Innovation and Markups: Firm Level Evidence*

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Abstract

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. Firm-level studies have focused on the effects of appropriation of innovation returns – typically focused on industry level characteristics – on the market value of the firm. In this paper we explore the more micro-level relation between innovation and appropriation through the markups a firm is able to extract after innovating. There exists little quantitative evidence on how innovation activities relate to price-cost margins. Theoretically one would expect product innovation to increase margins by creating a specific demand for the firm's product. Also process innovation can impact price-cost margins depending on the demand system and competitive environment in which the firm operates. Using a rich Spanish dataset we estimate firm-specific price-cost margins and find that both product and process innovations are positively related to these markups while controlling for other firm and market characteristics.

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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. Nevertheless, the focus in this literature has been on estimating an average relationship between a smoothed R&D investment function and improvements in the productivity of the firm. Most of these papers find a strong and substantial impact of R&D on firm level productivity, although determining the direction of causality is often a more difficult task (for an overview cf. Hall et al., 2009). More recent datasets, based on detailed surveys hold direct measures of actual outcomes of research and development such as product and process innovations. These data sets allow us to explore the effect of success or failure in the innovation activity on individual firm performance and survival. More importantly, the survey based measures allow us to explore the effect of different innovation activities such as the relative importance of product and process innovations. The few studies that have used these new datasets, generally find that product innovation has a substantial positive impact on productivity while the impact of process innovation is more ambiguous as in a number of studies no or even a negative relation between process innovation and productivity is found (Hall, 2011).

While the original literature has been cast as measuring the effects of innovation and R&D on firm productivity one should note that productivity is almost always defined as "measured productivity" as opposed to the more narrowly defined technical efficiency. Productivity is actually measured using firm sales rather than output quantity and given that firm level output prices are hardly ever observed "measured productivity" contains both demand (price) and cost related elements. Consequently, estimates of the impact

of innovative activities on "measured productivity" include, not only the impact on true productivity (i.e. technical efficiency of turning inputs into outputs), but also the impact on firm specific prices. This insight provides an explanation for the different impact of product versus process innovation on measured productivity. Product innovation has a positive impact through firm specific prices while the total impact of process innovation on measured productivity is a combination of a technical efficiency effect and the pass-through of the resulting reduction in marginal costs to firm specific prices. This connection between measured productivity on the one hand and these survey based measures of actual firm decisions and outcomes on the other hand opens up the productivity literature to examining the effect of different types of innovation on actual firm specific markups.

In this paper we complement and advance the literature in that we estimate the relation between innovation and appropriation through the markups a firm is able to extract after innovating, rather than focusing more narrowly on technical efficiency. 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] - so we opt to estimate markups instead of directly observing them. 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), the impact of privatization on markups (Konings, Van Cayseele and Warzynski, 2005), ... 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

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

specific markups. With firm specific markup estimates at hand, we can estimate the effects of innovation on market power of firms. In doing so, we moreover discriminate 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. 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 specific markups. More precisely we find markups to be 2.8% higher for firms realizing a process innovation and 3.9% 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, although the impact of innovation is estimated to be lower. Discriminating between the different types of product and process innovation shows that especially product innovation involving new design of the product and process innovation due to the introduction of new machinery influences the markup. Furthermore, 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. These effects are consistent with product innovation shifting out demand, and process innovation reducing costs. Our finding on the importance of product innovation in affecting markups and prices is very consistent with 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).

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 are presented in Section 4 while Section 5 disentangles the markup effects into variations in prices and marginal costs. Finally, Section 6 concludes the paper.

2 Empirical Strategy

This secton describes in more detail 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

This section describes the empirical methodology to infer markups from firm level production data. The 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, Hubbard and Petersen 1988 and Roeger 1995 among others). Typically, a sector level markup was estimated which was 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 thorough analysis, 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[3]. 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; $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$, 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.[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]This is obviously equivalent to computing the markup direct by dividing total revenue by total cost.

[4]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.

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

The advantage of the described methodology are the fairly modest assumptions that one has to make. One only needs a cost minimizing producer and does not have to make assumptions 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). The only assumptions imposed are cost minimization and freely adjustable inputs. The second assumption is needed because adjustments costs drive a wedge between output elasticities and revenue shares as well. 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. It is relatively common in the literature to assume the production function to take the Cobb-Douglas form. However, the drawback of this functional form is that it restricts the output elasticities to be constant across all firms and all heterogeneity in revenue cost shares is assumed to be due to firm-level variations in markups. Therefore we allow for more flexibility by estimating a translog production function rendering variation in output elasticities across firms. The translog production function has been introduced by Christensen et al. (1973) and

[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)

has been subsequently used in a number of empirical papers, its main advantage being its flexibility compared to the Cobb-Douglas production function. More precisely, the elasticity of substitution is not restricted to be constant and equal to one and firm level heterogeneity in output elasticities is allowed for. Note however, that the parameters of the production function are constant across firms (within the same industry), which is a necessary assumption in order to apply the identification strategy described below. The rest of the current section describes the identification strategy for the production function parameters, relying on recent econometric developments.

We assume Hicks neutral technological progress and the production process to be best described by a translog production function. Expressed in natural logarithms, the production function can be written as (Christensen et al., 1973):

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

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. After obtaining estimates for the coefficients on labor and capital, the output elasticity of labor can be computed as:

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

Obviously, with a Cobb-Douglas production function, there exists no variation in the output elasticities across firms or over time. With a translog production function, while 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 take into account the possible endogeneity of capital and labor as it is easy to show how input choices of a

[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)

profit maximizing firm are likely to be correlated with the unobserved productivity shock ω_{it}. To control for this we use the insight that optimal input choices hold information about the level of productivity. Olley and Pakes (1996) showed how optimal investment depends on capital and productivity. When investment is monotonically increasing in productivity, conditional on the capital stock, this investment demand function can be inverted to write unobserved productivity as a function of unobservables. Given certain timing assumptions on inputs, appropriate moment conditions to identify input coefficients can be constructed. While Olley and Pakes (1996) rely on an investment demand function to proxy for productivity, Levinsohn and Petrin (2003) advance the literature and introduce a material demand function. The latter has the advantage that one does not have to go back to the underlying dynamic model when introducing additional state variables such as exporting or R&D investments (De Loecker 2010).

Our procedure consists of two steps. In a first step, we estimate the labor coefficients and separate the productivity term ω_{it} from the i.i.d. error term η_{it}. To this end, we write material demand as a function of the capital stock and productivity as in Levinsohn and Petrin (2003). However, material demand does not only depend on capital and productivity ω_{it} but also on product and process innovation. For example, if a firm realizes a product innovation, this will have an impact on residual demand faced by the firm, given its level of productivity, and as such on the optimal input demand of the firm. More precisely one can write material demand as follows: $m_{it} \equiv m_t(k_{it}, \omega_{it}, prod_{it}, proc_{it})$, where $prod_{it}$ and $proc_{it}$ represent a dummy equal to one if the firm has realized a product or process innovation respectively.[8] If material demand, conditional on capital and innovation, is monotonically increasing in productivity, we can invert this equation and write productivity as a function of observables, i.e. $\omega_{it} = h_t(m_{it}, k_{it}, prod_{it}, proc_{it})$. Consequently, we run the following regression:

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

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

[8] Note that Ackerberg et al. (2006) also include labor in the material demand function.

process innovation dummies. 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]

The second step serves to identify the capital coefficients. We follow the standard assumption that productivity follows a first order Markov process but allow this process to be endogeneous (Aw, Roberts and Xu, 2011). More precisely, the firm can impact the productivity evolution by investing in R&D. Consequently productivity in year t is a function of lagged productivity as well as lagged R&D, i.e. by $\omega_{it} = g(\omega_{it-1}, RD_{it-1}) + \xi_{it}$, 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 $t-1$. We take the standard assumption that it takes one period to order, receive and install new capital. As a result, contemporaneous capital as well as capital squared are uncorrelated with the productivity shock ξ_{it}, which was unforeseen at period $t-1$ when the capital stock for period t was decided. The timing assumption on capital gives us the moment conditions we are going to identify the capital coefficients with. More precisely, the moment conditions are:

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

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[10] we retrieve an estimate for the unexpected productivity shock ξ_{it} which is used to construct the sample analogue of the above moment conditions.[11] Bringing this sample analogue as close as possible to zero,

[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.

[10]We include as well the innovation dummies in this equation. Since we do not observe physical quantities our dependent variable is revenue deflated by an industry wide price deflater. Consequently our estimate for productivity is likely to contain as well demand side elements. Assuming a functional form such as as CES demand system would allow us to filter out these demand factors (De Loecker, 2011). However, the purpose of this paper is to make as few assumptions as possible about the demand system such that we do not follow this avenue. We do control for possible demand shocks still included in our productivity estimate by including the innovation dummies as well as year dummies in the non-parametric regression of productivity on lagged productivity.

[11]In the non-parametric regression of productivity on lagged productivity and R&D spending we

one finds consistent estimates for the capital coefficients of the production function.[12]

3 Data Description

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.[14] 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 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.[15] 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

[14] 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.

[15] 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.

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 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 exports at least one product and 61% imports 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

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

where q_{it} is value added of firm i in period t. We estimate both translog and Cobb-Douglas production functions.[16] 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

[16] 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 for another application 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 firm decisions hold.

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 1. 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 the production function is well-behaved for all observed input choices.[17] In Appendix A we derive the conditions for well-behavedness of the translog production function and we drop all observations violating them.[18] 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 the derivation 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 an unrealistically high median

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

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

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.[19] 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 to allow 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. [20]

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 be found as well in the Publishing sector as well as in the Manufacturing of Food Products[21]. Sectors such as the Textiles, Leather Products, Wood Products and Office Machinery charge the lowest markups. The firm level correlation with the price-cost margin computed with average variable costs equals .57[22] 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 has fallen considerably during the economic crisis beginning of the nineties. Afterwards,

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.

4.3 Markups and Firm Decisions

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 dummies which pick up year specific variations in markups. Moreover we include in several specifications firm fixed effects, controlling for all unobservable firm and sector specific factors that influence the markup and are constant over time. X_{it} is a vector of control variables including the capital/labor ratio, log labor and size dummies.[23] The vector contains as well 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 intermediate products. We include as well variables that should pick up competition in the market. Instead of relying on concentration measures such as the Herfindahl Index, we rely on 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 for.

Results are reported in Table 4. The first two columns display results for the whole

[23] The size of a firm is categorized into 6 categories: $L < 20; 20 < L < 50$; $50 < L < 100$; $100 < L < 200$; $200 < L < 1000$ and $1000 < L$

sample. 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. In general, the results on the relation between market structure and markups increase confidence in the methodology to estimate firm level markups as well as in the quality of the responses given by the firms in the survey.

Turning to the relation between innovation and markups in the second column, it is obvious that product innovation as well as process innovation are related to higher firm level markups and this relationship is highly statistically significant. When output elasticities are inferred from a translog production function, markups of process innovators are around 2.8% higher and the markup premium of a product innovator is around 3.9%, which means, evaluated at the mean, the impact on the markup level is around 0.037 and 0.052 respectively.[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). Restricting attention to small firms alone, the estimated relationship between innovation and markups is even stronger while for the large firms there appears to be no relation between markups and innovations. The reason being that for large firms the product and/or process innovation is likely to refer only to a small part of production as large firms typically tend to produce a substantial amount of different products (Bernard et al.

[24]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.

2009). If the realized innovation is only relevant for part of total production, the impact on the markup at the firm level could be too small to be picked up by our procedure. [25]

Up till now, we have established that more innovative firms realize higher markups. However, it could be that the positive correlation between firm level markups and the innovation variables is driven by factors influencing both innovation and profitability such as conditions of appropriability, firm size and market structure. Especially market structure and the competition intensity has been cited to influence innovation activities, both theoretically (e.g. Schumpeter 1942; Vives 2009) and empirically (f.e. Aghion et al. 2005). Our approach however differs in a number of important aspects. First, we compute firm-level markups instead of market level markups and to control for market level differences in markups we included first of all sector dummies. Moreover, a measure for the number of competitors in the market was included, picking up the strength of competition in the market and the relation between the markup and innovation dummy is less likely to be driven by differences in competition intensity across sectors and or subsectors. To control for conditions of appropriability and firm size we have included control variables such as the capital intensity and firm size in our regressions. Moreover, we have experimented with variables influencing appropriation like promotional activities of the firm and patents. The inclusion of these variables in our regression framework did not qualitatively change our results.

To further 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] Note that 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

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

and markups.[30] The results also seem to point that prior to entering the export market, firms already invest in higher quality products which can be sold at higher margins in the domestic market. Concerning the import dummy, the coefficient drops substantially but remains positive and significant.

An important assumption we have taken 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 retrieve similar results, both quantitative as qualitative.

4.4 Different Types of Innovations

In this subsection, we disaggregate our measures of product and process innovations. More precisely 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) to the introduction of new components or intermediates, (c) to 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 Table 7. The first two columns report results for the disaggre-

[30] De Loecker and Warzynski (2010) find markups to increase after entry into the export market. However, note that their data set covers Slovenian manufacturing firms during the transition to a market economy, where it is more likely to find learning-by-exporting effects (De Loecker, 2007)

gation of product innovation while the last two columns report results for the disaggregation of process innovation. The same control variables as in the previous specifications are included but not reported in the table. Only product innovations that go hand in hand with new design of the product are positively and statistically significant associated with higher markups. This is true for both the OLS specification and the specification where we control for firm fixed effects. With firm fixed effects included, the introduction of new functions in the product is positively related to markups as well.[31] 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.[32] Focusing on the fixed effects results in Table 8 shows that especially the combination between New Design and New Functions is associated with higher markups whether or not new materials are included. The category of observations where product innovation has also higher markups compared to non-innovating observations, but the coefficient is not significantly different from zero. All in all, it appears that only product innovations that also include changes in the design or appearance of the product increase markups.

Turning to the disaggregation of process innovation in the last two columns of Table 7, 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 to be not affected.

[31] These results seem to indicate that the introduction of new functions to the product appear to be mainly done by firms experiencing on average lower markups.

[32] 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%].

4.5 Market Structure and the Impact of Innovation

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 9. 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 to an atomistic market.[33,34] 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.

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

[33] More precisely we estimate the following equation:

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

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_1 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.

[34] 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.

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 market, or equivalently are cost decreases not completely passed through to consumers but increase the markup as well.

4.6 Robustness Checks

In the previous subsections we have used firm fixed effects as well as time varying variables measuring the level of competition in the market. To control for possible time-varying effects influencing both innovation and markups, we include the lagged markup in the regression framework. 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 however on itself 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 ε_{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 $E(\ \mu_{it-1}(\gamma_i + \varepsilon_{it}))$ and $E(\ innov_{it}(\gamma_i + \varepsilon_{it}))$. The identifying assumption for the innovation variables is that they are not related to the contemporaneous markup shock ε_{it}, which is consistent with our assumption used in the identification of the production function, namely innovation is decided (at least) one year in advance. In a second estimation, we include furthermore the moment conditions $E(\mu_{it-2}\ \ \varepsilon_{it}) = 0$ as well as further lags of the innovation changes and markup changes and levels as instru-

ments. Moreover, the moment conditions are constructed in the spirit of Arellano and Bond (1991), namely we construct a moment condition for each time period. [35]

Results are reported in Table 10. The first column 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. The second column applies GMM using the (lagged) changes in markups and innovation as instruments. In line with theoretical predictions the coefficient on the lagged markup increases compared to the within estimate but remains below the (upward) biased OLS estimate.[36] 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. Columns (3) and (4) exploit additional moment conditions by using further lags (and lagged differences) as described above, thereby increasing the efficiency of the estimator. Column (4) creates one instrument per lag distance instead of one instrument per time period/lag distance reducing the number of instruments substantially.[37] 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. In the current framework, the coefficients on innovation only reflect their short-run impact. The long-run effect is measured by $\alpha_s/(1-\alpha_1)$ with α_1 the coefficient on the lagged markup. Focusing on Column (3) 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. Process innovation due to new machinery has a long term effect of 2.54%. All in all the results presented in

[35] 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.

[36] 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.

[37] We report as well the $p-$value of the test for autocorrelation in ε_{it}. In order for the instruments to be valid there may not be any serial correlation in the error term. Moreover we report the $p-$value of the Hansen test of overidentifying restrictions.

this subsection are largely in line with the previous findings.

5 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.[38] 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. $\ln c_{it} = \ln p_{it} - \ln \mu_{it}$. where $\ln p_{it}$ is the self reported percentage change in output prices, $\ln \mu_{it}$ the estimated percentage change in the markup and $\ln c_{it}$ is the percentage change in marginal costs.[39] We relate these price and marginal costs 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.[40] The results are the following:

$$\ln p_{it} = \underset{(.0007)}{.0014} * prodinnov_{it} - \underset{(.0005)}{.0025} * procinnovdum_{it} + year_t$$

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

[38] 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.

[39] 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 costs levels.

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

innovation on the other side increases prices on average by 0.14% points. Both coefficients are statistically significant at the 5% level.

Combining the 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 with process and product innovation:

$$\ln c_{it} = \underset{(.0027)}{.0014} * prodinnov_{it} - \underset{(.0025)}{.0048} * procinnovdum_{it} + year_t$$

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 marginal costs 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 impact 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.

However, 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. A possible solution could be to take averages of markups over a number of years before computing long differences (f.e. 5 years) and contrast these markup differences with price changes over the same period to obtain the change in marginal costs. Subsequently these indicators could be related to the innovative activities of the firms over this period. This procedure could average out measurement error and lead to more precise estimates of the impact of innovation on prices, marginal costs and markups.

6 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 initiuition 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.

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8 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: Output Elasticities

	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

	All Firms		Small Firms		Large Firms	
	Cobb-Doug	Translog	Cobb-Doug	Translog	Cobb-Doug	Translog
Process Innov.	0.0305**	0.0281**	0.0351**	0.0285**	0.0243*	0.0174
	(0.00704)	(0.00755)	(0.00857)	(0.00887)	(0.0113)	(0.0120)
Product Innov.	0.0309**	0.0389**	0.0424**	0.0509**	0.00835	0.0110
	(0.00868)	(0.00943)	(0.0117)	(0.0128)	(0.0121)	(0.0127)
10<Compet.<25	-0.0302**	-0.0299**	-0.0270*	-0.0246+	-0.0383*	-0.0368*
	(0.00981)	(0.0106)	(0.0117)	(0.0126)	(0.0166)	(0.0169)
Compet > 25	-0.0405**	-0.0340**	-0.0317*	-0.0252+	-0.0727**	-0.0712**
	(0.0122)	(0.0128)	(0.0138)	(0.0140)	(0.0242)	(0.0251)
Atom. Market	-0.0425**	-0.0408**	-0.0425**	-0.0415**	-0.0304	-0.0240
	(0.00979)	(0.0107)	(0.0105)	(0.0112)	(0.0239)	(0.0250)
Exporter	0.0659**	0.0487**	0.0767**	0.0699**	0.0146	-0.0391
	(0.0113)	(0.0121)	(0.0118)	(0.0129)	(0.0278)	(0.0284)
Importer	0.0884**	0.104**	0.0932**	0.100**	0.0725**	0.0869**
	(0.0107)	(0.0115)	(0.0114)	(0.0122)	(0.0271)	(0.0262)
N	29153	26828				

Table 5: Patents and R&D

	Patents		R&D	
Proc. Innov	.0268**	.0264**	.0265**	
	[0.0075]	[.0075]	[.0075]	
Prod. Innov.	.0334**	.0350**	.0335**	
	[.0093]	[.0093]	[.0093]	
Patent (Y/N)	.0473**			
	[.0149]			
Nr. Patents		.0105**		
		[.0032]		
Log(R&D)			.0014	.0028**
			[.0010]	[.0010]
N	26787	26647	26828	26828
R^2	0.207	0.206	0.206	0.204
Nr. Firms	3775	3775	3777	3777

Standard errors in brackets

+ $p < .10$, * $p < .05$, ** $p < .01$

Each time the usual control variables as well as market characteristics and import/export dummies are included.

In regression with nr. patents, observations with over 15 patents excluded.

Table 6: Relation between Firm Level Markups and Firm Decisions with Firm Fixed Effects

	(1) CobbDoug. All	(2) Translog All	(3) Translog Small	(4) Translog Large
Process Innov.	0.00813*	0.00859*	0.0114*	0.00476
	(0.00401)	(0.00421)	(0.00534)	(0.00678)
Product Innov.	0.0103*	0.00934+	0.00579	0.00912
	(0.00470)	(0.00499)	(0.00671)	(0.00736)
10 < Compet.< 25	-0.0130*	-0.0106+	-0.00751	-0.0128
	(0.00551)	(0.00580)	(0.00703)	(0.0102)
Compet.>25	-0.0140*	-0.00888	-0.00446	-0.00968
	(0.00694)	(0.00740)	(0.00859)	(0.0147)
Atom. Market	-0.00977+	-0.0120+	-0.0141*	-0.00696
	(0.00594)	(0.00638)	(0.00715)	(0.0146)
Exporter	0.00846	0.00698	0.0158*	-0.0127
	(0.00656)	(0.00699)	(0.00780)	(0.0164)
Importer	0.0199**	0.0232**	0.0196**	0.0506**
	(0.00615)	(0.00656)	(0.00731)	(0.0153)
N	29153	26828	18172	8656

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 firm fixed effects, year dummies and controls for factor intensities. The variables 10<Compet<25, Compet.> 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.

First Column results for Cobb-Douglas production function, other columns Translog production function

Column 1 and two: full sample. Column 3: small firms; Column 4: large firms

Table 7: Different Types of Product and Process Innovation

	(1) OLS	(2) FE	(3) OLS	(4) FE
Product Innov.			0.0426**	0.00906+
			(0.00950)	(0.00524)
New Components	-0.00263	-0.00449		
	(0.0134)	(0.00791)		
New Materials	0.00467	-0.00585		
	(0.0134)	(0.00768)		
New Design	0.0501**	0.0159*		
	(0.0114)	(0.00663)		
New Function	0.00324	0.0168*		
	(0.0124)	(0.00728)		
Process Innov	0.0253**	0.00600		
	(0.00802)	(0.00450)		
New Machinery			0.0419**	0.0153**
			(0.00982)	(0.00562)
New Methods			0.00369	-0.00752
			(0.0148)	(0.00873)
New Mach & Method			0.0155	0.00312
			(0.0109)	(0.00618)
N	23334	23334	23359	23359

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 nace, year dummies, controls for factor intensities and size dummies.

Import, export and market characteristics included but not reported.

Column (1) and (2) make distinction between different types of product innovation.

Column (3) and (4) between types of process innovation.

Table 8: Different Types of Product Innovation; Mutually Exclusive

	(1) OLS	(2) FE
Process Innov	0.0253**	0.00680
	(0.00807)	(0.00452)
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 nace, year dummies, controls for factor intensities and size dummies. Import, export dummies as well as market characteristics included but not reported. Mutually exclusive types of product innovation.

Table 9: Innovation Interacted with Market Characteristics

	(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)
N	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 nace, year dummies, controls for 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 10: Lagged Markups Included as Control

	(1) FE	(2) GMM	(3) GMM SYS	(4) GMM SYS
Lagged Markup	0.270**	0.307**	0.441**	0.313**
	(0.00712)	(0.0182)	(0.0159)	(0.0205)
Prod New Materials	-0.00816	-0.00643	0.00271	0.00450
	(0.00767)	(0.0127)	(0.0123)	(0.0130)
Prod New Components	-0.000767	-0.00505	-0.0111	-0.0127
	(0.00795)	(0.0133)	(0.0127)	(0.0137)
Prod New Function	0.0144*	0.0195	0.0238*	0.0266*
	(0.00727)	(0.0119)	(0.0117)	(0.0126)
Prod New Design	0.0134*	0.0123	0.0186+	0.0260*
	(0.00663)	(0.0117)	(0.0105)	(0.0117)
Proc New Machinery	0.0103+	0.0181+	0.0142+	0.00501
	(0.00562)	(0.00965)	(0.00855)	(0.00954)
Proc New Mach & Method	0.00107	0.0176	0.00202	0.00516
	(0.00625)	(0.0107)	(0.0102)	(0.0113)
Proc New Methods	-0.00486	0.00431	-0.00672	-0.0214
	(0.00866)	(0.0157)	(0.0126)	(0.0141)
N	20877	17601	20877	20877
$P-$ value AR			0.00498	0.659
Hansen $P-$ Value			0.112	0.0672

Standard errors robust against heteroskedasticity and within-group correlation.
+ $p < .10$, * $p < .05$, ** $p < .01$
Regressions with lagged markup included. Column (1) reports fixed effects. Column (2) applies GMM estimation using first differences as instruments for the firm dexisions and lagged first differences for the lagged markup. Column (3) applies System GMM whith 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. Column (4) reports results for a similar specification but now only with one instrument per variable/lag instead of one instrument per variable/lag/time period. All equations include the usual controls which are each time appropriately instrumented as well.

9 Figures

Figure 1: Distribution Output Elasticities

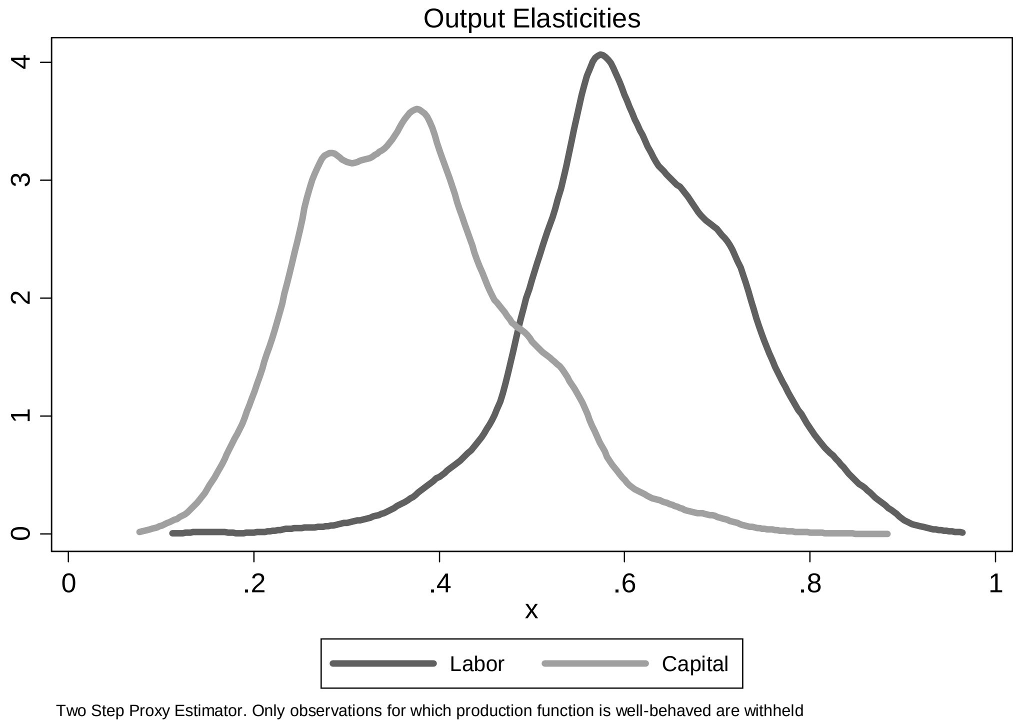


Figure 2: Markup per Sector

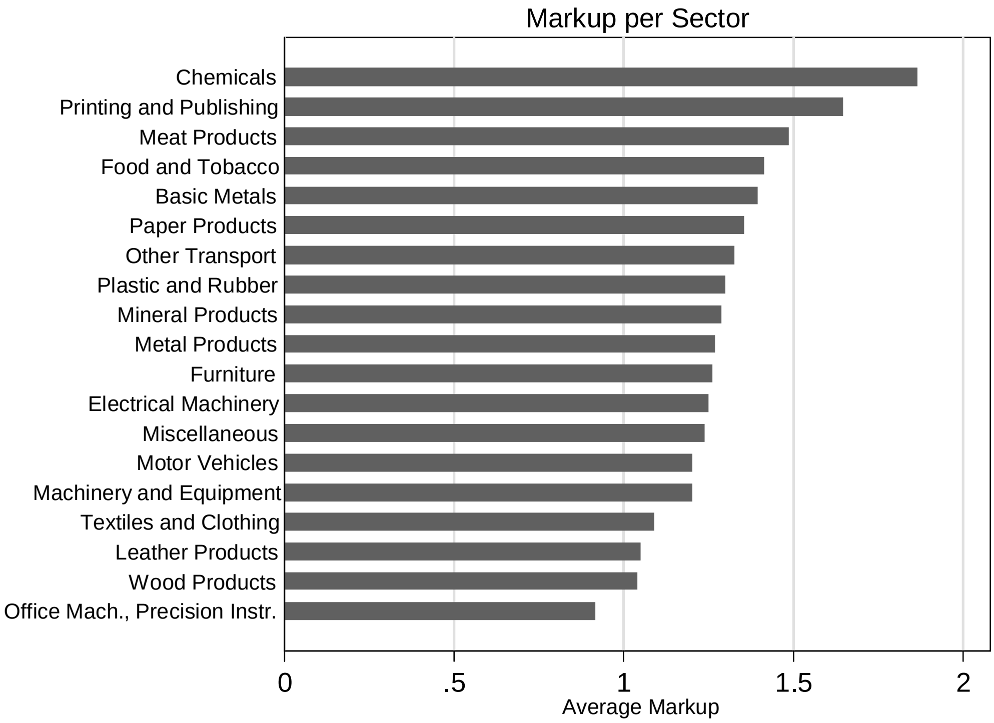
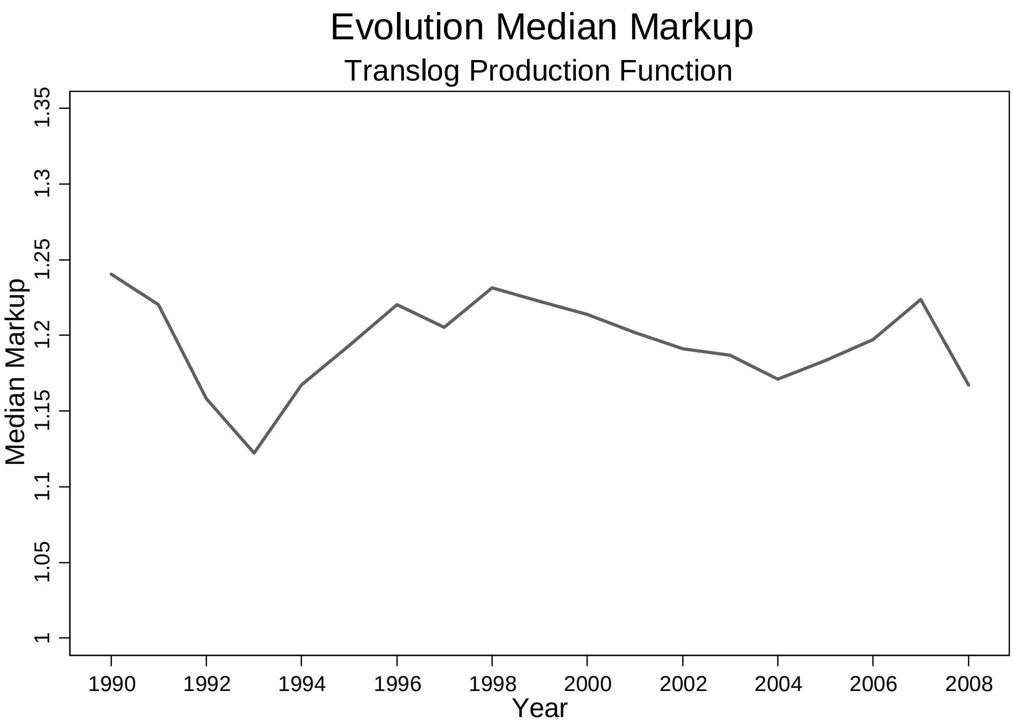


Figure 3: Evolution Median Markup



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[41]. 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 only increasing 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 needs to 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 labor. 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 be easily 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 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.

[41] 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.

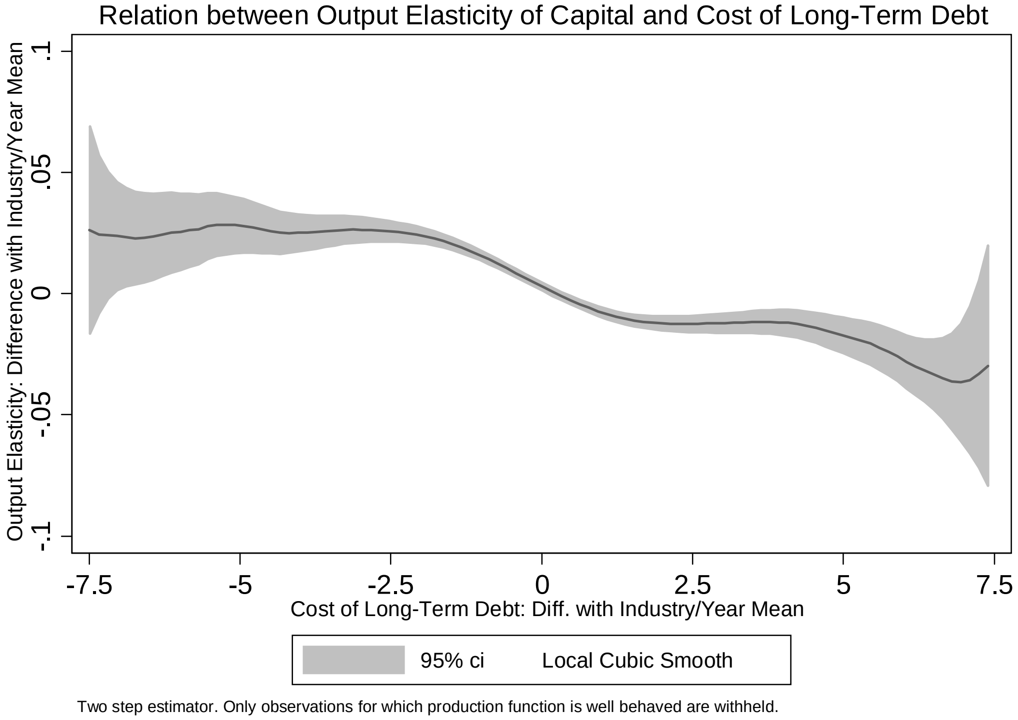
B Plausibility Output Elasticities Translog

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.[42] 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.

[42] 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

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



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 Textiles 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 could be for example 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.[43] Probit regressions of the exit probability on the markup showed a significant effect of the markup on the probability of exit.[44]

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. 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.

[43] 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.

[44] Results available on request.

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 Markup Differences

	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

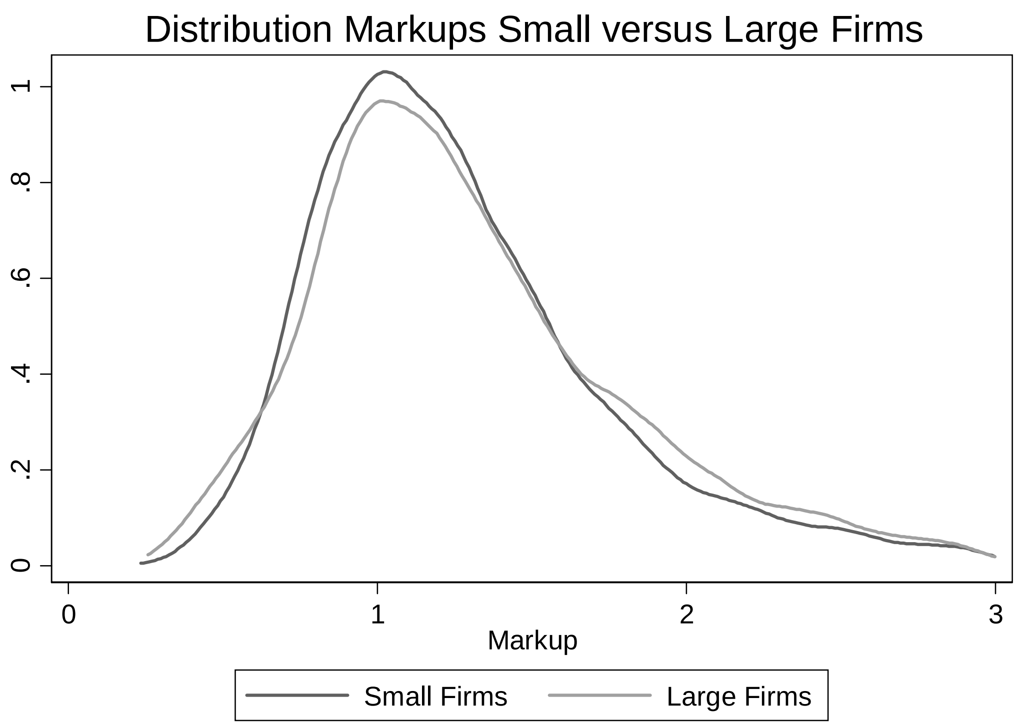


Figure C.2: Evolution Markup Selected Industries (1)

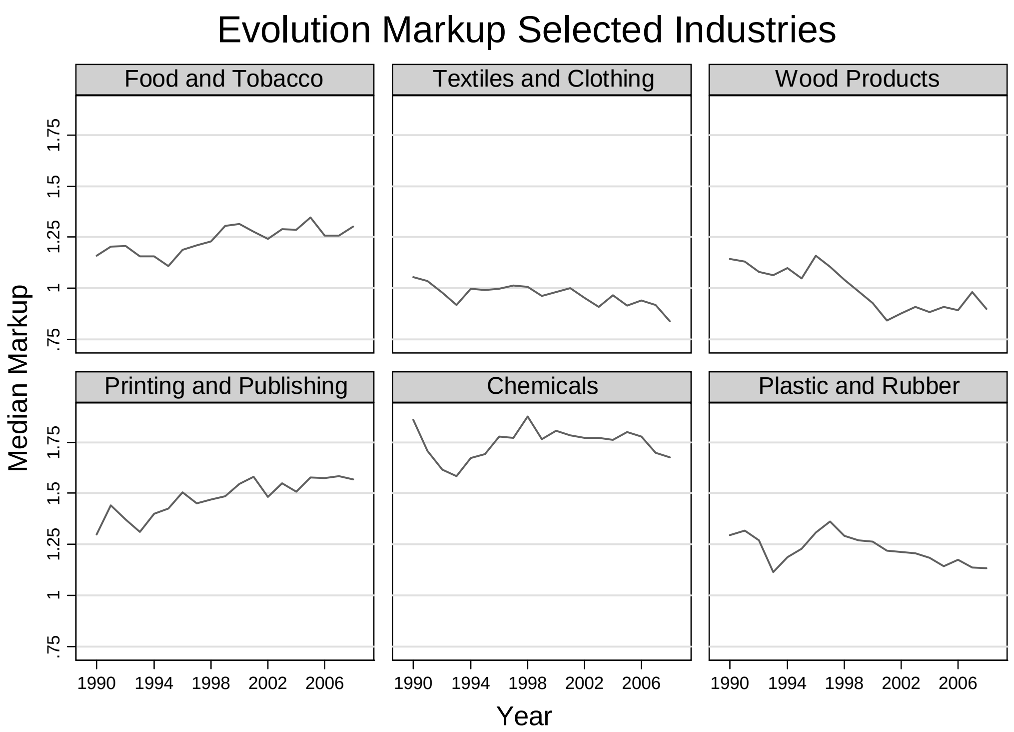


Figure C.3: Evolution Markup Selected Industries (2)

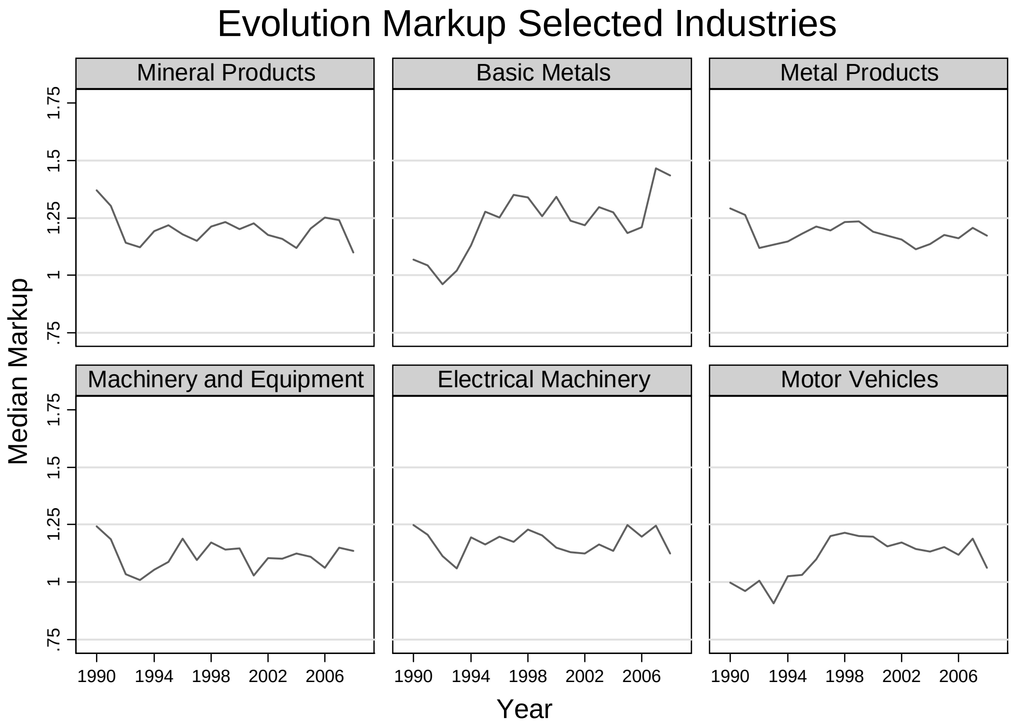
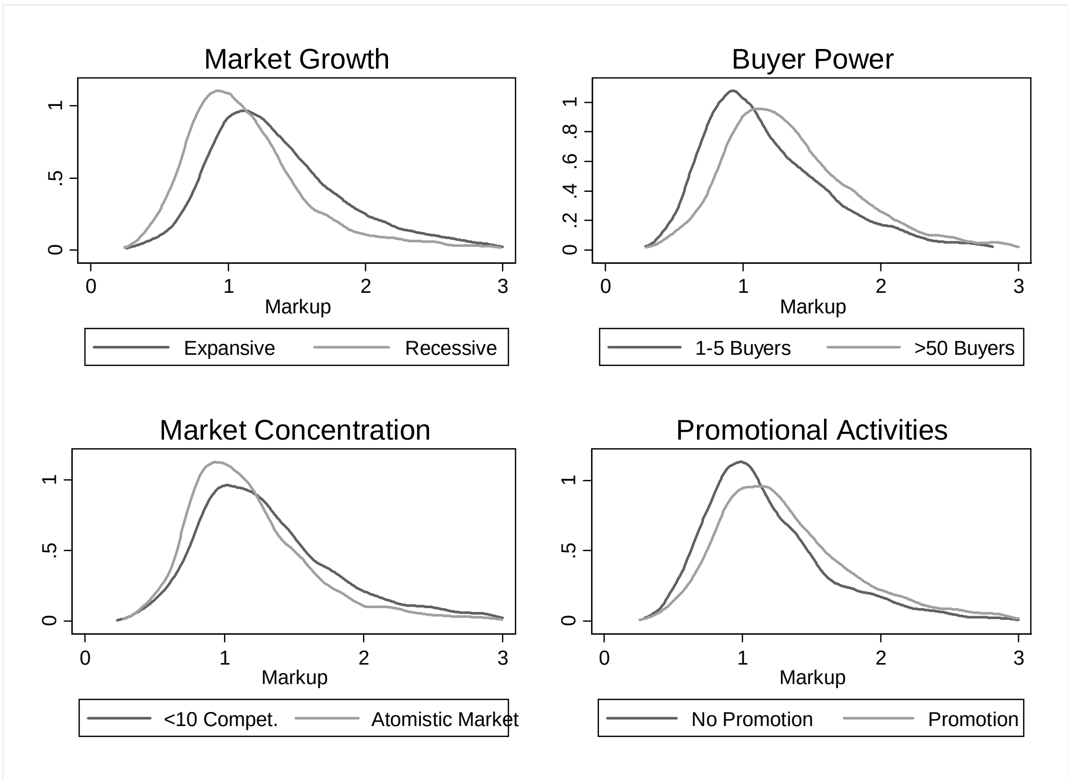


Figure C.4: Drivers of Markup Differences



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.[45] 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 be an underestimate of 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[46] 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 ($\mu_{acc} - \widehat{\mu} = -.01$), the accounting markup is substantially higher relative to our markup estimate for high capital intensive firms ($\mu_{acc} - \widehat{\mu} = .19$), 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. For increasing returns to scale, the accounting markup is lower compared to the estimated markup while for decreasing returns to scale the reverse holds.

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

For all variables the median value is reported

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

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

Figure D.1: Evolution Accounting Markup versus Estimated Markup