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A nonparametric panel data approach to the cyclical dynamics of price-cost margins

Andrea Vaona*

Abstract: By using nonparametric and panel data econometrics, this paper re-assesses the effect of both the current level of economic activity and of future expected demand on the dynamics of the price mark-up over marginal cost in US manufacturing industries from 1958 to 1996. Consistently with previous results, the current level of economic activity has a negative impact on the mark-up and expectations of future demand a positive one. Differences between consumer and producer goods and between more and less competitive sectors play a minor role. Differences between durable and nondurable goods, instead, find more empirical support.

Keywords: L60, L16, E32

JEL classification: mark-up, cyclical dynamics, durable goods, non-durable goods, nonparametric econometrics, panel data econometrics.

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Introduction and Literature Review

The cyclical dynamics of the price mark-up over the marginal cost has attracted considerable attention in the recent past, given that it could offer an explanation of why it is not possible to obtain empirical evidence of countercyclical real wages as implied by standard neo-classical models (Rotemberg and Woodford, 1991, p. 69).

Breshnan (1989) offers a broad review of the literature. Galeotti and Schiantarelli (1998) distinguish various empirical approaches to the issue. In the first place, there are studies assuming that marginal and average costs are equal (Domowitz, Hubbard and Petersen, 1986, 1987; Machin and Van Reenen, 1993; Chand and Sen, 2000). In the second place there are both static and dynamic models relying on production theory and estimating the optimality conditions for input demands under the assumption of flexible functional forms for firms' technology and variable inputs (Appelbaum, 1979; Gollop and Roberts, 1979; Morrison, 1993; Chirinko and Fazzari, 1988). Building on Hall (1986, 1988), some other studies derive estimates of the mark-up after estimating Solow's productivity residual (Domowitz, Hubbard and Petersen, 1988; Haskel, Martin and Small, 1995; Ryan, 1997, 2000). One further research strategy is the one by Bils (1987), based on a parsimonious specification of the production function. Galeotti and Schiantarelli (1998), finally, estimate the Euler equation for capital with additively separable adjustment costs, without parametrizing either the production or the cost functions.

The aim of this paper is to reassess, by means of a new testing procedure and by considering a finer level of sectoral disaggregation, the model of the mark-up proposed by Galeotti and Schiantarelli (1998). This is because their model carries a particular interest given that they managed to capture not only the role of the current level of economic activity in the temporal dynamics of the mark-up, but also that of expected future demand.

To understand our new testing procedure, it is worth recalling that Rotemberg and Woodford (1999) illustrate different possible formulations of the real marginal cost (the inverse of the mark-up) allowing for non-Cobb-Douglas technology, overhead labour, overtime pay, labour adjustment costs, labour hoarding, variable capital utilization, intermediate inputs, inventory fluctuations, and variation in the capital stock. Sticking to a "labour" measure of the marginal cost, in order to estimate it one would need not only labour's share of income, but also other variables such as output, labour input, the marginal wage, current and expected future growth of both idle labour input and hours per worker.

In this paper we follow an alternative procedure to estimate the mark-up. Starting from the cost minimization problem of the representative firm, it is possible to show that the mark-up is the ratio of the nominal marginal product of a production factor over its price. So, if we consider for instance material inputs, the mark-up is given by the following equation:

$$\mu_t = \frac{P_t F_M(\cdot_t)}{P_{Mt}} \tag{1}$$

where P_M is the price index of material inputs, P is the aggregate price index and $F_M(\cdot)$ is the marginal product of material inputs. All variables are taken at their time *t* values.

According to Rotemberg and Woodford (1999), (1) is an attractive measure of the mark-up because Basu (1995) showed that material inputs are not used in fixed proportions with primary inputs and because, on the basis of the results of Basu and Kimball (1997), material inputs do not appear to be characterized by adjustment costs.

The approach we adopt here consists in estimating $F_M(\cdot_t)$ nonparametrically, to compute μ_t, and then to investigate its cyclical properties. One of the advantages of using non-parametric econometrics to estimate the mark-up is that it is possible to avoid making any assumption regarding the functional form of $F(\cdot)$ to achieve an estimable model[2].

Regarding this issue, it is possible to say that researchers face a trade-off when estimating the marginal cost. A rough specification of the production function suffices when adopting an average cost measure. For instance, Bils (1987) considers the following production function:

$$Y_t = H_t^{\alpha} f_t$$

where Y is output, H is hours worked, α is a parameter and f is a bundle containing all the other possible inputs. On the other hand, once using a nonparametric approach to

[2] Given that we leave the production function unspecified we do not need to take logs of the variables, nor to introduce possible nonlinear effects or to assume additively separable adjustment costs as in Galeotti and Schiantarelli (1998).

the estimation of the marginal product, one can adopt a generic functional form, but she has to consider a broader list of possible production factors, as we do.

In the end the production function adopted here is:

$$Y_t=F(H_t, K_t, N_t, M_t, E_t, K_{t-1}, N_{t-1}, t) \qquad (2)$$

where the production inputs are working hours (H_t), the stock of real capital (K_t), the number of employees (N_t,), material inputs (M_t) and energy (E_t),[3] limiting possible biases deriving form the omission of relevant variables. We also insert in our production function a lag in the capital input and in employment to account for adjustment costs, together with a time trend to account for technological development.

One further assumption to discuss in detail is the existence of an aggregate production function, which might appear rather stringent. On this issue, Jorgenson (1996) writes: "[I]n technical jargon the existence of an aggregate production function requires that the technology of each sector is separable in value added and that value added is a function of capital and labour inputs and the level of technology. Moreover, the sectoral value-added functions must be identical for all sectors, while the functions relating labour and capital inputs to their components must also be identical for all sectors. Finally, each component of these input aggregates must receive the same price in all sectors" (p. 7). As a matter of consequence, inputs of

[3] Our variables are measured as follows. Gross output is the total value of shipments in $1,000,000. M_t is the total cost of materials in $1,000,000. Energy is the cost of electricity and fuels in $1,000,000. The total real capital stock is measured in $1,000,000, while total employment is in thousands and total hours in millions.

some sectors might contribute more to the performance of a macroeconomy than those in other sectors, as happened for IT capital inputs in the nineties (Oliner, Sichel and Stiroh, 2007; Colecchia and Schreyer, 2002). Jorgenson (1996) also states that, though an aggregate production function can be a useful tool to understand the performance of a macroeconomy over the long-run, for shorter periods it can well be a "straightjacket" and he recommends to use data disaggregated at the sectoral level as those used by Jorgenson and Stiroh (2000). Therefore, as in Bils (1987) or Galeotti and Schiantarelli (1998), we consider sectoral data in the attempt to overcome the possible pitfalls arising from estimating a partial derivative of an aggregate production function. Specifically, we rely on the NBER-CES Manufacturing Industry Database, which contains data on output, employment, investment, capital stocks, total factor productivity, various industry-specific price indexes, and payroll and other input costs. The database covers all 4-digit manufacturing industries from 1958-1996 at an annual frequency[4]. Therefore, we consider the same level of sectoral disaggregation as in Domowitz, Hubbard and Petersen (1986, 1987 and 1988), which is finer that the 2-digit disaggregation used in Galeotti and Schiantarelli (1998).

Finally, a nonparametric approach makes it possible to test one further assumption. In presence of a monopsonistic market, the following equation holds:

$$\mu_t = \frac{P_t F_M(\cdot_t)}{P_{Mt} + \frac{dP_{Mt}}{dM_t} M_t}$$

[4] For a broader description of the dataset see http://www.nber.org/nberces.

where $\frac{dP_{Mt}}{dM_t}$ is the derivative of the price of material inputs with respect to M_t.

Nonparametric econometrics offers a direct test for the hypothesis $\frac{dP_{Mt}}{dM_t} = 0$, helping to choose the most appropriate specification for the marginal cost (Pagan and Ullah, 1999, p. 178).

The rest of the paper is structured as follows. The next section deals with the nonparametric estimation of the marginal product of material inputs and with testing the monopsony hypothesis in the market for material inputs. In the third section we will explore the cyclical dynamics of the mark-up, while in the fourth one, similarly to Domowitz, Hubbard and Petersen (1986, 1987 and 1988), we will consider the issue whether this dynamics is different either in producer goods sectors versus consumer goods sectors or in more concentrated sectors versus less concentrated ones or in durable goods sectors versus non-durable goods sectors. The last section concludes.

Nonparametric estimation of the marginal product of material inputs and testing for the monopsony hypothesis.

In order to estimate the marginal product of intermediate inputs we build on Pagan and Ullah (1999). Consider the following model

$$Y_t = F(x_t) + u_t \tag{3}$$

where x_t is a $1xk$ vector containing the t-th values of our set of production inputs (with k being the number of inputs) and u_t is an error. It is possible to obtain an estimator of $F_M(\cdot)$ as follows:

$$\hat{F}_{M,t} = \frac{\hat{F}(x_t + e_M h) - \hat{F}(x_t - e_M h)}{2h} \tag{4}$$

where h is the bandwidth, $\hat{F}(\cdot)$ is the Nadaraya-Watson estimator of $F(\cdot)$, and e_M is a vector with unity for material inputs and zero elsewhere. The bandwidth was chosen equal to $n^{-1/(k+6)}$ after dividing all the inputs by their standard deviation, where n is the number of observations. We estimated $F_M(\cdot)$ separately for each sector and we used a Gaussian kernel.

Due to the presence of lagged values of the capital stock and employment, it is possible to estimate the mark-up only for the period 1959-1996.

To illustrate our estimates we compute the elasticities of gross output with respect to material inputs as $\hat{\varepsilon}_{MY,t} = \hat{F}_{M,t} \frac{M_t}{Y_t}$. The results are set out in Table 1. On average an increase of material inputs by 1% increases output of about 0.13%. There are some cases in which marginal product can be negative, that is there might be an over-utilization of material inputs. In order to check if these are just temporary occurrences or not, we also computed the time average of the elasticity and we show its minimum and maximum values in the last two columns of Table 1. These time averages can be considered as long-run elasticities and they can be negative if only if $F_{M,t}$ is negative. There is only one case where we obtained a negative value: the sector of "Roasted

Coffee" (SIC code: 2095), where the average marginal product was equal to -0.009857, though not being statistically different from zero. A negative marginal product in the short run could be due to the fact that firms are not temporarily maximizing their profits due to some shock and they are using an excessive quantity of a given input[5].

Once having at hand an estimate of $F_M(\cdot)$, it is easy to obtain an estimate of μ_t by using the price indexes for sectoral value added and material inputs. Given that we use price indexes the average value of μ_t does not carry any economic meaning. This implies that it cannot be used as an indicator of the sectoral degree of competitiveness.

Furthermore, visual inspection does not often help to understand the cyclical dynamics of the marginal cost (Morrison, 1993). Therefore, we move directly to regression analysis, not before checking, however, that our measure of the mark-up is not harmed by the existence of a monopsonistic market for material inputs.

In this context, we wish to check whether $P_{M,t}$, the price of material inputs, is a function of their quantity M_t, $P_{M,t}$,$=P_M(M_t)$. A Wald test statistic for the linear restriction, $\mathrm{d}P_M(M_t)\,/\mathrm{d}M_t=\beta(M_t)=0$, assumes the following form:

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[5] However, there exist several reasons why a negative marginal product might exist in the long-run as well. It might be due to a negatively sloped supply function of a given input (for instance due to economies of bulk purchase). One further reason is that a given input might require a minimum scale of production, under which it might entail costs that outweigh those of other variable production inputs. On this issues see Miller (1970), Ng (1972), Glustoff and Wickham (1991) and Ferguson (1969). Detecting what exactly is the specific case for the roasted coffee industry in the US is beyond the scope of this paper, all the more that it was not significantly different from zero.

$$W(M_t) = \frac{\widehat{\beta}(M_t)}{SE_t\left(\widehat{\beta}(M_t)\right)} \rightarrow N(0,1) \qquad (5)$$

where $SE(\widehat{\beta}(\mathrm{M}_t)) = \sqrt{\frac{1}{nh^3}\frac{\hat{\sigma}^2(\mathrm{M}_t)\int K(\psi)^2 d\psi}{\hat{f}(\mathrm{M}_t)}}$, $\hat{\sigma}^2(\mathrm{M}_t) = \frac{\sum K(\psi_t)\hat{u}_t^{\,2}}{\sum K(\psi_t)}$,

$\hat{f}(M_t) = \frac{\sum K(\psi_t)}{nh}$, $\psi_t = \frac{(M_t - M)}{h}$, M is the *nx1* vector of observations for material inputs, n is the number of observations and $K(\cdot)$ is the kernel function. We compute $W(M_t)$ separately for each sector. (3) is a pointwise test, so the null might be accepted at some points and rejected at some others. Remarkably, our results always accept the null that $\beta(M_t)=0$. So, as expected, we could not find any support for a monopsonistic market structure for material inputs.

The cyclical dynamics of the mark-up

It is interesting to check how our nonparametric measure of the mark-up moves over the cycle. We follow Bils (1987) and we pool all the sectors together. This is in contrast with the analysis by Galeotti and Schiantarelli (1998), who provide sector specific estimates. However, our choice is supported by Baltagi et al. (2003) and Baltagi et al. (2004), who recommended adopting pooled estimators because they provide better forecasts and more plausible estimates. Under this respect, the estimates by Galeotti and Schiantarelli (1998) are a clear example of the potential pitfalls of heterogeneous estimators, as their sign is rather unstable across different sectors.

We specify three different models, taken from Galeotti and Schiantarelli (1998). Building on Haltiwanger and Harrington (1991), Rotemberg and Woodford (1991, 1992, 1993) and Bagwell and Staiger (1995), they distinguish between the effect of the "current level of product demand relative to its normal level" (L_t) – called the "level effect" – and of the "future evolution of demand" (D_t) – called the "derivative effect". This is done in order to capture not only how the current state of the economy affects μ_t, but also how the expectations regarding its future developments might do it.

They measure L_t as

$$L_t = lnY_{i,t} - [0.25*ln(Y_{i,t-1}*Y_{i,t-2}*Y_{i,t+1}*Y_{i,t+2})] \tag{6}$$

with $Y_{i,t}$ being the real gross output in sector i at time t. Given the presence of two leads and two lags of output in (7), our estimation sample includes the years form 1961 to 1994.

D_t instead is measured in three different ways, that we label $D_{1,t}$ $D_{2,t}$ and $D_{3,t}$. $D_{1,t}$ is given by the deviations from a five-year centred geometric moving average of growth rates of industry outputs. $D_{2,t}$ is a time dummy indicating whether the aggregate economy is expanding or contracting based on the NBER Business Cycle Dating. The six recession years, contained in our sample, were defined as those with more than one quarter of economic downturn.

Finally, $D_{3,t}$ is the present discounted value of future demand changes, where expectations are assumed to be generated by a bivariate Vector Autoregression that includes real GNP:

$$\Delta logY_t = \alpha_1\, \Delta logY_{t-1} + \alpha_2\, \Delta logQ_t + \omega_{Yt} \tag{7}$$

$$\Delta logQ_t = \alpha_3\, \Delta logQ_{t-1} + \omega_{Qt} \tag{8}$$

where Q_t is U.S. real GNP and the ω's are i.i.d. errors.

$D_{3,t}= \Delta logY_{t-1}/(1-\beta\alpha_1) + \alpha_2\, \alpha_3\, \Delta logQ_t/(1-\beta\alpha_2)(1-\beta\alpha_3)$ where β is the discount factor which, building on the micro-founded new-keynesian or real business cycle literature, was calibrated and set equal to 0.98. Setting it to either 0.96 or 0.99 would not affect our results.

In the end our three models are:

$$\mu_t = m_{0,i} + m_{L,i} L_t + m_{D,i} D_{i,t} + \xi_{i,t} \tag{9}$$

for i=1,2,3, where $\xi_{i,t}$ are stochastic errors. $m_{0,i}$ can be interpreted as the portion of the mark-up that is invariant to the business cycle. However, due to our usage of price indexes to build μ_t, the value of this parameter cannot be considered as an indicator of the degree of competitiveness of each sector[6].

We make use of panel data techniques to take care of possible unobserved heterogeneity, relying on an instrumental variable random effect estimator[7], and

[6] The fact that we found evidence of negative short run marginal product implies that (9) cannot be specified in a logarithmic form.

[7] We specifically used Baltagi's EC2SLS estimator. Using the G2SLS estimator by Balestra and Varadharajan-Krishnakumar would not change our results as well as using the Baltagi and Chang variance component estimator. For an introduction to these estimators see Baltagi (2001).

instrumenting L_t with its first lag[8]. This identification strategy is consistent with that adopted by Galeotti and Schiantarelli (1998), assuming that the past history of the mark-up does not determine its present value. χ^2 tests in first stage regressions would reject the null of no correlation between the instruments and the instrumented variables with p-values equal to 0.00.

Our results are showed in equations (10) to (12).

$$\mu_t = \underset{\substack{(0.03)\\ [0.04]}}{0.41} - \underset{\substack{(0.02)\\ [0.04]}}{0.14} L_t + \underset{\substack{(0.03)\\ [0.02]}}{0.14} D_{1,t} + \xi_{1,t} \quad \text{Het.}=0.11 \qquad \text{Ser. corr.}=0.00 \tag{10}$$

$$\mu_t = \underset{\substack{(0.37)\\ [0.53]}}{2.28} - \underset{\substack{(0.38)\\ [0.55]}}{2.10} L_t + \underset{\substack{(0.02)\\ [0.03]}}{0.12} D_{2,t} + \xi_{2,t} \quad \text{Het.}=0.00 \qquad \text{Ser. corr.}=0.00 \tag{11}$$

$$\mu_t = \underset{\substack{(0.15)\\ [0.17]}}{0.76} - \underset{\substack{(0.15)\\ [0.17]}}{0.48} L_t + \underset{\substack{(0.01)\\ [0.03]}}{0.03} D_{3,t} + \xi_{3,t} \quad \text{Het.}=0.06 \qquad \text{Ser. corr.}=0.00 \tag{12}$$

Standard errors are in parentheses. Our sample includes 15144 observations and 459 sectors. Het. is the p-value of a general White test for heteroscedasticity (Greene, 2003, p. 222), while Ser. Corr. indicates the p-value of Wooldridge (2002) test for serial correlation in panel datasets[9].

In all three estimated equations we find strong evidence of serial correlation, while only in (11) the null of no heteroscedasticity could be rejected[10]. In order to overcome the possible distortions that serial correlation and heteroscedasticity might induce into the estimates of the standard errors of the coefficients, we resorted to bootstrapping.

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[8] Experimenting with the second lag of L_t would yield similar results.

[9] Drukker (2003) found that it has good properties in reasonable sample sizes.

[10] The presence of heteroscedasticity might be due to the fact that μ_t is an estimated dependent variable (Lewis and Linzer, 2005).

On the basis of 500 replications, we computed bootstrapped standard errors which are reported in brackets. As it is possible to see, bootstrapped standard errors have a tendency to be larger than non-bootstrapped ones. However, all the coefficients of the independent variables remain significant at a 1% level, with the exception of $D_{3,t}$ which is not significantly different from zero even at 10% level.

It is worth noting that Durbin-Wu-Hausman tests for endogeneity, comparing our estimator with a plain random effect one, would reject the null of no-endogenenity for all the three model considered, always returning a p-value of 0.00. The Hausman test would return a completely different result by instrumenting $D_{1,t}$ and $D_{3,t}$ by their first lag. In both the cases the null of no endogeneity could not be rejected and the test returned a p-value of 0.21 and 0.52. $D_{2,t}$ was not instrumented by its first lag being a dummy variable. When using the first lag of $D_{1,t}$ as instrument, the Hausman test returns a p-value of 0.20. We also compared the results obtained by our random effect estimator, with those obtained by using a fixed effect one. Hausman tests return a p-value of 0.36, 0.14 and 0.40 when applied to equations (10), (11) and (12), supporting our choice for the random effect estimator.

All in all, consistently with Galeotti and Schiantarelli (1998), we find that the mark-up is negatively correlated with the current state of the economy and positively with expectations about the future evolution of the economy. In other terms, the "level effect" decreases the mark-up, while the "derivative effect" increases it. However, once considering bootstrapped standard errors, we could not find thorough evidence that the "derivative effect" is really having a role in the cyclical dynamics of the mark-up as one of its measures proposed by Galeotti and Schiantarelli (1998) did not result to have a statistically significant coefficient[11]. This issue will be further explored when checking for sub-sample stability of the estimates.

Sub-sample stability of the estimates

In the present section we consider the sub-sample stability of our estimates. Building on the past literature we consider various possible breakdowns of our sample. We check whether our estimates are stable for consumer versus producer goods and durable versus non-durable ones. Finally, building on Domowitz, Hubbard and Petersen (1987), we interact an indicator of the degree of competitiveness of each economic sector – the Census four-firm concentration ratio (C4) – with the distinction between producer and consumer goods to obtain three categories: the sectors with C4<50, the sector of consumer goods with C4>50 and the sector of producer goods with C4>50.

Following Domowitz et al. (1988), we consider the breakdown between durable and non-durable goods, because they argue that price reductions will be less responsive to decreases in demand in concentrated durable-goods sectors, given that in downturns the demand for a durable good is not lost, but postponed. So it is possible to expect that the "level effect" will be weaker in durable goods sectors.

[11] We also investigated if either the "derivative effect" or the "level effect" is dominant, by standardizing the variables involved in (10), (11) and (12). However, this exercise returned inconclusive results as in (10) the derivative effect is dominating, while in (11) and (12) the level effect has a greater coefficient in absolute value.

The cyclical dynamics of the mark-up in concentrated industries versus competitive ones has attracted considerable attention in the past literature. Stigler (1964), Caves and Yamey (1971) and Green and Porter (1984) argued that during downturns collusive agreements are more likely to break down. Instead, Rotemberg and Saloner (1986) and Rotemberg and Woodford (1991, 1992, 1993), supported by Gallet (1997), argued that this is more likely to happen during booms. On the other hand, Qualls (1979) and Eckard (1984) argued that coordination might generate larger price-cost margins fluctuations as firms in more concentrated industries lower prices to a greater extent than those in less concentrated industries in an effort to support the demand for their products. For these reasons, it is interesting to consider a breakdown of industries according to their degree of concentration .

Finally, regarding the breakdown between consumer and producer goods industries, the former ones are less affected by import competition (Domowitz et al., 1986), so the cyclical dynamics of the mark-up might be different there compared to producer goods industries. Fariñas and Huergo (2003) found that the mark-up moves similarly in producer and consumer goods during recessions, but not so in booms. This happens because promotions of staff already working for firms have a greater role in the latter industries than in the former ones. In this way, firms in consumer goods industries can increase output without incurring into adjustment costs and enjoying higher margins[12].

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[12] Data on C4 were downloaded from http://www.census.gov/epcd/www/concentration.html and they were averaged over the period 1958-1992.

For the distinction between durable-goods and nondurable-goods we followed Domowitz, Hubbard and Petersen (1988) and Ornstein (1975). We assumed that durable goods were capital goods, including among them, with few exceptions, the following two-digit categories: Furniture (Sic code: 25), Machinery excluding Electrical Machinery (Sic code: 35), Electrical Equipment (Sic code: 36), Transportation Equipment (Sic code: 37), and Instruments and Related Products (Sic code: 38)[13].

To distinguish between consumer and producer goods we followed Ornstein (1975), whose classification "is based on the percentage of shipments of output to final demand in four categories: consumption, investment, materials and government". These shares can be derived from the U.S. Department of Commerce Input-Output Tables.[14] "If 50% or more of an industry's output went to consumption, it was classified as a consumer good industry and if 50% or more went to investment plus materials, it was classified as a producer good industry. When no category had 50% or more […] the industry was classified according to its largest output category." (p. 112).

In order to test whether the differences in the point estimates of the "level" and the "derivative" effects across groups of sectors are statistically significant or not, we

[13] The exceptions were the sectors whose SIC 4 digits codes were: 2273, 2371, 2391, 2392, 3161, 3262, 3263, 3911, 3914, 3915, 3931, 3942, 3944, 3949, 3961.

[14] Which can be downloaded from http://www.bea.gov/industry/io_benchmark.htm. We used the 1987 IO tables.

proceed in the following way. When having two sub-samples (let us call them *A* and *B*), we re-specified (9) as follows:

$$\mu_t = m_{0,i} + m_{0A,i}V_A + m_{LA,i}L_tV_A + m_{LB,i}L_tV_B + m_{DA,i}D_{i,t}V_A + m_{DB,i}D_{i,t}V_B + v_{i,t} \tag{13}$$

for i=1,2,3 where $m_{0,i}$, $m_{0A,i}$, $m_{LA,i}$, $m_{LB,i}$, $m_{DA,i}$, $m_{DB,i}$ are coefficients, V_A and V_B are dummy variables for sub-samples *A* and *B* and $v_{i,t}$ are stochastic errors. In order to check whether our coefficient estimates are different across categories of sectors, we tested by means of a χ^2 test, based on a bootstrapped variance-covariance matrix, the following restrictions:

$$m_{0A,i}=0$$

$$m_{LA,i}=m_{LB,i}$$

$$m_{DA,i}=m_{DB,i}$$

With three sub-samples *(A, B, C)* we re-specified the model as follows:

$$\mu_t = m_{0,i} + \sum_{j=A}^{B} m_{0j,i}V_j + \sum_{j=A}^{C} m_{Lj,i}L_tV_j + \sum_{j=A}^{C} m_{Dj,i}D_{i,t}V_j + \varepsilon_{i,t} \tag{14}$$

where $\varepsilon_{i,t}$ is the stochastic error. We tested the following restrictions

$$m_{0A,i}=m_{0B,i}=0$$

$$m_{LA,i}=m_{LB,i}=m_{LC,i}$$

$$m_{DA,i}=m_{DB,i}=m_{DC,i}$$

Tables 2, 3 and 4 display our results. Remarkably, in general the null hypothesis of poolability is not rejected, making the estimates presented in (10), (11) and (12) our preferred ones. The only exception to this general pattern is the case of the durable-nondurable goods breakdown for $D_{3,t}$. Interestingly, for durable goods the derivative effect is dominant, while for nondurable goods the level effect prevails. This evidence would support the arguing by Domowitz et al. (1988) about the role of postponed demand for the dynamics of the mark-up in durable-goods industries.

Conclusions

The purpose of this paper was to offer new tests of the model of the price mark-up over the marginal cost proposed by Galeotti and Schianatarelli (1998). In order to do so we used an innovative procedure: we first estimated nonparametrically the marginal product of material inputs, then we computed the mark-up and finally we offered estimates of the "level" and "derivative" effects of business cycles on the mark-up, both for all the US manufacturing industries and for groups of sectors. All in all our results support the model by Galeotti and Schiantarelli (1998) as we found a negative "level effect" and a positive "derivative effect". Only when considering a measure of the derivative effect based on a bivariate Vector Autoregression of sectoral real gross output and aggregate real GNP results are not so strong. However, this lack of strength can be attributed to the fact that for non-durable goods the "level effect" prevails, while for durable goods the "derivative" one prevails, which can be explained by the fact that during economic downturns the demand for durable goods is not lost, but postponed.

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Table 1 – Summary statistics, by 2-digit sectors, of the elasticity of output with respect to material inputs, US manufacturing industries, 1959-1996

SIC Industry Group	Observa-tions	Mean	Min.	Max.	Min. of time averages	Max. of time averages
Food and Kindred Products	1862	0.11	-1.01	0.91	-0.03	0.29
Tobacco Products	152	0.14	-0.32	2.25	0.05	0.19
Textile Mill Products	874	0.14	-0.06	0.78	0.09	0.25
Apparel And Other Textile Products	1178	0.16	-0.09	0.79	0.08	0.26
Lumber And Wood Products	646	0.11	-0.07	0.64	0.02	0.19
Furniture And Fixtures	494	0.12	0.00	0.68	0.04	0.34
Paper And Allied Products	646	0.11	-0.19	0.49	0.06	0.24
Printing And Publishing	532	0.11	-0.11	0.80	0.05	0.22
Chemicals And Allied Products	1102	0.12	-0.11	0.88	0.03	0.29
Petroleum And Coal Products	190	0.11	-0.28	0.50	0.07	0.14
Rubber And Miscellaneous Plastics Products	570	0.12	0.00	0.45	0.07	0.18
Leather And Leather Products	418	0.12	-0.05	0.54	0.05	0.26
Stone, Clay, And Glass Products	985	0.14	-0.55	0.79	0.01	0.25
Primary Metal Industries	988	0.15	-0.19	0.74	0.07	0.27
Fabricated Metal Products	1444	0.13	-0.15	0.77	0.02	0.24
Industrial Machinery And Equipment	1938	0.13	-0.02	0.94	0.05	0.26
Electronic And Other Electric Equipment	1406	0.13	-0.10	1.42	0.07	0.29
Transportation Equipment	684	0.13	-0.03	0.55	0.06	0.18
Instruments And Related Products	646	0.09	-0.03	0.51	0.05	0.20
Miscellaneous Manufacturing Industries	684	0.14	-0.20	0.83	0.07	0.30

Table 2 – The level and derivative effects on the mark-up for durable and nondurable goods industries

	Measure of the derivative effect		
	D1	**D2**	**D3**
"Level effect"*"Durables Dummy"	-0.19*** [0.07]	-2.00** [0.82]	0.06 [0.07]
"Level effect"*"Non-Durables Dummy"	-0.10 [0.07]	-2.12** [0.97]	-0.62*** [0.21]
"Derivative effect" * "Durables Dummy"	0.16*** [0.03]	0.14** [0.06]	0.17*** [0.05]
"Derivative effect"*"Non-Durables Dummy"	0.13*** [0.03]	0.11** [0.05]	0.02 [0.02]
Durable Dummy	0.11 [0.29]	-0.12 [1.28]	-0.66*** [0.22]
Constant	0.37*** [0.07]	2.31** [0.94]	0.89*** [0.21]
Poolability test (p-value)	0.42	0.10	0.00
Number of groups	459	459	459
Observations	15144	15144	15144

Bootstrapped standard errors in brackets. ***: significant at a 1% level. **: significant at a 5% level. The "level effect" is the effect of the current level of product demand relative to its normal level on the mark-up. The "derivative effect" is the effect of the future evolution of demand on the mark-up.

Table 3 – The level and derivative effects on the mark-up for consumer and producer goods industries

	Measure of the derivative effect		
	D1	**D2**	**D3**
"Level effect"*"Producer Dummy"	-0.20*** [0.07]	-2.31** [1.16]	-0.81* [0.43]
"Level effect"*"Consumer Dummy"	-0.10 [0.09]	-2.22** [1.07]	-0.39 [0.32]
"Derivative effect"*"Consumer Dummy"	0.10*** [0.03]	0.11* [0.06]	0.04 [0.03]
"Derivative effect"*"Producer Dummy"	0.17*** [0.03]	0.16** [0.08]	0.02 [0.07]
Producer Dummy	0.12 [0.12]	0.07 [1.53]	0.44 [0.55]
Constant	0.36*** [0.10]	2.41** [1.03]	0.66** [0.33]
Poolability test (p-value)	0.30	0.23	0.64
Number of groups	313	313	313
Observations	10326	10326	10326

Bootstrapped standard errors in brackets. ***: significant at a 1% level. **: significant at a 5% level. *: significant at a 10% level. The "level effect" is the effect of the current level of product demand relative to its normal level on the mark-up. The "derivative effect" is the effect of the future evolution of demand on the mark-up.

Table 4 – The level and derivative effects on the mark-up for consumer and producer goods industries and for different level of concentration

	Measure of the derivative effect					
	D1		D2		D3	
“Level effect”*“C4<50 Dummy”	-0.56**	[0.27]	-3.19***	[1.21]	-0.09	[0.07]
“Level effect”*“Consumer, C4>50 Dummy”	-1.15	[1.28]	-1.42	[13.10]	-0.63	[0.57]
“Level effect”*“Producer, C4>50 Dummy”	2.20**	[1.03]	1.94	[2.99]	-0.27***	[0.09]
“Derivative effect”*“C4<50 Dummy”	0.02	[0.03]	0.18***	[0.07]	0.14***	[0.05]
“Derivative effect”*“Consumer, C4>50 Dummy”	0.12	[0.16]	0.06	[0.57]	0.15	[0.15]
“Derivative effect”*“Producer, C4>50 Dummy”	-0.01	[0.09]	-0.10	[0.19]	0.16***	[0.05]
“Consumer, C4>50 Dummy”	0.64	[1.36]	-1.65	[12.65]	0.58	[0.60]
“Producer, C4>50 Dummy”	-2.77***	[1.06]	-4.94	[3.08]	0.19	[0.13]
Constant	0.84***	[0.28]	3.35***	[1.16]	0.37***	[0.08]
Poolability test (p-value)	0.10		0.48		0.53	
Number of groups	267		267		267	
Observations	8808		8808		8808	

Bootstrapped standard errors in brackets. ***: significant at a 1% level. **: significant at a 5% level. C4 is the four firms concentration ratio. The “level effect” is the effect of the current level of product demand relative to its normal level on the mark-up. The “derivative effect” is the effect of the future evolution of demand on the mark-up.