrade for import penetration from China.

Table 2: Evolution of Import Penetration from China

Industry	Year 2003	2006	2009	2012
15	0.00	0.00	0.00	0.00
17	0.07	0.25	0.23	0.34
18	0.15	0.36	0.32	0.43
19	0.05	0.16	0.17	0.17
20	0.00	0.01	0.03	0.03
21	0.00	0.01	0.01	0.00
22	0.00	0.00	0.01	0.01
24	0.03	0.05	0.06	0.07
25	0.03	0.06	0.06	0.09
26	0.01	0.05	0.05	0.06
27	0.00	0.02	0.04	0.07
28	0.01	0.04	0.05	0.08
29	0.05	0.11	0.16	0.18
31	0.04	0.07	0.11	0.29
32	0.09	0.19	0.35	0.53
33	0.03	0.09	0.09	0.13
34	0.01	0.02	0.11	0.14
35	0.08	0.22	0.64	0.58
36	0.12	0.32	0.26	0.42
Total	0.04	0.11	0.14	0.19

Source: UN Comtrade for imports from China to Uruguay and exports from Uruguay, and Survey of Economic Activity for domestic production.
Note: Import Penetration from China is the ratio between Chinese imports and apparent consumption (domestic production less exports plus imports) in sector j at year t. Industry codes are two-digits ISIC codes revision 3.

Table 3: First stage estimation: Effect of Import Penetration from China on Competition

Dependent Variable: Competition index	OLS-FE (1)
Import penetration from China	0.220***
	(0.062)
Log(Firm's age)	−0.014**
	(0.007)
Log(Firm's age)^2	0.002*
	(0.001)
Log(N of employees)	0.002
	(0.009)
Log(N of employees)^2	−0.001
	(0.001)
Holding company dummy	0.003
	(0.003)
First stage F-statistic	12.734
R-squared	0.296
Observations	2,591

Note: This table presents the first stage estimates for the IV regressions. The dependent variable is competition, the instrument is *Import penetration from China*, and the model include firm and time fixed effects. The first stage F-statistic is the cluster-robust F-statistic. Asymptotic standard errors clustered at the industry level are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4: Effect of Competition on Innovative Outcomes

	Technological innovation	Non-technological innovation	Any innovation	Any new innovation
	(1)	(2)	(3)	(4)
Panel A. OLS-FE				
Competition index	-0.246^{**}	-0.085	-0.213	-0.232
	(0.121)	(0.131)	(0.129)	(0.150)
Panel B. IV-FE				
Competition index	-1.337	-0.366	-1.538	-0.751
	(0.984)	(0.670)	(1.081)	(0.775)
First stage F-statistic	12.320	12.320	12.320	12.320
Observations	2,607	2,607	2,607	2,607

Note: This table presents the OLS and IV estimates with firm fixed effects for the effect of competition on innovation. Each column estimates the effect of competition on a different innovation outcome. Panel A reports OLS estimates, and Panel B reports IV estimates where competition is instrumented using *Import penetration from China.* All models include firm fixed effects, time fixed effects, and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. The first stage F-statistic is the cluster-robust F-statistic. Asymptotic standard errors clustered at the industry level are in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 5: Effect of competition on Innovative Expenditures

	R&D exp. over sales	R&D plus capital exp. over sales	Total innovative exp. over sales
	(1)	(2)	(3)
Panel A. OLS-FE			
Competition index	−0.214	−0.976	−2.601
	(0.286)	(1.523)	(1.620)
Panel B. IV-FE			
Competition index	−0.252	−17.869**	−19.394**
	(0.876)	(7.752)	(8.411)
First stage F-statistic	12.323	12.323	12.323
Observations	2,606	2,606	2,606

Note: This table presents the OLS and IV estimates with firm fixed effects for the effect of competition on innovation. Each column estimates the effect of competition on a different innovation outcome. Panel A reports OLS estimates, and Panel B reports IV estimates where competition is instrumented using *Import penetration from China*. All models include firm fixed effects, time fixed effects, and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. The first stage F-statistic is the cluster-robust F-statistic. Asymptotic standard errors clustered at the industry level are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 6: Effect of Competition on Innovative Expenditures

	Log R&D exp.	Log R&D plus capital exp.	Log Total innovative exp.
	(1)	(2)	(3)
Panel A. OLS-FE			
Competition index	-2.196^{*}	-3.136^{***}	-2.454^{***}
	(1.087)	(1.003)	(0.797)
Panel B. IV-FE			
Competition index	-1.025	-12.490^{**}	-12.015^{***}
	(3.934)	(4.939)	(4.238)
First stage F-statistic	12.320	12.320	12.320
Observations	2,607	2,607	2,607

Note: This table presents the OLS and IV estimates with firm fixed effects for the effect of competition on innovation. Each column estimates the effect of competition on a different innovation outcome. Panel A reports OLS estimates, and Panel B reports IV estimates where competition is instrumented using *Import penetration from China*. All models include firm fixed effects, time fixed effects, and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. The first stage F-statistic is the cluster-robust F-statistic. Asymptotic standard errors clustered at the industry level are in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 7: Effect of Competition on Innovative Productivity

	Indexes		
	N. of innovators	N. of any innovations	N of any new innovations
	(1)	(2)	(3)
Panel A. OLS-FE			
Competition index	0.885***	1.476***	0.423**
	(0.340)	(0.571)	(0.189)
Panel B. IV-FE			
Competition index	5.938***	11.407***	3.912**
	(1.984)	(4.038)	(1.685)
First stage F-statistic	12.355	12.355	12.355
Observations	2,591	2,591	2,591

Note: This table presents the OLS and IV estimates with firm fixed effects for the effect of competition on innovation. Each column reports the estimate of the effect of competition on a specific efficiency measure. Panel A reports OLS estimates, and Panel B reports IV estimates where competition is instrumented using *Import penetration from China*. All models include firm fixed effects, time fixed effects, and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. The first stage F-statistic is the cluster-robust F-statistic. Asymptotic standard errors clustered at the industry level are in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 8: Effect of Competition on Innovative Productivity

	Indexes		
	N. of technological innovators (1)	N. of technological innovations (2)	N of new technological innovations (3)
Panel A. OLS-FE			
Competition index	0.661***	0.938**	0.337**
	(0.240)	(0.354)	(0.151)
Panel B. IV-FE			
Competition index	4.119***	6.335***	3.073***
	(1.294)	(2.141)	(1.132)
First stage F-statistic	12.355	12.355	12.355
Observations	2,591	2,591	2,591

Note: This table presents the OLS and IV estimates with firm fixed effects for the effect of competition on innovation. Each column reports the estimate of the effect of competition on a specific efficiency measure. Panel A reports OLS estimates, and Panel B reports IV estimates where competition is instrumented using *Import penetration from China.* All models include firm fixed effects, time fixed effects, and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. The first stage F-statistic is the cluster-robust F-statistic. Asymptotic standard errors clustered at the industry level are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 9: Effect of Competition on Labor Practices and Incentives

	Labor practices		
	Job design (1)	Monitoring (2)	Incentives (3)
Competition index	−0.040	−0.066	0.294***
	(0.054)	(0.140)	(0.109)
R-squared	0.012	0.019	0.030
Observations	2,070	2,070	2,070

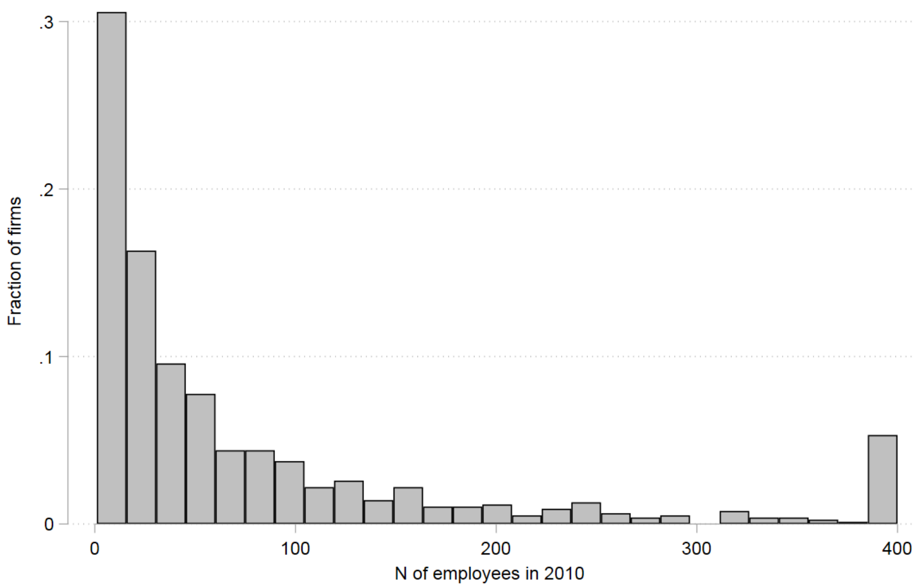
Note: This table presents OLS estimates with firm fixed effects for the effect of competition on labor practices and incentives. All models include time fixed effects, firm fixed effects and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. Asymptotic standard errors clustered at the industry level are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 10: Effect of Competition on Labor Practices and Incentives

	Labor practices		
	Job design z-score (1)	Monitoring z-score (2)	Incentives z-score (3)
Competition index	−0.135	−0.163	0.697***
	(0.180)	(0.344)	(0.259)
R-squared	0.012	0.019	0.030
Observations	2,070	2,070	2,070

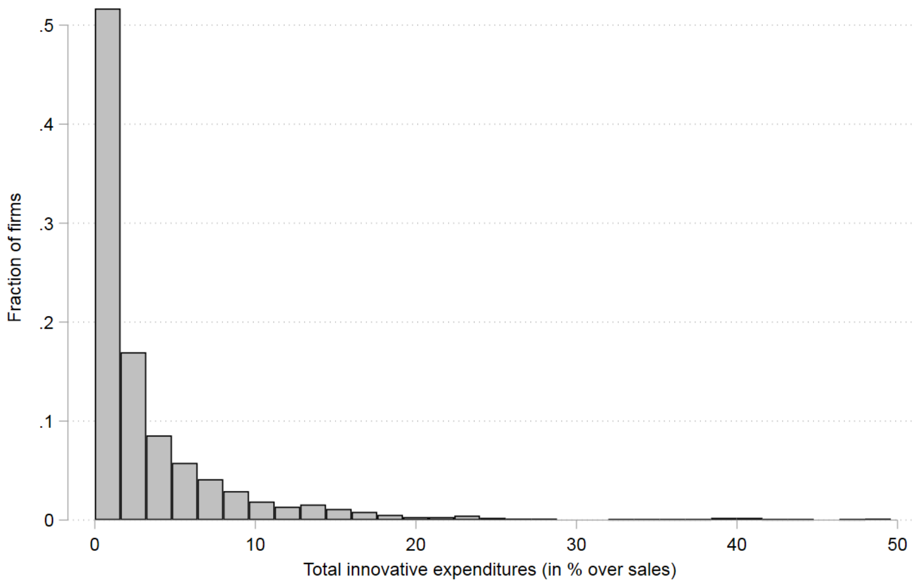
Note: This table presents OLS estimates with firm fixed effects for the effect of competition on labor practices and incentives. All models include time fixed effects, firm fixed effects and the following controls: $Log(age)$, $Log(age)^2$, $Log(employees)$, $Log(employees)^2$ and a holding company dummy. Asymptotic standard errors clustered at the industry level are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Appendix B: Figures



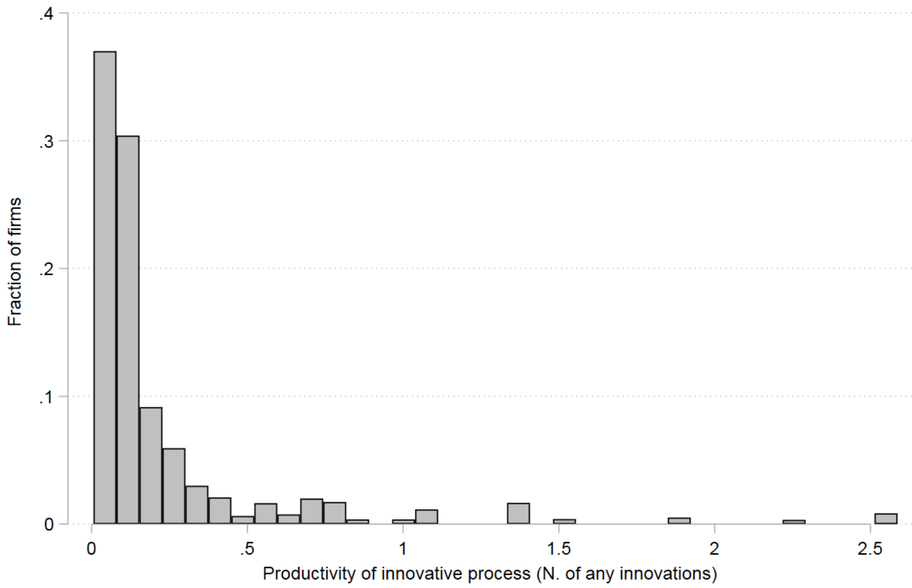
Source: Survey of Innovation Activities 2010–2012, Uruguay.
Note: Sample of manufacturing firms with positive employment and sales.

Figure 1: Firm Size Distribution



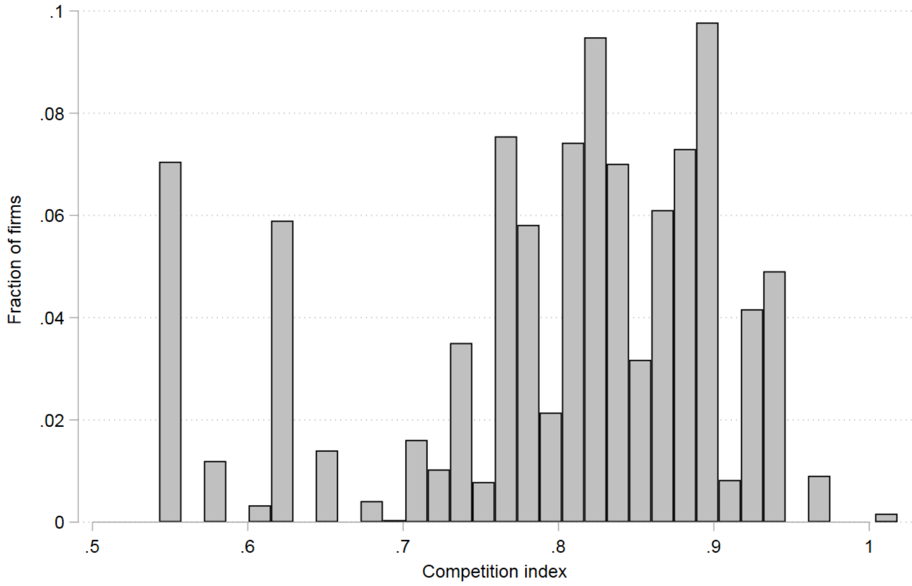
Source: Survey of Innovation Activities 2004–2006, 2007–2009, 2010–2012 and 2013–2015, Uruguay.
Note: Sample of manufacturing firms with positive employment and sales, and positive expenditure in innovative activities.

Figure 2: Distribution of Total Innovative Expenditures



Source: Survey of Innovation Activities 2004–2006, 2007–2009, 2010–2012 and 2013–2015, Uruguay.
Note: Sample of manufacturing firms with positive employment and sales.

Figure 3: Distribution of Productivity of Innovative Process



Source: Survey of Innovation Activities 2004–2006, 2007–2009, 2010–2012 and 2013–2015, Uruguay.
Note: Sample of manufacturing firms with positive employment and sales.

Figure 4: Distribution of the Competition Index

Appendix C: Construction of the labor practices and explicit incentives variables

The Survey of Innovation Activities includes a set of 8 questions about labor practices and incentives. We assign these questions to (i) 'job design', (ii) 'monitoring', and (iii) 'incentives'. In the job design group, we include 5 questions that measure changes in working responsibilities, job duties, team working practices and redesign of the hierarchical structure of the firm. The monitoring category contains 2 questions that capture changes in peer monitoring activities and communication channels. The incentives category includes a question that indicates if firms have introduced payment schemes based on the performance of their employees.

To compute a index for each category, for each firm we compute the mean across the questions in the category. This index goes from zero to one and it can be interpreted as the fraction of 'practices' in the category implemented by the firm.

For the z-scores we follow a similar procedure to Bloom and Van Reenen (2007) and Bloom et al. (2012). To compute the z-scores for each category, we normalize by subtracting the mean and dividing by the standard deviation of the category. By construction, the z-scores have mean zero and a standard deviation of one, independently of the number of questions used in each category.