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Carlos D. Santos, Luís F. Costa and Paulo Brito

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Demand, Supply and Markup Fluctuations*

Carlos D. Santos[†], Luís F. Costa[‡§], and Paulo Brito[‡§]

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Abstract

Markup cyclicality has been central for debating policy effectiveness and understanding business cycle fluctuations. However, there are two empirical challenges: separating supply (TFP) from demand shocks, and properly measuring the markups. In this article, we use a panel of Portuguese manufacturing firms for 2004-2014. Since it contains information on product-level prices, we can separate supply from demand shocks. We overcome the markup measurement by using the share of intermediate inputs on revenues, instead of the labor share. Our results suggest that markups are pro-cyclical with TFP shocks, and counter-cyclical with demand shocks. We also show that labor-based markups are pro-cyclical.

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[†]Nova School of Business and Economics, UNL, 1099-032 Lisboa, Portugal.

[‡]ISEG - Lisbon School of Economics & Management, *Universidade de Lisboa*, Rua do Quelhas 6, 1200-781 Lisboa, Portugal.

[§]REM – Research in Economics and Mathematics, UECE – Research Unit on Complexity and Economics, Rua Miguel Lupi 20, 1249-078 Lisboa, Portugal.

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JEL classification: C23, E32, L16, L22

1 Introduction

> How markups move, in response to what, and why, is almost terra incognita for macro.
>
> In: Blanchard (2009)[1]

The cyclical behavior of markups, that is, the wedge between prices and marginal costs, has been at the center of the macroeconomic debate on the origins of business-cycle fluctuations and policy effectiveness. Hall (2009), when analyzing the role of varying markups in fiscal-policy effectiveness refers: "models that deliver higher multipliers feature a decline in the markup ratio of price over cost when output rises (...)".[2]

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) - for a comprehensive survey see Rotemberg and Woodford (1999), and section 2 for a brief analysis of the relevant literature.

However, theory alone is not insufficient to determine by how much prices, and marginal costs, will move relative to each other along the business cycle. That is why empirical evidence is much needed.

Yet, the empirical evidence is mixed. First and foremost, the inconclusive results are related with the fact that separating demand and supply shocks is a difficult task in the absence of separate price and quantity data. Thus, if supply and demand shocks exhibit different cyclical patterns, a "weighted average" of the two may exhibit either pro- or counter-cyclical behavior, depending on which shock is more prevalent. Furthermore, for data availability, the literature has used the labor share to construct the markups. Labor is subject to adjustment cost, which

[1] Op. cit. p. 220.
[2] Op. cit. p. 183.

create a wedge between the markup and the labor share. Markup will thus be mismeasured and perhaps even exhibit the opposite cyclicality[3].

In this article, we make use of the availability of product-level prices for a panel of Portuguese manufacturing firms over the period 2004-2014, a period during which the country faced two of the main crisis in the recent past - the 2008-2009 financial crisis and the 2010-2011 European sovereign debt crisis. We merge these prices with the yearly census data containing balance sheet and income statement data. The detail of the data allows us to estimate a structural model of demand and production (supply side), and thus obtain separate measures of demand and supply (TFP) shocks for each individual company. On the supply side, we follow DeLoecker et al. (2016) to obtain production-function estimates for multi-product firms. This method also uses materials as the pivotal input to measure markups. Furthermore, it also allows us to control for unobserved input quality. On the demand side, we use a utility-based nested-homothetic demand function for a representative consumer, which is somewhat inspired by Foster et al. (2016). Since we impose very few restrictions, non-constant elasticities can be obtained for demand functions faced by each producer. The methodology used here can be easily extended to other countries and periods with the expansion of access by researchers to detailed firm-product micro information where prices are observed.

Our results show that markups are countercyclical with the demand shocks while they are pro-cyclical with supply shocks. The explanation for the behavior rests with the cost structure. When faced with a positive demand shock, companies increase prices slightly. However, the short run upward slopping marginal cost curves (due to the existence of fixed inputs such as capital and possibly also labor) implies an increase in costs. The price increase do not cover the cost increase which results in a reduction of the markup. We also show that multi-product firms exhibit a smaller degree of cyclicality with demand shocks, but not with supply shocks. This suggests that multi-product firms have a more flexible cost structure that allows costs to be more easily adjusted as a response to demand shocks. We believe this is due to the reallocation of inputs across products, but we do not have product-specific data on inputs to test this explanation.

[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.

Our findings have implications for macroeconomic policy. When facing a recession, while stimulating aggregate demand, governments and central banks may benefit from an efficiency gain from lower markups. "Hence recessions are not only bad because output is low, but also because microeconomic distortions are greater. This suggests that stabilization of output at a high level is desirable because it reduces these distortions" (Rotemberg and Saloner (1986))[4]. Empirically, without separate measures for markup and productivity, this effect looks like (is observationally equivalent to) a positive productivity shock, while it is actually an efficiency gain from reduced markups. Confounding the markup efficiency (demand-driven) gain with a productivity shock, leads to an underestimation of macroeconomic policy effectiveness. In addition, these stronger multiplier effects may be understated for samples of large and diversified firms that are regularly used for empirical analysis (such as COMPUSTAT), as diversified firms smooth markup responses by reallocating inputs (and costs) across different products. As for Portugal, the empirical evidence suggests that the 2010-4 financial crisis, that arguably started with a negative demand shock, may have been exacerbated by the side effects of fiscal consolidation, leading to a significant increase in the markups across the economy.

The article is organized as follows. In section 2 we present the related literature. Section 3 provides some preliminary macro and micro data and empirical motivation. Section 4 provides a birds-eye view of the problem. In section 5 we present the model an its components. Section 6 describes the data and reports the empirical results of the estimation procedures. Section 7 analyses the markups and their cyclicality. Finally, section 8 concludes.

2 Related literature

This article is related to several earlier contributions. Since our intent is not to produce a survey, but to supply evidence on the cyclicality of markups with demand and supply shocks, we summarize some of the more important contributions below.

On the theory side, there is a number of so-called endogenous-markup models. The undesired type is present in macroeconomic models that assume sticky prices

[4] Op. cit. p. 406.

as state-dependent models of the menu-costs sort, e.g. Mankiw (1985), and time-dependent models as Calvo (1983), Rotemberg (1982) or the sticky-information model of Mankiw and Reis (2002). The desired 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, that may be potential or existing, 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).

On the empirical side of the literature, 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, slightly related 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. Finally, Bils et al. (2018) use BLS and KLEMS data for the US and "find price markup movements are at least as cyclical as wage markup movements."

A strand of literature, closer to our article, has been recently developed using micro data to answer some of the relevant macro questions. Foster et al. (2013) uses US Census data to obtain separate estimates of the demand and productivity components and their effect on firm growth. The US Census data is at a 5 year frequency and is thus not very informative about short run fluctuations. On the other hand, Gilchrist et al. (2014) use monthly product level prices merged with quarterly data for a sample of large firms from COMPUSTAT to look at how financial behavior of firms influences the price responses. 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. To address the problem of multi-product firms, DeLoecker et al.

(2016) develop a methodology to estimate production and productivity estimates for multi-product firms, and 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. Finally, Hong (2017) uses Amadeus data for France, Germany, Italy, and Spain to estimate unconditional elasticities of markups to GDP.

3 Some preliminary evidence

We start with a preliminary analysis of the cyclical behavior of markups in the Portuguese economy from 2004 to 2014 using both aggregated and disaggregated data. A detailed description of the data is contained in Appendix A.2. The data is particularly useful as it overlaps the two largest crises in the last three decades: the 2008-2009 financial crisis and the 2010-2011 European sovereign debt crisis.

3.1 Macro evidence

The economy-wide markup in year t (μ_t), is the weighted geometric mean of the markup (μ_{it}) for each individual firm $i = 1, ..., n$:

$$\mu_t = \prod_{i=1}^{n_t} \mu_{it}^{\omega_{it}} \ ,$$

where n_t is the total number of firms in the census in year t and $\omega_{it} = y_{it} / \sum_{i=1}^{n_t} y_{it}$ is the share of firm i in total sales (production value) in year t, with y_{it} representing the sales (total revenue) of firm i in year t. The growth rate for the average markup is approximately given by[5]

$$\Delta \ln \mu_t \simeq \sum_{i=1}^{n_t} \left(\ln \mu_{it} \Delta \omega_{it} + \omega_{it} \Delta \ln \mu_{it} \right) \ .$$

The markup of firm i at time t is the ratio of price (p_{it}) over marginal cost (c_{it}):

[5] For simplicity, we ignore the effect of changes in n_t.

$$\mu_{it} = \frac{p_{it}}{c_{it}} \ . \tag{1}$$

For the case where the production function is Cobb-Douglas, including labor (ℓ) and materials (m) with constant parameters over time, then $\Delta \ln \mu_{it} = -\Delta \ln s^x_{it}$, where s^x_{it} is the ratio of the cost of input $x = \ell, m$ to total revenue.[6] This is a first-order approximation which we will relax later. Finally, letting weights be approximately constant ($\Delta\omega_{it} \simeq 0$), we obtain a measure for the growth rate of the average markup:

$$\Delta \ln \mu^x_t \simeq -\sum_{i=1}^{n_t} \omega_{it} \Delta \ln s^x_{it}, \ x \in \{\ell, m\} \ .$$

The growth rates of the input share (materials and labor) in the 2004-2014 period are calculated using the census data from IES (*Informação Empresarial Simplificada*[7]), which contains all non-financial companies. Figure 1 depicts the average markups (labor- and materials-based) and real GDP ($\bar{g}$) growth rates. Markups are counter-cyclical with respect to GDP when materials are used to measure it; however, they are pro-cyclical when labor is used instead. Overall, the pattern is explained by the high responsiveness of intermediate inputs and low responsiveness of labor relative to revenues.

Table 1 suggests that on average a 1 per cent increase in GDP is associated with a 0.4 per cent reduction in markups when we use the materials-based measure. However, the same 1 per cent increase in GDP is associated with a 1 per cent increase in markups, when we use the labor-based measure. This rough elasticity is not the same across firm size (employment) classes. Smaller firms exhibit a positive association with GDP growth, with micro firms (2 or less employees) reporting an elasticity of 0.3. The correlations become negative for firms above 10 employees and level off for really large firms (above 500 employees). No discernible patterns exists when markups are measured via labor.

These results compare for example with Bils et al. (2018) and Hong (2017), who estimate markup elasticities with respect to GDP in the order of (negative) 0.9-1.2.

[6] These are the most common measures of markups considered in the literature.

[7] Which can be translated as "Simplified Business Statistics."

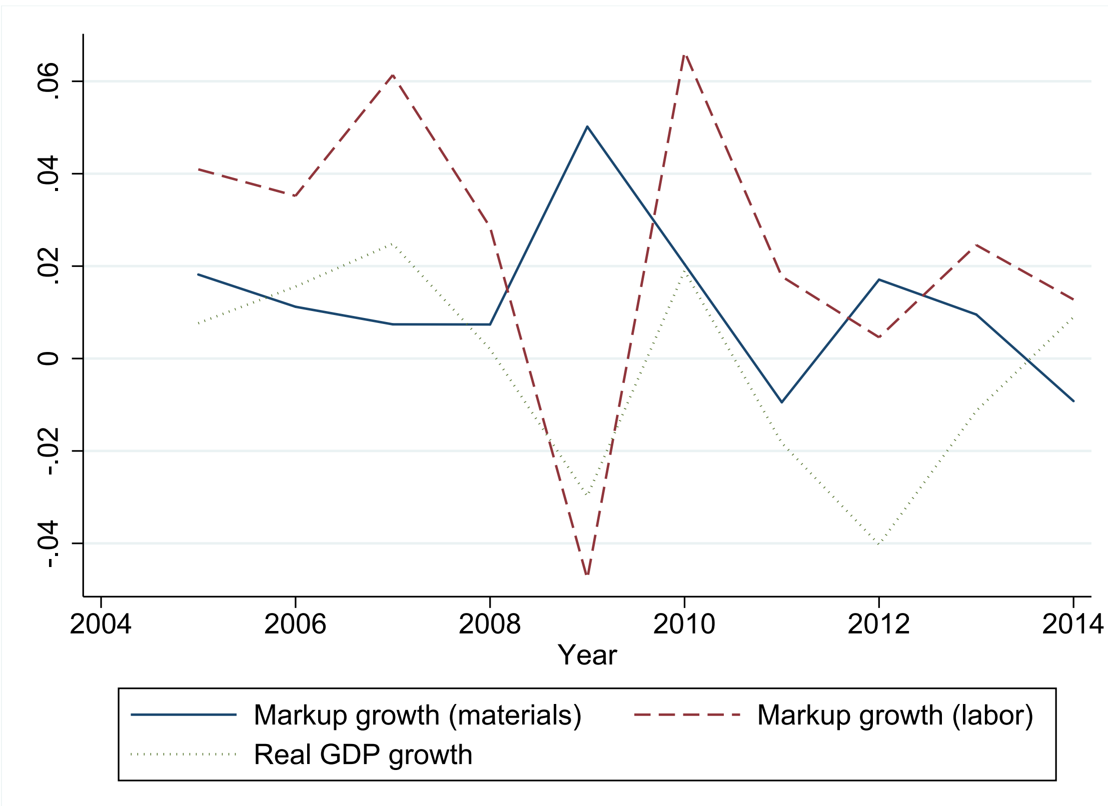


Figure 1: Economy-wide time-series for average markups (labor- and materials-based) and GDP growth. Source: SCIE (Census).

Table 1: Reduced-form GDP elasticities for firm (labor- and materials-based) markups. Source: SCIE (Census).

	Markup			
	Materials		Labor	
	(i)[(a)]	(ii)	(iii)[(a)]	(iv)
$\Delta ln\bar{g}$	-0.422*		1.104**	
	(0.219)		(0.440)	
by size (employment)				
2 or below		0.304***		1.196***
		(0.0289)		(0.0293)
3-10		0.0995***		1.056***
		(0.0220)		(0.0193)
11-25		-0.140***		1.049***
		(0.0426)		(0.0331)
26-100		-0.355***		1.018***
		(0.0557)		(0.0415)
101-500		-0.392***		1.162***
		(0.105)		(0.0779)
501 or above		-0.311		0.702***
		(0.227)		(0.145)
Observations	1,862,043	1,862,043	2,363,012	2,363,012

Notes: OLS results from the regression of growth rates of markups on growth rates of GDP. Markup growth truncated at ± 2. (a) Regressions are weighted by revenues. Standard errors (in brackets) clustered by firm and year. Significance levels: 1 per cent (***), 5 per cent (**), and 10 per cent (*).

Bils et al. (2018) use BLS and KLEMS data for the US. Hong (2017) uses a sample of mostly very large companies, covered by Amadeus (for France, Germany, Italy, and Spain) which can explain the larger estimates.

Unfortunately, the observed heterogeneity in responses implies that the GDP elasticity of markups depends on market structure so that we can not produce one "magic" number to educate policy makers. Furthermore, such simple regression results also abstract from two fundamental questions. First, the origin of the shocks to GDP: demand *vs.* supply. Fluctuations due to supply-side (productivity) shocks can generate the opposite response for markups when compared to those generated by demand-side shocks. Second, the mechanism by which markups react to such shocks requires we add some structure to study the problem. Quoting Rotemberg and Saloner (1986), who find a negative effect of GNP growth on price growth for the US Cement industry: "These results are of course not conclusive. First, it is possible that increases in GNP lower the demand for cement relative to that for other goods. Without a structural model, (...), this question cannot be completely settled."[8] Three important elements explain how markups respond: prices, quantities, and marginal costs. As we will see in the remaining of the article, this distinction is fundamental to understand the source of markup fluctuations.

3.2 Micro evidence

Let us start by decomposing the effects on prices and marginal costs at the micro level. First, we use the data from IAPI (*Inquérito Anual à Produção Industrial*[9]), a survey that collects product-level annual information on revenues and sales (quantities) of industrial goods to construct the 9-digit prices for each individual product-firm as the ratio of revenues to sales. We can also obtain direct proxies of the marginal cost for the two inputs, by computing the ratio of the total expenditure in intermediate inputs (and the wage bill) to physical output. A large ratio means that, on average, more inputs are required to produce a unit of output, e.g. if flour is used in larger amounts to produce x kg of bread, the marginal cost of producing bread is higher.

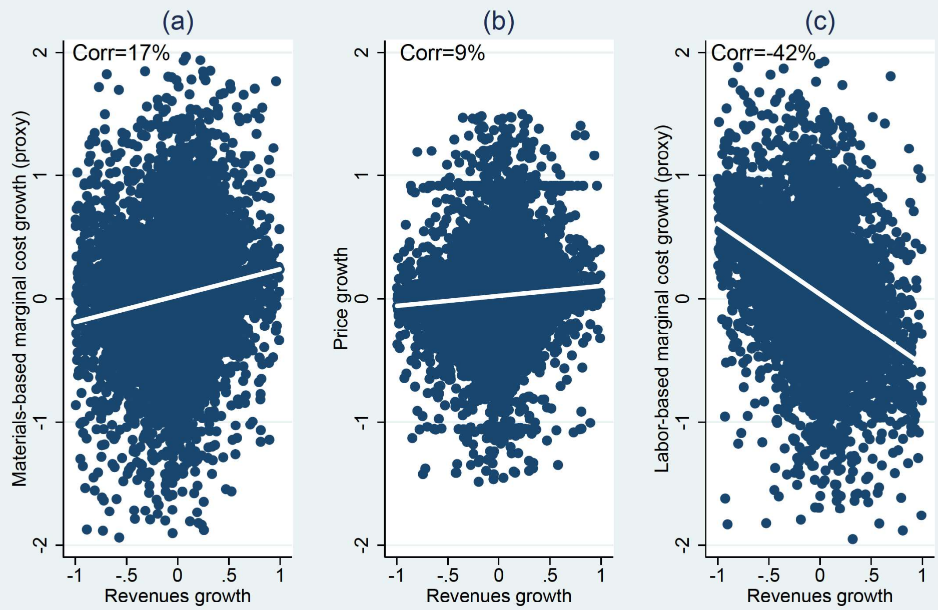
Figure 2 illustrates how the growth of prices and marginal costs vary with the growth of revenues. All variables are in first differences of logs, so that these are effectively within-firm (year on year) variations. First, panel (a) shows that the growth of (materials-based) marginal costs *increases* with the growth of revenues (the correlation is 17%), while panel (b) shows that prices are relatively unresponsive (the correlation is 9%). On the other hand, we can see in panel (c) that (wage-based) marginal cost growth *decreases* with revenue growth (the correlation is -42%).

These patterns produce an expected increase in labor-based markups and an expected decrease in materials-based markups to revenue growth. The different response of the two measures of marginal costs, together with the prices changes,

[8] Op. cit. p. 399

[9] Which can be translated as "Annual Industrial Production Survey."

are fundamental to explain the behavior of markups. In particular, the existence of predetermined factors such as capital and labor, generate an upward-sloping marginal cost function. Adding relatively mild price adjustments and stronger quantity responses generates the observed patterns for the markups.



Notes: Raw data for single-product firms. Materials-based (labor-based) marginal cost is the ratio of total expenditure in materials (labor) to revenues. Growth rates are log changes.

Figure 2: Marginal cost and price vs. revenue growth. Source: SCIE (Census) and IAPI.

While this evidence rationalizes the mechanism explaining markup cyclicality, we have still not addressed the source of the shocks: demand vs. supply. However, marginal costs and prices are expected to respond differently. While both prices and marginal costs are expected to increase with a positive demand shock, both are expected to decrease with a positive productivity shock. The simple framework presented in the following section introduces both demand and supply levels, and allows us to interpret the basic evidence through the lens of a structural model. Later, we will use our product and firm information to isolate the two shocks.

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

The product-firm markup is a function of firm-specific TFP (a), and firm-product specific demand (ϵ) shifters. Before delving into the measurement issues related to the three variables (μ, a, and ϵ), it is useful to understand the nature of the response of markups to the two shifters. The individual producer faces an inverse demand function generically given by $p = P(q, \epsilon, \cdot)$, where q represents the quantity sold, $P_q < 0$, and $P_\epsilon > 0$.[10] Similarly, the marginal cost function given by $c = C(q, a, \cdot)$, where $C_q \geq 0$, and $C_a < 0$. Finally, the markup is $\mu \equiv \mathcal{M}(q, \epsilon, a, \cdot) = P(q, \epsilon, \cdot) / C(q, a, \cdot)$. While function $\mathcal{M}(\cdot)$ captures the direct effect of productivity and demand shocks, there are also the indirect effects that, in equilibrium, cause changes in the quantity produced q.

For any product, the revenue obtained equals price times quantity, $y = Y(q, \epsilon, \cdot) = pq$. The regularity conditions imply that marginal revenue $Y_q = P_q(q, \epsilon, \cdot)\, q + P(q, \epsilon, \cdot) > 0$ is decreasing in q (i.e. $Y_{qq} = 2P_q + P_{qq} q < 0$) and is increasing in ϵ (i.e. $Y_{q\epsilon} = P_\epsilon + P_{q\epsilon} q > 0$). Consequently, from the optimality condition $Y_q = c$,[11] we obtain $q = Q(\epsilon, a, \cdot)$, where $Q_\epsilon = Y_{q\epsilon} / (C_q - Y_{qq}) > 0$, and $Q_a = -C_a / (C_q - Y_{qq}) > 0$. Markups are thus a function of the levels of productivity and demand, either by a direct effect to the marginal-cost and demand demand functions, or by an indirect effect to the (optimal) production level. We can decompose these two channels. A change in total factor productivity (TFP), has an impact on the markup that can be summarized by the following partial derivative[12]:

$$\mu_a = \underbrace{\frac{P_q Q_a}{c} - \frac{\mu C_q Q_a}{c}}_{\substack{\text{indirect effect} \\ = \underset{-}{\mathcal{M}_q}\ \underset{+}{Q_a}}} \quad \underbrace{-\frac{\mu C_a}{c}}_{\substack{\text{direct effect} \\ = \underset{+}{\mathcal{M}_a}}} \quad . \tag{2}$$

There is a positive direct effect of an increase in TFP as it reduces the marginal

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

[11] In fact, we do not need to assume optimal pricing here. Cost minimisation together with any (sub-)optimal production rule would suffice.

[12] See the appendix for a simple model with nominal rigidity.

cost ($-\mu C_a/c > 0$). However, there are two indirect effects with negative sign, due to the 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, there is a consensus in postulating it to be positive, i.e. that markups are pro-cyclical 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^{C_a},[13] is large enough, and the following condition holds:

$$\mu_a > 0 \Leftrightarrow -\eta^{C_a} > \left(\eta^{C_q} - \eta^{P_q}\right)\eta^{Q_a} > 0.$$

For demand, a change in the level leads to

$$\mu_\epsilon = \underbrace{\frac{P_q Q_\epsilon}{c} - \frac{\mu C_q Q_\epsilon}{c}}_{\substack{\text{indirect effect} \\ = \underset{-}{\mathcal{M}_q}\ \underset{+}{Q_\epsilon}}} \quad \underbrace{+\frac{P_\epsilon}{c}}_{\substack{\text{direct effect} \\ = \underset{+}{\mathcal{M}_\epsilon}}} \quad . \tag{3}$$

There is a positive direct effect on the price via shift in the demand ($P_\epsilon/c > 0$) 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 about the net effect of a positive demand shock on markups. Markups are counter-cyclical, 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 the price adjustment is relatively small). Thus, markups are counter-cyclical with demand shocks ($\mu_\epsilon < 0$) 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 the difference of the elasticities of marginal cost relative to demand for output changes ($\eta^{C_q} - \eta^{P_q} > 0$), and the following condition holds:

[13] From now on we denote by $\eta^{G_{x_1}} \equiv G_{x_1} x_1/g$ the elasticity of $g = G(x_1, \cdot)$ with respect to x_1.

$$\mu_\epsilon < 0 \Leftrightarrow \eta^{P_\epsilon}/\eta^{Q_\epsilon} < \eta^{C_q} - \eta^{P_q} \ .$$

Otherwise, they are pro-cyclical with these shocks.

Next we present our approach for estimating the markups, the TFP, and the demand shocks. The results, using two rich databases for Portuguese firms, are reported in section 6. In section 7 we report numerical estimates of the elasticities η^{μ_a} and η^{μ_ϵ}.

5 The model

In this section, we provide the theoretical elements to the problem of uncovering markup cyclicality, briefly analyzed above. We use a measure of markups adapted to our dataset and present a specification for the demand and production functions, allowing for the separate measurement of the TFP and demand shocks. Our final goal is to calculate the markup elasticities in Equations 2 and 3.

First, the production technology to produce good j by firm i at time t is

$$\ln q_{ijt} = \ln F_j \left(k_{ijt}, \ell_{ijt}, m_{ijt}\right) + a_{it} \ , \tag{4}$$

where k represents the stock of physical capital, ℓ is the labor input, and m is an intermediate input (materials). The production function parameters are product-specific, and are the same for all firms producing good j. We follow DeLoecker et al. (2016) and let inputs be product-firm specific, while TFP (a_{it}) is shared across all products within the firm. In this case, inputs and productivity are unobserved for two reasons: (i) we can only observe input usage at the firm level and (ii) input quality is not observed. We will address both issues below.

Second, similarly to Foster et al. (2016) we assume that the quantity demand of good j produced by firm i at time t is

$$\ln q_{ijt} = \ln D_{ij} \left(p_{ijt}, \bar{p}_{jt}, \bar{p}_t, \bar{g}_t, \nu_{ijt}\right) + \epsilon_{ijt} \ , \tag{5}$$

where p_{ijt} is its price, $\bar{p}_{jt}$ is the average price of product j, $\bar{p}_t$ is the aggregate price index, $\bar{g}_t$ is real GDP, ν_{ijt} is the quality level, and ϵ_{ijt} is the idiosyncratic demand level. The demand function is firm-product specific because we assume that firm i retains some market power over its product, although it operates in a competitive environment with other firms. All the arguments in Equation 5 are observed, except for the demand level and product quality.

Estimation proceeds in three steps. First, we estimate the production function in Equation 4 using data for single-product firms. Second, using the estimated production function parameters we calculate the input-shares for each multi-product firm together with the firm-level TFP. This step involves only solving, not estimating, a system of equations. Finally, we use the calculated TFP as an instrument to estimate the demand function in Equation 5 for each product-firm. Demand shocks are obtained as the residuals from this equation.

5.1 Markups measurement

We now start by addressing the measurement of markups. Consider Equation 4, where all inputs are substitutes, and at least one input is freely adjustable and not subject to adjustment costs. Furthermore, let firms be price takers in input markets, so that r is the rental on capital, w is the wage rate, and b is the price of materials, all exogenous. This assumption is important and is discussed at length in DeLoecker et al. (2016).

Under these conditions, an optimizing firm faces a marginal cost of producing good j equal to the ratio between the price of an input ($z^x \in \{r, w, b\}$) and its marginal product in the production of j ($F_{x,ijt}$ with $x \in \{k, \ell, m\}$), i.e. $c_{ijt} = z^x_t / F_{x,ijt}$. Therefore, the markup of firm i in the production of j at time t is given by

$$\mu_{ijt} = \frac{\eta^{F_x}_{ijt}}{s^x_{ijt}} , \tag{6}$$

where $s^x_{ijt} = z^x x_{ijt} / y_{ijt}$ is the share of the cost of input x on total revenues for product j ($y_{ijt} = p_{ijt} q_{ijt}$). The elasticity $\eta^{F_x}_{ijt}$, that is, the ratio between the marginal and the average product of input x in the production of j, depends on the functional form assumed for the production function $F_j(\cdot)$. The elasticity is not observed in the data and must be estimated via production function, which we assume to be the same for all firms producing j. For single-product firms, the share s^x is observable for labor and materials. For multi-product firms, we need to calculate the allocation of intermediate inputs for firm i across all products. From the estimated parameters for the production function, $F_j(\cdot)$ from Equation 4, we obtain an estimate of the input elasticity. The markup can then be constructed as specified in Equation 6 using the input share data - see section 7.

While earlier contributions used labor input to measure markups in Equation 6, we use intermediate inputs instead. In addition to data availability, the main reason is that labor tends to behave as a dynamic input subject to short-run adjustment costs (hiring and firing costs) which can be problematic and lead to incorrect results.

5.1.1 The troubles with input shares

An important share of the literature assumes that the production function is (approximately) Cobb-Douglas and so the input elasticities $(\eta_{ijt}^{F_x})$ become constant. In this case, the only variation in markups will be from variation in the revenue share of the variable input. But how do shares respond to quantities? If we assume the producer is price taker in the market for input x, considering that the optimal usage of this input is given by $x = X(q, \cdot)$ with $X_q > 0$, an increase in production will lead to

$$\frac{\partial s^x}{\partial q} = \frac{s^x}{q}\left(\eta^{X_q} - \frac{1}{\mu}\right) . \tag{7}$$

Thus, considering that $1/\mu \in (0, 1)$, the cyclicality of the input share depends on how much this input utilization varies with production. 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 6 in order to reflect distorted time series for input shares. This is particularly pungent when labor is used to measure markups, as shown by Rotemberg and Woodford (1999), or more recently by Nekarda and Ramey (2011).

An illustrative example may help us to clarify this point. Assume there are convex costs of adjusting labor from its current level. In that case, the elasticity η^{L_q} becomes small and it is more likely to obtain an acyclical or even counter-cyclical labor share, that is, an acyclical or even pro-cyclical 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 pro-cyclical 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 7 becomes $\eta^{L_q}\left(1+\eta^{W_\ell}\right) - \frac{1}{\mu}$. In this case, a fully-flexible labor input produces more pro-cyclical (counter-cyclical) labor shares (markups) than the real ones, using a corrected measure.

Consequently, we 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. One objection that may be raised to this strategy is that materials are a composite of several goods and services, with no clear quantity and price measures to be obtained in the data. This 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.

5.2 Demand function

We now deal with estimating Equation 5 and obtaining the firm-specific demand shifter. There is a standard endogeneity problem due to the presence of the price p_{ijt} as an argument. We follow an identification strategy similar Olley and Pakes (1996) by letting the demand shifter (ϵ_{ijt}) follow a Markovian process. The process can take any order κ, but due to the short time dimension of our panel we will use a first-order case.

Assumption 5.1 *The demand level follows a separable exogenous first-order Markovian process:*

$$\epsilon_{ijt} = \Lambda(\epsilon_{ijt-1}) + \psi^{\epsilon}_{ijt} \ , \tag{8}$$

where ψ^{ϵ}_{ijt} is i.i.d. over t (time) and i (firm).

5.2.1 Benchmark case: Nested-homothetic demand function

In industrial sectors, companies operate both in consumer markets (B2C) and intermediate markets (B2B). For example, bread or pastries are sold directly to final consumer, via retailer or to other companies like restaurants, hotels or cafés. For simplicity, we assume that the demand for good j is well represented by a consumer with homogeneous-of-degree-one CES preferences for classes of goods organized in baskets (we will use two-digit sectors) and then a homothetic-subutility function representing the preferences over individual goods (we will use nine-digit products). The demand for good j sold by firm i at time t in Equation 5 can thus be represented by[14]

$$\ln\left(q_{ijt}\right) = \lambda_0 + \lambda_1 \ln\left(\frac{\bar{p}_{jt}}{\bar{p}_t}\right) + \lambda_2 \ln\left(\bar{g}_t\right) + d\left(\frac{p_{ijt}}{\bar{p}_{jt}}\right) - \xi\nu_{ijt} + \epsilon_{ijt} \ , \tag{9}$$

Function $d(\cdot)$, which stems from the nested homothetic preferences, is decreasing and can be approximated by a cubic polynomial:

$$d\left(\frac{p_{ijt}}{\bar{p}_{jt}}\right) = \sigma_1 \ln\left(\frac{p_{ijt}}{\bar{p}_{jt}}\right) + \sigma_2 \ln^2\left(\frac{p_{ijt}}{\bar{p}_{jt}}\right) + \sigma_3 \ln^3\left(\frac{p_{ijt}}{\bar{p}_{jt}}\right) \ ,$$

providing us enough flexibility to accommodate a wide range of endogenous-markup models.

Notice that this representative-consumer model includes an intra-product competition component represented by $p_{ij}/\bar{p}_j$, an inter-product competition component represented by $\bar{p}_j/\bar{p}$, a proxy for macroeconomic shocks given by $\bar{g}$, dynamic demand (persistence) and a series of idiosyncratic shocks represented by ψ^{ϵ}. The quality shifter (ν_{ijt}) is estimated from the production function, following the approach used in DeLoecker et al. (2016), that we outline in section 5.4.

Given the Markovian assumption for ϵ_{ijt}, all information at $t-1$ becomes orthogonal to the news component (ψ^{ϵ}_{ijt}), as well as TFP shocks in period t. Note that this assumption still allows for the TFP level (a_{it}) to be correlated with the demand level (ϵ_{ijt}). Thus, we can write the following moment condition:

$$E(\psi^{\epsilon}_{ijt}|\mathbf{Z}) = 0 \ ,$$

[14] See the appendix for further details.

and estimate Equation 9 by GMM. The exact set of instruments ($\mathbf{Z}$) is detailed in the empirical section and includes current and lagged TFP, labor, capital, industry prices, and the estimated measure of input quality, together with lagged own prices.

5.3 Production function: TFP

To obtain the firm-level TFP (a_{it}), we estimate Equation 4. Before we consider the separation between single-product *vs.* multi-product firms and quantity *vs.* quality, in order to obtain valid estimates of a_{it}, we have to deal with the problems of endogeneity, identification, and specification of the production function.

5.3.1 Input endogeneity

Potential endogeneity exists in Equation 4 due to the fact that TFP is an unobserved state variable correlated with inputs. We address endogeneity in a similar way to what was done for demand: by using the method proposed by Olley and Pakes (1996), that introduces a Markovian assumption on the TFP process. A problem with this approach has been raised by Bond and Soderbom (2005) and Gandhi et al. (2013). This is because, conditional on all state variables and unobserved TFP, there is no variation left in intermediate inputs to adopt the inversion method developed by Levinsohn and Petrin (2003). The parameters in the production function are thus not identified. We show how to regain identification by allowing persistent shocks to demand. The idea is to have a second source of variation in materials, originated on the demand side, a point we discuss in detail in the next subsection.

In order to estimate Equation 4, we assume that function $F_j(\cdot)$ is the same for all producers of good j, including producer i. For simplicity, we ignore product (j) and producer (i) subscripts, whenever they are not required to understand the problem.

Assumption 5.2 *TFP is a separable exogenous κ-order Markovian process:*

$$a_{it} = \Gamma(\ln a_{i,t-1}, .., \ln a_{i,t-\kappa}) + \psi^a_{it} \ , \tag{10}$$

where ψ^a_{it} is i.i.d. over t (time) and i (firm).

Henceforth, we set $\kappa = 1$. While this is not strictly necessary, a larger κ would require longer time spans than the ones available in the dataset for estimation purposes. Under this condition, the production function in 4 can be written as

$$\ln q_{ijt} = \ln F\left(k_{ijt}, \ell_{ijt}, m_{ijt}\right) + \Gamma\left(\ln q_{ij,t-1} - \ln F\left(k_{ij,t-1}, \ell_{ij.t-1}, m_{ij,t-1}\right)\right) + \psi_{it}^{a} \ . \quad (11)$$

From assumption 5.2, we know that ψ_{it}^{a} 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 $(q_{ij,t-1}, k_{ij,t-1}, \ell_{ij,t-1}, m_{ij,t-1})$ are valid instruments. Intuitively, $q_{ij,t-1}$ traces out function $\Gamma(\cdot)$ while $(k_{ij,t-1}, \ell_{ij,t-1}, m_{ij,t-1})$ trace out function $F(\cdot)$. Pre-determined variables are also valid instruments - e.g. the capital stock and the labor input, which are chosen in period $t-1$.[15] Thus, we can derive the following moment conditions from Equation 11 and estimate it using GMM:

$$E\left(\psi_{it}^{a}\begin{bmatrix}\mathbf{Z}_{ij,t-1}^{\otimes 1}\\ ..\\ \mathbf{Z}_{ij,t-1}^{\otimes N}\\ k_{ijt}\\ \ell_{ijt}\end{bmatrix}\right) = \mathbf{0} \ , \quad (12)$$

where $\mathbf{Z}_{ij,t-1} = \begin{pmatrix} q_{ij,t-1} & k_{ij,t-1} & \ell_{ij,t-1} & m_{ij,t-1}\end{pmatrix}^{\top}$ and $\mathbf{Z}_{ij,t-1}^{\otimes n} = \mathbf{Z}_{ij,t-1} \otimes \mathbf{Z}_{ij,t-1}^{\otimes n-1} = \underbrace{\mathbf{Z}_{ij,t-1} \otimes ... \otimes \mathbf{Z}_{ij,t-1}}_{n\ times}$, for $n = 1, ..., N$, is the Kronecker self-product of order n. Note that we assume capital and labor are both pre-determined so that their choice is orthogonal to the "news" shock to TFP, ψ_{it}^{a}.[16]

5.3.2 Identification

A potential identification problem to the estimation of Equation 4 arises from the absence of variation in m_{ijt}, once we condition it on the set of pre-determined

[15] Violations of the Markov assumption generate serial correlation in ψ_{it}^{a} and the identifying condition would become invalid, i.e. variables chosen at or before period $t-1$ are correlated with ψ_{it}^{a} and are no longer valid instruments. This could be addressed using a second-order (or higher) Markov process and longer lags as instruments.

[16] We also estimated the model with endogenous labor, in which case ℓ_{ijt} drops from the moment condition. Results are available from the authors.

variables $(k_{ijt}, \ell_{ijt}, a_{it})$ - see Bond and Soderbom (2005) and Gandhi et al. (2013). This problem emerges from the optimality condition, as intermediate inputs are a direct function of the state variables, $m_{ijt} = M(k_{ijt}, \ell_{ijt}, a_{it})$. Conditional on the state variables $(k_{ijt}, \ell_{ijt}, a_{it})$, lagged instruments do not have any informative power about m_{ijt} and, as such, the production function coefficients are not identified. However, once we allow for two unobserved shifters and introduce the level of demand ϵ_{ijt} into our model, the optimality condition for intermediate inputs becomes a function of it: $m_{ijt} = M(k_{ijt}, \ell_{ijt}, a_{it}, \epsilon_{ijt})$. Therefore, considering that ϵ_{ijt} is assumed to be serially correlated, lagged values of m_{ijt} (conditional on $k_{ijt}, \ell_{ijt}, a_{it}$) are informative for the current values of m_{ijt}, which restores identification of the production-function coefficients.

5.3.3 Benchmark case: Translog production function

Using a second-order approximation to the production function, Equation 4 takes the standard translog form:

$$\ln q = \boldsymbol{\alpha}^\top \mathbf{x} + \mathbf{x}^\top \boldsymbol{\beta} \mathbf{x} + a \;, \tag{13}$$

$$\boldsymbol{\alpha} = \begin{pmatrix} \alpha_k \\ \alpha_\ell \\ \alpha_m \end{pmatrix}, \quad \mathbf{x} = \begin{pmatrix} \ln k \\ \ln \ell \\ \ln m \end{pmatrix}, \quad \boldsymbol{\beta} = \begin{pmatrix} \beta_{kk} & \frac{\beta_{k\ell}}{2} & \frac{\beta_{km}}{2} \\ \frac{\beta_{k\ell}}{2} & \beta_{\ell\ell} & \frac{\beta_{\ell m}}{2} \\ \frac{\beta_{km}}{2} & \frac{\beta_{\ell m}}{2} & \beta_{mm} \end{pmatrix} .$$

The elasticity in Equation 6 is a linear function of input utilization $\eta_{ijt}^{F_m} = \alpha_m + \beta_{km} \ln k + \beta_{\ell m} \ln \ell + 2\beta_{mm} \ln m$, so that we can obtain the level of μ_t simply by dividing this elasticity by the input share s_t^m.[17]

As for the $\Gamma(\cdot)$ function, we use a linear approximation:

$$\Gamma(a_{i,t-1}) \approx \gamma_a a_{i,t-1} \; .$$

Thus, the benchmark equation to be estimated is

[17] And if labor is fully flexible, the labor-based markup is given by dividing the elasticity $\eta_{ijt}^{F_\ell} = \alpha_\ell + \beta_{k\ell} \ln k + 2\beta_{\ell\ell} \ln \ell + \beta_{\ell m} \ln m$ by the input share s_t^ℓ.

$$\ln q_{ijt} = \boldsymbol{\alpha}^\top \mathbf{x}_{ijt} + \mathbf{x}_t^\top \boldsymbol{\beta} \mathbf{x}_{ijt} + \gamma_a \left(\ln q_{ij,t-1} - \boldsymbol{\alpha}^\top \mathbf{x}_{ij,t-1} - \mathbf{x}_{ij,t-1}^\top \boldsymbol{\beta} \mathbf{x}_{ij,t-1} \right) + \psi_{it}^a \ . \quad (14)$$

Notice that this equation cannot be estimated by OLS, as m_{ijt} is endogenous. Thus, we use the GMM estimator defined above.

5.4 Multi-product firms and input quality

The existence of price-level data and multi-product firms introduces two new measurability concerns to the estimation of Equation 4. First, a large proportion of firms produce more than one product and we do not observe the inputs allocated to each individual product. We only observe the aggregate input utilization by firm i. Second, except for labor, the values of inputs used by firm i are observed, instead of the quantities of each input. Multi-production further introduces a potential bias due to the existence of economies of scope, restricting rivalry in input utilization among different goods. Allocating inputs using the share of total revenues originated from product j does not address this bias. The presence of economies of scope is permitted, by letting total factor productivity vary across single and multi-product firms, while still maintaining the same cost function across all companies. A different, but not necessarily independent, bias is related to companies using inputs of varying quality to produce a given output. This is particularly problematic when we measure output in quantities. While the problem is also present when output is measured in revenues, it becomes less apparent (statistically) since input quality is partially "passed on" as higher output prices. Next, we consider the cases with input-quality and multiple products.

Input quality becomes visible once the production function is estimated in q, as output quality differences will show up as variations in q while they would be mitigated by larger prices in the case of revenues. Since output quality is positively correlated with input quality, we need a measure of inputs which is "cleaned" from quality variations. Thus, we cannot associate directly q_{ijt} (observable) with the inputs measured in value (materials, capital). Consequently, we use the method developed by DeLoecker et al. (2016) to assign inputs across produced goods and correct for the input-price bias. Firm i's allocation of input $x \in \{k, \ell, m\}$ to product

j at time t can be written as

$$\exp x_{ijt} = \exp\left(\tilde{x}_{it} + \rho_{ijt} - \chi_{ijt}\right) \ ,$$

where ρ represents the (log of the) share of product j in the quality-adjusted usage of input x and χ stands for the (log of the) input quality index (which is assumed to be the same across all inputs[18]). Finally, shares must add up to one for each firm, i.e. $\sum_{j=1}^{n_{it}} \exp\left(\rho_{ijt}\right) = 1$, where $n_{it} \geq 1$ represents the number of products produced by firm i at time t. Thus, the transformed input vector to use in Equation 13 is obtained as

$$\mathbf{x}_{ijt} = \tilde{\mathbf{x}}_{it} + \left(\rho_{ijt} - \chi_{ijt}\right) \boldsymbol{\iota} \ , \tag{15}$$

where $\tilde{\mathbf{x}}_{it} = \begin{pmatrix} \ln \tilde{k}_{it} & \ln \tilde{\ell}_{it} & \ln \tilde{m}_{it} \end{pmatrix}^{\top}$ and $\boldsymbol{\iota} = \begin{pmatrix} 1 & 1 & 1 \end{pmatrix}^{\top}$.

We use a reduced-form model to relate input quality (χ) with output prices. The relation between the input quality level and output prices can be derived from several economic models (e.g. see Appendix A in DeLoecker et al. (2016)). We assume that input quality (χ) is positively associated with product quality (ν), as in 'O-ring' theories. Consistently with the demand specification in Equation 9, we use demand perceptions of product quality (net of the effect of ϵ) and the production function to obtain the following reduced-form control function for input quality:[19]

$$\chi_{ijt} = \chi_p \ln\left(\frac{p_{ijt}}{\bar{p}_{jt}}\right) + \chi_{\bar{p}} \ln\left(\frac{\bar{p}_{jt}}{\bar{p}_t}\right) + \chi_{\bar{g}} \ln\left(\bar{g}_t\right) \ .$$

Parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ in Equation 14, and $\boldsymbol{\chi} = \begin{pmatrix} \chi_p & \chi_{\bar{p}} & \chi_{\bar{g}} \end{pmatrix}^{\top}$ above are jointly estimated for single-product firms. In a single-product firm ($n_i = 1$) using stable

[18]Note that $\exp\left(\rho_{ijt} - \chi_{ijt}\right)$ is not input-specific, i.e. it is the same for all $x \in \{k, \ell, m\}$. DeLoecker et al. (2016) show that different quality levels for different inputs are not identified in the Cobb-Douglas case, i.e. $\chi^x_{ijt} = \chi_{ijt}$ for all x). This is no longer true in the translog case but identification is dependent on the higher-order cross products, leading to unstable estimates, so we will ignore this variation and adopt the same assumption.

[19]As a robustness check to our reduced form input quality equation, we have also used the Jaimovich et al. (2017) approach. It uses labor intensity (ℓ/q) as a proxy for product quality. The rational behind this is that production of low-quality goods is generally less labor intensive than that of high-quality goods. The results remain robust to this alternative specification. Estimations are avaliable from authors upon request.

mature inputs, we observe $\rho = 0$, that is, the share of good j (ρ_j) is equal to one. Since function $F_j(\cdot)$ is the same for all firms producing good j (and for all periods), we can use the estimated parameters to recover ρ and productivity terms for the remaining multi-product firms. Using only single-product firms might create a problem of selection bias. The selection bias arises if firms' choice to add a second product and become multi-product, depends on the unobserved firm productivity and/or firms' input use. The estimation procedure utilizes the same selection correction adopted in DeLoecker et al. (2016), which follows Olley and Pakes (1996). In particular, we obtain a first-stage estimate for the probability of remaining single-product and use the fitted probabilities in the second stage.

Using the results above, the production function in Equation 13 for a multi-product firm is given by

$$\begin{aligned} \ln q_{ijt} &= \mathbf{A}_{ijt}^{\top}\mathbf{x}_{ijt} + \mathbf{x}_{ijt}^{\top}\boldsymbol{\beta}_j\mathbf{x}_{ijt} + a_{it} \ , \\ a_{it} &= \gamma_a a_{i,t-1} + \psi_{ijt}^{a} \ . \end{aligned} \tag{16}$$

We can specify the following product-specific term.

$$a_{ijt} = \ln q_{ijt} - \mathbf{A}_{ijt}^{\top}(\mathbf{x}_{ijt} - \chi_{ijt}\boldsymbol{\iota}) - \left(\mathbf{x}_{ijt} - \chi_{ijt}\boldsymbol{\iota}\right)^{\top}\boldsymbol{\beta}_j\left(\mathbf{x}_{ijt} - \chi_{ijt}\right) \ , \tag{17}$$

This is a nuisance variable in the estimation. By construction

$$a_{ijt} = \rho_{ijt}\left(\mathbf{A}_{ijt}^{\top}\boldsymbol{\iota} + 2\boldsymbol{\iota}^{\top}\boldsymbol{\beta}_j\mathbf{x}_{ijt}\right) + \rho_{ijt}^2\boldsymbol{\iota}^{\top}\boldsymbol{\beta}_j\boldsymbol{\iota} + a_{it} \ ,$$

which in the case with three inputs $x \in \{k, \ell, m\}$, and letting $x_{ijt} = x_{it} - \chi_{ijt}$, is given by

$$\begin{aligned} a_{ijt} = \ & a_{it} + \\ & + \begin{pmatrix} \alpha_\ell + \alpha_m + \alpha_k + 2\beta_{kk}k_{ijt} + 2\beta_{\ell\ell}\ell_{ijt} + 2\beta_{mm}m_{ijt} + \\ +\beta_{k\ell}(k_{ijt} + \ell_{ijt}) + \beta_{km}(m_{ijt} + k_{ijt}) + \beta_{\ell m}(m_{ijt} + \ell_{ijt}) \end{pmatrix}\rho_{ijt} + \\ & + (\beta_{kk} + \beta_{\ell\ell} + \beta_{mm} + \beta_{\ell k} + \beta_{\ell m} + \beta_{mk})\rho_{ijt}^2 \ . \end{aligned} \tag{18}$$

Furthermore, in order to close the model, the sum of the shares has to equal one, i.e. $\sum_{j=1}^{n_{it}} \exp(\rho_{ijt}) = 1$. Equation 18 allows us to recover one ρ_{ijt} for each firm-product-year, while the sum of shares restriction allows us to recover the firm-level TFP, a_{it}.

The DeLoecker et al. (2016) procedure can be summarized as follows:

1. Use single-product firms ($\rho_{ijt} = 0$) to estimate $\boldsymbol{\alpha}_j$, $\boldsymbol{\beta}_j$, and $\boldsymbol{\chi}_j$ via Equation 16. Calculate the production elasticities and markups.

2. Use the parameter estimates ($\hat{\boldsymbol{\alpha}}_j$, $\hat{\boldsymbol{\beta}}_j$, and $\hat{\boldsymbol{\chi}}_j$) in Equation 17 to obtain the nuissance variable, a_{ijt}.

3. Solve Equation 18 to obtain the values of ρ_{ijt} and calculate the firm-specific TFP (a_{it}) levels by imposing $\sum_{j=1}^{n_{it}} \exp(\rho_{ijt}) = 1$.

6 Empirical results: TFP and demand

We start with a description of the data used and sample construction. The existence of price data for a large set of small, medium, and large companies at an yearly frequency sets our work apart from most of the remaining literature. The data set has been constructed from two sources for the period 2004-2014: (i) IES and (ii) IAPI, both described in detail in Appendix A.2. We merge the detailed firm-product level data from IAPI with the financial firm level data from IES.

6.1 Sample

For estimation, we select two-digit sectors with at least 30 observations every year. Tables 2 and 3 report the resulting sample of eighteen sectors at two-digit classification codes (NACE). Products are defined at a nine-digit level, each one corresponding to an industrial product. Further details on data construction are contained in Appendix A.2.

On average, 12 per cent of the sample corresponds to single-product firms. Furthermore, nearly one third of the sampled firms produces only one or two products and the median firm produces up to three products. About one third of the sampled firms produces five or more products.

Table 2: Sample size by year.

Year	Number of products				
	1	2	3	4	5+
2004	3,081	4,574	3,057	2,240	9,234
2005	3,402	4,952	3,237	2,432	9,328
2006	3,341	4,754	3,135	2,412	9,148
2007	3,188	4,634	3,042	2,376	9,020
2008	3,025	4,196	2,820	2,220	8,761
2009	3,084	4,190	2,802	2,164	8,282
2010	3,023	3,984	2,826	2,272	8,090
2011	2,814	3,740	2,646	2,008	7,417
2012	5,521	11,286	11,004	10,072	15,553
2013	3,699	11,426	14,550	4,896	15,771
2014	3,879	11,430	12,057	11,460	11,673

Notes: Number of observations (firms) by year and number of products produced.
Source: IAPI.

Multi production is heterogenous across sectors. Almost half of the firms in the Other Manufacturing Activities sector are single-product and three quarters of them produce one or two products. Manufacture of motor vehicles, fabricated metals, basic metals, food, and paper pulp also exhibit a large concentration of firms that produce either one or two goods. On the other hand, the median firm in the manufacture of apparel and chemicals sectors produce five or more products.

6.2 Production function

Table 4 contains a summary of the estimation results for Equation 16. For the translog specification the estimated elasticities ($\widehat{\eta_t^{F_m}}$, $\widehat{\eta_t^{F_\ell}}$, and $\widehat{\eta_t^{F_k}}$) are not constant, so we report their average and standard deviation (s.d.)[20]. The complete set of parameter estimates and standard errors are reported in Tables A.5 and A.6 in the Appendix. The main concern with the translog specification is the unrestricted production elasticities which sometimes produce negative point estimates. Thus, we also report the estimates using a Cobb-Douglas production function (i.e. im-

[20]Note that the standard deviation is not to be confused with the standard error of the parameter estimates.

Table 3: Sample size by sector.

Industry	1	2	3	4	5+
	Number of Products				
Apparel	1,933	1,956	6,489	5,012	33,570
Basic Metals	547	634	381	384	533
Beverages	718	1,002	1,440	4,860	5,153
Chemicals	514	800	1,056	1,176	4,707
Electrical Equip.	799	1,152	804	660	1,191
Fabr. Metal Products	8,348	12,768	4,650	2,852	6,467
Food	4,629	27,240	4,224	4,984	20,426
Furniture	2,595	2,976	6,291	6,588	11,639
Leather Products	1,840	2,412	6,006	1,000	1,314
Machinery	1,931	2,142	1,800	1,236	3,952
Other Manufact. Activities	1,626	1,098	387	252	316
Motor Vehicles	815	686	399	824	150
Other Non-Met. Minerals	4,360	3,790	8,556	5,200	2,977
Paper and Pulp	689	1,776	459	384	625
Printing	820	684	3,858	2,444	3,780
Rubber and Plastics	1,512	1,586	1,068	1,268	2,451
Textiles	2,464	1,874	1,854	1,676	6,130
Wood Products	1,917	4,590	11,454	3,752	6,896

Notes: Number of product-year observations by sector, and number of products produced. Source: IAPI.

posing $\beta_{x_1x_2} = 0$ for $x_1, x_2 \in \{k, \ell, m\}$) and evaluate the sensitivity of our results to the specification.

We conclude the following. First, with the exception of Other Manufacturing Activities (sector 32), the remaining sectors exhibit returns to scale (RtS) that are close to constant. Second, capital elasticities tend to be smaller than labor elasticities (beverages and apparel are the exceptions), while materials elasticities are usually the largest. Third, the Cobb-Douglas specification appears to provide a good approximation. The two specifications not only produce similar elasticities, average in the case of the translog and constant ones in the case of the Cobb-Douglas, but also produce very similar estimates for TFP - see Figures A.1 and A.2 in the Appendix.

Table 4: GMM estimates for the production function in Equation 16 by sector.

	Sector	Translog elasticities								Cobb-Douglas elasticities			
		Materials		Labor		Capital		RtS		Materials	Labor	Capital	RtS
		Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.				
10	Food	0.51	0.10	0.17	0.05	0.14	0.08	0.82	0.02	0.70	0.17	0.11	0.98
11	Beverages	0.56	0.16	0.13	0.12	0.43	0.12	1.11	0.27	0.30	0.10	0.32	0.72
13	Textiles	0.72	0.20	0.22	0.08	0.11	0.12	1.04	0.07	0.48	0.31	0.08	0.87
14	Apparel	0.61	0.16	0.12	0.19	0.30	0.12	1.03	0.11	0.45	0.29	0.31	1.05
15	Leather Products	0.72	0.21	0.28	0.15	0.03	0.03	1.03	0.04	0.77	0.14	0.04	0.96
16	Wood Products	0.78	0.17	0.23	0.11	0.08	0.10	1.10	0.05	0.65	0.26	0.11	1.02
17	Paper and Pulp	0.68	0.08	0.16	0.08	0.07	0.06	0.91	0.07	0.79	0.11	0.05	0.95
18	Printing	0.80	0.23	0.20	0.13	0.13	0.21	1.14	0.09	0.56	0.24	0.25	1.04
20	Chemicals	0.74	0.18	0.23	0.10	-0.06	0.09	0.91	0.08	0.31	0.48	0.13	0.92
22	Rubber and Plastics	0.63	0.05	0.28	0.06	0.11	0.05	1.02	0.04	0.64	0.24	0.11	0.99
23	Other Non-Met. Minerals	0.62	0.16	0.32	0.19	0.12	0.08	1.06	0.12	0.65	0.27	0.08	1.00
24	Basic Metals	0.57	0.27	0.26	0.14	0.16	0.22	0.99	0.11	0.55	0.20	0.11	0.86
25	Fabr. Metal Products	0.69	0.06	0.24	0.09	0.04	0.05	0.97	0.03	0.72	0.20	0.04	0.96
27	Eletric. Equipment	0.70	0.07	0.23	0.16	0.05	0.07	0.97	0.08	0.73	0.25	0.02	1.00
28	Machinery	0.73	0.09	0.22	0.14	0.07	0.08	1.02	0.02	0.72	0.22	0.05	0.99
29	Motor Vehicles	0.62	0.20	0.14	0.06	0.14	0.15	0.90	0.09	0.77	0.04	0.08	0.88
31	Furniture	0.61	0.22	0.41	0.35	0.07	0.08	1.09	0.11	0.75	0.25	0.04	1.04
32	Other Manuf. Activities	0.45	0.05	0.22	0.04	0.03	0.03	0.71	0.02	0.38	0.28	0.03	0.69

Notes: Mean and standard deviation (s.d.) of the estimated translog elasticities. Cobb-Douglas specification also reported for comparison. Estimation method: GMM. Instrument set: current levels of labor and capital (their squares and product); lagged levels of capital, labor, materials, prices, and industry prices (their squares and products), real GDP, unit-product dummies, and the probability of remaining single-product. The probability of remaining single product is an estimated Probit on product and industry prices, real GDP and all inputs (their squares and products). RtS is sum of the input elasticities: a value larger/equal/smaller than one indicates increasing/constant/decreasing returns to scale.

6.3 The demand function

Figure 3 plots the estimated demand curves for the nested-homothetic specification in Equation 9 and Table 5 contains the estimated own-price elasticities (η^{q_p}). Because the log-cubic approximation for function $d(\cdot)$ produces varying own-price elasticities, we report their mean and standard deviation in Table 5, while a log-linear specification is also reported for robustness. Tables A.7 and A.8 in the Appendix document the full set of estimated coefficients and significance levels for the log-cubic and log-linear specifications, respectively. Average own-price elasticities are estimated in the range -1 to -4 and are similar in the linear and the cubic case. There is also little evidence of non-constant elasticities, as suggested by Figure 3.

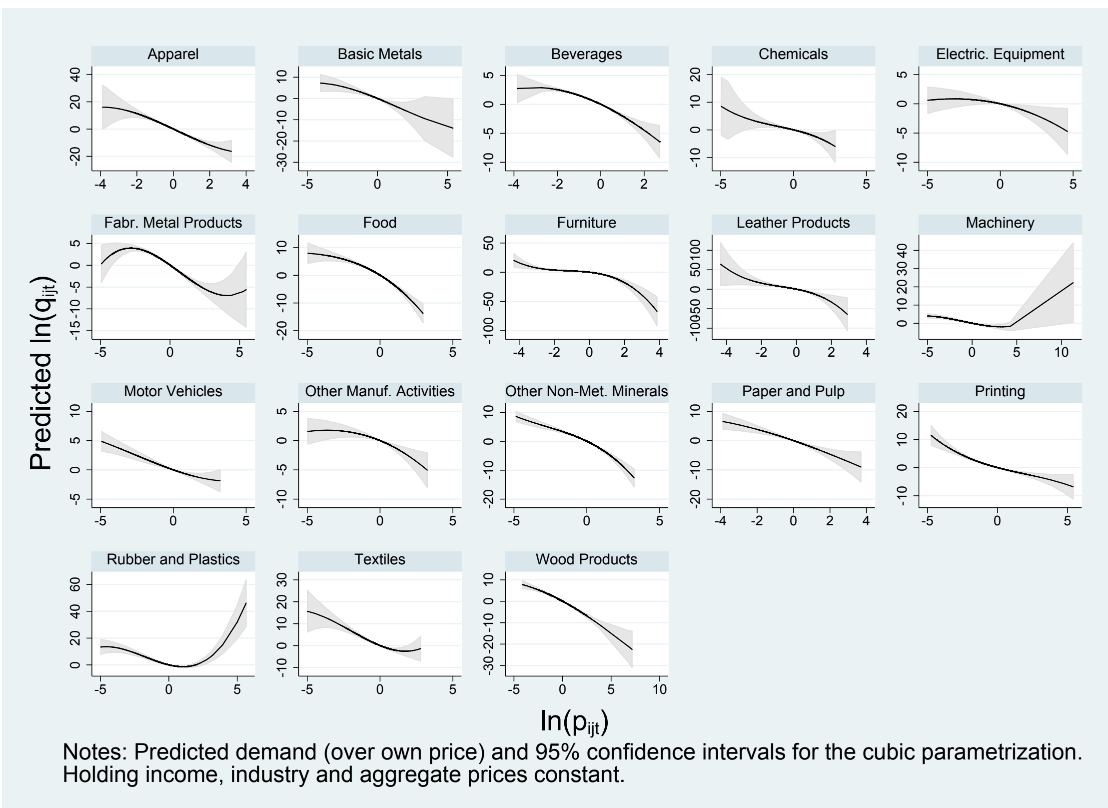


Figure 3: Estimated demand functions bysector

To further evaluate the robustness of our estimates, we also estimate a simple static model, assuming that the demand level is serially uncorrelated over time,

Table 5: Estimated demand own-price elasticities (η^{q_p})

	Sector	Cubic	Linear	LDV	Static
10	Food	-3.15	-3.03	-3.33	-0.11
		(0.39)	-	(0.38)	(0.32)
11	Beverages	-1.63	-1.46	-1.59	-0.94
		(0.34)	-	(0.43)	(0.46)
13	Textiles	-2.75	-2.93	-2.88	-0.86
		(0.53)	-	(0.45)	(0.45)
14	Apparel	-6.15	-6.15	-6.07	0.60
		(0.27)	-	(0.35)	(0.47)
15	Leather Products	-9.04	-8.61	-8.96	-0.40
		(1.72)	-	(1.71)	(0.20)
16	Wood Products	-2.41	-2.78	-2.97	-0.79
		(0.16)	-	(0.08)	(0.26)
17	Paper and Pulp	-2.12	-2.58	-1.79	-1.00
		(0.12)	-	(0.09)	(0.47)
18	Printing	-1.52	-1.53	-1.85	-0.54
		(0.33)	-	(0.34)	(0.26)
20	Chemicals	-1.34	-1.30	-2.21	-0.81
		(0.24)	-	(0.44)	(0.45)
22	Rubber and Plastics	-2.34	-1.77	-1.57	-0.60
		(1.48)	-	(1.40)	(0.33)
23	Other Non-Met. Minerals	-2.33	-2.30	-2.51	-0.86
		(0.40)	-	(0.29)	(0.19)
24	Basic Metals	-2.66	-2.05	-2.53	-0.92
		(0.20)	-	(0.21)	(0.47)
25	Fabr. Metal Products	-2.03	-2.17	-2.38	-0.66
		(0.67)	-	(0.63)	(0.30)
27	Eletric. Equipment	-0.48	-0.37	-0.65	-0.77
		(0.20)	-	(0.23)	(0.29)
28	Machinery	-0.92	-0.91	-0.91	-0.42
		(0.22)	-	(0.21)	(0.26)
29	Motor Vehicles	-0.92	-0.90	-1.03	-0.60
		(0.09)	-	(0.10)	(0.78)
31	Furniture	-3.17	-2.67	-2.90	-0.79
		(2.33)	-	(0.88)	(0.07)
32	Other Manuf. Activities	-0.96	-0.73	-1.46	-0.93
		(0.27)	-	(0.57)	(0.37)

Notes: Estimated demand elasticities: mean and s.d. (in brackets). Cubic, linear, LDV, and static specifications. LDV allows for persistence in addition to serial dependence.

i.e. $\Lambda(\epsilon_{t-1}) = 0$. Additionally, we consider a more general model, where besides the serially correlated (Markov) demand level (ϵ) we also allow for separate effects from the lagged dependent variable (LDV), i.e. true dependence. The results are displayed in the last two columns of Table 5. First, adding true dependence does not produce substantial changes to the estimated elasticities. This is due to the fact that the estimated effects from the LDV are small in magnitude. Second, the static model produces small own-price elasticities, in most cases smaller than one. This is due to the existence of strong observed persistence (serial correlation) in the demand level. By ignoring this persistence, we under-estimate price sensitivity due to the fact that a given price change will produce a much smaller response of sales, as most of sales are somehow pre-determined by the serially correlated demand level. In a static setting, it thus seems that sales are irresponsive to prices, where this irresponsive nature is due to the dynamic (persistent) element.

6.4 Markup measures and distribution

Having estimated the production function we can go back to our measure of markups in Equation 6. Then, using the observable shares, we can assess the relative performance of markup measures using materials and labor. If both labor and materials are fully flexible, the following equality holds:

$$\mu_t = \frac{\eta_t^{F_m}}{s_t^m} = \frac{\eta_t^{F_\ell}}{s_t^\ell}.$$

Thus, we would expect markups in Figure A.5 to sit on the 45^o line (or on some other line passing through the origin, in case the estimated elasticities were biased). We actually observe a negative relationship, suggesting some form of departure from equality. One of the several cases that can generate this departure is the existence of a labor wedge, as found in recent literature - see Bils et al. (2018).

Using materials for measuring markups properly, we find that they exhibit a substantial heterogeneity in the product-firm-year space in all eighteen industries considered. Figure A.3 in the Appendix, reports markup distributions using both our baseline translog specification with varying elasticities and constant elasticities from the Cobb-Douglas specification. In general, distributions are skewed to the right with many small markups and a heavy tail of large markups[21].

Figure A.4, also in the Appendix, reports the distribution of markups for single-product firms, for which the left tail disappears. This is particularly noticeable in sectors such as leather, basic metals, food or furniture, that actually exhibit multi-peaked distributions for all product-firm-year observations with the first peak vanishing once we only consider single-product firms.

7 Markups

In this section we gather the main results of the article. We show that markups are pro-cyclical with TFP and counter-cyclical with demand shocks, and we also demonstrate that this result is robust to both the presence of multi-production and to alternative demand function specifications. Finally, we go back to the decomposition in section 4 and disaggregate TFP and demand shocks into price *vs.* quantity and aggregate *vs.* idiosyncratic effects.

7.1 The cyclical behavior of markups

In Table 6, we evaluate the response of markups, prices, and sales to the TFP (ψ^a) and demand (ψ^ϵ) shocks estimated in the previous section. To control for potential biases, we also include firm-product fixed effects as well as input-quality shock ($\Delta\chi$) in the regressions. Overall, markups exhibit a positive response to supply shocks and a negative response to demand shocks. Changes in quality are also positively correlated with markups.

We can quantify the responses: a 10 per cent demand shock is predicted to increase prices by 0.2 per cent and sales by 5.7 per cent, while decreasing markups by 0.6 percentage points; a positive 10 per cent TFP shock is predicted to reduce prices by 0.2 per cent and to increase sales by 0.9 per cent, while increasing markups by 10.6 percentage points. In a nutshell, a positive TFP shock passes through as slightly lower prices, with the companies retaining the lower cost as a larger markup. On the other hand, a positive demand shock leads to a modest increase in prices and a reasonable expansion in sales; however, short-run production restrictions lead

[21] Very small markups (less than 1) are either explained by multi-product firms setting small markups for some of its products or by uncertainty around point estimates for the elasticities.

to an increase in marginal costs, which explains the observed decrease in markups. Overall, both demand and TFP shocks lead mostly to a response in sales, with prices remaining relatively irresponsive. Table A.9 in the Appendix shows that the effects are robust across sectors, with the exceptions being the printing and the furniture sectors, for which markups exhibit no statistically significant cyclicality.

The results can be interpreted in light of the analysis in section 4. First, prices increase with demand shocks and decrease with supply shocks. This is consistent with having $P_q Q_\epsilon + P_\epsilon > 0$ and $P_q Q_a < 0$. The second result is as expected, with a positive supply shock moving prices downward along the demand curve. However, a demand shock would have *a priori* an ambiguous effect, as it exhibits a positive direct effect on prices, but a negative indirect effect by increasing output (there is an upward shift in the demand schedule and downward slide caused by the expansion in quantity). Our result implies that the direct effect dominates.

Second, quantities sold (sales) are positively correlated with both supply and demand shocks, and are consistent with $Q_\epsilon > 0$ and $Q_a < 0$. Again, this is expected with standard slopes for the two above-mentioned curves.

As we can see, markups increase with supply shocks and decrease with demand shocks, consistent with $\mu_a > 0$ and $\mu_\epsilon < 0$. An increase in TFP pushes marginal costs down ($C_a < 0$) and this translates into a lower price. Results suggest that part of the lower marginal cost is absorbed by the company as a larger markup, at least in the short run[22]. Referring to Equation 2, the positive direct effect of a supply shock ($\mathcal{M}_a > 0$) dominates the negative indirect effect ($\mathcal{M}_q Q_a < 0$).

Finally, a shift in demand is associated with an increase in both prices and sales. As sales increase, so do marginal costs. The results suggest that the increase in marginal costs is stronger than the increase in prices, implying that the indirect effect ($\mathcal{M}_q Q_\epsilon < 0$) dominates the direct effect ($\mathcal{M}_\epsilon > 0$) in Equation 3.

Summing up, the results are consistent with relatively large values of Q_ϵ and C_a and relatively small values of P_ϵ. Before presenting the quantitative decomposition of these effects in section 7.3, we first provide a series of robustness checks.

[22]This is consistent with DeLoecker et al. (2016).

Table 6: Response to shocks

Model:	Cubic			Linear		
	$\Delta\mu_{ijt}$	$\Delta\ln p_{ijt}$	$\Delta\ln q_{ijt}$	$\Delta\mu_{ijt}$	$\Delta\ln p_{ijt}$	$\Delta\ln q_{ijt}$
TFP	1.064***	-0.0229***	0.0919***	1.059***	-0.0235***	0.0901***
shock	(0.00921)	(0.00128)	(0.00365)	(0.00916)	(0.00131)	(0.00357)
Demand	-0.0645***	0.0187***	0.573***	-0.0700***	0.0183***	0.584***
shock	(0.00354)	(0.000944)	(0.00371)	(0.00352)	(0.000918)	(0.00358)
Quality	1.777***	0.838***	-1.594***	1.769***	0.846***	-1.510***
shock	(0.0191)	(0.00423)	(0.0127)	(0.0185)	(0.00404)	(0.0121)
Observations	183,393	202,790	202,006	184,062	203,663	202,886
R^2	0.389	0.859	0.587	0.389	0.857	0.599
No. of firm-prod.	57,370	60,447	60,349	57,460	60,546	60,449

Model:	LDV			Static		
	$\Delta\mu_{ijt}$	$\Delta\ln p_{ijt}$	$\Delta\ln q_{ijt}$	$\Delta\mu_{ijt}$	$\Delta\ln p_{ijt}$	$\Delta\ln q_{ijt}$
TFP	1.090***	-0.0207***	0.0796***	1.058***	-0.0183***	0.0124***
shock	(0.00951)	(0.00128)	(0.00364)	(0.00875)	(0.00123)	(0.00113)
Demand	-0.0789***	0.0155***	0.561***	-0.167***	-0.0187***	0.972***
shock	(0.00368)	(0.000950)	(0.00358)	(0.00407)	(0.000950)	(0.000874)
Quality	1.917***	0.864***	-1.732***	1.664***	0.877***	-1.058***
shock	(0.0211)	(0.00449)	(0.0132)	(0.0148)	(0.00305)	(0.00312)
Observations	180,882	199,943	199,108	186,901	206,974	206,541
R^2	0.395	0.855	0.585	0.396	0.865	0.959
No. of firm-prod.	57,130	60,181	60,060	57,815	60,957	60,913

Notes: Regression results with fixed firm-product effects. Clustered std. errors in brackets. Cubic, linear, LDV, and static specifications. LDV allows for persistence in addition to serial dependence. Significance: *** 1%, ** 5% and * 10%.

7.2 Robustness checks

7.2.1 Alternative demand specifications

The qualitative results in the previous section are robust to a series of different specifications for the demand function. In Table 5, we reported how estimated elasticities varied in four different models: (i) cubic approximation (baseline), (ii) linear approximation, (iii) LDV (true dependence), and (iv) static demand. In Table 6 we display the response of markups, prices, and quantities to the demand shocks, estimated with the four different specifications. Overall, the numbers are very similar in the cubic, linear, and true-dependence cases, with the markup coefficient hovering between 1.05 and 1.09 for TFP shocks and between -0.065 and -0.079 for demand shocks.

However, a significant difference emerges if we use a static demand model. In this case, markup responses are much stronger, increasing to -0.17 for demand shocks, thus becoming more counter-cyclical with demand shocks. Price and sales response coefficients are also larger, becoming negative for prices. The stronger cyclicality of markups is due to the misspecification of the demand shock. In the static setting, we have seen that estimated demand curves are inelastic. This means that we obtain much smaller quantity responses to price changes and we underestimate demand shocks. For instance, the standard deviation of demand shocks is 1.14 in our baseline case and 0.70 in the static case. The smaller volatility of demand shocks in the static case, results in overestimating their effect on the markups.

7.2.2 Does the number of products matter?

The qualitative results in the previous subsection refer to averages across single- and multi-product firms. Table 7 contains the results obtained from splitting the sample by the number of products. By comparing it with Table 6, we readily observe that, although the qualitative responses of markups, prices, and quantities do not change, both for TFP and demand shocks, there is a substantial heterogeneity in the estimates: the markup coefficients estimates for single-product firms are 0.86 for TFP and -0.09 for demand shocks and they are 1.04 and -0.03 for firms producing 5 of more goods. The effects on markups are stronger for single-product firms and become weaker as firms produce more products. The effects on prices and quantities depend on the origin of the shocks: for TFP shocks, multi-product firms increase sales and reduce prices by less; for demand shocks, multi-product firms increase prices by less and sales by more. Consequently, markups tend to be more counter-cyclical with demand shocks for firms producing one or two goods and they are less counter-cyclical for firms that produce five or more goods. Furthermore, markups seem to become more pro-cyclical with TFP shocks for multi-product firms, but this pattern is much less clear and the discrepancy is not as large as in the demand shock.

Finally, Table A.10 in the Appendix shows that the heterogeneity remains when we control for size, measured as the logarithm of employment. Thus, reduced cyclicality in the response to shocks for multi-product firms is not purely driven by size (economies of scale), as economies of scope explain part of the firms' response to shocks.[23] Since both prices and quantities react similarly for single- and multi-product firms, the less responsive markups points to a larger flexibility from multi-product firms on the marginal-cost side, suggesting that multi-product firms can adjust production by reallocating productive capacity across goods[24], rather than changing its market power.

7.2.3 Labor-based markup and revenue-based TFP shocks

One question remains. How important are the corrections? In order to answer this, we compare our results to those obtained by using a revenue–based measure of TFP or by using a labor-based markup measure, as commonly found in the literature.

First, we start by using the alternative revenue-based TFP (TFPy) to obtain the TFP shocks. We use the estimated coefficients from the Cobb-Douglas production function reported in Table 4 and construct TFPy using revenues instead of quantity. This way we only change one element, the use of revenues to calculate TFP, while we hold fixed the potential differences originated by different production function elasticities. As reported in Table 8, when we use revenues instead of quan-

[23] Hong (2017) reports size-related heterogeneity in unconditional cyclicality of markups with respect to GDP.

[24] Thus facing a flatter marginal cost.

Table 7: Response to shocks by number of products.

Dep.var.			$\Delta\mu_{ijt}$		
N. of products	1	2	3	4	5+
TFP shock	0.861***	1.384***	1.160***	0.921***	1.037***
	(0.0328)	(0.0225)	(0.0206)	(0.0165)	(0.0126)
Demand shock	-0.0885***	-0.152***	-0.105***	-0.0445***	-0.0332***
	(0.00941)	(0.00967)	(0.00936)	(0.00989)	(0.00503)
Quality shock	1.524***	2.576***	2.136***	1.431***	1.582***
	(0.0635)	(0.0499)	(0.0514)	(0.0293)	(0.0278)
Dep.var.			$\Delta\ln p_{ijt}$		
N. of products	1	2	3	4	5+
TFP shock	-0.101***	-0.0157***	-0.0186***	-0.0193***	-0.0108***
	(0.00810)	(0.00236)	(0.00252)	(0.00250)	(0.00162)
Demand shock	0.0303***	0.0145***	0.0179***	0.0287***	0.0106***
	(0.00328)	(0.00195)	(0.00210)	(0.00257)	(0.00145)
Quality shock	0.725***	0.899***	0.919***	0.714***	0.868***
	(0.0178)	(0.00697)	(0.00929)	(0.00745)	(0.00725)
Dep.var.			$\Delta\ln q_{ijt}$		
N. of products	1	2	3	4	5+
TFP shock	0.255***	0.102***	0.104***	0.0977***	0.0879***
	(0.0164)	(0.00747)	(0.00703)	(0.00662)	(0.00538)
Demand shock	0.354***	0.592***	0.614***	0.624***	0.608***
	(0.0118)	(0.00881)	(0.00812)	(0.00966)	(0.00576)
Quality shock	-0.925***	-1.711***	-1.587***	-1.185***	-1.991***
	(0.0396)	(0.0282)	(0.0260)	(0.0155)	(0.0265)
Observations	196,357				
N. of firm-products	59,146				

Notes: Regression results with fixed effects. Clustered std. errors in brackets (firm-product level). All variables truncated at +-3.
Significance: *** 1%, ** 5% and * 10%.

tities, (materials-based) markups are still pro-cyclical with TFP shocks, but their sensitivity is reduced. Furthermore, we can see that using TFPy makes markups acyclical with demand shocks, i.e. counter-cyclicality disappears. Moreover, prices and output also become less responsive, which is in line with the findings of Foster et al. (2008). This result is explained by the fact that TFPy shocks are not purged from the demand-shock component, thus generating a downward bias to both sensitivities: to demand and the true TFP shocks.

Finally, when markups are calculated using the labor share, our preliminary results in Table 1 and Figure 1 suggested a GDP (unconditional) cyclicality with the opposite pattern to that of materials-based markups. Again, Table 8 reveals a pro-cyclical (conditional) response of markups to demand shocks, together with a much smaller sensitivity to the TFP(q) shocks. This outcome is again explained by the distortions to the labor share, pushing it away from its optimal level.

7.3 Decomposing effects

7.3.1 Price and quantity effects

We now return to the reduced-form effects of demand and supply shocks on markups from section 4 to decompose them into the "quasi-structural" (individual) elements on prices and quantities based on Equations 2 and 3:

$$\eta^{\mu_\epsilon} = \bar{\eta}^{p_\epsilon} - \eta^{C_q}\eta^{Q_\epsilon} \ , \tag{19}$$

$$\eta^{\mu_a} = \bar{\eta}^{p_a} - \eta^{C_q}\eta^{Q_a} - \eta^{C_a}, \tag{20}$$

where $\bar{\eta}^{p_\epsilon} = \left(P_q Q_\epsilon + P_\epsilon\right)\frac{\epsilon}{P}$ represents a "total" elasticity of prices with respect to demand shocks, including both the direct and the indirect effects, and $\bar{\eta}^{p_a} = \eta^{P_q}\eta^{Q_a}$ is the "total" elasticity of prices with respect to TFP shocks, operating through the sales channel. We label this decomposition as "quasi-structural" since we do not have a model for the relation between the individual shocks and both prices, and quantities. This is not by chance, but because we want to avoid the formulation of optimal pricing[25]. Dealing with optimal pricing requires introducing several

[25] Remember we only use cost minimization to obtain the markup measure.

Table 8: Responses to shocks using TFPy and the labor-based markup.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
	TFPy	TFPq	TFPq	TFPy	TFPq	TFPy	TFPq
Dep. Variable	$\Delta\mu_{ijt}^{m}$		$\Delta\mu_{ijt}^{\ell}$	$\Delta \ln p_{ijt}$		$\Delta \ln q_{ijt}$	
TFP	0.620***	1.064***	0.129***	0.000257	-0.0229***	0.0551***	0.0919***
shock	(0.0106)	(0.00921)	(0.00419)	(0.00115)	(0.00128)	(0.00497)	(0.00365)
Demand	0.00581	-0.0645***	0.0534***	0.0164***	0.0187***	0.575***	0.573***
shock	(0.00376)	(0.00354)	(0.00273)	(0.000977)	(0.000944)	(0.00377)	(0.00371)
Quality	0.838***	1.777***	-0.0886***	0.863***	0.838***	-1.664***	-1.594***
shock	(0.0126)	(0.0191)	(0.00761)	(0.00408)	(0.00423)	(0.0123)	(0.0127)
Observations	182,308	183,393	197,528	201,876	202,790	201,076	202,006
R^2	0.145	0.389	0.027	0.856	0.859	0.584	0.587
No. of firm-prod.	56,727	57,370	58,926	59,754	60,447	59,658	60,349

Notes: Regression results with fixed firm-product effects. Clustered std. errors in brackets. Columns (ii), (v) and (vii) denoted "TFPq" report the baseline results in Table 6; columns (i), (iv), and (vi) denoted "TFPy" uses TFP shocks obtained from the revenue-based production function, and column (iii) uses the labor-based markup as dependend variable. $\Delta\mu_{ijt}^{x}$ with $x = m, \ell$ denotes respectively the materials- or labor-based markup. Significance: *** 1%, ** 5% and * 10%.

additional assumptions to rationalize the observed pricing responses. For example, dynamic pricing considerations, or potential frictions on optimal static pricing, that make optimal prices depart from simple inverse elasticity rules, which is not the aim of this article. Yet, the "quasi-structural" decomposition lets us isolate each of the individual effects on prices and sales and understand if (and how) they "add up" to the overall estimated effect on the markup.

The individual elements in Equations 19 and 20 are obtained from Table 6 - the estimated elasticities that represent overall (direct and indirect) effects of demand shocks on prices ($\bar{\eta}^{p_\epsilon}$) and quantities (η^{Q_ϵ}), and also those of supply shocks on prices ($\bar{\eta}^{p_a}$) and quantities (η^{Q_a}). We also obtain the estimated overall (direct) effects ($\widehat{\mu\eta^{\mu_\epsilon}}$ and $\widehat{\mu\eta^{\mu_a}}$). The remaining two cost parameters we estimate by simple regression $\widehat{\eta^{C_q}} = 0.165$, and $\widehat{\eta^{C_a}} = -0.821$.

Table 9 reports the decomposition. Using the individual estimates together with Equations 19 and 20 we construct the predicted effects on the markups ($\widetilde{\mu\eta^{\mu_\varepsilon}}$ and $\widetilde{\mu\eta^{\mu_a}}$), which can be compared to the estimated values ($\widehat{\mu\eta^{\mu_\epsilon}}$ and $\widehat{\mu\eta^{\mu_a}}$). This is possible since we have one degree of freedom that does not require us to assume optimal pricing and impose Equations 19 and 20 on the data. Overall, the constructed effects ($\widetilde{\mu\eta^{\mu_\varepsilon}}$ and $\widetilde{\mu\eta^{\mu_a}}$) are similar (add up to) the estimated effects ($\widehat{\mu\eta^{\mu_\epsilon}}$ and $\widehat{\mu\eta^{\mu_a}}$). These results rationalize our findings: in general, output is sensitive to both supply and demand shocks, while prices are less responsive. Together with the fact that marginal-cost curves are increasing in sales, both results imply that a positive TFP shock generates direct efficiency gains (lower marginal costs) that outweigth the indirect cost increase and price reductions, so that markups increase. On the other hand, a positive demand shock generates a cost increase (output rises) that is much stronger than the corresponding price increase, so that markups decrease.

Table 9: Effect decomposition.

	$\widehat{\mu\eta^{\mu_\epsilon}}$	$\widehat{\mu\eta^{\mu_a}}$	$\widetilde{\mu\eta^{\mu_\epsilon}}^1$	$\widetilde{\mu\eta^{\mu_a}}^2$	$\widehat{\bar\eta^{P_\epsilon}}$	$\widehat{\bar\eta^{P_a}}$	$\widehat{\eta^{Q_\epsilon}}$	$\widehat{\eta^{Q_a}}$
Estimates	-0.065	1.064	-0.096	0.994	0.019	-0.023	0.573	0.0919

Notes: ${}^1\widetilde{\mu\eta^{\mu_\epsilon}} = \bar\mu(\widehat{\bar\eta^{P_\epsilon}} - \widehat{\eta^{C_q}}\widehat{\eta^{Q_\epsilon}})$, and
${}^2\widetilde{\mu\eta^{\mu_a}} = \hat\mu(\widehat{\bar\eta^{P_a}} - \widehat{\eta^{C_q}}\widehat{\eta^{Q_a}} - \widehat{\eta^{C_a}})$. $\bar\mu = 1.247$, $\widehat{\eta^{C_q}} = 0.165$, and $\widehat{\eta^{C_a}} = -0.821$.

7.3.2 Aggregate and idiosyncratic shocks

Our final exercise reconciles the micro results with the macro evidence reported in Figure 1. To do this we decompose the shocks into three components: a firm-product specific component (ψ^{ϵ}_{ij}), a year component (ψ^{ϵ}_{t}), and finally an idiosyncratic time-varying residual ($\tilde{\psi}^{\epsilon}_{ijt}$):

$$\psi^{\epsilon}_{ijt} = \psi^{\epsilon}_{ij} + \psi^{\epsilon}_{t} + \tilde{\psi}^{\epsilon}_{ijt} \; .$$

We repeat the same exercise for the quality and the TFP shocks. The results are reported in Table 10 where the shocks are separated into their aggregate and the idiosyncratic components (regressions already include product-firm fixed effects). While markups are counter-cyclical with both aggregate and idiosyncratic demand shocks, the magnitude is larger for the aggregate component. An aggregate-demand shock generates a response of markups and output, which are more than four times the size of a similar idiosyncratic shock. The size of quantity responses is roughly the triple while price responses actually become negative. Furthermore, markups have a similar pro-cyclicality either with aggregate or with product-firm TFP shocks.

The macro implications of our results are as follows. First, considering that markups are counter-cyclical with aggregate demand shocks, a fiscal[26] (expenditure) expansion can help stabilize the economy by generating an efficiency gain, as it reduces markups by inducing more competition amongst producers. When we look at the 2012-4 period for the Portuguese economy, our results imply that the strong demand shock induced by the Eurozone sovereign crisis, leading to the bailout program, induced a recession and the consequent increase in markups. Furthermore, the fiscal-consolidation program negotiated with the European Commission, European Central Bank, and the International Monetary Fund added to the negative demand shock leading to less competition and higher markups on the supply side. This further aggravated the recession.

[26] In the Portuguese case, it makes no sense to extend this argument to monetary policy, but that could be done for other economies with a similar cyclical pattern.

Table 10: Markups' response to shocks: decomposition of idiosyncratic and aggregate components.

		$\Delta\mu_{ijt}$	Δp_{ijt}	Δq_{ijt}
Demand shock	Aggregate ψ_t^{ϵ}	-0.323***	-0.0384***	1.625***
		(0.0512)	(0.00882)	(0.0320)
	Idiosyncratic $\tilde{\psi}_{ijt}^{\epsilon}$	-0.0692***	0.0216***	0.570***
		(0.00370)	(0.000954)	(0.00375)
TFP shock	Aggregate ψ_t^{a}	0.842***	0.00762	-0.612***
		(0.0449)	(0.00721)	(0.0270)
	Idiosyncratic $\tilde{\psi}_{ijt}^{a}$	1.072***	-0.0223***	0.0829***
		(0.00988)	(0.00121)	(0.00343)
Quality growth	Aggregate ψ_t^{χ}	1.043***	1.071***	-5.792***
		(0.173)	(0.0263)	(0.0998)
	Idiosyncratic $\tilde{\psi}_{ijt}^{\chi}$	1.817***	0.828***	-1.589***
		(0.0203)	(0.00412)	(0.0129)
Observations		182,479	201,586	201,418
R-squared		0.390	0.856	0.581
No. Firm-product		57,243	60,287	60,270

Notes: Regression results with fixed firm-product effects. Shocks decomposed into aggregate (t) and idiosyncratic (it) components. Clustered std. errors. Significance: *** 1%, ** 5% and * 10%.

8 Conclusion

Our objective has been to obtain a description for an aggregate behavior: how do markups respond to shocks? In order to answer such fundamental macroeconomic question, we use a rich and large firm–product database for a panel of Portuguese companies covering the period 2004-2014, a period during which the country faced two of the main crisis in the last 30 years - the 2008-2009 financial crisis and the 2010-2011 European sovereign debt crisis. The availability of product-level price information was central to our study, and allowed us to separate demand from supply. We combine the data with recent advances in the empirical analysis of market power using large sets of detailed microeconomic information, namely DeLoecker et al. (2016) and Foster et al. (2016).

We obtain a robust set of findings: markups are counter-cyclical with demand shocks in (nearly) all sectors, and they are pro-cyclical with productivity shocks. Our results are robust to alternative demand- and production-function specification and also controlling for size and quality. Furthermore, the cyclical response of markups to demand shocks is larger for aggregate than for idiosyncratic shocks. Finally, the effects of demand shocks tend to be smaller when the number of goods produced by firms increases, while the effects of supply shocks is similar across single- and multi-product firms. We believe the mechanism explaining the difference for multi-product firms is related with the flexibility of allocating inputs internally across different products, which is worth studying in future research. To do so one should obtain product-specific input data to test how inputs are allocated to products across single- and multi-product firms.

These results have important implications. They indicate that expansionary (contractionary) fiscal and monetary policy may benefit from a complementary efficiency externality, as they reduce (increase) markups in a recession. Furthermore, fiscal-consolidation programmes in a recessionary environment, as the one faced by Portugal in 2012-4, are likely to have induced an additional recessionary effect by increasing markups of surviving firms.

The approach used here can be easily replicated for other economies for which more detailed micro databases with price information become publicly available, especially those that also cover small- and medium-size firms.

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A Appendix - For Online Publication

A.1 Some additional theory

A.1.1 Sticky prices

In section 2 we assumed that prices were totally flexible. However, that may not be the case if firms face costs of adjusting their prices. If that is the case, this means that the reaction of prices to (current) production P_q is lower than in the flexible-price model.

One extreme case can be given by the menu-costs model. For small demand or productivity shocks, the optimal reaction of the firm is to keep the posted price (p_0)[27]. Therefore, we have $P_q = 0$ and $P_\epsilon = 0$.

As long as $p_0 > c$, production is demand driven, i.e. $p_0 = P(q, \epsilon) \Leftrightarrow q = Q(p_0, \epsilon)$. Thus, productivity shocks do not affect optimal production ($Q_a = 0$), but they still affect marginal costs.

Productivity shocks exhibit solely an unambiguous positive direct effect

$$\mu_a = -\frac{\mu C_a}{c} > 0 \ .$$

For demand shocks, we lose the direct effect and part of the indirect one, so we are left with an unambiguous negative indirect effect

$$\mu_\epsilon = -\frac{\mu C_q Q_\epsilon}{c} < 0 \ .$$

Other time- (e.g. Calvo (1983)) or state-dependent (e.g. Rotemberg (1982)) lie somewhere in between the flexible-price model and the fixed-price model above.

A.1.2 Utility-based demand function

Let us assume that the demand of good j produced by firm i can be well represented by the demand function of a representative consumer that maximizes her utility:

[27] For large shocks, the optimal pricing rule is the relevant one.

$$
\begin{aligned}
& \max_{\{q_{ij}\},q_{-j}} U(C) \\
s.t. \quad \sum_{i=1}^{n_j} p_{ij}\breve{q}_{ij} + p_{-j}\breve{q}_{-j} &= I^N \\
C &= \left(\breve{q}_j^{\frac{\theta-1}{\theta}} + \breve{q}_{-j}^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \\
\breve{q}_j &= \Omega\left(\breve{q}_{1j},...,\breve{q}_{ij},...,\breve{q}_{n_j j}\right) \ ,
\end{aligned}
$$

where $U(\cdot)$ is a utility function (with $U' > 0$ and $U'' < 0$), $\breve{q}$ are quality-adjusted quantities, and C is a CES basket of two goods: good j produced by n_j firms, each one producing a variety, and good $-j$.[28] Furthermore, I^N represents nominal income of this consumer, $\theta > 0$ is the elasticity of substitution between goods, and $\Omega(\cdot)$ is a homothetic basket of varieties of good j.

From the solution of the problem above, we obtain the true cost-of-living index for this consumer given by $\bar{p} = \left(\bar{p}_j^{1-\theta} + p_{-j}^{1-\theta}\right)^{\frac{1}{1-\theta}}$ and real income $\bar{g} \equiv I^N/\bar{p}$. Therefore, the overall demand for good j is represented by $\breve{q}_j = \left(\frac{\bar{p}_j}{\bar{p}}\right)^{-\theta}\bar{g}$. Furthermore, the demand for the variety produced by firm i is given by $\breve{q}_{ij} = D\left(\frac{p_{ij}}{\bar{p}_j}\right)\breve{q}_j$, with $D' < 0$ and the properties of $D(\cdot)$ depend upon $\Omega(\cdot)$. We also know that $\sum_{i=1}^{n_j} p_{ij}\breve{q}_{ij} = \bar{p}_j\Omega(\cdot)$, given the fact that $\Omega(\cdot)$ is homothetic.

The demand function to estimate includes a autonomous factor (λ_0), a free income elasticity (i.e. λ_2 may differ from one), a idiosyncratic shock (ϵ_{ij}), and implies that $\lambda_1 = -\theta$ and $d\left(\frac{p_{ij}}{\bar{p}_j}\right) = \ln D\left(\frac{p_{ij}}{\bar{p}_j}\right)$.

In order to control for unobserved product quality, let us simply assume that $\breve{q} = q\exp(\xi\nu)$, where ν stands for product quality, and parameter ξ is positive (negative) when quality is a q-substitute (complement) for quantity[29].

[28] Good $-j$ represents a basket of all the other goods in the economy.

[29] We use here a simplified model that can be seen as a reduced form for a more complex relationship between quantity and quality. See Nelson (1991), *inter alia*, for an example of substutability and discussion.

A.2 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 2004-2014. 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 hairdresser 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 hundred 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 1992-2014. The sample contains information on revenues and quantities sold at a very detailed 9 digit product level where each firm can produce multiple products (products go down to 12 digits but we use 9 digits). See the example for the Beverages sector in Table A.3. This consists of three separate sets of data for products sold, intermediate products consumed, and types of energy used.

A.2.1 Sample selection

Based on the availability of at least 30 observations per year in the IAPI. Table A.4 reports the selected sample of 2 digit sectors.

A.2.2 Data cleaning and construction

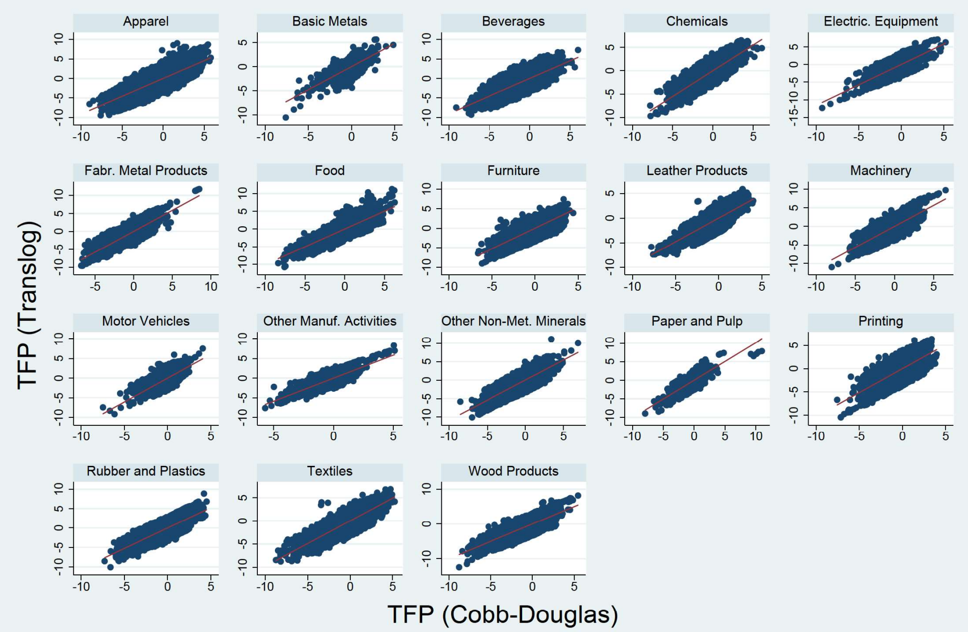
Prices are obtained from IAPI by dividing the product revenues by quantities sold. The obtained series is noisy and subject to outliers. To control for outliers the prices are winsorized at the top and bottom of the price distribution (cross section). Also, per firm prices are winsorized at the top and bottom 3% and log growth rates for prices are winsorized at $\pm 150\%$ for each sector. This treatment removes extreme variations in price levels. Price series are then reconstructed using the winsorized price variations and the base firm price level. We construct two aggregate prices, one at the product level and one aggregate price index. The average product level price is constructed using the weighted average of product level prices for each firm, where the weight is given by sales. For the aggregate price index we construct a weighted average of price changes (growth rates), where the weight is again given by the sales.

Physical output is constructed using the reported total revenues (from SCIE) multiplied by the share of revenues for each product (from IAPI) divided by the firm-product price. Employment is the employment level reported in number of workers. Intermediate inputs are constructed from reported cost of goods sold added with subcontracting, deflated by the previously constructed aggregate price index. The stock of capital is constructed using the perpetual inventory formula.

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

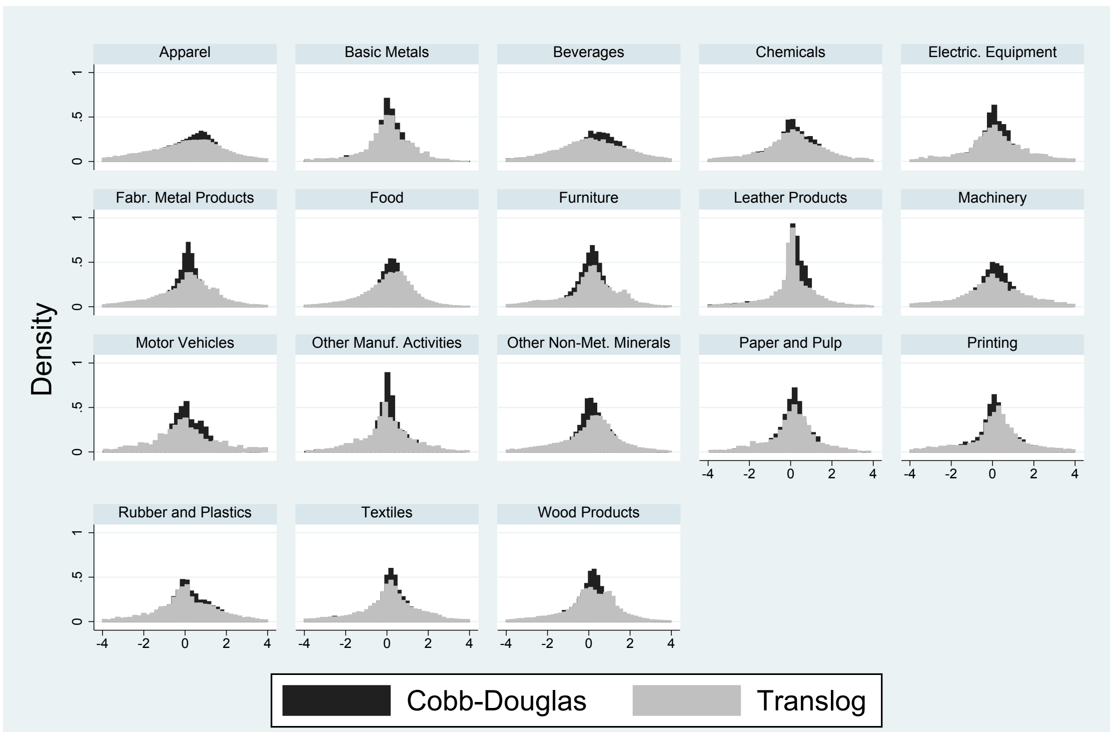
where δ is the rate of depreciation set to 0.05, k_{it} is the capital stock of firm i in period t and I_{it} is the investment of firm i in period t. All capital series are deflated using the capital deflator series obtained also from the Bank of Portugal´s statistics. The capital stock for the first 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).

A.3 Tables and Figures



Notes: Comparison of TFP estimates using a Cobb-Douglas and a Translog parametrization for the production function.

Figure A.1: Scatterplot of TFP for the Cobb-Douglas and Translog specifications.



Notes: Comparison of TFP estimates using a Cobb-Douglas and a Translog parametrization for the production function.

Figure A.2: Histogram of TFP for the Cobb-Douglas and Translog specifications.

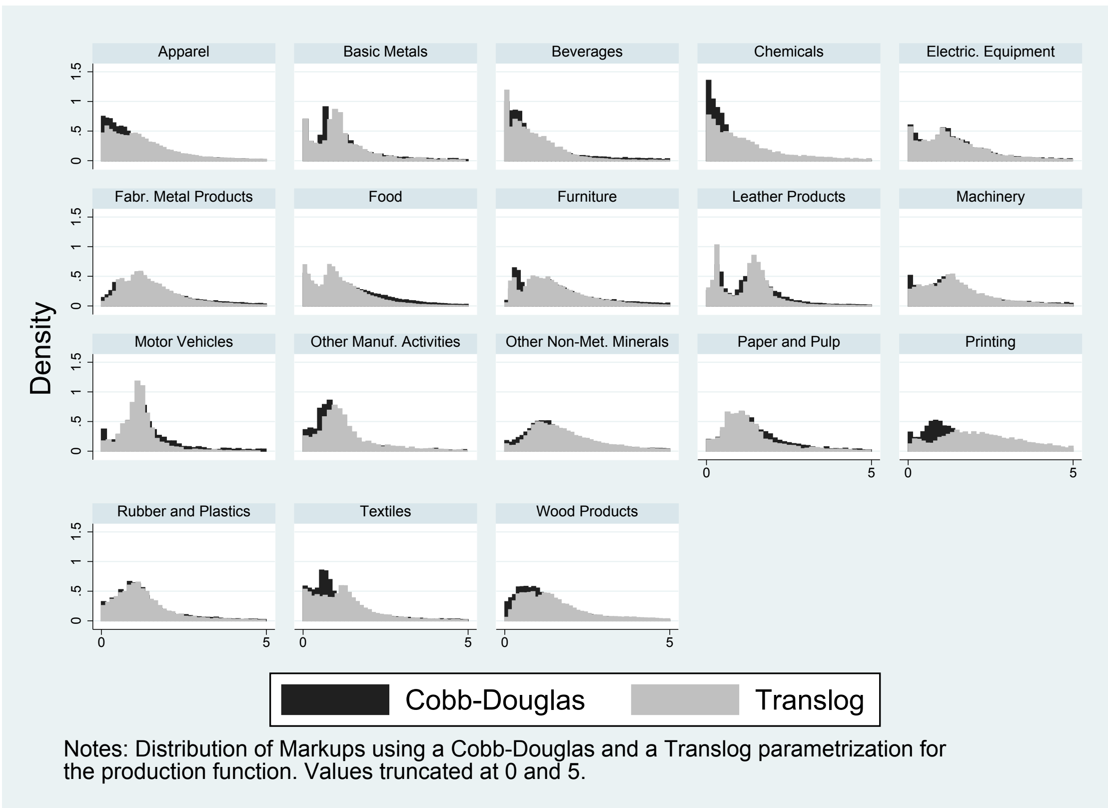


Figure A.3: Histogram of Markups for the Cobb-Douglas and Translog specifications.

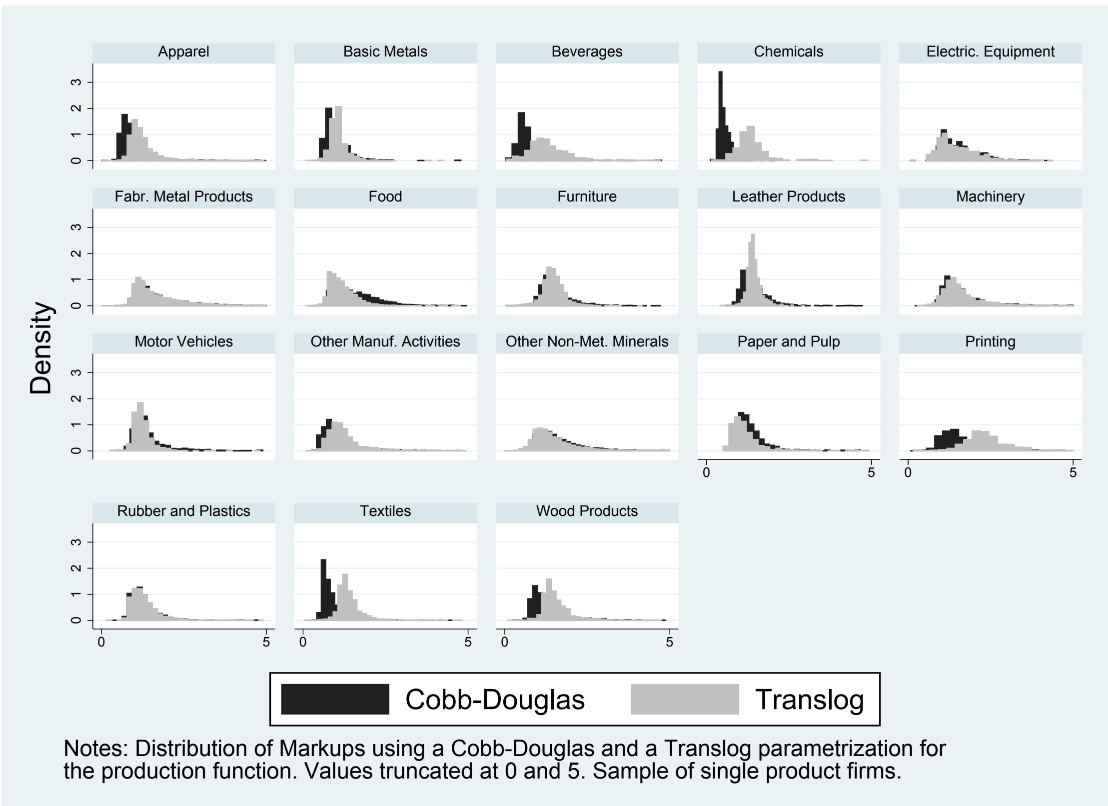


Figure A.4: Histogram of Markups for the Cobb-Douglas and Translog specifications for single product firms.

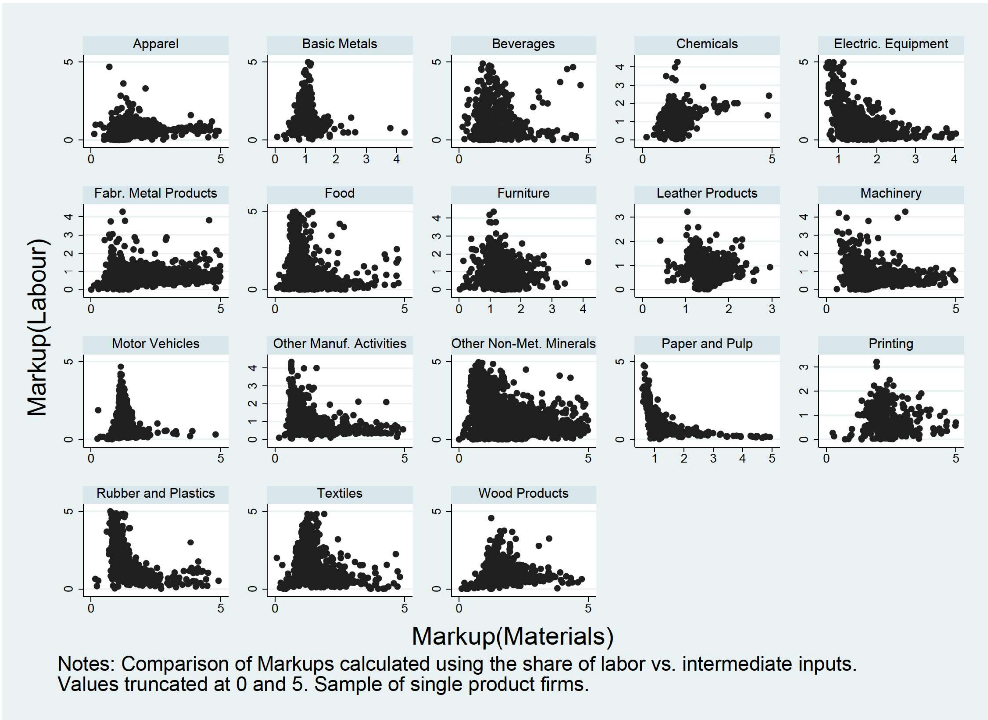


Figure A.5: Markup comparison (scatterplot): labor vs. materials.

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

Year	Firms
2004	349,764
2005	357,023
2006	367,597
2007	366,723
2008	370,970
2009	369,713
2010	360,767
2011	362,213
2012	381,220
2013	381,819
2014	387,437

Source: IES.

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

Year	Number of products					# firms	Total # observations
	1	2	3	4	5+		
2004	3,965	2,704	1,143	656	1,359	9,827	26,439
2005	4,305	2,881	1,197	670	1,397	10,450	27,417
2006	4,212	2,735	1,144	674	1,336	10,101	26,365
2007	3,676	2,563	1,087	660	1,312	9,298	25,043
2008	3,769	2,383	1,000	609	1,248	9,009	23,886
2009	3,799	2,357	1,005	584	1,185	8,930	23,229
2010	3,735	2,277	1,026	609	1,167	8,814	23,016
2011	3,303	2,115	943	550	1,072	7,983	20,986
2012	6,140	6,073	3,869	2,686	2,566	21,334	59,611
2013	4,117	6,077	5,152	1,227	2,589	19,162	54,848
2014	4,225	5,911	4,523	3,065	1,834	19,558	54,845

Source: IES and IAPI.

Table A.3: Example of two digit industry levels and subdivision up to nine digit products.

11	**Beverages**
11.01	**Distilled alcoholic beverages**
11.02	**Wine from grape**
11.03	**Cider and other fruit wines**
11.04	**Other non-distilled fermented beverages**
11.05	**Beer**
11.06	**Malt**
11.07	**Soft drinks; mineral wates and other bottled waters**
11.07.111	Mineral waters and aerated waters, not sweetened nor flavoured
11.07.111.30	*Mineral waters and aerated waters, unsweetened*
11.07.111.50	*Unsweetened and non flavoured waters; ice and*
	snow (excluding mineral and aerated waters)
11.07.219	Other non alcoholic beverages
11.07.219.30	*Waters, with added suga, other sweetening matter or flavoured,*
	i.e. soft drinks (including mineral and aerated)
11.07.219.50	*Non-alcoholic beverages not containing milk fat (excluding*
11.07.219.50	*sweetened or unsweetened mineral, aerated or flavoured waters)*
11.07.219.70	*Non-alcoholic beverages containing milk fat*

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

Industry	Merged	Usable
Apparel	10,356	10,193
Basic Metals	1,185	1,152
Beverages	3,810	3,763
Chemicals	2,197	2,146
Electrical equip.	2,003	1,910
Fabr. Metal Products	18,195	16,895
Food	23,435	23,174
Furniture	9,838	9,700
Leather Products	5,555	5,364
Machinery	4,490	4,159
Manufact. Activit.	2,447	2,040
Motor Vehicles	1,550	1,376
Other Non-Metallic Minerals	11,086	10,878
Paper and Pulp	1,929	1,904
Printing	3,676	3,174
Rubber and Plastics	3,309	3,120
Textiles	5,260	4,956
Wood Products	10,287	10,155

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

Table A.5: Full GMM estimates for the production function (translog).

Sector	Food	Beverages	Textiles	Apparel	Leather	Wood	Paper	Printing	Chemicals
β_k	0.487*	-0.523**	0.406**	0.0607	0.251	0.263	-0.432	1.208	0.389
	(0.26)	(0.26)	(0.18)	(0.50)	(0.31)	(0.28)	(0.27)	(0.85)	(0.30)
β_m	0.405	0.0302	-0.1	0.0203	-1.164**	0.315	1.204**	0.698	-0.923***
	(0.47)	(0.24)	(0.27)	(0.34)	(0.47)	(0.35)	(0.53)	(0.95)	(0.29)
β_l	-0.039	0.368	0.139	0.645	1.678***	0.678	0.605	0.278	0.999**
	(0.53)	(0.28)	(0.44)	(0.43)	(0.51)	(0.47)	(0.37)	(0.70)	(0.40)
β_{ll}	-0.00416	0.0370*	-0.0216	0.00702	0.0450***	0.0236	0.0245*	0.0692	0.0375
	(0.04)	(0.02)	(0.04)	(0.02)	(0.01)	(0.03)	(0.01)	(0.07)	(0.03)
β_{mm}	0.0469***	0.0284***	0.0828***	0.0495***	0.0933***	0.0703**	-0.0285	0.121*	0.0426**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)	(0.07)	(0.02)
β_{kk}	0.0162	0.0479***	0.0252**	0.00445	-0.0029	0.0274	0.0204	0.0421	-0.0435
	(0.01)	(0.01)	(0.01)	(0.03)	(0.00)	(0.02)	(0.02)	(0.06)	(0.03)
β_{lm}	-0.0407	0.0395	-0.0428	-0.145***	-0.129***	-0.0964*	0.0292	-0.0544	-0.0951***
	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.07)	(0.14)	(0.04)
β_{lk}	0.0561*	-0.0649**	0.0565*	0.101***	0.00014	0.0490*	-0.0699*	0.0169	0.0223
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.09)	(0.04)
β_{mk}	-0.0733**	-0.0208	-0.0893***	-0.0169	-0.0109	-0.0810*	0.0108	-0.193**	0.0528
	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.09)	(0.05)
L.ProbSINGLE	0.419***	-0.0785	-0.071	-0.004	0.0529	0.00372	0.147***	-0.354	-0.0064
	(0.10)	(0.21)	(0.08)	(0.09)	(0.03)	(0.14)	(0.04)	(0.34)	(0.07)
β_p	1.042***	0.907***	0.889***	1.478***	1.031***	0.845***	1.032***	0.938***	1.198***
	(0.18)	(0.22)	(0.05)	(0.20)	(0.12)	(0.09)	(0.12)	(0.14)	(0.16)
$\beta_{\bar{p}}$	-0.089	-0.264	0.0593	0.482***	0.134	-0.0557	-0.0816	0.107	0.0199
	(0.14)	(0.18)	(0.06)	(0.17)	(0.08)	(0.07)	(0.07)	(0.12)	(0.11)
β_{gdp}	-0.634**	-0.0576	0.521**	-0.294	0.119	0.451	0.0234	-2.166*	-0.875**
	(0.25)	(0.46)	(0.24)	(0.30)	(0.20)	(0.37)	(0.29)	(1.12)	(0.38)
γ_1^a	0.983***	0.956***	0.751***	0.954***	0.928***	0.735***	1.001***	0.506***	1.009***
	(0.02)	(0.02)	(0.05)	(0.02)	(0.03)	(0.13)	(0.02)	(0.12)	(0.04)
Sargan OID (pval)	0.000	0.189	0.009	0.036	0.327	0.331	0.885	0.002	0.012
Observations	3070	483	1597	1207	1170	1202	511	257	356
CRS test (pval)	0.718	0.00663	0.0329	0.584	0.653	0.342	0.241	4.6E-05	0.00286

Notes: Translog production function estimates. Std. errors in brackets. Also reported is a test for constant returns and the Sargan OID. Instrument set: Current levels of labour, capital and its squares and product. Lagged levels of capital, labour, materials, prices and industry prices (its squares and products), GDP, the probability of remaining single product and unit-product dummies. The probability of remaining single product is an estimated Probit on product and industry prices, GDP and all inputs (plus products and squares). Std. errors in brackets. Significance: *** 1%, ** 5% and * 10%.

Sector	Rubber	Other Non-Met. Minerals	Basic Metals	Fabr. Metal Products	Eletric. Equip.	Machinery	Motor Vehic.	Furniture	Other Manuf.
β_k	0.0765	0.318	1.177**	-0.25	0.758*	-0.806***	0.468	-0.365	0.0871
	(0.30)	(0.29)	(0.48)	(0.45)	(0.40)	(0.30)	(0.33)	(0.40)	(0.34)
β_m	0.909	1.014*	-0.0643	0.156	1.239	-0.331	-0.0405	-1.638*	0.306
	(0.93)	(0.61)	(0.62)	(0.67)	(0.84)	(0.61)	(0.51)	(0.94)	(0.34)
β_l	0.0923	0.242	0.769	1.298*	-1.377	2.016***	0.419	4.215***	0.242
	(0.77)	(0.72)	(0.60)	(0.74)	(0.84)	(0.71)	(0.64)	(1.20)	(0.45)
β_{ll}	0.024	0.0786**	0.0606*	0.063	-0.0687	0.0871*	0.0411	0.259***	-0.018
	(0.03)	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.03)	(0.07)	(0.02)
β_{mm}	0.0152	0.034	0.103***	0.00665	-0.007	0.00955	0.0727***	0.114***	0.0202
	(0.05)	(0.02)	(0.02)	(0.06)	(0.03)	(0.03)	(0.01)	(0.04)	(0.02)
β_{kk}	0.0245	0.0177**	0.0281*	-0.0091	-0.0266***	0.00289	0.0367**	0.0163***	0.00869
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
β_{lm}	0.00599	-0.1	-0.0931*	-0.0916	0.0184	-0.0937*	-0.0151	-0.307***	-0.0056
	(0.09)	(0.07)	(0.05)	(0.09)	(0.06)	(0.06)	(0.05)	(0.11)	(0.03)
β_{lk}	-0.0039	0.0651**	0.0266	-0.0197	0.129***	-0.0808**	-0.0259	-0.119***	0.0108
	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
β_{mk}	-0.049	-0.0705*	-0.135***	0.0469	-0.0294	0.0802	-0.0919**	0.027	-0.0254
	(0.04)	(0.04)	(0.04)	(0.06)	(0.02)	(0.06)	(0.04)	(0.04)	(0.03)
L.ProbSINGLE	-0.185	0.121	0.0125	-0.0716	0.0785	0.0226	-0.0342	0.465**	0.209
	(0.16)	(0.11)	(0.10)	(0.20)	(0.08)	(0.11)	(0.07)	(0.24)	(0.13)
β_p	0.996***	0.950***	0.830***	1.022***	1.026***	0.981***	0.679***	0.923***	1.464***
	(0.03)	(0.07)	(0.09)	(0.05)	(0.05)	(0.02)	(0.18)	(0.06)	(0.25)
$\beta_{\bar{p}}$	0.0593	0.0204	-0.246***	0.0195	-0.0066	0.0208	-0.351*	-0.0542	-0.0044
	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.02)	(0.21)	(0.06)	(0.17)
β_{gdp}	0.681	-0.257	-0.306	0.506**	0.0652	0.577	-0.547	0.0614	-0.156
	(0.45)	(0.31)	(0.35)	(0.21)	(0.49)	(0.42)	(0.52)	(0.51)	(0.52)
γ_1^a	0.659***	0.887***	1.065***	0.747***	0.746***	0.635***	0.995***	0.872***	0.984***
	(0.12)	(0.04)	(0.06)	(0.04)	(0.09)	(0.12)	(0.02)	(0.04)	(0.02)
Sargan OID (pval)	0.013	0.001	0.118	0.000	0.390	0.504	0.236	0.000	0.062
Observations	1050	2848	386	4866	492	1046	463	1576	907
CRS test (pval)	0.681	0.164	0.116	0.599	0.475	0.699	0.782	0.0013	0.0333

Notes: Translog production function estimates. Std. errors in brackets. Also reported is a test for constant returns and the Sargan OID. Instrument set: Current levels of labour, capital and its squares and product. Lagged levels of capital, labour, materials, prices and industry prices (its squares and products), GDP, the probability of remaining single product and unit-product dummies. The probability of remaining single product is an estimated Probit on product and industry prices, GDP and all inputs (plus products and squares). Std. errors in brackets. Significance: *** 1%, ** 5% and * 10%.

Table A.6: Full GMM estimates for the production function (Cobb-Douglas).

Sector	Food	Beverages	Textiles	Apparel	Leather	Wood	Paper	Printing	Chemicals
β_k	0.112***	0.317***	0.0784**	0.308***	0.0405**	0.109***	0.0485**	0.251***	0.125**
	(0.0285)	(0.0735)	(0.0323)	(0.0713)	(0.0167)	(0.0388)	(0.0225)	(0.0733)	(0.0540)
β_m	0.697***	0.297***	0.483***	0.452***	0.774***	0.647***	0.788***	0.557***	0.311***
	(0.0445)	(0.0782)	(0.0803)	(0.0778)	(0.0290)	(0.0890)	(0.0563)	(0.127)	(0.114)
β_l	0.172***	0.104**	0.309***	0.287***	0.144***	0.259***	0.113**	0.236*	0.484***
	(0.0305)	(0.0509)	(0.0720)	(0.0711)	(0.0456)	(0.0815)	(0.0501)	(0.122)	(0.132)
L.ProbSINGLE	0.307***	-0.217	0.00474	0.0892	0.0350	0.116	0.160***	0.140	0.0167
	(0.0887)	(0.237)	(0.0857)	(0.110)	(0.0413)	(0.128)	(0.0427)	(0.682)	(0.114)
β_p	1.051***	1.434***	1.012***	1.414***	0.982***	0.906***	1.007***	0.943***	0.873***
	(0.0466)	(0.311)	(0.208)	(0.166)	(0.0328)	(0.0810)	(0.0886)	(0.128)	(0.198)
$\beta_{\bar{p}}$	0.0708*	-0.0646	-0.0560	0.361**	0.0979	-0.114	-0.0500	0.119	-0.266
	(0.0389)	(0.286)	(0.177)	(0.150)	(0.0659)	(0.0843)	(0.0595)	(0.122)	(0.183)
β_{gdp}	0.495**	-0.721	-0.700**	-0.455	0.891***	0.0525	0.396	-2.115	-0.889
	(0.231)	(0.810)	(0.335)	(0.377)	(0.294)	(0.407)	(0.252)	(1.441)	(0.695)
γ_1^a	0.786***	1.006***	0.995***	0.900***	0.744***	0.839***	0.966***	0.456***	0.831***
	(0.0436)	(0.0119)	(0.0239)	(0.0302)	(0.0710)	(0.0544)	(0.0259)	(0.170)	(0.0436)
Sargan OID (pval)	0.000	0.003	0.016	0.000	0.000	0.000	0.686	0.000	0.093
Observations	3,070	483	1,597	1,207	1,170	1,202	511	257	356
CRS test (pval)	0.303	0.00853	0.0458	0.514	0.118	0.738	0.350	0.436	0.473

Sector	Rubber	Other Non-Met. Minerals	Basic Metals	Fabr. Metal. Products	Eletric. Equip.	Machinery	Motor Vehicles	Furniture	Other Manuf.
β_k	0.109***	0.0800***	0.110**	0.0416*	0.0162	0.0484	0.0804**	0.0370***	0.0306
	(0.0355)	(0.0303)	(0.0524)	(0.0217)	(0.0307)	(0.0390)	(0.0325)	(0.00974)	(0.0374)
β_m	0.640***	0.650***	0.553***	0.716***	0.729***	0.720***	0.765***	0.751***	0.380***
	(0.0398)	(0.0635)	(0.0785)	(0.0449)	(0.0680)	(0.0724)	(0.0551)	(0.0246)	(0.0411)
β_l	0.241***	0.265***	0.199**	0.203***	0.254**	0.220***	0.0381	0.254***	0.280***
	(0.0417)	(0.0610)	(0.0773)	(0.0390)	(0.113)	(0.0645)	(0.0372)	(0.0394)	(0.0583)
L.ProbSINGLE	-0.105	0.0851	-0.0457	-0.0187	0.115	0.122	0.0558	0.378*	0.155
	(0.146)	(0.123)	(0.0942)	(0.205)	(0.0817)	(0.0846)	(0.0841)	(0.226)	(0.121)
β_p	1.011***	1.035***	0.986***	1.041***	1.031***	1.009***	1.154***	0.970***	1.600***
	(0.0205)	(0.0511)	(0.139)	(0.0288)	(0.0780)	(0.0316)	(0.0747)	(0.0196)	(0.233)
$\beta_{\bar{p}}$	0.0654	0.0226	-0.230*	0.0455*	0.0134	0.0194	0.0864	0.157***	0.0805
	(0.0485)	(0.0431)	(0.136)	(0.0276)	(0.0526)	(0.0267)	(0.0567)	(0.0274)	(0.182)
β_{gdp}	0.833	-0.203	-0.588	0.634***	-0.0866	0.304	0.373	0.657*	-0.327
	(0.558)	(0.290)	(0.616)	(0.210)	(0.533)	(0.561)	(0.637)	(0.364)	(0.439)
γ_1^a	0.670***	0.816***	0.906***	0.731***	0.821***	0.701***	0.819***	0.405***	0.986***
	(0.122)	(0.0665)	(0.0430)	(0.0464)	(0.112)	(0.132)	(0.0995)	(0.0972)	(0.0209)
Sargan OID (pval)	0.000	0.000	0.000	0.000	0.003	0.001	0.000	0.000	0.325
Observations	1,050	2,848	386	4,866	492	1,046	463	1,576	907
CRS test (pval)	0.566	0.895	0.0402	0.0538	0.992	0.739	0.000537	0.0175	3.12e-06

Notes: Cobb-Douglas production function estimates. Std. errors in brackets. Also reported is a test for constant returns and the Sargan OID. Instrument set: Current levels of labour, capital and its squares and product. Lagged levels of capital, labour, materials, prices and industry prices (its squares and products), GDP, the probability of remaining single product and unit-product dummies. The probability of remaining single product is an estimated Probit on product and industry prices, GDP and all inputs (plus products and squares). Std. errors in brackets. Significance: *** 1%, ** 5% and * 10%.

Table A.7: Cubic GMM demand estimates.

Sector	Food	Beverages	Textiles	Apparel	Leather	Wood	Paper	Printing	Chemicals
price	-3.259***	-1.795***	-2.653***	-6.294***	-8.891***	-2.461***	-2.142***	-1.316***	-1.278***
	(0.117)	(0.0851)	(0.273)	(0.202)	(1.001)	(0.128)	(0.310)	(0.113)	(0.225)
$price^2$	-0.420***	-0.241***	0.533**	-0.0469	-2.161*	-0.122***	-0.0969	0.128**	-0.150
	(0.124)	(0.0866)	(0.222)	(0.289)	(1.291)	(0.0370)	(0.105)	(0.0518)	(0.187)
$price^3$	-0.0175	0.0105	0.0875*	0.131	-0.816*	0.00393	0.00492	-0.0218	-0.0478
	(0.0232)	(0.0368)	(0.0515)	(0.118)	(0.486)	(0.00885)	(0.0144)	(0.0137)	(0.0718)
Industry Price	0.614***	-0.852***	1.178***	0.00576	3.355***	-1.210***	-0.966**	-1.102***	0.821**
	(0.173)	(0.230)	(0.323)	(0.139)	(1.105)	(0.180)	(0.424)	(0.0906)	(0.326)
GDP	0.286	1.462**	3.701***	-2.094***	4.129**	-0.853**	0.276	3.859***	2.340***
	(0.308)	(0.635)	(0.816)	(0.675)	(2.026)	(0.404)	(0.635)	(0.952)	(0.725)
Quality	-0.496***	-0.178***	-0.367***	-0.154***	-0.638***	-0.144***	-0.287***	0.0963***	-0.237***
	(0.0204)	(0.0200)	(0.0417)	(0.0299)	(0.125)	(0.0172)	(0.0414)	(0.0175)	(0.0280)
AR1 term	0.962***	1.001***	0.945***	0.905***	0.958***	0.992***	1.006***	0.961***	0.957***
	(0.00291)	(0.00408)	(0.00796)	(0.00572)	(0.00923)	(0.00139)	(0.00760)	(0.00664)	(0.00842)
Sargan OID (pval)	0.224	0.824	0.937	0.647	0.988	0.257	0.992	0.440	0.996
Observations	44,117	8,256	8,948	30,526	8,393	18,358	2,772	6,705	5,900

Sector	Rubber	Other Non-Met. Minerals	Basic Metals	Fabr. Metal. Products	Eletric. Equip.	Machinery	Motor Vehicles	Furniture	Other Manuf.
price	-2.387***	-2.448***	-2.704***	-2.264***	-0.547**	-0.973***	-0.867***	-3.477***	-1.021***
	(0.313)	(0.105)	(0.539)	(0.133)	(0.250)	(0.137)	(0.159)	(0.214)	(0.221)
$price^2$	0.905***	-0.323***	-0.120	-0.127**	-0.0950**	0.0554	0.0643	-1.769***	-0.156**
	(0.139)	(0.0941)	(0.260)	(0.0621)	(0.0452)	(0.0388)	(0.0517)	(0.321)	(0.0793)
$price^3$	0.170***	-0.0378***	0.0262	0.0646***	-0.00195	0.0181**	0.00800	-0.477***	-0.00281
	(0.0320)	(0.0141)	(0.0353)	(0.0216)	(0.00573)	(0.00801)	(0.0107)	(0.143)	(0.00874)
Industry Price	0.190	-1.771***	0.337	0.244***	0.346	0.208***	-0.274*	0.102	0.107
	(0.328)	(0.113)	(0.364)	(0.0929)	(0.213)	(0.0610)	(0.143)	(0.180)	(0.191)
GDP	0.598	1.100**	-0.708	1.371***	3.675***	0.834	6.370***	-1.495**	0.997
	(0.893)	(0.428)	(1.423)	(0.386)	(0.811)	(0.725)	(1.137)	(0.752)	(0.636)
Quality	-0.245***	-0.197***	-0.258***	-0.143***	-0.117***	-0.147***	-0.117***	0.0434	-0.0518***
	(0.0321)	(0.0188)	(0.0813)	(0.0119)	(0.0223)	(0.0174)	(0.0350)	(0.0389)	(0.0197)
AR1 term	0.980***	0.997***	0.976***	0.976***	0.964***	0.928***	1.021***	0.938***	0.983***
	(0.00611)	(0.00172)	(0.0162)	(0.00347)	(0.0113)	(0.00886)	(0.0101)	(0.00648)	(0.00885)
Sargan OID (pval)	0.960	0.702	1.000	0.729	0.995	0.894	0.993	0.682	0.996
Observations	4,778	16,212	1,700	22,338	2,940	6,287	1,665	18,136	2,126

Notes: Demand function GMM estimates. Specification cubic in prices. Instruments include current and lagged employment and capital stock (product shares), gdp and TFP shock, as well as lagged own and industry prices and quality. Also reported is the Sargan test of OID. Std. errors in brackets. Significance: *** 1%, ** 5% and * 10%.

Table A.8: Linear GMM demand estimates.

Sector	Food	Beverages	Textiles	Apparel	Leather	Wood	Paper	Printing	Chemicals
Price	-3.027***	-1.461***	-2.934***	-6.149***	-8.613***	-2.780***	-2.583***	-1.526***	-1.303***
	(0.105)	(0.0502)	(0.237)	(0.167)	(0.823)	(0.129)	(0.344)	(0.0759)	(0.227)
Industry Price	0.181	1.337**	3.530***	-2.216***	4.041**	-0.493	-0.0335	3.773***	2.361***
	(0.312)	(0.603)	(0.788)	(0.674)	(1.782)	(0.416)	(0.678)	(0.948)	(0.724)
GDP	0.633***	-0.759***	0.954***	0.00749	2.831***	-1.986***	-2.236***	-1.090***	0.872***
	(0.169)	(0.200)	(0.296)	(0.141)	(1.004)	(0.160)	(0.464)	(0.0897)	(0.282)
Quality	-0.493***	-0.185***	-0.337***	-0.153***	-0.644***	-0.162***	-0.264***	0.0909***	-0.243***
	(0.0201)	(0.0186)	(0.0414)	(0.0286)	(0.112)	(0.0165)	(0.0406)	(0.0166)	(0.0240)
AR1 term	0.960***	1.000***	0.942***	0.906***	0.962***	0.995***	0.997***	0.957***	0.957***
	(0.00291)	(0.00402)	(0.00790)	(0.00567)	(0.00877)	(0.000928)	(0.00571)	(0.00625)	(0.00761)
Sargan OID (pval)	0.330	0.854	0.955	0.624	0.965	0.355	0.996	0.528	0.999
Observations	44,117	8,256	8,948	30,526	8,393	18,358	2,772	6,705	5,900

Sector	Rubber	Other Non-Met. Minerals	Basic Metals	Fabr. Metal. Products	Eletric. Equip.	Machinery	Motor Vehicles	Furniture	Other Manuf.
Price	-1.770***	-2.295***	-2.053***	-2.169***	-0.367*	-0.913***	-0.897***	-2.666***	-0.732***
	(0.143)	(0.0950)	(0.415)	(0.0927)	(0.206)	(0.106)	(0.144)	(0.0905)	(0.187)
Industry Price	2.611***	0.208	-0.163	2.146***	3.859***	0.840	5.565***	-0.301	1.028*
	(0.538)	(0.389)	(1.327)	(0.339)	(0.820)	(0.732)	(1.049)	(0.493)	(0.596)
GDP	-0.658***	-1.618***	0.438	-0.944***	0.294	0.204***	-0.356**	0.774***	0.0838
	(0.132)	(0.105)	(0.353)	(0.141)	(0.190)	(0.0616)	(0.162)	(0.142)	(0.202)
Quality	-0.108***	-0.198***	-0.225***	-0.148***	-0.105***	-0.141***	-0.100***	-0.132***	-0.0463**
	(0.0176)	(0.0157)	(0.0750)	(0.0106)	(0.0216)	(0.0174)	(0.0322)	(0.0164)	(0.0182)
AR1 term	0.965***	1.000***	0.981***	1.004***	0.966***	0.929***	1.018***	0.952***	0.985***
	(0.00584)	(0.00176)	(0.0143)	(0.00187)	(0.0105)	(0.00875)	(0.00936)	(0.00422)	(0.00829)
Sargan OID (pval)	0.915	0.504	1.000	0.840	0.998	0.935	0.996	0.783	0.997
Observations	4,778	16,212	1,700	22,338	2,940	6,287	1,665	18,136	2,126

Notes: Demand function GMM estimates. Specification linear in prices. Instruments include current and lagged employment and capital stock (product shares), gdp and TFP shock, as well as lagged own and industry prices and quality. Also reported is the Sargan test of OID. Std. errors in brackets. Significance: *** 1%, ** 5% and * 10%.

Table A.9: Markups' response to shocks by sector.

	Dep. Var	$\Delta\mu_{ijt}$			$\Delta\ln p_{ijt}$			$\Delta\ln q_{ijt}$		
	Indep. Var. (shocks)	TFP	Demand	Quality	TFP	Demand	Quality	TFP	Demand	Quality
10	Food	1.368***	-0.124***	-2.369***	-0.00523***	0.0195***	-0.903***	0.0157***	0.904***	3.467***
		(0.0219)	(0.00859)	(0.0498)	(0.00120)	(0.00221)	(0.00598)	(0.00542)	(0.00962)	(0.0273)
11	Beverages	0.886***	-0.336***	-1.279***	-0.0424***	0.0477***	-0.546***	0.0903***	0.844***	0.987***
		(0.0331)	(0.0251)	(0.0414)	(0.00394)	(0.00535)	(0.00560)	(0.00748)	(0.00928)	(0.0102)
13	Textiles	0.956***	-0.173***	-1.832***	-0.00708**	0.0328***	-0.777***	0.0534***	0.796***	2.337***
		(0.0401)	(0.0179)	(0.0862)	(0.00311)	(0.00444)	(0.0107)	(0.0119)	(0.0187)	(0.0481)
14	Apparel	0.961***	-0.0296***	-1.621***	-0.00262***	0.0185***	-0.722***	0.0177***	0.890***	4.442***
		(0.0172)	(0.00637)	(0.0385)	(0.000780)	(0.000957)	(0.00346)	(0.00485)	(0.00627)	(0.0248)
15	Leather	1.608***	-0.141***	-3.820***	-0.00244*	0.0129***	-0.854***	0.0500*	0.677***	6.670***
		(0.0583)	(0.0128)	(0.171)	(0.00129)	(0.000864)	(0.00773)	(0.0256)	(0.0170)	(0.148)
16	Wood Products	1.039***	-0.153***	-2.057***	-0.0182***	0.0221***	-1.053***	0.0551***	0.822***	1.855***
		(0.0282)	(0.0126)	(0.0664)	(0.00398)	(0.00233)	(0.00558)	(0.00806)	(0.00722)	(0.0245)
17	Paper and Pulp	1.476***	-0.172***	-2.689***	0.000925	0.0124***	-0.934***	0.0290*	0.859***	1.658***
		(0.0808)	(0.0366)	(0.140)	(0.00873)	(0.00464)	(0.0146)	(0.0169)	(0.0169)	(0.0364)
18	Printing	0.776***	-0.0322	-1.538***	-0.00854	-0.0217***	-1.090***	-0.00878	0.759***	0.912***
		(0.0495)	(0.0239)	(0.0807)	(0.00585)	(0.00483)	(0.0136)	(0.00925)	(0.0103)	(0.0208)
20	Chemicals	0.751***	-0.170***	-1.310***	-0.00677	0.0180**	-0.902***	0.0498***	0.902***	1.835***
		(0.0355)	(0.0228)	(0.0714)	(0.00510)	(0.00755)	(0.0110)	(0.0147)	(0.0241)	(0.0301)
22	Rubber and Plastis	1.033***	-0.270***	-2.339***	-0.0111***	-0.0154***	-1.037***	0.0469***	0.817***	1.965***
		(0.0655)	(0.0317)	(0.129)	(0.00426)	(0.00500)	(0.00768)	(0.0159)	(0.0279)	(0.0670)
23	Other non-met. Minerals	1.490***	-0.165***	-2.879***	-0.00856***	0.00322*	-0.975***	0.105***	0.696***	1.474***
		(0.0345)	(0.0136)	(0.0650)	(0.00242)	(0.00179)	(0.00320)	(0.00949)	(0.00949)	(0.0265)
24	Basic Metals	1.351***	-0.304***	-2.584***	-0.0159**	0.0553***	-0.694***	0.0436**	0.868***	2.180***
		(0.132)	(0.0435)	(0.238)	(0.00768)	(0.0127)	(0.0305)	(0.0193)	(0.0321)	(0.0746)
25	Fabric. Metal	1.634***	-0.270***	-2.975***	-0.0239***	0.0134***	-0.928***	0.0397***	0.945***	2.163***
		(0.0337)	(0.0176)	(0.0647)	(0.00474)	(0.00495)	(0.0119)	(0.00803)	(0.00982)	(0.0205)
27	Eletric. Equipment	0.973***	-0.183***	-1.733***	-0.0142	-0.0140	-1.042***	0.0227**	1.010***	1.006***
		(0.0770)	(0.0331)	(0.147)	(0.0110)	(0.0118)	(0.0178)	(0.0108)	(0.0132)	(0.0222)
28	Machinery	1.021***	-0.174***	-1.767***	-0.0313***	-0.0215***	-1.084***	0.00925	1.027***	1.243***
		(0.0508)	(0.0234)	(0.0902)	(0.00811)	(0.00705)	(0.0135)	(0.00764)	(0.00691)	(0.0164)
29	Motor Vehicles	0.976***	-0.341***	-1.654***	-0.0413***	-0.0431***	-0.810***	0.00321	1.015***	0.665***
		(0.0918)	(0.0645)	(0.138)	(0.0131)	(0.0110)	(0.0190)	(0.0117)	(0.0112)	(0.0186)
31	Furniture	1.010***	0.00469	-2.211***	-0.00462***	0.0420***	-0.968***	0.0884***	0.656***	3.055***
		(0.0331)	(0.0163)	(0.0783)	(0.00155)	(0.00328)	(0.00989)	(0.00904)	(0.0193)	(0.0594)
32	Other Manuf.	0.840***	-0.348***	-1.105***	-0.144***	0.0639**	-0.444***	0.184***	0.900***	0.496***
		(0.0935)	(0.0701)	(0.107)	(0.0333)	(0.0297)	(0.0327)	(0.0435)	(0.0395)	(0.0421)
Observations		183,393			202,790			202,006		
R-squared		0.435			0.900			0.830		
N. of firm-product		57,370			60,447			60,349		

Notes: Regression results with fixed firm-product effects. Clustered std. errors in brackets. Significance: *** 1%, ** 5% and * 10%.

Table A.10: Response to shocks, by number of products (controlling for size).

Dep.var.			$\Delta\mu_{ijt}$		
N. of products	1	2	3	4	5+
TFP shock	1.060***	1.585***	1.373***	1.140***	1.305***
	(0.0375)	(0.0299)	(0.0274)	(0.0252)	(0.0270)
Demand shock	-0.150***	-0.208***	-0.164***	-0.104***	-0.106***
	(0.0128)	(0.0127)	(0.0122)	(0.0134)	(0.0117)
Quality shock	1.792***	2.842***	2.426***	1.671***	1.951***
	(0.0741)	(0.0597)	(0.0608)	(0.0421)	(0.0558)
Dep.var.			$\Delta \ln p_{ijt}$		
N. of products	1	2	3	4	5+
TFP shock	-0.105***	-0.0191***	-0.0224***	-0.0231***	-0.0161***
	(0.00842)	(0.00336)	(0.00340)	(0.00343)	(0.00387)
Demand shock	0.0401***	0.0238***	0.0272***	0.0377***	0.0230***
	(0.00385)	(0.00280)	(0.00262)	(0.00315)	(0.00321)
Quality shock	0.653***	0.833***	0.848***	0.661***	0.774***
	(0.0195)	(0.0104)	(0.0116)	(0.00814)	(0.0135)
Dep.var.			$\Delta \ln q_{ijt}$		
N. of products	1	2	3	4	5+
TFP shock	0.291***	0.136***	0.139***	0.132***	0.139***
	(0.0180)	(0.0104)	(0.0101)	(0.00981)	(0.0108)
Demand shock	0.387***	0.628***	0.652***	0.672***	0.659***
	(0.0142)	(0.0113)	(0.0107)	(0.0124)	(0.0119)
Quality shock	-0.693***	-1.499***	-1.356***	-1.032***	-1.688***
	(0.0468)	(0.0360)	(0.0343)	(0.0231)	(0.0408)
Observations	196,357				
N. of firm-products	59,146				

Notes: Regression results with fixed effects. Clustered std. errors in brackets (firm-product level). All variables truncated at +-3.
Regressions include interaction effects with log employment to control for firm size. Significance: *** 1%, ** 5% and * 10%.