NOVA

Working Paper
609

2016

Demand, Supply and Markup Fluctuations

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13.10.2016

Abstract

The cyclical behavior of markups is at the center of macroeconomic debate on the origins of business-cycle fluctuations and policy effectiveness. In theory, markups may fluctuate endogenously with the business cycle due to sluggish price adjustment or to deeper motives affecting the price-elasticity of demand faced by individual producers. In this article we make use of a large firm- and product-level panel of Portuguese manufacturing firms in the 2004-2010 period. The biggest empirical challenge is to separate supply (TFP) from demand shocks. Our dataset allows to do so, by containing

*Financial support by FCT (Fundação para a Ciência e a Tecnologia), Portugal, is gratefully acknowledged. This article is part of the Strategic Project (UID/ECO/00436/2013), under the project Ref. UID/ECO/00124/2013 and by POR Lisboa under the project LISBOA-01-0145-FEDER-007722. Carlos Santos gratefully acknowledges FCT research fellowship CONT-DOUT/114/UECE/436/10692/1/2008 under the programme Ciência 2008. We would like to thank Vasco Matias and André Silva for their research assistance, and INE (Statistics Portugal), especially Sofia Pacheco, M. Arminda Costa, and Carlos Coimbra, for their help with micro-data. Comments and suggestions by How Dixon, Huiyu Li and by the participants at the 11th World Congress of the Econometric Society (Montréal), 30th Annual Congress of the European Economic Association (Mannheim), 8th Meeting of the Portuguese Economic Journal (Braga) and at at seminars in EIEF (Rome) and ISEG of ULisboa (Lisbon) are gratefully acknowledged. The usual disclaimer applies.

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information on product-level prices at a yearly frequency. Furthermore, markups are mismeasured when calculated with the labor share. We use the share of intermediate inputs instead. Our main results suggest that markups are pro-cyclical with TFP shocks and generally counter-cyclical with demand shocks. We also show how markups become procyclical if the markup is obtained using the labour share instead of intermediate inputs. Adjustment costs create a wedge between the labour share and the actual markup which explain the observed correlations.

KEYWORDS: Markups, Demand Shocks, TFP shocks

JEL CLASSIFICATION: C23, E32, L16, L22

1 Introduction

The cyclical behavior of markups, i.e. the wedge between prices and marginal costs, has been at the center of macroeconomic debate on the origins of business-cycle fluctuations and policy effectiveness. For instance, when analyzing the role of varying markups in fiscal-policy effectiveness, Hall [2009] refers: "models that deliver higher multipliers feature a decline in the markup ratio of price over cost when output rises (...)".[1]

In theory, markups may fluctuate endogenously with the business cycle due to sluggish price adjustment (undesired endogenous markups) or to deeper motives affecting the price-elasticity of demand faced by individual producers (desired endogenous markups). The undesired type is present in macroeconomic models that assume sticky prices as state-dependent models of the menu-costs sort, e.g. Mankiw [1985], and time-dependent models as Calvo [1983], Rotemberg [1982]

[1] Op. cit. p. 183.

or the sticky-information model of Mankiw and Reis [2002]. The undesired type comprises a large number of reasons including more general preferences outside the CES benchmark as in Bilbiie et al. [2012], Feenstra [2003] or Ravn et al. [2008], heterogeneity of demand as in Galí [1994] or Edmond and Veldkamp [2009], intra-industrial competition[2] as in Barro and Tenreyro [2006], Costa [2004] or Rotemberg and Woodford [1991], feedback effects as in Jaimovich [2007], amongst other motives. For a survey see Rotemberg and Woodford [1999]. de Loecker et al. [2016] use a similar methodology to the one followed in this article, to study the effect of trade liberalization on prices and markups of companies in India. They find evidence of increasing markups after trade liberalization due to the limited pass-through of cost savings into prices. This limits the gains from trade, at least in the short run.

The empirical evidence is mixed. Rotemberg and Woodford [1999] use the evidence on the cyclical behavior of the labor share in total income, a macroeconomic approach, to conclude that average markups are unconditionally counter-cyclical, so they have to be counter-cyclical with demand shocks. Martins and Scarpetta [2002] use a different approach, closer to Industrial Organization (IO), but reach similar conclusions for a sample of industries in G5 countries. More recently, Juessen and Linnemann [2012] provide evidence of counter-cyclical markups for a panel of 19 OECD countries; Afonso and Costa [2013] find that markups are counter-cyclical with fiscal shocks for 6 out of 14 OECD countries and pro-cyclical for 4 of them; Nekarda and Ramey [2013] find either acyclic or pro-cyclical markups with demand shocks for US industries.

The inconclusive results may be related with the fact that separating demand

[2] That may be potential or existing.

and supply shocks is a difficult task in the absence of separate price and quantity data. Thus, if the supply and demand shocks have different cyclicality, a "weighted average" of the two may exhibit either pro- or counter-cyclical behavior, depending on which shock is more prevalent. Furthermore, most articles use the labor share to obtain the markups. Labor is subject to adjustment cost, which create a wedge between the markup and the labor share.

Three empirical challenges are at the origin of the inconclusive results: (i) using revenues instead of quantities, results in productivity measures contaminated with demand shocks in imperfectly competitive markets, as noticed by Klette and Griliches [1996]; (ii) estimating total factor productivity (TFP) is usually poised by the input-endogeneity problem in production functions that has been identified since at least Marschak and Andrews [1944]; and (iii) using labor (and its share) as the flexible input that proxies marginal-cost fluctuations is problematic in the presence of labor-market frictions[3]. We overcome problem (i) by using meaningful quantities for single-product firms in the estimation of production and cost functions and overcome problem (ii) by extending recent results to address the endogeneity problem for input utilization - see Olley and Pakes [1996], de Loecker [2011] and Gandhi et al. [2013]. In particular, we show that there is no multicollinearity problem (Ackerberg et al. [2006], Bond and Soderbom [2005] and Gandhi et al. [2013]) when firm level prices are observed and demand shocks are persistent. Finally, to overcome problem (iii) we use intermediate inputs to obtain the markup. This is less subject to adjustment costs when compared to the labor share. We show how the behavior of markups using the labor share is very differ-

[3]Nekarda and Ramey [2013] correctly point out that it is the marginal wage and not the average wage that is the adequate measure do determine marginal costs. Rotemberg and Woodford [1999] present other types of labor frictions that also influence the markup level and cyclicality.

ent, even when we use the Nekarda and Ramey [2013] correction to account for the labor wedge of overtime labor. The correction reduces the cyclicality of the markup but it does not solve its fundamental irresponsive nature. The markups calculated via labor share are procyclical with demand shocks. This is rationalized by the labor market frictions. When faced with an unexpected positive shock to demand, firms increase output but cannot increase labor by the corresponding amount, due to labor-market frictions. The labor share goes down and the markup, calculated via labor share, goes up. However, to match the demanded output, firms substitute the needed labor increase with more intermediate inputs.

In this article, we make use of the availability of product-level prices for a panel of Portuguese manufacturing firms over the period 2004-2010. We merge these prices with the yearly census data (balance sheet and income statement). This allows us to jointly estimate demand and production (supply side) function and thus obtain separate measures of demand and supply (TFP) shocks for each individual company. Compared to other studies which also merge prices and company data, our data set has some advantages to study business-cycle fluctuations. Our data is at a yearly frequency while Foster et al. [2013] uses US Census data with a 5-year frequency. Such long frequencies are not very informative about business-cycle fluctuations. On the other hand, Gilchrist et al. [2014] use quarterly data for a sample of large firms from COMPUSTAT while we include both large and small firms. Pozzi and Schivardi [2016] use the firms' self-reported price changes to construct a firm-specific price index and purge the TFP measure from demand shocks and evaluate their importance for firm growth. Instead of price growth, we observe price levels, which allow us to impose very few restrictions on the demand model, in particular, we can allow for non-constant elasticities. Our main results suggest that markups are pro-cyclical conditional on TFP shocks, and generally counter-cyclical with demand shocks.

We perform a series of robustness checks to evaluate our results. First, in addition to the traditional production-function approach, we also present the evidence obtained from a cost-function approach. The good performance of both approaches is especially encouraging, as the cost-function can be more easily extended to multi-product firms, following Gandhi et al. [2013]. Second, we compare the results using the intermediate inputs *vs.* labor share. We show how using the labor share leads to very different results. Finally, we test different parametric specifications for the production and cost functions.

The article is organized as follows. Section 2 provides and overview of the problem, section 3 explores the microeconomic model, section 4 describes the data, section 5 reports the empirical results of the estimation procedures, section 6 analyses the markups and its cyclicality, and section 7 concludes.

2 A birds-eye view on the effects of shocks on markups

Let us define the markup (μ) between the producer's price (p) and the marginal cost of production (c): $\mu \equiv p/c$. Under standard regularity assumptions, an individual producer faces an "inverse" demand function given by $p = P(q, \epsilon)$, where q is the quantity produced, ϵ is the unobserved demand level, and $P_q < 0$ and $P_\epsilon > 0$.[4] Similarly, the same producer has a marginal cost function given by $c = C(q, a, \cdot)$, where a is the unobserved productivity level with $C_q \geq 0$ and

[4] We denote partial derivatives of function $g = G(x_1, x_2)$ as $G_{x_1} \equiv \frac{\partial G}{\partial x_1}$ and $G_{x_1 x_2} \equiv \frac{\partial^2 G}{\partial x_1 \partial x_2}$.

$C_a < 0$.

In equilibrium, the reduced form for the quantity produced is a function of "shocks" and exogenous variables. Considering that total revenue is a function $y = pq = Y(q, \epsilon)$, the usual regularity conditions imply that marginal revenue $Y_q = P_q(q, \epsilon)q + P(q, \epsilon) > 0$ is decreasing in q (i.e. $Y_{qq} = 2P_q + P_{qq}q < 0$) and increasing in ϵ (i.e. $Y_{q\epsilon} = P_\epsilon + P_{q\epsilon}q > 0$). Consequently, from the optimality condition $Y_q = c$, we obtain $q = Q(\epsilon, a, \cdot)$, where $Q_\epsilon = Y_{q\epsilon}/(C_q - Y_{qq}) > 0$ and $Q_a = -C_a/(C_q - Y_{qq}) > 0$.

A change in total factor productivity (TFP), has an impact on the markup that can be summarized by the following partial derivative:

$$\mu_a = \underbrace{\frac{P_q Q_a}{c} - \frac{\mu C_q Q_a}{c}}_{\substack{Indirect\ effect \\ = \underset{-}{\mu_q}\ \underset{+}{Q_a}}} \quad \underbrace{-\frac{\mu C_a}{c}}_{\substack{direct\ effect \\ = \underset{+}{\mu_a}}} \quad . \tag{1}$$

We can see that there is a positive direct effect of an increase in TFP as it reduces the marginal cost ($-\mu C_a/c > 0$). However, there are two indirect effects with negative sign, due to the fact that an increase in TFP leads to an increase in production: (i) the price decreases ($P_q Q_a/c < 0$) and (ii) the marginal cost increases ($-C_q Q_a/c < 0$). Despite the fact that theoretically μ_a can be positive or negative, the literature is consensual in postulating it to be positive, i.e., that markups are procyclical with TFP shocks. The effect operating through the increase in production (reduction in price and increase in marginal cost) is not sufficient to counteract the direct reduction in marginal cost. This is equivalent to assume that the absolute value for the elasticity of the marginal cost with respect to productivity (η^{Ca}) is large enough, i.e. that the following condition holds:

$$\mu_a > 0 \Leftrightarrow -\eta^{Ca} > \left(\eta^{Cq} - \eta^{Pq}\right)\eta^{Qa} > 0 \ ,$$

where $\eta^{Gx_1} \equiv G_{x_1} g/x_1$ represents the elasticity of $g = G\left(x_1, \cdot\right)$ with respect to x_1.

Now, a demand shock leads to

$$\mu_\epsilon = \underbrace{\frac{P_q Q_\epsilon}{c} - \frac{\mu C_q Q_\epsilon}{c}}_{\substack{Indirect\ effect \\ = \underset{+}{\mu_q} \ \underset{-}{Q_\epsilon}}} \quad \underbrace{+\frac{P_\epsilon}{c}}_{\substack{direct\ effect \\ = \underset{+}{\mu_\epsilon}}} \quad . \tag{2}$$

Here, we have a positive direct effect on the price via shift in the demand function ($P_\epsilon/c > 0$) and two negative indirect effects due to an increase in production: (i) the price decreases ($P_q Q_\epsilon/c < 0$) and (ii) the marginal cost increases ($-\mu C_q Q_\epsilon/c < 0$). There is no consensus in the literature on the net effect of a positive demand shock on markups. Markups are countercyclical, if the effect operating through the increase in production (reduction in price and increase in marginal cost) is sufficient to counteract the direct increase in prices (i.e. if prices adjust by less). We conclude that markups are countercyclical with demand shocks, i.e. $\mu_\epsilon < 0$ ($\mu_\epsilon > 0$), if the ratio of the elasticities of the inverse demand function and of output, both with respect to the demand shock, ($\eta^{P\epsilon}/\eta^{Q\epsilon} > 0$) is smaller than $\eta^{Cq} - \eta^{Pq} > 0$.

In the empirical section we decompose the estimated demand shocks using Equations [1] and [2]. This allows us to quantify and understand how large is each of the effects.

3 The model

In this section we present a supply and demand model capable of providing theoretical support to the problem of markup cyclicality briefly analyzed in the previous section. The supply side is general and has two main assumptions on total factor productivity: it is of the Hicks neutral type and follows a Markov process. The demand side is similarly modeled and not obtained from consumer behavior. This is because we lack the detail on consumer and market characteristics. We will return to this when we introduce our demand function.

3.1 Production function: markups and TFP

Let us have a closer look at the marginal cost function. We assume the firm uses the following technology to produce its good at time t:

$$q_t = a_t F\left(k_t, \ell_t, m_t\right) \ , \tag{3}$$

where k represents the stock of physical capital, ℓ is the labor input, and m is an intermediate input (materials). We assume that all inputs are substitutes and that both capital and labor are predetermined. This assumption is in accordance with the labor legislation in Portugal which restricts labor adjustments. We will check variations to this assumption by also considering the case with adjustable labor. We further assume that companies are price takers in the input markets: r (rental on capital), w (wage rate), and b (price of materials).

Under the previous assumptions, a profit-maximizing firm faces a marginal cost equal to the ratio between the price of an input ($z^x = r, w, b$) and its marginal product (F_x with $x = k, \ell, m$), i.e. $c_t = z_t^x / F_{x,t}$. Therefore, we can obtain the markup as

$$\mu_t = \frac{\eta_t^{Fx}}{s_t^x} \ , \tag{4}$$

where $s^x = z^x x/y$ is the share of the cost of input x on total revenues ($y = pq$).

The elasticity η^{Fx}, i.e., the ratio between the marginal and the average product of input x, depends on the functional form assumed for the production function $F(\cdot)$. The elasticity is not observed in the data and must be estimated via production or cost function. The share s^x is observable for labor and materials. Usually, labor is the chosen input. As we will see below this may raise some concerns when its subject to short run adjustment costs (non-convex hiring and firing costs).

From the estimated parameters for the production function, $F(\cdot)$, from Equation [3], we obtain an estimate of the input elasticity. From the input share data we can construct the markup as specified in Equation [4]. Total factor productivity is the residual, a. However, an endogeneity problem exists in equation [3] since TFP is an unobserved state variable correlated with inputs. We address this endogeneity using the method proposed by Olley and Pakes [1996] which introduces a Markovian assumption on the TFP process. Nonetheless, contrary to Olley and Pakes [1996] and the literature following it - e.g. Levinsohn and Petrin [2003], Ackerberg et al. [2006] or Wooldridge [2009] - we show that we do not suffer from the standard unidentification problem. This is due to the fact that we separate prices from quantities and allow persistent shocks to demand, a point we discuss in detail in the next subsection.

In order to estimate equation [3], we assume that function $F(\cdot)$ is the same for all producers of good j, including producer i. For simplicity, we ignore industry

(j) and producer (i) subscripts, as we did with time (t) in the previous section, whenever they are not required to understand the problem.

Assumption 3.1 *TFP is a separable exogenous first-order Markovian process:*

$$\ln a_t = \Gamma(\ln a_{t-1}) + \gamma_t, \tag{5}$$

where γ_t is i.i.d. over t (and also over i).

Under this condition the production function in [3] can be written as

$$\ln q_t = \ln F\left(k_t, \ell_t, m_t\right) + \Gamma\left(\ln q_{t-1} - \ln F\left(k_{t-1}, \ell_{t-1}, m_{t-1}\right)\right) + \gamma_t \,. \tag{6}$$

From assumption 3.1, we know that γ_t is orthogonal to any variable chosen at or before period $t-1$ - see Blundell and Powell [2004] and Hu and Shum [2012]. Thus, functions of $(q_{t-1}, k_{t-1}, \ell_{t-1}, m_{t-1})$ are valid instruments. Intuitively, q_{t-1} "traces out" function $\Gamma(\cdot)$ while $(k_{t-1}, \ell_{t-1}, m_{t-1})$ traces out function $F(\cdot)$.

Predetermined variables are also valid instruments - e.g. the capital stock and the labor input, which are chosen in period $t-1$. Violations of the Markov assumption will generate serial correlation in γ_t and the identifying condition becomes invalid, i.e. variables chosen at or before period $t-1$ are correlated with γ_t and are no longer valid instruments. This can be addressed using a second-order (or higher) Markov process and longer lags as instruments.

From Equation [6] we can derive the following moment conditions which can be estimated by GMM:

$$E\left(\gamma_t\begin{bmatrix}\Pi^1(Z_{t-1})\\ ..\\ \Pi^P(Z_{t-1})\\ k_t\\ \ell_t\end{bmatrix}\right)=0, \tag{7}$$

where $Z_{t-1}=[q_{t-1},k_{t-1},\ell_{t-1},m_{t-1}]'$ and $\Pi^p(\cdot)$ for $p=1,...,P$ is the Kronecker product of order p. Note that we assume capital and labor to be predetermined so that their choice is orthogonal to the "news" shock to TFP, γ. We also estimate the model with endogenous labour, in which case ℓ_t drops from the moment condition.

3.1.1 Identification

A standard identification problem of the production function [8] is due to the absence of variation in m_t once we condition on the set of predetermined variables (k_t,ℓ_t,a_t) - see Bond and Soderbom [2005] and Gandhi et al. [2013]. This problem emerges because from the optimality condition, intermediate inputs are a direct function of the state variables, $m_t=M(k_t,\ell_t,a_t)$. Conditional on the state variables, (k_t,ℓ_t,a_t), lagged instruments do not have any informative power about m_t and, as such, the production function coefficients are not identified. However, once we introduce shocks to demand (ϵ_t), the optimality condition for intermediate inputs is now a function of the demand shock, $m_t=M(k_t,\ell_t,a_t,\epsilon_t)$ and, letting ϵ_t be serially correlated, lagged values of m_t (conditional on k_t,ℓ_t,a_t) are informative of current values of m_t which restores identification of the production function coefficients.

3.1.2 Benchmark case: Cobb-Douglas production function

If we use a first order approximation to the production function, equation [3] takes the standard Cobb-Douglas form:

$$q_t = a_t k_t^{\alpha} \ell_t^{\beta} m_t^{\delta} \ ,$$

with $\alpha, \beta, \delta \in (0,1)$. The elasticity in the markup equation [4] is simply a constant $\eta_t^{Fm} = \delta$ ($\eta_t^{F\ell} = \beta$), so we can obtain the level of μ_t simply dividing it by the input share s_t^m (s_t^{ℓ}). Notice that fluctuations in markups are entirely driven by the cyclicality of the materials (labor) share in this case.

As for the $\Gamma(\cdot)$ function, we can use a cubic expansion:

$$\Gamma(\ln(a_{t-1})) \approx \rho_{a1} \ln(a_{t-1}) + \rho_{a2} \ln^2(a_{t-1}) + \rho_{a3} \ln^3(a_{t-1}) \, .$$

We call the linear approximation to imposing $\rho_{a2} = \rho_{a3} = 0$ and cubic approximation to the free-parameter version. We will evaluate both empirically.

Thus, the benchmark equation to be estimated is

$$\ln(q_t) = \alpha \ln(k_t) + \beta \ln(\ell_t) + \delta \ln(m_t) + \Gamma(\alpha \ln(k_{t-1}) + \beta \ln(\ell_{t-1}) + \delta \ln(m_{t-1})) + \gamma_t . \tag{8}$$

Notice that this equation cannot be estimated by OLS because m_t is endogenous. We use the GMM estimator defined above.

3.1.3 The troubles with input shares

If the production function is (approximately) Cobb-Douglas, all the action is concentrated on the input chosen to measure the markup. But how do the input shares react to quantities? If we assume the producer is price taker in the market for input x, considering that the optimal usage of this output is given by $x = X(q, \cdot)$ with $X_q > 0$, an increase in production will lead to

$$\frac{\partial s^x}{\partial q} = \frac{s^x}{q}\left(\eta^{Xq} - \frac{1}{\mu}\right) . \tag{9}$$

Thus, the cyclicality of the input share depends on how much this input utilization reacts to production, since $1/\mu \in (0, 1)$. If all inputs are equality flexible, optimality conditions will lead to similar time series for input shares. However, the presence of frictions in input markets leads to the need to alter equation [4] in order to reflect distorted time series for input shares. This is particularly pungent when labor is used to measure markups has clearly shown by Rotemberg and Woodford [1999] or more recently by Nekarda and Ramey [2011].

An illustrative example may help us to clarify this point. Let us assume there are convex costs of adjusting labor from its current level. In that case, the elasticity η^{Lq} becomes small and it is more likely to obtain an acyclical or even countercyclical labor share, i.e. an acyclical or even procyclical markup measure. Notwithstanding, changes in labor costs are clearly not the best indicators of changes in the marginal cost for this case. This is consistent with our empirical results using labor share to measure the markup. The restrictive labor legislation in Portugal generates procyclical results, when markups are calculated using the labor share. This is because the labor share does not equate to the marginal return to labor, thus creating a wedge between the share and the elasticity. The case becomes even more problematic when adjustment costs are non-convex.

Furthermore, when producers are not price takers in the labor market, e.g. in an efficiency-wages model, and face an upward-slopping labor supply $w = W(\ell, \cdot)$ with $W_\ell > 0$, the expression in brackets on the right-hand side of equation [9] becomes $\eta^{Lq}\left(1+\eta^{W\ell}\right)-\frac{1}{\mu}$. In this case, a fully-flexible labor input produces more procyclical (countercyclical) labor shares (markups) than the real ones, using a corrected measure.

Consequently, we will use materials to measure markups instead of labor, as these inputs are more likely to be used in a flexible manner than labor in the short run and also because producers are less likely to detain relevant market power in materials markets than in labor markets. Even in industries like cork, olive oil or wine, producers have very little market power due to the fragmentation of market structure.

Two objections may be raised to this strategy. First, materials are a composite of several goods and services, with no clear quantity and price measures to be obtained in the data. Second, materials may behave more like complements than substitutes to labor in a short-run production function.

The first objection is a real one, despite the fact that labor is not an homogeneous input either. Our assumption is that the composition of the materials basket is stable for a given technology, just like for labor. The second objection is not observed in our data. We show in Figure 5 that materials and labor are substitutes in the short run.

3.1.4 Quantities or values?

Estimating production functions as the one in Equation [3] is not possible with most of the existing data sets, as quantity information is not generally available. That is why revenues (y) or value added ($y - bm$), either at constant or current prices, have been used to estimate production functions. However, when the producer has market power in the good's market, he/she knows that the price depends on the quantity sold and also on a demand shock. Therefore, the estimates for the parameters of $F(\cdot)$ are distorted by both the parameters of $P(\cdot)$ and by ϵ.

This would not be a problem for the markup measure using a Cobb-Douglas specification, as its volatility comes only from the fluctuations in the input shares. However, the TFP estimates would be contaminated by demand shocks as noticed by Hall [1986].

3.2 Variable cost function: markups and TFP

One alternative to the previous approach is to estimate a (variable) cost function, instead of estimating the production function directly. This function for a cost-minimizing firm, assuming that capital and labor are predetermined (i.e. its cost is fixed) in the short run, is given by

$$v = b.m = V(q, k, \ell, a, b) \ , \tag{10}$$

and the marginal cost is simply $c = V_q$. By definition, we also know that $V_q = p\eta^{Vq}s^m$, so that we can obtain an alternative markup measure to [4] as

$$\mu_t \equiv \frac{1}{\eta_t^{Vq} s_t^m} \ . \tag{11}$$

The series for TFP can be obtained from the residual of the estimated equation [10] and taking into account the restrictions connecting the parameters of functions $F(\cdot)$ and $V(\cdot)$. We use the assumption that labor is predetermined to maintain consistency with the previous section. However, if labor is fully flexible, the markups would remain the same. Differences between markups are a signal that input flexibility is not valid. Note that if both inputs are fully flexible

$$\mu_t \equiv \frac{1}{\eta_t^{Vq} s_t^m} = \frac{\eta_t^{Fm}}{s_t^m} = \frac{\eta_t^{F\ell}}{s_t^\ell}.$$

In the empirical section we will present results comparing the markups with fully flexible and predetermined labor.

Again, we can use Assumption 3.1 to estimate equation [10] by GMM using a moment condition similar to Equation [7] .

3.2.1 Benchmark case: Cobb-Douglas production function

With a Cobb-Douglas production function, the variable cost function to be estimated for this producer is given by

$$v_t = b_t \left(\frac{q_t}{a_t}\right)^{\psi^q} k_t^{\psi^k} \ell_t^{\psi^\ell} \ ,$$

where $\psi^q = \frac{1}{\delta}$, $\psi^k = -\frac{\alpha}{\delta}$ and $\psi^\ell = -\frac{\beta}{\delta}$.

Again, we use the cubic approximation to the productivity transition as in the production function approach.

3.2.2 The pros and cons of cost functions

In theory, the cost-function approach should produce similar results to the production-function one, using the same assumptions on input flexibility. However, from an empirical perspective, the two approaches can produce very different estimates for the production/cost function parameters and consequently different estimates for TFP. To extend the approach to multi-product firms, it is thus important to evaluate the empirical performance of cost function estimation and compare it to the more standard production function estimates. We will do this in the next section.

3.3 Demand function

We have specified the supply side in the previous subsections. However, markups depend on TFP (a) and also on the level of demand (ϵ). Thus, we need the second component for the structural model: the demand function represented above by $p = P(q, \epsilon)$. We will follow a symmetric route and assume that ϵ follows a first-order Markovian. This is the identification condition.

Assumption 3.2 *The demand shock is a separable exogenous first-order Markovian process:*

$$\epsilon_t = \Gamma(\epsilon_{t-1}) + \varepsilon_t, \tag{12}$$

where ε_t is i.i.d. over t (and also over i).

3.3.1 Benchmark case: Cubic-log demand function

In industrial sectors, companies operate both in consumer markets (B2C) and intermediate markets (B2B). For example, bread or pastries, two of the industries in our dataset, are sold directly to final consumer, via retailer or to other companies like restaurants, hotels or cafés. To avoid the complications of market definition and market structure considerations, instead of modelling consumer behavior we model the demand faced by each company. Period-specific dummies take care of competition and market-structure responses for each industry. Since we do not want to impose a very restrictive parametric form on the price-elasticities of demand, we use the following cubic-log specification:

$$\ln(q_{it}) = \sigma_0 + \sigma_1 \ln(p_{it}) + \sigma_2 \ln^2(p_{it}) + \sigma_3 \ln^3(p_{it}) + \tau_t + \epsilon_{it} \ , \tag{13}$$

where q_{it} represents quantity demanded, τ_t is a year dummy, and ϵ_{it} stands for the (idiosyncratic) demand level. We also assume that ϵ follows an AR(1) process:[5]

$$\epsilon_{it} \approx \rho_{\epsilon 1}\epsilon_{it-1} + \varepsilon_{it} \ ,$$

where ε is i.i.d. over both i and t.

Note that we do not attempt to microfound the specified demand function from consumer behavior. In particular, we do not microfound the motives for persistence of the unobserved component, ϵ_{it}. This is due to data restrictions. If we had more detailed product level data, we could attempt to estimate the demand model using a variant of Berry et al. [1995] for the static case or Hendel and Nevo [2006] for the dynamic case. This would allow to perform a detailed analysis of the motives which explain the observed price sensitivity/rigidity. We are not aware of any dataset which can match detailed product level information as used in the standard I.O. models (prices, market shares and product characteristics for

[5] We have also estimated a model with cubic transition for the demand shock for comparison. The results are available from the authors.

individual firms and each competitor), with data from company accounts (supply data).

Similarly to what was done for the production function, all information date $t-1$ is orthogonal to ε_{it}. Furthermore, TFP shocks (γ) in period t should also be orthogonal to the news component on the demand side (ε_{it}). Note that still this lets TFP stock (a) be correlated with the demand level (ϵ). We can then form the following moment condition:

$$E(\varepsilon_{it}|\{\ln{(a_{it})^n}, \ln{(a_{i,t-1})^n}\}_{n=1}^{3}, \ln q_{i,t-1}) = 0 \ ,$$

and estimate equation [13] by GMM.

4 The data

The existence of price data for a large set of small and medium companies with an yearly frequency sets our work apart from the remaining literature. This allows us to address several concerns (namely the joint estimation of supply and demand and the imperfect-competition problem), by estimating the production function in quantities instead of revenues. The data set has been constructed from two sources for the period 2004-2010 at annual frequency: (i) IES (*Informação Empresarial Simplificada*[6]), a census of firm-level financial data and (ii) IAPI (*Inquérito Anual à Produção Industrial*[7]), a survey that collects annual information on production and sales of industrial goods, and also on intermediate consumptions. IAPI allows us to obtain information on quantities, as it provides information on prices and

[6] Which can be translated as "Simplified Business Statistics."
[7] Which can be translated as "Annual Industrial Production Survey."

sales per product for each firm. Then, we merge it with IES in order to obtain the financial data for the firms covered by IAPI.

To avoid specifying multiproduct production functions we have selected only single-product firms[8]. From these we selected industries that had a sufficient number of firms each year to allow estimation and that can also be well defined as industries, namely in the consistency of the units of measurement for quantities. Table 1 reports the resulting sample of eleven industries at five and seven CAE digits. Further details on data construction are contained in the Data Appendix.

Industry	Total	2004	2005	2006	2007	2008	2009	2010
Bakery	3,608	614	658	577	542	431	403	383
Cork	1,441	229	262	245	212	171	163	159
Kitchen Furniture	769	107	131	138	123	91	88	91
Metal Doors, Windows	2,335	287	325	349	342	305	363	364
Moulds	977	139	145	150	134	131	137	141
Olive Oil	428	31	35	72	71	69	74	76
Pastries	1,395	243	241	216	205	161	168	161
Shoes	1,785	276	289	271	242	228	239	240
Stone Cutting	2,100	252	299	287	280	305	362	315
Wine	975	82	81	159	157	158	153	185
Wood Furniture	2,248	323	368	341	300	287	329	300

Table 1: Sample size per industry and year.

As explained, we use the ratio of input materials to physical output as a first proxy for marginal costs. A large ratio means that more inputs are required to produce a given set of units, e.g. if flour is used in great amounts to produce x kg of bread, the marginal cost of producing bread is high. Figure 1 reports how marginal costs vary with output (net of TFP) and prices[9]. All variables are in first differences so that these are effectively within-firm (year on year) variations.

[8] Around 25 per cent of the sample are single-product firms and 45 per cent produce two products

[9] We net output from TFP due to the negative correlation (-0.8) between marginal cost and TFP, which dominates the relation with marginal cost.

First, we can observe that the proxy for marginal costs increases with quantities. Assuming that Portuguese firms are profit-maximizing, we expect marginal costs to increase with production, at least in the short run, as there are fixed inputs (e.g. capital stock). It is thus difficult to increase production in the short run without increasing marginal costs. This inflexibility will be a fundamental source of the cyclical component.

Second, we can also observe that this proxy for marginal costs increases with prices. This is expected, as firms increase prices when their marginal costs increase. If prices increase more (less) than proportionally, then markups (p/c) will increase (decrease) with prices. The simple framework presented in the previous section, considering both demand and supply shocks, allows us to interpret the basic evidence above through the lens of a structural model. This allows us to disentangle the effect of supply and demand shocks on prices, output and markups.

Notice the importance of having detailed micro-level data for single product firms in dealing with the aggregation problem of average markups. A firm producing two products with distinct cyclical behaviors may show at the aggregate level an acyclic average markup due to the changing composition of its revenues as it reallocates inputs from one to the other product. The same occurs at the industry, and the national level.

5 Empirical estimates for TFP and demand

5.1 Production function

We now present the estimation results for Equation [8] using both linear and cubic approximations to the productivity transition function $\Gamma(\cdot)$. Table 2 contains a

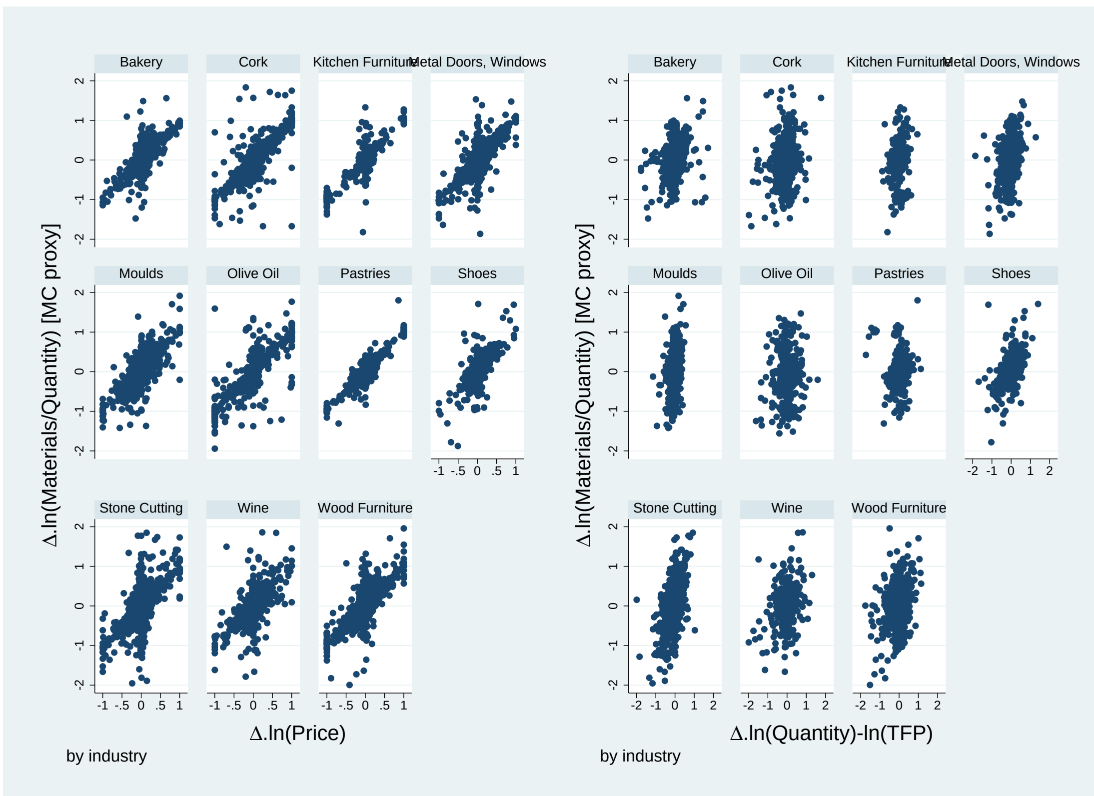

Figure 1: *Marginal cost (proxy) response to price and quantity changes.*

summary of the results.

Industry	RtS (H0:RtS=1)	δ	β	α	Median Markup	OID p-val
			Production Function Estimates			
			Linear Approximation			
Bakery	0.953	0.880***	0.029	0.044	2.39	0.04
Cork	1.057	0.524***	0.244***	0.290***	0.72	0.65
Kitchen Furnitur	1.001	0.533***	0.387***	0.081	0.96	0.77
Metal Doors, Win	0.769***	0.444***	0.298***	0.027	0.77	0.00
Moulds	1.014	0.296***	0.382***	0.270**	0.83	0.01
Olive Oil	0.868	0.685***	0.105	0.078	1.05	0.38
Pastries	1.094*	1.012***	0.025	0.058	2.37	0.13
Shoes	0.825***	0.646***	0.139***	0.041	1.07	0.00
Stone Cutting	0.806**	0.454***	0.218***	0.133*	1.05	0.05
Wine	0.811***	0.752***	0.026	0.033*	1.21	0.16
Wood Furniture	0.944	0.669***	0.107**	0.169***	1.55	0.00
			Cubic approximation			
Bakery	0.976	0.971***	-0.008	0.013	2.64	0.24
Cork	1.068	0.514***	0.262***	0.293***	0.70	0.68
Kitchen Furnitur	1.058	0.540***	0.423***	0.096	0.97	0.80
Metal Doors, Win	0.744***	0.468***	0.268***	0.008	0.81	0.00
Moulds	0.757***	0.291***	0.290***	0.115	0.89	0.34
Olive Oil	0.926	0.819***	0.086	0.021	1.26	0.53
Pastries	1.086	1.030***	0.012	0.044	2.42	0.24
Shoes	0.884***	0.683***	0.113***	0.088**	1.13	0.00
Stone Cutting	0.810**	0.463***	0.212***	0.134*	1.07	0.03
Wine	0.802***	0.719***	0.041	0.042**	1.15	0.15
Wood Furniture	0.950	0.650***	0.120***	0.180***	1.50	0.00

Notes: *** p<0.01, ** p<0.05, * p<0.1
The set of instruments are the logarithms of capital and employment and the lags of the capital stock, output, employment and prices. Instruments include quadratic, cubic terms and interactions. First column reports the test for constant returns to scale.

Table 2: GMM estimates for the production function.

First, the columns presenting the levels of returns to scale (RtS) show us that most industries are close to constant RtS, i.e. the estimated values for $\alpha + \beta + \delta$ are close to one. Manufacture of metal doors and window frames, shoes, and wine may exhibit slightly decreasing RtS.

Second, we notice that values for α are very low, not significantly different from zero in most cases. Given the short time span of our panel, this is not much of a surprise, as the capital stock does not exhibit enough time variability at the firm level. We can also observe that values for δ, the elasticity of materials, are always very high, as expected once we assume that labor, capital, and materials are substitutes.

The traditional approach uses revenues as a proxy for output. We compare our estimates to this case. Table B.1 in the Appendix reports the estimated parameters and Figure 2 compares the two TFP estimates. Overall, the two TFP measures exhibit a positive, but low correlation (0.01 to 0.60). The revenue-based TFP measure ($\hat{a}_y$) exhibits much smaller variation when compared to the quantity-based TFP measure ($\hat{a}_q$). This is due to the negative correlation between efficiency and prices. As such, when companies become more efficient, their $\hat{a}_q$ increases and their prices decrease leading to a smaller reduction in ($\hat{a}_y$). This is in line with the findings in Foster et al. [2013].

5.2 Cost function

Table B.2 in the Appendix contains a summary of the results when the cost function is estimated directly. Differences in the estimates for the parameters between the cost- and the production-function approach can be attributed to violations of the duality between production and cost functions. Figure 3 shows how the two TFP estimates compare to each other. Correlations are above 0.90 for all industries, except for metal doors and windows for which the correlation is 0.79.

When we look at the RtS indicators, i.e. $\left(1 + \psi^k + \psi^\ell\right) / \psi^q = \alpha + \beta + \delta$, we

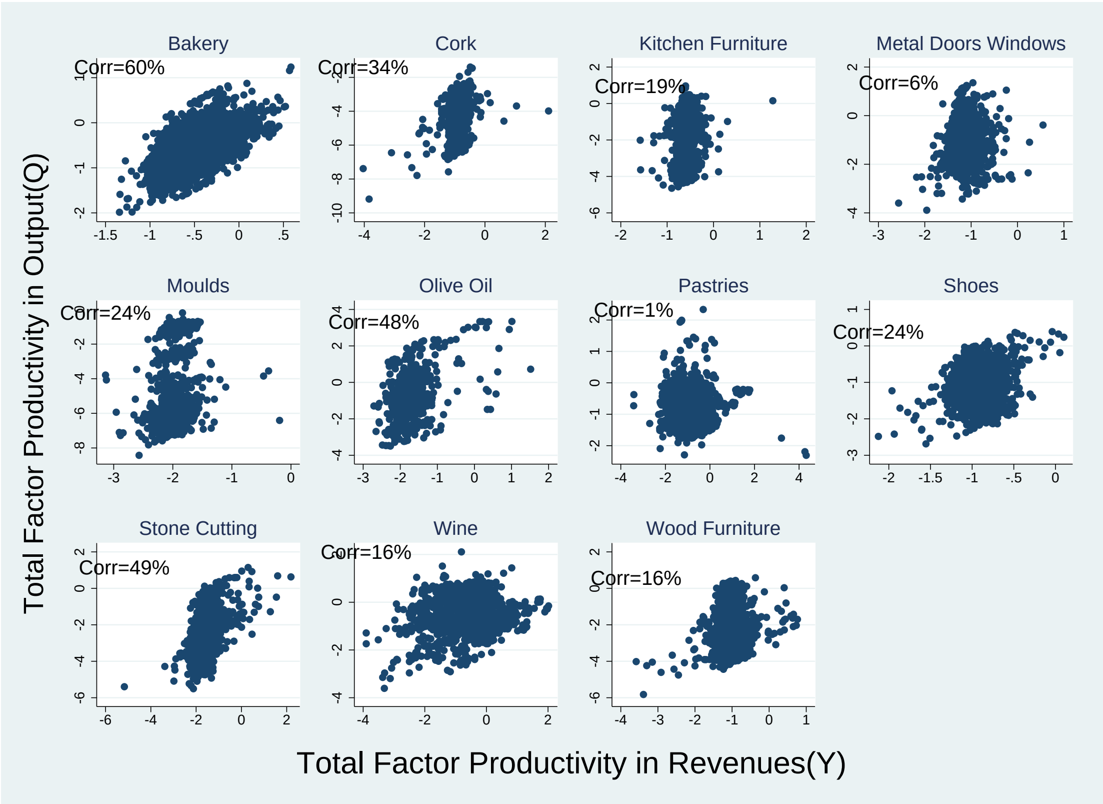

Figure 2: *Comparison of TFP estimates using the physical output (q) and revenuews (y).*

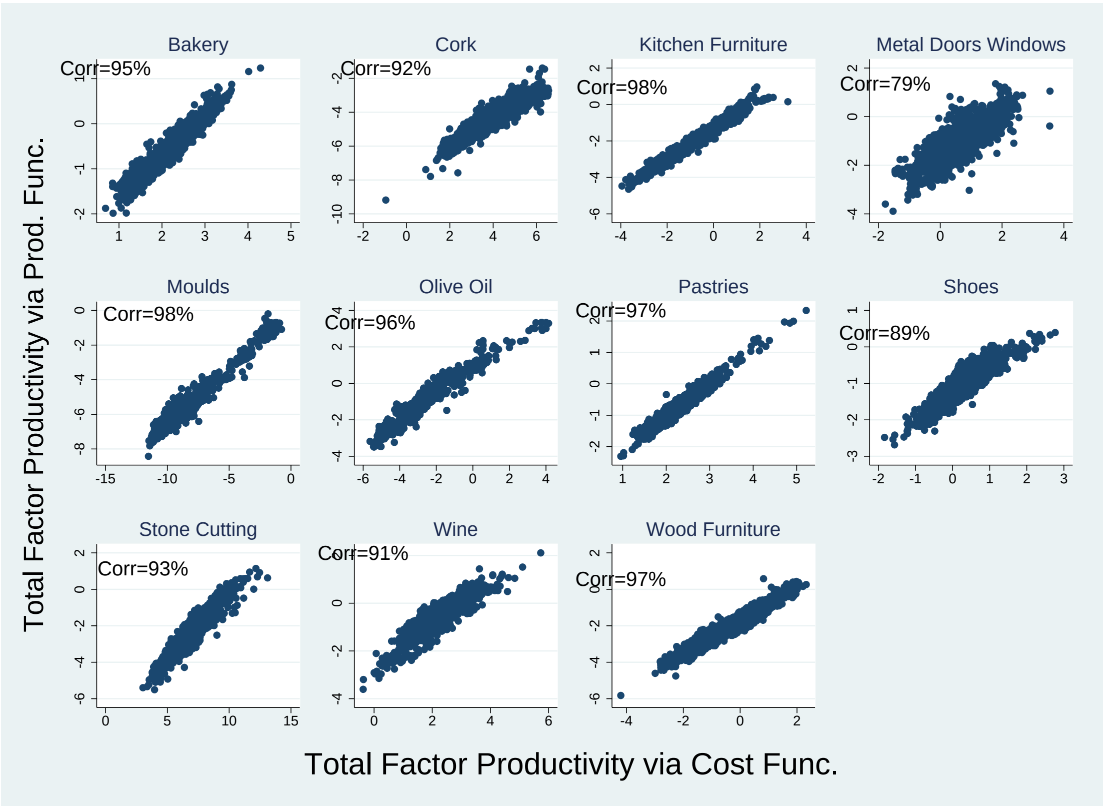

Figure 3: *Comparison of TFP estimates using the cost and the production function.*

can observe that the pattern exhibited by the production-function approach is kept here. Footwear and pastries are the only two exceptions.

5.3 The demand function

Figure 4 plots the estimated demand curves for the log-cubic specification in equation [13]. Table B.3 in the Appendix reports the estimated coefficients.

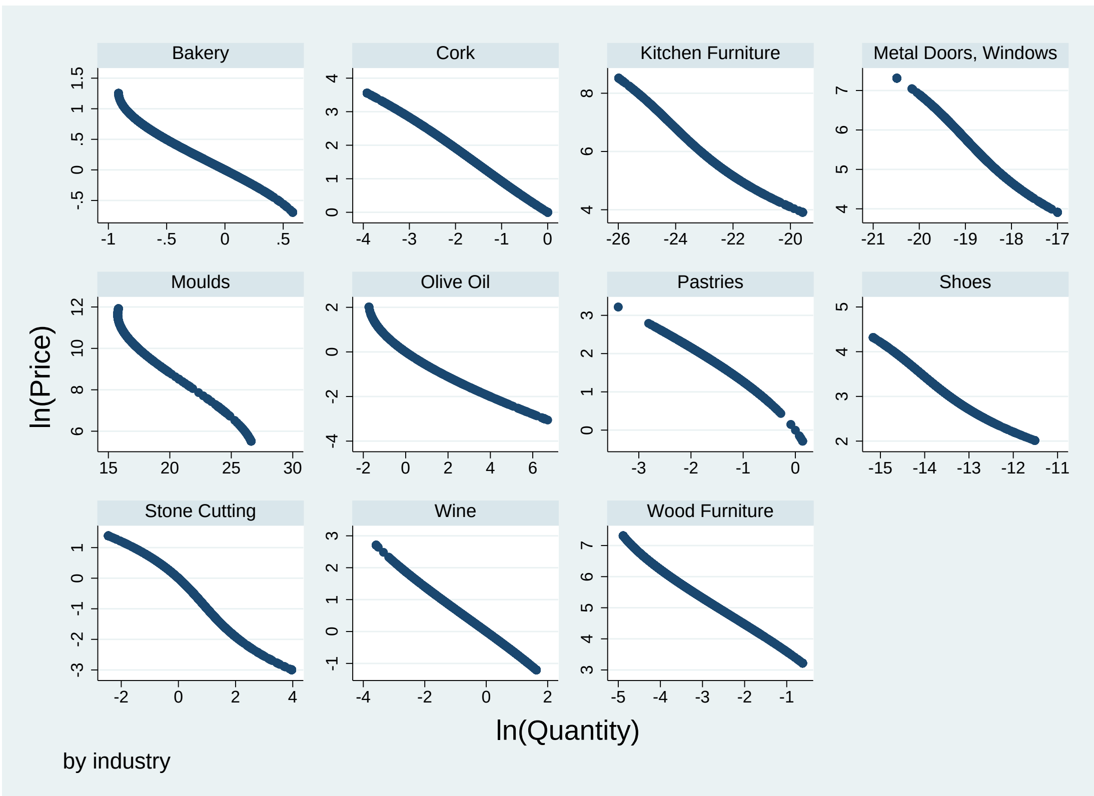

Figure 4: Estimated demand functions

Just like TFP, the unobserved demand level has two components due to the Markov specification: inertia (the 'stock') and the 'news' (or 'shock'). Note that we do not impose any type of orthogonality between the unobserved demand and supply components. In fact, the demand level is a stock and it might be positively correlated with the TFP level (also the stock). That is because more productive companies (stock) also face a larger demand (stock) for their products. This is consistent with the estimated correlations for the productivity and demand components. The correlation between the demand stock (ϵ) and the TFP stock (a) is 0.44, while the correlation between the demand shock (ε) and the TFP shock (γ) is 0.01. Demand is positively correlated with TFP while the correlation between the 'news' to demand and the 'news' to TFP is negligible.

6 Markups

6.1 Markups construction

Finally, we report estimates for the markups. Markups, are known directly from the data up to a constant. In the case where labor is also fully flexible, the following equality holds

$$\mu_t = \frac{\eta_t^{Fm} + \eta_t^{F\ell}}{s_t^m + s_t^\ell} = \frac{\eta_t^{Fm}}{s_t^m} = \frac{\eta_t^{F\ell}}{s_t^\ell} \ .$$

Figure 5 reports the results comparing the markups obtained using the labor share, with those obtained using the intermediate input share. If both inputs were fully flexible, we would expect the markups to be on the 45^o line since $\frac{\eta^{Fm}}{s_t^m} = \frac{\eta^{F\ell}}{s_t^\ell}$ (or some other line through the origin when the estimated elasticities are biased). What we observe is quite the opposite, the relation is negative and not positive. The observed negative correlation between the markup via labor and intermediate input share can be explained by cross-sectional variation in production technologies, i.e., input substitution. In other words, different firms use different production technologies and the production coefficients ($\eta^{F\ell}$ and η^{Fm}) are firm specific. In this case

$$\frac{\eta^{Fm}}{s_t^m} = \left(\frac{\eta_i^{F\ell}}{\eta_i^{Fm}}\frac{\eta^{Fm}}{\eta^{F\ell}}\right)\frac{\eta^{F\ell}}{s_t^\ell} = \xi_i \frac{\eta^{F\ell}}{s_t^\ell}$$

In estimation we assume they are the same across all firms in the same industry. A firm with a labor coefficient above the average ($\eta_i^{F\ell} > \eta^{F\ell}$) will probably have an intermediate input below the average ($\eta_i^{Fm} < \eta^{Fm}$) thus generating the observed negative correlation. To avoid this we net the markup components from the firm specific component. In particular, we regress the markup of firm i in period t (μ_{it}) on a firm specific effect (μ_i), a time specific effect (μ_t) and we allow for an idiosyncratic residual ($\tilde{\mu}_{it}^x$)

$$\mu_{it}^x = \mu_i^x + \mu_t^x + \tilde{\mu}_{it}^x \ ,$$

where $x = \ell, m$ denotes if markups are calculated using the labor or the intermediate inputs share ($\mu_{it}^\ell = \frac{\eta_t^{F\ell}}{s_t^\ell}$and $\mu_{it}^m = \frac{\eta_t^{Fm}}{s_t^m}$).

In Table 3 we report the mean and standard deviation of the two markups (μ_{it}^ℓ and μ_{it}^m) as well as the mean and standard deviation of the two residuals net from the firm and time specific components ($\tilde{\mu}_{it}^\ell$ and $\tilde{\mu}_{it}^m$). What we observe is that while μ_{it}^ℓ and μ_{it}^m have similar variances, which probably denote the variation in the fixed effect component μ_i^x, the variance of the labor residual, $\tilde{\mu}_{it}^\ell$ is much larger than the variance of the intermediate inputs residual $\tilde{\mu}_{it}^m$. This is consistent with labor being less flexible to adjust, as it reflects in the fact that the input share does not match the markup, i.e. when output decreases, intermediate inputs adjust, while labor use does not adjust. We will return to a comparison of the two markup

Figure 5: Markup comparison: labour vs materials.

measures below, when we study the cyclical behavior.

		μ_{it}^x		$\widetilde{\mu}_{it}^x$	
	N	Mean	s.d.	Mean	s.d.
Intermediate inputs	17,815	1.515	0.825	-0.017	0.320
Labor	17,815	0.768	0.817	-0.010	0.800

Table 3: Mark-ups via labor and intermediate input share: levels and net of firm and time components.

6.2 The cyclical behavior of markups

6.2.1 In-sample dynamics

Markups are considerably persistent, as reported in Figure 6. Such persistence is stronger in some industries like pastries and bakery, and less in other industries like cork and olive oil. This suggests that the degree of persistence varies with industry characteristics. In particular, this is consistent with industries producing more homogenous goods (e.g. cork and olive oil) being more competitive, which may also explain the smaller dispersion in markups for these industries. These more competitive industries (cork, olive oil) exhibit less persistent markups.

6.2.2 Cyclicality with GDP

As a first brief glance at the cyclicality of markups, we project the individual markup on (the log of) real GDP. Table 4 shows a negative correlation of markups with real GDP for the industries analyzed. This is also true when we extend the analysis to all the firms in IES, using (the change in) the reciprocal of the share of intermediate inputs as a proxy for markups. Thus, this is a preliminary indication that markups tend to be countercyclical with aggregate shocks affecting GDP.

Figure 6: Markup transition by industry

However, we do not know the source of the aggregate shocks to GDP and how they affect each of the industries. Are fluctuations in real GDP demand or supply shocks? To decompose the source of these two effects we need to move to the micro level.

Dep. Var:	Mark-up					
	Sample			Whole economy		
	Coef.	s.e		Coef.	s.e	
ln(GDP)	-0.48	0.14	***	-0.17	0.02	***
Constant	3.74	0.65	***	2.37	0.08	***
Observations	18,186			1,919,406		
Firms	4,406			438,188		
Fixed effects	Yes			Yes		

*** significant at 1%
Notes: The sample results are for the selected industries.
In the whole economy the dependent variable is the inverse of the input share for materials and the whole census data is used.

Table 4: Mark-up cyclicality with GPD.

6.2.3 Cyclicality with demand and supply shocks

The previous GDP regression is not the best way of determining the cyclicality of markups. In theory, we can expect different reactions when firms face supply and demand shocks. While it is relatively uncontroversial that markups tend to behave procyclically with supply (i.e. TFP) shocks, there is no consensus on the dynamic effect of demand shocks. It is thus important to empirically separate demand and supply shocks. We use the estimated shocks to TFP (γ) and demand (ε) from the previous section.

Using the estimated demand and TFP shocks, we can now assess how prices, output, and markups respond. Table 5 reports a set of results which are robust across industries. First, prices increase with demand shocks and decrease with supply shocks. This is what we should expect with standard marginal cost and demand (marginal revenue) slopes, as a demand shock pushes prices up the supply curve, while a supply shock moves prices down the demand curve. Second, quantities sold (sales) are positively correlated with both supply and demand shocks. Again, this is as expected with standard slopes for the two curves for the same reason. Finally, the markup increases with supply shocks and decreases with demand shocks. An increase in TFP pushes marginal costs down and is translated as a lower price. What the results suggest is that part of the lower marginal cost is absorbed by the company as a larger markup, at least in the short run (consistent with de Loecker et al. [2016]). On the other hand, a shift in demand is associated with an increase in prices and sales. As sales increase, so will marginal costs. These results suggest that the increase in marginal costs is stronger than the increase in prices, following a positive demand shock. We will decompose these effects and analyze them in greater detail in the next section. Our results show that markups are procyclical with TFP shocks and tend to be countercyclical with demand shocks. The exceptions to the latter are olive oil, pastries, and wine, where the results are not statistically different from zero, i.e. where markups can be classified as acyclical with demand shocks.

Decomposing effects We can decompose the effects of demand and supply shocks on the markups into its individual effects on prices and quantities using Equations [1] and [2] as follows

$$\mu_{\epsilon}\frac{\epsilon}{\mu} = \eta^{P_{\epsilon}} - \eta^{C_q}\eta^{Q_{\epsilon}} = \eta^{P_{\epsilon}} - (1/\delta - 1)\,\eta^{Q_{\epsilon}} \tag{14}$$

Industry / Indep. Var.	Olive Oil	Bakery	Pastries	Wine	Footwear	Cork	Stone Cutting	Metal Doors Windows	Moulds	Kitchen Furniture	Wood Furniture
	Dependent Variable: Δ.log prices										
ε^d	0.289***	-0.026	0.031	0.226***	0.184***	0.307***	0.221***	0.317***	0.313***	0.270***	0.178***
γ	-0.711***	-0.539***	-0.744***	-0.613***	-0.699***	-0.855***	-0.581***	-0.852***	-0.756***	-0.781***	-0.776***
	Dependent Variable: Δ.log quantity										
ε^d	0.287***	0.950***	0.858***	0.680***	0.705***	0.665***	0.687***	0.706***	0.243***	0.603***	0.788***
γ	1.037***	0.504***	0.767***	0.855***	1.068***	0.906***	0.690***	0.766***	0.994***	0.946***	0.834***
	Dependent Variable: Δ.Mark-up										
ε^d	0.309**	-0.410***	0.117	-0.147*	-0.221***	-0.338***	-1.010***	-0.585***	-0.159**	-0.802***	-0.341***
γ	0.993***	1.669***	0.694***	1.166***	0.542***	0.188***	1.836***	0.547***	0.457***	0.573***	0.733***
Observations	305	2610	1009	703	1361	1044	1504	1638	736	532	1593

Notes: Least squares results with firm fixed effects and time dummies. * $p<0.1$; ** $p<0.05$; *** $p<0.01$
The demand shocks is calculated as the residual from the demand function and supply shock as the residual from the production function. Mark-ups constructed via production function. Mark-up winsorized at 0.5;10.

Table 5: Cyclicality of markups with demand and supply shocks (markup estimates from production function).

$$\mu_a \frac{a}{\mu} = \eta^{P_a} - \eta^{C_q}\eta^{Q_a} - \eta^{C_a} = \eta^{P_a} - (1/\delta - 1)\,\eta^{Q_a} + 1/\delta \tag{15}$$

In Table 5 we estimated the overall (direct and indirect) effects of demand shocks on prices (η^{P_ϵ}) and quantities (η^{Q_ϵ}), and the effects of supply shocks on prices (η^{P_a}) and quantities (η^{Q_a}). We also estimated the effects on markups of demand ($\mu_\epsilon \frac{\epsilon}{\mu}$) and TFP ($\mu_a \frac{a}{\mu}$) shocks. Furthermore, $\eta^{C_q} = 1/\delta - 1$ and $\eta^{C_a} = -1/\delta$ so we can directly use the estimated parameter for δ from Table 2. Table 6 reports estimates for each of the individual items ($\eta^{P_\epsilon}, \eta^{Q_\epsilon}, \eta^{P_a}$ and η^{Q_a}) together with the cyclicality measures computed from Equations [14] and [15], which can be compared with the estimated cyclicality measures reported in Table 5, η^{μ_ϵ} and η^{μ_a}. Overall, the estimated effects of demand and supply shocks on the markup exhibit a remarkable similarity with the estimated effects constructed from Equations [14] and [15]. The results allow us to explain the cyclicality of the markups. Overall, output is sensitive to supply and demand shocks. On the other hand, prices are sensitive to supply shocks but not so much to demand shocks. Together with the increasing marginal cost curves, the results imply that the direct efficiency gains (lower marginal costs) outweight the indirect cost increases and price reductions following an increase to TFP. Markups increase when TFP increases. On the other hand, the cost increase generated by a positive shock to demand is much stronger than the price increases that follow the exact same shock to demand. Markups decrease when demand increases.

Industry	Olive Oil	Bakery	Pastries	Wine	Footwear	Cork	Stone Cutting	Metal Doors Windows	Moulds	Kitchen Furniture	Wood Furniture
η^{μ_ϵ}	0.309	-0.41	0.117	-0.147	-0.221	-0.338	-1.01	-0.585	-0.159	-0.802	-0.341
η^{μ_a}	0.993	1.669	0.694	1.166	0.542	0.188	1.836	0.547	0.457	0.573	0.733
η^{P_ϵ}	0.289	-0.026	0.031	0.226	0.184	0.307	0.221	0.317	0.313	0.27	0.178
η^{P_a}	-0.711	-0.539	-0.744	-0.613	-0.699	-0.855	-0.581	-0.852	-0.756	-0.781	-0.776
η^{Q_ϵ}	0.287	0.95	0.858	0.68	0.705	0.665	0.687	0.706	0.243	0.603	0.788
η^{Q_a}	1.037	0.504	0.767	0.855	1.068	0.906	0.69	0.766	0.994	0.946	0.834
δ	0.685	0.88	1.012	0.752	0.646	0.524	0.454	0.444	0.296	0.533	0.669
Computed cyclicality measures											
$\mu\eta^{\mu_\epsilon}$*	0.157	-0.156	0.041	0.002	-0.202	-0.297	-0.605	-0.567	-0.265	-0.258	-0.212
$\mu\eta^{\mu_a}$**	0.272	0.529	0.253	0.435	0.264	0.230	0.792	0.441	0.258	0.266	0.306

Notes: $^{*}\mu\eta^{\mu_\epsilon} = \mu(\eta^{P_\epsilon} - (1/\delta - 1) * \eta^{Q_\epsilon})$ and $^{**}\mu\eta^{\mu_a} = \mu(\eta^{P_a} - (1/\delta - 1) * \eta^{Q_a} + 1/\delta)$

Table 6: Effect decomposition.

6.3 Intermediate inputs *vs.* labor

Given the previous results from Figure 5 and Table 3, we would expect that markups obtained using the labor share would behave very differently from the markups obtained from the intermediate input share. This is because as output increases with a given shock, the labor share would decrease as labor does not fully adjust to its optimal level and create a wedge, while the share of intermediate inputs should stay constant at its optimal level. Table 7 shows that the behavior of the markups using the labor share is very different, even when we use the Nekarda and Ramey [2013] correction to account for the labor wedge of overtime. The correction reduces the cyclicality of the markup but it does not solve the fundamental irresponsive nature. The markups calculated via the labor share are procyclical with the demand shock. This is expected since when faced with an unexpected demand shock, firms increase output but cannot increase labor by the optimal amount. The labor share goes down and the calculated markup goes up. But to increase the output, firms have to substitute the increase in labour with an increase in intermediate inputs.

7 Conclusion

We used a rich firm-level database with a panel of Portuguese industries where information on prices allowed us to separate demand from supply shocks. To do so we developed a new identification mechanism that uses the existence of demand shocks to address the multicollinearity problem that is common in the production function literature. We have then used our estimated shocks to measure their implications for responses on prices, quantities sold, and markups.

Industry Indep. Var.	Olive Oil	Bakery	Pastries	Wine	Footwear	Cork	Stone Cutting	Metal Doors Windows	Moulds	Kitchen Furniture	Wood Furniture
	Dependent Variable: Δ.Mark-up (via intermediate input share)										
ε^d	0.309**	-0.410***	0.117	-0.147*	-0.221***	-0.338***	-1.010***	-0.585***	-0.159**	-0.802***	-0.341***
γ	0.993***	1.669***	0.694***	1.166***	0.542***	0.188***	1.836***	0.547***	0.457***	0.573***	0.733***
	Dependent Variable: Δ.Mark-up (via labor share)										
ε^d	0.836***	0.010***	0.014***	0.190***	0.543***	1.281***	0.667***	1.069***	0.638***	1.300***	0.210***
γ	0.229**	-0.001	-0.001	-0.093	0.307***	0.074	0.061***	-0.159***	0.299***	0.212***	0.023***
	Dependent Variable: Δ.Mark-up (via labor share, Nekarda and Ramey correction)										
ε^d	0.487***	0.018***	0.017***	0.107**	0.385***	1.019***	0.464***	0.750***	0.509***	0.940***	0.133***
γ	0.128	-0.003**	0.000	-0.101**	0.241***	0.085	0.043**	-0.104***	0.256***	0.160***	0.014**
Observations	305	2610	1009	703	1361	1044	1504	1638	736	532	1593

Notes: Least squares results with firm fixed effects and time dummies. * $p<0.1$; ** $p<0.05$; *** $p<0.01$
The demand shocks is calculated as the residual from the demand function and supply shock as the residual from the production function. Mark-ups constructed via production function. Mark-up winsorized at 0.5;10.

Table 7: Cyclicality of markups with demand and supply shocks (markups using labour share and intermediate inputs).

A first useful result is that both the production- and the cost-function approaches produce similar results. This is encouraging, as the latter may be extended to multi-product firms with a less stringent set of assumptions.

A second important result is that markups should be constructed using intermediate input usage, instead of labor. We offer evidence that labor exhibits patterns which are not consistent with fully flexible adjustment. Public entities should spend more time reporting intermediate input usage for the economy, as it reflects economic activity better than employment statistics, which are likely to react with lag.

Finally, our results contribute to the current macroeconomics discussion on the cyclicality of market power when firms are hit by both demand and supply shocks. We provide evidence of countercyclical markups with shocks to demand and procyclical with shocks to efficiency.

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A Appendix: Data

The dataset is obtained using two sources. The first source is a census of companies (IES) which includes all resident firms, excluding the financial sector and holding companies. The IES covers around 1 million companies per year for the period 2004-2010. Around seven hundred thousand are private individuals which have a simplified reporting and are excluded from the analysis. These are small businesses without obligations of maintaining an organized accounting (only total revenues and number of workers is reported). Some examples are hairdress saloons, restaurants, cafes, carpenters, construction and related services, auto repair, auto sales, wholesale, diverse retail, lawyers, accountants, consultants, architects, educational services, medical services, etc. We are left with the universe of registered companies in Portugal with organized accounting of over three hun-

Year	Firms
2004	330,113
2005	340,720
2006	351,601
2007	350,444
2008	350,871
2009	349,611
2010	360,279
Total	2,433,639

Table A.1: Number of firms per year for the IES database.

dred thousand per year. The IES contains financial information (balance sheet, income statement, investment) and some employment statistics.

The second source of data is a yearly sample of firms (IAPI) for the years 1992-2011. The sample contains information on revenues and quantities sold at a very detailed 12 digit product level where each firm can produce multiple products. This consists of three separate sets of data for products sold, intermediate products consumed, and types of energy used.

A.1 Sample selection

Based on the availability of sufficient number of observations per year in the IAPI, the following 5 and 7 digit industries were selected: olive oil processing (5 digits), production of bread/bakery (7 digits), production of fresh pastry and cakes (7 digits), wine (7 digits), leather footwear (7 digits), manufacture of cork (5 digits), cutting, shaping and finishing of stone (5 digits), manufacture of metal doors and window frames (5 digits), manufacture of industrial moulds (5 digits), manufacture of kitchen furniture (5 digits), and manufacture of wood furniture (5 digits). Kitchen furniture is much different from general wood furniture as it is typically custom made and involves proximity to the final customer.

Year	Products	Firms
1992	30,212	6,757
1993	30,424	6,771
1994	30,384	6,709
1995	29,783	6,336
1996	32,601	6,887
1997	37,236	7,274
1998	38,569	7,515
1999	40,274	7,909
2000	43,163	8,523
2001	44,379	8,852
2002	49,582	9,804
2003	52,560	10,609
2004	49,941	10,668
2005	51,065	11,300
2006	56,877	10,914
2007	51,020	9,813
2008	46,451	9,540
2009	44,894	9,424
2010	44,685	9,299
2011	36,372	8,343
Total	840,472	173,247

Table A.2: Number of products and firms per year for the IAPI database.

Number of Products	Firms	%
1	42,743	25%
2	33,855	20%
3	17,521	10%
4	20,646	12%
5	9,127	5%
6	12,115	7%
7	5,623	3%
8	6,947	4%
9	3,350	2%
10+	21,320	12%

Table A.3: Number of firms by number of products reported (IAPI database).

Industry	Total IAPI sample	Merged sample	Usable sample
Bakery	4,436	3,627	3,598
Cork	1,523	1,456	1,388
Kitchen Furniture	836	772	655
Metal Doors, Windows	2,518	2,345	2,309
Moulds	979	978	803
Olive Oil	745	538	267
Pastries	1,596	1,406	1,352
Shoes	1,812	1,794	1,776
Stone Cutting	2,168	2,112	2,053
Wine	1,222	1,170	947
Wood Furniture	2,469	2,270	2,169

Note: The usable sample excludes observations with missing values for the output or inputs.

Table A.4: Number of firms per industry (total available from the IAPI database, merged and usable sample).

A.2 Data cleaning

Prices are obtained from IAPI by dividing the product revenues by quantities sold. The obtained series is noisy and subject to outliers. To control for outliers the prices are winsorized at the top and bottom of the price distribution (cross section). Also, per firm prices (time series) are winsorized at $\pm 170\%$ (log prices at $\pm 100\%$). This treatment removes extreme variations in price levels. Price series are then reconstructed using the winsorized price variations and the base firm price level.

Physical output is constructed using the reported total revenues (from SCIE) divided by the per firm price level. Employment is the employment level reported in number of workers. Hours worked is only available for 2004-2009, so that is why we only use it for robustness checks. Intermediate inputs are constructed from reported cost of goods sold. The stock of capital is constructed using the perpetual inventory formula.

$$k_{it} = (1 - \delta_t)k_{i,t-1} + I_{it} \ ,$$

where δ_t is the year by year rate of depreciation and was obtained from the Bank of Portugal´s statistics, k_{it} is the capital stock of firm i in period t and I_{it} is the investment of firm i in period t. All capital series are deflated using the capital deflator series obtained also from the Bank of Portugal´s statistics. The capital stock for the first year the firm is observed in the data is the total gross amount of fixed assets. Finally, labor costs are constructed from reported total gross wages (including social security contributions).

B Appendix: Tables

Production Function Estimates with Revenues (Y)

Industry	RTS	δ	β	α	Median	Γ	OID p-val	N
Linear Approximation								
Bakery	0.96**	0.86	0.07	0.02	2.34	0.91	0.00	2195
Cork	1.000	0.79	0.15	0.07	1.08	0.72	0.19	904
Kitchen Furnitur	1.030	0.79	0.22	0.02	1.42	0.65	0.46	428
Metal Doors, Win	1.03**	0.75	0.22	0.07	1.30	0.76	0.00	1288
Moulds	0.96*	0.58	0.26	0.13	1.62	0.73	0.01	696
Olive Oil	1.003	0.71	0.07	0.22	1.09	0.64	0.54	216
Pastries	0.43***	0.21	0.18	0.04	0.49	1.02	0.17	723
Shoes	0.96***	0.75	0.17	0.04	1.24	0.80	0.00	1325
Stone Cutting	0.979	0.69	0.19	0.11	1.58	0.83	0.00	1213
Wine	0.48***	0.38	0.07	0.03	0.61	1.00	0.14	609
Wood Furniture	1.007	0.81	0.12	0.08	1.86	0.77	0.00	1406

Notes: The set of instruments are the logarithms of capital and employment and the lags of the capital stock, output, employment and prices. Instruments include quadratic, cubic terms and interactions. First column reports the test for constant returns to scale.

Table B.1: GMM estimates for the production function in revenues.

Cost Function Estimates

Industry	Olive Oil	Bakery	Pastries	Wine	Footwear	Cork	Stone Cutting	Metal Doors Windows	Moulds	Kitchen Furniture	Wood Furniture
ψ_k	-0.148***	0.0358	0.0316	-0.0298**	-0.0277	-0.0735***	-0.0445	0.0171	-0.106***	-0.0236	-0.0509*
	(0.0517)	(0.0269)	(0.0287)	(0.0135)	(0.0265)	(0.0180)	(0.0338)	(0.0263)	(0.0387)	(0.0187)	(0.0295)
ψ_l	-0.0624*	0.0244	-0.00413	0.00501	-0.155***	-0.147***	-0.186***	-0.0143	-0.301***	-0.191***	-0.0652**
	(0.0369)	(0.0348)	(0.0406)	(0.0238)	(0.0261)	(0.0283)	(0.0498)	(0.0560)	(0.0611)	(0.0543)	(0.0316)
ψ_q	1.228***	0.934***	0.917***	1.060***	1.237***	1.215***	1.233***	0.984***	1.445***	1.188***	1.116***
	(0.0404)	(0.0673)	(0.0605)	(0.0252)	(0.0334)	(0.0329)	(0.0538)	(0.0671)	(0.0466)	(0.0482)	(0.0453)
gamma1	0.653***	0.939***	0.873***	0.798***	0.778***	0.710***	0.811***	0.842***	0.653***	0.663***	0.813***
	(0.0627)	(0.0106)	(0.0233)	(0.0261)	(0.0299)	(0.0433)	(0.0272)	(0.0227)	(0.0351)	(0.0562)	(0.0254)
ψ_p	1.307***	0.734***	0.708***	0.748***	1.080***	1.236***	1.242***	0.992***	1.508***	1.199***	1.039***
	(0.0678)	(0.145)	(0.0985)	(0.0568)	(0.0543)	(0.0341)	(0.0717)	(0.0825)	(0.0460)	(0.0460)	(0.0610)
Observations	216	2,195	723	609	1,325	904	1,211	1,288	696	424	1,402
CRS test (stat)	-0.0138	0.00578	0.0611	-0.0336	-0.0440	0.00505	-0.00231	0.0131	-0.0266	0.0225	-0.000228
CRS test (s.e.)	0.0228	0.0390	0.0298	0.0198	0.0104	0.00881	0.0206	0.0221	0.0180	0.0153	0.0170
CRS test (pval)	0.545	0.882	0.040	0.090	0.000	0.567	0.911	0.553	0.139	0.141	0.989
Sargan stat	27.67	28.86	35.36	42.11	43.45	38.14	59.87	44.78	43.77	29.54	46.66
Sargan df	29	29	29	29	29	29	29	29	29	29	29

Notes: The set of instruments are the logarithms of capital and employment and the lags of the capital stock, output, materials, employment and prices. Instruments include quadratic, cubic terms and interactions for the cubic approximation. A test for constant returns to scale is also reported.

Table B.2: GMM estimates for the cost function.

Industry	Olive Oil	Bakery	Pastries	Wine	Footwear	Cork	Stone Cutting	Metal Doors Windows	Moulds	Kitchen Furniture	Wood Furniture
Parameters					Demand estimates						
σ_1	-1.501**	-1.026***	-0.547	-1.431***	-9.604	-1.163	-1.175***	-8.219	12.68	-8.339	0.902
σ_2	0.282	-0.0889	-0.212	-0.0317	2.385	0.115	-0.276	1.277	-1.830	1.049	-0.439
σ_3	0.0179	0.260	0.0169	0.0265	-0.226	-0.0275	-0.109	-0.0733	0.0736	-0.0503	0.0307
ρ_ϵ	0.978***	1.008***	1.014***	1.005***	0.987***	1.018***	1.005***	1.002***	0.992***	0.992***	1.023***
Joint test (pval)	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000
Observations	312	2,616	1,012	709	1,368	1,073	1,512	1,644	737	527	1,602

Notes: GMM results with time dummies. * $p<0.1$; ** $p<0.05$; *** $p<0.01$
The null hypothesis of the joint significance test is H0: $\sigma_1=\sigma_2=\sigma_3=0$

Table B.3: GMM demand estimates.

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