Using Cost Minimization to Estimate Markups*

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Abstract

De Loecker & Warzynski's (2012) method for recovering markups from cost-minimization conditions and estimated input elasticities yields either larger or smaller markups for exporters than for non-exporters depending on the input (labor or materials) employed. We point out two difficulties. First, under imperfect competition, an Olley & Pakes (1996) style estimator for input elasticities has to account for markups. Second, with commonly used specifications of the production function, the cost-minimization conditions do not match the variation in the data. We discuss how to address these difficulties. According to our estimates, the markups of exporters and non-exporters are essentially the same.

1 Introduction

Economists use markups to measure market power and performance of firms. Early work was theoretically founded, but did not distinguish marginal cost from average variable cost (Bain 1951). If marginal cost equals average variable cost, then the markup is the ratio of sales to variable costs and can be measured without price information.[1] The new empirical industrial organization (Bresnahan 1989, Schmalensee

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[1] Up to the error arising from unobserved differences in the quantities necessary to divide the numerator and denominator.

1989) pointed out the limits of this approach and switched the focus to the estimation of marginal costs. If marginal cost is not equal to average variable cost, then the markup cannot be easily measured even if the price is available.

Making assumptions on the behavior of firms the markup becomes dependent on structural parameters, mainly the elasticity of demand (see, for example, the influential works by Berry, Levinsohn & Pakes (1995) and Nevo (2001)), and can be estimated along with marginal costs without cost data. This method relies on the correct specification of both the strategic interaction between firms and dynamic pricing (which overrides pricing based on the elasticity of demand even if firms do not interact strategically). Thus there is renewed interest in measuring markups from prices and production data invoking the assumption of cost minimization rather than profit maximization. The ultimate goal of this paper is to infer markups under non-specified pricing with minimum restrictions on the production function; that is, we want to estimate robust markups.

Hall (1988) showed that marginal cost can be measured assuming cost minimization by relating the cost of an input per unit of output to its elasticity (page 925). De Loecker & Warzynski (2012), henceforth DLW, applied this insight to the computation of markups by dividing the elasticity of an input by its (corrected) revenue share. This method has been profusely applied since then (a non exhaustive list of works is De Loecker, Goldberg, Khandelwal & Pavcnik (2016), Brandt, Van Biesebroeck, Wang & Zhang (2017), De Loecker & Scott (2016), De Loecker, Eeckhout & Unger (2018), De Loecker & Eeckhout (2018) and Autor, Dorn, Katz, Patterson & Van Reenen (2019)).

When we use the DLW estimator as in the original paper to check how exporters' markups compare to those of non-exporters, we get different signs depending on whether we use labor or materials as input. We use the unbalanced panel ESEE sample of Spanish manufacturing firms from 1990 to 2012, but we repeat the exercise with the available data in a Slovenian sample similar to DLW. Using materials we obtain smaller exporters' markups, whereas DLW, using labor, found evidence of larger exporter's markups. Recently, Raval (2019*a*) has also found that markups estimated with the DLW method using labor and materials are negatively correlated in five different firm-level data sets (Chile, Colombia, India, Indonesia, and a US retailer). These results are discouraging because it is not clear a priori what the relationship between markups and exports should be, so an empirical answer would be a key contribution.

For example, after 2008, there was such an unexpected surge of Spanish manufacturing exports that it has been called the "Spanish miracle." The questions posed are so intriguing that Almunia, Antras, Lopez-Rodriguez & Morales (2018) built a new kind of trade model to explain the behavior of Spanish firms subject to the pressure of capacity underutilization because of the fall of domestic demand. The question of whether the firms sold in foreign markets with markups that were different than those in the domestic markets demands an answer.

Empirical work more broadly aims to consistently estimate associations of markups with variables of interest. Recent papers looked at the effect of exports, tariff reductions and trade liberalizations, mergers, changes in competition policy, and changes in competition among firms.

We analyze markups under the same framework used to structurally estimate production functions. Firms choose (at least) two variable inputs given capital and productivity that is unobserved by the researcher. We observe the planned output, for which the inputs have been chosen, up to an uncorrelated error. We first document the contradictory inferences arising from the DLW estimator, and then we explore possible reasons for bias.

A first conclusion is that input elasticities are a function of unobservables that should be taken into account. When cost minimization conditions are jointly considered we find that relative variable input elasticities and cost shares should match. Examining the mismatch of the commonly specified elasticities, the data strongly suggest that productivity is labor-augmenting. Doraszelski & Jaumandreu (2018) and Raval (2019*b*) have documented the relative importance of labor-augmenting productivity versus the commonly specified Hicks-neutral productivity. Adjustment costs also matter for the elasticities of all inputs. Other unobservables, linked to firms' non price-taking behavior in input markets and different kind of errors may be important as well.

The DLW estimator specifies elasticities that ignore non-neutral productivity. Markups of exporters seem to be larger when analyzed using labor input because exporters tend to employ more efficient labor than non-exporters.[2] In addition, we show that DLW markup estimates are also correlated with adjustment cost to different degrees.

[2] In fact DLW noticed that 70% of the estimated difference between the exporter's and non-exporter's markups was due to productivity when they included in the regression their estimate of Hicksian productivity (page 2460). They interpreted this result as indicating that the most important reason for markup differences are the differences in marginal cost.

A second conclusion is that the estimation of elasticities is in general not independent of markup. DLW first estimate the production function ignoring that marginal cost and thus markup are part of the first order conditions (FOCs) for the input demand or investment choice that is inverted to recover unobserved productivity (an Olley & Pakes (1996) and Levinsohn & Petrin (2003) procedure, henceforth an OP/LP procedure). We show that under imperfect competition, the relationships that come from the FOCs include either markup or unobserved heterogeneity that violate the "scalar unobservable assumption" of these procedures. Then we point out the econometric problems that arise when a first stage Ackerberg, Caves & Frazer (2015) procedure, henceforth ACF procedure, is carried out in the presence of these unobservables.

We build tools for robust inference of markups and provide two examples of inference under non-specified competition and a flexible production function. The examples combine the cost minimization conditions for variable factors of a translog production function with both labor-augmenting and Hicksian productivity. The examples differ in how we deal with the fact that the unobservability of the markup affects the estimation of the production elasticities. The first example is an easy to apply two-stage procedure, where we use the lagged inverted production function itself to control for lagged Hicksian productivity (dynamic panel estimation). The second example is a full simultaneous estimation of markups and the production function. Lagged Hicksian productivity is replaced by an expression in observables including the lagged markup (an OP/LP-type procedure). Our examples assume a linear Markov process, however. We are also not able to recover markups at the firm-level. We point out areas for further research.

We reach the conclusion that exporters' markups are basically the same as non-exporters markups, and exporting more is not systematically associated with different markups. We also find evidence of a general upward bias in markups when the input elasticities are estimated without controlling for markup.

The rest of the paper is organized as follows. Section 2 presents the structural framework. Section 3 is a short note on the data and its context. Section 4 shows the contradictory answers of DLW markups and explores the reasons for bias. Section 5 explains why consistent estimation of the production function under imperfect competition requires the markup. Section 6 provides two examples of robust inference. Section 7 concludes.

2 Framework

Firms compete in a way unknown to the researcher. We assume only cost minimization. Firm j produces output Q_{jt} in period t with a given amount of capital, K_{jt}, and freely variable amounts of labor and materials, L_{jt} and M_{jt}, with production function

$$Q_{jt} = Q^*_{jt} \exp(\varepsilon_{jt}) = F(K_{jt}, \exp(\omega_{Ljt}) L_{jt}, M_{jt}) \exp(\omega_{Hjt} + \varepsilon_{jt}), \tag{1}$$

where ω_{Ljt} and ω_{Hjt} are labor-augmenting and Hicks-neutral productivity. Both ω_{Ljt} and ω_{Hjt} are observed by the firm but not by the econometrician. We take capital as given since its adjustment is particularly costly and requires time. Following the literature, we also assume that variable inputs are chosen to produce the "planned" quantity q^*_{jt} (we adopt lowercase letters to represent logarithms). The disturbance ε_{jt}, uncorrelated over time and with the inputs, accounts for the difference between unobserved planned output q^*_{jt} and observed actual output q_{jt}.

The most natural way to interpret the difference between q_{jt} and q^*_{jt} is as shocks that were unanticipated at the time the firm chooses the variable inputs.[3] It can also be interpreted as pure measurement error. The unobservability of the relevant output q^*_{jt} characterizes the entire literature on structural estimation of production functions (see, for example, Griliches & Mairesse (1998)).

The above assumptions are slightly more general than the assumptions used in the literature on structural estimation of production functions and productivity. They allow for multidimensional productivity and include no assumption on its dynamic properties.[4]

Cost minimization. Variable cost is $VC_{jt} = W_{jt}L_{jt} + P_{M_{jt}}M_{jt}$, where W_{jt} and P_{Mjt} are the prices of labor and materials respectively. Firm j takes these prices as given.We characterize the cost minimization problem in Appendix A. A slight rewriting of the FOCs gives

$$\frac{1}{MC_{jt}} = \frac{\frac{\partial Q_{jt}}{\partial X_{jt}}}{W_{Xjt}},$$

[3]This implies that when the firm decides based on expectations it integrates over the distribution of these shocks. This integration will introduce constant terms in many equations that we do not make explicit. This is without loss of generality.

[4]Many studies adopt the stronger assumption that ε_{jt} is mean independent, or even independent, of all the relevant information available to the firm in period t, see Gandhi, Navarro & Rivers (2017) for a discussion.

for $X_{jt} = L_{jt}, M_{jt}$, $W_{Xjt} = W_{jt}, P_{Mjt}$, and where MC_{jt} is marginal cost at planned output Q^*_{jt}. The conditions say that the marginal productivity of the last dollar must be equal in every use, as Samuelson (1947) puts it.

Multiplying both sides by average variable cost AVC_{jt} at planned output Q^*_{jt} and completing the expressions in numerator and denominator we get a version of these conditions in terms of the implied elasticities,

$$\nu_{jt} = \frac{\beta_{Xjt}}{S_{X_{jt}}},$$

where $\beta_{X_{jt}} = \frac{X_{jt}}{Q^*_{jt}} \frac{\partial Q_{jt}}{\partial X_{jt}}$ is the elasticity of output with respect to input X_{jt}, and $S_{Xjt} = \frac{W_{Xjt} X_{jt}}{VC_{jt}}$ is the share of the input bill in variable cost. The ratio $\frac{AVC_{jt}}{MC_{jt}}$ is the inverse of the elasticity of variable cost with respect to output and this equals the short-run elasticity of scale ν_{jt} at the cost minimum.[5] This version stresses that relative variable input elasticities must be equal to relative cost shares, $\frac{\beta_{Ljt}}{\beta_{Mjt}} = \frac{S_{Ljt}}{(1-S_{Ljt})}$, and that the sum of these elasticities is ν_{jt}.

Hall (1988, 1990), drawing on Solow (1957), showed how the cost minimizing conditions can be used to infer the markup $\mu_{jt} = P_{jt}/MC_{jt}$. Multiplying both sides of the elasticities version by P_{jt}/AVC_{jt} we get

$$\mu_{jt} = \frac{\beta_{Xjt}}{S^*_{Xjt}},$$

where $S^*_{Xjt} = \frac{W_{Xjt} X_{jt}}{P_{jt} Q^*_{jt}}$ is the share of revenue of the amount spent on the given input. Thus the elasticity can be decomposed in μ_{jt} and S^*_{Xjt}. The model was framed in a firm-level panel data setting by Klette (1999).[6] Hall (2018), which is based on the original idea without derivatives, proposes to estimate the empirical marginal cost.

[5] $\nu_{jt} = \frac{VC_{jt}}{Q^*_{jt}} / \frac{\partial VC_{jt}}{\partial Q_{jt}} = 1 / \frac{Q^*_{jt}}{VC_{jt}} \frac{\partial VC_{jt}}{\partial Q_{jt}}$. The short-run elasticity of scale measures how output changes in response to a simultaneous variation of the variable inputs. It can be defined as $\nu_{jt} = \frac{\partial \ln F(K_{jt}, \lambda \exp(\omega_{Ljt}) L_{jt}, \lambda M_{jt})}{\partial \ln \lambda}$. The inverse of the elasticity of variable cost with respect to output equals the short-run elasticity of scale at the cost minimum, and everywhere if the production function is homothetic (Chambers (1988, pages 69-74)).

[6] Hall's method runs regressions based on the idea that the conventional Solow residual, computed as $Solow_{jt} = \Delta q_{jt} - \Delta k_{jt} - \Delta W_{jt}$, where $\Delta W_{jt} = S^*_{Ljt}(\Delta l_{jt} - \Delta k_{jt}) + S^*_{Mjt}(\Delta m_{jt} - \Delta k_{jt})$, gives $Solow_{jt} = v^*_{jt} \Delta k_{jt} + (\mu_{jt} - 1)\Delta W_{jt} + \omega_{jt}$, where $v^*_{jt} = v_{jt} + \beta_{Kjt}$ and ω_{jt} is true productivity. Klette (1999) proposes using a regression of the type $\Delta q_{jt} = v^*_{jt} \Delta k_{jt} + \mu_{jt} \Delta W_{jt} + \omega_j + u_{jt}$.

Wage bargaining, monopsony, and other distortions. The FOC for labor holds for a wide variety of labor market models. It is enough that the firm equates the marginal productivity of labor with the observed wage. This happens, for example, in wage bargaining under the right-to manage model (Oswald 1982, Nickell & Andrews 1983) or in efficiency wage models.

There are, however, cases in which the FOC includes an additional unobservable (see Dobbelaere & Mairesse (2013, 2018)).[7] If the firm is not a price-taker, then the FOC for labor includes an adjustment to the observed wage so that it becomes

$$\frac{1}{MC_{jt}} = \frac{\frac{\partial Q_{jt}}{\partial L_{jt}}}{W_{jt}(1+\tau_{jt})}.$$

One example of this is the "rent-sharing" that emerges from the efficient bargaining between the firm and union (McDonald & Solow 1981). With materials in addition to labor, the firm does not minimize costs and τ_{jt} is negative and related to the union bargaining power and the ratio profits to wage bill. In monopsony, the firm chooses the wage on an upward sloping inverse labor supply (Manning 2011) and τ_{jt} is the inverse of the labor supply elasticity.

Hsieh & Klenow (2009) introduce "distortions", that are reflected in the same way, as the result of unspecified government intervention (e.g. restrictions on size or favoritism in prices or loans) to explain marginal productivity gaps in China and India.[8] It has been used extensively in the literature on misallocation. Our firm-level price indices capture any government interventions that operate through prices.

We will proceed assuming $\tau_{jt} = 0$ but we come back to the effects of this unobservable in the empirical exercise.

Adjustment costs. If there are adjustment costs of variable inputs, then the cost minimization problem becomes dynamic. We characterize the dynamic problem in Appendix B. If input X_{jt} is affected by adjustment costs the relevant FOC can be

[7] They try to estimate the extent of labor market imperfections with firm-level data by looking at the mismatch between the relative elasticities (estimated with a production function) and the relative shares of labor and materials, defining joint product and labor market imperfections as $\Psi_{jt} = \frac{\beta_{Mjt}}{S^*_{Mjt}} - \frac{\beta_{Ljt}}{S^*_{Ljt}} = -\mu_{jt}\tau_{jt}$ where τ_{jt} is specific to the model of the labor market.

[8] Haltiwanger, Kulick & Syverson (2018) point out the parametric restrictions embodied in the measurement of the distortions and the ambiguity in the interpretation of the results.

written as

$$\frac{1}{MC_{jt}} = \frac{\frac{\partial Q_{jt}}{\partial X_{jt}}}{W_{Xjt}(1+\Delta_{Xjt})},$$

where Δ_{Xjt} represents the gap between the price and the shadow price of the input under adjustment costs. From now on we assume that only input L_{jt} has adjustment costs. Keeping the notation S_{Xjt}, VC_{jt}, and AVC_{jt} for the shares and variable costs measured without adjustment costs, the corresponding share, total, and average variable costs with adjustment costs are $S_{Xjt}\frac{1+\Delta_{Xjt}}{1+S_{Ljt}\Delta_{Ljt}}, VC_{jt}(1+S_{Ljt}\Delta_{Ljt})$, and $AVC_{jt}(1+S_{Ljt}\Delta_{Ljt})$, respectively. The elasticities version of the conditions become $\nu_{jt} = AVC_{jt}(1+S_{Ljt}\Delta_{Ljt})/MC_{jt} = \beta_{Xjt}/S_{Xjt}\frac{1+\Delta_{Xjt}}{1+S_{Ljt}\Delta_{Ljt}}$ and the relative elasticities are $\frac{\beta_{Ljt}}{\beta_{Mjt}} = \frac{S_{Ljt}}{(1-S_{Ljt})}(1+\Delta_{Ljt})$. Notice that relative elasticities are affected by the adjustments costs but $\nu_{jt} = \beta_{Ljt} + \beta_{Mjt}$ is as before.

Labor adjustment costs can be estimated using the method in Doraszelski & Jaumandreu (2013, 2018). We assume only permanent workers have adjustment costs and estimate a measure of adjustments costs based on the variations in the proportions of permanent and temporary workers around the cost minimum (see Appendix C for details).[9] Notice, however, that in our theoretical expressions we split prices into a flat (supposedly observed) price and adjustment costs. In practice many adjustment costs are already included in observed price of the inputs, so that empirically only a fraction remains unobserved. See below for how we treat this.

Markups. Rearranging the FOC with adjustment costs to leave in the left-hand side magnitudes that can be directly observed we have

$$\frac{R_{jt}}{W_{Xjt}X_{jt}} = \frac{(1+\Delta_{Xjt})}{\beta_{Xjt}}\mu_{jt}\exp(\varepsilon_{jt}), \tag{2}$$

where the error term ε_{jt} comes from measuring revenue R_{jt} with the observed output Q_{jt} instead of Q^*_{jt}. If we think that there are additional measurement problems in P_{jt} and/or $W_{Xjt}X_{jt}$, then the relevant error is a composite of errors. We continue writing ε_{jt} only for simplicity.

Replacing β_{Xjt} in equation (2) by its expression in terms of the elasticity of scale and share we get

[9] Almost all databases contain some cyclical firm-level variables that can be used to approximate adjustment costs.

$$\frac{R_{jt}}{VC_{jt}} = \frac{(1 + S_{Ljt}\Delta_{Ljt})}{\nu_{jt}} \mu_{jt} \exp(\varepsilon_{jt}). \tag{3}$$

Equation (3) is a simple transformation of equation (2).[10] We often refer to ln $\frac{R_{jt}}{VC_{jt}}$ as the price-average variable cost margin or $PAVCM$.[11] Equations (2) and (3) are equivalent in that they hold for the same markup when using elasticities consistent with cost minimization. We will see later that there are reasons to focus on equation (3).

System of equations. Equation (3) says that recovering markups from observed data assuming only cost minimization requires the separation of three unobservables: the ratio marginal cost to observed average cost (in the presence of adjustment costs) $\frac{(1+S_{Ljt}\Delta_{Ljt})}{\nu_{jt}}$, the markup μ_{jt}, and the error ε_{jt}.

We have to separate these three unobservables in the context of the system of equations formed by the logs of equations (3) and (1)

$$r_{jt} - vc_{jt} = \ln(1 + S_{Ljt}\Delta_{Ljt}) - \ln \nu_{jt} + \ln \mu_{jt} + \varepsilon_{jt} \tag{4}$$
$$q_{jt} = \ln F_{jt}(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt}) + \omega_{Hjt} + \varepsilon_{jt}. \tag{5}$$

How are the equations of this system linked? We need the production function to specify and estimate the elasticities $\beta_{Ljt} + \beta_{Mjt} = \nu_{jt}$. In turn, the elasticities in the production function should be logically consistent with the conditions of cost minimization. Finally, the estimation of the production function, either separately or simultaneously with the other equations needs to control for ω_{Ljt} and ω_{Hjt}. The way to deal with these unobservables implies typically the FOCs that determine equation (4). We discuss in detail these links in Sections 4 and 5. Identifying simultaneously markups and the elasticity of scale fits the tradition of Hall (1988) and Klette (1999).

3 Data

The main dataset we use comes from the Encuesta Sobre Estrategias Empresariales (ESEE) from 1990-2012. The Data Appendix provides details on the sample and

[10] Equation (3) can be also obtained by adding the FOCs.

[11] $\ln \frac{R_{jt}}{VC_{jt}} = \ln(1 + \frac{R^*_{jt} - VC_{jt}}{VC_{jt}}) + \varepsilon_{jt} \simeq \frac{P_{jt} - AVC_{jt}}{AVC_{jt}} + \varepsilon_{jt}$.

variables. Figures 1 to 3 summarize some relevant facts. Figure 1 shows that the proportion of firms that export increases steadily from 1990 to 1997, then becomes quite stable until 2007 when it again starts to rise. Figure 2 shows that the same trend occurs with the intensity of exports conditional on exporting. The average proportion of sales sold abroad, already high, hits 80% of sales at the end of the sample.

To compute the PAVCMs, which play a key role in the subsequent analysis, we estimate variable cost as the sum of the wage and material bills less the expenditure on advertising, the expenditure on R&D, and an estimate of the wage bill corresponding to white-collar employees (see Data Appendix for details).

Figure 3 shows how the PAVCM drops by more than 8 percentage points over the entire sample period. It seems natural to associate this decline with an increase in the level of competition faced by manufacturing firms. Using the variation in the exports of firms, on both the extensive and intensive margin, we expect the data to tell us if the variation in markup is something related to increasing participation in foreign markets. The fall in the cost of capital until 2004 may have also helped firms to moderate the markups charged.

The other key variable, the share of labor in variable costs, shows an important dispersion that is mainly cross-sectional. The mean of the share of labor S_{Ljt} is 0.304, the standard deviation 0.161, its between variance 0.864 and its within variance 0.136.[12] Figure 4 depicts the frequencies of the labor share and and Table A1 gives further details on the distribution as well as its evolution over time. The change in the mean during the sample period is always downward and significant (-6 percentage points on average across industries). However this change is only between one half and one third the value of the IQR of the distribution of shares at any moment in time. The decrease over time shows an important component of covariation between the labor share and the size of the firms as measured by their relative variable cost: bigger firms have lower labor shares and this relationship tends to become stronger over time.[13]

The decrease over time of the labor share in variable costs has been indirectly addressed by a long list of macro papers that explore the fall in the labor share of income. Elsby, Hobijn & Sahin (2013) attribute this fall to a combination of an elas-

[12] We compute the between dimension weighting the between deviations by the ratio of years in the sample to mean years.

[13] Kehrig & Vincent (2018) detect this type of relationship in their description of the evolution of the labor share in value-added with the US plant-level Census data 1967-2007.

ticity of substitution σ between labor and capital greater than one with offshoring; Karabarbounis & Neiman (2014) to the same kind of elasticity of substitution combined with the fall of the prices of investment; Autor et al. (2019) to the reallocation of sales towards high markup firms; Grossman, Helpman, Oberfield & Sampson (2017) to the accumulation of human capital in the presence of a more empirically consistent σ smaller than one; Oberfield & Raval (2014) to labor-augmenting productivity with σ less than unit and Acemoglu & Restrepo (2018) to automation which substitutes capital for tasks previously performed by labor. Our focus in labor-augmenting productivity is broadly consistent with the stories developed by the last three papers.

For comparing to the labor share, Table A1 also reports the joint relative total cost shares of labor and materials, estimated by adding to variable cost a firm-specific estimate of the user cost of capital times the amount of capital (see Data Appendix). In contrast to the labor share, it is less dispersed and more stable over time (it gains on average less than 1 percentage point).

4 DLW markups, puzzles, and reasons for bias

4.1 DLW markups

DLW propose estimating markups from equation (2). Choosing an input without adjustment costs, estimating its production elasticity $\widehat{\beta}_{Xjt}$, and the error in observed output $\widehat{\varepsilon}_{jt}$, the markup can be computed as

$$\widehat{\mu}_{jt} = \frac{\widehat{\beta}_{Xjt}}{S^R_{Xjt}} \exp(-\widehat{\varepsilon}_{jt}), \tag{6}$$

where $S^R_{Xjt} = \frac{W_{Xjt}X_{jt}}{R_{jt}}$.

We carry out this exercise for our sample of Spanish manufacturing firms. We compute markups separately using labor and materials. We also compute markups combining labor and materials into variable costs according to equation (3), again without adjustment costs.

For estimating the elasticities we specify, as in DLW, a Cobb-Douglas production function so $\widehat{\beta}_{Ljt}$ and $\widehat{\beta}_{Mjt}$ become constants. Following DLW, we employ an OP/LP procedure, implemented in the form proposed by ACF. This procedure sets $\omega_{Ljt} = 0$ and adds to the framework in Section 2 the assumption that ω_{Hjt} follows a first order

Markov process.

In a first step, we estimate the disturbance ε_{jt} that separates observed output from relevant output. This is accomplished by carrying out the nonparametric regression

$$q_{jt} = \phi(x_{jt}) + \varepsilon_{jt},$$

where $\phi(.)$ has a flexible functional form and x_{jt} collects all the arguments of the production function and the input demand that is inverted to control for ω_{Hjt}. In a second step, we estimate the elasticities in the regression

$$q_{jt} = \ln F(K_{jt}, L_{jt}, M_{jt}) + g_t(\widehat{\phi}_{jt-1} - \ln F(K_{jt-1}, L_{jt-1}, M_{jt-1})) + \xi_{jt} + \varepsilon_{jt},$$

based on the Markovian assumption on productivity.

A critical step is the specification of the demand function we will invert to replace ω_{Hjt}, usually the demand for materials (ACF). We include input prices and a demand shifter in the demand for materials.[14] This agrees with DLW who, in their gross output approach detailed in page 4 of their Appendix, explain that ω_{Hjt} should be replaced by $h_t(k_{jt}, m_{jt}, z_{jt})$, where z_{jt} includes input prices. Details on the estimation are given in Appendix D. In Table A2 we report estimated elasticities and in Table A3 markups.

Markups show a startling variation. The markups as computed using labor tend to be very high, which is partly due to our decision to deduct from the wage bill the wages of white collar workers. The markups computed with materials and with variable costs are much more reasonable.[15] We report in columns (1) and (2) of Table 1 the markups obtained using variable cost, and compare them with the PAVCMs reported in columns (3) and (4). They show that DLW markups can look extremely good (except for an unlikely value in industry 8).

For the next exercise, regressing markups on export status, what matters are the variables included in x_{jt} because they determine $\widehat{\varepsilon}_{jt}$ (nothing that has been included in x_{jt} can be correlated with $\widehat{\varepsilon}_{jt}$). The particular elasticity that we have estimated does not matter because with a Cobb-Douglas production function it is a constant. The differences in variation among the computed markups are exclusively driven by the denominator of equation (6), i.e. the revenue share of each input.

[14] Along the lines of Doraszelski & Jaumandreu (2013). This may address concerns about identification, as recognized by Gandhi et al. (2017).

[15] However, they are very volatile (often too high or too low) when we do not include input prices and the demand shifter.

4.2 Puzzling results

The surprising results come when we regress markups on export status, the same exercise as in DLW. The dummy of export status is included in the regression of the estimated markups on a constant and time dummies. The markups computed using S^R_{Ljt} and S^R_{Mjt} give completely different answers.[16] Exporters have positive sizable and very significant differences in markups when we use the labor measurement (column (5) in table 1), and negative sizable and very significant differences in markups when we use the materials measurement (column (6)). The only industry that escapes this pattern is industry 2. If we wanted the markups to compare exporters and non-exporters we have failed completely in our goal. What is the correct answer?

DLW report a coefficient of around 0.078 (page 2459) in this type of regression with markups using labor cost (see their Table 3). Using Slovenian data similar to theirs, we compute the markups using the cost of materials and their estimation procedure. Similar to the Spanish data, the regressions show a negative effect of the export status on estimated markup in all industries. Although we cannot check directly with the Slovenian data (our sample includes labor input but not its cost), we presume that the markups when computed with labor costs would show the same pattern as in the Spanish data.

When applied to labor, we drop adjustment costs from equation (2). We now incorporate the estimated term $\ln(1 + \widehat{\Delta}_{Ljt})$. The dummy of export status and the estimate $\ln(1 + \widehat{\Delta}_{Ljt})$ are included in the regression of the estimated markups on a constant and time dummies. The results for labor are reported in columns (8) and (9) of Table 1. Adjustment costs result in significant positive coefficients in the case of the markup computed with labor, as expected.[17] The experiment presents another surprising result however. Adjustment costs are confirmed as a source of bias, but the bias is in addition to the one picked up by export status. Adjustment costs cause their own effects, while the coefficient on export status remains almost constant across the regressions. The reason is that export status and adjustment costs turn out to be almost orthogonal (mean correlation across industries is 0.03).

Related to our results Raval (2019a) has recently found disparities in five firm-level data sets (Chile, 1979-96, Colombia, 1978-91, India, 1998-14, Indonesia, 1991-00, US

[16] And the markups using variable costs give something in between.

[17] Adjustment costs are insignificant, as expected, when we include it to explain the markups computed using materials.

retailer, 3 years) using two specifications of the production function (Cobb-Douglas and translog), and three ways to compute markups (labor, materials, and both). In particular, markups computed with labor and materials tend to show negative or null correlation across time, heterogeneous correlations with firm size and, in the case of the US, with competition measures. Note that most of the data sets come from developing countries, which may explain some differences with our results.

4.3 Sources of bias

One or both regressions have to be biased because the inferences of Table 1 are incompatible. Under a correctly specified model we expect identical or at least very similar answers using the different inputs. The combination of equations (1) and (6) provides a useful way to analyze the possible sources of bias. Subtracting (in logs) equation (1) from (6), we can write

$$\ln \widehat{\mu}_{jt} = \ln \mu_{jt} + (\ln \widehat{\beta}_{Xjt} - \ln \beta_{Xjt}) + (\varepsilon_{jt} - \widehat{\varepsilon}_{jt}) + \ln(1 + \Delta_{Xjt}) = \ln \mu_{jt} + u_{jt}. \quad (7)$$

Given a regressor d, since $E(\ln \widehat{\mu}_{jt}|d) = E(\ln \mu_{jt}|d) + E(u_{jt}|d)$ we will get biased inferences if $E(u_{jt}|d) \neq 0$. There are three non mutually-exclusive possibilities: d might be correlated with ε_{jt} (notice that d it is orthogonal to $\widehat{\varepsilon}_{jt}$ if it has been included in the first step of ACF), with adjustment costs of labor, or with the deviation in the estimation of the elasticity.

We have already checked the role of adjustment costs of labor. The correlation of the export status with ε_{jt} does not strike us as a plausible explanation for what we observe in the three regressions because the error ε_{jt} enters each of them in the same way and thus should provoke a similar bias. Nevertheless, we have performed a test for the possible endogeneity of the export status with respect to ε_{jt} (see Appendix E). In nine of ten industries, we cannot reject exogeneity at a 5% significance level. We conclude that the main problem must be in the estimate of the elasticities.

4.4 Varying elasticities

We have specified a Cobb-Douglas production function. If the real elasticities vary and the deviations are correlated with the regressor that we use, this may be the source of bias. Cost minimization implies that the relative elasticities of the inputs should match their equilibrium relative cost shares. Write the ratio of elasticities as an implicit function of its arguments

$$\frac{\beta_{Ljt}(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})}{\beta_{Mjt}(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})} = \frac{S_{Ljt}}{(1 - S_{Ljt})}(1 + \Delta_{L_{jt}})(1 + \tau_{jt}),$$

where we now include τ_{jt} as a generic notation for unobservables coming from non price-taking behavior in the labor market and possible government induced distortions (see section 2) as well as possible optimization errors (Marschak & Andrews 1944) and measurement errors. The common specifications of Cobb-Douglas, translog or CES functions raise a broad mismatch between relative elasticities and observed shares. When we regress the log of the relative shares on a complete polynomial of degree three in the log of $K_{jt,}L_{jt}$ M_{jt} and $(1 + \Delta_{L_{jt}})$ we get a RMSE of 0.319.[18] The number is sensible: the variation of the observed inputs and adjustment costs can explain with a flexible approximation about 2/3 of the variation in the relative shares. However we miss 1/3 of the variation, which means that we should look carefully at the role of the unobservables.

Labor-augmenting productivity. Heterogeneity in the efficiency of the labor input is a traditional and powerful candidate to explain the mismatch. Broadly defined, labor-augmenting productivity includes everything that may increase marginal productivity and wages, even if it is not strictly technology. For example, higher wages may reflect higher skill and higher marginal productivity of workers, or they may reflect the higher marginal productivity elicited from some workers through the application of efficient contracts.

In contrast to Hicks-neutral productivity, labor-augmenting productivity directly affects input elasticities. One can get an idea of how important labor-augmenting productivity is for the elasticities of the inputs by computing its impact for a CES function.[19]

[18] The relative variable input shares $S_{Ljt}/(1 - S_{Ljt})$ not corrected by adjustment costs have in our sample a mean of 0.634 and a standard deviation of 1.663.

[19] Call ν^* the returns to scale in the long-run. The elasticity of labor changes with labor-augmenting productivity according to the derivative $\frac{\partial \beta_{Ljt}}{\partial \omega_{Ljt}} = -\frac{1-\sigma}{\sigma}\beta_{Ljt}(1 - \frac{\beta_{Ljt}}{\upsilon^*})$, and the elasticity of materials according to the derivative $\frac{\partial \beta_{Mjt}}{\partial \omega_{Ljt}} = \frac{1-\sigma}{\sigma}\beta_{Ljt}\frac{\beta_{Mjt}}{\upsilon^*}$. The effect of labor-augmenting productivity in the short-run scale parameter is $\frac{\partial \nu_{jt}}{\partial \omega_L} = \frac{\partial(\beta_{Ljt}+\beta_{Mjt})}{\partial \omega_L} = -\frac{1-\sigma}{\sigma}\beta_{Ljt}\frac{\beta_{Kjt}}{\upsilon^*}$. Taking the standard values $\sigma = 0.5$, $\beta_K = 0.1$, $\beta_L = 0.3$, and $\beta_M = 0.6$, one percentage point increase in labor-augmenting productivity decreases β_L by 0.21 percentage points, increases β_M by 0.18, and decreases ν by only

In addition to the decreasing trend found in the labor share documented in section 3, a closer look at the evolution of the labor share shows that it is a decreasing function of the number of years that we observe the firm in the sample. Figure 5 depicts a nonparametric regression of the log of the labor share relative to the share in the first year on the number of years that the firm is observed. Only the first two years are an exception, which is driven by the big proportion of firms for which these are the two first years of life.

To do a quick check of whether labor-augmenting productivity can explain what we observe in the regressions, we compute an estimate of labor-augmenting productivity $\widehat{\omega}_{Ljt}$ and include it as a regressor. Following equation (5) in Doraszelski & Jaumandreu (2018), dropping the constant, we compute the estimate $\widehat{\omega}_{Ljt} = \frac{1}{1-\widehat{\sigma}}[m_{jt} - l_{jt} + \widehat{\sigma}(p_{Mjt} - w_{jt})]$ by plugging in the estimates of the elasticity of substitution from column (3) of their Table 4.

The results reported in columns (1) to (4) of Table 2, fully coincide with the theoretical predictions. Our measurement of labor-augmenting productivity attracts high, positive, significant coefficients when explaining the markups computed with labor and sharp, negative, significant coefficients when explaining the markups computed with materials. The coefficient on export status becomes much smaller in absolute value and tends to change sign. Average correlation across industries between the export status and our measure of labor-augmenting productivity is 0.309, which explains the changes.

Other unobservables. Even if labor-augmenting productivity explains the biggest part of the mismatch, there likely remain other unobservables that prevent a perfect match between elasticities and shares. We have enumerated them above as possible contents for τ_{jt}.

Several recent papers have claimed evidence on widespread monopsony power in the US (see, for example, Azar, Marinescu & Steinbaum (2019)). There is, however, a debate whether the trends followed by this market power can explain the fall in the labor share, with evidence that it cannot (Lipsius 2018). Dobbelaere & Mairesse (2013, 2018) conclude that "rent sharing" is more important than monopsony with French data. The size of the effect is unclear given their more moderate results with wage regressions that use firm-worker data instead of firm-level estimates. In addition,

0.03 percentage points.

there are reasons to think that their rent sharing model is picking up labor-augmenting productivity. There may be other unspecified sources of divergence. In the end, what is important is whether these errors can be assumed uncorrelated with the observed labor share in cost. While this seems a sensible assumption for most of the errors, it cannot be sustained in the case of monopsony and rent sharing. We continue this discussion when we talk about identification.

5 Controlling for marginal cost in elasticity estimation

The DLW proposal to estimate markups overlooks that, under imperfect competition, consistent estimation of the input elasticities and the error ε_{jt} by an OP/LP method requires marginal cost. This is regardless of whether an ACF or another implementation is used.[20]

Observing price, marginal cost MC_{jt} can obviously be replaced by P_{jt}/μ_{jt}. The problem can thus equivalently stated as the need to control for markup when estimating elasticities.

We show this problem in the framework of section 2 applied to static cost minimization but the arguments generalize. First, given cost minimization we show that to estimate elasticities either we observe marginal cost or we need to account for Q^*_{jt} and hence to replace it by its determinants. Second, we show that replacing Q^*_{jt} by its determinants introduces unobservable heterogeneity that violates the "scalar unobservable assumption" that OP/LP procedures need to work. Formally, we analyze the econometric problems generated in the estimation of the elasticities by means of an ACF procedure if one ignores this unobservable heterogeneity.

5.1 Equations generated by cost minimization

Cost minimization gives the three endogenous variables L_{jt}, M_{jt}, and MC_{jt} as a function of the exogenous (given) prices W_{jt} and P_{Mjt}, productivity levels ω_{Hjt} and ω_{Ljt}, and the output to be produced Q^*_{jt}. The output to be produced is an endogenous variable in the profit maximization problem, which we are agnostic about, but an

[20] Ackerberg et al. (2015) recognize the difficulty to integrate imperfectly competitive firms in their framework to estimate production functions (page 2436).

exogenous variable in the cost minimization problem. We show in what follows that while observing MC_{jt} is enough to control for ω_{Hjt}, the absence of this variable raises the problem of the observability of Q^*_{jt}.

The FOCs of cost minimization (Appendix A) are

$$\begin{aligned} MC_{jt}\frac{\partial F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})}{\partial L_{jt}} \exp(\omega_{Ljt}+\omega_{Hjt}) &= W_{jt}, \\ MC_{jt}\frac{\partial F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})}{\partial M_{jt}} \exp(\omega_{Hjt}) &= P_{Mjt}, \end{aligned}$$

and marginal cost, the derivative of variable cost, is

$$MC_{jt} = MC(K_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*_{jt}}{\exp(\omega_{Hjt})}) \exp(-\omega_{Hjt}).$$

How can these expressions be used to substitute for ω_{Hjt} in the production function? Inverting one of the FOCs is not a solution because they contain the unobservable MC_{jt}.[21] The same happens with the system that can be formed by solving the two FOCs.[22,23]

If one replaces MC_{jt} by its expression, we are left with equations in terms of $\frac{Q^*_{jt}}{\exp(\omega_{Hjt})}$. The FOCs written in this way have the same problem as the conditional demands (see Appendix A): we can invert them for ω_{Hjt}, but the resulting expressions depend on unobservable output Q^*_{jt}.[24]

Recall that Q^*_{jt} is what we want to estimate in the first stage of the ACF implementation. If we knew Q^*_{jt} then the most straightforward way to control for ω_{Hjt} would be the inversion of the (lagged) production function, avoiding any OP/LP procedure.

[21] Inverting materials, for example, produces what Ackerberg et al. (2015) call a materials input demand conditional on labor.

[22] The system that we can get by solving the FOCs for L_{jt} and M_{jt} in terms of K_{jt}, ω_{Hjt} and ω_{Ljt}, $\frac{W_{jt}}{MC_{jt}}$ and $\frac{P_{Mjt}}{MC_{jt}}$.

[23] Note that the system cannot be solved if there are constant returns to scale in L_{jt} and M_{jt} (marginal productivities are homogeneous of degree zero). Intuitively, with independence of output we have $MC_{jt} = MC(K_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})}, P_{Mjt}) \exp(-\omega_{Hjt})$ and ω_{Hjt} drops from the FOCs. Recall, however, that with short-run constant returns to scale the problem of observability of markups reduces to ε_{jt}.

[24] One may wonder what happens if the ratio $\frac{Q^*_{jt}}{\exp(\omega_{Hjt})}$ is replaced by inverting for this ratio one of the conditional demands, materials say. Interestingly enough, one gets an expression for MC_{jt} with no unobservables other than ω_{Ljt} and ω_{Hjt}, $MC_{jt} = \widetilde{MC}(K_{jt}, M_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})}, P_{Mjt}) \exp(-\omega_{Hjt})$. But the expression is not useful for our current purposes since ω_{Hjt} drops from the FOC.

We conclude that an OP/LP procedure needs either to observe MC_{jt} or to replace Q^*_{jt} by its determinants.

Notice that, departing from OP/LP, one way out is to specify MC_{jt} as observable up to a set of elasticities to be estimated. For example, $MC_{jt} = \frac{AMC_{jt}}{\beta_{Mjt}} \exp(\varepsilon_{jt})$, where $AMC_{jt} = \frac{P_{Mjt}M_{jt}}{Q_{jt}}$ or average cost of materials, or $MC_{jt} = \frac{AVC_{jt}}{\beta_{Ljt}+\beta_{Mjt}} \exp(\varepsilon_{jt})$, where $AVC_{jt} = \frac{VC_{jt}}{Q_{jt}}$. In both cases the disturbance ε_{jt} violates the "scalar unobservable assumption," but we can obtain an estimable model by giving up the nonlinearity of the Markov process.

5.2 Using observables to replace planned output

Replacing Q^*_{jt} by its determinants seems to be the route taken by DLW, although it is never explicitly stated. DLW state: "We follow Levinsohn & Petrin (2003) and rely on material demand

$$m_{jt} = m_t(k_{jt}, \omega_{jt}, z_{jt}),$$

to proxy for productivity by inverting $m_t(\cdot)$, where we collect additional variables potentially affecting optimal input demand choice in the vector z_{jt}"(page 2446).[25] Suppose for simplifying that $\omega_{Ljt} = 0$. According to our discussion, the list of variables that have to be included in z_{jt} in the absence of MC_{jt} is very precise: the input prices W_{jt} and P_{Mjt} as well as all the determinants of Q^*_{jt}. Here is exactly where the problem resides. Demanded Q^*_{jt} is in general a function $Q^*_{jt} = Q(P_{jt}, z^S_{jt}, \delta_{jt})$,[26] where z^S_{jt} stands for observed demand shifters and δ_{jt} is unobserved demand heterogeneity. The vector z_{jt} of observable variables can be specified as $z_{jt} = (w_{jt}, p_{M_{jt}}, p_{jt}, z^S_{jt})$ but, in addition, unobserved demand heterogeneity δ_{jt} has to be accounted for and the demand for materials becomes

$$m_{jt} = m_t(k_{jt}, \omega_{Hjt}, z_{jt}, \delta_{jt}).$$

[25]In using $m_{jt} = m_t(k_{jt}, \omega_{Hjt})$ Levinsohn & Petrin (2003) note that "input and output prices are assumed to be common across firms (they are suppressed)" (page 322). They had in mind a competitive industry, as page 338 in Appendix A makes clear. Under imperfect competition, equal (output and input) prices is neither a necessary nor sufficient condition to have an expression as above. Under profit maximization, for example, if prices are equal we still need the equality of the markups because the relevant variable is marginal revenue or marginal cost.

[26]Planned production can, however, be different from expected demand if the firm expects to cover part of the demand with inventories or, on the contrary, plans to accumulate some.

Unfortunately, the demand heterogeneity embodied in δ_{jt} violates the "scalar unobservable" assumption that we need for an OP/LP method to work.[27]

5.3 Econometric problems

Suppose that despite the unobservable demand heterogeneity δ_{jt} we proceed to apply an ACF estimation of $q_{jt} = \phi(x_{jt}, \delta_{jt}) + \varepsilon_{jt}$. As we do not observe δ_{jt}, the regression produces estimates of the $\phi(\cdot)$ function and the residuals ε_{jt} that differ from the true values. The first stage produces an integrated conditional expectation

$$q_{jt} = \widetilde{\phi}(x_{jt}) + r_{jt} + \varepsilon_{jt},$$

where $\widetilde{\phi}(x_{jt}) = E(q_{jt}|x_{jt})$, $r_{jt} = \phi(x_{jt}, \delta_{jt}) - \widetilde{\phi}(x_{jt})$, and $\widetilde{\varepsilon}_{jt} = r_{jt} + \varepsilon_{jt}$ is by construction mean-independent of x_{jt}.

The second stage of ACF is based on the regression

$$q_{jt} = \ln F(K_{jt}, L_{jt}, M_{jt}) + g_t(\widetilde{\phi}(x_{jt-1}) + r_{jt-1} - \ln F(K_{jt-1}, L_{jt-1}, M_{jt-1})) + \xi_{jt} + \varepsilon_{jt}.$$

A Taylor expansion of $g_t(\cdot)$ around $r_{jt-1} = 0$ gives

$$\begin{aligned} q_{jt} &= \ln F(K_{jt}, L_{jt}, M_{jt}) + g_t(\widetilde{\phi}(x_{jt-1}) - \ln F(K_{jt-1}, L_{jt-1}, M_{jt-1})) \\ &\quad + g_t^1 r_{jt-1} + \textstyle\sum_{s=2}^{\infty} g_t^s r_{jt-1}^s / s! + \xi_{jt} + \varepsilon_{jt}, \end{aligned}$$

where g_t^s denotes the $s-th$ derivative. The first term of the expansion can be written as $g_t^1 r_{jt-1} = g_t^1(\omega_{jt-1})[\phi(x_{jt-1}, \delta_{jt-1}) - \widetilde{\phi}(x_{jt-1})]$ to help with intuition. It is an unobservable error term positively related to the impact of δ_{jt-1} on q_{jt-1}^* that is not accounted for by the other variables included in $\widetilde{\phi}(\cdot)$. It is likely to be correlated with any variable that has not been included in constructing $\widetilde{\phi}(\cdot)$.

This extra error has at least two effects. First, it increases the variance of the estimated elasticities. Second, it invalidates many commonly used instruments, making the estimation inconsistent. This is the case of any input dated at t, such as K_{jt} or $L_{jt,}$.

[27] The first paper dealing with demand heterogeneity in the context of production function estimation, Klette & Griliches (1996), assumed δ_{jt} to be an uncorrelated error. This is also the assumption in De Loecker (2011) once z_{jt}^S has been accounted for. The more recent literature recognizes δ_{jt} as an autocorrelated unobservable, as important as ω_{jt} or even more, and correlated with it.

The sign of the bias is difficult to establish because it depends on many factors, including the nature of the unobservable. A clue to what can happen is given by Brandt et al. (2017), who get an average coefficient across industries on materials of 0.913[28] against an average estimate of 0.66 by Jaumandreu & Yin (2018), who with identical Chinese data try to control for heterogeneity of demand. In Appendix F we develop an example that suggests a positive bias in the elasticity of the input under the assumption of a positive relationship between the input in the production function and heterogeneity of demand δ_{jt}. In these circumstances we expect both elasticities and markups to be biased upwards.

6 Two examples of robust inference

In this section we develop two examples of robust inference on markups under non-specified competition and a flexible production function. Specifically we ask ourselves whether there is a systematic association between markups, export status, and export intensity.

Throughout we use a translog production function with both labor-augmenting and Hicksian productivity. The first example is an easy to apply two-stage procedure. We first estimate the translog, including the adjustment costs and controlling for labor-augmenting productivity. We assume that Hicksian productivity follows a linear Markov process and use the lagged inverted production function to control for it (dynamic panel estimation). In the second step, we correct $\ln \frac{R_{jt}}{VC_{jt}}$ using the estimated adjustment costs and scale parameter, regressing the result on export status and export intensity.

The second example is a full simultaneous estimation of equation (4) and the production function (5). Equation (4) is specified assuming that the unobservable markup follows an endogenous linear Markov process, shifted by the export status and other variables. Hicksian productivity in equation (5) is again assumed to be a (now endogenous) linear Markov process, but past productivity is replaced by an expression which includes lagged markup (an OP/LP-type procedure).

In what follows we first briefly introduce the translog that we use, discuss identification, then give details of both examples, and finally comment on the results of the estimation.

[28] See Table A2 of their Online Appendix.

6.1 A simple translog with two types of productivity

We use the (separable in K_{jt}) translog production function

$$
\begin{aligned}
q_{jt} &= \alpha_0 + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK}k_{jt}^2 + \alpha_L(\omega_{Ljt} + l_{jt}) + \frac{1}{2}\alpha_{LL}(\omega_{Ljt} + l_{jt})^2 + \alpha_M m_{jt} + \frac{1}{2}\alpha_{MM}m_{jt}^2 \\
&\quad + \alpha_{LM}(\omega_{Ljt} + l_{jt})m_{jt} + \omega_{Hjt} + \varepsilon_{jt},
\end{aligned}
$$

where we allow for Hicks-neutral productivity ω_{Hjt} and labor-augmenting productivity ω_{Ljt}.[29] We impose homogeneity of degree $\alpha_L + \alpha_M$ in L_{jt} and M_{jt} by setting $-\alpha_{LL} = -\alpha_{MM} = \alpha_{LM} \equiv \alpha$. The production function becomes

$$
q_{jt} = \alpha_0 + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK}k_{jt}^2 + \alpha_L(\omega_{Ljt} + l_{jt}) + \alpha_M m_{jt} - \frac{1}{2}\alpha(m_{jt} - \omega_{Ljt} - l_{jt})^2 + \omega_{Hjt} + \varepsilon_{jt}. \tag{8}
$$

The elasticities of the variable inputs L_{jt} and M_{jt} are[30]

$$
\begin{aligned}
\beta_{Ljt} &= \frac{\partial q_{jt}}{\partial l_{jt}} = \alpha_L + \alpha(m_{jt} - \omega_{Ljt} - l_{jt}), \\
\beta_{Mjt} &= \frac{\partial q_{jt}}{\partial m_{jt}} = \alpha_M - \alpha(m_{jt} - \omega_{Ljt} - l_{jt}).
\end{aligned} \tag{9}
$$

The short-run elasticity of scale $\nu_{jt} = \beta_{Ljt} + \beta_{Mjt} = \alpha_L + \alpha_M$ is constant.

Assume for a moment that there are no adjustment costs. Taking the FOCs for the two variable inputs and dividing one by the other yields the expression

$$
\omega_{L_{jt}} = (m_{jt} - l_{jt}) + \frac{\alpha_L}{\alpha} - \frac{\alpha_L + \alpha_M}{\alpha} S_{Ljt}, \tag{10}
$$

where $S_{Ljt} = \frac{W_{jt}L_{jt}}{W_{jt}L_{jt} + P_{Mjt}M_{jt}}$ is the share of labor cost in variable cost.[31] In the presence of adjustment costs on labor, we consider the share $\frac{W_{jt}L_{jt}}{W_{jt}L_{jt} + P_{Mjt}M_{jt}} \frac{1+\Delta_{Ljt}}{1+S_{Ljt}\Delta_{Ljt}}$.

Using equation (10) to replace the unobservable labor-augmenting productivity

[29] De Loecker et al. (2018) assume separability in capital. Separability in capital makes it a member of the class of functions referred by Doraszelski & Jaumandreu (2018).

[30] The elasticity with respect to observed labor L_{jt} is the same the the elasticity with respect to $\exp(\omega_{Ljt})L_{jt}$, since $\frac{\partial q_{jt}}{\partial l_{jt}} = \frac{\partial q_{jt}}{\partial(\omega_{Ljt} + l_{jt})} \frac{\partial(\omega_{Ljt} + l_{jt})}{\partial l_{jt}} = \frac{\partial q_{jt}}{\partial(\omega_{Ljt} + l_{jt})} = \beta_{Ljt}$.

[31] The equivalent expression for the CES production function is $\omega_{Ljt} = (m_{jt} - l_{jt}) + \frac{\sigma}{1-\sigma} \ln \frac{\gamma_L}{\gamma_M} - \frac{\sigma}{1-\sigma} \ln \frac{S_{Ljt}}{1-S_{Ljt}}$, where the gammas are the so-called distributional parameters.

ω_{Ljt} in equation (8) results in a new expression for the production function,

$$q_{jt} = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK} k_{jt}^2 + (\alpha_L + \alpha_M) m_{jt} - \frac{1}{2}\frac{(\alpha_L + \alpha_M)^2}{\alpha} S_{Ljt}^2 + \omega_{Hjt} + \varepsilon_{jt}, \quad (11)$$

in which only the unobservable Hicks-neutral productivity ω_{Hjt} is left.

Until now we have been treating the wage as split into a flat price of labor and the wedge introduced by the adjustment costs. While we are able to estimate this wedge, observed wages in practice already include an important part of the monetary components of adjustment costs and there is only a fraction of the adjustment costs that remains unobservable. To allow for this fact in a tractable way we split $W_{jt}(1 + \Delta_{L_{jt}}) = W_{jt}(1 + \Delta_{L_{jt}})^{1-\theta}(1 + \Delta_{L_{jt}})^{\theta}$, where the parameter θ represents roughly the proportion of non-observed adjustment costs. We slightly abuse notation by keeping the symbol W_{jt} for what in fact is now $W_{jt}(1 + \Delta_{Ljt})^{1-\theta}$. Similarly, we use the approximation $VC_{jt}(1+S_{Ljt}\Delta_{L_{jt}})^{\theta}$ and we specify the shares controlled by adjustment costs as

$$\frac{W_{jt}L_{jt}}{W_{jt}L_{jt} + P_{Mjt}M_{jt}} \left(\frac{1 + \Delta_{Ljt}}{1 + S_{Ljt}\Delta_{Ljt}}\right)^{\theta}.$$

6.2 Identification

If the entire gap between elasticities and shares can be attributed to the unobservable ω_{Ljt}, as equation (10) implicitly does, the elasticities simplify to

$$\begin{aligned} \beta_{Ljt} &= (\alpha_L + \alpha_M) S_{Ljt}, \\ \beta_{Mjt} &= (\alpha_L + \alpha_M) S_{Mjt}, \end{aligned} \quad (12)$$

as expected from theory.

However, as discussed in subsection 4.4, there can be additional sources of mismatch summarized in the error τ_{jt}. Because we are also likely to be estimating with error the adjustment costs of labor, suppose that $\Delta_{Ljt} = \Delta_{Ljt}^{*} + \zeta_{jt}$, where Δ_{Ljt}^{*} are the true adjustment costs. We can encompass the effects of these two types of errors in an error e_{jt} to be added to equation (10) to obtain

$$\omega_{L_{jt}} = (m_{jt} - l_{jt}) + \frac{\alpha_L}{\alpha} - \frac{\alpha_L + \alpha_M}{\alpha} S_{Ljt} - e_{jt}.$$

If we have a τ_{jt} error, then the share becomes $S_{Ljt}\frac{(1+\tau_{jt})}{(1+S_{Ljt}\tau_{jt})} \simeq S_{Ljt} + S_{Ljt}(1 - S_{Ljt})\tau_{jt}$

and $e_{jt} = \frac{\alpha_L+\alpha_M}{\alpha} S_{Ljt}(1-S_{Ljt})\tau_{jt}$. If we have a ζ_{jt} error, then $S_{Ljt}\frac{(1+\Delta^*_{Ljt}+\zeta_{jt})}{(1+S_{Ljt}\Delta^*_{Ljt}+S_{Ljt}\zeta_{jt})} \simeq S_{Ljt}\frac{(1+\Delta^*_{Ljt})}{(1+S_{Ljt}\Delta^*_{Ljt})} + \frac{S_{Ljt}(1-S_{Ljt})}{(1+S_{Ljt}\Delta^*_{Ljt})^2}\zeta_{jt}$ and $e_{jt} = \frac{\alpha_L+\alpha_M}{\alpha}\frac{S_{Ljt}(1-S_{Ljt})}{(1+S_{Ljt}\Delta^*_{Ljt})^2}\zeta_{jt}$. Of course, relevant errors can be a combination of both. Plugging in the new expression for ω_{Ljt} with error, the production function becomes

$$\begin{aligned} q_{jt} &= \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} + \alpha_K k_{jt} + \frac{1}{2}\alpha_{KK}k_{jt}^2 + (\alpha_L+\alpha_M)m_{jt} \\ &\quad -\frac{1}{2}\frac{(\alpha_L+\alpha_M)^2}{\alpha}S_{Ljt}^2 + \omega_{Hjt} + \varepsilon_{jt} - \frac{1}{2}\alpha e_{jt}^2 - (\alpha_L+\alpha_M)S_{Ljt}e_{jt}. \end{aligned}$$

The errors e_{jt} are likely to be correlated in many cases with S_{Ljt}, through both W_{jt} and L_{jt}, as well as M_{jt}. Contemporaneous values of these variables are not used as instruments because they are likely to be correlated with the innovations of the Markov processes for productivity as well (under the usual timing assumptions). Consistency can be reached if the errors e_{jt} are uncorrelated with the lags of these variables. This can be assumed in most of cases, but is unlikely if the sources are persistent wedges determined by a monopsony or rent sharing situation as pointed out in subsection 4.4. If the researcher thinks that this is the case, the best solution is to model the distortion with suitable variables, as we have done in the case of adjustment costs.

Notice that, even if estimation is consistent, the presence of errors implies that the individual values of labor-augmenting productivity and elasticities cannot be recovered. Elasticities, for example, are

$$\begin{aligned} \beta_{Ljt} &= (\alpha_L+\alpha_M)S_{Ljt} + \alpha e_{jt}, \\ \beta_{Mjt} &= (\alpha_L+\alpha_M)S_{Mjt} - \alpha e_{jt}. \end{aligned}$$

Estimating individual values is restricted to the cases that the researcher is willing to adopt a "scalar unobservable assumption" with respect to labor augmenting productivity (as the only relevant unobservable in the relative FOCs, as it is assumed for Hicksian productivity in an OP/LP procedure). However, averages of labor-augmenting productivity and elasticities can be estimated, even for groups of firms, as long as $E(e_{jt}) = 0$ can be sustained. This is what we do. In what follows we implicitly subsume the e_{jt} errors into the general composite error of the estimating equation.

6.3 Example 1

To deal with Hicksian productivity ω_{Hjt} in equation (11) we assume that follows the linear inhomogeneous Markov process $\omega_{Hjt} = \beta_t + \rho\omega_{Hjt-1} + \xi_{jt}$. A natural expression to replace the unobservable ω_{Hjt-1} is the lagged production function inverted to obtain $\exp(\omega_{Hjt-1}) = Q^*_{jt-1}/F_{jt-1}$, where F_{jt-1} is a shorthand for the observable part of the production function. Using $Q^*_{jt-1} = Q_{jt-1}\exp(-\varepsilon_{jt-1})$, we have $\omega_{Hjt-1} = q_{jt-1} - \ln F_{jt-1} - \varepsilon_{jt-1}$ and the model to take to the data can be written as

$$\begin{aligned} q_{jt} &= \gamma_0 + \beta_t + \rho q_{jt-1} + \alpha_K(k_{jt} - \rho k_{jt-1}) + \frac{1}{2}\alpha_{KK}(k^2_{jt} - \rho k^2_{jt-1}) \\ &\quad +(\alpha_L + \alpha_M)(m_{jt} - \rho m_{jt-1}) - \frac{1}{2}\frac{(\alpha_L + \alpha_M)^2}{\alpha}(S^2_{Ljt} - \rho S^2_{Ljt-1}) + u_{jt}, \quad (13) \end{aligned}$$

where $\gamma_0 = \alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha} - \rho(\alpha_0 + \frac{1}{2}\frac{\alpha_L^2}{\alpha})$ and the composite error is $u_{jt} = \xi_{jt} + \varepsilon_{jt} - \rho\varepsilon_{jt-1}$. This approach to control for unobserved productivity is usually called dynamic panel estimation.

In practice, the term in k^2_{jt} only complicates the estimation (presumably by a problem of exacerbation of errors in variable) so we drop it.

Under the assumptions of the general model all inputs and their prices are uncorrelated with the components ε_{jt} and ε_{jt-1} of the disturbance, but q_{jt-1} is obviously correlated with ε_{jt-1}. Variables l_{jt} and m_{jt} are endogenous under the assumption that they are chosen after the firm observes productivity ω_{jt}, and hence after the shock ξ_{jt}. This means that the variable S_{Ljt} is correlated with ξ_{jt}, too.

We estimate the model using nonlinear GMM. In addition to the constant and the 21 time dummies, we estimate five nonlinear parameters: ρ, α_K, $(\alpha_L + \alpha_M)$, α, and θ. The instruments are detailed in Appendix G. They give, across industries, a minimum of 4 overidentifying restrictions and a maximum of 7.

Once the production function is estimated, we run the regression

$$E(\ln \frac{R_{jt}}{VC_{jt}} + \ln\widehat{\nu} - \widehat{\theta}\ln(1 + S_{Ljt}\Delta_{Ljt})|d_{jt}) = E(\ln\mu_{jt}|d_{jt}) + E(\varepsilon_{jt}|d_{jt}).$$

We first regress the dependent variable on a constant, time dummies, and the export status. Then we select the observations corresponding to exporters and run nonparametric regressions of our estimated dependent variable on the export intensity of firms. The first kind of regression tells us if exporters have greater markups than non-exporters; the second if there is some systematic relationship between markups and the fraction of sales that is exported.

6.4 Example 2

To avoid cluttered notation and focus on the core of the example we develop it without adjustment costs.

System of equations. Equations (4) and (5) can be rewritten as

$$\begin{aligned} p_{jt} + \ln F_{jt} + \omega_{Hjt} + \varepsilon_{jt} - vc_{jt} &= -\ln \nu + \ln \mu_{jt} + \varepsilon_{jt}, \\ q_{jt} &= \ln F_{jt} + \omega_{Hjt} + \varepsilon_{jt}, \end{aligned}$$

where F_{jt} stands for the production function and the notation takes into account that we are going to estimate a constant ν.

Assuming that ω_{Hjt} follows an endogenous Markov process $\omega_{Hjt} = g(\omega_{Hjt-1}, z_{jt}) + \xi_{jt}$, and replacing ω_{Hjt-1} using the rewritten equation (4), we have the simultaneous model

$$\begin{aligned} r_{jt} - vc_{jt} &= -\ln \nu + \ln \mu_{jt} + \varepsilon_{jt}, \\ q_{jt} &= \ln F_{jt} + g(-\ln \nu + vc_{jt-1} - p_{jt-1} - \ln F_{jt-1} + \ln \mu_{jt-1}, z_{jt}) \\ &\quad + \xi_{jt} + \varepsilon_{jt}, \end{aligned} \tag{14}$$

where the only unobserved variable is markup (contemporaneous and lagged).

Equations (14) is a very general way to set the simultaneous estimation. If we were able to model $\ln \mu_{jt-1}$ or proxy for it up to an uncorrelated error, then we could estimate the model considering a general Markov process. Proxying or modeling $\ln \mu_{jt-1}$ is nontrivial and so we choose a linear version of the model for now:[32]

$$\ln \mu_{jt} = \beta_t + \rho_1 \ln \mu_{jt-1} + z_{1jt}\gamma_1 + \xi_{1jt},$$

[32] A recent paper by Blum, Claro, Horstmann & Rivers (2018) writes the markup as a function of the price, observed shifters and unobserved heterogeneity proxied by the observed quantity. One may think that this is all we need because we pick up the determinants of the firm-specific elasticity of demand. However this implicitly restricts pricing to static and assumes that oligopoly interactions not embodied in the elasticity of demand are ignorable.

where z_{1jt} are shifters and ξ_{1jt} a mean independent innovation.[33] We assume similarly that $g(\cdot)$ is an inhomogeneous endogenous linear Markov process with parameter ρ_2, innovation ξ_{2jt}, and shifters z_{2jt}. The model can be written as[34]

$$\begin{aligned} r_{jt} - vc_{jt} &= -\ln\nu + \beta_t + \rho_1 \ln \mu_{jt-1} + z_{1jt}\gamma_1 + \xi_{1jt} + \varepsilon_{jt}, \\ q_{jt} &= -\rho_2 \ln\nu + \beta'_t + \ln F_{jt} - \rho_2 \ln F_{jt-1} + \rho_2(vc_{jt-1} - p_{jt-1}) \\ &\quad + \rho_2 \ln \mu_{jt-1} + z_{2jt}\gamma_2 + \xi_{2jt} + \varepsilon_{jt}. \end{aligned} \tag{15}$$

Notice that the model treats each Markov process very differently. While we assume that $\ln \mu_{jt-1}$ is unobservable, we have replaced ω_{Hjt-1} by an expression in terms of observables and $\ln \mu_{jt-1}$.

In contrast with the two stage procedure, modeling the processes is important to improve the estimation. One advantage of the Markov processes is the focus on the shifters of markups and productivity. As shifters of the markups, z_1, we consider: market dynamism, the dummies representing the introduction of process and product innovations, and the export status. As shifters of productivity, z_2, we consider the dummies of process and product innovation.

Estimation. Since $\ln \mu_{jt-1}$ is unobservable, equations (15) cannot be estimated as they stand. We use the following transformations to take the model to the data. From the first equation of (15) we subtract the first equation of (14) lagged and multiplied by ρ_1. In the second equation of (15), we plug in the first equation solved for $\ln \mu_{jt-1}$.[35]

[33] Jaumandreu & Lin (2018) develop and estimate a model in which firms dynamically choose markups. The resulting policy function takes the form of an endogenous Markov process. They argue that this specification is robust to forms of interaction among firms that stay stable over time.

[34] Notice that β_t and β'_t differ because the time dummies of the second equation come from the collapse of two different inhomogeneous processes.

[35] We take the first equation of (15) as the equation for an "indicator" of the unobserved $\ln \mu_{jt-1}$. Everything is like we have $y_1 = \beta_1 x + v_1$ and $y_2 = \beta_2 x + v_2$, with x unobserved, and we use $x = \frac{y_1 - v_1}{\beta_1}$ to replace x in the second equation getting $y_2 = \frac{\beta_2}{\beta_1} y_1 + u_1$ with $u_1 = v_2 - \frac{\beta_2 u_1}{\beta_1}$. See Griliches & Mason (1972) and Wooldridge (2010).

The equations that we take to the data are

$$
\begin{aligned}
r_{jt} - vc_{jt} &= -(1-\rho_1)\ln\nu + \beta_t + \rho_1(r_{jt-1} - vc_{jt-1}) + z_{1jt}\gamma_1 + u_{1jt}, \\
q_{jt} &= -(\rho_2 - \frac{\rho_2}{\rho_1})\ln\nu + \beta_t' + \ln F_{jt} - \rho_2 \ln F_{jt-1} + \rho_2(vc_{jt-1} - p_{jt-1}) \\
&\quad + \frac{\rho_2}{\rho_1}(r_{jt} - vc_{jt} - z_{1jt}\gamma_1) + z_{2jt}\gamma_2 + u_{2jt},
\end{aligned}
$$

after adding the adjustment costs that we have dropped here to simplify notation. The composite errors are $u_{1jt} = \xi_{1jt} + \varepsilon_{jt} - \rho_1\varepsilon_{jt-1}$ and $u_{2jt} = -\frac{\rho_2}{\rho_1}(\xi_{1jt} + \varepsilon_{jt}) + \xi_{2jt} + \varepsilon_{jt}$.

Under the assumptions of the general model, variable r_{jt-1} is endogenous in the first equation (because includes output q_{jt-1} while the equation error contains ε_{jt-1}), and variable r_{jt} is endogenous in the second equation (the equation error contains ε_{jt}). Variables l_{jt}, m_{jt}, and S_{Ljt} are endogenous in the second equation as well because of ξ_{2jt} (see the discussion in Example 1). Current capital and lagged quantities and prices of all inputs are uncorrelated with ε_{jt} and ε_{jt-1} and can be used to form moments. The shifters z_{1jt} and z_{2jt} are uncorrelated by assumption with ξ_{1jt} and ξ_{2jt} and it is natural to consider them uncorrelated with ε_{jt}. So we use them to form moments, as lags to be on the safe side.

We estimate the system by nonlinear GMM. In addition to the two constants and the 21 time dummies of each equation we have to estimate six nonlinear parameters, ρ_1, ρ_2, α_K, $(\alpha_L + \alpha_M)$, α and θ. The instruments are detailed in Appendix H. They give a minimum of 9 overidentifying restrictions and a maximum of 18. The modeling of the markup implies that we can compute its variance separate from the errors. Appendix I details how we measure the mean markup and its variance.

6.5 Results

Table 3 reports in column (1) the mean of the markups estimated in example 1 (two-stage estimation) and Table 4 reports in column (1) the mean and standard deviations of the markups estimated in example 2 (simultaneous estimation). Compared with the DLW markups of Table 1, they show systematically lower mean values, especially in the case of simultaneous estimation. The markups in Table 3 are lower than the markups in Table 1 in seven industries and the markups in Table 4 are lower than the markups in Table 3 in nine industries.

Our interpretation of the results is that they confirm the suggestion of an upward bias in the elasticity of scale due to demand heterogeneity when an ACF procedure is used in the presence of unobservables (section 5.3). The simultaneous estimation might be decreasing the estimates further because of better control of all kinds of heterogeneity in the estimation of the production function. In fact, the level of the markups is in all cases closely associated to the estimated scale parameter.

Columns (2) and (3) of Table 3 report, as a benchmark, the mean and standard deviation of the PAVCM. The mean of the markups diverges from the mean of the PAVCMs for two reasons. The first is the amount by which the short-run elasticity of scale ν is below unity: $\ln \nu \simeq -(1-\nu) = -\frac{MC-AVC}{MC}$ subtracts the percentage points by which -according to technology- marginal cost is above average variable cost. In our examples we estimate the elasticity of scale below unity for all industries (column (4) of Table 3 and column (2) of Table 4).

The second reason is adjustment costs. The correction for adjustment costs is significant, but affects the mean markups very little. Adjustment costs determine the increase and decrease of the marginal cost according to the states of the firm over time, but these movements tend to cancel out when the whole period is considered. This is why, in columns (5) and (6) of Table 3, we chose to report the average difference between the max correction up and down for every firm during the time it stays in the sample and the standard deviation of these differences. We discover that markups can change on average between 1 and 8 percentage points due to unobserved adjustment costs.

The effect of export status on markups are reported in column (7) of Table 3 for example 1 and in column (6) of Table 4 for example 2. With the two-stage model, the dummy for export status is significant at levels higher than 5% in only six cases. Four are positive, ranging from 3.8 to 5.7 percentage points, while two are negative, about 3.9 and 4.6 percentage points. This depicts the lack of systematic variation of the markups with export status.

Turning from export status to export intensity, there is no evidence of any systematic relationship between markups and export intensity, although in some industries one can tell particular stories that often go in opposite directions. The results of the regressions are shown in Figure OA1 of the Online Appendix.

The effects in the simultaneous model in Table 4 are even smaller. It is true that now export status has to explain the shift in the markups simultaneously with other variables. The impact of market expansion is significant in six industries, and there are some effects from the introduction of innovations. There is only one (negative) effect of export status that is statistically significant.

Because the estimation of markups is backed by the estimation of the production function, it is important that we evaluate these estimates. Table 3 (cont'd) summarizes the results for the two-step procedure and Table 4 reports similar information for the simultaneous estimation. The elasticities of the inputs, reported in columns (8) to (11) of Table 3 (cont'd), and in columns (7) to (10) of Table 4, are sensible. The coefficient on capital is the most difficult to estimate. Some of the elasticities of capital are very imprecisely estimated. It remains to be seen if this can be improved by using a production function with non-separability of capital. The mean elasticities of labor and materials seem, in contrast, very well estimated and we have already commented on the differences of the elasticity of scale.

Columns (12) to (14) of Table 3 (cont'd) detail the quartiles of the labor elasticity in the production function estimation of example 1. The IQR ranges from 0.141 to 0.243, which implies a notable variation across firms and over time. The distribution of the output effects of labor augmenting productivity, defined as $\beta_{Ljt}\omega_{Ljt}$, is reported in columns (15) to (17) and displays significant heterogeneity. The differences in productivity stemming from labor-augmenting productivity range, for the 50% of firms in the center of the distribution, from almost 40 to more than 70 percentage points.

The implicit elasticity of substitution, computed from the parameters of the production function and the average value of the labor share (including estimated adjustment costs) ranges, across the two estimations of the production function, from 0.616 to 0.935.[36]

The tests of overidentifying restrictions, reported in columns (18) and (19) of Table 3 (cont'd) and columns (11) and (12) of Table 4 are slightly different. While the tests are easily passed for the two-stage estimation in all industries but industry 7, they are only passed in 6 industries for the simultaneous model, sometimes marginally. Of course in the second case we are simultaneously testing the production function and the specification of the markup, so the results are in fact notable.

The autoregressive parameters estimated in the simultaneous model, reported in columns (13) and (14) of Table 4, are sensible and indicate a high persistence of both

[36] Equation (10) can be used to compute the elasticity of substitution of the translog $\sigma = \frac{(\alpha_L+\alpha_M)(1-S_{Ljt})}{\alpha+(\alpha_L+\alpha_M)(1-S_{Ljt})}$. The elasticity is decreasing in S_{Ljt}, as one would expect if relaxing the constant elasticity assumption of the CES. The values found are consistent with Doraszelski & Jaumandreu (2018).

markups and productivity.

7 Concluding remarks

The estimation of markups when there is no knowledge about how firms compete, and imposing the minimum possible assumptions about the form of the technology, is an important goal for economists that has recently attracted much work.

This paper has argued that, with the cost-minimization conditions at hand, if we have reasonable measures of variable cost and revenue we are already quite close properly measuring markups. Between the measure provided by the price-average variable cost ratio margin and the markup in which economists are actually interested are three things that should be addressed: adjustment costs, elasticity of scale, and the shocks which are not a component of the markups targeted by the firms. The problem is that addressing these three concerns is not straightforward.

Solving the cost-minimization conditions for markups, and plugging in estimates of input elasticities does not produce good results. We have shown how it can produce diverging and misleading conclusions in the case of markups of exporters versus non-exporters. The relative shares of variable inputs, which should be a good statistic for the relative elasticities according to cost minimization, typically show a sharp mismatch with the usual Cobb-Douglas, CES and translog specification of elasticities due to labor-augmenting productivity and possibly the added effects of other unobservables.

In addition, with imperfect competition we need to control for the markup to estimate the elasticity of scale. Because price differs from marginal cost, either marginal cost or the markup are necessarily part of the FOCs used by a structural method to control for Hicks-neutral productivity. Getting rid of the marginal cost or the markup in a procedure designed for structural estimation such as ACF, leads to biased results because the regression is affected by correlated unobservable heterogeneity of demand. Our estimates show that markups obtained by the DLW method are sensibly better if one adds variables to control for the heterogeneity of demand, and very noisy otherwise. In addition, our alternative empirical estimates detect an (expected) upward bias in DLW markups.

We have approached the markup estimation by controlling the price average-variable cost margin for the ratio MC/AVC, estimating the short-run elasticity of scale and adjustment costs. We have implemented two examples. The simplest method is the use of an autoregressive method to control for productivity (dynamic panel), but this drops the structural nonlinear control for Hicksian productivity that works well in production function estimation. The more complicated way is to estimate a simultaneous specification, allowing the markup to enter the controls for the unobserved Hicks-neutral productivity. Both approaches work even in the case where the estimation of the elasticity of scale is subject to error.

Both methods work well in assessing the markups of our sample of Spanish firms for the period 1990-2012, a sample with dramatic changes in participation of firms in the export market. We get basically one answer: the are no systematic markup effects associated with the action of exporting and the level of exports (export intensity). This agrees well with the classic structural IO evidence on the matter, that usually has found similar or lower markups for the same products in the more competitive export markets.[37]

[37] See for example Bernstein & Mohnen (1991), Bughin (1996), Moreno & Rodriguez (2004), and Das, Roberts & Tybout (2007). More recently Jaumandreu & Yin (2018) conclude that Chinese exporters have slightly higher margins in the domestic market, but lower than non-exporters in the foreign market (page 28). This is basically what Blum et al. (2018) also find using a Chilean database that has the big advantage that firms separately report domestic and export prices.

Data appendix

Spain. The data come from the Encuesta Sobre Estrategias Empresariales (ESEE) for the period 1990-2012. The ESEE is a firm-level survey of Spanish manufacturing sponsored by the Ministry of Industry. At the beginning of the survey, about 5% of firms with up to 200 workers were sampled randomly by industry and size strata. All firms with more than 200 workers were included in the survey and 70% of these larger firms responded. Firms disappear over time from the sample due to either exit (shutdown or abandonment of activity) or attrition. To preserve representativeness, samples of newly created firms were added to the initial sample almost every year and some additions counterbalanced attrition.

We observe firms for a maximum of 23 years between 1990 and 2012. The sample is restricted to firms with at least three years of observations, giving a total of 3026 firms and 26977 observations. The number of firms with 3, 4,. . . , 23 years of data is 398, 298, 279, 278, 290, 324, 122, 111, 137, 96, 110, 66, 66, 98, 66, 40, 37, 44, 37, 42 and 87 respectively. Table D1 gives the industry labels along with their definitions in terms of the ESEE, ISIC and NACE classifications, and reports the number of firms and observations per industry in columns (3) and (4). Columns (5) and (6) give the numbers for the sample restricted to firms with temporary workers.

In what follows we list the variables that we use, beginning first with the variables that we take directly from the data source.

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

- *Exports* (X). Value of exports.

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

- *Capital* (K). Capital at current replacement values is computed recursively from an initial estimate and the data on investments I at $t-1$ using industry-specific depreciation rates. Capital in real terms is obtained by deflating capital at current replacement values by the price index of investment.

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

- *Intermediate consumption* (MB). Value of intermediate consumption or materials' bill.

- *Proportion of temporary workers* (ptw). Fraction of workers with fixed-term contracts and no or small severance pay.

- *Proportion of white collar workers* (pwc). Fraction of non-production workers.

- *Advertising* (adv). Firm expenditure in advertising.

- *R&D Expenditure* ($R\&D$). Cost of intramural R&D activities, payments for outside R&D contracts with laboratories and research centers, and payments for imported technology in the form of patent licensing or technical assistance, with the various expenditures defined according to the OECD Frascati and Oslo manuals.

- *Price of output* (P). Firm-level price index for output. Firms are asked about the price changes they made during the year in up to five separate markets in which they operate. The price index is computed as a Paasche-type index of the responses.

- *Wage* (W). Hourly wage cost computed as wage bill divided by total hours worked.

- *Price of materials* (P_M). Firm-specific price index for intermediate consumption. Firms are asked about the price changes that occurred during the year for raw materials, components, energy, and services. The price index is computed as a Paasche-type index of the responses.

- *User cost of capital* (P_K). Computed as $P_{It}(r_{jt} + \delta - CPI_t)$, where P_{It} is the price index of investment, r_{jt} is a firm-specific interest rate, δ is an industry-specific estimate of the rate of depreciation, and CPI_t is the rate of inflation as measured by the consumer price index.

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

- *Innovation variables* (z, d). The dummy of process innovation takes the value one when the firm reports the introduction of important modifications on the way products are produced. The dummy of product innovation takes the value one when the firm reports the introduction of new or significantly modified products.

We construct a number of variables from the original. We consistently subtract advertising from intermediate consumption because it is not a production input. We define variable cost as the wage bill plus the cost of intermediate consumption (minus advertising), minus the expenditures on R&D and an estimate of the part of the wage bill corresponding to white collar workers. The estimation assumes that white-collar employees work the same number of hours but have an average wage 1.25 times higher. This is important to better approximate variable cost. Because we are unable to split R&D expenditures between labor and intermediate consumption, we define the share of labor in variable cost and the shares in revenue of labor and materials without deducing the R&D expenditures. This implies that the share of variable cost in revenue is slightly lower than the sum of the shares of labor and materials.

- *Output* (Q). Revenue deflated by the firm-specific price index of output.
- *Export status* (xst). Takes the value one when exports are positive.
- *Export intensity* (xi). Value of exports divided by revenue.
- *Materials* (M). Value of intermediate consumption minus advertising deflated by the firm-specific price index of materials.
- *Variable cost* (VC). Wage bill (including social security payments) plus the cost of intermediate consumption minus advertising, R&D, and white collar pay.
- *Share of labor in variable cost* (S_L). Wage bill minus white collar pay over the sum of this amount plus the cost of materials minus advertising.
- *Share of labor in revenue* (S_L^R). Wage bill minus white collar pay over revenue.
- *Share of materials in revenue* (S_M^R). Cost of intermediate consumption minus advertising over revenue.
- *Price Average Variable Cost Margin* ($PAVCM$). Logarithm of the ratio of revenue to variable cost.

Slovenia. The sample in DLW comes from the Slovenian Central Statistical Office (page 1 of the Appendix) and is described as the "full annual company accounts of firms operating in the manufacturing sector between 1994-2000" . We have data on Slovenian firms for 1994-2003. We start by eliminating the data that are incomplete (some variable is missing, e.g., there are no exports recorded in 2003 for any firm) or anomalous (share of materials in revenue and/or export intensity greater than unity).[38] Dropping the firms that do not belong to manufacturing and firms with a single observation (that do not allow to compute the lagged values), we end with 3974 firms and 23688 observations with the industry composition reported in columns (7) and (8) of Table D1. We observe firms for a maximum of 9 years between 1994 and 2002, and the number of firms with 2, 3, 4,. . . ,9 years of data is 467, 483, 415, 396, 401, 358, 333, and 1121, respectively.

Table D2 compares our sample with the original DLW sample. The left panel reproduces the information of Table 1 in DLW, the right panel computes the same

[38] There remain 5323 firms and 28916 observations. We later check that imputing the anomalous data does not change our results.

numbers for our sample. The number of firms year by year is roughly 60% of the number of firms used by DLW, the rate of entry is clearly higher, and the rate of exits comparable. The proportion of exporters is about 10% higher, but the evolution of value added labor productivity is very similar (we transform it in an index to avoid the issue of different units of measurement in both data sets).

Table D3 compares the Spanish and Slovenian samples. The Spanish sample is smaller in number of firms and longer in the years covered (allowing some interesting trends to be precisely detected). For the exercises we perform, the following differences are important: the average size of the Spanish firms is three times the average size of the Slovenian firms, the proportion of exporters is quite close, and the proportion of sales that is exported (export intensity), conditional on exporting, is more than double for the case of the Spanish firms.

Variable definitions are as in DLW:

- *Revenue* (R). Total operating revenue of the firm deflated by the appropriate industry price index.
- *Exports* (X). Value of exports.
- *Capital* (K). Book value of total fixed assets.
- *Labor* (L). Number of full-time equivalent employees per year.
- *Materials* (M). Intermediate consumption deflated by the appropriate industry price index.
- *Export status* (xst). Takes the value one when exports are positive.
- *Export intensity* (xi). Value of exports divided by revenue.

Appendix A

The problem of static cost minimization is

$$Min_{L_{jt},M_{jt}} \;\; W_{jt}L_{jt} + P_{Mjt}M_{jt} \;\; s.t. \; F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})\exp(\omega_{Hjt}) = Q^*_{jt},$$

and the solution states that at the minimum there is a number λ_{jt} (Lagrange multiplier) that makes proportional the gradients of the objective and unique restriction

$$\begin{aligned} W_{jt} &= \lambda_{jt}\frac{\partial F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})}{\partial L_{jt}}\exp(\omega_{Ljt} + \omega_{Hjt}), \\ P_{Mjt} &= \lambda_{jt}\frac{\partial F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})}{\partial M_{jt}}\exp(\omega_{Hjt}). \end{aligned}$$

Inspection shows that $\lambda_{jt} = MC_{jt} = \frac{\partial VC_{jt}}{\partial Q_{jt}}$, which is confirmed by the envelope theorem.

Using the ratio of FOCs together with the production function we can solve for the demand for the variable inputs conditional on capital, input prices, productivity and planned output

$$\begin{aligned} M_{jt} &= M(K_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})P_{Mjt}}, \frac{Q^*_{jt}}{\exp(\omega_{Hjt})}), \\ L_{jt} &= L(K_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})P_{Mjt}}, \frac{Q^*_{jt}}{\exp(\omega_{Hjt})})\exp(-\omega_{Ljt}). \end{aligned}$$

Plugging these demands into the objective function, variable cost is

$$VC_{jt} = VC(K_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*_{jt}}{\exp(\omega_{Hjt})})$$

and hence marginal cost is

$$MC_{jt} = \frac{\partial VC_{jt}}{\partial Q_{jt}} = VC_4(K_{jt}, \frac{W_{jt}}{\exp(\omega_{Ljt})}, P_{Mjt}, \frac{Q^*_{jt}}{\exp(\omega_{Hjt})})\exp(-\omega_{Hjt}).$$

Appendix B

The problem of dynamic cost minimization can be conveniently cast in a Bellman equation that defines the value function $V(L_{-1}, \Omega)$ as

$$\begin{aligned} V(L_{-1}, \Omega) = \min_{L,M} WL + CL(L, L_{-1}) + P_M M + \beta E[V(L, \Omega')|\Omega], \\ s.t. \;\; F(K, \exp(\omega_L)L, M)\exp(\omega_H) \;\; = \;\; Q^*, \end{aligned}$$

where $CL(\cdot)$ is the cost of adjusting labor, β is the discount factor and $\Omega = (Q^*, K, W, P_M, \omega_L, \omega_H)$ is the vector of state variables and a prime represents the value in the next period. The Lagrangian for the minimization problem on the right-hand side of the Bellman equation is

$$\pounds = WL + CL(L, L_{-1}) + P_M M + \beta E[V(L, \Omega')|\Omega] - \lambda[F(K, \exp(\omega_L)L, M)\exp(\omega_H) - Q^*]$$

and the first order conditions are

$$\begin{aligned} W(1+\Delta_L) &= \lambda \frac{\partial F(K, \exp(\omega_L)L, M)}{\partial L} \exp(\omega_L + \omega_H), \\ P_M &= \lambda \frac{\partial F(K, \exp(\omega_L)L, M)}{\partial M} \exp(\omega_H), \end{aligned}$$

where $\Delta_L = \frac{1}{W}\left(\frac{\partial CL(L, L_{-1})}{\partial L} + \beta E[\frac{\partial V(L,\Omega')}{\partial L}|\Omega]\right)$. Applying the envelope theorem to the Bellman equation, we get $\frac{\partial V(L,\Omega')}{\partial L} = \frac{\partial CL(L_{+1}, L)}{\partial L}$, and the expression

$$\Delta_L = \frac{1}{W}\left(\frac{\partial CL(L, L_{-1})}{\partial L} + \beta E[\frac{\partial CL(L', L)}{\partial L}|\Omega]\right)$$

for the gap between the wage and the shadow cost of a unit of labor.

Appendix C

To estimate adjustment cost we assume that the labor input is the aggregate of the labor services of permanent labor L_{Pjt} and temporary labor $L_{T_{jt}}$, and that temporary labor is a perfectly flexible input. We solve a problem analogous to the problem in Appendix B, with the adjustment cost CL_{jt} of permanent workers. Assuming a linearly homogeneous Cobb-Douglas aggregator, we have

$$L_{jt} = L_{Tjt}^{\alpha} L_{Pjt}^{1-\alpha},$$

and the FOCs with respect to these two types of workers yield

$$\frac{W_{Pjt}}{W_{Tjt}}(1+\Delta_{Pjt}) = \frac{\frac{\partial F}{\partial L_{jt}}\frac{\partial L_{jt}}{\partial L_{Pjt}}}{\frac{\partial F}{\partial L_{jt}}\frac{\partial L_{jt}}{\partial L_{Tjt}}} = \frac{(1-\alpha)L_{Tjt}}{\alpha L_{Pjt}},$$

where $\Delta_{Pjt} = \frac{1}{W_{Pjt}}\left(\frac{\partial CL_{jt}}{\partial L_{Pjt}} + \beta E_t[\frac{\partial CL_{jt+1}}{\partial L_{Pjt}}]\right)$. Aggregating the two conditions gives a condition in terms of the labor aggregate:

$$\begin{aligned} W_{Pjt}L_{Pjt}(1+\Delta_{Pjt})+W_{Tjt}L_{Tjt} &= W_{jt}L_{jt}(1+\Delta_{Ljt}) \\ &= \lambda_{jt}\frac{\partial F(K_{jt},\exp(\omega_{Ljt})L_{jt},M_{jt})}{\partial L_{jt}}\exp(\omega_{Ljt}+\omega_{Hjt}), \end{aligned}$$

where $\Delta_{Ljt} = \frac{W_{Pjt}L_{Pjt}}{W_{Pjt}L_{Pjt}+W_{Tjt}L_{Tjt}}\Delta_{Pjt}$.

Letting S_{Tjt} be the share of temporary workers in the total workforce and assuming that the ratio W_{Tjt}/W_{Pjt} is constant and equal to $(1-\gamma)$, we can rewrite the ratio of FOCs as

$$\frac{\alpha}{1-\alpha}(1+\Delta_{Pjt}) = (1-\gamma)\frac{S_{Tjt}}{1-S_{Tjt}}.$$

We estimate $\frac{\widehat{\alpha}}{1-\widehat{\alpha}}$ as proportional to the mean across observations of $\frac{S_{Tjt}}{1-S_{Tjt}}$ and we estimate $\widehat{\gamma}$ by the negative industry wage premiums obtained in the wage regressions of Doraszelski & Jaumandreu (2013). Because our measure is not valid with corner solutions we restrict the sample to firms that have both permanent and temporary workers. Table D1 reports the number of firms and observations for the restricted sample. Using the estimates we compute permanent workers adjustment costs as

$$\widehat{\Delta}_{Pjt} = [(1-\widehat{\gamma})\frac{S_{Tjt}}{1-S_{Tjt}}/\frac{\widehat{\alpha}}{1-\widehat{\alpha}}]-1,$$

$$\widehat{\Delta}_{Ljt} = \frac{1-S_{Tjt}}{1-S_{Tjt}+(1-\widehat{\gamma})S_{Tjt}}\widehat{\Delta}_{Pjt}.$$

Appendix D

To estimate $\phi(\cdot)$ in the first stage, we regress output by OLS on a constant, the set of time dummies, and a complete polynomial of order three of the variables included in x_{jt}. With three variables the polynomial has 19 terms, with six variables it has 83 terms.

The second stage estimates the coefficients of the production function using the predicted values $\widehat{\phi}_{jt}$. We specify an inhomogeneous Markov process $g_t(\cdot) = \beta_t + g(\cdot)$, and approximate the $g(\cdot)$ function by a polynomial of order three in its argument (the loglinear form $\widehat{\phi}_{jt-1} - \ln F(K_{jt-1}, L_{jt-1}, M_{jt-1})$). This second stage is a nonlinear GMM estimation that uses as instruments the constant, the time dummies, $\widehat{\phi}_{jt-1}$, $\widehat{\phi}^2_{jt-1}$ and $\widehat{\phi}^3_{jt-1}$, and the values or lagged values of the inputs as specified below for each case.

We include in x_{jt} the real prices of the inputs $w_{jt} - p_{jt}$ and $p_{Mjt} - p_{jt}$ and a demand shifter.[39] This model hence includes six variables in the estimation of $\phi(\cdot)$.[40] In the second stage we estimate the three coefficients β_K, β_L and β_M. We use as instruments $k_{jt}, k_{jt-1}, l_{jt-1}$, and m_{jt-1}.. The results are reported in columns (7)-(10) of Table A2. The relative magnitude of the coefficients looks sensible. The short-run scale parameter is above unity in five cases, but in four only very slightly and shows reasonable values in the remaining industries. The markups are reported in columns (4) to (5) of Table A3.

For comparison purposes we exclude the input prices and the demand shifter from x_{jt}, and instead include the export status as in DLW. Since the export status is a dummy, we should adapt the polynomials (excluding the powers and interaction of the powers of the export status). We use as instruments $k_{jt}, k_{jt-1}, l_{jt-1}$, and m_{jt-1}.. The results can be checked in columns (3)-(5) of Table A2. Now four industries show a short-run scale parameter quite above unity, and another an abnormally low value. We interpret this as evidence that firms really differ in the prices they set for the output and pay for the inputs, as well as in the shocks to their demands. Columns (1) to (3) of Table A3 report the markups.

Appendix E

We perform a Hausman test on the null hypothesis of exogeneity of the export status in regression form. We first regress the export status on the list of variables included in the nonparametric regression $(k_{jt}, l_{jt}, m_{jt}, w_{jt} - p_{jt}, p_{Mjt} - p_{jt}, d_{jt})$ and on lagged export status xst_{jt-1}. The lagged export status a valid instrument for the export status because the shock ε_{jt} is only known later. Then we include the error obtained from this regression in the original nonparametric regression, and compute a heteroskedasticity robust t statistic.

Appendix F

Here we drop firm and time subscripts for simplicity. The production function is $q = \beta l + \omega + \varepsilon = q^* + \varepsilon$ and the demand function is $q^* = -\eta p + \delta$. From cost minimization it turns out that $\omega = q^* - \beta l$ so substitution gives $\phi(l, p, \delta) = \beta l + q^* - \beta l = -\eta p + \delta$. Assume that $E(\delta | l, p) = \gamma l$ (we assume no relation between δ and p for simplicity) and write $\delta = \gamma l + r$ in error form. We have $\widetilde{\phi}(l, p) = -\eta p + \gamma l$. The equation underlying

[39] We also estimate a value-added production function "in the sense that the intermediate input m_{jt} does not enter the production function to be estimated" (ACF, page 2428). The scale coefficient is always above unity, often significantly. Our interpretation is that the value-added specification is not sustained by the data: the missing term in materials is systematically biasing upwards the coefficients on capital and labor.

[40] The differences in the regression between using $w_{jt} - p_{jt}$ and $p_{Mjt} - p_{jt}$ or simply w_{jt} and p_{Mjt} are small. We also run this regression with and without the export status with almost no perceptible differences.

the second stage of ACF is $q = \beta l + g(-\eta p_{-1} + \gamma l_{-1} + r_{-1} - \beta l_{-1}) + \xi + \varepsilon$. To put a sign on the bias, assume that $g(\cdot)$ is autoregressive with known parameter ρ. The equation becomes, using the knowledge of ρ and $\widetilde{\phi}(l,p)$, $\overline{q} = q - \rho\widetilde{\phi}(l,p) = \beta(l - \rho l_{-1}) + v$, where $v = \rho r_{-1} + \xi + \varepsilon$. An IV estimation for β using l as instrument is upward biased if $E(lr_{-1}) > 0$:

$$\widetilde{\beta} = \frac{E(l\overline{q})}{E(l(l - \rho l_{-1}))} = \beta + \frac{\rho E(lr_{-1})}{E(l_{-1}(l - \rho l_{-1}))}.$$

Appendix G

To form the moments we use the constant, the 21 time dummies, and the lagged values and squared lagged values of labor, materials, the (uncorrected) share of labor and the proportion of temporary workers (that helps to predict the adjustment costs). We add in some industries the lagged interest rate paid by firms and/or the amount of investment, sometimes squared. Lagged interest rate is used in all industries but 7, and the square in industries 4 and 6. Investment and investment squared are used in industries 1,2,3, 6 and 7, and investment in 8. We include capital directly among the instruments in industry 5, and lagged capital in industries 1,2,3, 6 and 7. In industry 8 we drop the squares of the labor share and proportion of temporary workers and we use as additional instruments the lagged wage and materials bills.

Appendix H

To form the moments we use the two constants and the 42 time dummies. In the set of instruments for the markup equation we use the lagged values of variable cost, capital, labor, materials, the proportion of temporary workers (to help to predict the adjustment costs) and this proportion squared, the lagged dummies of process and product innovation, lagged R&D accumulated up to the latest innovation, and the lagged export status.

In the production function equation we use, as before, the lagged values and squared lagged values of labor, materials, the (uncorrected) share of labor and the proportion of temporary workers. As before we also add in some industries the lagged interest rate paid by firms and/or the amount of investment, sometimes squared. We also include capital, contemporaneous or lagged, sometimes squared, and interactions of capital with lagged materials and labor. The moments for this second equation also include lagged innovation and accumulated R&D, the market dynamism indicator, lagged export status and, sometimes, lagged variable cost and lagged output price.

Appendix I

To measure the mean markup we proceed as follows. From the equation that comes from (4) we have

$$E(r_{jt} - vc_{jt}) = -\ln\nu + \theta E(\ln(1 + s_{Ljt}\Delta_{Ljt})) + E(\ln\mu_{jt}),$$

so we apply the empirical counterpart of

$$E(\ln\mu_{jt}) = E(r_{jt} - vc_{jt}) + \ln\nu - \theta E(\ln(1 + s_{Ljt}\Delta_{Ljt})).$$

Let us call $a = r_{jt} - vc_{jt} + \ln\nu - \theta\ln(1 + s_{Ljt}\Delta_{Ljt}), b = a - z_{1jt}\gamma_1$ and $c = b - \rho_1(r_{jt-1} - vc_{jt-1}) + \rho_1\ln(1 + s_{Ljt-1}\Delta_{Ljt-1})$. It is not difficult to show that under stationarity we have $Var(a) = Var(\ln\mu_{jt}) + Var(\varepsilon_{jt})$, $Var(b) = \rho_1^2 Var(\ln\mu_{jt}) + Var(\zeta_{jt}) + Var(\varepsilon_{jt})$, and $Var(c) = Var(\zeta_{jt}) + (1 + \rho_1^2)Var(\varepsilon_{jt})$. It follows that

$$Var(\ln\mu_{jt}) = \frac{Var(a)}{2} + \frac{Var(b) - Var(c)}{2\rho_1^2}.$$

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Table 1: The different answers of DLW markups.

	Example of estimated markup		PAVCM		Effect of export status Markup uses		Slovenia Export status	Effects of export status and labor adjustment costs Markup uses labor costs	
					Labor costs	Material costs	Material costs	Export status	Adjustment costs
	Mean	Std. dev.	Mean	Std. dev.	(s. e.)	(s. e.)	(s. e.)	(s. e.)	(s. e.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Metals and metal products	0.285	0.095	0.210	0.161	0.463	-0.173	-0.098	0.457	0.043
					(0.052)	(0.023)	(0.019)	(0.054)	(0.013)
2. Non-metallic minerals	0.244	0.125	0.231	0.191	0.027	0.059	-	-0.023	0.043
					(0.077)	(0.031)		(0.079)	(0.017)
3. Chemical products	0.295	0.169	0.286	0.218	0.469	-0.110	-0.124	0.452	0.079
					(0.094)	(0.050)	(0.011)	(0.097)	(0.021)
4. Agric. and ind. Machinery	0.261	0.109	0.250	0.168	0.617	-0.224	-0.131	0.614	0.034
					(0.086)	(0.042)	(0.018)	(0.088)	(0.025)
5. Electrical goods	0.164	0.157	0.279	0.203	0.431	-0.171	-0.112	0.406	0.035
					(0.099)	(0.049)	(0.035)	(0.104	(0.030)
6. Transport equipment	0.252	0.133	0.205	0.183	0.316	-0.208	-0.061	0.294	0.019
					(0.112)	(0.085)	(0.025)	(0.119)	(0.022)
7. Food, drink and tobacco	0.218	0.172	0.259	0.220	0.531	-0.190	-	0.537	0.048
					(0.081)	(0.025)		(0.082)	(0.024)
8. Textile, leather and shoes	0.022	0.096	0.178	0.160	0.796	-0.581	-0.162	0.822	0.000
					(0.077)	(0.065)	(0.018)	(0.081)	(0.021)
9. Timber and furniture	0.103	0.107	0.182	0.166	0.228	-0.069	-0.107	0.217	0.079
					(0.062)	(0.030)	(0.049)	(0.064)	(0.017)
10. Paper and printing products	0.242	0.152	0.283	0.197	0.254	-0.129	-0.137	0.242	0.036
					(0.088)	(0.030)	(0.033)	(0.089)	(0.033)

Table 2: Checking motives of bias: Labor-augmenting productivity.

	Effects of export status and labor-augmenting productivity if markup uses share in revenue of			
	Labor costs		Material costs	
	Status (s. e.)	LA prod. (s. e.)	Status (s. e.)	LA prod (s. e.)
	(1)	(2)	(3)	(4)
1. Metals and metal products	-0.003	0.331	0.022	-0.137
	(0.024)	(0.009)	(0.008)	(0.007)
2. Non-metallic minerals	0.025	0.197	0.036	-0.080
	(0.034)	(0.007)	(0.013)	(0.004)
3. Chemical products	0.138	0.219	0.030	-0.093
	(0.064)	(0.012)	(0.012)	(0.010)
4. Agric. and ind. Machinery	0.129	0.304	0.001	-0.140
	(0.044)	(0.014)	(0.014)	(0.006)
5. Electrical goods	0.069	0.285	-0.015	-0.151
	(0.076)	(0.023)	(0.014)	(0.014)
6. Transport equipment	-0.028	0.155	-0.062	-0.066
	(0.063)	(0.008)	(0.027)	(0.005)
7. Food, drink and tobacco	-0.076	0.267	0.020	-0.088
	(0.056)	(0.011)	(0.014)	(0.003)
8. Textile, leather and shoes	0.020	0.328	0.035	-0.248
	(0.049)	(0.015)	(0.023)	(0.011)
9. Timber and furniture	0.010	0.379	0.055	-0.186
	(0.034)	(0.024)	(0.010)	(0.021)
10. Paper and printing products	-0.058	0.301	0.001	-0.144
	(0.075)	(0.024)	(0.012)	(0.007)

Table 3: Robust two-stage markups inference.

	Markup Mean	PAVCM Mean	PAVCM Std. dev.	$\beta_{Ljt} + \beta_{Mjt}$ (s. e.)	Intrafirm adjustment costs effects Max. diff.	Intrafirm adjustment costs effects Std. dev.	Effect on markups of Export status (s. e.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Metals and metal products	0.136	0.209	0.161	0.931	0.013	0.011	-0.002
				(0.028)			(0.011)
2. Non-metallic minerals	0.153	0.236	0.192	0.916	0.038	0.029	0.057
				(0.031)			(0.019)
3. Chemical products	0.256	0.285	0.217	0.973	0.016	0.013	0.047
				(0.028)			(0.019)
4. Agric. and ind. Machinery	0.090	0.249	0.166	0.848	0.042	0.030	0.038
				(0.208)			(0.018)
5. Electrical goods	0.261	0.280	0.204	0.972	0.059	0.048	0.020
				(0.031)			(0.019)
6. Transport equipment	0.131	0.204	0.183	0.925	0.041	0.035	0.011
				(0.019)			(0.030)
7. Food, drink and tobacco	0.239	0.258	0.219	0.974	0.053	0.053	-0.039
				(0.022)			(0.019)
8. Textile, leather and shoes	0.180	0.178	0.155	0.987	0.083	0.081	0.020
				(0.024)			(0.012)
9. Timber and furniture	0.099	0.182	0.163	0.914	0.033	0.027	0.050
				(0.093)			(0.013)
10. Paper and printing products	0.184	0.285	0.198	0.898	0.044	0.031	-0.046
				(0.139)			(0.022)

Table 3 (cont'd): Robust two-stage markups inference.

	Elasticities				Distribution of labor elasticity			Labor Augmenting Productivity: Distribution of output effects			Overidentification Test	
	Capital (s. e.)	Labor Mean	Materials Mean	L and M Std. err.	Q_1	Q_2	Q_3	Q_1	Q_2	Q_3	χ^2 (df)	p-Value
	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1. Metals and metal products	0.052	0.299	0.632	0.142	0.192	0.284	0.391	-0.374	0.007	0.170	9.519	0.218
	(0.020)										(7)	
2. Non-metallic minerals	0.081	0.282	0.634	0.130	0.194	0.251	0.337	-0.218	0.051	0.175	13.175	0.068
	(0.033)										(7)	
3. Chemical products	0.037	0.249	0.724	0.127	0.165	0.228	0.306	-0.231	0.026	0.154	7.196	0.409
	(0.026)										(7)	
4. Agric. and ind. Machinery	0.109	0.286	0.562	0.123	0.200	0.274	0.354	-0.269	0.021	0.156	3.682	0.596
	(0.180)										(5)	
5. Electrical goods	0.026	0.294	0.678	0.139	0.195	0.274	0.363	-0.387	0.067	0.242	8.315	0.216
	(0.036)										(6)	
6. Transport equipment	0.057	0.265	0.659	0.145	0.162	0.243	0.338	-0.291	0.046	0.172	12.619	0.082
	(0.019)										(7)	
7. Food, drink and tobacco	0.045	0.221	0.754	0.145	0.109	0.183	0.307	-0.468	0.065	0.156	20.946	0.002
	(0.020)										(6)	
8. Textile, leather and shoes	0.015	0.328	0.659	0.209	0.171	0.279	0.414	-0.420	0.157	0.308	8.585	0.127
	(0.019)										(5)	
9. Timber and furniture	0.076	0.278	0.636	0.121	0.196	0.261	0.340	-0.265	0.031	0.179	4.159	0.385
	(0.084)										(4)	
10. Paper and printing products	0.101	0.269	0.629	0.118	0.186	0.246	0.338	-0.309	0.047	0.182	4.693	0.103
	(0.128)										(4)	

Table 4: Simultaneous estimation of the markup and the production function.

			Effect on markups of				Elasticities				Overident. test		Autocorrelation parameters	
	Markup		Market	Process.	Product	Export	Capital	Labor	Materials	L and M			ρ_1	ρ_2
Ind.	Mean	$\beta_{Ljt} + \beta_{Mjt}$ (s. e.)	Expansion (s. e.)	Innov. (s. e.)	Innov. (s. e.)	status (s. e.)	(s. d.)	Mean	Mean	Std. dev.	χ^2 (df)	p-Value	(s. e.)	(s. e.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1.	0.129	0.925	0.024	0.003	-0.002	0.007	0.052	0.299	0.626	0.170	21.706	0.060	0.795	0.809
	(0.114)	(0.047)	(0.006)	(0.005)	(0.005)	(0.005)	(0.048)				(13)		(0.033)	(0.054)
2.	0.064	0.843	0.023	0.009	0.001	-0.001	0.111	0.271	0.572	0.164	25.947	0.055	0.865	0.757
	(0.136)	(0.066)	(0.010)	(0.009)	(0.008)	(0.007)	(0.058)				(16)		(0.055)	(0.063)
3.	0.204	0.922	0.016	0.025	-0.002	-0.003	0.030	0.232	0.690	0.135	45.200	0.000	0.886	0.951
	(0.154)	(0.040)	(0.008)	(0.009)	(0.010)	(0.005)	(0.015)				(16)		(0.020)	(0.024)
4.	0.189	0.940	0.023	0.008	0.006	0.009	0.061	0.325	0.615	0.154	13.275	0.151	0.736	0.779
	(0.118)	(0.053)	(0.011)	(0.012)	(0.013)	(0.009)	(0.053)				(9)		(0.053)	(0.063)
5.	0.081	0.818	0.006	0.008	0.022	0.001	0.171	0.259	0.559	0.158	32.898	0.001	0.837	0.965
	(0.145)	(0.159)	(0.009)	(0.006)	(0.007)	(0.007)	(0.289)				(12)		(0.026)	(0.112)
6.	0.095	0.895	0.024	0.015	0.001	0.005	0.076	0.264	0.631	0.169	13.097	0.440	0.679	0.783
	(0.129)	(0.067)	(0.011)	(0.016)	(0.011)	(0.013)	(0.052)				(13)		(0.082)	(0.105)
7.	0.219	0.961	-0.003	0.008	0.008	-0.006	0.038	0.228	0.732	0.163	20.467	0.116	0.831	0.754
	(0.155)	(0.033)	(0.005)	(0.005)	(0.005)	(0.005)	(0.036)				(14)		(0.020)	(0.059)
8.	0.061	0.887	0.014	0.015	0.013	0.005	0.010	0.310	0.577	0.270	40.561	0.000	0.830	0.946
	(0.110)	(0.053)	(0.006)	(0.012)	(0.011)	(0.005)	(0.025)				(12)		(0.053)	(0.017)
9.	0.089	0.906	0.006	0.022	0.013	-0.001	0.051	0.276	0.630	0.142	38.892	0.003	0.812	0.680
	(0.115)	(0.035)	(0.010)	(0.019)	(0.016)	(0.007)	(0.028)				(18)		(0.088)	(0.102)
10.	0.101	0.831	0.005	0.003	0.004	-0.010	0.144	0.257	0.574	0.142	27.536	0.051	0.854	0.783
	(0.140)	(0.059)	(0.008)	(0.006)	(0.009)	(0.005)	(0.052)				(17)		(0.030)	(0.032)

Table A1: Share of labor in variable cost and share of variable cost in total cost.

	Labor share in variable cost								
	Mean share		Distribution						
	1991-93	2010-12	1991-93			2010-12			
	(s.d.)	(s.d.)	Q_1	Q_2	Q_3	Q_1	Q_2	Q_3
	(1)	(2)	(6)	(7)	(8)	(10)	(11)	(12)
1	0.308 (0.162)	0.253 (0.151)	0.186	0.285	0.402	0.134	0.230	0.359
2	0.326 (0.160)	0.239 (0.138)	0.215	0.277	0.412	0.138	0.203	0.303
3	0.175 (0.131)	0.146 (0.140)	0.082	0.135	0.240	0.056	0.091	0.189
4	0.334 (0.153)	0.206 (0.120)	0.240	0.313	0.444	0.116	0.190	0.255
5	0.239 (0.136)	0.194 (0.136)	0.128	0.223	0.324	0.091	0.157	0.277
6	0.314 (0.152)	0.211 (0.150)	0.191	0.309	0.394	0.106	0.180	0.277
7	0.186 (0.153)	0.139 (0.118)	0.070	0.143	0.254	0.051	0.101	0.194
8	0.325 (0.218)	0.284 (0.219)	0.167	0.279	0.407	0.120	0.225	0.403
9	0.299 (0.158)	0.265 (0.144)	0.187	0.260	0.372	0.166	0.232	0.338
10	0.274 (0.158)	0.229 (0.126)	0.161	0.248	0.373	0.131	0.215	0.284

	Variable cost share in total cost								
	Mean share		Distribution						
	1991-93	2010-12	1991-93			2010-12			
	(s.d.)	(s.d.)	Q_1	Q_2	Q_3	Q_1	Q_2	Q_3
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
1	0.838 (0.076)	0.845 (0.082)	0.793	0.849	0.893	0.791	0.857	0.908
2	0.820 (0.068)	0.812 (0.091)	0.777	0.828	0.868	0.746	0.819	0.881
3	0.756 (0.145)	0.815 (0.104)	0.678	0.796	0.865	0.745	0.829	0.890
4	0.786 (0.103)	0.804 (0.077)	0.729	0.798	0.864	0.757	0.808	0.861
5	0.787 (0.122)	0.751 (0.142)	0.746	0.817	0.864	0.653	0.778	0.861
6	0.823 (0.066)	0.832 (0.092)	0.786	0.827	0.867	0.794	0.840	0.890
7	0.798 (0.125)	0.851 (0.109)	0.700	0.816	0.902	0.809	0.882	0.934
8	0.865 (0.072)	0.854 (0.084)	0.819	0.875	0.921	0.799	0.869	0.918
9	0.853 (0.067)	0.839 (0.086)	0.808	0.866	0.907	0.797	0.850	0.906
10	0.796 (0.105)	0.818 (0.095)	0.757	0.820	0.872	0.768	0.834	0.891

Table A2: Revenue shares and estimated input elasticities.

	Shares in Revenue		Estimated excluding prices and shifter				Estimated including prices and shifter			
	Labor (s.d.)	Materials (s.d.)	Capital (s. e.)	Labor (s. e.)	Materials (s. e.)	SR Scale (s.e.)	Capital (s. e.)	Labor (s. e.)	Materials (s. e.)	SR Scale (s. e.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Metals and metal prod.	0.204	0.621	0.069	0.230	0.736	0.966	0.076	0.323	0.755	1.078
	(0.126)	(0.159)	(0.024)	(0.083)	(0.102)	(0.066)	(0.023)	(0.129)	(0.119)	(0.144)
2. Non-metallic minerals	0.209	0.603	0.063	0.285	0.689	0.975	0.110	0.478	0.534	1.012
	(0.140)	(0.153)	(0.052)	(0.187)	(0.184)	(0.052)	(0.037)	(0.109)	(0.174)	(0.193)
3. Chemical products	0.118	0.664	0.034	0.591	0.538	1.128	0.063	0.414	0.595	1.009
	(0.140)	(0.148)	(0.035)	(0.283)	(0.158)	(0.159)	(0.024)	(0.490)	(0.337)	(0.163)
4. Agric. and ind. Mach.	0.202	0.602	0.029	0.464	0.707	1.171	0.052	0.330	0.681	1.011
	(0.128)	(0.160)	(0.037)	(0.958)	(0.319)	(0.670)	(0.102)	(1.783)	(1.166)	(0.621)
5. Electrical goods	0.168	0.619	-0.006	0.185	0.541	0.726	0.030	0.257	0.635	0.892
	(0.123)	(0.157)	(0.070)	(0.628)	(0.220)	(0.804)	(0.025)	(0.186)	(0.063)	(0.148)
6. Transport equipment	0.191	0.656	0.048	0.243	0.697	0.940	-0.006	0.239	0.809	1.048
	(0.142)	(0.169)	(0.050)	(0.717)	(0.509)	(0.272)	(0.026)	(0.058)	(0.037)	(0.041)
7. Food, drink and tobacco	0.125	0.667	0.132	0.352	0.547	0.899	0.128	0.280	0.681	0.960
	(0.115)	(0.170)	(0.045)	(0.128)	(0.069)	(0.065)	(0.029)	(0.063)	(0.026)	(0.057)
8. Textile, leather and shoes	0.263	0.591	0.051	0.258	0.600	0.858	0.039	0.295	0.561	0.856
	(0.227)	(0.212)	(0.087)	(1.797)	(0.703)	(1.098)	(0.031)	(0.271)	(0.120)	(0.164)
9. Timber and furniture	0.228	0.621	0.031	0.622	0.448	1.070	0.107	0.197	0.727	0.924
	(0.150)	(0.147)	(0.032)	(0.252)	(0.302)	(0.515)	(0.021)	(0.037)	(0.037)	(0.023)
10. Paper and printing prod.	0.170	0.600	0.041	0.608	0.503	1.111	0.074	0.271	0.689	0.960
	(0.110)	(0.152)	(0.074)	(1.647)	(0.412)	(1.967)	(0.022)	(0.187)	(0.184)	(0.031)

Table A3: Estimated markups.

	Markups from estimates excluding prices			Markups from estimates including prices		
	Labor (s. d.)	Materials (s. d.)	Variable cost (s. d.)	Labor (s. d.)	Materials (s. d.)	Variable cost (s. d.)
	(1)	(2)	(3)	(4)	(5)	(6)
1. Metals and metal products	0.317	0.211	0.175	0.659	0.235	0.285
	(0.626)	(0.300)	(0.164)	(0.671)	(0.282)	(0.095)
2. Non-metallic minerals	0.507	0.173	0.206	1.023	-0.082	0.244
	(0.643)	(0.268)	(0.170)	(0.625)	(0.253)	(0.125)
3. Chemical products	1.948	-0.178	0.406	1.592	-0.076	0.295
	(0.814)	(0.273)	(0.181)	(0.826)	(0.257)	(0.169)
4. Agric. and ind. Machinery	1.053	0.202	0.408	0.713	0.165	0.261
	(0.719)	(0.285)	(0.140)	(0.708)	(0.282)	(0.109)
5. Electrical goods	0.369	-0.096	-0.042	0.698	0.064	0.164
	(0.784)	(0.329)	(0.181)	(0.785)	(0.321)	(0.157)
6. Transport equipment	0.506	0.111	0.143	0.489	0.259	0.252
	(0.788)	(0.321)	(0.161)	(0.775)	(0.318)	(0.133)
7. Food, drink and tobacco	1.396	-0.160	0.152	1.166	0.058	0.218
	(0.887)	(0.269)	(0.200)	(0.876)	(0.262)	(0.172)
8. Textile, leather and shoes	0.322	0.134	0.025	0.455	0.067	0.022
	(0.868)	(0.574)	(0.154)	(0.853)	(0.580)	(0.096)
9. Timber and furniture	1.183	-0.291	0.249	0.035	0.194	0.103
	(0.619)	(0.278)	(0.132)	(0.604)	(0.283)	(0.107)
10. Paper and printing products	1.514	-0.137	0.380	0.705	0.178	0.242
	(0.756)	(0.274)	(0.185)	(0.742)	(0.269)	(0.152)

[a] Log of the elasticity of labor, materials, and the sum of labor and materials, divided by the share of labor cost, materials cost and variable cost in corrected revenue.

Table D1. Industry definitions, equivalences, and numbers of firms and observations.

	Industry	ESEE	ISIC (R.4), NACE (R.2)	Spain		Spain (restricted)[a]		Slovenia	
				Firms	Obs.	Firms	Obs.	Firms	Obs.
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Metals and metal products	12+13	24+25	433	3970	387	3677	425	2577
2	Non-metallic minerals	11	23	228	2016	205	1879	-	-
3	Chemical products	9+10	20+21+22	370	3263	335	3059	1011	5951
4	Agric. and ind. machinery	14	28	194	1833	178	1731	863	5093
5	Electrical goods	15+16	26+27	265	2297	247	2188	238	1488
6	Transport equipment	17+18	29+30	206	1898	196	1833	491	2998
7	Food, drink and tobacco	1+2+3	10+11+12	432	3836	409	3731	-	-
8	Textile, leather and shoes	4+5	13+14+15	395	3369	346	3079	307	1914
9	Timber and furniture	6+19	16+31	265	2282	238	2138	226	1508
10	Paper and printing products	7+8	17+18	238	2213	215	2067	413	2159
	Total			3026	26977	2756	25382	3974	23688

[a] Firms that never show a positive share of temporary workers are dropped with all their observations. Occasional zero share of temporary workers of firms that show a positive time mean of the share of temporary workers are set to 0.01.

Table D2: The DLW and accessed samples.

	DLW sample					Accessed sample[a]				
Years	Firms	Entry rate	Exit rate	Proportion exporters	Labor Productivity[b]	Firms	Entry rate	Exit rate	Proportion exporters	Labor Productivity[b]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1995	3820	0.131	0.033	0.455	1.000	2258	0.195	0.028	0.576	1.000
1996	4152	0.054	0.026	0.458	1.118	2512	0.150	0.064	0.543	1.073
1997	4339	0.045	0.034	0.439	1,239	2661	0.132	0.035	0.530	1.198
1998	4447	0.041	0.039	0.450	1.279	2848	0.108	0.048	0.538	1.216
1999	4695	0.033	0.033	0.467	1.429	2980	0.095	0.049	0.533	1.326
2000	4906	0.034	0.027	0.476	1.445	3054	0.078	0.073	0.544	1.430
2001						2943	0.069	0.031	0.560	1.444
2002						3080	0.054	0.096	0.563	1.454

[a] Including single-observation firms.

[b] Value-added per worker (we transform it in an index to avoid the issue of different units of measurement in both data sets).

Table D3: Comparison of samples Spanish and Slovenian.

	Spain				Slovenia			
Years	Firms	Workers[a]	Prop. exporters	Cond. export intensity[a]	Firms	Workers[a]	Prop. exporters[a]	Cond. export intensity
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1991	660	213	0.524	0.718				
1992	922	224	0.538	0.723				
1993	965	218	0.547	0.750				
1994	984	216	0.558	0.773	1882	85	0.598	0.306
1995	1051	226	0.595	0.765	2258	73	0.576	0.302
1996	1067	231	0.625	0.770	2512	65	0.543	0.289
1997	1142	231	0.644	0.784	2661	57	0.530	0.292
1998	1306	216	0.642	0.784	2848	56	0.538	0.291
1999	1260	223	0.649	0.783	2980	52	0.533	0.295
2000	1256	220	0.644	0.782	3054	51	0.544	0.308
2001	1289	224	0.638	0.786	2943	53	0.560	0.320
2002	1264	214	0.639	0.791	3080	51	0.563	0.315
2003	1067	228	0.647	0.801				
2004	1072	230	0.655	0.798				
2005	952	233	0.666	0.793				
2006	1253	206	0.642	0.783				
2007	1436	196	0.622	0.771				
2008	1342	192	0.628	0.776				
2009	1158	184	0.650	0.785				
2010	977	177	0.669	0.790				
2011	835	178	0.687	0.798				
2012	693	180	0.730	0.811				

[a] Simple means.

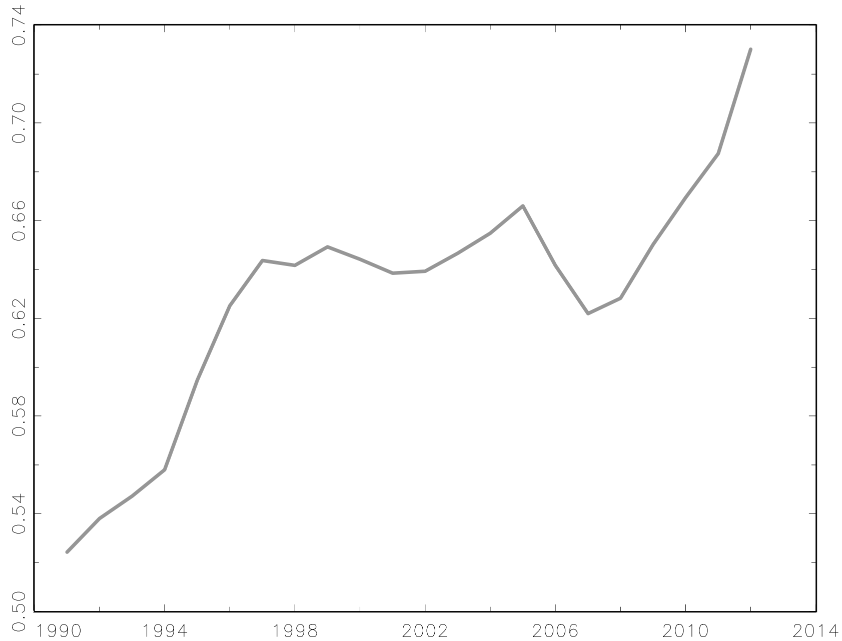

Figure 1: Proportion of firms with exports

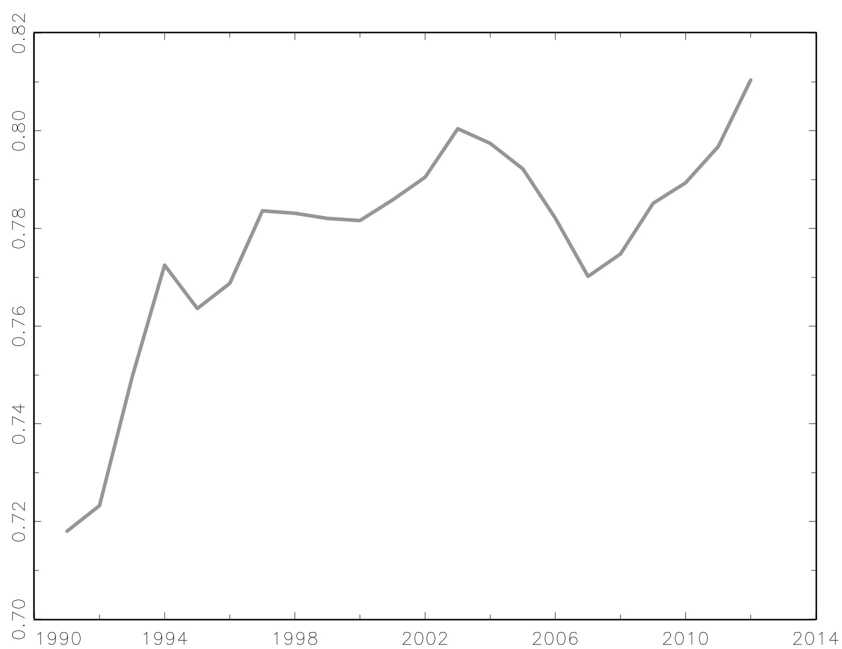

Figure 2: Export intensity conditional on exporting

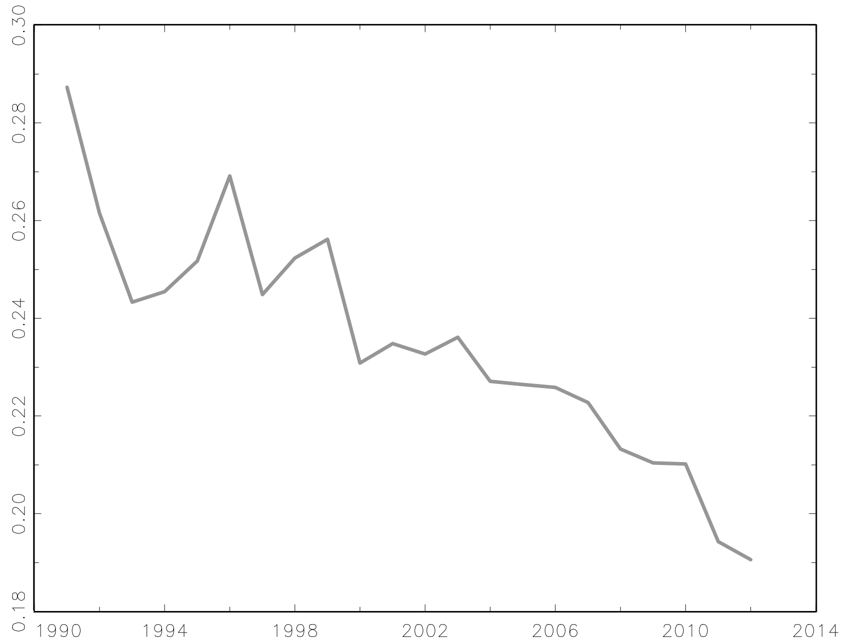

Figure 3: Ln of revenue over variable costs (PAVCM)

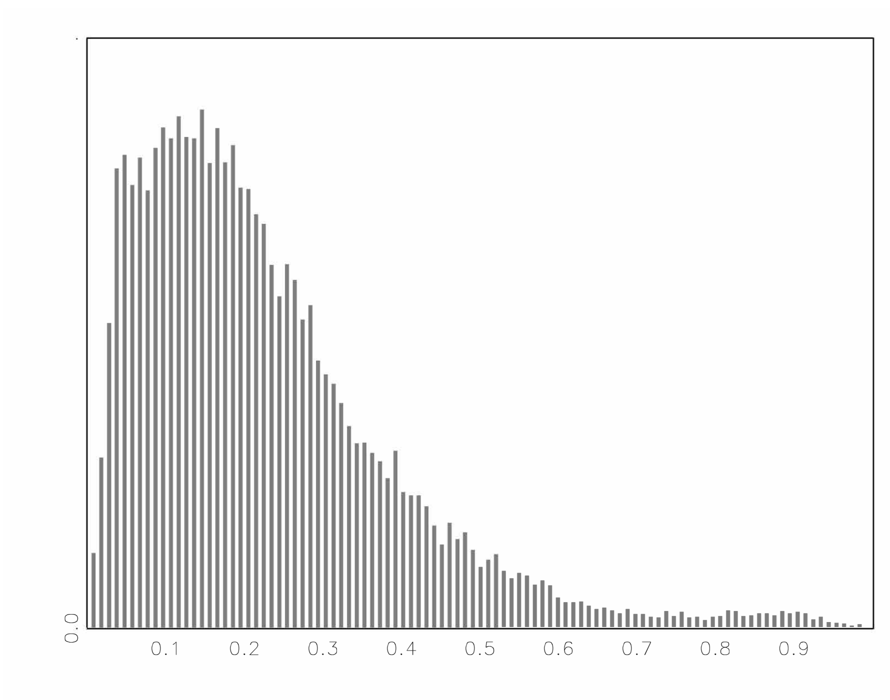

Figure 4: Frequencies of the labor share in variable cost

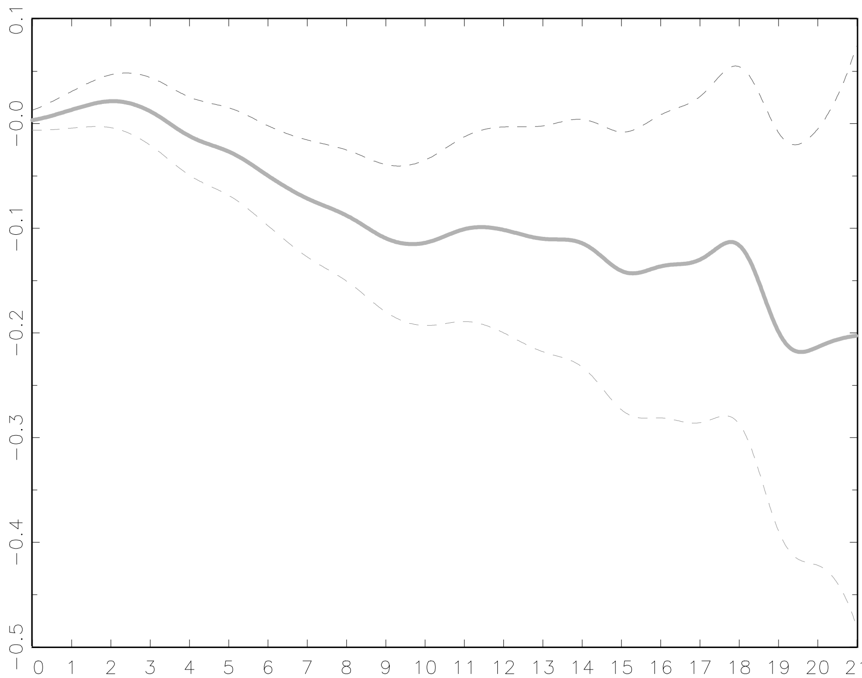

Figure 5: Labor share relative to first year as a function of years observed

Using Cost Minimization to Estimate Markups

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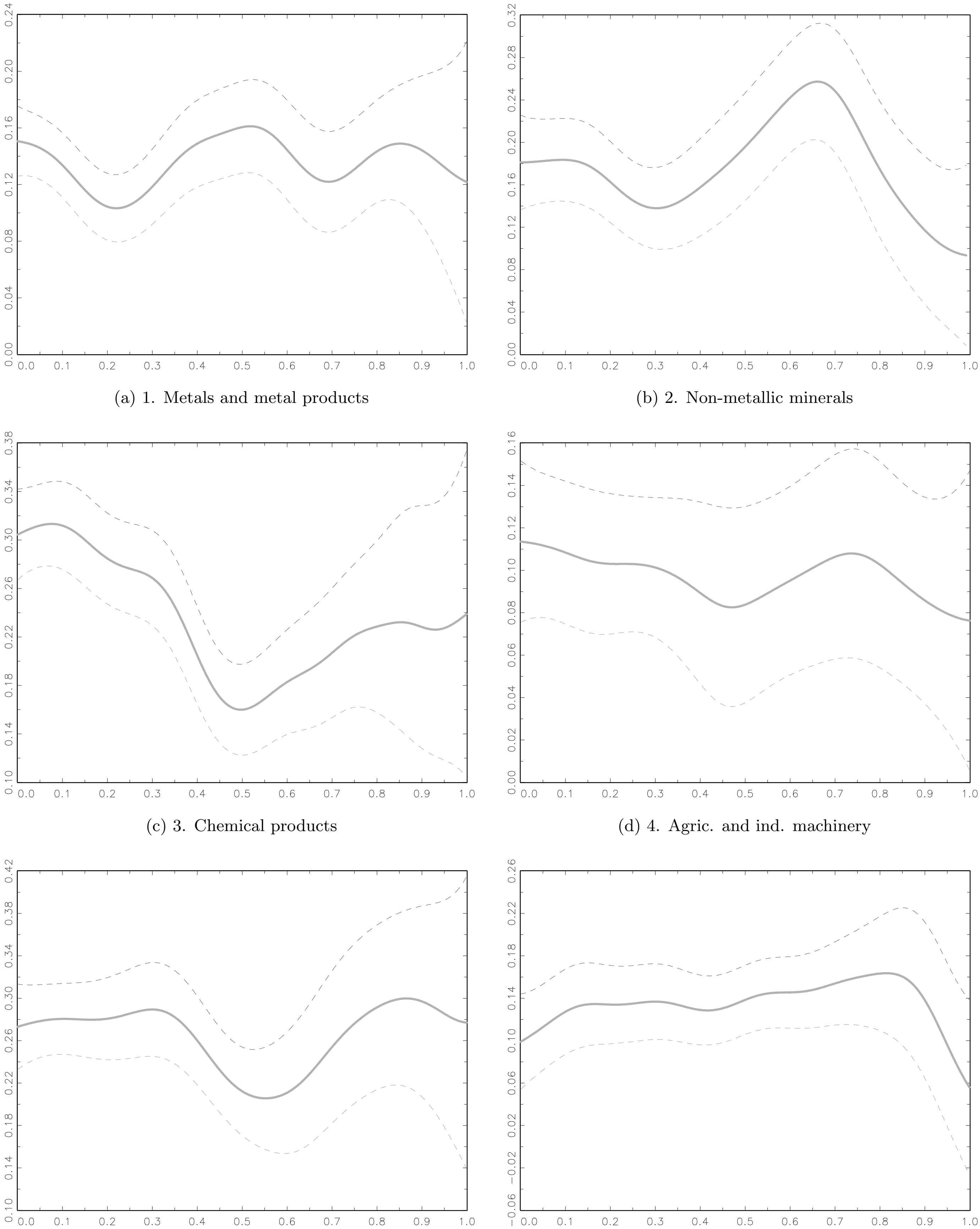
Figure 1: Nonparametric regressions of markup on export intensity



(a) 1. Metals and metal products

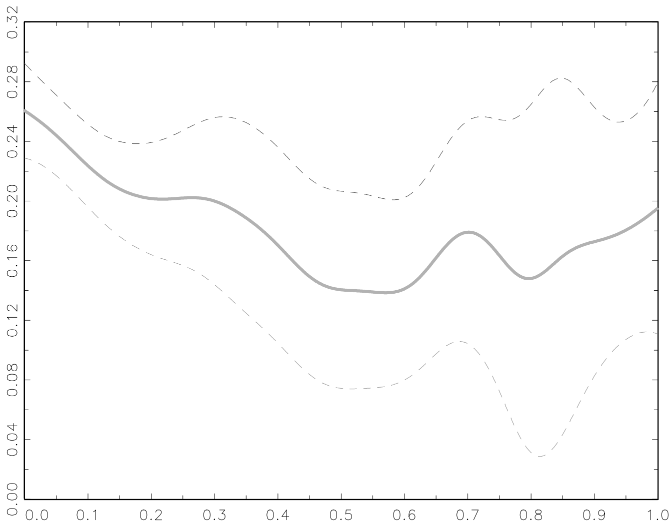
(b) 2. Non-metallic minerals

(c) 3. Chemical products

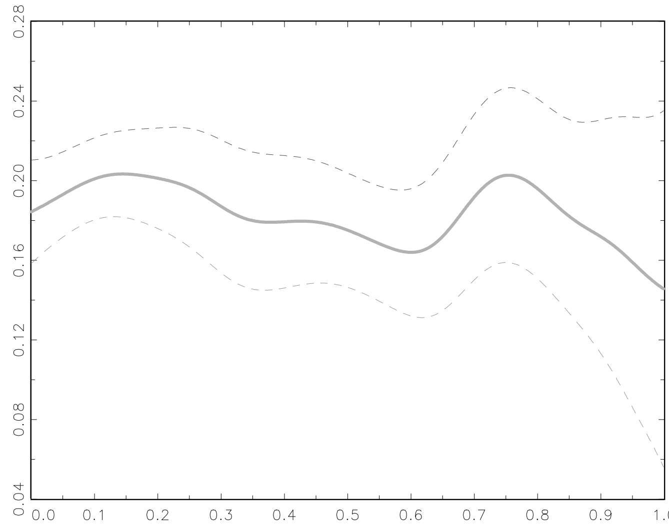
(d) 4. Agric. and ind. machinery

(e) 5. Electrical goods

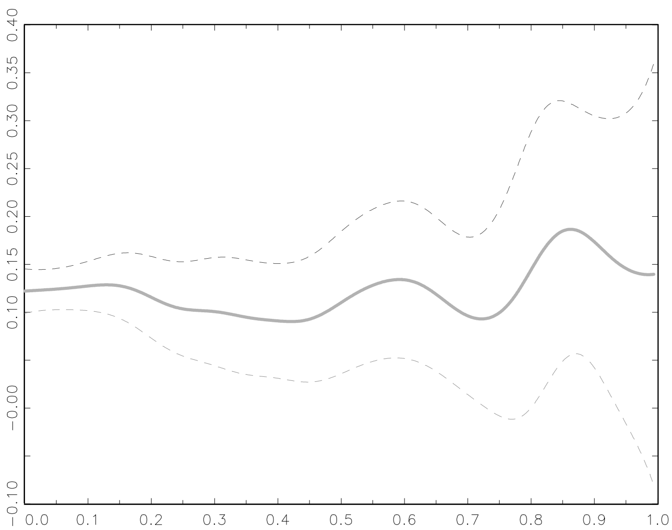
(f) 6. Transport equipment



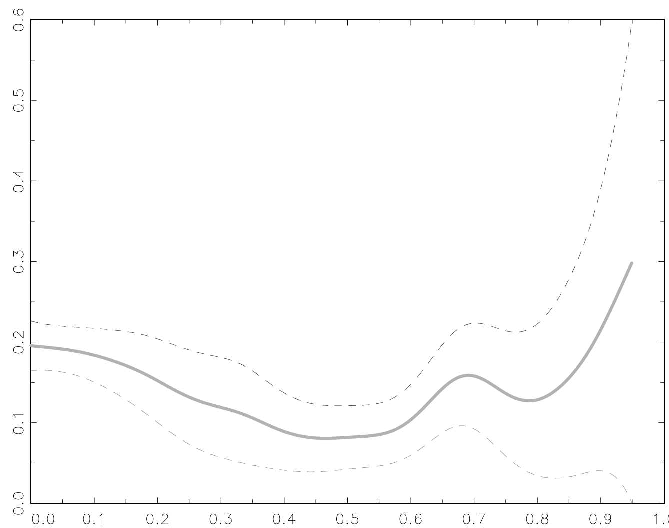
(g) 7. Food, drink and tobacco



(h) 8. Textile, leather and shoes



(i) 9. Timber and furniture



(j) 10. Paper and printing products