Prices under Innovation: Evidence from Manufacturing Firms[*]

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August 2018

Abstract

We study how firms' innovations impact prices with endogenous productivity and markup, under imperfect competition and dynamic pricing. Absent innovation, productivity plus markup changes curb price growth to half of variable inputs cost growth. Innovation's additional impact on costs is negatively correlated with markup changes. We detect two prevalent strategies. When marginal cost goes down, firms *cash-in innovation* by increasing the markups to enlarge profits. When marginal cost goes up, firms practice *countervailing pricing* by decreasing markups. With no innovation aggregate manufacturing price growth had multiplied by 1.4, but innovation without cash-in strategies had multiplied it by 0.8.

Keywords: price indices, marginal cost, markup, innovation

JEL: D43, L11, L16, O31

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[*] We are grateful to Ulrich Doraszelski, Sam Bazzi, Stefania Garetto, Shane Greenstein, John Harris, Kevin Lang, Jacques Mairesse, Shiko Maruyama, Bettina Peters, Mark Roberts, Marc Rysman and Heng Yin, as well as participants at numerous presentations for helpful comments. Lin acknowledges grant support (No. 20720171065) from the Fundamental Research Funds for the Central Universities.

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1. Introduction

Economic theory establishes that, under imperfect competition, profit maximizing firms set prices with a markup over marginal cost.[1,2] This implies at least two ways innovation impacts prices. On the one hand, marginal cost depends on firm-level productivity, which in turn evolves endogenously according to innovations. On the other hand, the firm may find that innovation (particularly product innovation) shifts demand and perhaps also its elasticity, thus innovation may impact price via its influence on the optimal markup. If adjustment costs of prices are present, then innovation might play a further role in affecting the costs to adjust prices.

This paper sets out to study pricing when the firm experiences a sequence of process and product innovations. The innovations that we consider are the incremental innovations that firms periodically introduce in their production processes and products as result of their R&D and other innovative activities.[3] As we show later, in our sample median process and product innovators introduce innovations every 2.3 years, but 24% of the firms do not innovate. Our model starts by specifying how these innovations possibly affect the marginal cost of the firm, the demand for its products, and the costs of adjusting prices.

Input neutral productivity enters the cost function multiplicatively and drives cost changes. Process innovations, often aimed at reducing cost, can be expected to shift productivity up and the marginal cost function downwards. However, the converse could happen if process innovations alter the product and its quality. Product innovations, in the form of improved or new goods, are expected to change cost in more heterogeneous ways. For example, quality upgrades may imply greater production cost, at least temporarily. The production of the new good may require new labor skills and different material qualities.[4] Similarly, when

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[1] Hall and Hitch (1939) is a departure from this view, which Ellison (2006) characterizes as an early contribution to behavioral industrial organization.

[2] This markup can be temporarily negative when dynamic pricing and sunk cost are present.

[3] Data on innovation have been collected for the last 20 years in firm-level innovation surveys all around the world (for example in the Community Innovation Surveys in Europe and the NSF-enlarged United States Business R&D and Innovation Survey, BRDIS) and used in many analyses (see Mairesse and Mohnen, 2010).

[4] The degree to which these additional skills and qualities are not fully accounted for in the observable

"learning by doing" is important, firms may lack experience in producing the new good and productivity goes down initially as a result.

Demand can be shifted by the degree of product attractiveness induced by innovation (relative to competitors' products), and as a result the price elasticity can be modified upward, downward, or upward and downward successively over time. Innovation is also likely to modify the cost of adjusting the price; a productivity-enhancing innovation enlarges the markup without the need of changing the price, a cost-increasing innovation implies costs of conveying new information to consumers when altering the price.

We construct a model of endogenous productivity and markup with dynamic pricing under imperfect competition. The discrete cost changes induced by innovation at different points in time affect profits for the following years, which clearly calls for a dynamic model. This in fact adds to an extensive literature on price changes that shows dynamic pricing to be empirically relevant. On the side of competition, our model perfectly fits the case of monopolistically competitive firms, but it is more general. It can be extended to include strategic interactions among competitors by specifying the right state variables (or even interpreted as consistent with some special cases of interaction). Finally, our approach to modeling is robust in that it is valid under many detailed specifications, including a fully nonparametric one. Thus our parametric specification should be taken as a simplifying representation of something that is more general.

Identification of the model proceeds as follows. Log price is the sum of the log of marginal cost plus the log of the markup ratio (which may be thought of as the markup in percentage points). One should estimate at the same time marginal cost and the markup, as well as the effects of innovation on both. However, estimating marginal cost implies estimating unobserved persistent productivity, which cannot be done consistently without the markup,[5] and there is no way to separate the effects of innovation on the markup and marginal cost in the same equation. Thus we augment the relationship to model simultaneously the log of the price to average variable cost ratio. This ratio is observable up to an uncorrelated

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part of cost is going to decrease productivity.

[5] See the literature review.

error, is independent of productivity and includes the effects of innovation on the markup. However, the ratio of price to average variable cost measures the markup up to the elasticities of the variable factors that characterize marginal cost (the short-run scale parameter). As a result, we have two equations with different dependent variables (price average variable cost margin and price). Each equation cannot separately identify our variables of interest (productivity, markups and the effects of innovation), but their simultaneous estimation provides identification. In our model firms choose markups. We show that this gives the same outcome as choosing prices since one variable determines the other. In writing the system we specify the markup as the policy function of the dynamic pricing problem of the firm.

Next we estimate the model using output price indices constructed over an extended period of time (17 years) for a sample of Spanish manufacturing firms. Firm-level price indices are computed from the reported yearly output price changes in the markets of the firm, information that's rarely available. In addition, we have the process and product innovations introduced by firms and the relevant data to construct margins, output and input use.[6] The data contain ten (unbalanced panel) industry samples, which in total amount to more than 2,300 manufacturing firms and 20,000 observations during 1990-2006.

The model gives sensible estimates of the distributions of markups and productivity. They reveal that markups are persistent over time, although much less so than productivity. Furthermore, markups are procyclical and productivity is less so; the firm clearly sets larger markups when its markets are in expansion. We also find that the relevant marginal cost for pricing is the short-run marginal cost that includes labor adjustment cost. Our testing results show that the dynamic specification fits the data better than a static model in which the firm prices according to the elasticity of demand.

The results on the behavior of prices can be summarized as follows. In the absence of innovation (about 50% of the observations), prices evolve according to a stylized law of

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[6] The data come from the firm-level survey ESEE (see Section 3). The innovation data of a very similar sample has been used by Guadalupe, Kuzmina and Thomas (2012) to analyze the relationships between multinational entry through firm's acquisition and innovative performance of these firms.

motion: variable input cost pushes up unit cost by 3%, but productivity growth combined with a continuous margin markup moderation curbs price increase to half of this rate at 1.5%.[7]

When an innovation is introduced, productivity sometimes increases (particularly when it is process innovation) and sometimes decreases, which leads to the respective decrease and increase in marginal cost. These innovation-induced cost changes turn out to be negatively correlated with markup changes. As a result, we detect two prevalent strategies in firms' pricing behavior that we call "cash-in innovation" and "countervailing pricing." When productivity goes up, and hence marginal cost goes down, most firms "cash-in"innovation by increasing the markup to enlarge profits. When productivity goes down, and hence marginal cost goes up, many innovators "countervail" the cost increase by decreasing the margin.

Lastly, we evaluate the impact of innovation on aggregate manufacturing prices. In the absence of innovation involving process innovation,[8] the rate of increase of the aggregate manufacturing price had multiplied by a factor of 1.4. The main component of the moderation of aggregate price is the productivity improvements, despite the firms' tendency to "cash-in" innovations that enhance productivity. Innovation without these "cash-in" strategies had multiplied the rate of increase of aggregate manufacturing price by 0.8. This suggest a possible scope for policymaker to sharpen the aggregate price effect of innovation, but at the risk to dampen the incentives of firms for innovation.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses the data and presents descriptive statistics. In Section 4 we lay out the model, and in Section 5 we specify the econometric implementation. Section 6 presents the estimation results. Finally, Section 7 concludes.

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[7] The continuous markup moderation is a country-period specific trait.

[8] Introduction of a process innovation or simultaneous introduction of a process and a product innovation.

2. Related Literature

We are the first, up to our knowledge, to address the impact of innovation on output prices with an empirical structural model.[9,10] Other papers have separately looked at how innovation affects profitability/markups and (more structurally) on productivity. The simultaneous impact of innovation on the two is often overlooked, but needed in a study that wishes to investigate the effect of innovation on prices. It seems difficult to dismiss the interest of any evidence that can be gathered on this research question: the transmission of technological improvements to prices is a basic mechanism of the economy and is key for allocation and welfare. The reason for the lack of studies is probably that it is rare to have information on prices, or output price indices, and at the same time the information needed to model unobserved heterogeneous markups and productivity. We have such data for a sample of manufacturing firms and exploit them. The prices we use are not the usual statistical indices employed in descriptive analyses of price setting, such as the recent examples of Goldberg and Hellerstein (2011) and Bhattarai and Shoenle (2014). Nonetheless, the behavior of prices in our data is reasonable and can be compared with the findings in these studies.

In our model, we mix elements of two strands of literature: the estimation of endogenous productivity and the estimation of markups under imperfect competition. The literature on estimating heterogeneous unobserved productivity with structural methods starts with Olley and Pakes (1996), and two important subsequent contributions are Levinsohn and Petrin (2003) and Ackerberg et al. (2015). Latest models allow productivity to be endoge-

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[9] Smolny (1998) uses a structural model to investigate how innovation affects prices, output and employment but estimates the impact in a reduced form. Cassiman and Vanormelingen (2013) analyze how innovation affects markups also in a reduced form and only partially address the question of prices.

[10] This goal can be apparently compared with the objective of the more structural stream of literature that explores the exchange rate pass-through to prices. See, for example, Atkenson and Burstein (2008), Nakamura and Zerom (2010) or Garetto (2016). The main difference is that the exchange rate changes are costs changes that can be observed (or approximated) while our cost change is the unobservable productivity effect of innovation. Other differences are that these studies employ a detailed parametric model of competition and do not consider dynamic pricing (but see Nakamura and Zerom, 2010).

nously determined. In Aw, Roberts and Xu (2011), Doraszelski and Jaumandreu (2013), Bøler, Moxnes and Ulltveit-Moe (2015), and Bilir and Morales (2016), endogenous efficiency depends on R&D expenditure. Peters, Roberts, Vuong and Fryges (2017) model firms' productivity, and hence marginal cost, to depend on process and product innovations in a form that we adopt in this paper.

On the side of the markup, we develop a way to estimate it under imperfect competition that at the same time allows one to assess the impact of innovation on it. Markup estimation with production data has been heavily influenced by the early work of Hall (1988, 1990) based on Solow (1957). Hall (2018) obtains the same estimating equation from a discrete approximation to the definition of marginal cost in the problem of cost minimization (the derivative of the objective function with respect to output). However, the parameter used to estimate the markup in this equation is not very amenable to a rich modeling of its determinants.

De Loecker and Warzynski (2012) improve this setting by estimating the markup using the first order condition from the cost minimization of a variable input (or set of inputs, as in De Loecker and Eeckhout, 2017). Markup is computed as the estimated elasticity of these inputs divided by the share of the inputs in revenue (adjusted to the output in the moment the inputs were chosen). Unfortunately, as Ackerberg et al. (2015) show, to consistently estimate the production elasticity of inputs under imperfect competition and unobserved productivity one needs to know the markup.[11] We address this problem by using the same first order condition(s) but estimating the elasticity of the inputs and the adjustment to the output simultaneously with the markup.[12] Then we model the markup flexibly in terms of its determinants.

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[11] Marginal cost includes unobserved productivity, and unobserved persistent productivity must be estimated using an Olley and Pakes (1996)/Levinsohn and Petrin (2003) procedure that inverts an input demand. Consistent estimation involving this demand needs the knowledge of the markup, because in imperfect competition input demands depend on market power. See Jaumandreu (2018).

[12] Instead of computing $\mu = \frac{\beta_X}{S_X} e^{-\varepsilon}$ (where β_X is the elasticity of input (s) indexed X, S_X the observed share in revenue of X, and ε the observational error in output) from previously estimated β_X and ε, we estimate (in logs) the equation $\frac{1}{S_X} = \frac{1}{\beta_X} \mu(\cdot) e^{\varepsilon}$.

In modeling the markup we innovate by considering dynamic pricing. To do so we rely on a third strand of literature that has shown in theory and in practice that prices are likely to be subject to adjustment costs and display inertia. Models of adjustment costs in prices at the firm level were advanced, for example, in the works of Barro (1972) and Sheshinski and Weiss (1977, 1992) with lumpy costs generating inaction, and in Rotemberg (1982) with strictly convex costs generating partial adjustment. Carlton (1989) discussed the issue of price rigidity from the point of view of industrial organization.[13] Early works described the micro price-setting of particular industries and cases, e.g. Cecchetti (1986), Carlton (1986), Slade (1991), Lach and Tsiddon (1992) and Kashyap (1995). Slade (1998) and Aguirregabiria (1999) are full dynamic structural models that estimate firm-level fixed and variable adjustment costs. Newer evidence has incorporated interindustry studies and surveys on price setting.[14] Inspired by this literature we develop a dynamic model in which firms choose markups subject to adjustment costs. This provides us a policy function for the markup. Modeling the markup as dynamic produces measurements that are alternative to the current markup estimates. This adds an important refinement to the models that rely on production data versus the use of the elasticity of demand to estimate markups (the two alternative approaches described, for example, in De Loecker and Scott, 2016).

Our results on prices are a combination of effects of innovation on productivity and markup. The former can be compared with studies that look at how innovation affects endogenous productivity, and the latter with those that look at the impact on profitability. Examples of the first type are Peters, Roberts, Vuong and Fryges (2017), Doraszelski and Jaumandreu (2013, 2018), Bilir and Morales (2016), and Jaumandreu and Mairesse (2017). Studies of the second type are scarce, but Geroski, Machin and Van Reenen (1993) study the impact of innovations of UK companies on profitability, and Cassiman and Vanormelingen

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[13] A recent contribution to the theory of rigid prices (in the presence of collusion) is Athey and Bagwell (2008).

[14] Reviews of the extensive accumulated evidence can be found in Álvarez et al. (2006) for Europe and Klenow and Malin (2010) for the US. A recent study using firm-level data is Eichenbaum et al. (2011). It is part of a huge literature that combines detailed micro-evidence with the macro discussion of the neutrality of money. Another recent contribution of this kind is Midrigan (2011).

(2013) use the same database as ours to study the impact on markups after estimating them by a De Loecker and Warzynski (2012) procedure.

3. Data and Descriptive Analysis

In this section we start by describing our data source and the construction of the main variables (prices, innovation variables). Then we move to a detailed analysis of the price changes, the evidence on adjustment costs and dynamics of prices, and firms' innovative activities. We conclude with a reduced form analysis of the relation between price growth and innovation.

3.1 Data Source, Price Indices, Innovation Variables

We estimate the model with data from the Encuesta Sobre Estrategias Empresariales (ESEE), a firm-level survey of the Spanish manufacturing sector sponsored by the Ministry of Industry. The data that we use span 1990 to 2006. At the beginning of the survey, 5% of firms with 10-200 workers were sampled randomly by industry and size strata. All firms with more than 200 workers were asked to participate and the response rate was about 70%. Some firms drop from the sample because of exit (shutdown or change of activity) or attrition over time. Exit can be distinguished from attrition and the latter was kept moderate. To preserve approximate representativeness, firms were added to the sample almost every year, including the right proportion of newly created firms.

Our sample selects firms with at least three years of data, which in the end amounts to a total of 2375 firms from across ten industries. Table 1 reports in columns (1) and (2) the sample sizes over industries. In this subsection we comment with detail how the dependent variable and other prices are constructed (and can be validated), as well as the information available on innovation. A Data Appendix details the industries equivalence and reports the definition for the rest of variables.

Price indices

Firms are asked to report the average transaction price changes introduced from the previous to the reporting year in percentage points, for its activity optionally broken down in up to five markets.[15] Most firms report more than one market, but this does not imply the rest of the firms are single product or that the markets can be observed.[16] The questionnaire is carefully framed to avoid any ambiguity between a zero change in price and no answer.[17] Price changes should be understood to have included the increases due to product improvements.[18]

ESEE computes a global percentage change of the prices of firm j across markets for each year using a Paasche type formula (current quantities, changing prices):

$$\%\ price\ variation_{jt} = \left(\frac{1}{\sum_k \frac{WEIGHT_{jtk}}{100+\%\ price\ variation_{jtk}}} - 1 \right) \times 100,$$

where k indexes market and $WEIGHT_{jtk}$ is the share of sales of market k in total sales of firm j at time t.[19] We first compute recursively a price index for each firm from these variations

$$P_{jt} = P_{jt-1}(1 + \frac{\%\ price\ variation_{jt}}{100}),$$

with $P_{jt} = 1$ when t is the first year of firm j in the sample. We finally normalize P_{jt} by the average of its values for each firm.[20] Price variations in materials are computed in a

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[15] The question is "State if the firm has changed, with respect to the previous year, the effective price charged for the product or products sold in this market, and the average change in percentage points."

[16] Firms decide whether they want to split the activity into markets and how many markets. The directions are: "Define the main market or markets of the firm in such a way that: they represent in whole at least 50% of total sales; each market is identified by a product line, type of consumers or another characteristic that you judge necessary."0.524 of the small firms and 0.727 of the bigger firms report several markets, most of them two or three.

[17] The question is split into a yes/no part and a quantitative assessment. The box of the question includes a separate space to make explicit the sign of the change.

[18] This is implicit in the conditional multiple choice question that follows in the questionnaire if the firm reports a change in the price: "Indicate the motive of the price variation: Market changes; Change in quality; Change in cost; Profit improvement; Other (specify). You may specify a maximum of two motives."

[19] See "Variables ESEE (Definiciones)."Notice that with two markets and two periods (first and second subindices respectively), in per unit terms, the formula would give the change $\frac{P_{01}Q_{01}+P_{11}Q_{11}}{P_{00}Q_{01}+P_{10}Q_{11}} - 1$.

[20] We could alternatively normalize each firm's starting year index with that year's industry index.

similar way from the answer to the firm specific price changes reported for materials (raw materials and parts), energy and services bought during the year.

Figure 1 compares the average rates of growth of output prices in our sample with that of the Industrial Price Index computed by the national statistical office INE, for 1991-2006.[21] The comparison should take into account the important methodological differences, mainly that we take a unweighted average of firm rates against a detailed product-level price rates aggregation with constant weights (to form a chained Laspeyres index), and that our prices are "transaction "as opposed to list prices. Despite these differences our prices match the yearly index variations very well, with the only remarkable difference being the larger magnitude of the sharpest upward changes in the index.[22,23]

Innovation variables

The ESEE innovation variables follow the guidelines in the OECD Frascati and Oslo manuals. Firms are asked whether during the year they have introduced important modification in the way products are produced, as well as whether they have introduced new or significantly modified products. We use a dummy variable of process innovations that takes the value 1 when the firm reports the introduction of process innovations in its production process. Similarly, we use a dummy variable of product innovations that takes the value 1 when the firm reports the introduction of product innovations.

Firms perform R&D and other innovation activities to obtain and introduce process and product innovations in the hopes that they will eventually enhance profits.[24] But the process of discovery and development of innovations embody uncertainty and heterogeneity, so

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[21] Indice de Precios Industriales, Base 2010, CNAE-09, Annual averages, Instituto Nacional de Estadistica (INE).

[22] The similarity is a notable result since we are comparing the yearly information obtained from a sample of about 2,000 firms to the information provided by the monthly collection of data on prices of about 27,000 products.

[23] An important part of the difference may be due to the ESEE reporting of "effective"changes, i.e. once various kinds of discounts are deducted. Another source of difference could be the character of "matched model index "of the Industrial Price Index (see Pakes 2003), inducing some bias towards new products.

[24] See, for example, Jaumandreu and Mairesse (2017). Guadalupe, Kuzmina and Thomas (2012) find that the acquisition by multinationals of highly productive firms reinforces their innovation performance.

we should expect the timing of the resulting innovations and their introduction to be heterogeneous and random. Particular innovations cannot be traced to specific expenditures, but we do observe the total R&D expenditures that include the cost of intramural R&D activities, payments for outside R&D contracts with laboratories and research centers, and payments for imported technology in the form of patent licensing or technical assistance. In the ESEE these expenditures are defined according to the standard manuals. We use R&D expenditure to construct an instrument for innovation.

3.2 A Bird's Eye View of the Price Changes

Table 1 reports the sample means of growth rates of output and input prices in columns (3)-(5), and information on two more constructed variables that we comment now. First, in column (6) we compute the growth rates of the observed average variable cost (AVC). Observed variable cost is defined for each firm as the sum of the wage and materials bill, divided by revenue and deflated by the firm level price index. We take the log rates of growth of this ratio. Second, we compute in column (7) the level of the observed price average variable cost margin (PAVCM) as the log of revenue over variable cost. In both cases we talk of observed magnitudes because they use the observed output as opposed to the output that was planned by firms when choosing the inputs (only the model can estimate the planned output).

The period 1990-2006 is a period of regular growth. The formal accession of Spain to the European Union was completed a few years before (1986) and the period stops right before the financial crisis (2008). There is a brief sharp recession in 1993 followed by a strong recovery during 1994-1999 and growth tapers off during 2000-2006. To illustrate what happens to prices and margins Figure 2 constructs rough aggregate indices for prices, AVC, wages and price of materials using the sample average rates of growth for each variable. The index for prices starts at 1 plus the average value of the PAVCM in 1990 (0.147) to allow the evolution of the curves of prices and AVC to provide an idea of the subsequent evolution of the PAVCM.

Two observations can be highlighted from Figure 2. First, input prices increased at much faster rates than average variable cost, revealing the importance of the underlying variable inputs compensating productivity growth during the period.[25] If part of this productivity is related to innovation, this means that we have a lot of variation that has impacted prices in this way. Second, the PAVCM tends to become narrower over time. There are two main economic developments that can be related to this fact. On the one hand, firms increasingly sell in foreign markets that are more competitive, which forces them to charge lower markups.[26] On the other hand, there is a large continuous decrease in the user cost of capital (which stimulates an investment surge) that should have modified downward the long-run minimum profitability requirements of firms.[27] Column (8) of Table 1 allows one to check that a standard calculation of cost of capital suggests on average a greater margin than is needed to retribute capital when compared with column (7).

Lastly, column (9) of Table 1 reports the proportion of negative PAVCMs. Since negative values contradict the static view of profit maximization (see next subsection) we ask ourselves how reliable these numbers are. It could be argued that they result from including in variable cost some outlays that are in fact fixed costs. Since we know the total amount of R&D and promotion expenditures of the firm, as a rough test we compute the margins again by subtracting these expenditures from variable cost. The global number of negative PAVCMs only drops from 14.6 to 12%. Given this mild effect, we give up in doing any correction.[28]

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[25] Write variable cost as the sum of input prices times the demands of variable inputs indexed by i, $AVC = \frac{\sum_i W_i X_i(W,\omega,K)}{Q}$. These demands depend on relative prices, productivity and the fixed factor capital. If vector W is multiplied by λ and AVC turns out to be multiplied by less than λ then it means that ω and K have increased the productivity of the variable factors $\frac{Q}{X_i}$.

[26] Average (unconditional) export intensity rises in the sample during the period from 10% to 27%.

[27] Average marginal cost of funds reported by firms decreases, during the period, from 12.5% to 4.8%.

[28] In fact we do not have any reliable methods to determine which part of these outlays must be subtracted nor the amounts that should be subtracted respectively from the wage and material bills.

3.3 Changes in Prices and Evidence on Adjustment Costs

Table 2 examines the AVC and price changes with more detail in columns (1)-(5) and (6)-(12) respectively. Together with the quartiles of the distribution of changes (nonzero changes in the case of prices), we report the proportion of negative and positive changes, as well as the proportion of inaction in the case of prices. We complete the statistics with the observed median price duration.

The table provides striking evidence in support of dynamic pricing. First, despite the yearly frequency of our data, there is a significant share of price inaction that ranges from 35% to almost 45% of the observations across industries.[29] The median price duration is about 1.4 years, or a mean duration between 10 and 14 months depending on industries, if we compute it using the conventions of the microeconomic pricing literature to avoid censoring. [30,31] The changes in cost are however never zero.

Second, there is a clear asymmetry in how prices respond to cost changes. There are more price increases than decreases.[32] The proportion of positive changes in cost and price are in fact quite close (60% versus 52% on average), whereas the opposite is true for cost and price decreases (41% versus 12% on average). These observations allow one to interpret nicely what is happening. When cost increases, the firm is confronted with a margin that is much less than the desired margin (may even be negative, see below). However, the firm

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[29] Using IKEA catalog of yearly prices for over 17 years across six countries, Baxter and Landry (2017) find that 59% of the price changes are zero, 18% are decreases and 23% are increases.

[30] Take F as the cross-section proportion of price changes in a given year. Suppose that this proportion is constant across years and hence measurable by the whole proportion of no inaction. A model with constant hazard rate λ (instantaneous probability of price change), implies a probability of change of $F = 1 - \exp(-\lambda)$ and hence the implicit hazard rate is $\lambda = -\ln(1 - F)$. The inverse of this value can be read as the mean duration without left censoring (many prices are expected to change within the year). See Bils and Klenow (2004).

[31] This matches well the median duration of 8-11 months calculated in Nakamura and Steinsson (2007) using nonsale US PPI prices, as well as with the 10.6 months for the Euro area calculated in Álvarez et al. (2006).

[32] The fact that price increases are more numerous than decreases is also found in Goldberg and Hellerstein (2011) for small firms where they use monthly US Producer Price Index survey data.

might not fully update the price because the costs to raise prices are important. But when the cost goes down, the firm is given the opportunity to redress the margin with no price change or a minimum price change.[33]

Third, the dispersion of price changes is much narrower than that of cost changes. The interquartile range (IQR) of the distribution of cost changes is 2 to 4 times the IQR of the nonzero price changes.

Lastly, we saw in the previous subsection that between 12% and 20% of the PAVCM are negative. This is incompatible with the static view of the working of the market. The firm should shut down its activity when it is incurring a loss on perfectly variable factors. However, this situation can be temporarily accepted as part of the maximization of the present discounted stream of profits, when sunk costs render it unprofitable to abandon the activity.

3.4 Dynamics

Figure 3 further characterizes the way in which dynamics is an important trait of the price changes. The y-axis depicts $\Delta p - \Delta avc$, the degree by which, at time t, the change in price exceeds or falls short the change in average variable cost. If the relationship between average and marginal cost is constant, it can also be read as the degree by which prices adjust to the current changes in marginal cost. The x-axis depicts $r_{-1} - vc_{-1}$, the PAVCM at time $t-1$.

Imagine first that markups of the firms have a constant value from which they diverge randomly. Then one would see the values of $\Delta p - \Delta avc$ scattered around the zero level line without any relationship with the values of the lagged margin depicted in the x-axis. However, what happens is something very different, which we pick up by means of a nonparametric regression of $\Delta p - \Delta avc$ on $r_{-1} - vc_{-1}$, or a kernel estimator of $E[\Delta p - \Delta avc | r_{-1} - vc_{-1}]$.

The resulting figure shows positive and negative relative adjustments in prices that are

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[33] Using supermarket scanner data, Eichenbaum et al. (2011) also uncover that grocery store prices do not always change when costs change.

systematically related to the value of the PAVCM in the previous period. Price adjustments in excess of the variation in costs are larger when the previous period margins are very low. Price adjustments fall below the variation in costs more when the the previous margins are high. The relationship is close to linear.

The depicted relationship implies a strong autoregressive character of the margin,[34] which we interpret as indicative of the partial adjustment relationship that one expects to result from a variable that changes subject to adjustment costs. It could however also be that the exogenous determinants of a margin that is adjusted instantaneously, are varying with some persistence. Both cases highlight anyway the importance of dynamics. To disentangle the two possibilities we need to estimate the model.

3.5 Innovation

Table 3 summarizes the innovative behavior across firms and industries. Columns (1) to (4) indicate that around one quarter of firms do not innovate at all, a small fraction only introduces product innovations, a fraction only introduces process innovations and almost half of the firms introduce both types of innovations. This last type of firms introduce simultaneously a process and a product innovation one year out of each four in which they innovate, and either a process or a product innovation the remaining three. Relative proportions vary in a non-negligible way across industries, reflecting the different relevance of product differentiation.

Columns (5) to (10) take a closer look at the flow of process and product innovations by depicting the quartiles of the frequencies (number of innovations introduced by the firm divided by the number of years in the sample). The median firm in both distributions innovates every 2.3 years. But the top 25% innovators introduce innovations almost every year. And the bottom 25% innovators introduce a process innovation every four years and a product innovation every five years or more. These numbers also fluctuate significantly

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[34] Notice that $\Delta p - \Delta avc = \Delta p - [\Delta vc - (\Delta r - \Delta p)] = \Delta r - \Delta vc$, so the variable in the y-axis can also be read as the variation of the PAVCM. A linear relationship $\Delta r - \Delta vc = -\lambda(r_{-1} - vc_{-1})$ implies that the margin is $r - vc = (1-\lambda)(r_{-1} - vc_{-1})$.

across industries.

Columns (11) to (14) report the number of sample observations without innovation, with a process innovation, with a product innovation, and with the simultaneous introduction of a process and a product innovation. These proportions inform us of the number of observations over which we average when we look at the means of some variable, such as productivity or markup with observations split in these categories.

3.6 Reduced Form Analysis

"Why do we need a complicated, highly-stylized model of the supply side to answer the question of how process and product innovations influence prices that a reduced-form model would also be able to answer?"These were the words used by a reviewer to discard the access to funding of an early version of this project. To see what can be learned with a reduced form analysis we regress price growth on a set of time dummies and the determinants of marginal cost and markup that can be taken as exogenous: capital, prices of the variable factors (wage and price of materials) and the firm-specific state of the market indicator, the *market dynamism* variable (see the Data Appendix). Process and product innovation are included lagged one period, and taken as predetermined variables. Regression is carried out by OLS. We compute standard errors robust to arbitrary heteroskedasticity and autocorrelation of the errors.

The main results are reported in Table 4. Among the nonreported control variables, the coefficient on the variation of the price of materials is always positive and significant, with elasticities that range from 0.10 to 0.50. The table highlights in column (2) that the growth of prices tends to increase with the state of the market of the firm (market dynamism has positive coefficients with different degrees of significance in 8 industries). The introduction of a process innovation always shows a negative impact in column (3), but the estimates are imprecise. Product innovation in column (4) tend to have a small positive impact and also imprecisely estimated.

The "all industries"regression is a summary of what the reduced forms produce. It reveals a negative impact of process innovation on price growth, and that product innovation has no effect. Interestingly, the results are quite close to what we obtain in net terms in our structural model both qualitatively and quantitatively. However, our exercise helps one understand why the reduced form estimates are so imprecise. We uncover that the effects of innovation are often the result of simultaneous impact on cost and margin that partially compensate each other, which would be overlooked in a simple regression on prices. Our exercise additionally clarifies which mechanisms and behavior of firms the aggregate result comes from. Finally, it allows one to perform counterfactuals, one of which reveals that if innovative firms did not “cash-in”then it would amplify the effect of innovation on price

4. Model

We assume that firm j operates in an imperfectly competitive market and sets the price of its product with a markup on short-run marginal cost, or the marginal cost of the firm taking capital as given. Specifically, we assume that observed price meets the relationship

$$P_{jt} = P_{jt}^{*} \exp(e_{jt}) = \mu_{jt} MC_{jt} \exp(e_{jt}),$$

where P_{jt} is the observed price, MC_{jt} stands for the marginal cost, μ_{jt} is the markup chosen by the firm, P_{jt}^{*} is the price corresponding to this markup, and e_{jt} is an error orthogonal to all information available when the firm makes the decisions. Note that in general, marginal cost is determined endogenously because it depends on the quantity needed to serve demand at the price set by the firm. Using lowercase letters to denote logs, the price equation is

$$p_{jt} = \ln \mu_{jt} + mc_{jt} + e_{jt}. \tag{1}$$

This equation shows that prices evolve according to marginal cost and markup, both of which are likely to be impacted by innovation simultaneously. In order to assess this impact, we develop a model with dynamic pricing where firms choose markup to set price.

Let us emphasize that adopting the choice of markups rather than prices offers advantages on observability and simplicity. First, firms are multiproduct and hence the representation of their prices should be cast in terms of price indices, as their levels are not informative.

Markup levels are, however, observable up to the average variable cost to marginal cost ratio (and an uncorrelated error). Second, prices are subject to inaction. Their changes should be typically modeled as a non-continuous function of the degree of markup disequilibrium, which triggers updating when it reaches a certain level. This implies modeling the discrete choice of whether to update and then subsequently by how much. Markups vary continuously in a "passive" way due to periodical cost variations or innovation-induced changes, even when firms do not update prices. By modeling markups we model directly the level of the variable the firm is concerned about. Even if the firm chooses not to change the markup actively we can still write its value as a continuous function of the underlying factors (including adjustment costs).

Our framework can be understood as perfectly fitted to a situation of monopolistic competition, from which it uses the properties that each firm faces a downward sloping demand for its product, and a price change by one firm has a negligible effect on the demand of any other firm (Tirole, 1989). But our dynamic pricing modeling, and the resulting equilibrium "shadow"elasticities, can accommodate competition settings in which firms interact strategically. One would then specify rival prices as state variables and modify the expectations of firms to also include the behavior of competitors. Our current specification is in fact already consistent with some restrictive versions of this setting (e.g all competitors behave symmetrically and the only relevant price is the aggregate industry price).

We develop the model without adding any assumption to the existing methods employed to estimate productivity and markups. We rely on the usual timing distinction between the moments at which capital and variable factors are chosen. We also admit that output is imperfectly observed, to which we add the imperfect observation of price. In the implementation we will use for simplicity a Cobb-Douglas production function, but any other production function, or even a nonparametric specification, can be employed.

In what follows we first specify demand and production cost, and then discuss the resulting per-period profitability that depends on the state variables and the markup. We then focus on the dynamic choice of the optimal markup while sketching (as background) the simultaneous capital and R&D investment decisions of the firm. Finally, we discuss the modifications of the model when labor input is subject to adjustment costs. In the next section, we develop the econometric model to estimate the parameters relevant to the pricing decision.

4.1 Firm Demand

Firm j's demand is assumed to depend on own product price (P_{jt}) and industry prices (P_{It}), as well as three shifters: firm-specific state of the market (D_{jt}) and process and product innovations introduced in the previous period (z_{jt-1}, d_{jt-1}).[35] We introduce demand heterogeneity unobserved by the econometrician with a multiplicative persistent unobservable δ_{jt}.[36] Specifically, firm j's demand is written as

$$Q_{jt} = Q^*_{jt} \exp(\varepsilon_{jt}) \equiv Q(P^*_{jt}, P_{It}, D_{jt}, z_{jt-1}, d_{jt-1}) \exp(\delta_{jt}) \exp(\varepsilon_{jt}),$$

where ε_{jt} is an error that renders observed quantity (Q_{jt}) and demanded quantity (Q^*_{jt}) different (see below).

4.2 Cost

We assume that the firm's production function is

$$Q_{jt} = Q^*_{jt} \exp(\varepsilon_{jt}) \equiv F(K_{jt}, L_{jt}, M_{jt}) \exp(\omega_{jt}) \exp(\varepsilon_{jt}),$$

where K_{jt}, L_{jt}, and M_{jt} stand for capital, labor and materials, and ω_{jt} represents the Hicks neutral firm- and time-specific level of efficiency.[37] Following the literature we call ω_{jt} productivity and, symmetrically to δ_{jt}, we assume it is observed by the firm but unobservable to

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[35] Whether innovations affect demand and productivity with a lag is an empirical question, so we experimented with a contemporaneous specification as well and arrived at the conclusion that the specification with a lag is better.

[36] δ_{jt} plays a role similar to productivity in the production function. See Jaumandreu and Yin (2018) for the literature concerning this heterogeneity and an assessment of the importance of δ_{jt}.

[37] Notice that we assume that the decided output is equal to demand Q^*_{jt}. The unique observed quantity Q_{jt} diverges both from demand and production by ε_{jt} without loss of generality. We are largely going to ignore inventories, which in practice balance demand, realized demand and production.

the econometrician. In contrast, we assume that ε_{jt} is an error orthogonal to all information when the firm makes price and input decisions. It implies that we cannot directly observe the decided quantity $Q^*_{jt} = F(K_{jt}, L_{jt}, M_{jt}) \exp(\omega_{jt})$ for which the inputs were chosen.

The firm takes prices in the input markets as given and minimizes the cost of the variable factors (labor and materials) given capital, $VC_{jt} = W_{jt}L_{jt} + P_{Mjt}M_{jt}$, where W_{jt} and P_{Mjt} are the prices of labor and materials. Variable cost minimization gives the function $VC_{jt} = VC(K_{jt}, W_{jt}, P_{Mjt}, Q^*_{jt}/\exp(\omega_{jt}))$ and marginal cost can be written as

$$MC_{jt} = MC(X_{jt}) \exp(-\omega_{jt}), \tag{2}$$

where $X_{jt} = \{K_{jt}, M_{jt}, W_{jt}, P_{Mjt}\}$ is a vector of observable variables (see Appendix A for derivations). We will often refer to equation (2) as reflecting the econometrician's observed and unobserved parts of marginal cost. Cost minimization given capital implies $(\beta_{Ljt} + \beta_{Mjt})MC_{jt} = AVC_{jt}$, where $AVC_{jt} = \frac{VC_{jt}}{Q^*_{jt}}$ and β_{Ljt} and β_{Mjt} are the output elasticities of labor and materials.[38] Given that capital is fixed in the short-run we expect the short-run scale elasticity $\nu_{jt} = \beta_{Ljt} + \beta_{Mjt}$ to be less than unity.

We assume, as in the literature subsequent to Olley and Pakes (1996), that ω_{jt} follows a first order Markov process. However, our interest lies in an endogenous ω_{jt}, so we let it depend on not only past productivity but also the shifts induced by the introduction of process and product innovations. Specifically,

$$\omega_{jt} = g(\omega_{jt-1}, z_{jt-1}, d_{jt-1}) + \xi_{jt}, \tag{3}$$

where g is a function aimed at picking up both the path dependence of productivity and the impact of innovations, and ξ_{jt} is a random shock mean-independent of all the arguments in $g(\cdot)$.[39] For additional flexibility we are going to use a time-inhomogeneous Markov process denoted as $g_t(\cdot)$.

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[38] First order conditions are $MC_{jt}\frac{\partial Q^*_{jt}}{\partial L_{jt}} = W_{jt}$ and $MC_{jt}\frac{\partial Q^*_{jt}}{\partial M_{jt}} = P_{Mjt}$. Multiplying both sides by L_{jt} and M_{jt}, respectively, dividing by Q^*_{jt}, and aggregating the result, gives the relationship $(\beta_{Ljt} + \beta_{Mjt})MC_{jt} = AVC_{jt}$.

[39] See Peters, Roberts, Vuong and Fryges (2017) for a similar specification of productivity.

4.3 Profits

Our specification of the demand and cost function imply that price over marginal cost, i.e. the markup $\mu_{jt} = \frac{P^*_{jt}}{MC_{jt}}$, is subject to the following equilibrium relationship:

$$\mu_{jt} = \mu(Q^*_{jt}, K_{jt}, P_{It}, W_{jt}, P_{M_{jt}}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt}).$$

This functional relation is invertible in Q^*_{jt} given the other arguments (see Appendix B for derivations), and hence we can write $Q^*_{jt} = Q^*(\mu_{jt}, K_{jt}, P_{It}, W_{jt}, P_{M_{jt}}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt})$. Then (gross or short-run) profit,

$$\begin{aligned} \pi_{jt} &= P^*_{jt}Q^*_{jt} - VC(K_{jt}, W_{jt}, P_{Mjt}, Q^*_{jt}/\exp(\omega_{jt})) \\ &= (\frac{\mu_{jt}}{\nu_{jt}} - 1)VC(K_{jt}, W_{jt}, P_{Mjt}, Q^*(\mu_{jt}, K_{jt}, P_{It}, W_{jt}, P_{M_{jt}}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt})/\exp(\omega_{jt})), \end{aligned}$$

is a function of the state variables and the markup. An important observation is that the pricing problem of the firm can be seen as choosing the optimal markup over marginal cost given the state variables, a dynamic choice we specify next.

4.4 Choice of the Markup

We assume that, in period t, the firm chooses the investment I_{jt} in physical capital that becomes productive the next period, and the investment RD_{jt} that makes innovations possible. These innovations will impact demand and productivity next period as well. $C_I(I_{jt})$ and $C_R(RD_{jt})$ are the cost of the investments. Capital accumulates according to $K_{jt} = (1-d)K_{jt-1} + I_{jt-1}$, where d is the rate of depreciation. Process and product innovations, z_{jt} and d_{jt}, occur randomly with joint density $G(z_{jt}, d_{jt}|RD_{jt})$ that depends on the R&D investment of the firm at time t.[40,41]

Simultaneously, the firm sets the price of the output by choosing the markup μ_{jt} over marginal cost. The markup determines the production that needs to be carried out to

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[40] Notice that we assume that demand and productivity are impacted by z_{jt-1} and d_{jt-1}, and hence indirectly by the R&D expenditure at $t-1$. Alternatively we could assume that innovations at time t are determined by the R&D expenditure at $t-1$ and impact demand and productivity contemporaneously.

[41] This is basically the modeling of innovation in Peters, Roberts, Vuong and Fryges (2017).

serve demand. Production employs L_{jt} and M_{jt} quantities of variable inputs, which can be adjusted without any friction, an assumption we relax later for labor. However, the firm sets the markup μ_{jt} by taking into account that it is subject to adjustments costs of the form

$$A(\mu_{jt}, \mu_{jt-1}, D_{jt}, z_{jt-1}, d_{jt-1}).$$

We assume the adjustment costs depend on the firm-specific state of the market and can be impacted by process and/or product innovations (see Appendix C). The introduction of a process innovation is likely to reduce marginal cost and thus enlarge the margin, lessening the costs of an upward adjustment of the markup. The introduction of a new product may facilitate or hinder the change of the markup, depending on consumers' reception of the price change.

The Bellman equation relevant for the choice of I_{jt} and RD_{jt} is sketched in Appendix D. The Bellman equation relevant for the choice of the markup μ_{jt}, collecting the state variables in the vector $S_{jt} = (\mu_{jt-1}, K_{jt}, P_{It}, W_{jt}, P_{Mjt}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt})$, can be written as

$$\begin{aligned} V(S_{jt}) \quad = \quad & \max_{\mu_{jt}}[\Big(\frac{\mu_{jt}}{v} - 1\Big) \\ & VC(K_{jt}, W_{jt}, P_{Mjt}, Q^*(\mu_{jt}, K_{jt}, P_{It}, W_{jt}, P_{M_{jt}}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt})/\exp(\omega_{jt})) \\ & -A(\mu_{jt}, \mu_{jt-1}, D_{jt}, z_{jt-1}, d_{jt-1}) - C_I(I_{jt}) - C_R(RD_{jt})] + \beta E_t[V(S_{jt+1})|S_{jt}]. \end{aligned}$$

From the first order condition of this equation it turns out that optimal markup has the form

$$\mu_{jt} = \frac{\eta_{jt}}{\eta_{jt} - 1}(1 + \Delta^{\mu}_{jt}),$$

where $\Delta^{\mu}_{jt} = 0$ if there are no adjustment costs of the markup (see Appendix E). If markup is not costly to adjust, dynamic pricing collapses to the well known static pricing rule based on the elasticity of demand.[42] However, under dynamic pricing, prices are usually going

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[42] Computing markups according to the elasticity of demand is a practice prevalent in recent empirical analysis, due to the difficulty in getting reliable observations on cost. This kind of computation of the markup is even used to estimate marginal cost from prices. De Loecker and Scott (2016) compare the results

to be above or below the value consistent with the elasticity of demand. In addition, since there is no restriction on the negative values that Δ_{jt}^{μ} can take, the value of μ_{jt} can be under unity and the (log) markup be negative. Under sunk costs of its activity, the firm may find that the present value of the stream of profits which involves some negative values is greater that the present value that would obtain discontinuing the activity.

Notice that the markups, when strictly positive, are consistent with a finite "shadow"elasticity that differs from the elasticity of demand. The shadow elasticity is the demand elasticity from which the observed markups would be derived from, i.e. η_{jt}^{*} such that $\frac{\eta_{jt}^{*}}{\eta_{jt}^{*}-1} = \mu_{jt}$).

Consequently, under dynamic pricing we don't have a simple relationship linking the markup to demand elasticity. The Bellman equation, however, implies a policy function relating markup to the state variables. Using lower case letters to denote logs of the variables, this policy function is

$$\ln \mu_{jt} = \widetilde{\widetilde{h}}_t(\ln \mu_{jt-1,} k_{jt}, w_{jt}, p_{Mjt}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt}),$$

where the subindex t indicates that in the function we have replaced the industry variables by time dummies.

In order to reduce the dimensionality of the problem, in what follows we adopt the simplifying assumption that the level of the input prices and the unobservable state variables ω_{jt} and δ_{jt} are ignorable in the law of motion of markups.[43] That is,

$$E(\ln \mu_{jt} | \ln \mu_{jt-1,} k_{jt}, w_{jt}, p_{Mjt}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt}) = \widetilde{h}_t(\ln \mu_{jt-1,} k_{jt}, D_{jt}, z_{jt-1}, d_{jt-1}),$$

or

$$\ln \mu_{jt} = \widetilde{h}_t(\ln \mu_{jt-1,} k_{jt}, D_{jt}, z_{jt-1}, d_{jt-1}) + \zeta_{jt}' \tag{4}$$

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obtained by this method with the assessment of markups using a production approach. Their conclusion of absence of important differences is however dependent on their static approach.

[43] That the level of ω_{jt} and δ_{jt} plays a role in the evolution of μ_{jt}, once that the innovations that impact demand and productivity have been controlled for, is not very likely. The model, however, could allow for this possibility at the cost of increasing complexity. On the one hand, the unobservable ω_{jt} could be replaced in a similar way to what is done in the marginal cost function. The unobservable δ_{jt} could also be replaced using the inversion of a demand relationship.

4.5 Adjustment Costs of Labor

If there are adjustment costs of labor, then the problem of cost minimization becomes also a dynamic problem and cannot be separated from the dynamic choice of the price. Intuitively, if the amount of labor that the firm uses today is going to affect labor costs tomorrow, then the firm needs to take this into account in choosing today's price and hence output in relation to tomorrow's price and output. The cost minimization problem can be however written as

$$Min\, E_t[\sum_s \beta^s (W_{jt+s}L_{jt+s} + P_{Mjt+s}M_{jt+s} + AL(L_{jt+s}, L_{jt+s-1})]$$

$$s.t.\, F(K_{jt+s}, L_{jt+s}, M_{jt+s}) = Q^*_{jt+s}/\exp(\omega_{jt+s}), \quad s = 0...\infty,$$

where $AL(\cdot)$ stands for the adjustment costs of labor. The infinite sequence of outputs are the productions decided in the simultaneous dynamic choice of the sequence of prices. The Lagrangean multiplier of the production constraint at time $t+s$ can be seen as the marginal cost corresponding to the variation of output Q^*_{jt+s}.

Let's focus on $s = 0$. The first order condition for labor can be written as

$$\begin{aligned} MC_{jt}\frac{\partial F_{jt}}{\partial L_{jt}} &= W_{jt} + \frac{\partial AL_{jt}}{\partial L_{jt}} + \beta E_t[\frac{\partial AL_{jt+1}}{\partial L_{jt}}|S_{jt}, L_{jt-1}] \\ &= W_{jt}(1 + \frac{1}{W_{jt}}\frac{\partial AL_{jt}}{\partial L_{jt}} + \beta\frac{1}{W_{jt}}E_t[\frac{\partial AL_{jt+1}}{\partial L_{jt}}|S_{jt}, L_{jt-1}]) = W_{jt}(1 + \Delta^L_{jt}), \end{aligned}$$

where Δ^L_{jt} represents the gap between the wage and the shadow price of labor under adjustment costs. Similarly, there is a first order condition for materials:

$$MC_{jt}\frac{\partial Q_{jt}}{\partial M_{jt}} = P_{Mjt}.$$

The variable cost that results from the choice of the firm can be written as $VC_{jt} = VC(K_{jt}, W_{jt}(1 + \Delta^L_{jt}), P_{Mjt}, Q^*_{jt}/\exp(\omega_{jt}))$ and is contingent on the choice of the firm. The Bellman equation for the choice of μ_{jt} is still valid, but the solution of the problem of cost minimization that raises variable cost and the choice of the price are nonseparable.

Adding the two first order conditions we can see that, under adjustment costs of labor, the relationship between marginal and average variable cost becomes

$$\begin{aligned}\nu_{jt}MC_{jt} &= \frac{W_{jt}L_{jt}+P_{Mjt}M_{jt}}{Q^{*}_{jt}}(1+s_{Ljt}\Delta^{L}_{jt}) \\ &= AVC_{jt}(1+s_{Ljt}\Delta^{L}_{jt}),\end{aligned}$$

where s_{Ljt} is the share of labor in variable cost.

5. Econometric Estimation

We started with equation (1), that describes the (log of) price as the result of the (log of) markup plus the (log of) marginal cost. We have developed a specification for both components. Equation (2) details marginal cost and equation (3) allows one to write the unobservable productivity component of marginal cost in terms of the Markov process that depends on innovation. Equation (4) specifies the law of motion of the markup including the effects of innovation. Substituting these relationships for the components of (1) we have

$$p_{jt}=\widetilde{h}_t(\ln\mu_{jt-1,}k_{jt},D_{jt},z_{jt-1},d_{jt-1})+mc(X_{jt})-g_t(\omega_{jt-1},z_{jt-1},d_{jt-1})+\zeta'_{jt}-\xi_{jt}+e_{jt}. \quad (5)$$

Equation (5) elucidates the structural link between innovation and prices. Later, we enrich this specification with the correction for the adjustment costs of labor.

5.1 A System

Estimation of (5) faces several econometric problems. First, lagged productivity ω_{jt-1} is an unobservable. Second, lagged markup μ_{jt-1} cannot be observed directly either. Third, there is an obvious identification problem regarding the impacts of innovation. These effects cannot be separated since they enter two additive components of the equation (functions $\widetilde{h}_t(\cdot)$ and $g_t(\cdot)$), which are natural to model and estimate nonparametrically.

The first problem can be addressed by using an Olley and Pakes (1996)/Levinsohn and Petrin (2003) procedure, which is replacing the unobservable ω_{jt-1} by the inversion of an input demand that contains it. For example, from the first order conditions of the solution of the dynamic problem for variable inputs we know that the demand for materials is $M_{jt} = M(K_{jt}, W_{jt}, P_{Mjt}, P^*_{jt}/\mu_{jt}, \omega_{jt})$. The fourth argument of this demand is marginal revenue (which is equivalent to marginal cost due to profit maximization). Solving this demand for lagged unobserved productivity we can write

$$\omega_{jt-1} = \widetilde{f}(K_{jt-1}, W_{jt-1}, P_{Mjt}, M_{jt-1}, p^*_{jt-1} - \ln \mu_{jt-1}).$$

This solves the problem of unobservable productivity, although at the cost of introducing in the equation the unobserved markup μ_{jt-1} one additional time.[44]

We address the second and third problems as follows. We do not observe μ_{jt}, but most databases allow one to compute the price average cost ratio, a variable closely related to the markup. Effectively, when the database contains measures of revenue R_{jt} and variable costs VC_{jt}, then

$$\ln \frac{R_{jt}}{VC_{jt}} = \ln \frac{P_{jt}}{VC_{jt}/Q_{jt}} = \ln \frac{P_{jt}}{VC_{jt}/Q^*_{jt}} \frac{Q_{jt}}{Q^*_{jt}} = \ln \frac{P^*_{jt}}{AVC_{jt}} + \varepsilon_{jt} + e_{jt}.$$

If there are no adjustment costs of labor we know that $AVC_{jt} = \nu_{jt} MC_{jt}$, so from the price average cost ratio we get an expression for the markup and the value of the elasticity of scale up to an uncorrelated error (in logs):

$$r_{jt} - vc_{jt} = -\ln \nu_{jt} + \ln \mu_{jt} + \varepsilon_{jt} + e_{jt}.$$

We use this fact to write an additional equation that solves the identification problem and, at the same time, gives a way to estimate the unobservable μ_{jt-1}. We estimate the system

$$\begin{aligned} r_{jt} - vc_{jt} &= -\ln \nu_{jt} + h_t(r_{jt-1} - vc_{jt-1} + \ln \nu_{jt-1}, k_{jt}, D_{jt}, z_{jt-1}, d_{jt-1}) + \zeta_{jt} + \varepsilon_{jt} + e_{jt}, \\ p_{jt} &= h_t(r_{jt-1} - vc_{jt-1} + \ln \nu_{jt-1}, k_{jt}, D_{jt}, z_{jt-1}, d_{jt-1}) + mc(X_{jt}) \\ &\quad - g_t(f(K_{jt-1}, W_{jt-1}, P_{Mjt}, M_{jt-1}, p_{jt-1} - r_{jt-1} + vc_{jt-1} - \ln \nu_{jt}), z_{jt-1}, d_{jt-1}) \\ &\quad + \zeta_{jt} - \xi_{jt} + e_{jt}, \end{aligned} \tag{6}$$

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[44] This substitution seems also to introduce in the equation the problem of unobserved p^*_{jt}. We will see below that this is not the case.

where $h_t(\cdot)$ is the conditional expectation of $\ln \mu_{jt}$ on the included variables (we integrate the error $\varepsilon_{jt-1} + e_{jt-1}$) and $f(\cdot)$ is the conditional expectation of ω_{jt-1} on the included variables (we integrate the error ε_{jt-1}).[45]

The first equation cannot in general provide by itself an estimation of the parameter of scale ν_{jt}. This is the traditional reason that prevents the use of the price average cost ratio to assess markups despite its closeness to what we want to measure. However, when an estimate of the lagged markup is included in the second equation, it can provide a consistent estimate of the input elasticities of the inputs, and hence ν_{jt}. As a result, the two equations together provide identification.[46]

The system of equations (6) constitute a model for the consistent estimation of endogenous productivity and markups under imperfect competition and dynamic pricing. Markups are estimated simultaneously and used to specify the inverted input demand that is needed to estimate the parameters of the cost function (production function). It includes as a particular case the solution of static pricing, so we can test for the presence of dynamic pricing.

5.2 Detailed Specification

To take equations in (6) to the data, four pieces need to be specified: the observable component of marginal cost, the Markov process that governs the endogenous productivity process, the flexible form for the markup and the estimate of the adjustment costs of labor.

Marginal cost function

Let us start with the marginal cost function. We consider for simplicity the Cobb-Douglas

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[45] Notice that $p^*_{jt-1} - \ln \mu_{jt-1}$

$= p_{jt-1} - e_{jt-1} - (r_{jt-1} - vc_{jt-1} + \ln \nu_{jt} - \varepsilon_{jt-1} - e_{jt-1})$

$= p_{jt-1} - r_{jt-1} + vc_{jt-1} - \ln \nu_{jt} + \varepsilon_{jt-1}$.

[46] Doraszelski and Jaumandreu (2013) used $MR_{jt} = P_{jt}(1 - \frac{1}{\eta_{jt}})$, modeling η_{jt} by means of a polynomial of D_{jt} and P_{jt}. The elasticity may be understood as a shadow elasticity. While this is a solution to the the unobservability of $MC_{jt} \equiv MR_{jt}$ circumscribed to one equation, it probably gives a poorer identified estimate of the markups. Our solution here draws on Jaumandreu and Yin (2018).

production function

$$q_{jt} = \beta_0 + \beta_K k_{jt} + \beta_L l_{jt} + \beta_M m_{jt} + \omega_{jt},$$

which gives the short-run marginal cost function in terms of materials as

$$mc_{jt} = \kappa - \beta_K k_{jt} + (1 - \beta_L - \beta_M) m_{jt} + (1 - \beta_L) p_{Mjt} + \beta_l w_{jt} - \omega_{jt}, \tag{7}$$

where $\kappa = -\ln \beta_0 - \beta_L \ln \beta_L - (1 - \beta_L) \ln \beta_M$. Notice that the use of a Cobb-Douglas will make the short-run elasticity of scale a constant: $\nu = \beta_L + \beta_M$.

Markov process for productivity

For the productivity process we use the inhomogeneous Markov process $\omega_{jt} = \beta_t + g(\omega_{jt-1}, z_{jt-1}, d_{jt-1}) + \xi_{jt}$. To replace ω_{jt-1} we use the lagged inverted demand for materials $f_{jt-1} = \kappa - \beta_K k_{jt-1} + (1 - \beta_L - \beta_M) m_{jt-1} + \beta_L (w_{jt-1} - p_{jt-1}) + (1 - \beta_L)(p_{mjt-1} - p_{jt-1}) + (r_{jt-1} - vc_{jt-1} + \ln \nu)$, referred to in what follows as the shorthand f_{jt-1}. Specifying $g_t(\cdot)$ as time dummies plus a polynomial with powers of $f_{jt-1}, z_{jt-1}, d_{jt-1}$ and their interactions we have:[47]

$$\begin{aligned}
\omega_{jt} &= \beta_t + g(f_{jt-1}, z_{jt-1}, d_{jt-1}) + \xi_{jt} \\
&= \beta_t + \gamma_1 f_{jt-1} + \gamma_2 f_{jt-1}^2 + \gamma_3 f_{jt-1}^3 + \gamma_4 z_{jt-1} + \gamma_5 d_{jt-1} + \gamma_6 z_{jt-1} \cdot d_{jt-1} \\
&\quad + \gamma_7 f_{jt-1} \cdot z_{jt-1} + \gamma_8 f_{jt-1}^2 \cdot z_{jt-1} \\
&\quad + \gamma_9 f_{jt-1} \cdot d_{jt-1} + \gamma_{10} f_{jt-1}^2 \cdot d_{jt-1} \\
&\quad + \gamma_{11} f_{jt-1} \cdot z_{jt-1} \cdot d_{jt-1} + \gamma_{12} f_{jt-1}^2 \cdot z_{jt-1} \cdot d_{jt-1} + \xi_{jt}.
\end{aligned} \tag{8}$$

Flexible and static forms for μ

Next we set the law of the motion of the markup. We specify $h_t(\cdot)$ as dummies plus a polynomial of order three in the lagged markup, capital, the firm-level state of the market indicator md_{jt} or *market dynamism,* product and process innovations, and interactions between the lagged markup and md_{jt}, z_{jt-1} and d_{jt-1} :

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[47] We implicitly collapse the constant of the unknown function in the constant of the equation.

$$
\begin{aligned}
h_t(\cdot) = \beta'_t &+ \lambda_1(r_{jt-1} - c_{jt-1} + \ln \nu) + \lambda_2(r_{jt-1} - c_{jt-1} + \ln \nu)^2 + \lambda_3(r_{jt-1} - c_{jt-1} + \ln \nu)^3 \\
&+ \lambda_4 k_{jt} + \lambda_5 md_{jt} + \lambda_6 z_{jt-1} + \lambda_7 d_{jt-1} \\
&+ \lambda_8(r_{jt-1} - c_{jt-1} + \ln \nu) md_{jt} + \lambda_9(r_{jt-1} - c_{jt-1} + \ln \nu) z_{jt-1} \\
&+ \lambda_{10}(r_{jt-1} - c_{jt-1} + \ln \nu) d_{jt-1}. \qquad (9)
\end{aligned}
$$

In the case without adjustment costs of the markup, that we test against our main specification, we use

$$h(\cdot) = \ln \frac{\eta_{jt}}{\eta_{jt} - 1} = \ln \frac{1 + \exp(y_{jt}\lambda)}{\exp(y_{jt}\lambda)} = \ln(1 + \exp(y_{jt}\lambda)) - y_{jt}\lambda,$$

where $y_{jt} = \{md_{jt}, d_{jt-1}, z_{jt-1}\}$. The function makes the markup equal to the elasticity of demand and restricts this elasticity to be greater than one while allowing for cyclical fluctuations according to the firm-level state of the market indicator md_{jt} or *market dynamism* and the introduction of innovations.

Adjustment costs of labor

With adjustment cost of labor the statistical model becomes slightly more complicated. The model for the margin is now

$$r_{jt} - vc_{jt} = \theta \ln(1 + s_{Ljt}\Delta^L_{jt}) - \ln \nu + \ln \mu_{jt} + \varepsilon_{jt} + e_{jt},$$

where parameter θ accounts for the fact that observed average variable costs are likely to already include part of the adjustment costs.[48] On the other hand, the second equation of the system should also be corrected because now marginal cost should be specified in terms of the shadow cost of labor (we approximate the correction with the inclusion of the term $\theta \ln(1 + s_{Ljt}\Delta^L_{jt})$). To estimate Δ^L_{jt} we use of the fact that under Cobb-Douglas production function, the ratio of first order conditions gives

$$\frac{P_{Mjt}M_{jt}}{W_{jt}L_{jt}} = \frac{\beta_M}{\beta_L}(1 + \Delta^L_{jt}).$$

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[48] That is, $AVC_{jt}(1 + s_{Ljt}\Delta^L_{jt}) = AVC^{obs}_{jt}(1 + s_{Ljt}\Delta^L_{jt})^{\theta}$.

If we further assume that the average of the gaps for a firm tends to cancel over time, we have that $\widehat{\left(\frac{\beta_M}{\beta_L}\right)} = \frac{1}{T_j}\sum_t \frac{P_{Mjt}M_{jt}}{W_{jt}L_{jt}}$. Hence, an estimate of Δ^L_{jt} is

$$\widehat{\Delta^L_{jt}} = \frac{\frac{P_{Mjt}M_{jt}}{W_{jt}L_{jt}}}{\widehat{\left(\frac{\beta_M}{\beta_L}\right)}} - 1.$$

We construct $\ln(1 + s_{Ljt}\widehat{\Delta^L_{jt}})$ using the observed cost shares.[49]

5.3 Nonlinear GMM

We plug expressions (7), (8) and (9) into (6) to estimate the system of equations by nonlinear GMM. Write the residuals $\nu_{1jt} = \zeta_{jt} + \varepsilon_{jt} + e_{jt}$ and $\nu_{2jt} = \zeta_{jt} - \xi_{jt} + e_{jt}$ as a function of the variables x_{jt} and the vector θ of parameters to estimate. Stacking the moments for each firm j and adding them, the GMM problem is

$$\min_\theta \begin{bmatrix} \frac{1}{N}\sum\limits_j A_1(z_j)\nu_{1j}(x_j,\theta,) \\ \frac{1}{N}\sum\limits_j A_2(z_j)\nu_{2j}(x_j,\theta) \end{bmatrix}' \widehat{W} \begin{bmatrix} \frac{1}{N}\sum\limits_j A_1(z_j)\nu_{1j}(x_j,\theta) \\ \frac{1}{N}\sum\limits_j A_2(z_j)\nu_{2j}(x_j,\theta) \end{bmatrix}$$

where $A_1(\cdot)$ is an $L_1 \times T_j$ and $A_2(\cdot)$ an $L_2 \times T_j$ matrix of functions of exogenous variables z_j (a vector partially overlapped with x_j); $\nu_{1j}(\cdot)$ and $\nu_{2j}(\cdot)$ are the $T_j \times 1$ vectors of residuals, and N is the number of firms. $L = L_1 + L_2$ denotes the total number of moments that we use and T_j the number of observations for firm j. Notice that the subscript on $A(\cdot)$ implies that we use different set of instruments for each of the two equations in the system.

For the first step of GMM we use the consistent weighting matrix

$$\widehat{W} = \begin{bmatrix} (\frac{1}{N}\sum\limits_j A_1(z_j)A_1(z_j)')^{-1} & 0 \\ 0 & (\frac{1}{N}\sum\limits_j A_2(z_j)A_2(z_j)')^{-1} \end{bmatrix},$$

and for the second the optimal weighting matrix. We present first stage coefficients and use the second to compute the specification test. Stacking all moments of a firm in the vector

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[49] A possible alternative could be the use of the share of temporary workers in total employment (temporary plus permanent, see Doraszelski and Jaumandreu, 2013).

$g(w_j, \theta) = \begin{bmatrix} A_1(z_j)v_{1j}(x_j, \theta) \\ A_2(z_j)v_{2j}(x_j, \theta) \end{bmatrix}$, where w_j is the union of vectors x_j and z_j, the GMM problem can be more compactly written as

$$\min_{\theta}[\frac{1}{N}\sum_j g(w_j, \theta)]'\widehat{W}[\frac{1}{N}\sum g(w_j, \theta)],$$

We estimate the asymptotic variance as

$$Avar(\widehat{\theta}) = \frac{(G'WG)^{-1}G'WDWG(G'WG)^{-1}}{N},$$

where $G = E[\bigtriangledown_{\theta} g(w_i, \theta_0)]$, W is the probability limit of $\widehat{W}$, and $D = E[g(w_j, \theta_0)g(w_j, \theta_0)']$, replacing them by the estimated counterparts.

5.4 Instruments

Let's discuss the moments used to estimate system (6). The basic instruments that we use for the first equation include: constant, time dummies (15), lagged log of revenue over variable cost, the market dynamism variable and the two dummies of lagged innovation (a total of 20 instruments). The basic instruments that we use for the second equation include: the previous 20 instruments plus a complete polynomial of order three in the lagged input prices (w_{jt-1}, p_{mjt-1}) plus the interactions of this polynomial with the dummies of innovation (a total of 47 instruments). To these basic instruments we find it useful to add lagged capital, labor and/or materials and lagged output price and perhaps a few powers of one or two of these variables. Which additional instruments are suitable changes a little from industry to industry, which we interpret as sensitivity to errors in variables that can be exacerbated in the case of powers. In some industries we also find it useful to employ a sum of lagged R&D expenditures to weight innovations (the expenditures accumulated since the latest innovation when a new innovation takes place). We add a minimum of 3 and a maximum of 11 instruments, which gives a total that ranges from 70 to 78 instruments.[50]

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[50] In the first equation we include lagged capital in industries 1,5,7-10, and the R&D instrument in 2,5,7 and 8. In the second equation, we include lagged capital in all industries (a polynomial of order three in industry 7), lagged labor in all but industries 8 and 9, and lagged materials in all but industry 1 (polynomial

We have to estimate 4 parameters that enter nonlinearly: $\beta_k, \beta_l, \beta_m$, the parameters of the marginal cost/production function, and θ, the parameter on the labor adjustment cost. We have 53 other parameters that enter linearly (10 coefficients from the law of motion for markup, 32 coefficients from the two sets of constant and time dummies that correspond to each equation, and 11 polynomial coefficients in the productivity process). We estimate the 53 parameters by "concentrating them out." As the parameters to estimate are 57, this gives overidentifying restrictions that range from 13 to 21 (see Table 5) and that we use to test the specification.

6. Results

In this section we present the results. We first show the estimation results of the dynamic model, and then we compare them with those of the static specification. The two subsequent subsections give a detailed account of the results without innovation and the additional impact determined by innovation. Lastly, we perform a couple simple counterfactuals that allow us to determine the impact of innovation on the aggregate manufacturing price.

6.1 Estimation Results under Dynamic Pricing

We estimate the system of equations (6), markup and price, including adjustment costs of labor and subject to the specification details of subsection 5.2. The results are summarized in Table 5. Columns (1)-(3) report the estimates for the elasticities of the production function, which enter the equations through marginal cost and the inverse demand for materials. These coefficients, together with the parameter of the adjustment costs of labor reported in column (4), are the nonlinear parameters of the system. We report first step estimates of the nonlinear GMM optimization.

The elasticities of the inputs look sensible and the standard errors reasonable, although the estimate of capital elasticity is imprecise at times. The short-run elasticity of scale

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in 2,3,5,7 and 8). We also add a polynomial of order three in lagged price in industries 2-5 and simply lagged price in 6 and 9, and the R&D instrument in industries 2,5,7-10 (polynomial in 9 and 10).

($\nu = \beta_L + \beta_M$) is slightly below unity in two industries and slightly above in the rest. Our theoretical preference is a short-run elasticity of scale below unity, but the differences found are likely to have little impact on the rest of the estimates. In fact it cannot be rejected that the parameter is below 1 in any industry at the 5% signification level (see appendix Table A2).[51]

The adjustment costs parameter gives values that range from 0.18 to 1.20 in seven industries. These numbers are estimated at standard levels of significance in four cases and imprecisely in three more (at 15, 20 and 25% levels of significance). The lack of precision is not surprising given the rough specification.[52] According to our model these coefficients mean that there are adjustment costs of labor not included in the reported wage bill and that the included part is important.[53] The results imply that the shadow cost of labor is larger than the observed wage in times of expansion of the firm and falls below the observed wage during a slump. The shadow cost of labor is a component of marginal cost that the model specification includes and estimates.

Column (5) reports the overidentifying restrictions test and (6) the corresponding probability value. The test checks how far the used moments are statistically from zero, and hence can be read as assessing the validity of the instruments. It is passed in all but industry 3 at the 5% level of significance. We take this as an overall validation of the used moments.

Columns (7) and (8) provide a first look at the level of the estimated markups. We report the proportion of observations in which we estimate that price is below marginal cost, and hence the log of the markup is negative, and the mean of the positive (log) markups. The proportion of negative (log) markups ranges from 5 to 22%. The average positive markups

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[51] We assume that the short-run elasticity of scale is in any case different from unity. Otherwise the demand for materials that we invert would not be defined. The first order conditions for variable inputs would be homogeneous of degree zero and the determinant of the system singular.

[52] We have been experimenting with an alternative simple specification based on the representation of adjustment costs by means of the proportion of temporary workers in total employment. Although we prefer the current specification we allow this indicator to play a partial role in industry 7.

[53] The exceptions are industries 2, 3 and 8, where we cannot be sure if there are no costs of adjustment or they are completely included in the wage bill.

fall in the reasonable range of 9 to 29%. Columns (9) and (10) report the persistence of both the estimated (log) markups and productivity, which is measured as the coefficient of autocorrelation (AC). The high persistence of productivity seen here is also a common finding of many recent studies (see, for example, Doraszelski and Jaumandreu, 2018). The persistence of markups is also strong but much lower than that of productivity. This seems consistent with the fact that markups have many more variables impacting them.

In summary, the dynamic model provides a good estimation of the underlying production function parameters and confirms the importance of the unobserved adjustment costs of labor, for which it provides an estimate. Markup levels and the proportions that are negative seem reasonable. Markups and productivity are persistent, and especially so for productivity.

6.2 Dynamic versus Static Pricing

Does it make a difference to estimate the dynamic specification rather than the static one? Recall that the static specification constrains the markup to be nonnegative by specifying it as a function of the elasticity of demand ($\frac{\eta(\cdot)}{\eta(\cdot)-1}$), with the elasticity in turn depending on the state of the market and (lagged) innovations.[54] The static model is non-nested in the dynamic model because it cannot be obtained by simply shutting down parameters of the latter. Thus we estimate it with nonlinear GMM and try to use basically the same instruments as in the estimation of the dynamic specification.[55]

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[54] Even in a static framework one can argue that the value of this elasticity is including the effect of the expected behavior of the rivals, and in this sense it must be considered different from the pure price elasticity of demand.

[55] The degrees of freedom increase as a result, however, because we have seven parameters fewer than the dynamic specification. The estimation with exactly the same instruments as in the dynamic specification induces problems in many industries with the sign and the significance of capital. We solve them by slightly adapting the instruments of the second equation. We estimate with the same instruments in industries 1,3,4 and 6, and we simply take out lagged capital in industries 5 and 8. Among the additional instruments, we only leave capital (contemporaneous) and the R&D instrument in industry 2, lagged capital in 10, lagged R&D instrument in 7, and materials in 9. Notice that all this refers to subtraction of instruments. We

The results of the estimation are reported in Table 6. Columns (1)-(3) show the input elasticities and column (4) the labor adjustment cost parameter. At the first sight, the model does a good job in accounting for the main parameters.[56] The production elasticities of the inputs are also sensible and the short-run scale parameter is also slightly above or below unity. Again it cannot be rejected that the parameter of scale is smaller than unity in any industry at 5% level of signification (see appendix Table A2). The adjustment costs of labor roughly match the estimates under the dynamic model in five industries, and diverge in the other five (adjustment costs are important/unimportant when the other dynamic model has shown the opposite). The variables that impact the elasticity tend to be significant and have the expected signs (see appendix Table A2).

However, a closer look at the estimates reveals important differences. The elasticity of labor is always lower than in the dynamic specification, and the elasticity of materials always greater with the exception of two industries.[57] One may then question which estimates are closer to the true parameters. Columns (5) and (6) report the specification test of the static model: it passed in only one industry. The coefficients estimated in the static model are hence expected to be biased by the correlation between the instruments and the error of the equations.

The reason the static model fails is that part of the law of motion of the markups is not picked up by the specification and is then left in the errors. This part is autocorrelated and correlated with the included variables and the instruments. Therefore the inadequate specification of the markups not only generates biases in the estimated markups, but also in the estimated productivity through production function coefficients and markup, which enter the specification of the inverse input demand.

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only make two additions: a polynomial of order three in the variable representing the adjustment costs in industries 7 and 9. Since we have few additional instruments it can be argued that we do not make the expected value of the moments worse.

[56] The model fails however to give a reliable estimate of the elasticity of demand in industry 5. It seems to be a problem of identification of the parameters of the different variables impacting it, that we are not able to solve in a straightforward manner.

[57] The elasticity of capital does not seem to follow any systematic pattern of divergence.

Columns (7)-(12) report the quartiles of the distribution of the levels of the estimated markups in the dynamic and static specification. The median markup estimated by the static model is larger in three industries, roughly equal in two, and narrower in the rest that can be compared. However, the estimated markups have very different spreads. While the average of the median markup across industries is similar (about 0.13), the average IQR is three times larger in the markups estimated under the dynamic model (0.12 versus 0.038).

To assess the relative fit of the models to the data we perform the Rivers and Vuong (2002) test for selection among non-nested models.[58] The result, in column (13), is overwhelming: the static model fits the data much worse in all industries. This formally confirms what could be discerned from the broad difference in the values of the minimized functions. The model comparison highlights the important restrictions embodied in a specification of the markup based on the elasticity of demand, even if this elasticity is allowed to vary with sensible covariates. From now on we continue our exercise with the estimates of the dynamic model.

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[58] Write the moments $g(w_j, \theta)$ of subsection 5.3 as $A_{Dj}\widehat{\nu}_{Dj}$ for the dynamic model and $A_{Sj}\widehat{\nu}_{Sj}$ for the static. The Rivers and Vuong (2002) test, can be written as the following normalized difference between the two first-step objective functions

$$\frac{\sqrt{N}}{\sigma}[(\textstyle\sum_j A_{Dj}\widehat{\nu}_{Dj})' W_{DN}(\sum_j A_j\widehat{\nu}_{Dj}) - (\sum_j A_{Sj}\widehat{\nu}_{Sj})' W_{SN}(\sum_j A_{Sj}\widehat{\nu}_{Sj})] \rightarrow N(0,1),$$

where σ must be computed from the variance (of the difference between objectives) formula

$$\begin{aligned}\sigma^2 \quad = \quad & 4[(N^{-1}\textstyle\sum_j A_{Dji}\widehat{\nu}_{Dj})' W_{DN}\widehat{\Omega}_{DD}W_{DN}(N^{-1}\sum_j A_{Dj}\widehat{\nu}_{Dj}) \\ & +(N^{-1}\textstyle\sum_j A_{Sji}\widehat{\nu}_{Sj})' W_{SN}\widehat{\Omega}_{SS}W_{SN}(N^{-1}\sum_j A_{Sj}\widehat{\nu}_{Sj}) \\ & -2(N^{-1}\textstyle\sum_j A_{Dj}\widehat{\nu}_{Dj})' W_{DN}\widehat{\Omega}_{DS}W_{SN}(N^{-1}\sum_j A_{Sji}\widehat{\nu}_{Sj}),\end{aligned}$$

where $W_{XN} = (N^{-1}\sum_j A_{Xj}A'_{Xj})^{-1}$ and $\widehat{\Omega}_{DS} = N^{-1}\sum_j A_{Dj}\widehat{\nu}_{Dj}\widehat{\nu}'_{Sj}A'_{Sj}$.

6.3 The Evolution of Prices with no Innovation

Let's write the adjusted price equation of system (6) as

$$p_{jt} = \ln \widehat{\mu}_{jt} + \widehat{mc}(\cdot) - \widehat{g}(\cdot) + \widehat{u}_{jt}. \tag{10}$$

This equation allows one to split price into the estimated markup, the observed component of marginal cost (including the estimated unobserved labor adjustment cost), and the estimated expected productivity (the function $\widehat{g}(\cdot)$, reported with its negative sign). We are going to omit the residual term that would make the sum of the determinants add up to exactly the value of price and focus on the analysis on markup, input cost and productivity for simplicity.

We compute the individual yearly changes in prices, markup, input cost and productivity. Then we average the changes, replicating those of the small firms, and construct weighted averages by using the firms' sales lagged two periods. The aim of replication is to obtain representative estimates.[59] The double lag in sales is aimed at getting aggregate figures while minimizing the effects due to correlation between the weights and variables.

Columns (1)-(4) of Table 7 average across observations that correspond to when there is no innovation.[60] They allow us to look at the evolution of price as the result of the growth of marginal cost and markup. The numbers reveal that price grew across industries, in the absence of innovation, between 0.3 and 2%, and input cost grew between 2.5 and 4%. The averages across industries are 1.4 and 3.2%, respectively. The model estimates the growth of productivity in the absence of innovation, which reaches an average across industries of almost 1%. We also see a systematic decrease of the markup by an average of 0.5 percentage points, which could be anticipated from the descriptive statistics on the margin.

The components of the evolution of prices during the period 1992-2006, in the absence

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[59] Recall from subsection 3.1 that firms with less than 200 workers were sampled in the survey to include a 5%, while firms with 200 workers or more answered approximately in 70% of cases, so we multiply the observations of the former by 14.

[60] Recall that innovations enter both the markup and productivity lagged one year, so in fact we average the observations corresponding to the absence of innovation the previous year.

of innovation, are very clear. The periodical rises in input cost are systematically counterbalanced by improvements in productivity and a trend decrease in the markups. There is heterogeneity across industries, but the law of motion in the absence of innovation may be summarized with this stylized fact: a growth of 3% in the input cost results in a price increase of half this value due to the joint effects of productivity improvements and markup moderation.

Recall that we have an indicator of the state of the main market for the firm (slump, stable, expansion) and that our model has explicitly included this indicator as a determinant in the evolution of the markup. Columns (5)-(8) show the cycle effects on productivity growth and markup changes for all observations. Both productivity and the markup tend to be procyclical. Productivity grows more during expansion in seven industries. Markups are even more procyclical. They grow more or decrease less during expansion in all industries but two, and the average difference of growth is a sizeable amount of 2 percentage points. An exploration of the interactions of innovation and cycle shows a lot of heterogeneity in which we are not particularly interested here. Thus we want to simply characterize the important cyclical behavior of productivity and markups first, and then move onto the analysis on the impact of innovation next.

6.4 The Impact of Innovation on Pricing

We want to assess the impact of innovation on prices through its effect on marginal cost and markup. In order to do so Table 8 reports the average of the changes in input cost, productivity and markup for the observations with innovation, split in three categories: process innovation only, product innovation only and the simultaneous innovation in process and product.[61] We measure the changes in differences with respect to the average industry changes for the same variable when there is no innovation (see Table 7). The effects are therefore in addition to the changes when there is no innovation (we often recall this speaking

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[61] Recall again that we are speaking of innovation in the previous period.

of “relative”effects). For example, the first number in column (4) should be interpreted as “with process innovation productivity drives marginal cost down on average by 3.7% points, in addition to the 0.1% points fall in marginal cost that is driven by productivity improvement in the absence of innovation.”And the first number in column (7) should be interpreted as “with process innovation the markup increase is 1.1% points higher than that when there is no innovation.”To get these averages we replicate again the observations for the small firms and weigh all the changes by the firms’ sales lagged twice.

The effects of innovation on input costs, reported in columns (1)-(3), are small and do not show a particularly defined pattern (although it is true that the simultaneous introduction of process and product innovation drives costs down by small amounts in eight out of the ten industries). Therefore we are going to focus on the examination of the effects on productivity and markups, columns (4)-(6) and (7)-(9).

The first thing to notice is that the model and the data confirm that innovation does not always increase relative productivity. Innovation increases productivity and hence reduces cost in only sixteen of the thirty industry-innovation category averages reported in columns (4)-(6). In the rest productivity decreases and marginal cost rises. Average increases in relative productivity are prevalent in process innovation (seven industries out of ten) but less frequent when product innovation is involved (five out of ten industries in product innovation only, and four in simultaneous process and product innovation). We take this as linked to the nature of the innovations.

The innovation effect on marginal cost through productivity, either positive or negative, is by and large more important than the impact of input costs. And the evolution of cost as a result of productivity changes presents a strong negative correlation with markup changes across industries and innovation categories. The sign of the evolution of cost differs from the sign of the evolution of markup in 70% of the cases. Markup goes up when cost decreases or does not change in 13 cases, and goes down when cost increases in 9 cases. Both variables decrease together in 3 cases and increase in 5.

Recall that we model the expected productivity effects as forecastable when the firm makes its R&D investment decisions but currently outside its control. The evolution of the markup can be seen as reacting to the evolution of productivity (including the unforecastable shock). The model does not tell us the precise reasons by which the markup increases or decreases. It may be due to the evolution of the elasticity of demand given the innovation, or it may be the optimal intertemporal strategy of the firm given its price adjustment costs. But the model characterizes the paths seen in the data, from which we distinguish two important patterns.

First, when innovation increases relative productivity, and hence decreases cost, the firm reacts in general by increasing its relative markup. This can be done by increasing the markup or simply by decreasing it less than the industry average. The sign of productivity is negative (the cost savings are greater than average) and the sign of the change in markup is positive (markup evolves more positively than average). This happens in 13 cases out of the 16 cases in which productivity increases with different intensities. We will call this strategy "cash-in innovation."By not reducing the price according to the marginal cost reduction the firm gets a temporary increase in profits. In the 3 remaining cases of marginal cost reduction the firm instead reduces the relative markup, so there is more than downward cost "pass-through."For some reason, the firms find it optimal to reduce price more than the reduction in cost.

When innovation decreases productivity, and hence increases cost, the firm frequently reacts by decreasing the margin, so there is some compensation of the cost effects on price. As a result, the sign of productivity is positive and the sign of markup is negative. This happens in 9 of the 14 cases of productivity decrease. We will call this strategy "countervailing pricing."Firms are behaving as if to soften the cost increases induced by innovation by pricing relatively more carefully. In the 5 remaining cases, both cost and markup increase instead, so there is again more than cost "pass-through,"now upwards. Figure 4 illustrates the cases of "cash-in innovation"and "countervailing pricing."

There are two important things to remark on these results. First, prices under innovation imply some positive direct effect for consumer welfare (cost or/and markup decrease) in the overwhelming majority of cases (25 out of 30). If we weight the impact on consumer welfare of the change in the products' characteristics we could have even a larger number. Second, both "cash-in innovation"and "countervailing pricing"strategies induce inertia in prices. They can be seen as creating downward and upward "rigidity"of prices respectively.

6.5 The Impact of Innovation on Aggregate Manufacturing Price

Are innovation and firms' pricing behavior under innovation important for prices in manufacturing? In what follows we answer this question by using the model and estimates to perform some counterfactuals.

Consider equation (10). By weighting adequately the dependent variable we can define an (industry) aggregate price and split it into different subprices

$$p = \sum_{j,t} w_{jt} p_{jt} = \sum_X w_X \sum_{j \in X,t} w^*_{jt} p_{jt} = \sum_X w_X p_X,$$

where X indexes the appropriate split of the observations. For example non innovation, process only, product only and both. In addition, $w_{jt} = \frac{S_{jt}}{\sum_{j,t} S_{jt}}$, $w^*_{jt} = \frac{S_{jt}}{\sum_{j \in X,t} S_{jt}}$ and $w_X = \frac{\sum_{j \in X,t} S_{jt}}{\sum_{j,t} S_{jt}}$. Doing the same with each price component, and assuming that the aggregate error is close to zero, we can rewrite with straightforward notation

$$p = \sum_X w_X p_X \simeq \sum_X w_X \ln \widehat{\mu}_X + \sum_X w_X \widehat{mc}_X - \sum_X w_X \widehat{g}_X.$$

Finally, calling 0 to some basic category (for example non innovation) and taking into account that $w_0 = 1 - \sum_{X \neq 0} w_X$, we can write

$$p \simeq \ln \widehat{\mu}_0 + \widehat{mc}_0 - \widehat{g}_0 + \sum_{X \neq 0} w_X (\ln \widehat{\mu}_X - \ln \widehat{\mu}_0) + \sum_{X \neq 0} w_X (\widehat{mc}_X - \widehat{mc}_0) - \sum_{X \neq 0} w_X (\widehat{g}_X - \widehat{g}_0).$$

In our example the three sums give the contributions of markups, input cost and productivity of innovations to the aggregate (industry) price. In differences over time this equation provides contributions to growth. In what follows we compute differences over time and aggregate across industries using value added weights of the National Accounts in 2000 (see appendix Table A1). The corresponding terms in markup and productivity constitute an assessment of the contribution of innovation to the growth of the aggregate manufacturing price.

The first two panels of Table 9 provide the evaluation of the terms corresponding to productivity and markups using alternatively innovation category proportions and the corresponding sales (lagged twice). Process innovations plus the simultaneous introduction of process and product innovations explain a reduction in aggregate price growth in 0.54 percentage points. As yearly aggregate price growth is evaluated at 1.2%, this means that the growth rate of aggregate price had been multiplied, in the absence of this innovation that includes process innovation, by a factor of 1.4. This is a very important effect, which attributes a key role to innovation in moderating the evolution of prices.

It is worthwhile to point out two additional observations. First, product innovation contributes to push price upwards but the contribution is negligible. Second, firms that simultaneously introduce product and process innovations tend to be big. This can be seen from comparing the aggregate effect of simultaneous process and product innovation in the first two panels, where one can see that when sales weights are used the effects are larger.

The third panel adopts a different perspective to decompose the effects. We look at the aggregate impact of the firms' pricing strategies uncovered in the previous subsection (it is enough to reorder the sums of effects according to the strategy in which each term can be classified). It is clear that the downward impact on price growth comes from the firms that experience productivity improvements, particularly when these improvements are more than "passed-through."It also shows that innovation without the "cash-in" strategies had decreased the price by 0.24 additional percentage points and hence multiplied the rate of increase of aggregate manufacturing price by 0.8. This suggests a possible scope for policymakers to sharpen the aggregate price effect of innovation, where one could in principle try to penalize "cash-in innovation"strategies. However, it is important to take into account that this counterfactual is done given the innovations of the firms and hence given the R&D investments. It does not evaluate how these investments would react to a policy that moderates the incentives. The risk of such policies would be to dampen the incentives to innovate for firms.

7. Concluding Remarks

How technological progress is transmitted to prices is an important question with many allocative and welfare consequences. Using price indices of a panel of manufacturing firms and their introduction of innovations, as well as data on the firms' revenue, input use and margins, we have studied, from a structural point of view, the impact of innovation on prices. Our modeling shows at least three novel characteristics. First, we estimate the effects of innovation on endogenous productivity using price as the dependent variable, while modeling productivity as an unobserved and persistent component of the marginal cost with respect to which price is set. Second, we estimate simultaneously the endogenous markup modeled as the price to average variable cost ratio corrected by the average variable cost to marginal cost ratio (i.e. the short run elasticity of scale estimated from the production elasticities). Third, we have modeled the markup as the result of dynamic pricing. The estimation results confirm the validity of the approach we follow and show a much better fit of the data than the static markup modeling does.

Our findings show that innovation do not always raise productivity and thus decreases cost, although that often is the case with process innovation. Faced with cost decreases and increases associated with innovation, we detect that firms tend to "cash-in innovation"and practice "countervailing pricing"respectively. These strategies result in price rigidity, adding to other sources found in the prices literature. Overall, the impact of innovation on prices tend to improve consumer welfare (cost decreases passed onto prices, markup moderation when price increases), but the "cash-in"strategies tend to dampen this effect.

Our study raises many research questions for future work, some technical and others more substantial. On the technical side we want to mention three. First, the price to average variable cost ratio (measured with the revenue to variable cost ratio) seems to measure the markups well. But it would be even more reliable if one has a better measure of variable costs, a question that deserves some additional effort. Second, the average variable cost to marginal cost ratio is a key technological characteristic, relevant to markup estimation, that would be interesting to estimate under more general technologies or even nonparametrically.

This would add robustness to the estimated markups. Third, as many databases do not have information on firm-level prices, would it still be possible to apply the model? When firm-level prices are not available, it is not possible to estimate productivity disentangled from demand effects, but it is possible to estimate the elasticity of scale in production, so the answer to the question seems to be yes concerning the estimation of the markups. This suggests an interesting possible avenue for future research.

On the side of the more substantial questions let's stress two. First, our estimation of markups (persistent but varying, with some negatives, cyclical, and subject to the effects of innovation) poses the question of how much we may be missing in analyses where economists model markups based on static pricing. It would be interesting to check the effects using the type of markups we estimate in the empirical analysis of relevant trade, IO, or development questions. Second, the effect of innovation on prices seems to be quite heterogeneous and affected by pricing strategies. A clear implication is that this should be pursued further in an analysis of allocation effects.

Data Appendix

We observe firms for a maximum of 17 years between 1990 and 2006. The sample is restricted to firms with at least three years of observations on all variables required for the estimation of the model. The number of firms with 3, 4,…, 17 years of data is 313, 240, 218, 215, 207, 171, 116, 189, 130, 89, 104, 57, 72, 94 and 160 respectively. Table A1 gives the industry labels along with their definitions in terms of the ESEE, National Accounts, and ISIC classifications, columns (1)–(3), and details in column (4) the value added weight of each industry in 2000.

The sample and variable definitions are the same as in Doraszelski and Jaumandreu (2018). Here we only give the definitions of the variables not defined in subsection 3.1.

- *Revenue.* Value of produced goods and services computed as sales plus the variation of inventories.

- *Output.* Value of produced goods and services computed as sales plus the variation of inventories deflated by the firm-specific price index of output.

- *Investment.* Value of current investments in equipment goods (excluding buildings, land, and financial assets) deflated by the price index of investment. The price of investment is the equipment goods component of the index of industry prices computed and published by the Spanish Ministry of Industry.

- *Capital.* Capital at current replacement values $\widetilde{K}_{jt}$ is computed recursively from an initial estimate and the data on current investments in equipment goods $\widetilde{I}_{jt}$. We update the value of the past stock of capital by means of the price index of investment P_{It} as $\widetilde{K}_{jt} = (1-d)\frac{P_{It}}{P_{It-1}}\widetilde{K}_{jt-1} + \widetilde{I}_{jt-1}$, where d is an industry-specific estimate of the rate of depreciation. Capital in real terms is obtained by deflating capital at current replacement values by the price index of investment as $K_{jt} = \frac{\widetilde{K}_{jt}}{P_{It}}$.

- *Labor.* Total hours worked computed as the number of workers times the average hours per worker, where the latter is computed as normal hours plus average overtime minus average working time lost at the workplace.

- *Materials.* Value of intermediate goods consumption (including raw materials, components, energy, and services) deflated by a firm-specific price index of materials.

- *Wage.* Hourly wage cost computed as total labor cost including social security payments divided by total hours worked.

- *Market dynamism.* Firms are asked to assess the current and future situation of the main market in which they operate. The demand shifter codes the responses as 0, 0.5, and 1 for slump, stability, and expansion, respectively.

- *Share of temporary labor.* Fraction of workers with fixed-term contracts and no or small severance pay.

Appendix A

Variable cost minimization implies the cost function

$$C_{jt} = C(K_{jt}, W_{jt}, P_{Mjt}, Q^*_{jt} / \exp(\omega_{jt})).$$

Marginal cost is

$$MC_{jt} = \frac{\partial C_{jt}}{\partial Q^*_{jt}} = \frac{\partial C}{\partial (Q^*_{jt} / \exp(\omega_{jt}))}(K_{jt}, W_{jt}, P_{Mjt}, Q^*_{jt} / \exp(\omega_{jt})) \exp(-\omega_{jt}).$$

On the other hand, by Shephard's lemma, optimal materials choice conditional on output is

$$M_{jt} = \frac{\partial C_{jt}}{\partial P_{Mjt}} = C_{P_M}(K_{jt}, W_{jt}, P_{Mjt}, Q^*_{jt} / \exp(\omega_{jt})).$$

Inverting this latest equation for $Q^*_{jt} / \exp(\omega_{jt})$, and using the resulting expression to replace $Q^*_{jt} / \exp(\omega_{jt})$ in marginal cost, we get

$$MC_{jt} = MC(K_{jt}, M_{jt}, W_{jt}, P_{Mjt}) \exp(-\omega_{jt}) = MC(X_{jt}) \exp(-\omega_{jt}),$$

where $X_{jt} = \{K_{jt}, M_{jt}, W_{jt}, P_{Mjt}\}$ is a vector of observable variables. Variable M_{jt} could be alternatively replaced by L_{jt}.

Appendix B

The markup $\mu_{jt} = \frac{P^*_{jt}}{MC_{jt}} = \nu_{jt} \frac{P(Q^*_{jt}, P_{It}, D_{jt}, z_{jt-1}, d_{jt-1}, \delta_{jt}) Q^*_{jt}}{C(K_{jt}, W_{jt}, P_{Mjt}, Q^*_{jt} / \exp(\omega_{jt}))}$, where $P(\cdot)$ is inverse demand and ν_{jt} the scale parameter, is a monotonic function of Q^*_{jt} given the rest of variables, and the inverse function $Q^*_{it} = Q^*(\mu_{jt}, K_{jt}, P_{It}, W_{jt}, P_{M_{jt}}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt})$ exists. Monotonocity holds because the derivative $\frac{\partial \mu_{jt}}{\partial Q^*_{jt}} = -\frac{\mu_{jt}}{Q^*_{jt}}(\frac{1}{\eta_{jt}} + \frac{1}{\nu_{jt}} - 1)$, where η_{jt} stands for the (absolute value of) elasticity of demand, is negative if $\nu_{jt} < \frac{\eta_{jt}}{\eta_{jt}-1}$. The condition is likely to hold everywhere.

Appendix C

What are the costs of changing the markup that the firm compares the induced increase in profits with? Lets define $\mu^*_{jt} = \frac{P^*_{t-1}}{MC^*_{jt}}$ as the markup that will result if the firm chooses not to change the price. Marginal cost MC_t^* is hence the cost that results from a purely "passive" change in cost, which follows from the change in cost induced by input prices variation, innovations, the state of demand and productivity (i.e. without adjusting price and hence quantity). This markup may be greater or smaller than the markup μ_{jt-1}, depending whether the net effect of the change in input prices, innovation, state of demand and productivity enlarge or deteriorate the margin.

The cost-relevant change in markup that the firm must face is hence $\ln \mu_{jt} - \ln \mu_{jt}^*$, which is from the "passive"markup to the chosen markup. It is the cost of this change that the derived increase in profits should be compared with. This change $\ln \mu_{jt} - \ln \mu_{jt}^*$ can be related to observed change in markup in the following way:

$$\ln \mu_{jt} - \ln \mu_{jt}^* = \ln \mu_{jt} - \ln \mu_{jt-1} + (\ln MC_{jt}^* - \ln MC_{jt-1}),$$

where the term $(\ln MC_{jt}^* - \ln MC_{jt-1})$ represents the passive change induced in the markup μ_{jt-1}. In the specification of adjustment costs it is hence important to allow for the separated impact of variables that determine the passive jump $\ln \frac{MC_{jt}^*}{MC_{jt-1}}$.

Appendix D

Profits can be written as $\pi_{jt} = P(Q_{jt}^*, P_{It}, D_{jt}, z_{jt-1}, d_{jt-1}, \delta_{jt})Q_{jt}^* - VC(K_{jt}, W_{jt}, P_{Mjt}, Q_{jt}^*/\exp(\omega_{jt}))$, where $Q_{jt}^* = F(K_{jt}, L_{jt}, M_{jt})\exp(\omega_{jt})$. The Bellman equation relevant for the choice of I_{jt} and RD_{jt} is

$$\begin{aligned} V(S_{jt}) \;\; = \;\; & \max_{I_{jt}, RD_{jt}} [\pi(K_{jt}, L_{jt}, M_{jt}, P_{It}, W_{jt}, P_{Mjt}, D_{jt}, z_{jt-1}, d_{jt-1}, \omega_{jt}, \delta_{jt}) \\ & - A(\mu_{jt}, \mu_{jt-1}, D_{jt}, z_{jt-1}, d_{jt-1}) - C_I(I_{jt}) - C_R(RD_{jt})] + \beta E_t[V(S_{jt+1})|S_{jt}], \end{aligned}$$

where, in computing the expectation, it is taken into account that $G(z_{jt}, d_{jt}|RD_{jt})$.

Appendix E

First order condition for μ_{jt}, using the functions indexed as shorthand, is

$$\frac{1}{\nu_{jt}}VC_{jt}+\left(\frac{\mu_{jt}}{\nu_{jt}}-1\right)\frac{\partial VC_{jt}}{\partial Q^*_{jt}}\frac{\partial Q^*_{jt}}{\partial \mu_{jt}}-\frac{\partial A_{jt}}{\partial \mu_{jt}}+\beta E_t[\frac{\partial V_{jt+1}}{\partial \mu_{jt}}|S_{jt}]=0,$$

where replacing $\frac{\partial Q^*_{jt}}{\partial \mu_{jt}}$ by $-\frac{Q^*_{jt}}{\mu_{jt}(\frac{1}{\eta_{jt}}+\frac{1}{\nu_{jt}}-1)}$ and $\frac{\partial V_{jt+1}}{\partial \mu_{jt}}$ by $-\frac{\partial A_{jt+1}}{\partial \mu_{jt}}$, we have

$$\frac{1}{\nu_{jt}}VC_{jt}-\left(\frac{\mu_{jt}}{\nu_{jt}}-1\right)\frac{\partial VC_{jt}}{\partial Q^*_{jt}}\frac{Q^*_{jt}}{\mu_{jt}(\frac{1}{\eta_{jt}}+\frac{1}{\nu_{jt}}-1)}-\frac{\partial A_{jt}}{\partial \mu_{jt}}-\beta E_t[\frac{\partial A_{jt+1}}{\partial \mu_{jt}}|S_{jt}]=0.$$

Reordering, this gives

$$\mu_{jt}=\frac{\eta_{jt}}{\eta_{jt}-1}(1-(\frac{1}{\eta_{jt}}+\frac{1}{\nu_{jt}}-1)\frac{\mu_{jt}\nu_{jt}}{VC_{jt}}\frac{\partial A_{jt}}{\partial \mu_{jt}}-(\frac{1}{\eta_{jt}}+\frac{1}{\nu_{jt}}-1)\frac{\mu_{jt}\nu_{jt}}{VC_{jt}}\beta E_t[\frac{\partial A_{jt+1}}{\partial \mu_{jt}}|S_{jt}]),$$

or

$$\mu_{jt}=\frac{\eta_{jt}}{\eta_{jt}-1}(1+\Delta^{\mu}_{jt}).$$

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Table 1: Descriptive statistics.

			Rates of growth						
	Firms	Observations^a	Price (s.d.)	Wage (s.d.)	Price of materials (s.d.)	AVC^b (s.d.)	PAVCM^c (s.d.)	Cost of K over VC^d (s.d.)	Prop. of neg. PAVCM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Metals and metal products	313	2365	0.017	0.041	0.049	0.023	0.113	0.032	0.127
			(0.052)	(0.067)	(0.163)	(0.139)	(0.131)	(0.022)	
2. Non-metallic minerals	163	1270	0.012	0.031	0.043	0.020	0.143	0.048	0.144
			(0.058)	(0.034)	(0.144)	(0.153)	(0.175)	(0.031)	
3. Chemical products	299	2168	0.008	0.032	0.047	0.013	0.109	0.033	0.121
			(0.055)	(0.065)	(0.138)	(0.134)	(0.125)	(0.023)	
4. Agric. and ind. Machinery	178	1411	0.015	0.030	0.045	0.017	0.090	0.027	0.166
			(0.026)	(0.038)	(0.150)	(0.146)	(0.143)	(0.019)	
5. Electrical goods	209	1505	0.008	0.030	0.051	0.016	0.099	0.026	0.167
			(0.046)	(0.044)	(0.168)	(0.151)	(0.141)	(0.017)	
6. Transport equipment	161	1206	0.008	0.026	0.047	0.011	0.083	0.034	0.184
			(0.031)	(0.048)	(0.162)	(0.144)	(0.156)	(0.023)	
7. Food, drink and tobacco	327	2455	0.021	0.033	0.052	0.027	0.106	0.039	0.128
			(0.054)	(0.058)	(0.170)	(0.136)	(0.131)	(0.031)	
8. Textile, leather and shoes	335	2368	0.015	0.031	0.052	0.025	0.084	0.029	0.181
			(0.041)	(0.044)	(0.178)	(0.151)	(0.134)	(0.023)	
9. Timber and furniture	207	1445	0.020	0.035	0.054	0.028	0.093	0.034	0.162
			(0.031)	(0.039)	(0.166)	(0.153)	(0.138)	(0.021)	
10. Paper and printing products	183	1414	0.017	0.035	0.052	0.018	0.131	0.047	0.103
			(0.074)	(0.076)	(0.139)	(0.136)	(0.130)	(0.037)	
All industries	2375	17607	0.015	0.033	0.049	0.020	0.105	0.034	0.146
			(0.050)	(0.054)	(0.160)	(0.144)	(0.140)	(0.026)	

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[a] 1991-2006.

[b] Computed as $\Delta \ln VC - (\Delta \ln R - \Delta \ln P)$, where $VC = Wage\ bill + Materials\ bill$, $R = Revenue$ and $P = Price\ index$.

[c] Computed as $\ln \frac{R}{VC}$.

[d] Computed as $\frac{uc*K}{VC}$, where $uc = interest\ rate + depreciation - inv.\ price\ growth\ rate$, and $depreciation = 0.10$.

Table 2. The distributions of price and AVC changes[a]

	AVC changes					Price changes						
	Prop. neg.	Prop. pos.	Distrib. of changes			Prop. inaction	Prop. neg.	Prop. pos.	Median duration (years)[b]	Distrib. non zero changes		
			Q_1	Q_2	Q_3					Q_1	Q_2	Q_3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. Metals and metal products	0.403	0.597	-0.038	0.020	0.086	0.348	0.123	0.529	1.250	0.010	0.030	0.049
2. Non-metallic minerals	0.428	0.572	-0.041	0.016	0.081	0.368	0.125	0.507	1.370	0.010	0.030	0.049
3. Chemical products	0.425	0.575	-0.040	0.015	0.065	0.362	0.192	0.446	1.429	-0.010	0.020	0.039
4. Agric. and ind. Machinery	0.423	0.576	-0.041	0.016	0.077	0.402	0.071	0.527	1.499	0.014	0.030	0.039
5. Electrical goods	0.434	0.565	-0.048	0.016	0.077	0.355	0.171	0.474	1.353	-0.009	0.020	0.039
6. Transport equipment	0.454	0.546	-0.044	0.008	0.067	0.381	0.186	0.433	1.333	-0.010	0.020	0.030
7. Food, drink and tobacco	0.361	0.639	-0.022	0.023	0.069	0.305	0.089	0.605	1.285	0.020	0.030	0.049
8. Textile, leather and shoes	0.391	0.609	-0.038	0.024	0.085	0.391	0.071	0.538	1.376	0.020	0.030	0.039
9. Timber and furniture	0.385	0.615	-0.035	0.025	0.088	0.364	0.043	0.593	1.499	0.020	0.030	0.049
10. Paper and printing products	0.405	0.595	-0.039	0.020	0.076	0.433	0.128	0.439	1.499	0.008	0.030	0.049
All industries	0.406	0.593	-0.038	0.019	0.077	0.366	0.118	0.516	1.376	0.010	0.030	0.045

[a] 1991-2006.

[b] Inverse of the median of the relative frequency of change (nonzero changes firm j/years in sample of firm j).

Table 3. The introduction of innovations[a]

	Proportion of firms with				(Conditional) Innovation frequency						Observations with			
	No innov.	Process only	Product only	Process & Product	Process			Product			No innov.	Process only	Product only	Both
					Q_1	Q_2	Q_3	Q_1	Q_2	Q_3				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1. Metals and metal products	0.211	0.323	0.054	0.412	0.250	0.500	0.750	0.188	0.333	0.500	0.554	0.251	0.057	0.138
2. Non-metallic minerals	0.294	0.233	0.043	0.429	0.200	0.375	0.556	0.167	0.268	0.500	0.640	0.180	0.080	0.101
3. Chemical products	0.147	0.171	0.070	0.612	0.258	0.500	0.707	0.250	0.500	0.750	0.469	0.184	0.121	0.226
4. Agric. and ind. Machinery	0.219	0.152	0.129	0.500	0.250	0.500	0.727	0.313	0.571	0.800	0.495	0.144	0.162	0.198
5. Electrical goods	0.225	0.153	0.077	0.545	0.258	0.500	0.793	0.250	0.545	0.833	0.476	0.160	0.142	0.221
6. Transport equipment	0.112	0.255	0.050	0.584	0.277	0.517	0.878	0.222	0.500	0.750	0.439	0.250	0.088	0.222
7. Food, drink and tobacco	0.272	0.171	0.073	0.483	0.200	0.429	0.707	0.167	0.333	0.750	0.622	0.149	0.072	0.156
8. Textile, leather and shoes	0.373	0.188	0.093	0.346	0.200	0.333	0.667	0.200	0.400	0.629	0.643	0.133	0.107	0.117
9. Timber and furniture	0.256	0.222	0.097	0.425	0.200	0.385	0.563	0.200	0.500	0.714	0.584	0.154	0.120	0.141
10. Paper and printing products	0.240	0.366	0.049	0.344	0.200	0.375	0.567	0.133	0.250	0.545	0.635	0.219	0.059	0.086
All industries	0.241	0.220	0.074	0.465	0.250	0.444	0.700	0.200	0.429	0.714	0.561	0.181	0.099	0.160

[a] Table computed using the $t-1$ first observations of every firm. The years included are hence 1990-2005.

Table 4. Reduced form results on price growth and innovation.[a] OLS[b]

Industry	Constant (s.d.)[d]	Market dynamism (s.d.)[d]	Process innovation[c] (s.d.)[d]	Product innovation[c] (s.d.)[d]
	(1)	(2)	(3)	(4)
1. Metal and metal products	-0.008	0.017	-0.002	-0.005
	(0.006)	(0.004)	(0.002)	(0.003)
2. Non-metallic minerals	-0.022	0.027	-0.007	0.006
	(0.012)	(0.007)	(0.006)	(0.005)
3. Chemical products	-0.010	0.016	-0.005	0.004
	(0.006)	(0.005)	(0.003)	(0.003)
4. Agric. and ind. machinery	0.018	0.002	-0.003	0.003
	(0.004)	(0.003)	(0.002)	(0.002)
5. Electrical goods	0.001	0.008	-0.006	-0.003
	(0.008)	(0.005)	(0.003)	(0.003)
6. Transport equipment	0.004	0.005	-0.004	0.004
	(0.010)	(0.003)	(0.002)	(0.002)
7. Food, drink and tobacco	0.009	0.005	-0.001	0.000
	(0.007)	(0.003)	(0.002)	(0.002)
8. Textile, leather and shoes	-0.002	0.017	-0.003	0.003
	(0.006)	(0.003)	(0.003)	(0.002)
9. Timber and furniture	0.018	0.002	-0.001	0.009
	(0.005)	(0.003)	(0.002)	(0.002)
10. Paper and printing products	0.004	0.023	-0.002	0.001
	(0.008)	(0.010)	(0.005)	(0.005)
All industries	-0.001	0.012	-0.004	0.001
	(0.002)	(0.001)	(0.001)	(0.001)

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[a] 1991-2006

[b] Includes time dummies and variation of capital, wage and price of materials.

[c] Lagged one period.

[d] Estimated using the robust matrix $\widehat{V} = (\sum_j x_j' x_j)^{-1} (\sum_j x_j' \widehat{e}_j \widehat{e}_j' x_j) (\sum_j x_j' x_j)^{-1}$, where x_j are the $T_j \times k$ matrices of explanatory variables, and $\widehat{e}_j$ are the estimated residuals.

Table 5: Estimation results under dynamic pricing. Nonlinear GMM.

	Elasticities (std. dev.)^a			Adj. cost	Overidentifying restrictions test^b		Estimated markups ($\ln \mu$)		Persistence $(AC)^c$	
Industry	Capital	Labor	Materials	param. (s. d.)^a	$\chi^2(df)$	p value	Prop. of neg.	Mean of pos.	Markup	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Metals and metal products	0.153	0.277	0.704	0.277	3.756	0.994	0.071	0.115	0.379	0.829
	(0.052)	(0.063)	(0.078)	(0.142)	(13)					
2. Non-metallic minerals	0.090	0.347	0.710	0.299	11.272	0.939	0.072	0.223	0.605	0.779
	(0.058)	(0.141)	(0.120)	(0.256)	(20)					
3. Chemical products	0.118	0.216	0.762	0.119	32.542	0.019	0.155	0.118	0.388	0.790
	(0.045)	(0.057)	(0.058)	(0.208)	(18)					
4. Agric. and ind. Machinery	0.098	0.271	0.802	0.255	17.723	0.340	0.051	0.181	0.421	0.868
	(0.039)	(0.055)	(0.067)	(0.139)	(16)					
5. Electrical goods	0.063	0.373	0.631	0.175	27.831	0.145	0.092	0.089	0.266	0.671
	(0.043)	(0.077)	(0.073)	(0.120)	(21)					
6. Transport equipment	0.076	0.321	0.704	0.438	23.296	0.056	0.180	0.155	0.364	0.755
	(0.050)	(0.099)	(0.096)	(0.043)	(14)					
7. Food, drink and tobacco	0.049	0.568	0.471	0.425	16.263	0.700	0.215	0.089	0.494	0.852
	(0.029)	(0.125)	(0.119)	(0.180)	(20)					
8. Textile, leather and shoes	0.075	0.367	0.644	0.082	10.300	0.891	0.200	0.136	0.224	0.673
	(0.031)	(0.069)	(0.062)	(0.130)	(17)					
9. Timber and furniture	0.029	0.267	0.741	0.301	14.674	0.619	0.114	0.123	0.197	0.498
	(0.028)	(0.068)	(0.070)	(0.169)	(17)					
10. Paper and printing products	0.067	0.232	0.889	1.198	3.109	1.000	0.069	0.294	0.208	0.817
	(0.061)	(0.128)	(0.114)	(0.402)	(17)					

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[a] First stage coefficients of nonlinear GMM.

[b] Value of the second stage or optimal GMM objective function appropiately scaled.

[c] Coefficient of regression of the corresponding variable on its lagged value.

Table 6: Dynamic versus static pricing.

	Estimation under static pricing						Quartiles of estimated markups ($\ln \mu$)						Dyn. vs. Stat. spec. test[c]
	Elasticities (std. dev.)[a]			Adj. cost p. (s. d.)[a]	Over. restr. test[b]		Dynamic pricing			Static pricing			
Industry	Capital	Labor	Materials		$\chi^2(df)$	p value	Q_1	Q_2	Q_3	Q_1	Q_2	Q_3	N (p value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1. Metals and metal products	0.040	0.249	0.810	0.067	76.910	0.000	0.078	0.108	0.132	0.174	0.188	0.204	-67.108
	(0.053)	(0.063)	(0.053)	(0.122)	(20)								(0.000)
2. Non-metallic minerals	0.074	0.194	0.910	-0.005	38.472	0.008	0.123	0.184	0.263	0.248	0.280	0.322	-29.454
	(0.070)	(0.139)	(0.109)	(0.208)	(20)								(0.000)
3. Chemical products	0.107	0.210	0.753	0.411	73.774	0.000	0.033	0.093	0.155	0.067	0.076	0.089	-58.889
	(0.055)	(0.075)	(0.066)	(0.157)	(25)								(0.000)
4. Agric. and ind. Machinery	0.099	0.185	0.818	0.236	33.080	0.080	0.125	0.170	0.222	0.084	0.098	0.117	-32.197
	(0.036)	(0.040)	(0.056)	(0.110)	(23)								(0.000)
5. Electrical goods	0.126	0.105	0.804	0.225	52.806	0.002	0.045	0.098	0.152	-	-	-	-38.495
	(0.032)	(0.10)	(0.097)	(0.047)	(27)								(0.000)
6. Transport equipment	0.290	0.225	0.927	0.528	37.592	0.014	0.031	0.105	0.191	0.240	0.263	0.299	-35.360
	(0.098)	(0.153)	(0.184)	(0.170)	(21)								(0.000)
7. Food, drink and tobacco	0.081	0.066	0.871	-0.039	104.191	0.000	0.007	0.052	0.102	0.026	0.042	0.062	-62.336
	(0.041)	(0.055)	(0.075)	(0.109)	(23)								(0.000)
8. Textile, leather and shoes	0.056	0.043	0.909	0.674	72.707	0.000	0.021	0.095	0.155	0.031	0.044	0.062	-58.487
	(0.027)	(0.028)	(0.037)	(0.173)	(23)								(0.000)
9. Timber and furniture	0.057	0.097	0.864	0.856	36.970	0.000	0.048	0.095	0.148	0.051	0.063	0.084	-11.608
	(0.054)	(0.049)	(0.083)	(0.422)	(22)								(0.000)
10. Paper and printing products	0.125	0.207	0.835	0.973	33.815	0.019	0.147	0.256	0.363	0.071	0.084	0.095	-26.397
	(0.089)	(0.095)	(0.104)	(0.392)	(19)								(0.000)

[a] First stage coefficients of nonlinear GMM.

[b] Value of the second stage or optimal GMM objective function appropiately scaled.

[c] Test Rivers and Vuong (2002). Difference of values of the first stage minimized objective function (dynamic model minus static model) divided by the appropriate standard error.

Table 7: The determinants of price growth when there is no innovation, 1992-2006.[a] Cycle effects.[b]

					Cycle effects on			
		MC growth components			Productivity growth		Markup change	
Industry	Price gowth	Input cost	Productivity[c]	Markup change	Slump	Expansion	Slump	Expansion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Metals and metal products	0.018	0.040	-0.001	-0.013	0.000	0.066	-0.015	-0.004
2. Non-metallic minerals	0.012	0.026	-0.011	-0.005	0.040	0.000	-0.031	0.010
3. Chemical products	0.006	0.025	-0.013	0.012	0.011	0.002	-0.039	-0.002
4. Agric. and ind. Machinery	0.012	0.029	0.004	-0.012	-0.011	0.010	-0.024	0.016
5. Electrical goods	0.003	0.034	-0.021	-0.008	0.019	0.034	-0.022	0.008
6. Transport equipment	0.011	0.028	-0.016	-0.005	0.000	0.003	-0.009	-0.004
7. Food, drink and tobacco	0.020	0.035	-0.013	0.003	0.008	0.013	0.007	0.000
8. Textile, leather and shoes	0.018	0.035	-0.011	-0.001	0.002	0.024	-0.024	-0.003
9. Timber and furniture	0.015	0.034	-0.011	-0.007	-0.006	0.028	-0.018	0.010
10. Paper and printing products	0.022	0.037	0.001	-0.010	0.047	0.012	0.011	0.006
Average across industries	0.014	0.032	-0.009	-0.005	0.011	0.019	-0.016	0.004

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[a] Weighted average of price growth and the change in the regression estimates for the componens of marginal cost and markup for the observations without innovation. Weights are sales lagged twice. The determinants of price growth omit the (weighted) error term.

[b] Weighted average values of productivity growth and markup change (all observations) when the firm state of the market indicator signals Slump and Expansion. Weights are sales lagged twice.

[c] Productivity as component of marginal cost included with its negative sign

Table 8. Additional changes when there is a process innovation, product innovation or both.[a]

	MC growth components								
	Input cost			Productivity[b]			Markup change		
Industry	Process only	Product only	Both	Process only	Product only	Both	Process only	Product only	Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Metals and metal products	-0.003	-0.017	-0.005	-0.037	0.020	-0.073	0.011	0.017	-0.010
2. Non-metallic minerals	0.001	-0.011	-0.009	-0.006	0.068	0.014	0.007	-0.037	0.005
3. Chemical products	-0.002	-0.008	-0.002	0.007	-0.007	0.005	-0.028	-0.010	-0.020
4. Agric. and ind. Machinery	-0.008	-0.002	-0.009	-0.028	-0.016	0.001	0.018	0.010	0.009
5. Electrical goods	0.001	-0.009	-0.019	-0.021	-0.000	-0.018	0.021	0.004	0.004
6. Transport equipment	0.004	0.003	-0.006	-0.023	0.007	0.021	0.017	0.014	-0.012
7. Food, drink and tobacco	-0.008	-0.001	0.011	-0.016	0.008	0.017	-0.009	-0.001	-0.011
8. Textile, leather and shoes	0.002	0.008	-0.005	0.029	-0.018	0.009	0.004	0.007	-0.003
9. Timber and furniture	-0.006	0.003	0.003	0.008	0.018	-0.010	-0.002	-0.006	0.013
10. Paper and printing products	0.015	0.014	-0.002	-0.026	-0.007	-0.089	0.000	0.014	0.023
Average across industries	-0.000	-0.002	-0.004	-0.011	0.007	-0.012	0.004	0.001	0.000

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[a] Weighted average of the change in the regression estimates for the components of marginal cost and markup, for the observations with process or product innovation only or both innovations, in differences with respect to the average industry effect without innovation. Weights are sales lagged twice.

[b] Productivity as component of marginal cost included with its negative sign.

Table 9. The impact of innovation on aggregate price.

Aggregate price growth 1992-2006[a]: 0.012

Impact of innovation by innovation effect and type of innovation (innovation weights)[b]:

	Process only	Product only	Both innovations	*Total*
Productivity growth	−0.0029	0.0004	−0.0010	−0.0035
Markup change	0.0005	0.0001	−0.0008	−0.0002
Total	−0.0024	0.0005	−0.0018	

Impact of innovation by innovation effect and type of innovation (sales weights)[c]:

	Process only	Product only	Both innovations	*Total*
Productivity growth	−0.0028	0.0004	−0.0014	−0.0039
Markup change	0.0004	0.0002	−0.0016	−0.0010
Total	−0.0024	0.0005	−0.0030	

Impact of innovation by innovation effect and firm strategy (sales weights)[d]:

	Cash-in innovation	Countervailing price	More than pass-through down	More than pass-through up	*Total*
Productivity growth	−0.0055	0.0037	−0.0028	0.0008	−0.0039
Markup change	0.0024	−0.0033	−0.0007	0.0007	−0.0010
Total	−0.0031	0.0004	−0.0036	0.0014	

[a] The industry weighted average price growth are agregated across industries using National Accounts 2000 weights of value added.

[b] The relative effects by innovation type are aggregated within industries using innovation proportions. Aggregation across industries as in *a*.

[c] The relative effects by innovation type are aggregated within industries using sales proportions. Aggregation across industries as in *a*.

[d] The relative effects by firm strategy are aggregated within industries using sales proportions. Aggregation across industries as in *a*.

Table A1. Industry definitions and equivalences.

	Industry	ESEE (1)	National Accounts (2)	ISIC (Rev. 4) (3)	Share of Value Added (4)
1	Metals and metal products	12+13	DJ	C 24+25	0.132
2	Non-metallic minerals	11	DI	C 23	0.082
3	Chemical products	9+10	DG-DH	C 20+21+22	0.139
4	Agricultural and industrial machinery	14	DK	C 28	0.071
5	Electrical goods	15+16	DL	C 26+27	0.075
6	Transport equipment	17+18	DM	C 29+30	0.116
7	Food, drink and tobacco	1+2+3	DA	C 10+11+12	0.145
8	Textile, leather and shoes	4+5	DB-DC	C 13+14+15	0.076
9	Timber and furniture	6+19	DD-DN38	C 16+31	0.070
10	Paper and printing products	7+8	DE	C 17+18	0.089

Table A2: Additional regression results. Nonlinear GMM.

	Short-run scale param (std. dev.)[a]		Static model: Effects on elasticity $\eta(\cdot)$		
Industry	Dynamic model	Static model	Market dynamism	Process inn.	Product inn.
	(1)	(2)	(3)	(4)	(5)
1. Metals and metal products	0.982	1.058	-0.175	-0.098	0.038
	(0.053)	(0.065)	(0.057)	(0.047)	(0.048)
2. Non-metallic minerals	1.057	1.103	-0.347	-0.096	-0.070
	(0.065)	(0.089)	(0.104)	(0.061)	(0.081)
3. Chemical products	0.978	0.963	-0.215	-0.166	0.133
	(0.045)	(0.057)	(0.138)	(0.121)	(0.107)
4. Agric. and ind. Machinery	1.073	1.003	-0.491	-0.216	0.334
	(0.049)	(0.042)	(0.312)	(0.142)	(0.219)
5. Electrical goods[b]	1.004	0.908	-	-	-
	(0.041)	(0.021)			
6. Transport equipment	1.025	1.152	-0.318	-0.022	-0.003
	(0.037)	(0.143)	(0.204)	(0.053)	(0.057)
7. Food, drink and tobacco	1.040	0.937	-0.139	-0.354	-0.126
	(0.027)	(0.036)	(0.137)	(0.220)	(0.163)
8. Textile, leather and shoes	1.011	0.952	-0.231	-0.415	-0.186
	(0.031)	(0.024)	(0.209)	(0.218)	(0.132)
9. Timber and furniture	1.009	0.961	-0.496	-0.404	0.065
	(0.028)	(0.053)	(0.213)	(0.188)	(0.142)
10. Paper and printing products	1.121	1.042	0.009	0.015	-0.145
	(0.091)	(0.104)	(0.727)	(0.364)	(0.615)

[a] Standard error computed by the delta method.

[b] Coefficients of the elasticity effects are affected by a problem of multicollinearity.

Figure 1. Sample prices versus the Industrial Price Index. Rates of growth.

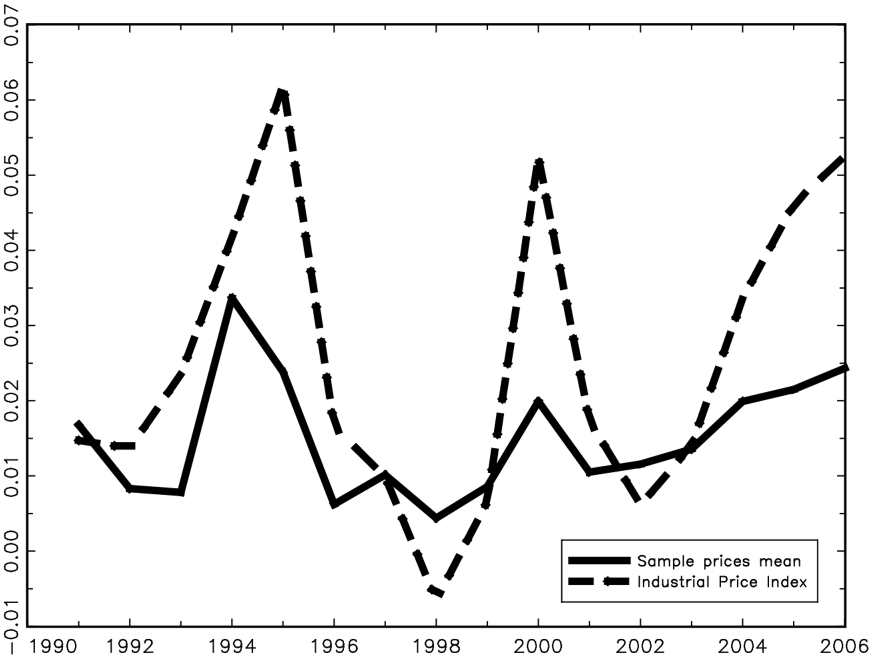

Figure 2. Evolution of prices, input prices and variable costs. Indices.

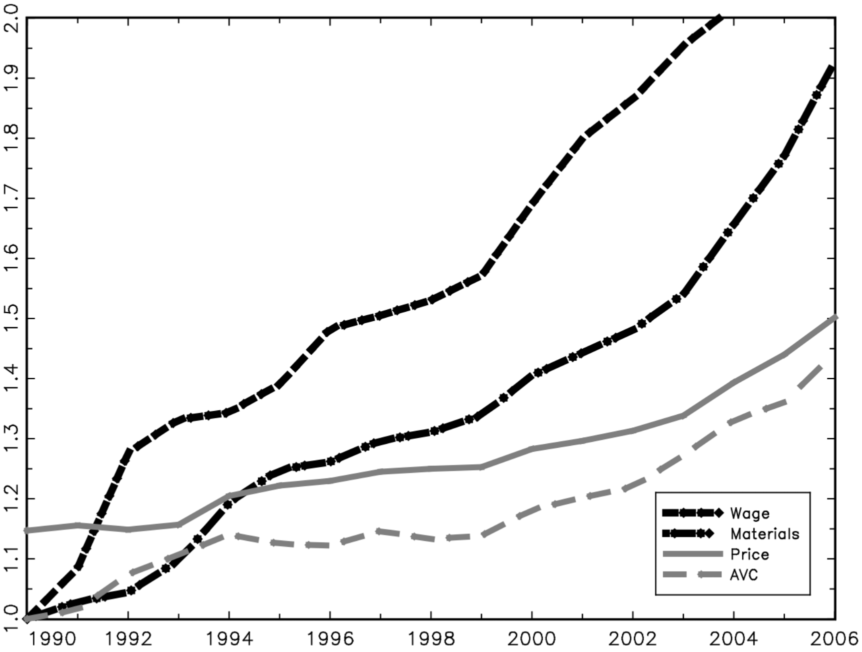

Figure 3. Adjustment of price to cost according to lagged margin.
Nonparametric estimate of $E[\Delta p - \Delta avc | r_{-1} - vc_{-1}]$.

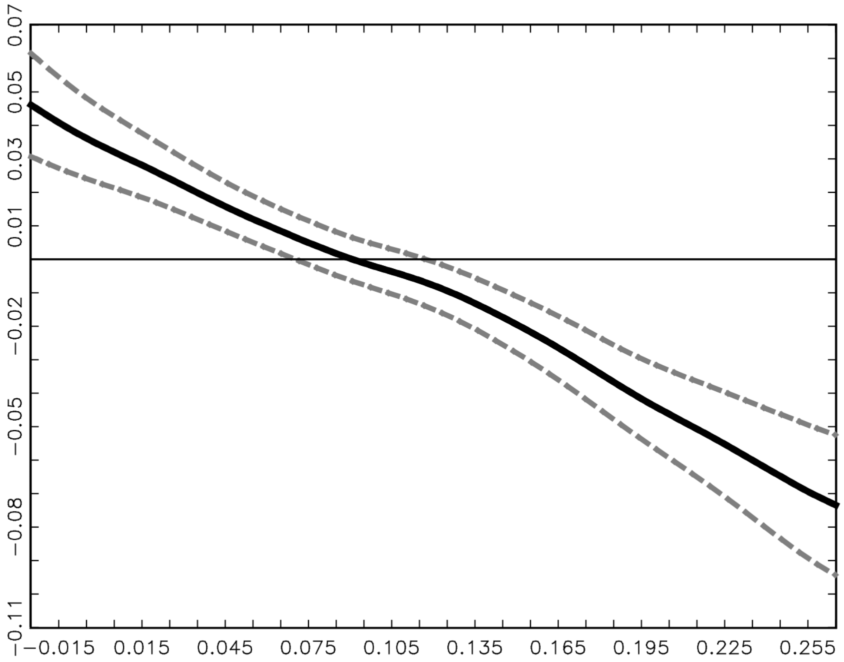

Figure 4. Percentage change in cost and markup for cashing-in innovation and countervailing-price cases.