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ABSTRACT

Profiting from Innovation: Firm Level Evidence on Markups*

While innovation is argued to create value, private incentives of firms to innovate are driven by what part of the value created firms can appropriate. In this paper we explore the relation between innovation and the markups a firm is able to extract after innovating. We estimate firm-specific price-cost margins from production data and find that both product and process innovations are positively related to these markups. Product innovations increase markups on average by 5.1% points by shifting out demand and increasing prices. Process innovation increases markups by 3.8% points due to incomplete pass-through of the cost reductions associated with process innovation. The ability of the firm to appropriate returns from innovation through higher markups is affected by the actual type of product and process innovation, the firm's patenting and promotion behavior, the age of the firm and the competition it faces. Moreover, we show that sustained product innovation has a cumulative effect on the firm's markup.

JEL Classification: D24, L11 and O31
Keywords: markup, process innovation, product innovation and productivity

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1 Introduction

Today innovation is being hailed as a key driver of growth for the economy and for the survival and success of individual firms. Understanding the returns to investments in R&D and other innovative activities is, therefore, a critical step in convincing managers and policy makers of the importance of making such investments. The debate is not new and over the past decades, researchers have related research and development spending with measures of labor and total factor productivity, suggesting a positive relation between R&D and firm profitability and survival (Hall and Mairesse, 2010). Furthermore, a long tradition exist in estimating the effect of R&D and innovation on the market value of firms (Czarnitzki et al. 2006).

In this paper we complement and advance the literature by focusing on how firms profit from their innovation activities through its effect on the markups a firm is able to extract after innovating. As such, the paper is related to Geroski et al. (1993) who estimate the relationship between innovation and profitability for a sample of large UK firms, where profitability is measured as the accounting net profit margin. However, accounting margins are only noisy measures for true economic margins (Schmalensee, 1989) - and more importantly the errors in accounting margins are expected to be correlated with the innovative activities of firms.[1] Therefore, we opt for estimating markups instead of directly observing them from the data. To this end, we rely on the basic insight of Hall (1988) that market power drives a wedge between the observed share of input costs in total revenue and the output elasticities of the particular input. The methodology has been applied in various papers, investigating the impact of trade liberalization on domestic markups (Levinsohn, 2003; Abraham et al. 2009) and the impact of privatization on markups (Konings, Van Cayseele and Warzynski, 2005) among others. De Loecker and Warzynski (2012) show how the methodology can generate firm specific markups. Basically one needs to identify the output elasticities of inputs and by comparing them with the share of input costs in revenue, one can infer a measure for firm specific markups.

With these firm specific markup estimates at hand, we can estimate the effects of innovation on these markups. These estimates provide us with some insight on how firms profit from their innovation activities. Moreover, we distinguish between product and process innovations. In principle, one would expect process innovations to increase technical efficiency while the impact on markups depends essentially on the demand system and the implied cost pass-through. On the other side, product innovation is thought to increase markups by generating a firm specific demand while its impact on technical efficiency should be negative, if anything.

In our analysis we find that both product and process innovation increase firm spe-

[1] For example, accounting depreciation rates do not reflect returns to scale or the economic user cost of capital. If innovative firms differ systematically in their returns to scale or their capital intensity from non-innovative firms, this could introduce biases in the estimate for the relationship between innovation and markups.

cific markups. More precisely we find markups to be 3.8% percentage points higher for firms realizing a process innovation and 5.1% points higher for firms realizing a product innovation. This is particularly true for smaller firms where the effect of product innovation is more likely felt at the firm level compared to large multi-product firms. This relationship is robust against controlling for firm and market specific factors influencing both innovation and markups.

Our finding on the importance of product innovation in affecting markups and prices is very consistent with the findings of Foster et al. (2008) that show that idiosyncratic demand shocks seem to affect firm performance and survival more than shocks to pure technical efficiency. While we cannot claim to have isolated all possible effects on markups and firm productivity through innovation, a substantial part of the demand side variation found across firms could be explained by these product innovation activities at the firm level. Hence, we argue that the role of R&D investments related to product innovation and more importantly, ex post successful product innovation could be an important factor in explaining observed heterogeneity between firms (Syverson, 2011). Our results on process innovation contrast with the findings of the productivity literature that have typically found no effect or a negative effect on revenue productivity of process innovation.

In separate analyses we confirm that changes in firm prices are directly related to product innovation and process innovation. While product innovations tend to increase prices, process innovation is more likely to decrease prices. From our analysis we can also infer marginal costs and show that only process innovation tends to lower marginal costs. Product innovation has no significant effect on costs. These effects are consistent with product innovation shifting out demand, and process innovation reducing costs, while both affect the the firm specific markup.

After confirming the positive and economically significant effect of both product and process innovation on the firms markups, we attempt to dig a little deeper into how firms actually profit from these innovations. First, we examine the effect of different types of product and process innovation. Our results indicate that especially product innovation involving new design or new functions of the product and process innovation due to the introduction of new machinery influence the markup positively.

Second, following a long literature on the relation between market structure and innovation, we show that product innovation allows innovative firms in intermediately competitive markets to appropriate returns from their innovation efforts through increases in their markups. Atomistic and monopolistic markets are less related to increases in markups through innovation. Process innovations only impact markups in less competitive markets as cost improvements are not fully passed through to clients.

When the intellectual property rights regime is tight, appropriation of returns to innovation is often related to the ability of the firm to protect outcomes from their R&D efforts through patenting. We do find an important increase in markups due to the existence of patents of the firm. But interestingly, very few firms apply for patents at the time they innovate. So the innovation remains a significant driver of firm level markups. Moreover, after controling for actual successful innovation in the form of product or process innovations, R&D does not affect firm level markups.

When the intellectual property rights regime is weak, Teece (1986) argues that firms can attempt to profit from innovation through access and ownership of complementary assets. An important complementary asset is related to the ability of firms to market their products. We find that promotion activities do affect our firm level markups significantly in addition to product innovation.

Finally, we investigate the dynamic consequences of product and process innovation for the firm's markups. Firms can appropriate the returns to innovation over time through the persistent effect on their markups over time. Indeed, our results indicate that product and process innovation increase long run markups by about 3 percent. Furthermore, sequential product innovations push up the markups for small firms that innovate persistently.

The remainder of the paper is organized as follows. Section 2 describes the empirical strategy for estimating firm specific markups. Section 3 presents the dataset. The main results on markups and the effect of product and process innovation are presented in Section 4. Section 5 discusses how firms appropriate returns from their innovation activities and Section 6 disentangles the markup effects into variations in prices and marginal costs. Finally, Section 7 concludes the paper.

2 Empirical Strategy

This secton introduces the methodology we use to infer markups from production data. First, we show how markups can be derived from the difference between input cost shares and output elasticities. Second, we demonstrate our empirical strategy to consistently estimate the output elasticities.

2.1 Markups

Our methodology builds on the seminal work by Hall (1988) who used for the first time production data, i.e. data on inputs usage and the total value of output, to estimate markups. The work by Hall generated an entire literature on estimating markups using production data either at the industry level or more recently at the firm level (f.e. Domowitz et al. 1988 and Roeger 1995 among others). Typically, a sector level markup was estimated and subsequently related with the variable of interest, measured at the sector level as well. For example in the international trade literature, the methodology was used to test the imports-as-market disciplining device (Levinsohn, 1993). Konings et al. (2001, 2005) relate markups with competition policy and privatization during the transition process in Central and Eastern European countries respectively. The methodology is equally suited to estimate firm specific markups needed for our purposes. De Loecker and Warzynski (2012) use production data to retrieve markups at the firm level and related these with firm level export status. The remainder of this section briefly describes the methodology to infer firm level markups using production data. For a more detailed exposition, we refer the interested readers to De Loecker and Warzynski (2012).

The basic insight of Hall (1988) is that only under perfect competition input revenue shares equal input cost shares.[2] The gap between the two measures could in principle be used to identify the markups charged by the firm. Basically this identification strategy poses two problems. First, total costs of the firm are hard to determine as for example the user cost of capital is unknown. Second, the returns to scale are not readily observable such that it is hard to infer marginal costs from average costs. The solution is to add a fairly mild behavioral assumption, namely that of cost minimization. It is easy to show that any cost minimizing entity will choose its input level such that the output elasticity of the particular input equals its input cost share, namely

$$\frac{P_{it}^X X_{it}}{c_{it} Q_{it}} = \frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}} \tag{1}$$

where X_{it} is the input choice of input X by firm i in period t, P_{it}^X is the price of that input, c_{it} represents marginal costs and Q_{it} total output of the firm. The right hand side is the output elasticity of input X. When we define the markup μ_{it} as the ratio of price over marginal costs; $\mu_{it} \equiv \frac{P_{it}}{c_{it}}$, it immediately follows that

$$\mu_{it} \frac{P_{it}^X X_{it}}{P_{it} Q_{it}} = \varepsilon_{it}^X$$

with ε_{it}^X the output elasticity. Under perfect competition, prices equal marginal costs and consequently the cost minimizing input choice will be such that the revenue share equals the output elasticity of the input. Under imperfect competition, the revenue shares are typically lower compared to the output elasticities. Define $\alpha_{it}^X \equiv \frac{P_{it}^X X_{it}}{P_{it} Q_{it}}$ such that the markup can be written as

$$\mu_{it} = \varepsilon_{it}^X / \alpha_{it}^X \tag{2}$$

and one can immediately see that with an estimate for the output elasticity, one can easily compute a firm level markup as α_{it}^X is directly observable in a typical dataset.[3,4]

[2] The revenue share of an input is the total cost of that input divided by total revenue. The input cost share is defined as total cost of the input over marginal cost times total output. Under constant returns to scale, marginal cost equals average costs and the denominator is then equal to the total cost.

[3] In principle, one could derive exactly the same expression for capital input and infer markups from a comparison between the share of the user cost of capital in total value added and the output elasticity of capital input. However, one can expect the capital stock to have substantial adjustment costs, which drives a wedge between the cost shares and output elasticities. Separating adjustment costs from markup differences would require specfic assumptions about the functional form of adjustment costs.

[4] The methodology is based on the same intuition which is often used to infer total factor productivity

The advantage of the described methodology are the fairly modest assumptions that one has to make. The only assumptions imposed are cost minimization and the presence of at least one freely adjustable input and one can remain agnostic about the mode of competition or the functional form of demand. The framework encompasses a wide variety of static models of price and quantity competition (De Loecker and Warzynski, 2012). We will estimate a value added production function to determine output elasticities. As capital is highly likely to have substantial adjustment costs, we will use labor as input to measure firm specific markups.[5,6]

2.2 Identifying output elasticities

As input revenue shares are readily observable in standard datasets, the main difficulty is to consistently estimate (firm level) output elasticities. We depart from the standard Cobb-Douglas production function and estimate a translog production function (Christensen et al. 1973). This is important as the Cobb-Douglas functional form restricts the output elasticities to be constant across firms within one industry and all firm level heterogeneity in the revenue shares is assumed to be due to firm-level variations in markups. The translog production function is more flexible and renders firm level variation in output elasticities. Assuming Hicks neutral technological progress, the translog production function can be written as:

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \eta_{it} \tag{3}$$

where lower case variables denote natural logarithms, so l_{it} is log labor in firm i in period t and q_{it} denotes log value added.[7] Productivity shocks anticipated by the firm are represented by ω_{it}, while η_{it} consists of measurement error and shocks in output the firm does not take into account when making its input decisions. A Cobb-Douglas production function is nested in the above representation and can be obtained by restricting the higher order term parameters β_{ll}, β_{lk} and β_{kk} to be equal to zero. With the coefficients

by applying the so-called index number approach. Under the assumption of perfect competition, one does not need to estimate output elasticities but can easily compute them as the input revenue shares. Under imperfect competition the revenue shares need to be adjusted with a factor equal to the markup.

[5] Note that also labor could have adjustment costs which would bias our estimates for the markup levels. However, the empirical strategy to determine the relationship between markups and innovation will not be affected as long as the size of adjustment costs is not systematically related to our variables of interest.

[6] Imperfect competition in the labor market could also create a wedge between input revenue shares and output elasticities. For example, the presence of unions tend to bias the markup estimates, but only under an efficient bargaining regime. When bargaining between unions and firms is best described by right-to-manage, a cost minimizing firm will again choose its optimal labor input such that the output elasticity equals the labor cost share. (Crépon et al. 2007, Abraham et al. 2009)

[7] We estimate a value added production function given the problems to separately identify the labor and materials coefficient in a revenue production function (Bond and Soderbrom, 2005). Moreover, using a translog production function we would not only have to estimate a coefficient on material input but on the interactions between materials, labor and capital as well.

on labor and capital at hand, the output elasticity of labor can be computed as:

$$\varepsilon_{it}^{L} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lk} k_{it}$$

Clearly, although production function coefficients are the same for all producers, output elasticities differ across firms depending on their input use.

In order to consistently estimate the input coefficients, one has to solve for the possible endogeneity of capital and labor as the input choices of a profit maximizing firm are likely to be correlated with the unobserved productivity shock ω_{it}. To control for this we rely on the insights of Olley and Pakes (1996) and Levinsohn and Petrin (2003). The basic idea is that optimal input choices – either investment (Olley and Pakes, 1996) or materials (Levinsohn and Petrin, 2003) – hold information about the level of productivity. We opt to use the material demand function $m_{it} = m_t(\omega_{it}, k_{it}, \mathbf{z}_{it})$ which can be inverted to proxy for productivity if optimal material demand is monotonically increasing in ω_{it}. The $\mathbf{z}_{it}$ vector represents additional variables affecting material demand across firms and within firms over time. Given our setting, these include product and process innovation. For example if an innovation coincides with the use of new intermediate inputs, this is likely to change optimal input demand. Inverting the material demand function allows us to write ω_{it} as a function of observables, i.e. $\omega_{it} = h_t(m_{it}, k_{it}, prod_{it}, proc_{it})$ where $prod_{it}$ and $proc_{it}$ represent a dummy equal to one if the firm has realized a product or process innovation respectively. When we plug this in in (3), we obtain an equation

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_t(m_{it}, k_{it}, prod_{it}, proc_{it}) + \eta_{it} \qquad (4)$$

that allows us to estimate the labor coefficients β_l, β_{ll} and β_{lk}. In the estimation, we approximate the $h_t()$ function by including a fourth order polynomial in materials and capital where each term is interacted with the product as well as process innovation dummies.[8] Clearly, the capital coefficients are not separately identified from the $h_t()$ function, but we can retrieve an estimate $\widehat{\phi}_{it}$ for the composite function containing the capital terms and productivity, $\phi_{it} \equiv \beta_k k_{it} + \beta_{kk} k_{it}^2 + h_t(m_{it}, k_{it}, prod_{it}, proc_{it})$.[9] This first stage provides us in principle with sufficient information to compute the labor output elasticities and thus firm specific markups. However, we will use the capital coefficients as well to check at each observation whether the production function is quasi-concave – which is not ascertained for a translog production function. Moreover we want to infer returns to scale and relate them with our markups estimates.

In the second stage we can identify the capital coefficients by relying on timing assumptions on the capital stock and the law of motion of productivity. We follow the standard assumption that productivity follows a first order Markov process but consistent with the economic environment, firms can influence their productivity level in period

[8] We include time dummies as well and estimate the production function for each sector separately.

[9] Although the presence of log labor provides sufficient variation to identify the coefficient β_{lk} on the interaction term $l_{it} k_{it}$, we also experimented with a specification where we identify β_{lk} in the second stage and the main results did not change.

t through investments in R&D in period $t-1$, similar to Aw, Roberts and Xu (2011). The productivity evolution can be written as $\omega_{it} = g(\omega_{it-1}, RD_{it-1}) + \xi_{it}$, where RD_{it-1} is total R&D spending in period $t-1$ and ξ_{it} represents a shock to productivity in period t, unexpected at period $t-1$. For each candidate vector of capital coefficiens (β_k, β_{kk}), we can compute productivity $\widehat{\omega}_{it} = \widehat{\phi}_{it} - \beta_k k_{it} - \beta_{kk} k_{it}^2$ which we non-parametrically regress on lagged productivity and lagged R&D. We include as well the innovation indicators in this equation to control for unobserved demand factors (cf. infra). The result is an estimate for the unexpected shock in productivity, ξ_{it}. To identify the capital coeffcients, we take the standard assumption that it takes one period to order, receive and install new capital. As a result, contemporaneous capital and capital squared are uncorrelated with the productivity shock ξ_{it}, unforeseen at period $t-1$. The resulting moment conditions are

$$E\left[\xi_{it} | \begin{array}{c} k_{it} \\ k_{it}^2 \end{array}\right] = 0 \tag{5}$$

which are used to estimate the capital coefficients applying GMM. To sum up, our empirical strategy goes as follows: after obtaining an estimate $\widehat{\phi}_{it}$ by executing a semi-parametric regression of output on inputs in the first stage, we take a candidate vector of input coefficients to compute $\widehat{\omega}_{it} = \widehat{\phi}_{it} - \beta_k k_{it} - \beta_{kk} k_{it}^2$. By non-parametrically regressing $\widehat{\omega}_{it}$ on its lagged value – controlling for time effects and including innovation dummies – we retrieve an estimate for the unexpected productivity shock ξ_{it} which is used to construct the sample analogue of the above moment conditions. By bringing this sample analogue as close as possible to zero, one finds consistent estimates for the capital coefficients of the production function.

We add two remarks about the estimation procedure. First, our measure for firm level output is in fact value added deflated with a sector level price deflator. Consequently, the error term of the production function (3) includes unobserved firm specific deviatons from the average industry price which are potentially correlated with the inputs of the production function. This could introduce a bias in our estimates for the output elasticities and consequently in our markup estimates. However, as long as the bias is not systematically related to the innovative activities of a firm, our results are not affected.[10] Moreover, as De Loecker and Warzynski (2012) show, the bias in the markup estimate when using a translog production function are a function of the log input quantities which we include in our markup regressions as control.[11] A second consequence of the use of deflated value

[10] Mairesse and Jaumandreu (2005) have access to output price information for a sample of Spanish and French firms and find that the estimated output elasticities hardly change when moving from a sector level price deflator to a firm level price deflator.

[11] Assuming a functional form for the demand system – such as a CES demand – would allow us to filter out these demand side elements (De Loecker, 2011) and to estimate for example the impact of product innovation on demand and physical productivity directly. However, we want to make as few assumptions as possible about the demand system. Moreover, the assumption of any demand system with

added as the output measure is that our productivity estimate $\widehat{\omega}_{it} = \widehat{\phi}_{it} - \beta_k k_{it} - \beta_{kk} k_{it}^2$ contains demand side elements as well, such as demand shocks induced by innovation. Hence we include the innovation dummies in the non-parametric regression of productivity on lag productivity and R&D in the second stage of our estimation procedure.

Second, Ackerberg et al. (2006) point to identification problems of the labor coefficient in the first stage of the estimation procedure. Basically, their critique is that conditional on a non-parametric function in materials and capital there is no useful variation left in the labor stock to identify the coefficients. As a robustness check we experimented with the methodology proposed by Wooldridge (2009) to estimate the production function in one step, which is robust to this critique. More precisely, under the above assumptions ω_{it} can be written as a function of lagged capital, materials, innovation dummies and R&D, i.e. $q_{it} = \beta_l l_{it} + \beta_{ll} l_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_k k_{it} + \beta_{kk} k_{it}^2 + f_t(m_{it-1}, k_{it-1}, prod_{it-1}, proc_{it-1}, R\&D_{it-1}) + \xi_{it} + \eta_{it}$. Approximating the $f_t(.)$ function by a fourth order polynomial, we can estimate this equation applying linear GMM techniques. Given our timing assumptions, we can use the lagged labor terms as well as contemporaneous capital as instruments and elements of the polynomial can act as their own instruments. The drawback of this procedure is the high amount of polynomial terms included in the equation (around 140 if we take a fourth order polynomial). In order to reduce the dimensionality of the problem, we do not interact the polynomial terms with the innovation variables. Applying the Wooldridge (2009) estimator leaves our main results unaffected, although the number of observations that do not satisfy the conditions for well-behavedness of the production function increases.

3 Data Description

We make use of the ESEE (Encuesta sobre Estrategias Empresariales) dataset which is a firm level survey that has been running from 1990 till 2008, resulting in an unusually long panel dataset of almost 20 years. The project was started by the Fundación Empresa Pública with financial support of the Spanish Ministry of Science and Technology and is now continued within the Fundación SEPI with continued government support. The sample includes the population of Spanish firms with 200 or more employees as well as a stratified sample of small firms comprising 4% of the population of small firms with more than 10 and less than 200 employees. Small firms that exited the original sample are replaced by firms with similar characteristics drawn from the current population. The outcome is a panel dataset of over 4,600 firms active in the manufacturing industries, of

constant markups across firms/over time would be at odds with our findings. Note that the methodology proposed by De Loecker (2011) would imply the inclusion of industry output – which would be absorbed in our framework by the time dummies in our industry level production function – as well as other factors that influence firm specific prices, such as innovation.

which around 3,400 are small and 1,200 are large.[12] Previous research has used the same data set as it is representative for the Spanish manufacturing industry over this long period (Delgado et al (2002); Campa (2004); Huergo and Jaumandreu (2004); Salomon and Shaver (2005); Cassiman and Martines-Ros (2008) among others). We observe the usual variables needed for the estimation of production functions. We take value added, double deflated by sector wide input and output price indices, as measure for output. Labor is defined as the number of employees and the real net capital stock is obtained using the perpetual inventory method.[13] Next to these standard variables the dataset contains information about the innovative activities of the firms. More precisely, we observe whether a firm has introduced a process or product innovation in a given year and the total amount of R&D spending, internal as well as external. Moreover it is observed whether the product innovation was due to the introduction of a new function, new materials, new components or new design of the product. For process innovation, we observe whether the innovation was due to the introduction of new production techniques, to the introduction of new machinery or both. Firms have to report in the survey as well whether they are exporting part of their production and the total value of exports. Moreover, they report the total value of imports they make.

Next to the data about innovation and internationalization, firms are asked to report some market indicators that have possibly an impact on markups and productivity. One obvious indicator of the fierceness of competition in the market is the number of competitors. The ESEE survey asks the respondents to indicate the number of competitors in their five most important markets. The answers are classified into four categories, namely (1) Less than 10 competitors, (2) Between 11 and 25 competitors, (3) Over 25 competitors and (4) Atomistic Market. The fourth category groups firms without competitors with a significant market share and who hold themselves a market share of less than 10%

Table 1 displays some summary statistics for the firms included in the dataset. The sample contains 3,366 firms with less than 200 employees and 1,277 firms employing over 200 workers.[14] The average firm realizes a value added of 21 million euros with 256 employees and a value of the capital stock of 12 million euros. Average labor productivity equals 57,300 euro and large firms are substantially more productive compared to small firms. Moreover the share of labor costs in value added is slightly higher for small firms compared to large firms. Around one fourth of the firms realizes a product innovation in a given year while around one third realizes a process innovation. Not surprisingly, the percentage of both product and process innovators is higher for large firms. Note that this

[12] Firms are defined as large when they employ over 200 workers in the period they enter the dataset. Even if employment drops below 200, they remain "large". Likewise, a small firm is defined as small if it employs less than 200 employees in the entering year.

[13] We experimented as well with number of hours worked as a measure for labor input and the book value of tangible fixed assets as a measure for the capital stock and results did not change.

[14] The number of small and large firms do not sum up to the total number of firms as the firm gets re-evaluated to be either small or large after a merger or split of the company.

does not imply that large firms can be considered to be more innovative. As large firms are involved in more activities, they are more likely to produce an innovation in one of them (Hall, 2011). Finally, around 60% of the firms export at least one product and 61% import from abroad. Concerning the number of competitors in the market, the majority of the firms is active in a market with less than 10 competitors while almost a quarter of the small firms is active in an atomistic market (no competitor with a significant market share and own market share less than 10%).

4 Results

This section discusses the results of the identification of firm level markups and their relation with the innovative activities of the firms. Firstly, we show results for the production function parameter estimates. Secondly, we use these estimates to compute markups and thirdly we relate them with the variables of interest.

4.1 Production Function

In a first step, we estimate firm level output elasticities. More precisely we estimate equation (3). We estimate both translog and Cobb-Douglas production functions.[15] Under Cobb-Douglas, the coefficients of the higher order terms in the production function are equal to zero. In a first step, we estimate the production function for each sector separately. The manufacturing sector is divided into 20 separate sectors which coincide approximately with NACE 2 digit sectors. The production functions are estimated using a proxy estimator described in the previous section. For comparison purposes we moreover report output elasticities obtained using Ordinary Least Squares. Results are displayed in Table 2. Controlling for the endogeneity of labor input lowers the output elasticity of labor substantially, as expected. This will have important consequences for the estimate of the level of markups as an upward bias in the labor coefficient estimates will increase the markup estimates. Not surprisingly, the average output elasticity from the translog production function is close to the Cobb-Douglas output elasticity.

For the translog production function, the reported output elasticities are averages across all firms in the industry, hiding substantial heterogeneity. Moreover, there is no guarantee that the production function is well-behaved for all observed input choices.[16]

[15] Moreover, given the importance of allowing for firm level variation in the output elasticities, we estimated the production function using random coefficients techniques which results in firm specific output elasticities, not depending on a specific functional form like for the translog production function (cf. Knott, 2008 and Alcacer et al., 2013 for other applications of the random coefficients model). The drawback is that we can not control for the endogeneity of inputs. Not surprisingly, the markup is estimated to be higher, but the conclusions about the relation between markups and innovation are very similar.

[16] We say a production function is well-behaved if 1) the function is quasi-concave, so it has convex isoquants and 2) output increases monotonically with all inputs.

In Appendix A we derive the conditions for well-behavedness of the translog production function and we drop all observations violating them.[17] Figure 1 displays the distribution of the output elasticities of labor and capital after the cleaning procedure. Clearly, there exists substantial variation in these elasticities.

While the translog production function is known to work well on average, less is known about the firm level output elasticities implied by the production function parameter estimates. In order to check whether these are sensible, we relate these elasticities with firm size and costs of long term loans. In accordance with expectations, we find large firms and firms with lower costs of long-term loans use more capital intensive technologies. More detailed results are reported in Appendix B.

4.2 Markups

With our estimates at hand, we can compute average firm level markups using equation (2) derived in Section 2.1, i.e. $\mu_{it} = \varepsilon_{it}^L/\alpha_{it}^L$. The median markup as well as its standard deviation for Cobb-Douglas and translog production functions are reported in Table 3. Not controlling for the endogeneity of labor input renders a median markup of around 1.64 and 1.48 for the Cobb-Douglas and translog production function respectively. Using our estimates from the translog production function and correcting for endogenous labor input results in a median markup of 1.20, (average markup 1.32) in line with previous studies.[18] It is interesting to see that moving from the Cobb-Douglas production function to the translog production function lowers substantially the variation in the markups as the standard deviation drops from .717 to .579. This points again to the importance of allowing for firm specific output elasticities. Making a distinction between small and large firms shows that large firms charge higher markups. The difference in markups is larger when we restrict the output elasticities to be the same across firms.[19]

In Figure 2 we report the average markup per sector, computed using the estimates for a translog production function where we control for the endogeneity of labor input. Not surprisingly, highest markups can be found in the Chemical Industry. High markups can also be found in the Publishing sector as well as in the Manufacturing of Food Products.[20] Sectors such as the Textiles, Leather Products, Wood Products and Office

[17] As a result we lose around 8% of observations.

[18] For example Siotis (2003) found an average price-cost margin of around 0.25 (which implies a markup of 1.33) for Spanish manufacturing firms in the beginning of the 90's. Abraham et al. (2009) report an average markup of 1.29 in their sample of Belgian manufacturing firms. De Loecker and Warzynski (2012) report the median markup to be in the range of $1.17 - 1.28$ for Slovenian manufacturing firms.

[19] This is a direct consequence of restricting the output elasticities to be the same across different producers. It is well established that large firms are more capital intensive compared to small firms and consequently the labor share is likely to be lower. It is important to allow the output elasticities to reflect these differences in production technology, namely to allow large firms to have higher capital output elasticities and lower labor output elasticities. If not, an upward bias is introduced in the markup estimate for large firms and a downward bias in the markup estimate for small firms.

[20] The high ranking of the Food Products Sector and Printing and Publishing sector is less obvi-

Machinery charge the lowest markups. The firm level correlation with the price-cost margin computed with average variable costs equals 0.57.[21] In Appendix D we explore in more depth the difference with the accounting markups and show how they systematically differ from one another in line with theoretical predictions. The evolution of the median markup is plotted in Figure 3 and is found to be strongly pro-cyclical consistent with our prior and other empirical studies (e.g. Machin and Van Reenen, 1993). The markup fell considerably during the economic crisis beginning of the nineties. Afterwards, the markup recovered and has seen a slow but steady decrease between 1996 and 2004. During the last years before the start of the economic crisis, the markup had been rising again. All in all, the evolution over time as well as the sectoral distribution of markups look sensible, increasing confidence in the methodology to infer markups. In Appendix C we show more evidence on the relation between markups and firm/sector level drivers of firm performance such as market structure, promotional activities, buyer power and market growth. Correlations between our markup measure and these firm and sector drivers correspond to our expectations.

4.3 Markups and Innovation

In this section, we relate the markups with firm decisions such as innovation, exports and imports as well as with market characteristics. The dependent variable is each time the natural logarithm of the markup such that the coefficients can be interpreted as percentage differences. In general, the estimated specification is the following:

$$\ln \mu_{it} = \beta_0 + \beta_1 prodinn_{it} + \beta_2 procinn_{it} + X_{it}\gamma + \gamma_t + \gamma_i + \varepsilon_{it} \tag{6}$$

where $prodinn_{it}$ and $procinn_{it}$ are dummies equal to 1 if firm i has realized a product or process innovation in year t. In the framework we include year and sector dummies which pick up year and sector specific variations respectively in markups. Moreover we include in several specifications firm fixed effects, controlling for all unobservable firm specific factors that influence the markup and are constant over time. X_{it} is a vector of control variables. The vector contains other firm decisions that can possibly have an impact on markups such as a dummy variable indicating whether the firm exports (De Loecker and Warzynski, 2012). Similarly, we define a dummy variable indicating whether the firm imports.

Furthermore, we include variables that should pick up competition in the market. Market structure and the competition intensity has been argued to influence innovation activities, both theoretically (e.g. Schumpeter 1942; Vives 2008) and empirically (f.e.

ous. However, Siotis (2003) obtains the same result, namely relatively high markups in these sectors. Moreover, these sectors are typically less subject to foreign competition.

[21] The median markup computed with accounting data equals 1.30, higher compared to the markup estimate applying the methodology described above.

Aghion et al. 2005). Instead of relying on concentration measures such as the Herfindahl Index, we use a self-reported indicator of the number of competitors in the market. This way we avoid the problems of defining the relevant market to compute the concentration indices. To control for conditions of appropriability and firm size we have included control variables such as the capital intensity and firm size dummies in our regressions.[22]

Results without firm fixed effects are reported in Table 4. The specification in column (1) includes a dummy indicating whether the firm has introduced either a process or product innovation. The estimates indicate that a firm realizing an innovation has on average a 4.8% higher markup than non-innovative firms. Making a distinction between product and process innovation in column (2) shows that both innovations are significantly related to higher markups. More precisely, markups of process innovators are 2.8% higher and the markup premium of a product innovator is around 3.9%, implying that evaluated at the mean, the impact on the markup level is respectively around 3.8 percentage points and 5.1 percentage points for process and product innovation.[23,24] The rest of the table reports robustness checks altering the estimation sample and the functional form of the production function. Column (3) reports results when the output elasticities are obtained using a Cobb-Douglas production function and column (4) reports results when the production function is estimated by OLS. Results are very similar to the base specification. In Column (5) we restrict attention to firms reporting 100% of their sales coming from the same product.[25] As expected, the estimated markup premium for innovators increases – although not substantially – and especially so for product innovators. In columns (6) and (7) we split the sample between small and large firms.[26] For small firms, the estimated relationship between product innovation and markups is even stronger while for the large firms the coefficient on process and product innovation drops substantially, especially so for product innovation. For large firms product and/or process innovation is likely to refer only to a small part of production as large firms typically tend to produce many different products (Bernard et al. 2009). If the realized innovation is only relevant for

[22] The size of a firm is categorized into 6 categories based on the number of employees (L): $L < 20; 20 < L < 50; 50 < L < 100; 100 < L < 200; 200 < L < 1000$ and $1000 < L$

[23] Finding that product innovation increases the markup, should not come as a surprise as product innovation is believed to shift out residual demand thereby increasing price as well as the markup if marginal costs do not change. Similarly, process innovation is expected to work on the cost side of the firm. For the most commonly used demand systems, price changes less than proportionally with marginal costs, leading to an increase in the markup when marginal costs decrease. Weyl and Fabinger (2008) make a distinction between cost absorbing and cost amplifying demand systems for which the markup (defined in absolute terms) respectively decreases or increases in marginal costs. Often demand is assumed to be log-concave, implying the demand system to be cost absorbing.

[24] When we exclude the dummies capturing whether the firm is an exporter and/or an importer, the coefficient on product innovation increases to .052 while the coefficient on process innovation remains similar in magnitude (results not reported).

[25] However, the definition of a product is very coarse, namely at a level comparable to the NACE 2 digit level. Not surprisingly, the vast majority of sales comes from the main product defined this way. For example the median of the percentage of sales realized by the main product is equal to 93%.

[26] Again, small firms are defined as firms with less than 200 employees.

part of total production, the impact on the markup at the firm level could be too small to be picked up by our procedure.[27,28]

The coefficients on the other firm level variables included in the regressions have the expected signs. Concerning the market structure, in line with expectations, there exists a significantly negative relation between the firm level markups and the number of competitors in the most important market. Firms active in an atomistic market set markups around 4% lower compared to markets with less then 10 competitors in the market. For the subsample of large firms, the coefficient is somewhat lower in absolute value and not significant. However, note that there exists only a small number of observations of large firms active in atomistic markets. Moreover, it is not clear how this market structure can be reconciled with firms having over 200 employees.

Exporting and importing at the firm level are associated with considerable markup premia, namely 4.9% and 10.4% respectively. The result of the export premium is in line with De Loecker and Warzynski (2012) who report a markup premium for exporters of around 7.8%. The strong relation between importing activities and markups is also interesting in its own right and could be explained by the use of high quality inputs in the production process. Again the relation between exporting and markups drops for large firms which is not surprising given that the vast majority of large firms export/import.

The effect of innovation on markups might not be contemporaneous. For this reason we experimented with different lag structures. Table 5 columns (1) and (2) lags innovation by one year. In columns (3) and (4) the innovation dummy takes the value of 1 if the firm innovated at least one time in the past 3 years. In columns (5) and (6) we take the cumulative innovations over the past 3 years. As one can observe, results are very consistent across specifications, probably due to the persistence of innovation activities within companies.

To control for unobservables influencing both innovation and markups we include firm fixed effects in our framework. Now the variation within a firm over time is used to identify the relevant coefficients. Results are reported in Table 6. The coefficients for both product and process innovation remain positive and significant, although the size of the coefficients drops. This can be caused by measurement error in the innovation variables which display a substantial amount of persistence.[29] Results indicate that

[27] This is consistent with Cohen and Klepper (1996) who take the assumption that process innovation benefits the price cost margin of all output while product innovation only increases price-cost margins of part of total production. This mechanism gives rise to large firms spending more resources on process R&D as total returns to process R&D rise proportionally with output while returns to product R&D increase less than proportionally.

[28] We observe as well how many product innovations a firm has realized in one year. We find that the markup is increasing in the number of product innovation but at a decreasing rate. The results are available on request.

[29] Griliches and Hausmann (1986) show that if the variable of interest is highly persistent, the signal to noise ratio, i.e. the variance in the observed variable due to true variance in the variable versus

product and process innovation increase markups by close to 1 percent.[30] However, the simple innovation dummy can mask important heterogeneity in the type of innovation. Different types of product and process innovations might allow firms to appropriate the returns to their innovations through markup increases to a different extent. We observe whether the process innovation consisted of (a) the introduction of new machinery, (b) the introduction of new methods for organizing production or (c) the introduction of both new methods and new machinery. Note that the three categories are mutually exclusive. Around 42% of all process innovations involved the introduction of new machinery only, 12% involved the introduction of new methods only and 44% consisted of both the introduction of new machinery and methods.

For product innovation, we can distinguish between product innovations due to (a) the introduction of new materials, (b) the introduction of new components or intermediates, (c) new design and appearance (d) the incorporation of new functions in the product. In contrast to the disaggregation of process innovations, these different types of product innovation are not mutually exclusive. The vast majority of product innovations include the change of design or appearance (namely around 78% of all product innovations). The other types - new materials, new components and new functions - are prevalent in 49.3%, 48.8% and 45.8% of product innovations respectively.

Results are reported in Column (2) of Table 6. Only product innovations that go hand in hand with a new design or function of the product are positively and statistically significant associated with higher markups. As the different types of product innovation are not mutually exclusive, this does not necessarily mean that the introduction of new materials in the product has no impact on markups. If this introduction goes hand in hand with a new design of the product, as is often the case, markups will be higher. Constructing mutually exclusive categories using the four different classifications would result in a high number of categories with a relatively small number of observations within each category. In order to reduce the dimensionality of the categories, we merge the category of new materials and new components (a and b) and subsequently we disaggregate product innovation into 7 different mutually exclusive categories.[31] Focusing on the fixed effects results in Table 7 shows that especially the combination between New Design and New Functions is associated with higher markups whether or not new materials are included. All in all, it appears that only product innovations that also include changes in the design

the variance due to measurement error, drops when applying a within estimator. Consequently this exacerbates measurement error bias.

[30] All regressions include the usual controls as well as the number of competitors and the import and export dummies. Interestingly, when including fixed effects, the estimated export premium in markups goes away. This result is consistent with the empirical literature that has found the exporter productivity premium to be due to selection effects instead of learning-by-exporting, where productivity is typically measured as revenue productivity, i.e. the measure includes firm specific prices and markups

[31] These are (percentage of product innovations between brackets): (1) Only new materials or components [9.9%], (2) Only new functions [6.9%], (3) Only new design [20.5%], (4) Both new materials and new functions [4.8%], (5) Both new materials and design [23.5%], (6) Both new function and design [6.8%] and (7) New materials as well as new function as well as new design [27.2%].

or appearance of the product increase markups.

Turning to the disaggregation of process innovation, shows that only the introduction of new machinery is positively related with firm specific markups. Surprisingly, when the new machinery is combined with new methods to organize production, markups appear not to be affected.

To further control for possible time-varying effects influencing both innovation and markups we include the markup lagged one period in the regression framework and instrument for the possibly endogeneous variables. More precisely, we estimate the following equation:

$$\ln \mu_{it} = \alpha_0 + \alpha_1 \ln \mu_{it-1} + \alpha_2 prodinn_{it} + \alpha_3 procinn_{it} + X_{it}\gamma + \gamma_t + \gamma_i + \varepsilon_{it} \qquad (7)$$

As is well known, OLS will lead to inconsistent estimates of the lagged markup coefficient given the correlation between the lagged markup and the firm fixed effect γ_i. To eliminate these firm fixed effects, we firstly apply the within groups estimator which creates a downward bias in the estimated coefficient on the lagged markup (Arellano and Bond, 1991). To control for the bias in the estimate for the lagged markup, we estimate equation 7 applying the insight of Blundell and Bond (1998) that first differences of the lagged markup are uncorrelated with the error term ($\gamma_i+\varepsilon_{it}$) and that the levels of the two period lagged markup are uncorrelated with the first differenced error term $\Delta\varepsilon_{it}$. Moreover changes in firm decisions are not correlated with the firm fixed effects and can be used as instruments to estimate the above equation. More precisely, we use the moment conditions $E(\Delta\mu_{it-1}(\gamma_i + \varepsilon_{it}))$ and $E(\Delta innov_{it}(\gamma_i + \varepsilon_{it}))$. The identifying assumption for the innovation variables is that they are not related to the contemporaneous markup shock ε_{it}. In a second estimation, we include furthermore the moment conditions $E(\mu_{it-2}\Delta\varepsilon_{it}) = 0$ as well as further lags of the innovation changes and markup changes and levels as instruments. Moreover, the moment conditions are constructed in the spirit of Arellano and Bond (1991), namely we construct a moment condition for each time period.[32]

Results are reported in Columns 3 to 5 of Table 6. Column (3) reports results from the within estimator. As long as the downward bias in the coefficient on the lagged markup does not spill over to the other variables – which depends on the correlation between them – the procedure provides consistent estimates of the impact of innovation on markups. The results are in line with our previous findings, namely that product innovation due to new functionalities or new design and process innovation due to the introduction of new machinery have a positive impact on markups. Column (4) applies GMM using the (lagged) changes in markups and innovation as instruments. In line

[32] This procedure results in a large number of instruments. Windmeijer (2005) shows that standard errors can be substantially downward biased when the number of instruments is large relative to the number of cross-sectional units. We apply his proposed correction of the standard errors.

with theoretical predictions the coefficient on the lagged markup increases compared to the within estimate but remains below the (upward) biased OLS estimate.[33] The point estimates for the innovation variables do not change substantially but the standard errors increase as expected, leading most variables to be insignificant at the 10% level. Column (5) exploits additional moment conditions by using further lags (and lagged differences) as described above, thereby increasing the efficiency of the estimator. Qualitatively the results do not change although the impact of product innovation due to new functions or new design is estimated to be somewhat higher.[34] All in all the results presented in this subsection are largely in line with the previous findings.

An important assumption we have made so far is that firms realizing a product or process innovation use the same production technology as non-innovative firms within one industry. When we relax this assumption and estimate separate production functions for firms that report an innovation and firms that do not, we obtain similar results, both quantitative as qualitative.

5 Appropriation of Innovation

5.1 Market Structure and the Impact of Innovation

The relation between market structure and innovation has been the subject of a long debate starting with Schumpeter. As Cohen (2010) indicates, no firm conclusions have been reached. While markups have been used in the literature to measure market power, they were calculated at the industry level. We use firm level markups and do control for the number of competitors of the firm. We check whether the relation between markups and innovation varies with the market structure. More precisely, we look at the differential impact of innovation when the firm is active in an atomistic market, a market with less than 10 competitors or a market with over 10 competitors (but not atomistic). The results are reported in Table 8. The excluded market structure in the interaction is each time the atomistic market structure. As such, the coefficient on innovation must be interpreted as the effect of innovation on the markup in an atomistic market and the coefficients on the interactions as the differential impact of innovation in other market structures compared

[33] An OLS regression of the markup on the lagged markups and the other variables results in an estimate of 0.69 for the coefficient on the lagged markup.

[34] In the current framework, the coefficients on innovation only reflect their short-run impact. The long-run effect of sustained innovation is measured by $\alpha_s/(1-\alpha_1)$ with α_1 the coefficient on the lagged markup and α_s the coefficient on the innovation dummy. Focusing on Column (5) the estimates imply that the long run impact of product innovation due to new functions or new design is to increase markups by 4.25% and 3.00% respectively. Note again that the categories are not mutually exclusive. For example, an innovation that entails both the introduction of a new function and new design increases the markup by 7.25%. Process innovation due to new machinery has a long term effect of 2.54%.

to an atomistic market.[35,36] Turning to the coefficient on product innovation, it appears that product innovation in atomistic markets has no impact whatsoever on the markup. Only firms active in less competitive markets increase their markups following a product innovation. Note however, that when firm fixed effects are included, there appears to be no impact of product innovation on the markup in markets with less than 10 competitors as both β_1 and $\beta_0 + \beta_1$ are not significantly different from zero. We do find an important effect of product innovation on markups when firms move from an atomistic market to a less competitive market structure (fixed effects regressions in column (3) and (4)). This could be evidence of the competition escaping effect of product innovations (Aghion et al. 2005).

Turning to the results of process innovation, again in an atomistic market, there appears to be no effect of process innovation on the markup as α_0 is estimated to be zero. Only process innovations realized in markets with less than 10 competitors are associated with markup premia. Although the coefficient on the interaction between a market with less than 10 competitors and process innovation, α_0, is not always significantly different from zero, the total effect $\alpha_0 + \alpha_1$ is always significant at the 1% level. These findings are consistent with previous literature on cost-pass through, establishing that pass-through will be (close to) one if the market is (close to) competitive. Only in less competitive markets, part of cost increases are absorbed by a decrease in the markup, or equivalently, cost decreases are not completely passed through to consumers and as a result increase the markup as well.

5.2 R&D, Patents and Markups

When protection of intellectual property rights is tight, firms appropriate returns to innovation through patents (Teece (1986); Ceccagnoli (2009)). In our sample, only 7% of firms applied for a patent in a given year. Furthermore, firms investing in R&D incur an important fixed cost of investing in innovation and require a higher markup in return for this investment. In Table 9 column (1) and (2) we control for whether the firm applied

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[35] More precisely we estimate the following equation:

$$\begin{aligned} \ln \mu_{it} \; = \; & \beta_0 prodinnov_{it} + \beta_1 MS1_{it-1} \times prodinnov_{it} + \beta_2 MS2_{it-1} \times prodinnov_{it} \\ & + \alpha_0 procinnov_{it} + \alpha_1 MS1_{it-1} \times procinnov_{it} + \alpha_2 MS2_{it-1} \times procinnov_{it} \\ & + \delta_0 + \delta_1 MS1_{it-1} + \delta_2 MS2_{it-1} + controls + \varepsilon_{it} \end{aligned}$$

with $MS1$ a dummy equal to 1 if there are less than 10 competitors in the market and $MS2$ a dummy equal to one if there are over 10 competitors in the market (but the market is not atomistic). The effect of product innovation in an atomistic market is given by β_0 while the effect in a market with less than 10 competitors and more than 10 competitors is given by $\beta_0 + \beta_1$ and $\beta_0 + \beta_2$ respectively. The same holds for process innovation.

[36] We include lagged market structure in the regressions instead of contemporaneous market structure to take into account that innovation might alter market structure. However, a simple regression of changes in the number of competitors on innovation indicators does not confirm this hypothesis. Moreover, this market structure variable is highly persistent over time.

for a patent in a given year and we estimate the equation by OLS and FE respectively. Indeed, the markup for patenting firms is significantly higher, but the effect of product and process innovation remains significant in the OLS specification. When including firm fixed effects the coefficient on the patent dummy becomes insignificant. Patents are clearly not the only mechanism to appropriate returns from innovation outcomes. Columns (3) and (4) control for the number of patents applied for in a given year.[37] Results are very similar. We add R&D expenditures in columns (5) to (8). R&D expenditures are not significantly related to the markup level. This seems to indicate that our other variables are good controls for firm heterogeneity in markups related to firms investing in R&D. Furthermore, when we drop the innovation dummies in column (6), the R&D variable becomes significant, but has only a small effect on the markup.[38] However, in the fixed effects regression, the coefficient on R&D remains statistically significant when including the innovation variables as well. Consistent with the findings of Geroski et al. (1993) we interpret these findings as the fact that the innovation event as an outcome is more important in explaining variation in markups than the R&D variable as an input into the innovation process. Moreover, firms can innovate without investing in R&D. More precisely, 41% of firms report zero R&D spending when realizing either a product or process innovation.

5.3 Complementary Assets and Markups

When the appropriation regime is weak, access or ownership of complementary assets becomes more prominent in the appropriation of returns to innovation (Teece, 1986). Complementary assets can range from manufacturing to distribution, to marketing and commercialization abilities. In our data we observe whether the firms engage in promotions at the firm, brand or product level.[39] Advertising and promotion activities can shift out the demand curve and reduce substitution. As a result we would expect a positive effect on the markup. Table 10 shows that firms that engage in promotion activities do have higher markups. The effect of product and process innovation on the markup remains intact. We find a positive coefficient on the interaction between product innovation and promotion activities in column (3). The interaction coefficient and the product innovation coefficient are not statistically significant. Note however that these coefficients are jointly significant, indicating the markup increases by 2.7% in response to a product innovation combined with promotion activities.

[37] The distribution of the number of patents registered by a firm in a given year - conditional on having registered at least one patent- is heavily skewed to the right with an average of seven and a median of two registered patents.

[38] Results did not change when we included lag R&D instead of contemporaneous R&D.

[39] We only observe this variable every 4 years. As a result we have fewer observations

5.4 Markup Dynamics

In this subsection we estimate the dynamic effect of innovation on the level of the markup. We classify the firm observations according to the cumulative number of innovations we have observed by the firm up to the year of observation and control for the time we observe the firm in the sample and time and industry effects. Results are displayed in Table 11 and Figures 4 and 5. Table 11 indicates that the first product innovation creates a 2.3% differential in markups with non-innovating firms. After realizing their 11^{th} or more product innovation, the markup differential has increased to 10%. Similar results are obtained for process innovations. The results are even stronger for small firms for whom the markup premium after realizing more than 10 product innovations is equal to 20%. When using the full set of control variables in columns (3) and (4) we do find that for small firms product innovations have a cumulative effect and returns are indeed appropriated over time. We do not seem to find the same effect for process innovations. One possible explanation is that product innovations can be cumulative. A process innovation might be more likely to substitute the earlier technology. It is as well interesting to note that the coefficient on the cumulative number of years the firm is already observed in the sample is negative and significant, indicating that on average firms that do not realize any innovation witness a continuous drop in their markup.

5.5 Young Firms and Innovation

Recently, so called young innovative companies have received considerable attention, both from policy makers as well as from academics. Although they are small in numbers – and obviously small in size as well– they are thought to have a superior innovative performance compared to incumbents. For example, Schneider and Veugelers (2008) find that young innovative companies achieve significantly higher innovative sales compared to other innovation-active firms. To test whether young firms realize higher innovation returns we interact both the product and process innovation dummies with a dummy equal to 1 if the firm is less than 6 years old. Results are reported in Table 12. The results in columns (1) and (2) indicate that the markup premium of product innovation is indeed higher for young firms, especially in the regression where fixed effects are included. For process innovation, there appears to be no positive effect of being young. On the contrary, the estimates indicate that process innovation has no effect on the markup of young firms as the interaction coefficient is negative, albeit barely statistically significant. As most young firms are small, we ran the same regressions on the subsample of small firms in columns (3) and (4). The results remain the same.

6 Prices, Marginal Costs and Innovation

We have established that innovative firms have higher markups compared to non-innovative firms, even after controlling for market characteristics and firm fixed effects. In this last subsection we disentangle these markup differences into marginal costs and price differences. In the ESEE survey, firms are asked to report the percentage change in output prices compared to the previous year.[40] We can combine these price changes with our estimates for markups to obtain a measure for year-on-year variations in marginal costs, i.e. $\Delta \ln c_{it} = \Delta \ln p_{it} - \Delta \ln \mu_{it}$. where $\Delta \ln p_{it}$ is the self reported percentage change in output prices, $\Delta \ln \mu_{it}$ the estimated percentage change in the markup and $\Delta \ln c_{it}$ is the percentage change in marginal costs.[41] We relate these price and marginal cost changes with both product and process innovation. Product innovation is expected to positively affect firm level prices while we expect to find no or even a positive relation with marginal costs. Process innovation on the other hand is thought to put downward pressure on both marginal costs and prices. Given that we have found process innovation to increase markups, pass-through is less than one and the drop in prices should be lower than the drop in marginal costs.

In a first step we regress the self reported price changes at the firm level on the product and process innovation dummies and a time fixed effect.[42] The results are the following:

$$\Delta \ln p_{it} = \underset{(.07)}{.14} * prodinnov_{it} - \underset{(.05)}{.25} * procinnovdum_{it} + year_t$$

As expected, process innovation puts downward pressure on prices and firms reporting to realize a process innovation increase their prices less compared to other firms. A process innovation in a given year depresses output prices on average by 0.25% points. Product innovation on the other hand increases prices on average by 0.14% points. Both coefficients are statistically significant at the 5% level.

Combining self reported price changes with the changes in markups provides us with an estimate for variations in firm specific marginal costs and we regress these computed year-on-year marginal cost estimates on process and product innovation and a time fixed effect:

$$\Delta \ln c_{it} = \underset{(.27)}{.14} * prodinnov_{it} - \underset{(.25)}{.48} * procinnovdum_{it} + year_t$$

These results seem to indicate that in line with expectations, process innovation lowers marginal costs by .48% points while product innovation is not significantly related to

[40] To be precise, the firms report the own price change for the five most important markets it is active in. The firm specific price change is then the weighted average of these firm/market specific price changes with the share of each market in total firm sales as weights.

[41] Note that we only observe price changes and not the level of prices. De Loecker et al. (2012) combine markup estimates for their sample of Indian firms with observed firm level prices to back out marginal cost levels.

[42] The average price increase over the whole sample period was equal to 1.72%.

marginal cost changes. The coefficient on product innovation is positive but with a high standard error such that the estimate is insignificant at any conventional level. Note that the size of the effects of innovation on prices and marginal costs are in the same order of maginitude as its effects on the markups estimated in Table 6. The results presented here confirm the hypothesis that product innovation only affects output prices and as such impacts revenue productivity. Process innovation on the other hand reduces marginal costs but these cost savings are only partly passed through to lower output prices leading to higher markups. The results moreover show that the previous literature estimating the impact of process innovation on productivity by using deflated sales as a measure for output, underestimates its impact on physical productivity as process innovation tends to depress firm specific prices. Nevertheless, one has to bear in mind that our measures for both the price increases and markups contain measurement error that spill over to the estimate for marginal costs. Expressing the markups and marginal costs in first differences is likely to exacerbate these errors (Griliches and Hausman, 1986) and the estimated coefficients should be interpreted with caution.

7 Conclusions

In this paper we seek to estimate the impact of innovation activities of firms on markups. In order to obtain a firm level measure for markups, we follow the inituition by Hall (1988) that uses the wedge between input revenue shares and output elasticities to identify them. To this end, we estimate translog production functions using recent developments in the identification of production functions, firstly introduced by Olley and Pakes (1996). Consistent with the economic environment, we allow firms to endogeneously impact their productivity evolution. Combining the estimated output elasticities with the input revenue shares allows us to infer firm level markups. We link the variation in these markups with a number of indicators that are expected to drive markup differences. The results are in line with theoretical predictions, increasing confidence in our procedure to identify markups.

Turning to innovative activities of firms, we find that both product and process innovation are positively related with firm-level markups. Especially a change in design of the product is associated with higher markups as well as process innovations due to the introduction of new machinery. These findings are robust against various specifications. Finally we show, consistent with our markup results, that product innovation leads to larger firm level price increases and does not have an impact on marginal costs while process innovation puts downward pressure on both prices and marginal costs. The results shed new light on the findings of previous studies that have related innovative activities of firms with measured productivity as this indicator includes both demand as well as technical efficiency elements.

8 References

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9 Tables

Table 1: Summary Statistics

	All	Small	Large
Nr. of Firms	4,567	3,366	1,277
Nr. of Observations	33,570	22,574	10,996
Value Added (X1000 €)	20,810	2,649	58,091
Employment	256	46	687
Capital Stock (X1000 €)	12,222	1,542	34,992
Labor Productivity (X1000 €)	57.3	45.9	80.8
Labor Cost Share	.54	.56	.50
Product Innovation	.24	.18	.38
Process Innovation	.33	.25	.48
Exporter	.60	.45	.90
Importer	.61	.45	.92
Nr. of Competitors			
10 or less	57%	49%	73%
Between 11 and 25	15%	16%	14%
Over 25	10%	12%	6%
Atomistic Market	18%	23%	8%

Table 2: Estimated Output Elasticities per Industry

	Labor				Capital				Obs.
	OLS CD	OLS TL	CD Control	TL Control	OLS CD	OLS TL	CD Control	TL Control	
Meat Products	.873	.794	.645	.655	.239	.287	.413	.419	894
Food and Tobacco	.687	.783	.565	.562	.402	.297	.451	.451	2,998
Beverages	1.13	.725	1.151	1.08	.148	.358	.130	.283	563
Textiles and Clothing	.737	.837	.560	.568	.295	.244	.374	.375	3,014
Leather Products	.668	.864	.426	.490	.276	.213	.309	.229	959
Wood Products	.779	.795	.525	.511	.261	.280	.336	.361	895
Paper Products	.791	.734	.500	.532	.306	.345	.513	.494	837
Printing and Publishing	1.056	.785	.814	.806	.146	.291	.324	.301	1,652
Chemicals	.871	.759	.703	.713	.265	.324	.345	.328	2,051
Plastic and Rubber	.813	.777	.598	.612	.269	.302	.402	.409	1,644
Mineral Products	.780	.777	.577	.562	.314	.303	.433	.463	2,247
Basic Metals	.677	.747	.512	.509	.376	.339	.487	.476	959
Metal Products	.853	.810	.653	.659	.213	.268	.314	.313	3,191
Machinery and Equipment	.914	.816	.648	.650	.146	.267	.306	.298	2,316
Office Machinery	.957	.833	.536	.545	.163	.253	.429	.272	464
Electrical Machinery	.895	.815	.647	.644	.196	.272	.347	.351	1,832
Motor Vehicles	.810	.784	.631	.609	.247	.307	.352	.361	1,447
Other Transport	.853	.829	.718	.721	.153	.260	.222	.241	628
Furniture	1.049	.843	.750	.762	.120	.235	.236	.231	1,558
Miscellaneous	.792	.810	.585	.658	.285	.267	.388	.280	663
Total	.832	.796	.625	.627	.241	.286	.382	.384	30,812

Results from estimating Cobb-Douglas (CD) and Translog (TL) production functions by ordinary least squares or control function approach. For the translog production function, the average elasticity over all firms is reported. Note that the number of observations for the control function estimation is actually lower (26,357) because we need to observe lagged capital as well. The resulting paramer estimates are used to compute output elasticities for all observations.

Table 3: Markups

	All Firms		Small Firms		Large Firms	
	Median	S.D	Median	S.D.	Median	S.D.
Cobb Douglas, OLS	1.64	.853	1.57	.811	1.78	.914
Cobb Douglas, Control	1.22	.717	1.17	.654	1.34	.813
Translog, OLS	1.48	.654	1.45	.671	1.53	.618
Translog, Control	1.20	.579	1.19	.573	1.22	.592

Table 4: Relation between Firm Level Markups and Firm Decisions

	(1) Translog	(2) Translog	(3) Cobb-Doug	(4) TL OLS	(5) TL Single	(6) TL Small	(7) TL Large
Innovation	0.0481**						
	(0.00768)						
Process Innov.		0.0281**	0.0305**	0.0276**	0.0313**	0.0285**	0.0174
		(0.00755)	(0.00704)	(0.00863)	(0.0117)	(0.00887)	(0.0120)
Product Innov.		0.0379**	0.0309**	0.0311**	0.0460**	0.0509**	0.0110
		(0.00930)	(0.00868)	(0.0108)	(0.0169)	(0.0126)	(0.0127)
$10 <$ Compet.< 25	-0.0296**	-0.0299**	-0.0302**	-0.0401**	-0.0221	-0.0246+	-0.0368*
	(0.0105)	(0.0105)	(0.00981)	(0.0125)	(0.0177)	(0.0126)	(0.0169)
Compet.>25	-0.0334**	-0.0340**	-0.0405**	-0.0529**	-0.0213	-0.0252+	-0.0712**
	(0.0124)	(0.0124)	(0.0122)	(0.0144)	(0.0187)	(0.0140)	(0.0251)
Atom. Market	-0.0408**	-0.0408**	-0.0425**	-0.0572**	-0.0286+	-0.0415**	-0.0240
	(0.0106)	(0.0106)	(0.00979)	(0.0121)	(0.0156)	(0.0112)	(0.0250)
Exporter	0.0490**	0.0487**	0.0659**	0.0716**	0.0566**	0.0699**	-0.0391
	(0.0120)	(0.0121)	(0.0113)	(0.0141)	(0.0176)	(0.0129)	(0.0284)
Importer	0.104**	0.104**	0.0884**	0.0806**	0.117**	0.100**	0.0869**
	(0.0115)	(0.0115)	(0.0107)	(0.0132)	(0.0175)	(0.0122)	(0.0262)
Nr. Obs.	26828	26828	29153	18345	9397	18172	8656
R^2	0.206	0.206	0.364	0.139	0.207	0.206	0.326
Nr. Firms	3777	3777	4025	2679	2176	2731	1105

Standard errors clustered at the firm level in parentheses. $+\ p < .10$, $^{*}\ p < .05$, $^{**}\ p < .01$

The dependent variable is the natural logarithm of the markup which is computed using the estimates for the output elasticities from a translog production function except for column (3) which reports results for Cobb-Douglas. In column (1) both product and process innovation are taken together to form a general innovation dummy. Columns (2) to (7) make a distinction between product and process innovation. Column (2) reports results for our preferred specification. Columns (3) and (4) report results for the a Cobb-Douglas production function and a translog production function estimated by OLS respectively. In column (5) we only keep single product firms. Columns (6) and (7) report results for the subsample of small and large firms respectively. Specifications include sector, year, size dummies and controls for input factor intensities. The variables 10<Competitors<25, Competitors> 25 and Atomistic Market are dummy variables capturing the strength of competition in the most important market of the firm. The coefficient should be interpreted with respect to the base category, namely less than 10 competitors.

Table 5: Relation between Firm Level Markups and Innovation; Different Lag Structures

	Innov. 1 year Lagged		Innov. 3 Year Dummy		Innov. 3 Year	
	Cobb-Douglas	Translog	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Prod. Innov.	0.0265**	0.0358**	0.0304**	0.0358**	0.0113*	0.0158**
	(0.00901)	(0.00971)	(0.00859)	(0.00918)	(0.00466)	(0.00497)
Proc. Innov.	0.0260**	0.0212**	0.0249**	0.0231**	0.0129**	0.0104*
	(0.00733)	(0.00795)	(0.00759)	(0.00816)	(0.00415)	(0.00447)
Nr. Obs	26393	24334	26828	26828	29153	26828
Nr. Firms	3659	3436	3777	3777	4025	3777

Clustered standard errors in parentheses + $p < .10$, * $p < .05$, ** $p < .01$
The table reports results for the relation between markups and innovation where innovation is measured using different lag structures. Columns (1) and (2) report results for innovation lagged 1 year. In columns (3) and (4), innovation is measured by a dummy equal to one if the firm has realized at least one innovation over the past three years. In columns (5) and (6) innovation is measured by the cumulative number of innovations over the past three years. All regressions include controls for the market structure and export and import status of the firm as well as sector and year dummies, controls for input factor intensities and size dummies.

Table 6: Relation between Firm Level Markups and Innovation Controlling for Endogeneity

	(1) FE	(2) FE	(3) FE	(4) GMM	(5) GMM SYS
Product Innov.	0.00941+				
	(0.00498)				
New Components		-0.00410	-0.000767	-0.00505	-0.0111
		(0.00791)	(0.00795)	(0.0133)	(0.0127)
New Materials		-0.00616	-0.00816	-0.00643	0.00271
		(0.00768)	(0.00767)	(0.0127)	(0.0123)
New Design		0.0161*	0.0144*	0.0195	0.0238*
		(0.00663)	(0.00727)	(0.0119)	(0.0117)
New Function		0.0170*	0.0134*	0.0123	0.0186+
		(0.00728)	(0.00663)	(0.0117)	(0.0105)
Process Innov	0.00899*				
	(0.00420)				
New Machinery		0.0144*	0.0103+	0.0181+	0.0142+
		(0.00561)	(0.00562)	(0.00965)	(0.00855)
New Methods		-0.00914	-0.00486	0.00431	-0.00672
		(0.00873)	(0.00866)	(0.0157)	(0.0126)
New Mach & Method		0.00158	0.00107	0.0176	0.00202
		(0.00619)	(0.00625)	(0.0107)	(0.0102)
Lagged Markup			0.270**	0.307**	0.441**
			(0.00712)	(0.0182)	(0.0159)
N	26828	23334	20877	17601	20877
Hansen $P-$ Value					0.112

Standard errors robust against heteroskedasticity and within-group correlation. + $p < .10$, * $p < .05$, ** $p < .01$
Column (1) reports fixed effects. Column (2) reports fixed effects making a distinction between different innovation types. Columns (3) to (5) include the markup lagged 1 period as an extra control. Column (3) reports fixed effects estimates. Column (4) applies GMM estimation using first differences as instruments for the firm decisions and lagged first differences for the lagged markup. Column (5) applies System GMM with markups starting from $t-2$ are used as instruments for the first difference equation. First differences starting from $t-1$ are used together with contemporaneous and lagged first differences of firm decision variables as instruments for the level equation. All specifications include sector and year dummies, controls for factor intensities and size dummies. Import, export dummies as well as market characteristics are included as well but not reported.

Table 7: Mutually Exclusive Types of Product Innovation

	(1)	(2)
	OLS	FE
Only Materials	-0.0211	-0.0219+
	(0.0182)	(0.0117)
Only Function	0.0279	0.00452
	(0.0231)	(0.0142)
Only Design	0.0543**	0.0142
	(0.0152)	(0.00886)
Mat & Func	0.0332	-0.000318
	(0.0236)	(0.0164)
Mat & Des	0.0624**	0.00120
	(0.0174)	(0.00878)
Func & Des	0.0249	0.0360**
	(0.0190)	(0.0138)
Mat & Func & Des	0.0514**	0.0245**
	(0.0161)	(0.00852)
N	23334	23334

Standard errors in parentheses + $p < .10$, * $p < .05$, ** $p < .01$
The dependent variable is the natural logarithm of the markup which is computed using the estimates for the output elasticities. All specifications include sector and year dummies, controls for factor intensities and size dummies. Import, export dummies as well as market characteristics and process innovation are included as well but not reported.

Table 8: Innovation and Market Structure

	(1) OLS	(2) OLS Small	(3) FE	(4) FE Small
Product Innovation	-0.0196	-0.0268	-0.0128	-0.0133
	(0.0214)	(0.0235)	(0.0139)	(0.0160)
(Comp.<10) × Prod. Innov	0.0602*	0.0832**	0.0192	0.0214
	(0.0239)	(0.0284)	(0.0149)	(0.0179)
(10< Comp.) × Prod Innov	0.0822**	0.125**	0.0386*	0.0404*
	(0.0270)	(0.0322)	(0.0168)	(0.0200)
Process Innovation	0.0146	-0.00262	0.000134	-0.00290
	(0.0165)	(0.0181)	(0.0110)	(0.0124)
(Comp.< 10) × Proc Innov	0.0199	0.0401+	0.0181	0.0254+
	(0.0192)	(0.0222)	(0.0121)	(0.0142)
(10< Comp.) × Proc. Innov	-0.0160	0.0119	0.000355	0.00680
	(0.0210)	(0.0240)	(0.0137)	(0.0158)
Nr. Obs.	23080	15532	23080	15532

Standard errors in parentheses + $p < .10$, * $p < .05$, ** $p < .01$
The dependent variable is the natural logarithm of the markup which is computed using the estimates for the output elasticities. All specifications include sector and year dummies, controls for input factor intensities and size dummies. Import, export + interactions with market structure included but not reported. Market structure variables in interactions are one year lagged

Table 9: Firm Level Markups, Patents, R&D and Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	OLS	FE	FE
Product Innov.								
New Components	-0.00262	-0.00424	-0.00230	-0.00398	-0.00255		-0.00483	
	(0.0135)	(0.00793)	(0.0135)	(0.00798)	(0.0133)		(0.00791)	
New Materials	0.00591	-0.00581	0.00445	-0.00603	0.00356		-0.00684	
	(0.0134)	(0.00769)	(0.0135)	(0.00774)	(0.0134)		(0.00768)	
New Design	0.0474**	0.0152*	0.0501**	0.0161*	0.0490**		0.0145*	
	(0.0115)	(0.00665)	(0.0115)	(0.00667)	(0.0115)		(0.00664)	
New Function	-0.000758	0.0166*	0.000481	0.0186*	0.00212		0.0164*	
	(0.0124)	(0.00730)	(0.0125)	(0.00735)	(0.0125)		(0.00728)	
Process Innov.								
New Mach.	0.0407**	0.0146**	0.0402**	0.0137*	0.0409**		0.0132*	
	(0.00975)	(0.00562)	(0.00977)	(0.00564)	(0.00983)		(0.00562)	
New Method	0.000412	-0.00863	0.00134	-0.00842	0.000231		-0.0106	
	(0.0147)	(0.00875)	(0.0147)	(0.00876)	(0.0147)		(0.00874)	
New Mach & Meth	0.0125	0.00138	0.0115	0.000140	0.0125		-0.000190	
	(0.0108)	(0.00620)	(0.0108)	(0.00623)	(0.0108)		(0.00620)	
Patent (Y/N)	0.0554**	0.0127						
	(0.0157)	(0.00872)						
Nr. Patents			0.0103**	0.000393				
			(0.00339)	(0.00203)				
Log(R&D)					0.00124	0.00283**	0.00212**	0.00254**
					(0.00104)	(0.000997)	(0.000562)	(0.000522)
N	23293	23293	23172	23172	23334	26828	23334	26828

Clustered Standard errors in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$
All specifications include sector and year dummies, controls for factor intensities and size dummies. Import, export dummies and market characteristics are also included. In the regression with nr. patents, observations with over 15 patents are excluded.

Table 10: Firm Level Markups, Innovation and Promotional Activities

	(1)	(2)	(3)
Process Innov.	0.0348**	0.0335**	0.0335**
	(0.0108)	(0.0108)	(0.0108)
Product Innov.	0.0274*	0.0253*	0.0108
	(0.0124)	(0.0124)	(0.0344)
Promotion Activities		0.0667**	0.0643**
		(0.0140)	(0.0149)
Promotion × Prod.			0.0162
			(0.0358)
Nr. Obs.	6349	6349	6349
R^2	0.215	0.218	0.218
Nr. Firms	2985	2985	2985

Clustered standard errors in parentheses + $p < .10$, * $p < .05$, ** $p < .01$

All specifications include sector and year dummies, controls for factor intensities and size dummies. Import, export dummies and market characteristics are also included but not reported.

Table 11: Cumulative Number of Innovations and Markups

	Controls Sector and Year		All Controls	
	All Firms	Small Firms	All Firms	Small Firms
Product Innovation				
1^{st} Innov.	0.0228+	0.0416**	0.0151	0.0265+
	(0.0128)	(0.0155)	(0.0125)	(0.0145)
$2^{nd} - 3^{rd}$ Innov.	0.0522**	0.0708**	0.0409**	0.0460**
	(0.0145)	(0.0176)	(0.0139)	(0.0165)
$4^{th} - 6^{th}$ Innov.	0.0607**	0.105**	0.0447*	0.0642**
	(0.0188)	(0.0258)	(0.0177)	(0.0233)
$7^{th} - 10^{th}$ Innov.	0.0947**	0.108**	0.0754**	0.0599*
	(0.0249)	(0.0321)	(0.0241)	(0.0304)
$11^{th} - 19^{th}$ Innov.	0.0980*	0.196**	0.0765+	0.154**
	(0.0421)	(0.0597)	(0.0396)	(0.0545)
Process Innovation				
1^{st} Innov.	0.0248*	0.0223+	0.0123	0.00269
	(0.0120)	(0.0133)	(0.0118)	(0.0126)
$2^{nd} - 3^{rd}$ Innov.	0.0470**	0.0621**	0.0190	0.0233
	(0.0135)	(0.0158)	(0.0131)	(0.0145)
$4^{th} - 6^{th}$ Innov.	0.0552**	0.0795**	0.0192	0.0227
	(0.0176)	(0.0216)	(0.0171)	(0.0200)
$7^{th} - 10^{th}$ Innov.	0.0828**	0.0797*	0.0422+	0.00510
	(0.0244)	(0.0345)	(0.0241)	(0.0321)
$11^{th} - 19^{th}$ Innov.	0.101*	0.111+	0.0560	0.0211
	(0.0406)	(0.0587)	(0.0385)	(0.0518)
Nr. Obs	28295	19078	26828	18172
R^2	0.165	0.148	0.212	0.212
Nr. Firms	3785	2735	3777	2731

Clustered standard errors in parentheses + $p < .10$, * $p < .05$, ** $p < .01$
All specifications estimated by OLS. Columns (1) and (2) include sector and year dummies as well as the number of years the firm is already included in the data set. Column (3) and (4) include as well controls for the size of the firm, the market structure, the import and export status and input factor intensities.

Table 12: Young Innovative Firms

	(1) All OLS	(2) All FE	(3) Small OLS	(4) Small FE
Process Innov.	0.0292**	0.0126**	0.0297**	0.0124*
	(0.00813)	(0.00465)	(0.00994)	(0.00600)
YoungXProc. Innov	-0.00700	-0.0290+	-0.00396	-0.0133
	(0.0232)	(0.0150)	(0.0252)	(0.0164)
Product Innov.	0.0303**	0.000920	0.0413**	-0.00390
	(0.0103)	(0.00547)	(0.0145)	(0.00748)
YoungXProd. Innov.	0.0342	0.0448*	0.0368	0.0491*
	(0.0278)	(0.0180)	(0.0315)	(0.0200)
Young Firms	0.0500**	0.0335**	0.0541**	0.0207+
	(0.0168)	(0.0101)	(0.0174)	(0.0109)
N	23994	23994	16410	16410

Clustered standard errors in parentheses + $p < .10$, * $p < .05$, ** $p < .01$
Column 1 and 2 report results for the full sample. Columns 3 and 4 focus on the subsample of small firms. All specifications include sector and year dummies, controls for factor intensities and size dummies. Import, export dummies and market characteristics are also included but not reported.

10 Figures

Figure 1: Distribution Output Elasticities

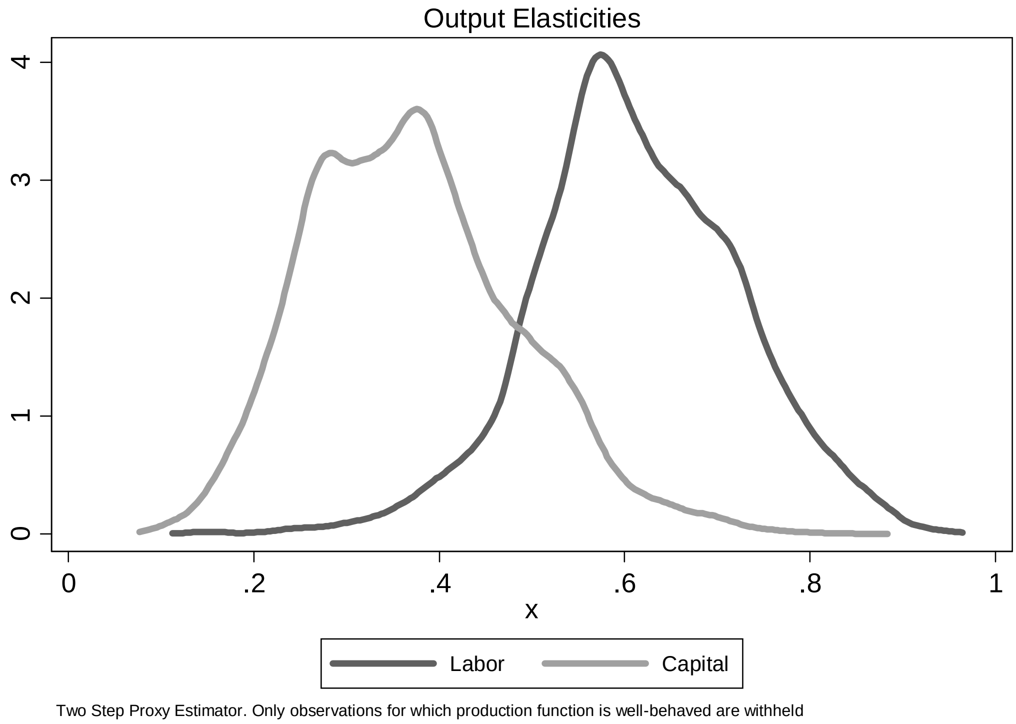


Figure 2: Markup by Sector

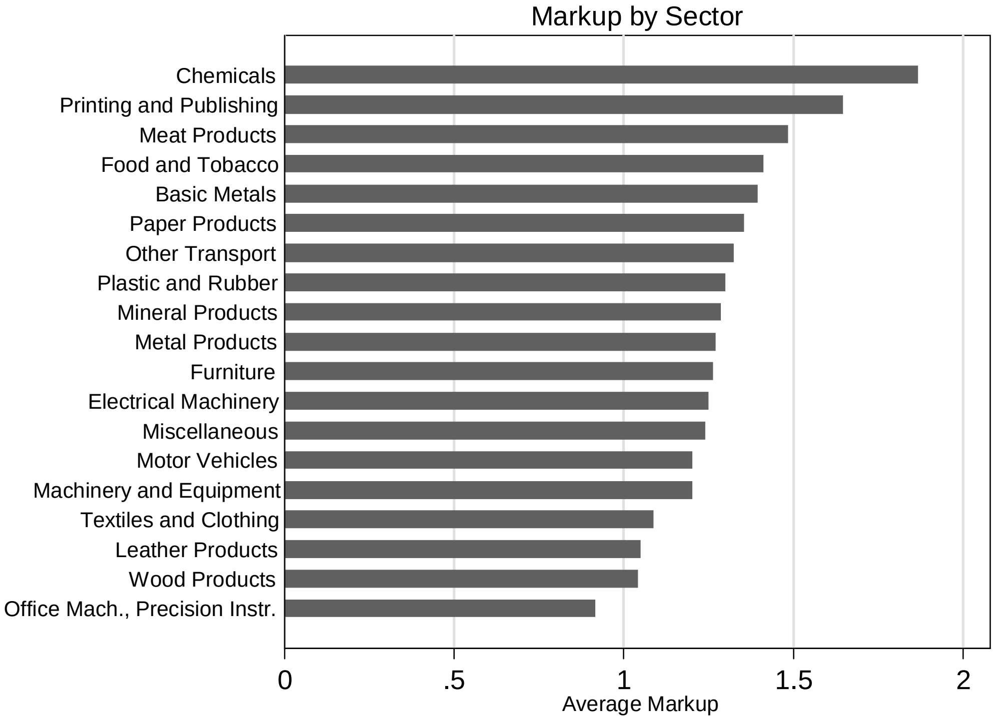


Figure 3: Evolution Median Markup

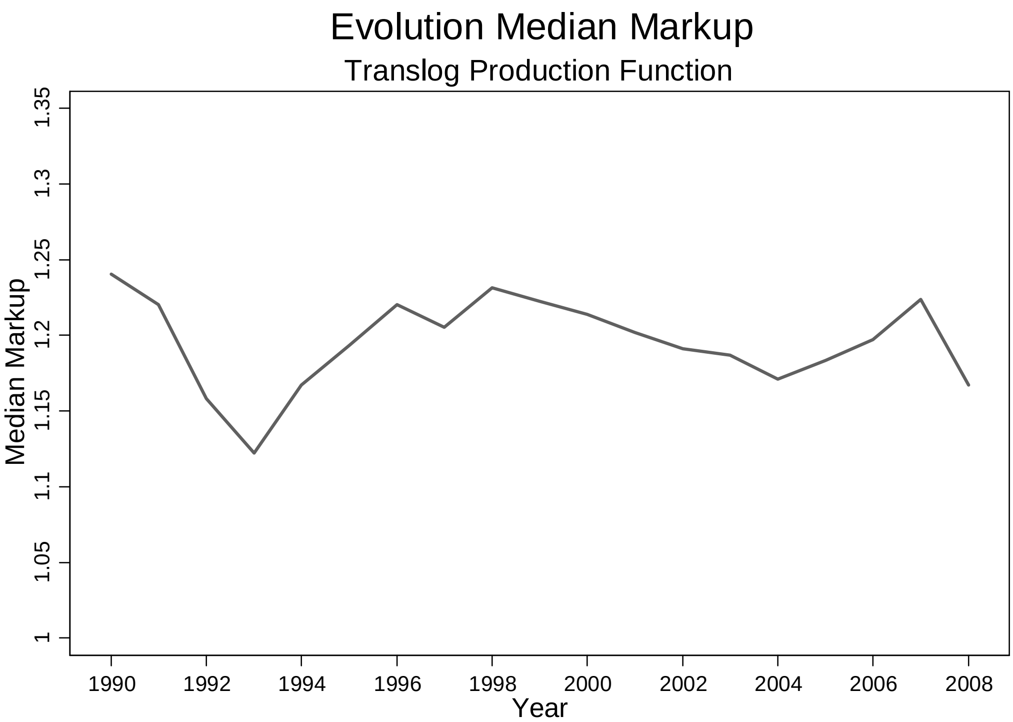


Figure 4: Cumulative Innovations; All Firms

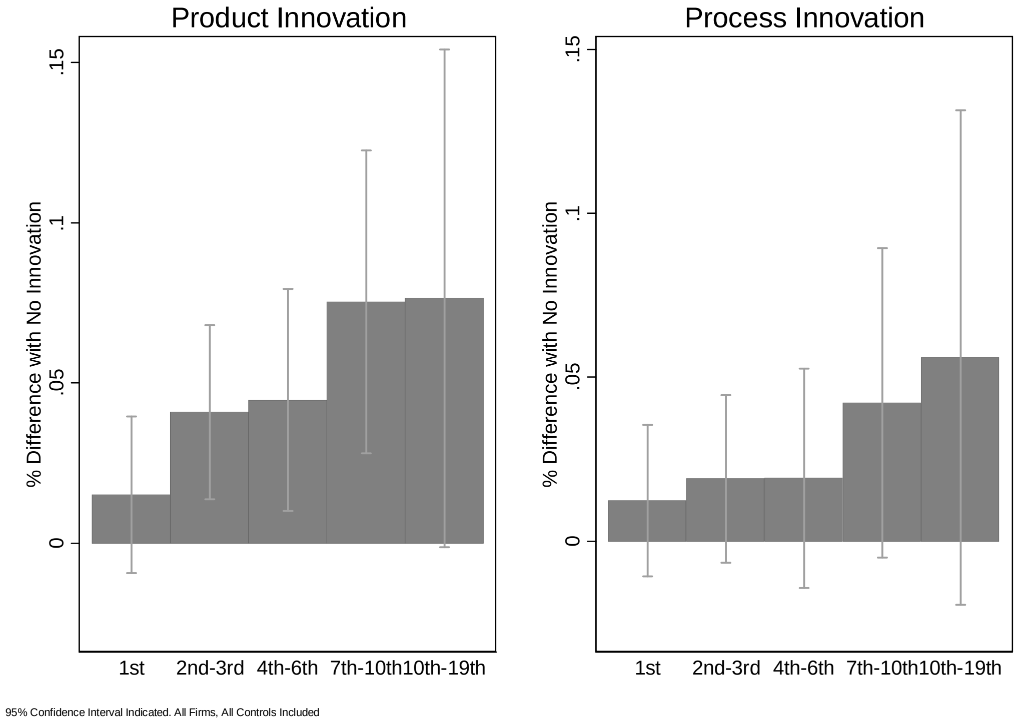
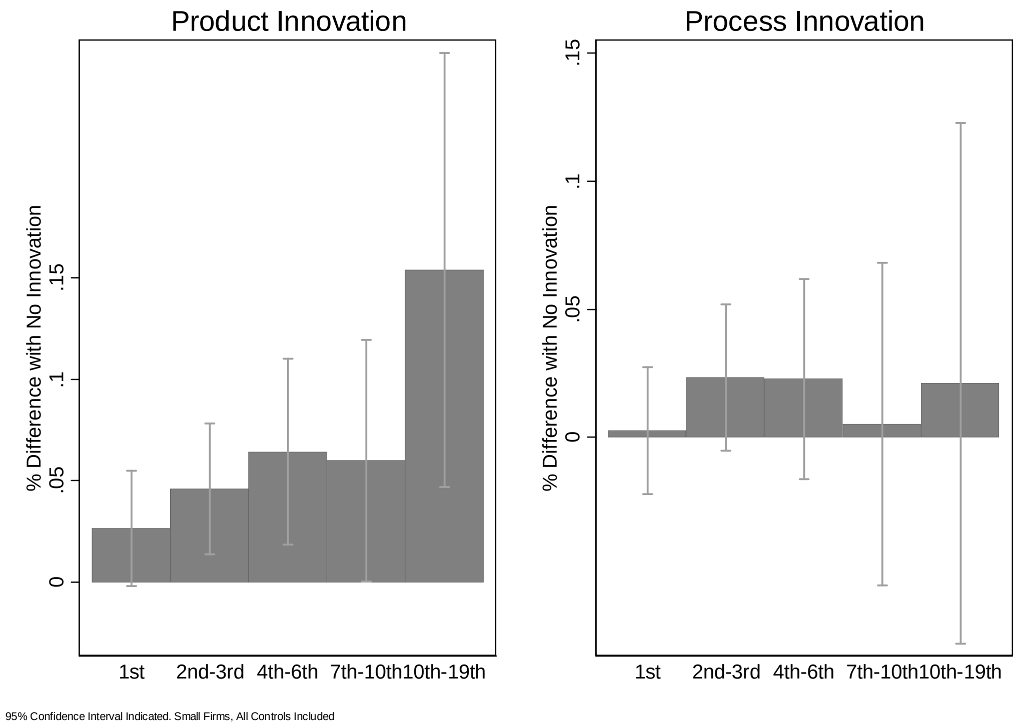


Figure 5: Cumulative Innovations; Small Firms



Appendix

A Properties Translog

A production function is usually considered to be well-behaved only if its marginal products are positive for all inputs and if the production function is quasi-concave, i.e. has convex isoquants. However, there is no guarantee the translog production function satisfies these conditions at all data points.[43] To compute markups, we only keep the observations for which these conditions are satisfied. Moreover, we drop observations for which the marginal product of either capital or labor is increasing.

The marginal product of an input is positive if and only if its output elasticity is positive, which is easily checked in the data. To determine whether the production function is quasi-concave the bordered Hessian of the production function needs to be negative semi-definite. The bordered Hessian is given by:

$$H = \begin{pmatrix} 0 & f_L & f_K \\ f_L & f_{LL} & f_{LK} \\ f_K & f_{LK} & f_{KK} \end{pmatrix} \tag{A.1}$$

where $f_L = \partial Q/\partial L$, the marginal product of labor and $f_K = \partial Q/\partial K$ the marginal product of capital. The second order partial derivatives of the production function are defined as follows: $f_{LL} = \partial^2 Q/\partial L^2$, $f_{KK} = \partial^2 Q/\partial K^2$ and $f_{LK} = \partial^2 Q/\partial L \partial K$. For this bordered Hessian to be negative semidefinite, its principle leading minors should alternate in sign. Specifically, for a two input case, this implies that $-f_L f_L \leq 0$ and $2 f_L f_K f_{LK} - f_K^2 f_{LL} - f_L^2 f_{KK} \geq 0$. The first condition is always satisfied while the second condition can easily be checked for every single data point as for a translog production function the first and second order partial derivates are given by:

$$\begin{aligned} f_L &= (\beta_L + 2\beta_{LL} \ln L + \beta_{LK} \ln K)\frac{Q}{L} \\ f_K &= (\beta_K + 2\beta_{KK} \ln K + \beta_{LK} \ln L)\frac{Q}{L} \\ f_{LL} &= (2\beta_{LL} + \varepsilon_L^2 - \varepsilon_L)\frac{Q}{L^2} \\ f_{KK} &= (2\beta_{KK} + \varepsilon_K^2 - \varepsilon_K)\frac{Q}{K^2} \\ f_{LK} &= (\beta_{LK} + \varepsilon_L \varepsilon_K)\frac{Q}{LK} \end{aligned}$$

with ε_L and ε_K the output elasticity of labor and capital respectively. Note that we do not impose in our estimation procedure these conditions to be satisfied for each observation, but we choose to drop the observations not satisfying the criteria. Moreover, we get rid of the observations for which the marginal products are increasing. The result of this cleaning procedure can be found in Table A.1. The production function is well behaved for over 90% of the observations when estimating the parameters applying the methodology to control for the endogeneity of input choices. The observations where the production function is ill behaved are concentrated in a number of smaller sectors. The condition that is most often violated is the one requiring the marginal product of labor to be decreasing. Note that the OLS parameter estimates result in a substantially larger number of observations where the conditions are not satisfied. This is obviously due to the upward bias in the labor coefficients, resulting in a larger number of observations having an increasing marginal product of labor.

[43] For a Cobb-Douglas production function, these conditions are globally satisfied if the input parameters β_l and β_k are estimated to be positive.

Table A.1: Cleaning translog production function

	OLS	Control
Meat Products	46.6%	12.5%
Food and Tobacco	0.0%	0.0%
Beverages	100.0%	100.0%
Textiles and Clothing	6.3%	0.8%
Leather Products	100.0%	23.1%
Wood Products	4.0%	5.3%
Paper Products	100.0%	0.1%
Printing and Publishing	99.2%	0.0%
Chemicals	96.4%	1.1%
Plastic and Rubber	11.3%	3.1%
Mineral Products	7.4%	5.7%
Basic Metals	16.0%	0.0%
Metal Products	8.0%	2.6%
Machinery and Equipment	73.1%	0.2%
Office Machinery	81.3%	11.0%
Electrical Machinery	5.8%	0.1%
Motor Vehicles	0.0%	0.0%
Other Transport	0.0%	0.0%
Furniture	86.6%	61.2%
Miscellaneous	100.0%	38.2%
Total	37.5%	8.2%

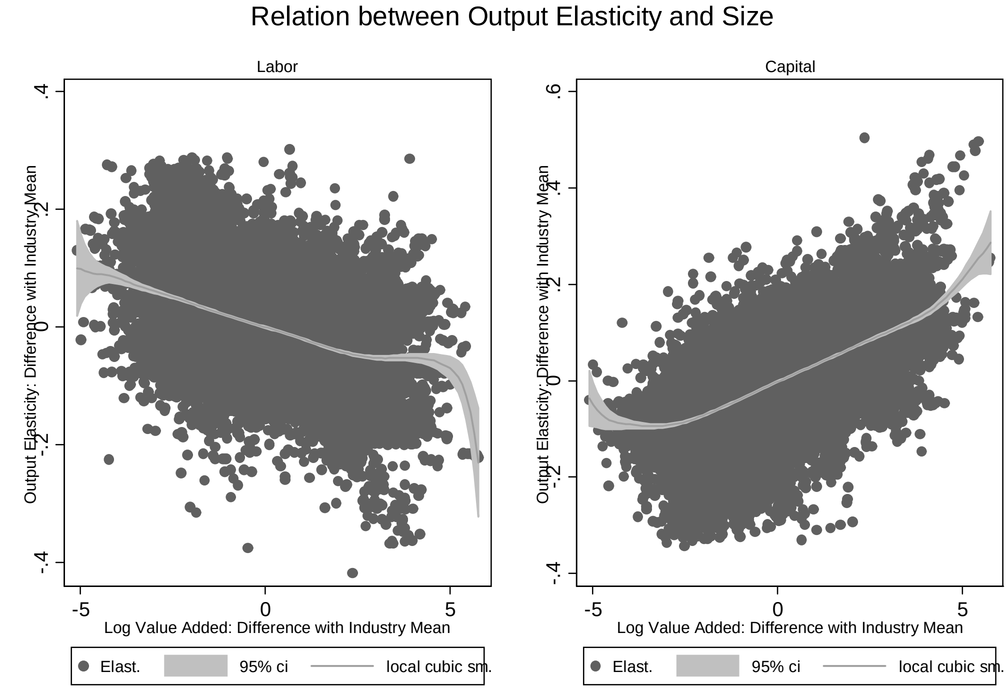
The above table shows the percentage of observations that do not satisfy the following conditions:
1) the production function has to be quasiconcave
2) the marginal products have to be decreasing and
3) the marginal products have to be positive.

B Plausibility Output Elasticities Translog

In this section we check whether the implied firm level output elasticities of the translog production function make sense economically. To this end, we first correlate the output elasticities with the size of the firm and second, we check whether firms with low costs of long term loans are using more capital intensive technologies. The results of these exercises are reported in figures B.1 and B.2 respectively. In Figure B.1 the output elasticities of labor and capital relative to the industry average are plotted against the size of the firm, in terms of value added, relative to the industry average. The dark grey line represents the smoothed values of a local cubic polynomial of the output elasticity on the size of the firm together with the 95% confidence interval. Clearly, large firms appear to use more capital intensive technologies, while smaller firms use more labor intensive technologies which is in accordance with our prior. Figure B.2 relates the costs of long term loans as a percentage of the outstanding total long-term debt.[44] Since these costs are an important component of the user cost of capital, firms facing lower costs of long-term debt are expected to use more capital intensive technologies. This hypothesis is confirmed as the costs of long term debt is negatively related to the capital output elasticity. This relationship holds in a regression framework controlling for the size of the firm.

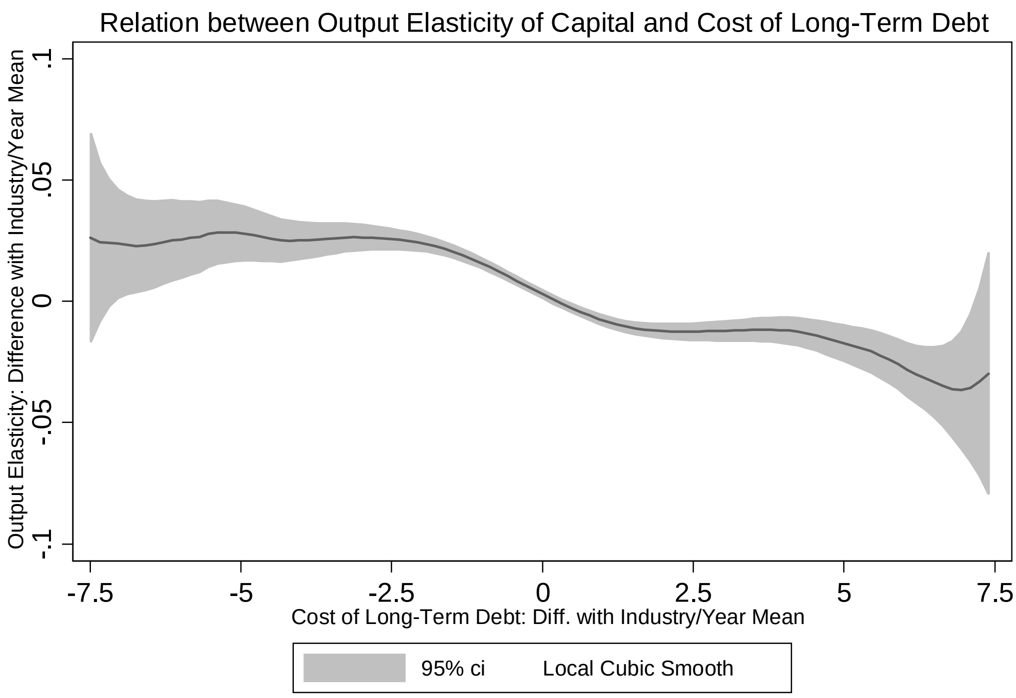
[44] Firms self-report the average cost of raising external funds with a payment term longer than one year, expressed as a percentage of the total loan. We observe whether the loan is acquired at a financial institution or other party. We take a weighted average of the two with total loans at either financial or other institutions as weights.

Figure B.1: Relation between Output Elasticities and Size



Two step estimator. Only observations for which production function is well behaved are withheld.

Figure B.2: Relation between costs of long-term loans and output elasticity of capital.



Two step estimator. Only observations for which production function is well behaved are withheld.

C Firm Level Variation in Markups

This section explores in more detail the firm level variation in the estimated markups. First we display the distribution of markups, second we briefly touch upon the dynamics of markups and its persistence. Finally we link our measure of markups with the most often cited drivers of markup differences.

Figure C.1 displays the distribution of markups for large and small firms for all industries pooled together. Clearly, there exists substantial variation in the markup around the median with large firms having higher markups in general. In the main text, we already showed markups to be pro-cyclical while highest markups can be found in the Chemical Industry and lowest markups in the Office Machinery Industry. In Figures C.2 and C.3 we plot the evolution of the markup for the largest sectors in the dataset. Again, the evolution of the markups appear to make sense and confirm our priors. For example, the Textiles Industry has witnessed a decline in its market power since the end of the nineties, which is due to increased competition from low wage countries in general and China in particular (cf. Abraham et al. 2009, for evidence from Belgium).

Given the persistence of most performance indicators used in other studies, we expect the firm level markups to display a substantial amount of persistence. Moreover, firms with lower markups are more likely to exit the market. To test these hypotheses, we divide the markups into five different quintiles and estimate the transition probabilities. Results are reported in Table C.1. The results show a five-year transition matrix between the different quintiles, higher persistence would show up as heavier entries on the diagonal while the in the absence of persistence each of the elements of the transition matrix should be approximately equal. Clearly, markups display a substantial amount of persistence. The diagonal elements are the highest percentages and the values of the matrix decline in the distance to the diagonal. For example a firm realizing today a markup in the lowest quintile in a sector has a probability of almost 50% to be located in the bottom quintile five years from now. Moreover, these firms have a probability of almost 20% to exit the industry over the next five years, significantly higher than the other firms active in the sector. Note moreover that when the markup reaches a certain threshold, for example is located in the upper three quintiles, a further increase in the markup appears not to influence the exit probability any further as only the lowest two quintiles have a higher probability of exiting.[45] Probit regressions of the exit probability on the markup showed a significant effect of the markup on the probability of exit.[46]

Finally we relate the firm specific markups with variables that are expected to be drivers of market power (f.e. Perloff et al. 2007, p.30). More precisely we link the markups with (1) market evolution, (2) market structure, (3) buyer power and (4) advertising. Results are reported in Table C.2 and Figure C.4. First, for the market evolution, firms report whether their main market is expanding, stable or shrinking. In line with theoretical predictions, markups are higher in expansive markets compared to stable and recessive markets. Second, we obtain the common finding that markups are higher in more concentrated markets. Third, market power of firms can be constrained by buyer power. In the ESEE survey, there is a question asking how many companies the firm is selling to.[47] Although imperfect, this gives a measure for buyer power. It appears that if the firm has only a limited number of clients, markups are substantially lower. Fourth, we link the markups with the promotional activities of a firm. Consistent with our priors, firms carrying out promotional activities in relation to the brand or product image have substantially higher markups compared to firms refraining from promotional activities.

[45] We have as well estimated one-year transition matrices, which - not surprisingly - resulted in higher transition probabilities on the diagonal. Moreover we experimented with absolute levels of the markup instead of deviations from the industry/year average. These markup levels displayed an even higher level of persistence, again consistent with our prior.

[46] Results available on request.

[47] Zero buyers means that the firm only sells directly to consumers.

Table C.1: Transition Matrix Markups

	Quint. 5	Quint. 4	Quint. 3	Quint. 2	Quint. 1	Disappear	Total
Quint. 5	45.5%	17.5%	9.8%	4.5%	5.0%	17.68%	100.0%
Quint. 4	25.0%	28.1%	18.6%	11.0%	5.8%	11.48%	100.0%
Quint. 3	13.8%	24.8%	26.4%	17.6%	9.9%	7.39%	100.0%
Quint. 2	7.1%	14.8%	21.5%	30.9%	19.4%	6.35%	100.0%
Quint. 1	5.2%	7.1%	11.7%	22.1%	45.6%	8.44%	100.0%

Estimated 5 year transition matrix. Firm specific deviations from the sector/year average. Quintile 5 represents the lowest markups relative to the sector/year average. Quintile 1 represents the highest markups relative to the industry/year average

Table C.2: Drivers of Average Markups

	All	Small
Market Evolution		
Expansive	1.29	1.30
Stable	1.21	1.19
Recessive	1.07	1.07
Nr. Competitors		
10 or less	1.23	1.24
11 to 25	1.18	1.18
+25	1.17	1.16
Atomistic	1.10	1.09
Nr. buyers (companies)		
1-5	1.09	1.07
6-50	1.17	1.18
+50	1.29	1.31
Zero	1.19	1.16
Promotional Activities		
Product	1.29	1.30
Brand	1.30	1.34
Company	1.20	1.21
No Promotion	1.09	1.08

Figure C.1: Distribution markups small versus large firms

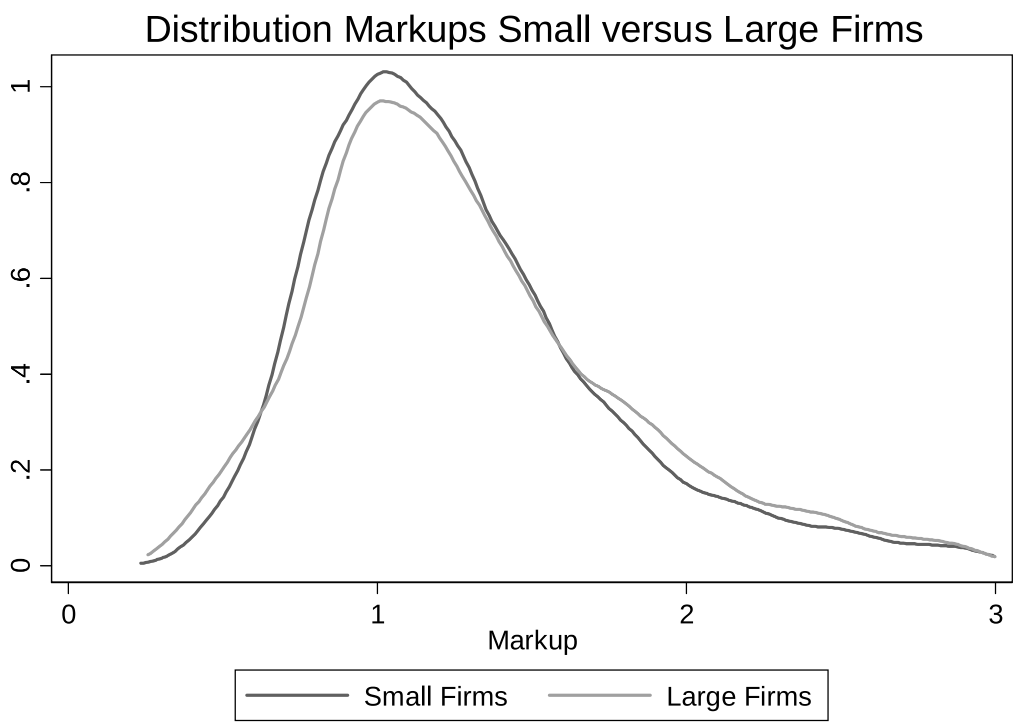


Figure C.2: Evolution Markup Selected Industries (1)

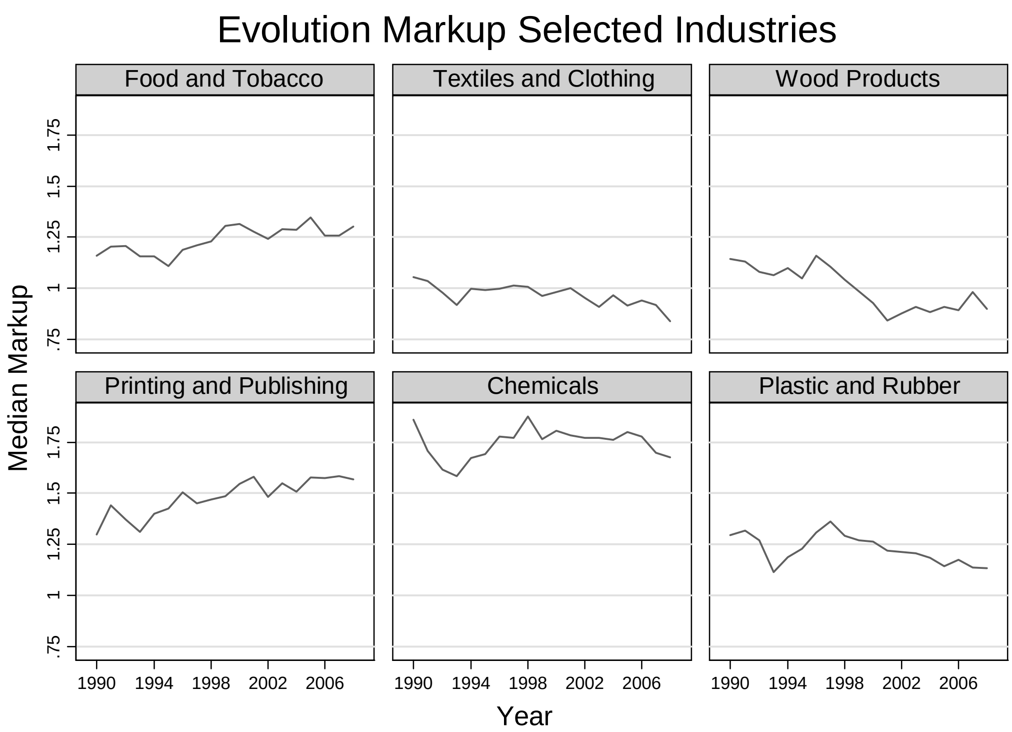


Figure C.3: Evolution Markup Selected Industries (2)

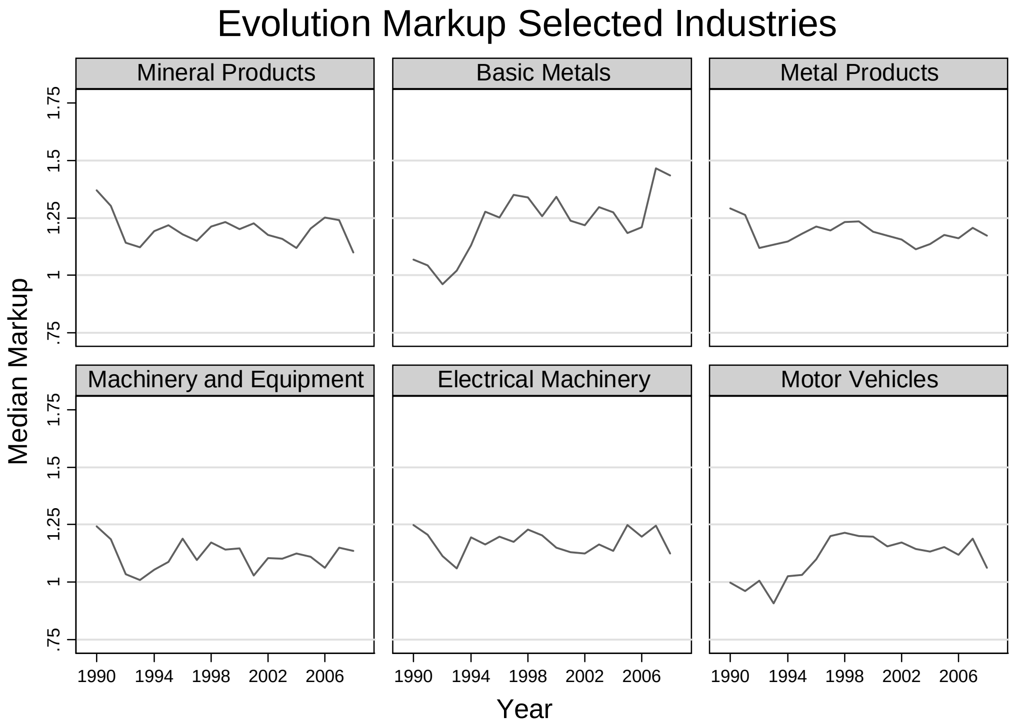
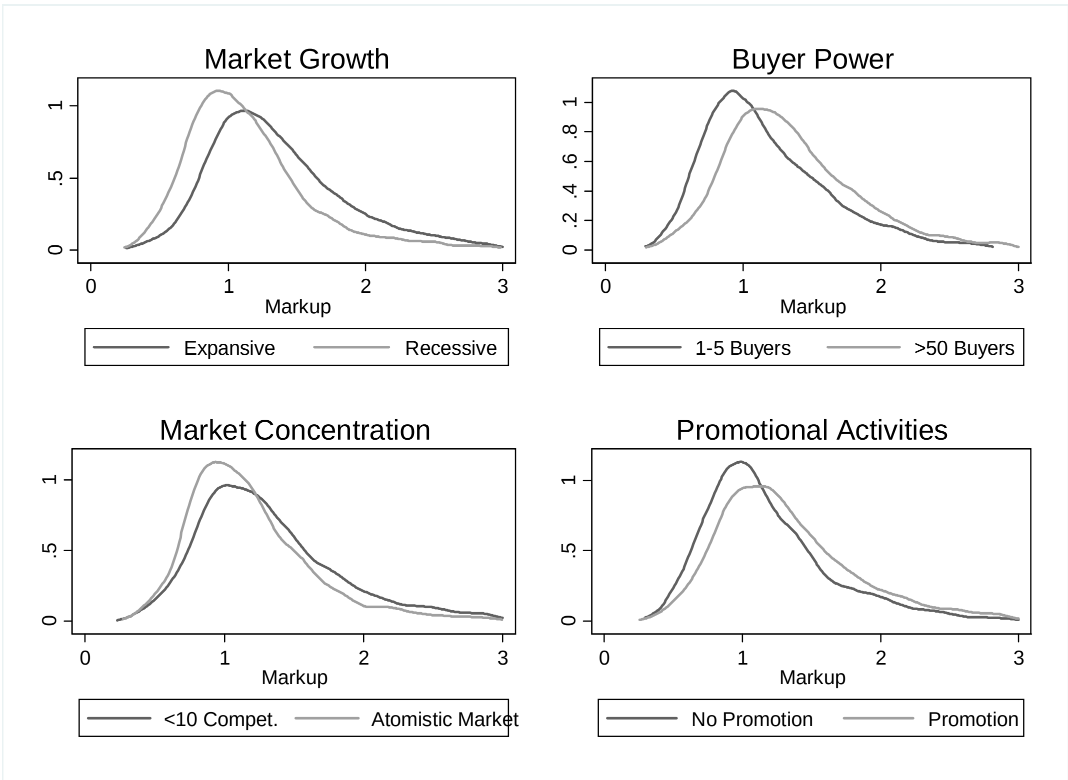


Figure C.4: Drivers of Average Markups



D Accounting Markups

In the empirical industrial organization literature, the so-called accounting markup is often used as an imperfect measure for market power. The accounting price-cost margin is defined as $PCM_{acc} = \frac{PQ - zM - wL}{PQ}$ which is equal to true price-cost margin when there are constant returns to scale and all capital costs are fixed. We compute the accounting price-cost margin and compare it with our estimate for the true markup.[48] The simple raw correlation between the accounting and estimated markups equals .57. In general the accounting markup is higher compared to the estimated markup as can be seen in Figure D.1, but the evolution over the business cycle is similar for both measures as they are both pro-cyclical. The estimated markup appears to be more responsive to economic down- and upturns which is consistent with a view that managers have incentives to understate high profits and overstate low profits both for strategic as for tax reasons (Schmalensee 1989).

Despite the high correlation, there exist systematic differences between the two measures in line with the theoretical predictions. First, we expect the estimated markup to be relatively lower compared to the accounting markup for capital intensive firms. As at least part of the capital costs are variable, the accounting markup will overestimate the true markup and more so if capital intensity is higher. Second, under increasing returns to scale, the average variable costs are an overestimate of marginal costs and the accounting markup will underestimate the true markup. With decreasing returns to scale the accounting markup will be higher than the true markup. To test these hypotheses we link differences between our markup estimates and the accounting markups with capital intensity and returns to scale. First, we divide our sample into high and low capital intensive firms[49] and compute the median markup for these two types of firms. While the accounting markup is close to the estimated markup for low capital intensive firms ($\mu_{acc} - \widehat{\mu} = .05$), the accounting markup is substantially higher relative to our markup estimate for high capital intensive firms ($\mu_{acc} - \widehat{\mu} = .15$), consistent with our story. Second, we link markups with our returns to scale obtained from our production function estimates. Although there are constant returns to scale on average , there exists substantial variation in returns to scale across firms. In Table D.1 we report the median accounting and estimated markup for different returns to scale.[50] For increasing returns to scale, the accounting markup is lower compared to the estimated markup while for decreasing returns to scale the reverse holds.

When measuring the returns to innovation, it is especially important to obtain estimates for the true markup instead of relying on the accounting markup if the bias in the accounting markup is systematically related to the innovative activities of firms, i.e. if the returns to scale and capital intensity differs between innovative and non-innovative firms. Table D.2 reports the percentage of observations that report a product and process innovation, split between high and low returns to scale and high and low capital-labor ratio's. Clearly, firms with high returns to scale are more likely to introduce a product innovation. For process innovation the difference between high and low returns to scale firms are even larger. Note that when returns to scale are higher for innovative firms, this means that the accounting markup will underestimate the true markup difference between innovative and non-innovative firms, leading the returns to innovation to be underestimated when relying on the accounting markup. The capital-labor ratio works in the other direction as the presence of a higher capital stock for innovative firms will lead the accounting markup to overestimate the true markup by more for innovative firms compared to non-innovative firms and the markup premium of innovation will be overestimated.

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[48] To be precise, we compute the accounting markup $\mu_{acc} = \frac{1}{1 - PCM_{acc}}$ which is directly comparable with our markup estimate.

[49] High capital intensive firms are firms with a ratio of the value of machinery and equipment to labor above the median of this ratio. Low capital intensive firms have a ratio below the median.

[50] The category of increasing returns to scale is defined as all observations for which the returns to scale are higher than 1.05. Likewise decreasing returns to scale is defined as having returns to scale below 0.95.

Figure D.1: Evolution Accounting Markup versus Estimated Markup

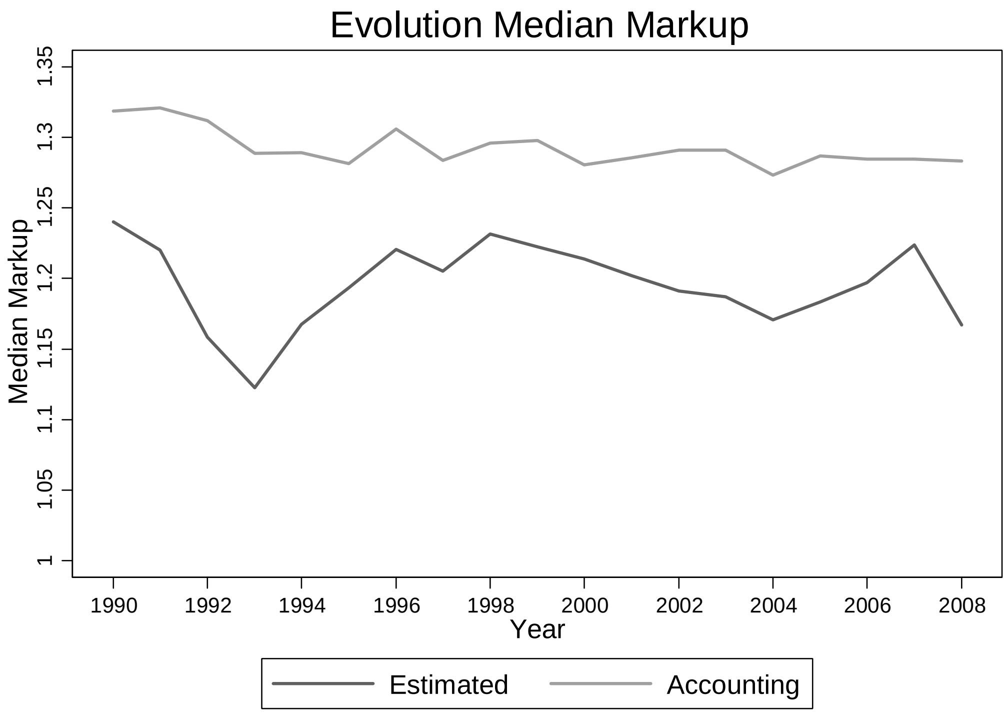

Table D.1: Returns to Scale and Markups

	Accounting μ_{acc}	Estimated μ	Returns to Scale
All	1.29	1.20	0.99
Increasing Returns	1.33	1.53	1.09
Decreasing Returns	1.26	1.03	0.91

Low returns to scale and high returns to scale refer respectively to observations with returns lower than 0.95 and higher than 1.05 respectively where returns to scale are estimated with a translog production function controlling for the endogeneity of inputs. For all variables the median value is reported

Table D.2: Returns to Scale, Capital-Labor Ratio and Innovation

	All Firms		Small Firms	
	Product Innov.	Process Innov.	Product Innov.	Process Innov.
Low Returns	20.0%	24.0%	15.4%	18.3%
High Returns	28.3%	39.7%	20.3%	30.2%
Low K/L Ratio	19.8%	22.8%	17.2%	20.1%
High K/L Ratio	28.9%	42.6%	20.1%	34.7%

Low returns to scale and high returns to scale refer respectively to observations with returns lower than 0.95 and higher than 1.05 respectively where returns to scale are estimated with a translog production function controlling for the endogeneity of inputs. Low and high K/L ratio refer respectively to observations above and below the median of the capital to labor ratio distribution. Each time the percentage of observations that report a product and process innovation is displayed.