

Markups and Firm-Level Export Status[†]

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In this paper, we develop a method to estimate markups using plant-level production data. Our approach relies on cost-minimizing producers and the existence of at least one variable input of production. The suggested empirical framework relies on the estimation of a production function and provides estimates of plant-level markups without specifying how firms compete in the product market. We rely on our method to explore the relationship between markups and export behavior. We find that markups are estimated significantly higher when controlling for unobserved productivity; that exporters charge, on average, higher markups and that markups increase upon export entry. (JEL D22, D24, F14, L11, L60)

Estimating markups has a long tradition in industrial organization and international trade. Economists and policymakers are interested in measuring the effect of various competition and trade policies on market power, typically measured by markups. The empirical methods that were developed in empirical industrial organization often rely on the availability of very detailed market-level data with information on prices, quantities sold, characteristics of products, and more recently are supplemented with consumer-level attributes.¹ Often, both researchers and government agencies cannot rely on such detailed data, but still need an assessment of whether changes in the operating environment of firms had an impact on markups and therefore on consumer surplus. In this paper, we provide a simple empirical framework in the spirit of Hall (1986) to estimate markups. Our approach nests various price-setting models used in applied industrial organization and international trade and relies on optimal input demand conditions obtained from standard cost minimization and the ability to identify the output elasticity of a variable input free of adjustment costs. The methodology relies crucially on the insight that the output elasticity of a variable factor of production is only equal to its expenditure share

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¹See Goldberg (1995) and Berry, Levinsohn, and Pakes (2004) for examples.

in total revenue when price equals marginal cost of production. Under any form of imperfect competition, however, the relevant markup drives a wedge between the input's revenue share and its output elasticity.

Markup estimates are obtained using production data where we observe output, total expenditures on variable inputs, and revenue at the plant level, a condition that is satisfied in most plant-level datasets. In principle the approach relies on estimating output elasticities and we therefore require a measure of output that does not pick up price differences across firms. Ideally, we directly observe physical output and in fact those types of datasets are becoming increasingly available to empirical researchers, making our approach very much suitable to these data. For instance, US census data collects physical output for a set of industries as documented in Foster, Haltiwanger, and Syverson (2008) and Goldberg et al. (2010) and Kugler and Verhoogen (2008), who observe output in Indian and Colombian manufacturing firms, respectively. Alternatively, we need to convert revenues to physical output using price indices. When only (deflated) revenue is observed in the data, however, our approach is still informative about the correlation between markups and firm-level characteristics, such as export status in our application. We discuss the additional assumptions we need to use revenue data, but want to stress that the main approach to get at markups is not affected. We show that when relying on revenue data, only the level of the markup is potentially affected but not the estimate of the correlation between markups and firm-level characteristics or how markups change over time, which is after all the main focus of our application.

By modeling firm-specific productivity we can relax a few important assumptions maintained in previous empirical work. First, we do not need to impose constant returns to scale, and second, our method does not require observing or measuring the user cost of capital. We show that this approach leads to a flexible methodology and reliable estimates. We then use our empirical model to verify whether exporters, on average, charge higher markups than their domestic counterparts in the same industry, and how markups change upon export entry. Our framework is well suited to relate markups to any observed firm-level activity, such as research and development, foreign direct investment, import status, etc., that are potentially correlated with firm-level productivity.

The remainder of this paper is organized as follows. We briefly put our paper in the context of the literature in Section I. In particular, we contrast our methodology to current approaches and preview our empirical application and main results. Section II introduces our empirical framework and our estimation routine. Section III provides a short discussion on the relationship between markups and firm-level export status. In Section IV, we turn to the data, and in Section V we discuss our main results. Section VI provides a few robustness checks and we discuss remaining caveats. The final section concludes.

I. Recovering Markups from Production Data

Robert Hall published a series of papers suggesting a simple way to estimate (industry) markups based on an underlying model of firm behavior (Hall 1986, 1988, 1990). These papers generated an entire literature that was essentially built

upon the key insight that industry-specific markups can be uncovered from production data with information on firm- or industry-level usage of inputs and total value of shipments (e.g., Domowitz, Hubbard, and Petersen 1988; Waldmann 1991; Morrison 1992; Norrbin 1993; Roeger 1995; Basu and Fernald 1997; or Klette 1999)². This approach is based on a production function framework and delivers an average markup using the notion that under imperfect competition, input growth is associated with disproportional output growth, as measured by the relevant markup. An estimated markup higher than one would therefore immediately reject the perfect competitive model.³

A. Challenges and Outstanding Problems

Some important econometric issues are still not addressed in the series of modified approaches, however. The main concern is that unobserved factors can impact output growth as well, and an obvious candidate in the framework of a production function is productivity (growth).⁴ Not controlling for unobserved productivity shocks biases the estimate of the markup as productivity is potentially correlated with the input choice. While previous papers relied on the use of instrumental variables or, more recently, generalized method of moments (GMM), we relate our approach to the literature on estimating production functions. Olley and Pakes (1996) and Levinsohn and Petrin (2003) introduced a full behavioral model to solve for unobserved productivity as a function of observed firm-level decisions (investment and input demand) to deal with the endogeneity of inputs when estimating a production function.⁵ We refer to this approach as the proxy approach.

The increased availability of firm- or plant-level datasets further boosted empirical studies using some version of the Hall approach on micro data. Dealing adequately with unobserved productivity shocks becomes an ever bigger concern when applying the Hall method to plant-level data given the strong degree of heterogeneity, as the set of instruments suggested in the literature were mostly aggregate demand factors such as military spending and oil prices. Moreover, the Hall methodology and further refinements have become a popular tool to analyze how changes in the operating environment—such as privatization, trade liberalization, and labor market reforms—have impacted market power, measured by the change in markups. Here again, the correlation between the change in competition and productivity potentially biases the estimates of the change in the markup. Let us take the case of trade liberalization. If opening up to trade impacts firm-level productivity, as has been documented

²The literature also spread to international trade. See Levinsohn (1993), Harrison (1994), and Konings and Vandebussche (2005).

³In the original model, Hall actually tests a joint hypothesis of perfect competition and constant returns to scale. In an extended version, however, a returns to scale parameter is separately identified (Hall 1990). Importantly, our approach does not require any assumptions on the returns to scale in production as opposed to the Roeger (1995) approach.

⁴In addition, there has been quite a long debate in the literature on what the estimated markup exactly captures and how the model can be extended to allow for intermediate inputs and economies of scale among others (see Domowitz, Hubbard, and Petersen 1988 and Morrison 1992).

⁵Various refinements have since been proposed in the literature. Akerberg et al. (2007) show, however, that the basic framework remains valid. The methodology is now widespread in industrial organization, international trade, development economics (see, e.g., Van Biesebroeck 2005 and De Loecker 2007, who apply modified versions in the context of sorting out the productivity gains upon export entry).

extensively in the literature, it is clear that the change in the markup due to a change in a trade policy is not identified without controlling for the productivity shock.⁶

We introduce the notion of a control function to control for unobserved productivity in the estimation of the output elasticity of a variable input, which, combined with standard first-order conditions on cost minimization, generate estimates of firm-level markups. Our approach provides estimates of markups while controlling for unobserved productivity and relying on clearly spelled out behavioral assumptions. In addition, we identify markups while allowing for flexible production technologies and can accommodate dynamic and/or fixed inputs of production such as capital.

We show that our approach and the Hall (1986) approach are linked in a straightforward way by considering a special case of our model where the markup is constant across producers.⁷ We also compare our estimates to those obtained using an alternative suggested by Klette (1999), who relies on dynamic panel estimation techniques. Our approach relaxes a few important assumptions on how productivity shocks enter the model. In particular, we allow for unobserved serially correlated productivity, which is potentially affected by firm-level decisions. In addition, we recover firm- and time-specific markups, as opposed to an average markup for a set of producers, allowing for an analysis of how markups are related to economic variables such as productivity, firm size, and a firm's export status. Finally, we estimate our model in levels as opposed to the current literature where first differences of the production function are considered. We hereby increase the sample size and the efficiency of the estimates considerably, while reducing the role of measurement error.⁸

B. *Markups and Export Status*

In addition to providing a simple empirical framework to estimate markups using standard production data, we provide new results on the relationship between firms' export status and markups using a rich micro dataset where we observe substantial entry into export markets over our sample period. The latest generation of models of international trade with heterogeneous producers (e.g., Melitz 2003) were developed to explain the strong correlation between export status and various firm-level characteristics, such as productivity and size. In particular, the correlation between productivity and export status has been proven to be robust over numerous datasets. The theoretical models, such as Bernard et al. (2003) and Melitz and Ottaviano (2008), emphasize the self-selection of firms into export markets based on an underlying productivity distribution, creating a strong correlation between productivity and export status. These models also have predictions regarding markups and firm-level export status, however, and our empirical framework can be used to verify these predicted correlations between a firm's markup and its export status.

⁶The same is true in the case where we want to estimate the productivity response to a change in the operating environment such as a trade liberalization. See De Loecker (2011) for more on this.

⁷We are not the first to rely on the insight of Hall (1986) and adopt it to plant-level production data. Both Levinsohn (1993) and Harrison (1994) rely on a version of the Hall approach to analyze markups using micro-level production data.

⁸The sample size under first differencing is further reduced when instrumenting with lagged input growth, which requires at least three consecutive years of data for a given producer. The latter has, in addition, the potential of increasing a selection bias by conditioning on firm survival over a three-year period.

Furthermore, we explore the dynamics of export entry and exit to analyze how it impacts markups. The latter will also allow us to shed more light on the often mentioned learning by exporting hypothesis, which refers to significant productivity improvements for exporters upon export entry. This has recently been confirmed for mostly developing countries.⁹ Almost all empirical studies that relate firm-level export status to (estimated) productivity, however, rely on revenue to proxy for physical output and therefore do not rule out that part of the export premium captures product quality improvements and market power effects. Related to this, recent studies by Kugler and Verhoogen (2008) and Hallak and Sivadasan (2009) report higher product quality for exporters, whereas Manova and Zhang (2012) report higher export prices for richer and more distant markets using Chinese transaction-level data. They suggest that their results are consistent with a model where firms adjust quality and markups across destinations in response to market toughness. Therefore, differences in pricing behavior between exporters and nonexporters could, at least partially, be responsible for the measured productivity trajectories upon export entry. Our framework is especially well suited to address this question since our method generates firm-level estimates of markups and productivity, while controlling for potentially endogenous productivity improvements as a result of past export participation.

We study the relationship between markups and export status for a rich panel of Slovenian firms over the period 1994–2000. Slovenia is a particularly useful setting for this. First, the economy was a centrally planned region of former Yugoslavia until the country became independent in 1991. A dramatic wave of reforms followed that reshaped market structure in most industries. This implied a significant reorientation of trade flows toward relatively higher-income regions like the European Union (EU) and led to a quadrupling of the number of exporters over a seven-year period (1994–2000). Second, it has become a small open economy that joined the EU in 2004, and its gross domestic product (GDP) per capita is rapidly converging toward the EU average. This opening to trade has triggered a process of exit of the less productive firms, while deregulation and new opportunities facilitated the entry of new firms as well as entry into export markets, which contributed substantially to aggregate productivity growth.¹⁰

We find that markups differ dramatically between exporters and nonexporters and are both statistically and economically significantly higher for exporting firms. The latter is consistent with the findings of productivity premia for exporters, but at the same time requires a better understanding of what these (revenue-based) productivity difference exactly measure. We provide one important reason for finding higher measured revenue productivity: higher markups. Finally, we find that markups significantly increase for firms entering export markets.

⁹ See, e.g., Van Biesebroeck (2005) and De Loecker (2007). The literature also emphasizes the importance of self-selection into export markets (e.g., Clerides, Lach, and Tybout 1998).

¹⁰ See De Loecker and Konings (2006) for more on the importance of entry in aggregate productivity growth in Slovenian manufacturing.

II. A Framework to Estimate Markups

We introduce an empirical model to obtain firm-level markups relying on standard cost minimization conditions for variable inputs free of adjustment costs. These conditions relate the output elasticity of an input to the share of that input's expenditure in total sales and the firm's markup.¹¹ After we derive this relationship for a general production function, we discuss the estimation of the output elasticities, which together with data on input expenditures and total sales generate estimated markups.

To obtain output elasticities, we need estimates of the production function, for which we rely on proxy methods developed by Olley and Pakes (1996; hereafter, OP), Levinsohn and Petrin (2003; hereafter, LP) and Akerberg, Caves, and Frazer (2006; hereafter, ACF). We present our empirical framework in this particular order to highlight the flexibility of our approach with respect to the underlying production technology, consumer demand, and market structure. We view the restrictions that we impose, and which we discuss in detail in below, to be mild especially given the state of the literature.

A. Deriving an Expression for Markups

A firm i at time t produces output using the following production technology:

$$(1) \quad Q_{it} = Q_{it}(X_{it}^1, \dots, X_{it}^V, K_{it}, \omega_{it}),$$

where it relies on V variable inputs such as labor, intermediate inputs, and electricity. In addition, a firm relies on a capital stock, K_{it} , which is treated as a dynamic input in production. The only restriction we impose on $Q_{it}(\cdot)$ to derive an expression of the markup is that $Q_{it}(\cdot)$ is continuous and twice differentiable with respect to its arguments.¹²

We now assume that producers active in the market are cost minimizing and we can therefore consider the associated Lagrangian function

$$(2) \quad L(X_{it}^1, \dots, X_{it}^V, K_{it}, \lambda_{it}) = \sum_{v=1}^V P_{it}^{X^v} X_{it}^v + r_{it} K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot)),$$

where $P_{it}^{X^v}$ and r_{it} denote a firm's input price for a variable input v and capital, respectively. The first-order condition for any variable input free of any adjustment costs is

$$(3) \quad \frac{\partial L_{it}}{\partial X_{it}^v} = P_{it}^{X^v} - \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^v} = 0,$$

¹¹ Our approach is similar to Basu and Fernald (2002) and Petrin and Sivadasan (2010).

¹² Note that this expression encompasses both value added and gross output production function. In the former, only labor and capital enter the specification while we assume that intermediate inputs are used in a fixed proportion, purging output from intermediate input use.

where the marginal cost of production at a given level of output is λ_{it} as $\frac{\partial L_{it}}{\partial Q_{it}} = \lambda_{it}$. Rearranging terms and multiplying both sides by $\frac{X_{it}}{Q_{it}}$, generates the following expression:

$$(4) \quad \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^v} \frac{X_{it}^v}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{X^v} X_{it}^v}{Q_{it}}.$$

Cost minimization implies that optimal input demand is satisfied when a firm equalizes the output elasticity of any variable input X_{it}^v to $\frac{1}{\lambda_{it}} \frac{P_{it}^{X^v} X_{it}^v}{Q_{it}}$. It is important to stress that the above conditions on the use of dynamic inputs of production such as capital, and potentially other inputs facing adjustment costs. It is the use of this *conditional cost function* that will allow us to uncover a firm's markup, as cost minimization implies that we can simply condition on the dynamic inputs of production and therefore not have to consider the full dynamic problem of the firm and avoid having to make additional assumptions.¹³

A final step to obtain an expression for the markup μ_{it} is to simply define it as $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$. This expression is robust to various (static) price setting models, and does not depend on any particular form of price competition among firms. The markup will, however, depend on the specific nature of competition among firms. One restriction we do impose on price setting is that prices are set period by period, and hereby rule out dynamics in pricing such as menu pricing or simply costly adjustment of changing prices.¹⁴ It is important to realize that we identify the markup from the difference in price and marginal cost. Markups are determined in equilibrium, however, depending on the specific model of competition and strategic interaction between firms. We briefly discuss some leading cases of price competition in applied industrial organization and international trade in the online Appendix and cast them in our empirical framework.

For our purpose, it is sufficient to define the markup μ_{it} as the price-marginal cost fraction. Using this definition, we can rewrite equation (4) as

$$(5) \quad \theta_{it}^X = \mu_{it} \frac{P_{it}^X X_{it}}{P_{it} Q_{it}},$$

where the output elasticity on an input X is denoted by θ_{it}^X . This expression will form the basis for our approach: we obtain the output elasticity from the estimation of a

¹³Note that, in the special case where marginal costs are constant across all levels of output, the output elasticity is only then equal to the input's cost share. The constant marginal cost assumption was implicitly introduced in the original Hall article. Under that assumption, the markup could in theory be measured by directly comparing revenue and cost shares.

¹⁴Our data is at the annual level and at this level of frequency prices are adjusted frequently, and we therefore away from this issue. We refer to Bils and Klenow (2004) who find that half of goods' prices last 5.5 months or less, which implies that prices are adjusted much more at the annual level and reducing the price stickiness at the annual frequency. Although we do not want to stress this too much in our paper, since it is not the focus of the paper, our methodology can in principle deliver an estimate of the markup consistent with dynamic pricing (under adjustment costs due to say menu costs for instance). A different first order condition (FOC) on pricing will be obtained that will imply that the wedge between an input's marginal product and the real input price will not measure the markup as the relevant markup is no longer simply price over marginal cost. Under a specific structure, we can back out both parameters of the model. This lies beyond the scope of this paper.

production function and need only to measure the share of an input's expenditure in total sales. Or put differently, we obtain an expression of the markup as follows:

$$(6) \quad \mu_{it} = \theta_{it}^X (\alpha_{it}^X)^{-1},$$

where α_{it}^X is the share of expenditures on input X_{it} in total sales $(P_{it}Q_{it})$. In order to obtain a measure of firm-level markups using production data, we require only an estimate of the output elasticity of one (or more) variable input(s) of production and data on the expenditure share. The latter is directly observed in most micro data. A different way to interpret the last expression is to note that the markup is identified as the ratio of an input's output elasticity and its revenue share, where we can recover an estimate of the output elasticity by estimating the production function.

Although this derivation is standard and has been used throughout the literature, our contribution is to provide consistent estimates of the output elasticities while allowing some inputs to face adjustment costs and recover firm-specific estimates of the markup that we can relate to various economic variables. We also show how our approach relaxes the current literature, which relies on a single-equation approach to estimate industry-level markups, in a few important ways.

It is important to stress that our approach can accommodate inputs with adjustment costs. The most obvious candidate is the firm's capital stock. The wedge between the firm's output elasticity of capital and its revenue share contains the expected stream of costs and revenues and adjustment costs, in addition to the current markup, and we will revisit this implication by comparing markups obtained from both variable inputs and the capital stock.

B. Estimating Output Elasticities and Markups

In order to obtain estimates of the output elasticities θ_{it}^X , we restrict our attention to production functions with a scalar Hicks-neutral productivity term and with common technology parameters across the set of producers. The latter does not imply that output elasticities of inputs across firms are constant, except for the special case of Cobb-Douglas.

The two restrictions imply the following expression for the production function

$$(7) \quad Q_{it} = F(X_{it}^1, \dots, X_{it}^V, K_{it}; \beta) \exp(\omega_{it}),$$

where we highlight that a set of common technology parameters β govern the transformation of inputs to units of output, combined with the firm's productivity ω_{it} .

We view this restriction to be very mild and the expression above contains most, if not all, specifications used in empirical work such as the Cobb-Douglas and the Translog production function.¹⁵ The main advantage of restricting our attention to production technologies of this form is that we can rely on proxy methods suggested by OP, LP, and ACF to obtain consistent estimates of the technology parameters β .

¹⁵ We can relax the technology parameters to be time variant, and have β_t . In our empirical work, we check the importance of this assumption for our results.

From now on, we consider the log version of equation (6) given that the output elasticity of a variable input v , $\theta_{it}^{X^v}$, is given by $\frac{\partial \ln F(\cdot)}{\partial \ln X_{it}^v}$ and is by definition independent of a firm's productivity level.¹⁶ We discuss the details of how we estimate the production function parameters, which we need to compute $\theta_{it}^{X^v}$, in the next section.

Estimation Procedure.—Moving toward the empirical specification of our model, we implicitly allow for measurement error in output observed in the data and for unanticipated shocks to production, which we combine into ϵ_{it} . More precisely, we observe logged output y_{it} and assume that it is given by $y_{it} = \ln Q_{it} + \epsilon_{it}$, where ϵ_{it} are unanticipated shocks to production and i.i.d. shocks including measurement error.¹⁷ It is important to stress that we explicitly rely on the fact that firms do not observe ϵ_{it} when making optimal input decisions. We come back to this distinction when computing markups using our estimates.

The production function we take to the data, and estimate for each industry separately, is therefore given by

$$(8) \quad y_{it} = f(x_{it}, k_{it}; \beta) + \omega_{it} + \epsilon_{it},$$

where we subsume the constant term in productivity and collect all variable inputs in x_{it} , and β contains all relevant coefficients.¹⁸ We consider flexible approximations to $f(\cdot)$ and therefore explicitly write the production function we estimate on the data in general terms. For instance, our main empirical specification relies on a translog production function that implies that $f(\cdot)$ is approximated by a second-order polynomial where all (logged) inputs, (logged) inputs squared, and interaction terms between all (logged) inputs are included.¹⁹ We recover the Cobb-Douglas (CD) production function when we drop higher-order and interaction terms. The departure from the standard CD production function is important for our purpose. If we were to restrict the output elasticities to be independent of input use intensity when analyzing how markup differs across firms, we would be attributing variation in technology to variation in markups, and potentially bias our results.

Our approach nests various specifications of the production function, such as the value added and gross output production functions. The latter has the potential advantage of providing us with multiple first-order conditions to recover the markup and test for overidentifying restrictions. In order to guarantee identification

¹⁶We can in principle extend our model to incorporate input-biased technological change where another productivity shock enters the model, which directly affects one particular input of production.

¹⁷Most firm-level production data will record output as total value of shipments or value added. Therefore revenues have to be converted to physical output measures using price indices. Unobserved price variation that is uncorrelated with input choices will therefore be picked up by ϵ_{it} and our procedure explicitly corrects for this when computing markups. We revisit this measurement problem in more detail in Section VI and discuss the additional assumptions required to rely on deflated revenue data.

¹⁸See below for a specific case when we introduce a value added production function.

¹⁹In fact we can approximate $f(\cdot)$ by a higher-order polynomial and make the coefficients time-dependent without affecting our method of moments approach. In practice, however, the search over a very large set of parameters in the GMM setting becomes much more computationally intensive. For instance, when we consider a translog gross output production function in three inputs (labor, materials, and capital) we are already left with ten production functions coefficients over which we need to search jointly. Moving to a higher-order polynomial approximations raises the number of parameters substantially.

of all variable factors of production, however, we need to make explicit that all input prices of variable inputs of production vary across firms and are serially correlated. The latter allows us to rely on lagged input choices to identify the production coefficients. The value added production function relies on an extra assumption that a fixed proportion of materials is used for producing a unit of output. We discuss more details of our estimation procedure for a gross output production function in the online Appendix. We will also revisit this distinction below when discussing adjustment costs in labor demand.

In order to obtain consistent estimates of the production function, we need to control for unobserved productivity shocks, which are potentially correlated with input choices. We deal with this standard simultaneity problem by relying on the insight of OP/LP and use the ACF approach while relying on materials to proxy for productivity. The latter has the advantage of not having to revisit the underlying dynamic model when considering modifications to the original OP setup when dealing with additional state variables.²⁰ We do, however, describe the estimation routine while relying on a dynamic control, investment, and discuss the additional assumptions we require. In our empirical work we run both procedures on the data.

We follow Levinsohn and Petrin (2003) and rely on material demand,

$$(9) \quad m_{it} = m_t(k_{it}, \omega_{it}, \mathbf{z}_{it}),$$

to proxy for productivity by inverting $m_t(\cdot)$, where we collect additional variables potentially affecting optimal input demand choice in the vector $\mathbf{z}_{it}$. The inclusion of these additional control variables illustrates the only restriction we impose on the underlying model of competition; i.e., we need to include the relevant variables potentially affecting differences in input demand choices of firms. Once those variables are appropriately accounted for in the estimation routine to obtain output elasticities, we do not have to take a stand on the exact model of competition and can analyze how markups are different across firms and time, and how they relate to firm-level characteristics. The exact variables to be included in $\mathbf{z}_{it}$ depend on the application but will definitely capture variables leading to differences in optimal input demand across firms such as input prices. Anticipating the application of this paper, a firm's export status, for instance, will be included in the control function.²¹

We therefore rely on $\omega_{it} = h_t(m_{it}, k_{it}, \mathbf{z}_{it})$ to proxy for productivity in the production function estimation. The use of a material demand equation to proxy for productivity is important for us. The monotonicity of intermediate inputs in productivity holds under a large class of models of imperfect competition. As long as $\frac{\partial m}{\partial \omega} > 0$ conditional on the firm's capital stock and variables captured by $\mathbf{z}_{it}$, we can use $h_t(m_{it}, k_{it}, \mathbf{z}_{it})$ to proxy for ω_{it} and rely on the latter to index a firm's productivity. This monotonicity is preserved for a wide range of models of imperfect competition. In this setting, we also find it useful to refer to Melitz and Levinsohn (2006) who also rely on intermediate inputs to proxy for unobserved productivity while allowing for

²⁰When relying on investment as a proxy, all relevant state variables, both observed and unobserved, have to be incorporated into the control function. We discuss this approach in the online Appendix.

²¹Note that both additional state variables and other demand conditions are required to be included when considering intermediate inputs as a proxy. See De Loecker (2011) for another application where both additional state variables and serially uncorrelated demand factors are included.

imperfect competition. They show that this monotonicity condition holds as long as more productive firms do not set inordinately higher markups than less productive firms.²² Just as in their setting, we therefore rule out these cases and impose this restriction in our empirical application.²³

We do depart from Levinsohn and Petrin (2003) and give up on identifying any parameter in the first stage since conditional on a nonparametric function in capital, materials, and other variables affecting input demand, identification of the labor coefficient is not plausible.²⁴ Note that the latter observation is true even for a CD production function. Given that we are concerned with more flexible production functions and allow for interaction terms between the various inputs, identification of the labor coefficients in the first stage would rely heavily on functional form assumptions.

Our procedure consists of two steps and follows ACF closely. Let us consider a value added translog production function for simplicity, which is given by

$$(10) \quad y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \epsilon_{it}.$$

In a first stage, we run

$$(11) \quad y_{it} = \phi_t(l_{it}, k_{it}, m_{it}, \mathbf{z}_{it}) + \epsilon_{it},$$

where we obtain estimates of expected output ($\hat{\phi}_{it}$) and an estimate for ϵ_{it} . Expected output is given by

$$(12) \quad \phi_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_t(m_{it}, k_{it}, \mathbf{z}_{it}).$$

Note that under a gross output production function the first stage is identical. Only expression (10) will contain extra terms related to the material input m_{it} , including interaction terms with labor and capital.²⁵

The second stage provides estimates for all production function coefficients by relying on the law of motion for productivity.

$$(13) \quad \omega_{it} = g_t(\omega_{it-1}) + \xi_{it}.$$

We can easily allow for the potential of additional (lagged and observable) decision variables to affect current productivity outcomes (in expectation), in addition to the

²² Melitz and Levinsohn (2006, p.14) further state that “[i]n this situation, an inordinate markup difference would imply that a productivity increase would lead a firm to increase its markup by such an amount that it would lead to a decrease in the firm’s input usage.”

²³ For instance, De Loecker (2011) and Aw, Roberts, and Xu (2011) show that under a constant elasticity of substitution (CES) monopolistic competition setup, m_{it} is increasing in productivity. Under models of strategic interaction we require firms with higher productivity not to have disproportionately higher markups, putting restrictions on the markup-productivity elasticity. For the case of Cournot, for example, lower marginal cost (higher productivity) implies a higher use of intermediate inputs, and hence output produced, at any level of residual demand.

²⁴ See Akerberg, Caves, and Frazer (2006) and Wooldridge (2009) for a discussion.

²⁵ To be precise, under a value added specification y_{it} is measured by subtracting material inputs from gross output. Under a gross output specification we include $\beta_m, \beta_{mm}, \beta_{lm}, \beta_{mk}$ and β_{lmk} and their corresponding variables in the specification.

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