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MARKUPS AND FIRM-LEVEL EXPORT STATUS

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ABSTRACT

Estimating markups has a long tradition in industrial organization and international trade. Economists and policy makers 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 supplemented with consumer-level attributes. 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 derive an estimating equation to estimate markups using standard production plant-level data based on the insight of Hall (1986) and the control function approach of Olley and Pakes (1996). Our methodology allows for various underlying price setting models, dynamic inputs, and does not require measuring the user cost of capital or assuming constant returns to scale. We rely on our method to explore the relationship between markups and export behavior using plant-level data. We find that i) markups are estimated significantly higher when controlling for unobserved productivity, ii) exporters charge on average higher markups and iii) firms' markups increase (decrease) upon export entry (exit).We see these findings as a first step in opening up the productivity-export black box, and provide a potential explanation for the big measured productivity premia for firms entering export markets.

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1 Introduction

Estimating markups has a long tradition in industrial organization and international trade. Economists and policy makers 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 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 crucially relies on the insight that the cost share of factors of production, in our case labor and intermediate inputs, are only equal to their revenue share if output markets are perfectly competitive. However, under (any form of) imperfect competition the relevant markup drives a wedge between revenue and cost shares.

Markup estimates are obtained using standard production data where we observe total expenditures on variable inputs and revenue at the plant level, a condition which is satisfied in almost all plant-level datasets. By modelling the firm specific (unobserved) productivity process we can relax a few important assumptions maintained in previous empirical work. First of all, we do not need to impose constant returns to scale, and secondly, 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, and use our empirical model to verify whether exporters, on average, charge higher markups than their counterparts in the same industry, and how markups change upon export entry. However, our framework is well suited to relate markups to any observed firm-level activity, such as R&D, FDI, import status, etc., which is potentially correlated with firm-level productivity.

1.1 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 et al., 1988; Waldmann, 1991; Morrison, 1992; Norrbin, 1993; Roeger, 1995; Basu and Fernald, 1997 or

[1] See Goldberg (1995) and Berry, Levinsohn and Pakes (2004) for example.

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]

However, some important econometric issues are still unaddressed in the series of modified approaches. 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. This problem relates to another strand of the literature that stepped away from looking for the right set of instruments to control for unobserved productivity. 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 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, 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 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]

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

[3] In the original model, Hall actually tests a joint hypothesis of perfect competition and constant returns to scale. However, in an extended version 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.

[4] In 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 *et. al* 1988 and Morrison 1992).

[5] Various refinements have since been proposed in the literature. However, Ackerberg, Benkard, Berry and Pakes (2007) show 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).

[6] The 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 (2010a) for more on this.

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 straight forward way by considering a special case of our model where the markup is constant across producers. We also compare our estimates to those obtained using an alternative suggested by Klette (1999) who relies on a dynamic panel estimation techniques. We discuss in details how our methodology differs and show that Klette's approach can be considered as a special case of our estimation strategy while relaxing a few important assumptions on how productivity shocks impact choice variables. In particular, we relax the assumptions on the productivity dynamics and allow for markups to vary across producers and time, and in this way we can correlate markups with economic variables such as productivity and export status. In addition, both the sample size and the efficiency of the estimates increase considerably since we do not rely on first differencing.

1.2 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 data set 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 correlations 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, Eaton, Jensen and Kortum (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.[7] However, these models also have predictions regarding markups and firm-level export status and our empirical framework can be used to test these.

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 coun-

[7] A few recent papers have provided similar evidence on importers (Halpern, Koren and Szeidl, 2006).

tries.[8] However, almost all empirical studies that relate firm-level export status to (estimated) productivity 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 (2009) 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 non exporters 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 towards relatively higher income regions like the EU and led to a quadrupling of the number of exporters over a 7 year period (1994-2000). Second, it has become a small open economy that joined the European Union in 2004, and its GDP per capita is rapidly converging towards 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.[9]

We find that markups differ dramatically between exporters and non exporters 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 differences 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.

The remainder of this paper is organized as follows. Section 2 introduces our empirical framework and introduces our estimation routine and how we compute markups using our estimates and the data. Section 3 provides a short discussion on the relationship between markups and firm-level export status, and how our empirical model can be used to test some recent models of international trade. In section 4 we turn to the data and in section 5 we

[8] 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).

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

discuss our main results . Section 6 provides a few robustness checks and we discuss remaining caveats. The final section concludes.

2 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.[10] 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), Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazier (2006). 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 we do impose, and which we discuss in detail in below, to be mild especially given the state of the literature.

2.1 Deriving an expression for markups

A firm i at time t produces output using the following production technology, $Q_{it} = Q_{it}(X_{it}, K_{it})$, where it relies on a set of variable inputs X_{it} and capital K_{it}. The only restriction we impose on $Q_{it}(.)$ to derive an expression of the markup is that $Q_{it}(.)$ is continuous and twice differentiable with respect to its arguments. Note that this expression encompasses a value added production function when X_{it} is simply labor; and a gross output production function when X_{it} contains labor and intermediate inputs such as materials.

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

$$\mathcal{L}(X_{it}, K_{it}, \lambda_{it}) = P_{it}^X X_{it} + r_{it} K_{it} + \lambda_{it}(Q_{it} - Q_{it}(X_{it}, K_{it})) \tag{1}$$

where P_{it}^X and r_{it} denote a firm's input price for variable inputs and capital, respectively. Taking the first order conditions with respect to the variable inputs without adjustment costs, we get that

$$\frac{\partial \mathcal{L}}{\partial X_{it}} = P_{it}^X - \lambda_{it} \frac{\partial Q_{it}(X_{it}, K_{it})}{\partial X_{it}} = 0 \tag{2}$$

and λ_{it} measures the marginal cost of production as $\frac{\partial \mathcal{L}}{\partial Q_{it}} = \lambda_{it}$. Rearranging terms and multiplying both sides by $\frac{X_{it}}{Q_{it}}$, generates the following expression.

$$\frac{\partial Q_{it}(X_{it}, K_{it})}{\partial X_{it}} \frac{X_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^X X_{it}}{Q_{it}} \tag{3}$$

[10] Our approach is similar to Basu and Fernald (2002) and Petrin and Sivadasan (2010).

Cost minimization implies that optimal input demand is satisfied when a firm equalizes the output elasticity of input X_{it} to its cost share $\frac{1}{\lambda_{it}}\frac{P_{it}^X X_{it}}{Q_{it}}$. Note that this expression holds under any form of competition and underlying consumer demand. 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.[11] It is important to realize that we identify the markup from the difference in price and marginal cost. However, markups are determined in equilibrium depending on the specific model of competition and strategic interaction between firms. We briefly discuss some leading cases of price competition (Cournot, Bertrand and monopolistic competition) in applied industrial organization and international trade in Appendix B 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 obtain an expression of the markup

$$\mu_{it} = \frac{\theta_{it}^X}{\alpha_{it}^X} \tag{4}$$

where we use θ_{it}^X to denote the output elasticity of input X_{it} and 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 only require estimates of the output elasticities of one (or more) variable input 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 of the difference between a firm's variable input cost share and revenue share, where the cost share is not observed but by optimality conditions has to equal the output elasticity of the relevant input.

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 which 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.

[11] Our data is at the annual level and at this level of frequency prices are adjusted frequently, and we therefore abstract 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 principal deliver an estimate of the markup consistent with dynamic pricing (under adjustment costs due to say menu costs for instance). A different FOC on pricing will be obtained which 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.

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 cost share of capital and its revenue share contains the expected stream of costs and revenues and adjustment costs, in addition to the current markup.[12]

2.2 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

$$Q_{it} = F(X_{it}, K_{it}; \beta) \exp(\omega_{it}) \tag{5}$$

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.[13] 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 produce consistent estimates of the technology parameters β.

From now on we consider the log version of (5) given that the output elasticity θ_{it}^X is given by $\frac{\partial \ln F(X_{it}, K_{it}; \beta)}{\partial \ln X_{it}}$ and is by definition independent of a firm's productivity level. We discuss the details of how we estimate the production function parameters β, which we need to compute θ_{it}^X, for the translog production function which nests the Cobb-Douglas production function.[14]

2.2.1 Estimation procedure

Moving towards 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 $y_{it} = \ln Q_{it} + \varepsilon_{it}$, where ε_{it} are iid shocks. Importantly firms do not observe ε_{it} when making optimal input decisions. We come back to this distinction when computing markups using our estimates.

[12] We will revisit this implication by comparing markups obtained from both variable inputs and the capital stock.

[13] We can relax the technology parameters to be time variant. In our empirical work we check the importance of this assumption for our results.

[14] We like to note that the identification of the translog production function using proxy estimators has not been discussed as far as we know. In Appendix C we discuss the case of the CES production function as well.

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

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \varepsilon_{it} \tag{6}$$

where we subsume the constant term in productivity and lower cases denote the log of a variable, e.g. $l_{it} = \ln L_{it}$. We recover the Cobb Douglas (CD) production function when omitting higher order terms ($\beta_{ll} l_{it}^2, \beta_{kk} k_{it}^2$) and the interaction term ($\beta_{lk} l_{it} k_{it}$). The departure from the standard CD production function is important for our purpose. We identify firm-level markups from the wedge between revenue and cost shares of inputs, and analyze how markups differ across firms and more specifically whether markups are different for exporters and whether a firm's markup changes with export entry. If we were to restrict the output elasticities to be independent of input use intensity, we would be attributing variation in technology to variation in markups, and potentially bias the exporter effect.

We discuss our estimation procedure for a value added production function. In Appendix C, we discuss the gross output production function case, which is very similar and requires additional moments to identify the coefficients related to material inputs. We will 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 labor and capital 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[15]. We do, however, describe our estimation routine when 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, $m_{it} = m_t(k_{it}, \omega_{it})$, to proxy for productivity by inverting $m_t(.)$. We therefore rely on $\omega_{it} = h_t(m_{it}, k_{it})$ 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 use (the fixed input in production), we can use $h_t(m_{it}, k_{it})$ 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 (2000) and Melitz and Levinsohn (2006) who also rely on intermediate

[15] As discussed by Ackerberg et al (2006), any additional (serially correlated) state variables which are not modelled and hence unobservable will actually help identification when relying on a static input to control for productivity. In contrast, when 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 Appendix C. See De Loecker (2010a) for a more detailed discussion on this.

inputs to proxy for unobserved productivity while allowing for imperfect competition. Melitz (2000) shows that this monotonicity condition holds as long as more productive firms do not set inordinately higher markups than less productive. Melitz and Levinsohn (2006) further state that *"In 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."*. Just like in their setting, we therefore rule out these cases and impose this restrictions in our empirical application.[16]

We do depart from Levinsohn and Petrin (2003) and give up on identifying any parameter in the first stage since conditional on a non parametric function in capital and materials, identification of the labor coefficient is not plausible.[17] Note that the latter observation is true even for a Cobb-Douglas production function. Given that we are concerned with more flexible production functions and allow for interaction terms between labor and capital, identification of the labor coefficients in the first stage would rely heavily on functional form assumptions.

Our procedure consists of two steps and follows Ackerberg, Caves and Frazier (2006) closely. In a first stage, we run

$$y_{it} = \phi_t(l_{it}, k_{it}, m_{it}) + \varepsilon_{it} \tag{7}$$

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

$$\phi_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_t(m_{it}, k_{it}) \tag{8}$$

The second stage provides estimates for all production function coefficients by relying on the law of motion for productivity. We follow the standard assumption that productivity follows a first order Markov process and is given by

$$\omega_{it} = g_t(\omega_{it-1}) + \xi_{it} \tag{9}$$

De Loecker (2010b) discusses the importance of restricting this productivity process to be completely exogenous, or in other words no firm-level action such as investment, R&D or exporting can affect a firm's future productivity level in expected terms. We can easily accommodate this by allowing additional variables z_{it}, such as a firm's export status, to be included in $g_t(.)$. As we will show below, this will not impact our ability to identify the coefficients of the production function.[18]

[16] For instance De Loecker (2010a) and Aw, Roberts and Xu (forthcoming) show that under a CES monopolistic competition setup, materials is increasing in productivity. Under models of strategic interaction we require firms with higher productivity not to have disproportionally 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.

[17] See Ackerberg, Caves and Frazier (2006) and Wooldrigde (2009) for a discussion.

[18] In a similar way we can control for the non random exit of firms by including the propensity to exit P_{it} as in Olley and Pakes (1996), i.e. $g_t(\omega_{it-1}, P_{it})$.

After the first stage we can compute productivity for any value of $\boldsymbol{\beta}$, where $\boldsymbol{\beta} = (\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk})$, using $\omega_{it}(\boldsymbol{\beta}) = \widehat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_{ll} l_{it}^2 - \beta_{kk} k_{it}^2 - \beta_{lk} l_{it} k_{it}$. By non parametrically regressing $\omega_{it}(\boldsymbol{\beta})$ on its lag, $\omega_{it-1}(\boldsymbol{\beta})$, we recover the innovation to productivity given $\boldsymbol{\beta}$, $\xi_{it}(\boldsymbol{\beta})$.[19] We can now form moments to obtain our estimates of the production function, where we rely on

$$E\left(\xi_{it}(\boldsymbol{\beta})\begin{pmatrix} l_{it-1} \\ k_{it} \\ l_{it-1}^2 \\ k_{it}^2 \\ l_{it-1}k_{it} \end{pmatrix}\right) = 0 \tag{10}$$

to estimate the production function parameters and we use standard GMM techniques to obtain the estimates of the production function and rely on block bootstrapping for the standard errors.[20]

The moments above are similar to the ones suggested by Ackerberg, Caves and Frazier (2006) and exploit the fact that capital is assumed to be decided a period ahead and therefore should not be correlated with the innovation in productivity. We rely on lagged labor to identify the coefficients on labor since current labor is expected to react to shocks to productivity, and hence $E(l_{it}\xi_{it})$ is expected to be non zero. However, in order for lagged labor to be a valid instrument for current labor, we require input prices to be correlated over time. We found very strong evidence in favor of this by running various specifications that essentially relate current wages to past wages.[21]

The estimated output elasticity of an input X_{it} under the translog production function is given by

$$\widehat{\theta}_{it}^X = \widehat{\beta}_l + 2\widehat{\beta}_{ll} l_{it} + \widehat{\beta}_{lk} k_{it} \tag{11}$$

and under a Cobb-Douglas production it is simply given by $\widehat{\beta}_l$. We now turn to how we compute markups using our estimates and data on firm-level input expenditures and revenues.

2.2.2 Obtaining markups from estimates and data

We now have everything in hand to compute markups. Using expression (4) and our estimate for the output elasticity, we can directly compute markups. However, as mentioned above, we do not directly observe the correct expenditure share for input X_{it} since we only observe $\widetilde{Q}_{it}$, which is given by $Q_{it}\exp(\varepsilon_{it})$. The first stage of our procedure does provide us with an

[19] If we want to allow the export status to impact expected future productivity, we simply regress it on $(\omega_{it}(\boldsymbol{\beta}), \mathbf{z}_{it})$, and obtain $\xi_{it}(\boldsymbol{\beta})$ appropriately.

[20] Wooldrigde (2009) provides a similar procedure where all coefficients are estimated in a one step system GMM approach which delivers standard GMM standard errors and higher efficiency by relying on cross equation restrictions. However, we follow the two step procedure since we only have to search over five parameters in the second stage, after recovering estimates for ϕ_{it} and ε_{it} in the first stage. The Wooldridge (2009) approach is computationally much more demanding since it requires to search jointly over all five parameters and all coefficients of the polynomial functions we use to approximate $h_t(.)$ and $g_t(.)$.

[21] We come back to this point in Appendix C when we discuss the approach using investment, which requires including wages in the investment policy function since they are serially correlated.

estimate for ε_{it} and we use it to compute the expenditure share as follows,

$$\alpha_{it}^X = \frac{P_{it}^X X_{it}}{P_{it}\frac{\widetilde{Q}_{it}}{\exp(\widehat{\varepsilon}_{it})}} \tag{12}$$

This correction is important as it will eliminate any variation in expenditure shares that comes from variation in output not correlated with $\phi_t(l_{it}, k_{it}, m_{it})$, or put differently from output variation not related to variables impacting input demand including input prices, productivity, technology parameters and output prices.

We obtain an estimate for the markup by simply applying the FOC on input demand for a variable input in production in the following way:

$$\widehat{\mu}_{it} = \widehat{\theta}_{it}^X(\alpha_{it}^X)^{-1} \tag{13}$$

Markups for each firm i at each point in time t are obtained while allowing for considerable flexibility in the production function, consumer demand and competition.

2.2.3 Some remarks

Before we turn to our application we want to make four remarks. First of all, we briefly discuss the extension towards a gross output production function and the trade-off between using a potentially more variable input to compute markups and the ability to identify the output elasticity of that input. Secondly, we summarize how our procedure changes when we were to rely on investment to proxy for productivity. Thirdly, we show how the standard and mostly used specification, the Cobb-Douglas production function, is a special case of our estimation routine. Finally, we briefly discuss a special case of our empirical model where markups are constant across producers in an industry, and recover the specifications suggested by Hall (1986) and subsequent work of Klette (1999).

Gross output and adjustment costs We presented our estimation routine under the assumption that labor is a static input into production, which is consistent with the notion that we can learn about markups from the optimal labor demand decisions. However, if labor is a dynamic input, due to say adjustment costs such as hiring and firing costs, our procedure can still produce consistent estimates of the production function. In that case we can rely on current labor to identify the coefficients on labor, just like with capital. It does have implications for computing markups. In fact, if firms face adjustment costs the wedge between a firm's cost and revenue share contains more than just the markup. It is easy to show that the FOC on labor demand will introduce an additional component which contains adjustment costs.[22] In this case, we can rely on a gross output production function and compute the markups using the output elasticity of materials and its expenditure share. Material inputs

[22] See Petrin and Sivadasan (2010) for such an application.

are potentially much less prone to adjustment costs, up to inventory management, and in our empirical work we will check the robustness of our results to this. We refer the reader to the Appendix C for a detailed discussion of the estimation of the production function parameters under a gross output production function.

Using investment to proxy for productivity In order to rely on the Olley and Pakes (1996) version of the ACF estimator and use investment to proxy for productivity, we need to incorporate any additional state variable in the investment policy function and check invertibility. Obvious candidates for additional state variables are serially correlated input prices and a firm's export status. Adding the extra state variables, up to showing monotonicity, has no implications on our ability to identify the coefficients of interests.[23]

Cobb-Douglas production function The Cobb-Douglas production function is obtained by simply shutting the parameters β_{ll}, β_{kk} and β_{lk} to zero in equation (6). The rest of the procedure is unchanged. The output elasticity of labor for instance simply reduces to β_l and implies a constant elasticity across producers and time. Therefore all variation in the expenditure share will carry over to the variation in markups across firms. The latter implies that under this restrictive model choice, we can immediately rank firms' markups by ranking their expenditure shares. In our empirical work we compare markups under both production technologies.

Special case: constant markup We can use our framework to recover the original Hall approach, as well as Klette (1999), by assuming that markups are constant across firms and time, $\mu_{it} = \mu$, and that productivity is simply a fixed effect, $\omega_{it} = \omega_i + \nu_{it}$, which can be eliminated by taking first differences. When considering a Cobb-Douglas production function for simplicity, we obtain the following expression

$$\Delta y_{it} = \beta_l \Delta l_{it} + \beta_k \Delta k_{it} + \Delta \widetilde{\varepsilon}_{it} \tag{14}$$

where Δ is a first difference operator such that $\Delta x_{it} = x_{it} - x_{it-1}$ and the error term $\Delta \widetilde{\varepsilon}_{it} = \Delta \varepsilon_{it} + \nu_{it}$. A final step in recovering the Hall framework is to directly impose the first order conditions from cost minimization on *all* inputs of the production function. The estimating equation then reduces to

$$\Delta y_{it} = \mu \Delta x_{it} + \Delta \widetilde{\varepsilon}_{it} \tag{15}$$

where $\Delta x_{it} = (\alpha^L \Delta l_{it} + \alpha^K \Delta k_{it})$.[24] It is worth emphasizing that the constant markup condition can either be imposed through economic theory, such as considering a constant

[23] Appendix C provides the details of the estimation routine. We refer to Van Biesebroeck (2005) and De Loecker (2007) for a detailed discussion, and we rely on their results to use investment when considering export as a state variable.

[24] In general, the revenue shares are firm and time specific. However, in the case of Cobb Douglas with a constant markup, they need to be constant across firms since $\beta_l = \alpha^L \mu$.

elasticity of demand model, or by restricting the goal of the estimation routine to estimate the average markup. Both constraints lead to the same estimating equation but identification of the parameter μ is quite different. Equation (15) further highlights that capital is assumed to be a variable input since the static first order condition is used to substitute the capital coefficient. In addition, we require a measure of the user cost of capital (r_{it}) which, as discussed before, is hard to come by. Variants of this equation have been used extensively in the literature and this paper brings forward the strong assumptions required to obtain markup estimates. In our empirical work we will compare our estimates to those obtained with the Hall approach.

Finally, we can directly verify the importance of relaxing the assumptions on the productivity shock by relying on our control function in the first difference setting. The proxy for productivity has the advantage of not having to treat capital as a static input since we collect all terms on capital and materials in $\widetilde{h}_t(.)$. More precisely we have that $\Delta\omega_{it} = \omega_{it} - \omega_{it-1}$ and $\omega_{it} = h_t(m_{it}, k_{it})$. This approach generates the following estimating equation.

$$\Delta y_{it} = \mu \Delta \widetilde{x}_{it} + \widetilde{h}_t(m_{it}, k_{it}) + \Delta\varepsilon_{it} \tag{16}$$

where $\Delta\widetilde{x}_{it} = (\alpha^L \Delta l_{it})$, and $\widetilde{h}_t(m_{it}, k_{it}) = \beta_k \Delta k_{it} + h_t(m_{it}, k_{it}) - h_{t-1}(m_{it-1}, k_{it-1})$. We can turn to similar moment conditions as discussed extensively under section 2.2 to identify μ, although efficiency is further sacrificed by requiring instruments at least twice lagged (l_{it-2}).

3 Exporters, productivity and markups

We can now rely on our empirical framework to analyze markup differences between exporters and non exporters. In addition, we are interested in how new exporters' markups change as they enter foreign markets. To answer this, we correlate markups with a firm's export status and check whether markups change with export entry, while controlling for input usage. We further explain our empirical model in detail once we have introduced the data and discuss the information we can rely on. We stress that we want to verify whether exporters charge different markups without taking a stand on any specific model of international trade. However, when interpreting the estimated markup parameters, we can turn to various models to interpret and explain our findings.

A number of models of international trade with heterogeneous producers and firm specific markups have predictions on the relationship between a firm's export status and its productivity level. Most of the empirical work in this literature has focussed on the latter, while not much attention has been devoted on the relationship between a firm's export status and its markup. These models generate the result that more productive firms set higher markups, and given that those firms can afford to pay an export entry cost therefore predict that exporters will have higher markups. Bernard et al (2003) rely on a Bertrand pricing game while allowing for firm-level productivity differences and show that on average exporters have

higher markups. Recently, Melitz and Ottaviano (2008) model firms, in an international trade setting, that compete in prices where products are horizontally differentiated. This model generates a firm specific markup which is a function of the difference between the firm's marginal cost and the cut-off marginal cost where the firm is indifferent between staying in the industry or exiting. Therefore, when a firm is relatively more productive, it can charge a higher markup and enjoy higher profits. Markups therefore drive a wedge between actual and measured productivity, and disproportionately so for exporting firms.

A wide range of models will predict the aforementioned relationship which essentially comes from a single source of heterogeneity on the supply side (productivity). Another strand of the trade literature explores the role of quality differences between exporters and non exporters. If exporters produce higher quality goods, while relying on higher quality inputs, all things equal they can charge higher markups. For an empirical analysis see Kugler and Verhoogen (2008) and Hallak and Sivadasan (2009).

Both mechanisms are thus expected to generate higher markups for exporters in the *cross section*. In the *time series* dimension, however, it is not clear how markups change as firms enter export markets compared to already exporting firms and domestic producers. We therefore see this paper as providing both a check of current models of international trade generating a relationship between export status and markups, as well as new evidence on markup dynamics and export status. Since most theories are static in nature, they cannot speak to this time dimension. More recently, Cosar, Guner and Tybout (2009) develop a dynamic general equilibrium trade model to explain certain features of the labor market, and their model implies that exporters charge higher markups because factor market frictions prevent them from freely adjusting their capacity as exporting opportunities come and go over time.

Taking stock of the above, we therefore expect higher markups for exporters. However, it is clear that markup differences are related to both supply and demand factors impacting both costs and prices. Our procedure delivers both markup and productivity estimates and allows us to further decompose the markup difference between domestic producers and exporters. In this way we can verify whether after controlling for differences in marginal costs (i.e. productivity) exporters still have higher markups. In this way we can, once we have established our main results, eliminate the productivity component from the markup difference and provide some suggestive evidence on the role of other factors impacting price. We therefore relate our results to a recent literature that has put forward the importance of these factors, such as differences in elasticities of demand across markets and product quality for instance.

4 Background and data

We rely on a unique dataset covering all firms active in Slovenian manufacturing during the period 1994-2000. The data are provided by the Slovenian Central Statistical Office and contains the full company accounts for an unbalanced panel of 7,915 firms.[25] We also observe market entry and exit, as well as detailed information on firm level export status and export sales. At every point in time, we know whether the firm is a domestic producer, an export entrant, an export quitter or a continuing exporter.

Table 1 provides some summary statistics about the industrial dynamics in our sample. While the annual average exit rate is around 3 percent, entry rates are very high, especially at the beginning of the period. This reflects new opportunities that were exploited after transition started.

Table 1: Firm Turnover and Exporting in Slovenian Manufacturing

Year	Nr of firms	Exit rate	Entry rate	#Exporters	Labor Productivity
1995	3820	3.32	13.14	1738	14.71
1996	4152	2.60	5.44	1901	16.45
1997	4339	3.43	4.47	1906	18.22
1998	4447	3.94	4.14	2003	18.81
1999	4695	3.26	3.30	2192	21.02
2000	4906	2.69	3.38	2335	21.26

Labor Productivity is expressed in thousands of Tolars.

Our summary statistics show how labor productivity increased dramatically, consistent with the image of a Slovenian economy undergoing successful restructuring. At the same time, the number of exporters grew by 35 percent, taking up a larger share of total manufacturing both in total number of firms, as in total sales and total employment.

We study the relationship between exports and markups since exports have gained dramatic importance in Slovenian manufacturing. We observe a 42 percent increase in total exports of manufacturing products over the sample period 1994-2000. Furthermore, entry and exit has reshaped market structure in most industries. Both the entry of more productive firms and the increased export participation was responsible for significant productivity improvements in aggregate (measured) productivity (De Loecker and Konings, 2006 and De Loecker, 2007). Therefore, we want to analyze the impact of the increased participation in international markets on the firms' ability to charge prices above marginal cost using our proposed empirical framework.

[25] We refer to Appendix A for more details on the Slovenian data, and to De Loecker (2007). In the Appendix we also list the variables we use in our empirical work and how they are measured. The unit of observation is an establishment (plant) level, but we refer to it as a firm.

5 Results

In this section we use our empirical model to estimate markups for Slovenian manufacturing firms, and test whether exporters have, on average, different markups. In addition, we rely on substantial entry into foreign markets in our data to analyze how markups change with export entry and exit, and as such we are the first, to our knowledge, to provide robust econometric evidence of this relationship.

After estimating the output elasticity of labor and materials, we can compute the implied markups from the FOCs as described above. We use our markup estimates to discuss several major findings. First, we compare our markup estimates to the literature (Hall and Klette) and we consider a restricted version of our approach which revisits the Hall/Klette framework but relies on our proxy for productivity. Secondly, we look at the relationship between markups and firm-level export status in both the cross section and the time series. Thirdly, we briefly discuss the relationship between markups and other economic variables. This analysis cannot be done using previous methods where a common markup across a set of producers is estimated.[26] Finally, we discuss an important aggregate implication given our results.

5.1 Firm-level markups

We obtain an estimate of each firm's markup and can compare the average or median with the Hall/Klette approach. Although that our focus is not so much on the exact level of the markup, we do want to highlight that the markup estimates are comparable to those obtained with different methodologies, but are different in an important way.

Our procedure generates industry specific production function coefficients which in turn deliver firm specific output elasticity of variable inputs. The latter are plugged in FOC of input demand together with data on input expenditure to compute markups. We list the median markup using a wide set of specifications to highlight our results. We first present results using the standard methods in the literature, using Hall and Klette. We present our results using both value added or gross output production functions, allowing for endogenous productivity processes, under a translog and Cobb-Douglas technology. We also consider a specification where we include the export dummy as an input.[27] Finally, we estimate a few restricted versions of our model where we impose a common markup by industry, and take first differences while controlling for productivity using our proxy method. For value added production functions we rely on the output elasticity of labor to compute markups and compare them with markups obtained from the output elasticity of materials under a gross

[26] An exception is Klette (1999) who estimates the covariance of time averaged markups and productivity, $cov(\mu_i, \omega_i)$, while relying on additional assumptions. We discuss those in detail and compare it to our framework.

[27] Some literature has followed this approach to generate the result that exporters produce under different technologies. However, this specification does not sit well with the Cobb-Douglas framework which implies that a firm can substitute any other input for exporting.

output production function.[28] More specifically we run the following specifications: **I**: Value Added under Cobb-Douglas, **II**: **I** + endogenous productivity process, where past exporting can impact current productivity as given by $\omega_{it} = g(\omega_{it-1}, z_{it-1}) + \xi_{it}$, **III**: **I** + impose both moments on capital, $E(\xi_{it}(\beta)k_{it-s}) = 0$ for $s = \{0, 1\}$, and rely on a weighing matrix in the GMM procedure, **IV**: Value Added under Translog, **V**: **II** and include an export dummy as an additional input, **VI**: Gross output production function under Cobb-Douglas, **VII** : **I** with a common markup, **VIII**: **VII** estimated in first differences as describe in equation (16).

The table below presents the median markup for the various specifications. The standard deviation across the various specifications (I-VI) results are similar and around 0.5, and indicate a substantial variation in markups across all firms of the manufacturing sector, as expected.

Table 2: Estimated Markups

Methodology	Markup (St.error)
Hall*	1.03 (0.004)
Klette*	1.12 (0.020)
Specification	
I	1.17
II	1.10
III	1.23
IV	1.28
V	1.23
VI	1.26
VII*	1.16 (0.006)
VIII*	1.11 (0.007)

*: Markups are estimated and we report the standard errors in parentheses. The standard deviation around the markup in specifications I-VI is about 0.5.

The table above clearly highlights that our estimates of the markup are consistently higher compared to the Hall and Klette approach. The markup estimate under Hall is obtained by regressing output growth on an index of input growth where each input is weighted by their expenditure share as given by equation (15), and we find a markup of 1.03. In the second row, we estimated a higher markup of 1.12 using Klette's algorithm [29]. Both these models

[28] We report both and want to note the trade-off facing both. Material inputs are potentially less costly to adjust and satisfy the conditions we rely on more. However, as shown by Bond and Soderbom (2002), identification of a variable and freely chose input can be challenging in a Cobb-Douglas framework. We choose to simply run all our regressions using both estimates to check for robustness of our results.

[29] Instead of using Arellano and Bond (1991), we use the more efficient method of Arellano and Bover (1995) and Blundell and Bond (1998). Also see Blundell and Bond (2000) for an application to production functions. We only use employment and capital (as in Klette), lagged from $t-2$ onwards as instruments (this corresponds to model V in Klette), following the discussion in section 2.2.

are estimated in first differences, and it is well known to lead to a downward bias of the estimates, here the markup, by exacerbating measurement error.[30]

We obtain markups in the range of $1.17 - 1.28$ and our various specifications give very similar results. Note that the markups obtained using specifications **I - VI** are simply medians over the underlying distribution, and in all cases the standard deviations are substantial as expected. We explore the variation across firms in the next section when we relate markups to various economic variables, with a focus on export status.

As mentioned before our methodology requires the availability of a variable input of production without adjustment costs, in order to rely on the FOC. We compare our markups obtained using cost minimization conditions on the labor input (**I-V**), with markups obtained using materials, **VI**, by running a gross output production function and our results are very similar.[31]

It is worth noting that the markups obtained imposing a static FOC on capital, which clearly goes against the evidence of important adjustment costs in capital, are considerably higher. The latter is as expected since the wedge between the output elasticity of capital and the revenue share contains current markups as well as capital adjustment costs, and should therefore be higher. We find a median markup of 1.5 using this approach.

It is interesting to note that when relying on our methodology while imposing a common markup, **VII**, we obtain an estimate of 1.16, which is below our other estimates but still much higher than the standard Hall estimate.[32] This estimate of the markup is obtained directly within our estimation routine by imposing the FOCs on the variable inputs in the production function. This approach is similar to the original Hall approach, except that the regression is estimated in levels and productivity shocks are explicitly controlled for using economic theory. To further demonstrate the importance of controlling for unobserved productivity shocks, we consider a first difference version of our approach, **VIII**, while keeping the markup constant and we obtain an estimate of 1.11, which is higher than the standard Hall approach and closer to our preferred estimates.[33] More specifically, comparing the first and the last row shows the importance of controlling for unobserved productivity shocks

[30] In the traditional Hall model, a Taylor expansion of the production function gives rise to estimating the model in first differences. However, this implicitly restricts the underlying demand system whereby markups do not change between two time period. We refer to De Loecker and Warzynski (2009) for more. Klette (1999) first considers deviations from the median output/input firm before taking first differences.

[31] We obtain two separate measures for the markup using the gross output production function. It is feasible to use both estimates to learn about potential frictions in labor demand. This lies beyond the scope of this paper.

[32] We consider a value added production function and obtain the following estimating equation $y_{it} = \mu l^*_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}$, where $l^*_{it} = l_{it}\alpha^L_{it}$. Note that we do not impose the FOC on the capital coefficient. Relying on our empirical framework and using $h_t(m_{it}, k_{it})$ to control for productivity we directly obtain an estimate for the markup. The steps are as before and we obtain an estimate of the markup by relying on the same moments as discussed in section 2.2.1.

[33] We estimate equation (16) and use materials to proxy for productivity and identify the markup in a second stage. Alternatively when we rely on investment to proxy for productivity, we can estimate the markup in a first stage when relying on additional assumptions as discussed in ACF.

when estimating markups. These restricted versions, **VII-VIII**, of our model highlight the additional assumptions and restrictions of previous approaches in the literature. We run these specifications to highlight the set of assumptions we relax in our approach, and how it impacts the results. In particular relaxing the constant markup assumption across firms and allowing for time varying productivity shocks leads to substantially higher markups, ranging up to twelve percent higher.

5.2 Markups and Exporting

We can now turn to main focus of our application, whether exporters on average have higher markups and whether markups change when firms enter export markets. We first discuss the cross sectional results, before turning to the time series dimension of our data and verify whether markups change when firms enter export markets. Finally, we also show how our method allows to shed light on the correlation of markups and other economic variables such as productivity.

5.2.1 Do exporters have different markups?

Given that we have firm specific markups, we can simply relate a firm's markup to its export status in a regression framework. As noted before, we are not per se interested in the level of the markup, and we therefore estimate the percentage difference in markups between exporters and domestic producers. We do convert these percentages into absolute markup differences in order to compare our results to those obtained using the Hall approach. The specification we take to the data is given by

$$\ln \mu_{it} = \theta_0 + \theta_1 e_{it} + z_{it}\delta + \upsilon_{it} \tag{17}$$

where e_{it} is an export dummy and θ_1 measures the percentage markup premium for exporters.[34] We control for labor and capital use in order to capture differences in size and factor intensity, as well as year (T)-industry (I) dummies to take out aggregate trends in markups, and collect them all in z_{it} with δ the corresponding vector of coefficients. We stress that we are not interpreting θ_1 as a causal parameter. We rely on our approach to test whether on average exporters have different markups. The latter, to our knowledge, has not been documented and we see this as a first important set of results. We are not interested in δ, but later on we will revisit the separate correlations of markups and other economic variables. We estimate this regression at the manufacturing level and include a full interaction of year and industry dummies.[35] Once we have estimated θ_1, we can compute the level markup difference by applying the percentage difference to the constant term which captures

[34] We consider logged markups since the variation in firm-level markups is quite substantial and therefore rely on OLS to minimize proportional deviations, rather than absolute deviations. We discuss an additional advantage of estimating this relationship in logs in section 6.

[35] We have also run this by industry and the magnitude varies across the different industries as expected.

the domestic markup average. We denote this markup difference by μ_E and we compute it by applying $\mu_E = \theta_1 \exp(\theta_0)$ after estimating the relevant parameters. Table 3 presents our results.

Table 3: Markups and Export Status I: Cross Section

Methodology	Export Premium (St. error)
Hall	0.0155^{ns} (0.010)
Klette	0.0500^{ns} (0.090)
Specification	
I	0.1633 (0.017)
II	0.1608 (0.017)
IV	0.1304 (0.014)
V	0.1829 (0.017)
VIII	0.1263 (0.013)

The standard errors under specifications I-V are obtained from a non linear combination of the relevant parameter estimates. *ns* indicates not significant at 10 percent level. All regressions include labor, capital and full year and industry dummies.

We run the regression for the various estimates of the markups as described above. The parameter θ_1 is estimated very precisely in all specifications (**I-V**) and is around 0.078. We rely on these estimates to compute the level markup differences reported in the table above. As expected, the results relying on a Cobb-Douglas technology are very similar because the variation in markups is identical across the various specifications. Only the level of the markup differs due to different β_l estimates, which is captured by the constant term θ_0. The results using a translog production function, **IV**, rely on firm specific output elasticities and we get a somewhat lower estimated μ_E of 0.1304. One important message that comes from this table is that no significant markup differences are detected when relying on the Hall or the Klette approach. In order to check whether restricting the markup to be constant across firms is important for this difference, we consider a restricted version of our approach (**VIII**). The markup premium is estimated to be 0.1263 which is similar to the results under the more general framework. These results highlight the importance of controlling for unobserved productivity shocks when estimating markups directly.

An important advantage of considering log markups is that our results are unchanged even if all variable inputs we considered to compute markups are subject to adjustment costs. As long as exporting firms are not more or less subject to these adjustment costs, our results are not affected.[36]

[36] We can write the first order condition with adjustment costs in general as follows, $\theta^X_{it} = \mu_{it}(\alpha^X_{it})^{-1}(1+\tau^X_{it})$, where the term $(1+\tau^X_{it})$ contains the additional wedge between the input's marginal product and the input price coming from the adjustment cost. We thus require $E(\ln(1+\tau^X_{it})e_{it}) = 0$ in order to obtain consistent estimates of the percentage difference in markups, while controlling for l_{it} and k_{it} which further control for potential differences in adjustment costs related to the size of the firm.

These results are consistent with recent models of international trade such as the model of Bernard et al (2003) where exporters charge on average higher markups, simply because they are more productive and can therefore undercut their rivals. This prediction is supported by comparing the average markup of exporters to non exporters in the cross section. However, in their model firms of the same productivity will charge the same markup, making productivity differences the only source for markup differences. Our procedure generates estimates for both markups and productivity and we can shed light on this by including both. When including both a firm's export status and productivity, the coefficient on export θ_1, expressed in percentages, goes down from 0.076 to 0.021, as expected. Once we control for productivity, we control for differences in marginal cost and the coefficient on export status picks up the variation in average prices between exporters and domestic firms. To see this note that we are actually running

$$(\ln P_{it} - \ln C_{it}) = \theta_0 + \theta_1 e_{it} + \theta_2 \omega_{it} + z_{it}\delta + \upsilon_{it} \tag{18}$$

which shows clearly that θ_1 will measure the average price difference (in percentages) if ω_{it} picks up $\ln C_{it}$ fully. As discussed in Katayama, Lu and Tybout (2009) and De Loecker (2010a), we know that ω_{it} potentially picks up price differences and therefore we expect θ_2 to pick up additional variation across producers related to market power, and demand conditions. An important point to take away from this is that the export effect is still present even after controlling for productivity differences. In fact, the export dummy still explains around thirty percent of the markup difference, while controlling for productivity. The latter implies that other factors, which are reflected in price differences, play an important role in explaining markup differences between exporters and domestic producers. Our results are therefore consistent with a recent literature emphasizing differences in product and input quality between exporters and domestic producers. However, simple differences in demand elasticities and income across markets can equally explain price differences. Given our data constraints, we cannot further discriminate between those various mechanisms.

Taking stock of the results described above has potential important policy implications. The well documented productivity premium of exporters could, at least partly, be reflecting markup differences. Recent models of international trade with heterogeneous firms emphasize the reallocation of market share from less efficient producers to more efficient exporters. This mechanism relies on exporters being more productive, because they can cover the fixed cost of entering foreign markets. A growing list of empirical studies has documented (measured) productivity premia for exporters, and furthermore recent work has found evidence on further improvements in (measured) productivity post export entry (learning by exporting). Our results, however, require a more cautious interpretation of the exporter productivity premium and how exporting contributes to aggregate productivity growth. More specifically, given that measured productivity is a simple residual of a sales generating production function, it is well known that it contains unobserved quality differences in both inputs and output, as well as

market power effects broadly defined.[37] Our results therefore provide additional information in explaining the measured productivity premium, and emphasize the importance of studying the export-productivity relationship jointly with market power in an integrated framework. We further investigate the markup trajectory as a function of export status in the next section. The latter will allow us to dig deeper in the (measured) productivity trajectories after export entry.

5.2.2 Export entry and markup dynamics

So far, we have just estimated differences in average markups for exporters and domestic producers. Our dataset also allows us to test whether markups differ significantly *within the group* of exporters. It is especially of interest to see whether there is a specific pattern of markups for firms that enter export markets, i.e. before and after they become an exporter. This will help us to better interpret the results from a large body of empirical work documenting productivity gains for new exporters. These results are used to confirm theories of self-selection of more productive firms into export markets as in Melitz (2003) or learning by exporting. We now turn our attention to the various categories of exporters that we are able to identify in our sample: starters, quitters and firms that export throughout the sample period.

We run the following regressions on the data where we simply compare markups before and after export entry (and exit), while also estimating the markup differential for firms who continuously export in our sample.[38]

$$\ln \mu_{it} = \gamma_0 + \gamma_1 e_{it} * Entry_i + \gamma_2 e_{it} * Exit_i + \gamma_3 Always_i + z_{it}\delta + \nu_{it} \tag{19}$$

The constant term captures the average log markup for domestic producers and pre export entrants/exiters. The interest lies in the coefficient γ_1 which measures the markup percentage difference, for starters, between the post and pre export entry periods. The other coefficient γ_2 measures a similar effect but for export exit. Finally, γ_3 measures the markup difference for firms exporting throughout, and we expect this coefficient to be positive. There is little guidance from theory on the coefficient γ_1, given that almost all models are static in nature as discussed before. We therefore see our results as as providing new evidence on markup dynamics and export status.

We compute the implied markup level effects from export entry as before, $\mu_{st} = \gamma_1 \exp(\gamma_0)$, and report them for our various specifications in Table 4 below.

[37] In fact the markup differences between exporters and domestic producers only fully reflect cost (productivity) differences if both domestic producers and exporters set the same output prices.

[38] We eliminate the very small fraction of firms that enters or exits export markets more than once in our sample.

Table 4: Markups and Export Status II: Export Entry Effect

Methodology	Export Entry Effect	
	Percentage (γ_1)	Level (μ_{st})
I	0.0467	0.0939
	(0.0127)	(0.0260)
II	0.0467	0.0925
	(0.0127)	(0.0250)
IV	0.0481	0.0797
	(0.0128)	(0.021)
V	0.0497	0.0994
	(0.0127)	(0.0260)
VIII	n.a.	0.0700
		(0.022)

The standard errors under DLW1-5 are obtained from a non linear combination of the relevant parameter estimates. All regressions include labor, capital and full year and industry FE.

The table in Appendix D lists the detailed results and we find that export entry is associated with substantially higher markups, ranging around four percent while controlling for aggregate markup changes. The other coefficients are also as expected. Interestingly, we can include productivity (as before) and still find a significant positive effect for export entry. The latter suggest again that price changes are associated with export entry, which can come from: differences in demand conditions (elasticities, etc.) and quality differences, as discussed before. Table 4 lists both the percentage and the level estimates and our estimates suggest that export entry is associated with a significant increase in markups of around four to five percent, or between 0.079 and 0.099 in levels. We compare our results to the restricted common markup model in a first difference setting and we obtain a similar export entry effect of 0.07 in the level of the markup. The estimates across the various rows demonstrate that our results are robust with respect to various production technologies and assumptions on the underlying productivity process.

When relying on the same regression framework and allow the markup effect to depend on export intensity, by replacing the export dummy e_{it} by the share of export sales in total sales, e_{it}^{share}. The coefficient on the export entry effect is larger, 0.097, and allows us to plot the post export entry markup trajectory as obtained by tracing e_{it}^{share} over time. Figure D.1 in Appendix D illustrates this graphically.

It is important to note that the finding and patterns discussed above are not found when we rely on standard methods, and when not controlling for unobserved productivity shocks. In fact markups are not significant and much lower in magnitude.

5.2.3 Interpreting our results

In sum, we report two major findings: 1) in the cross section we find that exporters have higher markups than their domestic counterparts in the same industry, and 2) in the time

series we find that markups increase when firms enter export markets, while controlling for aggregate demand and supply effects through year dummies. How can we explain our results?

A few recent models (Bernard et al., 2003; Melitz and Ottaviano, 2008) provide a theoretical analysis of the relationship between firm export status and (market specific) markups. Under various hypotheses regarding the nature of competition, more efficient producers are more likely to have more efficient rivals, more likely to charge lower prices, to sell more on the domestic market and also to beat rivals on export markets. They benefit from a cost advantage over their competitors, set higher mark-ups (under certain conditions regarding the relative efficiency between firms on the domestic and the export market in the case of the Melitz and Ottaviano model) and have higher levels of measured productivity. An alternative explanation could be that the elasticity of demand is different on the export market, or that consumers have different valuation for the good. The exact mechanism underlying these results is not testable given the data at hand. For instance we do not have firm specific information on prices which could allow us to separate out the markup difference into a cost and price effect. We did show that controlling for cost differences, exporters on average still have higher markups which suggests additional factors impacting prices are important, and is consistent with recent work by Manova and Zhang (2009) and Hallak and Sivadasan (2009).

Finally, at a broader level our evidence suggests that the gap between the notion of (physical) productivity in theoretical models of international trade with heterogeneous producers and the empirical measurement of productivity is an important one given that markups are different for exporters and that they change significantly, both economically and statistically, when firms enter export markets.

5.3 Markups and other economic variables.

We can rely on our estimates of firm-level markups and relate them to other economic variables of interest, such as productivity. Note that our procedure generates both estimates for markups and productivity. A large class of models in industrial organization predict that firms with lower marginal cost (higher productivity) will be able to charge higher markups, all things the same. In Cournot, higher productivity firms will have a higher market share and have a higher markup. Recent models of international trade with heterogeneous firms also predict that more productive firms will have higher markups. We run the same regression as in (17) and replace the export status by productivity. We obtain a highly positive estimate of 0.3 for the coefficient on productivity, and it does not change when adding a firm's export status. Our results are therefore consistent with a wide range of theory models, and confirms that more productive firms have higher markups. We briefly mention this result and do not pursue any further analysis given that productivity measures potentially contain price/demand variation as well, and might be poor measures of marginal cost as discussed by Katayama, Lu and Tybout (2009) and De Loecker (2010a).

5.4 Aggregate implications

The Hall framework was initially set out to obtain estimates for productivity growth while appropriately controlling for imperfect competition. We briefly revisit this by considering the Hall version of our framework and use it to back out estimates for productivity growth after estimating markups. Note that our methodology generates estimates for productivity and markups, for each firm. We could compute productivity growth directly after estimating the production function. However, here we revisit the literature using a restricted version of our model to highlight the importance of correctly estimating markups. We rely on our estimates of the markup $\widehat{\mu}$ and compute productivity growth as follows

$$\Delta y_{it} - \widehat{\mu}\Delta\widetilde{x}_{it} - \widehat{\beta}_k \Delta k_{it} = \Delta\omega_{it} \tag{20}$$

We rely on our estimates of the markup $\widehat{\mu}$ and the capital coefficient β_k. In addition to a different estimate for the markup, as presented in Table 2, our approach does not impose any restrictions on returns to scale. It is clear that using standard techniques will lead to biased estimates for productivity growth since they are based on downward biased markup estimates. Within the context of sorting out markup differences between exporters and domestic producers, the uncorrected approach would actually predict no differences in productivity growth, conditional on input use, between the two, which is clearly in contradiction with empirical evidence.

It is clear that productivity growth is overestimated without controlling for the endogeneity of inputs and markup differences. This bias is further increased when we allow for markups to change when firms switch export status. Although our method is not intended to directly provide estimates for productivity growth, we see this as an important cross validation of the estimated markup parameters. Our estimates suggest average annual productivity growth rates for Slovenian manufacturing between 3 and 1.5 percent.

Our results have some important implications for aggregate productivity. It is immediately clear that when relying on the standard framework, markups are underestimated for domestic producers and even more so for exporters. It first of all implies that we will overestimate aggregate manufacturing productivity growth, which is obtained by a weighted average of firm-level productivity growth, even when ignoring differences in markups between exporters and domestic producers. However, when analyzing productivity growth of sectors or countries during a period where export participation increased substantially, an additional bias kicks in. Based on our estimates it is straightforward to show how aggregate productivity growth is overestimated when not controlling for different markups across domestic producers and exporters. In the case of Slovenia, the bias in aggregate productivity growth becomes larger as resources were reallocated towards exporters and therefore accounting for a growing share in aggregate output as the number of exporters quadrupled and export sales grew substantially. These results therefore suggest that the estimated aggregate productivity gains from increased export participation are biased upward when ignoring that exporters

charge, on average, higher markups. The wedge between *measured* and *actual* aggregate productivity growth increases as a larger share of manufacturing firms are becoming exporters and are accounting for a larger share of total output. This distinction between measured productivity growth and actual productivity due to market power effects is consistent with recent models of international trade with heterogeneous producers.

6 Robustness and final remarks

We discuss two robustness checks below. In turn we discuss the use of deflated sales to proxy for output and we allow for different markups for exporters in foreign markets and the domestic market.

6.1 Unobserved prices and revenue data

Implicitly we have treated deflated sales as a measure of physical quantity when estimating output elasticities, and therefore our approach is potentially subject to the omitted price variable bias discussed in Klette and Griliches (1996). However, in our context we are not concerned with obtaining correct productivity estimates. As discussed by De Loecker (2010a) not controlling for unobserved prices is particularly problematic for obtaining reliable estimates for productivity. In our setting unobserved prices are expected, if anything, to bias the output elasticities downward. The correlation between inputs and prices is expected to be negative as mentioned in the original work by Klette and Griliches (1996) under quite general demand and cost specifications, i.e. all things equal more inputs will lead to higher output and push prices down. This implies that if anything we are underestimating markups. However, unobserved prices will only affect our estimates of the *level* of the markup, and will not impact our results on the relationship of markups and export status.

The use of the proxy for productivity does help against not observing prices as well. Price variation that is correlated with variation in productivity will be controlled for and will therefore not bias the estimates of the production function. However, price variation due to demand shocks not correlated with $\phi_t(.)$ can still bias the estimates of the input coefficients. The latter will potentially bias the output elasticity estimates but will not impact our main results because in all of our empirical work we correlate log markups to export status. Given our framework this implies that we ran

$$(\ln \theta_{it}^X - \ln \alpha_{it}^X) = \theta_0 + \theta_1 e_{it} + \nu_{it} \tag{21}$$

on the data. Under a Cobb-Douglas technology the output elasticity θ_{it}^X reduces to a constant, β_l in the case of using labor, and therefore the bias induced by unobserved prices only impacts the estimate of the constant term θ_0. In other words, we obtain the correct percentage difference in markups between exporters and domestic producers, and if anything

underestimate the difference in levels. When considering a more flexible production technology, like the translog, we face a trade-off between allowing for variation in output elasticities and potentially introducing a bias through unobserved prices. Our estimates of the average percentage difference in markups are consistent as long as the difference $(\ln \widehat{\theta}_{it}^{X} - \ln \theta_{it}^{X})$ is not correlated with the firm's export status e_{it}. The estimated percentage differences presented in Appendix D show that the results using Cobb-Douglas (**I**,**II**,**V**) and Translog (**IV**) are very similar, and we see those in support of the fact that unobserved prices are not impacting our main estimates. The estimated markup level differences are somewhat lower under the translog production function. This is consistent with a potential downward bias in the production function coefficients, which leads to a lower average output elasticity and hence a lower θ_0 used to compute markup levels.[39] However, variation in output elasticities also impacts the point estimate of the constant term.

6.2 Exporting and markups: digging deeper

We documented that exporters have on average higher markups, and that markups increase after export entry. However, exporters sell products on different markets and our estimate of the markup contains potentially different market specific markups. We rely on firm specific export destination information and check whether we can detect differences in markups across destination markets. Secondly, we revisit the effect of export entry on markups and include the intensity of exporting to shed light on the separate effect of export entry on domestic and foreign markups.

6.2.1 Export destinations and markups

We rely on firm-level export destination information to check whether markups are different across various export destination markets.[40] For the case of Slovenia exporting includes shipping products to regions formerly part of the Yugoslavian Republic prior to Slovenia's independence in 1991, as well as high income regions such as the US and Western Europe.

As mentioned above, recent work has documented that exporters produce and ship higher quality products while controlling for a host of firm-level characteristics including size, where quality is measured indirectly by either unit prices or whether a firm has an ISO 9000 certification.[41] In order to see whether markups are higher for exporters sending their products to high income regions such as Western Europe, we simply include interaction terms with

[39] If unobserved prices are negatively correlated with inputs, all production function coefficients estimates $\widehat{\boldsymbol{\beta}}$ are biased downward. This in turn implies that the estimated output elasticities $\widehat{\theta}_{it}^{X}$ and hence the markups $\widehat{\mu}_{it}$ are downward biased as well. Consequently the (log) average of the markups are estimated lower, and result in lower estimates of the constant term. The table in Appendix D demonstrates this potential effect.

[40] As mentioned in De Loecker (2007), the destination information is not available at each point in time in our sample. We therefore return to our cross sectional comparison of exporters and domestic producers.

[41] For instance, Kugler and Verhoogen (2008) document this for Colombia, and Hallak and Sivadasan (2009) provide evidence for manufacturing establishments in India, the U.S, Chile and Colombia.

the various export destination regions to the estimating equation (17). We obtain a 0.045 higher markup (in levels) for firms exporting to Western Europe, but estimated less precise as expected given the remaining degree of heterogeneity within the region of Western Europe. This implies that exporters shipping to this region, on average, charge a higher markup compared to the average exporter shipping to other regions. Our results are consistent with the quality hypothesis, given that it is expected that quality standards are higher in Western European markets than in the Slovenian domestic market. Given the data constraints we cannot measure quality at the firm level and therefore leave this for future research.

6.2.2 Decomposing export entry markup effect

So far we have shown that markups increase when firms enter export markets. However, for exporting firms we rely on an average markup across the domestic and foreign market. In principal our methodology can generate markup estimates by market. Applying the first order condition of labor by market s, where $s = \{d(Domestic), e(Export)\}$, we can compute the markup as before. However, in our data we do not observe hours worked or number of employees used in production by destination market. We only observe total number of workers in production and this is a standard restriction in plant-level data. Using equation (4) and explicitly relying on the assumption that an exporting plant produces with a given technology in a given location where it faces a given wage rate, implies that we can write

$$\mu_{it}^{s} = \theta_{it}^{L} \left(\frac{\rho_{it}^{s}[w_{it}L_{it}]}{[P_{it}Q_{it}]_{s}} \right)^{-1} \tag{22}$$

where ρ_{it}^{s} measures the share of the wage bill used in exported production. Total export sales, $[P_{it}Q_{it}]_{s}$, and the total wage bill are directly observed in our data. Therefore, in order to compute the domestic markup for an exporter and compare it with the average markup across all destination markets, we can compare ρ_{it}^{e} to ρ_{it}^{d} by plant. We adopt the following strategy to verify whether the domestic markup of export entrants changes with export entry. We run the same procedure as in (19), but we rely on the share of export sales in total sales, and interact this with the $Entry_i$ dummy. This specification allows us to inspect whether the increase in the firm's average markup (across domestic and foreign markets) due to export entry, depends on the intensity of exporting. We can look at firms with a very small fraction of sales coming from exporting, say less than one percent, when they enter the export market which can be informative about what happens to their domestic markup. We obtain a significant coefficient of 0.097 for γ_1 and this implies a level estimate of 0.16, which is substantially higher than the estimates reported before. However, to get the total effect of export entry we need to multiply this estimate with the relevant export share ρ_{it}^{s}, and this implies that the markup entry effect is very small for firms selling a small share of their production abroad. For exporters selling less than one percent on foreign markets, markups only increase with 0.00097 percent, suggesting that domestic markups do

not change. This approach is clearly not without problems as the export share increases over time and the separation between domestic and export markups becomes harder to make. In addition, this approach does not necessarily use the optimal weight which will depend on how we aggregate inputs across production by destination within a firm. The export sales weight implicitly assumes that inputs are used in proportion to final sales. The latter is an assumption maintained throughout most empirical work, see Foster, Haltiwanger and Syverson (2008) for example. Given the data constraints, we leave the discussion of the optimal weight for future research.

7 Conclusion

This paper investigates the link between markups and exporting behavior. In order to analyze this relationship we propose a simple and flexible methodology to estimate markups building on the seminal paper by Hall (1986) and the work by Olley and Pakes (1996). The advantages of our method are that we can accommodate a large class of price setting models while recovering firm specific markups and do not need to rely on the assumption of constant returns to scale and measuring the user cost of capital.

We use data on Slovenia to test whether i) exporters, on average, charge higher markups and ii) whether markups change for firms entering and exiting export markets. Slovenia is a particularly interesting emerging economy to study as it has been successfully transformed from a socially planned economy to a market economy in less than a decade, reaching a level of GDP per capita over 65 percent of the EU average by the year 2000. More specifically, the sample period that we consider is characterized by considerably productivity growth and relative high turnover. Our methodology is therefore expected to find significantly different markups as we explicitly control for unobserved productivity shocks. Our results confirm the importance of these controls.

Our method delivers higher estimates of firm-level markups compared to standard techniques that cannot directly control for unobserved productivity shocks. Our estimates are robust to various price setting models and specifications of the production function. We find that markups differ dramatically between exporters and non exporters, and find significant and robust higher markups for exporting firms. The latter is consistent with the findings of productivity premium for exporters, but at the same time requires a better understanding of what these (revenue based) productivity differences exactly measure. We provide one important reason for finding higher measured revenue productivity: higher markups. Furthermore, we provide new econometric evidence that markups increase when firms enter export markets.

Our evidence suggests that the gap between the notion of (physical) productivity in theoretical models of international trade with heterogeneous producers and the empirical measurement of productivity is an important one, i.e. markups are different for exporters and they change significantly, both economically and statistically, when firms enter export

markets. We see these results as a first step in opening up the productivity-export black box, and provide a potential explanation for the big measured productivity gains that go in hand with becoming an exporter. In this way our paper is related to the recent work of Costantini and Melitz (2008) who provide an analytic framework that generates export entry productivity effects due to firms making joint export entry-innovation choice, where innovation leads to higher productivity.

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Appendix A: Data Description

In this appendix we describe the firm-level data used more in detail. The data are taken from the Slovenian Central Statistical Office and are the full annual company accounts of firms operating in the manufacturing sector between 1994-2000. The unit of observation is that of an establishment (plant). In the text we refer to this unit of observation as a firm. Related work using the same data source includes De Loecker (2007) and references herein. We have information on 7,915 firms and it is an unbalanced panel with information on market entry and exit and export status. The export status - at every point in time - provides information whether a firm is a domestic producer, an export entrant or a continuing exporter. If we only take into account those (active) firms that report employment, we end up with a sample of 6,391 firms or 29,804 total observations over the sample period. The industry classification NACE rev. 1 is similar to the ISIC industry classification in the U.S.A. and the level of aggregation is presented in Table A.1 below.

Table A.1.: Industry Classification

Nace 2-Digit	Description
15	Food Products
16	Tobacco Products
17	Textiles
18	Wearing Apparel
19	Leather and Leather Products
20	Wood and Wood Products
21	Pulp, Paper and Paper Products
22	Publishing and Printing
23	Coke and Petroleum Products
24	Chemicals
25	Rubber and Plastic Products
26	Other Non-Metallic Mineral Products
27	Basic Metals
28	Fabricated Metal Products
29	Machinery and Equipment n.e.c.
30	Office Machinery and Computers
31	Electrical Machinery
32	RTv and Communication
33	Medical, Precision and Optical Instr.
34	Motor Vehicles
35	Other Transport Equipment
36	Furniture/ Manufacturing n.e.c.
37	Recycling

All monetary variables are deflated by the appropriate two digit NACE industry deflators (for output and materials). Investment is deflated using a one digit NACE investment deflator. The variables used in the analysis are: Sales (PQ): Total operating revenue in thousands of Tolars, total operating revenue from exporting in thousands of Tolars, Value added in thousands of Tolars (VA), Employment (L): Number of full-time equivalent employees in a given year, Capital (K): Total fixed assets in book value in thousands of Tolars, Material consumption in thousands of Tolars (M), Total cost of employees (wage bill) in thousands of Tolars (wL), and export status (e) at each point in time. We experimented with both reported investment and computed investment from the annual reported capital stock and depreciation. Investment is calculated from the yearly observed capital stock in the following way $I_{ijt} = K_{ijt+1} - (1 - \delta_j)K_{ijt}$ where δ_j is the appropriate depreciation rate (5%-20%) varying across industries j.

Finally, the firm-level dataset has information on the ownership of a firm, whether it is private or state owned. The latter is very important in the context of a transition country such as Slovenia. In our sample around 85 (5,333 in 2000) percent of firms are privately owned and a third of them are exporters (1,769 in 2000).

Year 2000		Export Status		
		0	1	Total
	0	227	690	917
Private Owned	1	3,564	1,769	5,333
	Total	3,791	2,459	6,250

The ownership status of a firm serves as an important control by comparing productivity trajectories of exporting and non exporting firms with the same ownership status (private or state). All our results are robust to controlling for ownership differences and by comparing exporters to privately owned domestic firms.

Appendix B Price Setting

In the main text we show that we simply require the FOCs from cost minimization. In this appendix we want to show how a few leading cases of price setting fit in our framework and show how they relate to our procedure. The various expressions can be used to further test implications of those price setting theories using our estimates.

As such we can interpret the markup under various assumptions regarding the nature of competition in the industry, as suggested by Levinsohn (1993). We consider this flexibility an important strength of the model which can be important if we want to relate a specific theoretical model to the empirical methodology. We now turn to some specific price setting models to show how we derive our main estimating equation.

Consider firms that produce a homogeneous product and compete in quantities (play Cournot) while operating in an oligopolistic market where profits π_{it} are given by

$$\pi_{it} = P_t Q_{it} - w_{it} L_{it} - p_{it}^m M_{it} - r_{it} K_{it} \tag{B.1}$$

where all firms take input prices (w_{it}, p_{it}^m and r_{it}) as given. The optimal choice of labor is simply given by setting the marginal revenue product equal to the wage,

$$\frac{\partial Q_{it}}{\partial L_{it}} = \frac{w_{it}}{P_t} \left(1 + \frac{s_{it}}{\eta_t}\right)^{-1} \tag{B.2}$$

where $s_{it} = \frac{Q_{it}}{Q_t}$ is the market share of firm i, η_t is the market elasticity of demand. The optimal output choice Q_{it} will satisfy the following F.O.C.

$$\frac{P_t}{C_{it}} = \left(1 + \frac{s_{it}}{\eta_t}\right)^{-1} \equiv \mu_{it} \tag{B.3}$$

where C_{it} is the marginal cost of production and we define μ_{it} as the relevant firm specific markup.[42] Under Cournot differences in markups across firms are generated by differences in productivity and market structure (s_{it}, η_t). Intuitively, if firms set prices equal to marginal costs ($\mu_{it} = 1$), the share of each input in output growth is simply given by the relevant share in total revenue, whereas under imperfect competition it is the cost share ($\mu_{it}\alpha_{Lit} = \frac{w_{it}L_{it}}{TC_{it}}$).[43] We stress that the input shares for variable inputs (such as labor and intermediates) are directly observed in the data. We can then rewrite $(B.2)$ and obtain the same expression as in the main text.

A similar expression can be obtained with a more general model of Bertrand competition (Nash in price) with differentiated products.[44] The markup over marginal cost, P_{it}/C_{it}, in

[42] See Shapiro (1987) for a discussion of what the markup measures.

[43] Hall (1986) obtains this estimating equation starting from the observation that the conventional measure of total factor productivity (TFP) growth is biased by a factor proportional to the markup under the presence of imperfect competition.

[44] Also see Röller and Sickles (2000) for an explicit treatment of markups in a product differentiated equilibrium.

a Nash equilibrium among firms is in fact given by $\left(1+\frac{1}{\eta_{it}}\right)^{-1}$, which is our measure of the markup, and $\mu_{it} \equiv \left(1+\frac{1}{\eta_{it}}\right)^{-1}$. A firm's individual residual demand elasticity η_{it} will in general depend on the degree of product differentiation, the number of firms and the elasticities of demand, both own and cross price elasticities.

The same notion applies when considering multiproduct firms such as in Berry, Levinsohn and Pakes (1995) and Goldberg (1995) where the markup is a function of the sensitivity of market share to price, given the set of prices set by competitors, the characteristics of all products on the markets and the characteristics of the consumers on the market. As mentioned in section 6.2 a FOC will apply for each product which will allow to recover each product's relevant markup up to observing product specific input expenditures and the ability to estimate product specific output elasticities. The latter is clearly a challenge given current data where input usage is not recorded by product across a wide range of industries (or by destination of the product produced as mentioned before). Our methodology can therefore be thought of providing a firm specific markup, potentially averaged across various products. But we would like to emphasize that our methodology is readily applicable whenever we see input expenditure by product, coupled with estimates on technology.

In this way our empirical model can take into account pricing heterogeneity between firms, and is flexible enough to consider various assumptions regarding the nature of competition and accommodates the most common static model of competition used in industrial organization and international trade. It is important to stress that regardless of the exact model of competition we always estimate the correct markup. What is important to note though, is that the estimates μ_{it} will depend on different economic variables depending on the underlying economic model. Our framework can further shed light on the relationship between markups and such economic variables.

Appendix C Estimating Output Elasticities: Alternative Approaches

In this Appendix we briefly discuss our estimation routine under a gross output production function which will generate estimates of both the output elasticity of labor and materials, and allows us to rely on materials to compute markups. Furthermore, we describe our estimation routine when relying on investment to proxy for productivity (as suggested by Olley and Pakes, 1996). Finally, we briefly discuss the case of a CES production function to highlight the flexibility of our approach regarding technology.

1. Gross output production function.

Moving to a gross output production function allows us to recover the markup from a potentially more variable input, i.e. materials. However, under this setting we face a trade-off between the ability to identify the coefficient on materials, and being able to recover the markup from a potentially more variable input than labor, and hence eliminating potential frictions that can generate a wedge between the marginal product and the input price, other than the markup, for instance hiring or firing costs. Furthermore, we can allow labor to a dynamic input and explicitly allow this in our estimation routine. The ability to identify the coefficient on the material input - in the context of the ACF approach - relies on the assumptions one makes on timing and whether input prices are serially correlated (see Bond and Soderbom, 2001). The second part on computing markups is as before, except that we can calculate them using either the coefficient on materials only, or use both the labor and the materials coefficient.[45]

We briefly discuss the estimation of those coefficients. The first stage is now given by

$$y_{it}^g = \phi_t(l_{it}, m_{it}, k_{it}) + \varepsilon_{it} \tag{C.1}$$

where y_{it}^g is gross output and $\phi_t(.) = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + h_t(k_{it}, m_{it})$.[46] The second stage is similar to the one described before. We rely on the following moments, where $\xi_{it+1}(.)$ is again obtained after non parametrically regressing $\omega_{it+1}(.)$ on $\omega_{it}(.)$,

$$E\left(\xi_{it+1}(\beta_l, \beta_m, \beta_k)\begin{pmatrix} l_{it} \\ m_{it} \\ k_{it+1} \end{pmatrix}\right) = 0 \tag{C.2}$$

Note that the instrument on labor depends on whether we assume labor to be a variable input or a dynamic one. If labor is decided a period ahead (just like capital), we have potentially two instruments (l_{it+1} and l_{it}) to identify the coefficient β_l.

[45] Note that the coefficient on capital is not informative for recovering a measure of the markup, since the static first order condition does not hold given capital's fixed nature. In fact, the wedge between the marginal product of capital and the user cost of capital will in general capture capital adjustment costs in addition to markups. Our approach can potentially be informative about the extent of those adjustment cost if we are willing to specify a particular form.

[46] If labor is a dynamic input we have that $h_t(l_{it}, m_{it}, k_{it})$.

Markups can now be computed using

$$\widehat{\beta}_m \left(\frac{P_{it}^M M_{it}}{P_{it} Q_{it}} \right)^{-1} = \widehat{\mu}_{it} \tag{C.3}$$

and we can directly compare them using

$$\widehat{\beta}_l \left(\frac{w_{it} L_{it}}{P_{it} Q_{it}} \right)^{-1} = \widehat{\mu}_{it} \tag{C.4}$$

depending on whether we want to assume that a firm's labor choice is not restricted due to any frictions. Strictly speaking, if the implied markups differ (significantly) using both equations, it would suggest that additional important frictions or adjustment costs in labor demand are present. We ran all the regression reported in the results section using the FOC on materials and are results are very similar.[47]

2. Using Investment as a Proxy.

In order to rely on the Olley and Pakes version of the ACF estimator we need to incorporate input prices that are serially correlated. Furthermore, given our focus on markup differences between domestic producers and exporters, we need to incorporate the export status of a firm into the investment policy function. This has no implications on our ability to identify the coefficients of interests. The only extra requirement is that the investment function is still invertible when including the export status. We refer to Van Biesebroeck (2005) and De Loecker (2007) for a detailed discussion, and given that we do not rely on this approach, we simply assume we can follow the OP approach.

We show the OP version under a value added production functions setting. The investment policy function is given by

$$i_{it} = i_t(k_{it}, \omega_{it}, w_{it}, e_{it}) \tag{C.5}$$

Note that the firm's export status is either at time t or lagged depending on whether we assume a firm's export entry decision is taken one period ahead. For our purposes the difference is not important. We can write a firm's productivity as a function of its capital stock, investment, wage and export status,

$$\omega_{it} = h_t(k_{it}, i_{it}, w_{it}, e_{it}) \tag{C.6}$$

The first stage of the ACF procedure therefore consists of running

$$y_{it} = \phi_t(l_{it}, k_{it}, i_{it}, w_{it}, e_{it}) + \varepsilon_{it} \tag{C.7}$$

[47] For presentation purposes we choose to not compare the small differences in point estimates across both, and draw conclusions from them.

where we are explicit about the wage rate being serially correlated over time. The latter is important for the identification of the labor coefficient. The second stage of the modified OP/ACF approach is as before, except for the fact that ω_{it+1} is now calculated using a different estimate for ϕ_{it}. Note that we can easily allow the export status of a firm to impact its future productivity shock by considering $\omega_{it+1} = g_t(\omega_{it}, e_{it}) + \xi_{it+1}$. The moments we take to the data are identical to the one in our main approach.

$$E\left(\xi_{it}(\beta_l, \beta_k)\begin{pmatrix} l_{it-1} \\ k_{it} \end{pmatrix}\right) = 0 \tag{C.8}$$

We can now rely on l_{it-1} as an instrument for l_{it} given we allowed for serial correlated wages, which create a correlation between labor choices over time, but the productivity shock at t should not be correlated with the labor choice at time $t-1$.

Our approach shows that we can easily accommodate various proxy estimator approaches, and also makes it clear that - for the Cobb-Douglas case - differences in parameter estimates for β_l will not affect the variation in markups across firms, since this comes entirely from the variation in the share of the wage bill in total sales.[48] The level of the markup is affected, however, by differences in estimates for the labor coefficient.

3. CES Production Function

The CES production function relaxes the substitution elasticity among inputs and nests the fixed proportion (Leontief) and Cobb-Douglas production function. For our purpose it is important to note that this production function will, as in the translog case, deliver firm specific output elasticities and impact the estimate for the markups. We consider the following CES production function[49]

$$Q_{it} = \left[a_l^{1-r} L_{it}^r + a_k^{1-r} K_{it}^r\right]^{\frac{1}{r}} \exp(\omega_{it}) \tag{C.9}$$

and where the elasticity of substitution, σ, is given by $\frac{1}{1-r}$. The marginal product of labor is then given by

$$\frac{\partial Q_{it}}{\partial L_{it}} = {a_l}^{1-r} L_{it}^{r-1} Q_{it} \left[{a_l}^{1-r} L_{it}^r + a_k^r K_{it}^r\right]^{-1} \tag{C.10}$$

and the output elasticity of labor, θ_{it}^L, is given by

$$\theta_{it}^L = {a_l}^{1-r} L_{it}^r \left[{a_l}^{1-r} L_{it}^r + a_k^{1-r} K_{it}^r\right]^{-1} \tag{C.11}$$

In order to compute the output elasticity of a firm i at time t we need estimates for a_l, a_k and r. We obtain estimates by running the following regression,

$$y_{it} = \frac{1}{r} \ln\left[{a_l}^{1-r} L_{it}^r + a_k^{1-r} K_{it}^r\right] + \omega_{it} + \varepsilon_{it} \tag{C.12}$$

[48] Note that the different procedures do produce different estimates for ε_{it} and therefore potentially also change the variation in the labor share as well.

[49] Note that for a value added production function, we already assumed that intermediates are used in a fixed proportion to output.

We rely on the same proxy method as before, and replace unobserved productivity by a function in capital and intermediate inputs. The functional form of the CES production function in principal allows identification of all parameters using a $NLLS$ estimation procedure. From this routine we obtain estimates for the CES parameters and using the FOC on labor,$\frac{\partial Q_{it}}{\partial L_{it}} = \frac{w_{it}}{P_{it}}\mu_{it}$, we recover estimates for the markups

$$\widehat{\mu}_{it} = \left(\frac{w_{it}L_{it}}{P_{it}\frac{Q_{it}}{\exp(\widehat{\varepsilon}_{it})}}\right)^{-1} \widehat{a}_l{}^{1-\widehat{r}} L_{it}^{\widehat{r}} \left[\widehat{a}_l{}^{1-\widehat{r}} L_{it}^{\widehat{r}} + a_k^{1-\widehat{r}} K_{it}^{\widehat{r}}\right]^{-1} \tag{C.13}$$

We recover the same expression as in the main text under a Cobb-Douglas production technology when $r = 0$, or equivalently when the elasticity of substitution is equal to one, where $\frac{\alpha_l}{\alpha_l+\alpha_k}$ is then the output elasticity of labor (β_l under Cobb-Douglas).

This appendix illustrates how our methodology can accommodate any production function, as long as the coefficients are common across a set of producers. However, we do not have to restrict the output elasticity of labor (or any other input) to be the same across all firms, as is the case with Cobb-Douglas. The only condition we require is that we can write the FOC of labor as $\frac{\partial Q}{\partial L} = \frac{wL}{PQ}\mu$, where we drop subscripts. Note that this the case as long as the production function can be written as $Q_{it} = F(L_{it}, K_{it}; \beta)\exp(\omega_{it})$, where $F(.)$ is described by a set of technology parameters β constant across firms, as discussed in detail in the main text.

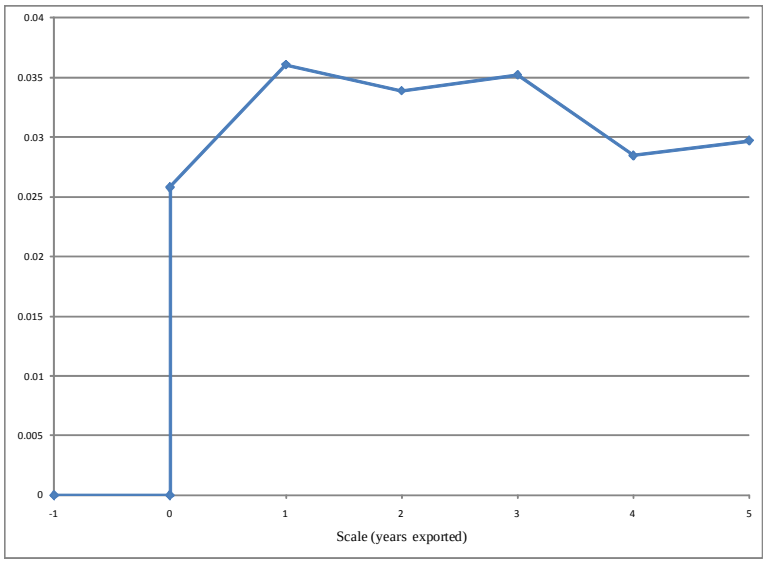
Appendix D Extra Results

Table D.1. Estimates of regression (19)

Parameters	Markup Estimates obtained using			
	DLW1	DLW2	DLW5	DLW4
γ_0	0.6980	0.6824	0.6936	0.5042
	0.0174	0.0174	0.0174	0.0174
γ_1	*0.0467*	*0.0467*	*0.0497*	*0.0481*
	0.0127	0.0127	0.0127	0.0128
γ_2	-0.0166	-0.0166	-0.0246	-0.0138
	0.0138	0.0138	0.0138	0.0139
γ_3	0.0160	0.01604	0.0218	0.0151
	0.0094	0.0094	0.0094	0.0094

Regressions are $\ln \mu_{it} = \gamma_0 + \gamma_1 e_{it} * Entry_i + \gamma_2 e_{it} * Exit_i + \gamma_3 Always_i + z_{it}\delta + \nu_{it}$,
All regressions include labor, capital and year/industry dummies as controls,
and standard errors are reported below the coefficients.

Figure 1: Markup Trajectory Upon Export Entry



Estimated markup increase in level compared to pre-export entry, based on estimate of γ_2 using e_{it}^{share}. Average over all entrants in the sample.