

Markups and Firm-Level Export Status ^{*}

Jan De Loecker
Princeton University, NBER and CEPR

Frederic Warzynski
Aarhus School of Business
Aarhus University

April 2009 - first version April 2008

Abstract

We derive an estimating equation to estimate markups using the insight of Hall (1986) and the control function approach of Olley and Pakes (1996). We rely on our method to explore the relationship between markups and export behavior using plant-level data. We find significantly higher markups when we control for unobserved productivity shocks. Furthermore, we find significant higher markups for exporting firms and present new evidence on markup-export status dynamics. More specifically, we find that firms' markups significantly increase (decrease) after entering (exiting) 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 premia for firms entering export markets.

Keywords: *Markups, Control Function, Productivity, Exporting Behavior*

^{*}This paper was previously circulated under the name "A control function approach to estimate markups" and has benefitted from seminar and conference participants at K.U. Leuven, NYU, Aarhus University and the IIOC 2008. In particular we thank Dan Akerberg, Allan Collard-Wexler, Jeremy Fox, Penny Goldberg, Joep Konings, Marc Melitz, Patrick Van Cayseele, Hylke Vandenbussche and Frank Verboven for discussions on an earlier draft. Contact authors at jdeloeck@princeton.edu and fwa@asb.dk.

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 (see e.g. Goldberg, 1995, Petrin, 2002 and Berry, Levinsohn and Pakes, 2004). 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 a simple estimating equation in the spirit of Hall (1986) and Levinsohn (1993) that nests various price setting models and allows to estimate markups using standard plant-level production data. 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. The markup parameter is identified given we observe total expenditures on the 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.

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 Melitz (2003) emphasize the self-selection of firms into export markets based on an underlying productivity distribution, creating a strong correlation between productivity and export status.

More recently the impact of export status on firm-level productivity has been confirmed

for mostly developing countries, often referred to as learning by exporting.¹ 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 market power effects. Therefore, differences in pricing behavior between exporters and non exporters could, at least partially, be responsible for the measured productivity trajectories upon export entry. We use our method to first of all verify whether markups are different for firms that are engaged in international activities, exporting more specifically.² Our framework is especially well suited to address this question since our method allows to control for unobserved productivity shocks which is key in order to identify a separate markup for exporters. In addition, we study the relationship between markups and changes in firm-level export status and provide new evidence on how markups change as firms move into export markets.

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. Entry into export markets contributed quite substantially to aggregate productivity growth through.³

It is therefore imperative to control for productivity growth and in fact, our method delivers higher estimates of firm-level markups compared to standard techniques that do not 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 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

¹See eg. 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).

²A few recent papers have provided similar evidence on importers (Halpern, Koren and Szeidl 2006; Kasahara and Rodrigue, 2008; Lööf and Anderson, 2008). Our framework is also well suited to analyze this relationship, but we do not observe import status at the firm level in this dataset, and therefore the discussion lies beyond the scope of this paper.

³See De Loecker and Konings (2006) for more on the importance of entry in aggregate productivity growth and De Loecker (2007a) for more on the export-productivity relationship.

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. Again, this is in line with empirical evidence on the learning by exporting effect, but offers at the very least a potential channel through which measured productivity increases upon export entry.

Section 2 provides a brief overview on how production data has been used to recover markups, and we discuss some of the problems with current methods. Section 3 introduces our empirical model and shows how our approach is robust to various price setting models and can be easily extended to allow for richer production technologies and various proxy estimators that have been put forward in the literature. In section 4 we turn to the data and discuss our main results. We conclude with some final remarks.

2 Recovering markups from production data

Around twenty years ago, 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 or Basu, 1997)⁴. This approach is based on a production function framework and allows identifying a (constant) markup using the notion that under imperfect competition input growth leads to disproportional output growth, as measured by the relevant markup. An estimated markup higher than one would therefore immediately reject the perfect competitive model⁵.

However, some important econometric issues are still unaddressed in the series of modified approaches. The main concern is that other factors that are *not observed* can impact output growth as well.⁶ An obvious candidate in the framework of a production function is productivity (growth). Not controlling for unobserved productivity shocks biases the estimate of the markup as productivity is potentially correlated with the input

⁴The literature also spread to international trade. See Levinsohn (1993), Harrison (1994), Krishna and Mitra (1998) and Konings and Vandebussche (2005).

⁵In 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.

⁶In 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).

choice. The sign of the bias will depend on the correlation between the input growth and productivity growth. 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. Instead, a full behavioral model was introduced to solve for unobserved productivity as a function of observed (firm-level) decisions, i.e. investment and input demand. Olley and Pakes (1996) were the first to propose a way to deal with unobserved productivity and the endogeneity of inputs when estimating a production function.⁷

Dealing with unobserved productivity shocks becomes an ever bigger concern when applying this method to plant-level data given the strong degree of firm-level productivity heterogeneity as the set of instruments suggested in the literature were mostly aggregate demand factors such as military spending, and oil prices. However, The increased availability of firm or plant-level datasets further boosted empirical studies using some version of the Hall approach on micro data (for instance Konings et al., 2005). This further poses the problem on how to deal with (firm-level) unobserved productivity in the context of the basic Hall approach.

We introduce the notion of a control function to control for unobserved productivity in the estimation of markups.⁸ We show that the Olley and Pakes (1996) and Hall (1986) approach are linked in a straight forward way. In this way we identify markup parameters by controlling for unobserved productivity relying on clearly spelled out behavioral assumptions. In addition, we identify markups without taking a stand on the exact timing of inputs, adjustment costs of inputs (hiring and firing costs for instance) since we only need to include the control function (in investment, capital and potentially other inputs) in a one-stage procedure. We show that this approach leads to a flexible methodology and reliable estimates. We also check whether our method is robust to recent developments using proxy estimators to estimate production functions. We then 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.

3 A Framework to estimate markups

In this section we derive the estimating equation relating output growth to a weighted average of input growth, allowing the identification of a markup parameter. We then

⁷Various refinements have since been proposed in the literature (Levinsohn and Petrin, 2003; Akerberg, Caves and Frazier, 2007). However, Akerberg, 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, 2007a who apply modified versions in the context of sorting out the productivity gains upon export entry).

⁸Note that all of this is relevant at the firm-level. Industry wide productivity shocks are controlled for by the introduction of (a combination of) year dummies and time trends.

provide a simple control function approach to control for unobserved productivity in this context. Importantly, our main estimating equation is shown to be robust to various price setting models such as Cournot and Bertrand. We briefly describe how other proxy estimators that have been put forward in the literature (such as Levinsohn and Petrin, 2003 and Akerberg et. al, 2006) can be used in our framework.

3.1 An underlying model of firm behavior

We derive a simple relationship between output growth and input growth which allows us to identify markups from standard production data. The estimating equation is obtained by i) considering a Taylor expansion of a general production function and ii) adding the conditions from profit maximization for firms that take input prices as given and compete in either Nash in prices or quantities.

Let us start by considering a general production function $f(\cdot)$ that generates an output Q_{it} from using labor L_{it} , material inputs M_{it} and capital K_{it} and depends on the firm's productivity level Θ_{it} . The latter is an input neutral technology shock.

$$Q_{it} = \Theta_{it} f(L_{it}, M_{it}, K_{it}) \quad (1)$$

The first step simply takes a Taylor expansion of Q_{it} (around Q_{it-1})

$$\Delta Q_{it} = \Theta_{it} \left(\frac{\Delta f_{it}}{\Delta L_{it}} \Delta L_{it} + \frac{\Delta f_{it}}{\Delta M_{it}} \Delta M_{it} + \frac{\Delta f_{it}}{\Delta K_{it}} \Delta K_{it} \right) + f_{it} \Delta \Theta_{it} \quad (2)$$

and nothing behavioral was assumed.

In a second step, we can interpret the markup in a very flexible way, i.e. under various assumptions regarding the nature of competition in the industry. 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. We show our approach under the standard Cournot/Bertrand homogenous good model and briefly discuss how we can easily extend it to richer settings.

Consider firms producing a homogeneous product and competing in quantities while operating in an oligopolistic market where profits π_{it} are given by

$$\pi_{it} = P_t Q_{it} - w_{it} L_{it} - m_{it} M_{it} - r_{it} K_{it} \quad (3)$$

where all firms take input prices (w_{it} , m_{it} and r_{it}) as given. The optimal choice of labor is then given by

$$\Theta_{it} \frac{\Delta f_{it}}{\Delta L_{it}} = \frac{w_{it}}{P_t} \left(1 + \frac{s_{it} \theta_{it}}{\eta_t} \right)^{-1} \quad (4)$$

and analogous conditions apply for material and capital, where $s_{it} = \frac{Q_{it}}{Q_t}$ is the market share of firm i , η_t is the market elasticity of demand, and θ_{it} is equal to zero under perfect competition, and equal to one if firms play Nash in quantities, respectively. The optimal output choice Q_{it} will satisfy the following F.O.C.

$$\frac{P_t}{c_{it}} = \left(1 + \frac{s_{it}\theta_{it}}{\eta_t}\right)^{-1} \equiv \mu_{it} \quad (5)$$

where c_{it} is the marginal cost of production and we define μ_{it} as the relevant firm specific markup.

Now we follow Levinsohn (see also Shapiro, 1987 for a discussion of what the markup measures) and use the optimal input choices for labor and materials (4) together with the pricing rule (5) into the Taylor expansion (2).⁹

$$\Delta Q_{it} = \mu_{it} \left(\frac{w_{it}}{P_t} \Delta L_{it} + \frac{m_{it}}{P_t} \Delta M_{it} + \frac{r_{it}}{P_t} \Delta K_{it} \right) + f_{it} \Delta \Theta_{it}$$

We now have to take one last step to recover a well known estimation equation suggested by Hall (1986)¹⁰ by noticing that $\frac{\Delta X_{it}}{X_{it}} = \Delta \ln X_{it} = \Delta x_{it}$.

$$\Delta q_{it} = \mu_{it} \left(\frac{w_{it}L_{it}}{P_t Q_{it}} \Delta l_{it} + \frac{m_{it}M_{it}}{P_t Q_{it}} \Delta m_{it} + \frac{r_{it}K_{it}}{P_t Q_{it}} \Delta k_{it} \right) + \Delta \omega_{it} \quad (6)$$

$$= \mu_{it} (\alpha_{Lit} \Delta l_{it} + \alpha_{Mit} \Delta m_{it} + \alpha_{Kit} \Delta k_{it}) + \Delta \omega_{it} \quad (7)$$

where $\omega_{it} = \ln(\Theta_{it})$ and α_{Lit} , α_{Mit} and α_{Kit} are the share of the relevant input's costs in total revenue. 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 ($\mu_{it}\alpha_{Lit} = \frac{w_{it}L_{it}}{c_{it}Q_{it}}$). We stress that the input shares are assumed to be directly observed in the data, except for the capital share α_{Kit} .

A similar expression can be obtained *with a more general model* of Bertrand competition (Nash in price) with differentiated products. The Lerner index, or price cost margin,

⁹This somewhat restricts the underlying class of demand systems we can work with. More precisely, we either do not allow for a change in the curvature of demand during $t - 1$ and t , the CES demand system being a well known example of this. Under more general demand systems we consistently estimate the average elasticity and can still bound the estimate of the markup by verifying the interaction between input growth and the change in the markup.

¹⁰Hall (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. Note how our structural derived equation is exactly the same as the one suggested by Hall (1986). The traditional way to estimate μ_{it} follows the instrumental variables approach, the choice of which can easily be criticized. Roeger (1995) offers an alternative method that uses information from the primal and the dual Solow residual. This paper proposes another alternative using the insight of Olley and Pakes (1996) on the estimation of production functions using a structural model of industry dynamics.

β_{it} would then depend on the own price elasticity $\eta_{ii} = -\frac{\partial q_i}{\partial p_i} \frac{p_i}{q_i}$ and the cross price elasticity $\eta_{ij} = -\frac{\partial q_i}{\partial p_j} \frac{p_j}{q_i}$:

$$\beta_{it} \equiv \frac{P_{it} - c_{it}}{P_{it}} = \frac{1}{\eta_{ii} - \vartheta' \frac{p_{it}}{p_{jt}} \eta_{ij}} \quad (8)$$

where $\vartheta' = \frac{\partial p_j}{\partial p_i}$ (see e.g. Röller and Sickles, 2000).

The method could also be adapted to consider multiproduct firms (e.g. Berry, Levinsohn and Pakes, 1995)¹¹ and to take into account pricing heterogeneity between firms, as advocated by Klette and Griliches (1996), Klette (1999), and more recently by Foster, Haltiwanger and Syverson (2008) and De Loecker (2007b).¹²

In other words, the method is flexible enough to consider various assumptions regarding the nature of competition and accommodates two of the most common static model of competition used by industrial economists. The markup can also reflect the result of more complex dynamic games. What is important to note though, is that the estimated parameter μ will clearly have a different interpretation and will depend on elasticities in various forms depending on the model we assumed. The extent of the bias of not controlling appropriately for unobserved firm-level productivity shocks ultimately depends on the data at hand. However, the sign of the bias is not straightforward to determine.

The Hall methodology and further refinements by Roeger (1995) 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 (Konings et al., 2005). 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.¹³

3.2 Controlling for Unobserved Productivity Using a Control Function

Another strand of the literature focuses on the estimation of the coefficients of a production function. A standard production function is assumed to generate output Q_{it} given various

¹¹See Appendix B for an expression of markups within the context of our approach.

¹²The recent model of Melitz and Ottaviano (2008), where firms compete in prices and products are horizontally differentiated, generates a firm specific markup as a function of the difference between the firm's marginal cost and the average marginal cost in the industry. Therefore, when the firm is more efficient than its competitors, it charges an higher markup and enjoys higher profits.

¹³The 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. As output is usually proxied by sales the change in markup and the productivity response are hard to separate without bringing more structure and data to problem. See De Loecker (2007b) for more on this.

inputs and a residual. This residual can be decomposed into a productivity shock (ω_{it}), which is potentially correlated with inputs, and an *i.i.d.* term (ε_{it}).

$$\log \Theta_{it} = \omega_{it} + \varepsilon_{it} \tag{9}$$

To deal with this potential endogeneity, Olley and Pakes (1996) rely on a dynamic model of investment with heterogeneous firms and generates an equilibrium investment policy function which forms the basis of the estimation procedure, $i_{it} = i_t(\omega_{it}, k_{it})$. Provided that investment is a monotonic increasing function in productivity, we can proxy the unobserved productivity shock by a function of i_{it} and k_{it} .

$$\omega_{it} = h_t(i_{it}, k_{it}) \tag{10}$$

Our approach simply relies on the insight of Olley and Pakes (1996) to control for unobserved productivity shocks in the markup regression, described in equation (6). We provide two alternative strategies to correct for unobserved productivity shocks $\Delta\omega_{it}$. The first is directly built on the control function approach suggested by Olley and Pakes (1996). The second relies specifically on the (non parametric) Markov process of productivity and on firms' exit rules. We also discuss the use of different proxy estimators in the context of our approach.

Both alternatives allow to estimate the markup using standard semi-parametric regression techniques and GMM techniques. It is important to note, however, that the estimation of the markup is not affected by the presence of non *constant returns to scale*. As will become clear below, this is related to the fact that we do not need to observe the user cost of capital (r_{it}) which is very hard to come by.¹⁴ In terms of studying the relationship between export status and markups, we take a very simple approach by simply interacting the markup term with various export status dummies. In this way, we compare average markup differences between exporters and non exporters, and further between various export categories (starters, quitters and always exporters). We provide more details when we discuss the results.

3.2.1 First approach: pure difference

As Olley and Pakes (1996) showed, we can proxy unobserved productivity by a function in investment and capital. This implies that productivity growth $\Delta\omega_{it}$ is simply the difference

¹⁴We have to note that capital is a fixed input and a firm might thus face a cost of adjustment. This will slightly change the optimal input choice condition for capital. However, since we will collect the capital terms in the control function, we do not have to specify the exact adjustment costs and the optimal capital choice. It will imply that expression (6) will look different. For notation purposes we stick to the original expressions.

between the control function at time t and $t - 1$.

$$\Delta\omega_{it} = h_t(i_{it}, k_{it}) - h_{t-1}(i_{it-1}, k_{it-1}) \quad (11)$$

This will generate the following estimating equation for the markup parameter μ , where we emphasize that we are only interested to estimate an average markup across a given set of firms. Note that we now decompose $\ln(\Theta_{it}) = \omega_{it} + \varepsilon_{it}$, and explicitly allow for measurement error and idiosyncratic shocks to production.

$$\Delta q_{it} = \mu [\alpha_{Lit}\Delta l_{it} + \alpha_{Mit}\Delta m_{it} + \alpha_{Kit}\Delta k_{it}] + h_t(i_{it}, k_{it}) - h_{t-1}(i_{it-1}, k_{it-1}) + \Delta\varepsilon_{it} \quad (12)$$

We collect all terms on capital and investment in $\Delta\phi_t(\cdot)$ and obtain our estimating equation

$$\Delta q_{it} = \mu\Delta x_{it} + \Delta\phi_t(i_{it}, k_{it}) + \Delta\varepsilon_{it} \quad (13)$$

where we use the following notation,

$$\Delta x_{it} = \alpha_{Lit}\Delta l_{it} + \alpha_{Mit}\Delta m_{it} \quad (14)$$

$$\Delta\phi_t(i_{it}, k_{it}) = \mu\alpha_{Kit}\Delta k_{it} + h_t(i_{it}, k_{it}) - h_{t-1}(i_{it-1}, k_{it-1}) \quad (15)$$

We note that some terms in the control function will drop out due to collinearity that are generated by the law of motion on capital, $k_t = (1 - \delta)k_{t-1} + i_{t-1}$. In particular, under the assumption that the capital stock depreciates at the same rate for all firms, investment and capital at time $t - 1$ fully determine the capital stock at time t .¹⁵

This approach delivers an estimate for the markup (μ) by simply adding a non linear function in capital and investment. It does, however, not explicitly control for the non random exit of firms. Our second approach enables us to verify the impact on the estimated markup of controlling for the selection process.

3.2.2 Second approach: selection control

Here we rely on one of the crucial assumption in Olley and Pakes (1996), namely productivity follows a first order Markov process, where ξ_{it} denotes the news term in the Markov process. We explicitly rely on the notion that the growth rate of output and the various inputs is only available for surviving firms. This implies that productivity growth $\Delta\omega_{it}$ at time t can be written as

$$\Delta\omega_{it} = \omega_{it} - \omega_{it-1} = g(\omega_{it-1}, P_{it}) - \omega_{it-1} + \xi_{it} \quad (16)$$

$$= \tilde{g}(i_{it-1}, k_{it-1}, P_{it}) + \xi_{it} \quad (17)$$

¹⁵This will depend on the availability of investment data and whether it needs to be constructed from capital stock data and depreciations.

where P_{it} is the survival probability at time $t - 1$ to next year t . Empirically, we obtain an estimate for this survival probability by running a probit regression of survival on a polynomial in investment and capital. The second step uses the result from the inversion $\omega_{it-1} = h_t(i_{it-1}, k_{it-1})$, and the final step simply collects all observables in function $\tilde{g}(\cdot)$. We now have the following estimating equation for our model.

$$\Delta q_{it} = \mu \Delta x_{it} + \tilde{\phi}_t(i_{it-1}, k_{it-1}, P_{it}) + \Delta \varepsilon_{it}^* \quad (18)$$

where again we have that

$$\begin{aligned} \tilde{\phi}_t(i_{it-1}, k_{it-1}, P_{it}) &= \mu \alpha_{Kit} \Delta k_{it} + g_t(h_t(i_{it-1}, k_{it-1}), P_{it}) \\ \Delta \varepsilon_{it}^* &= \Delta \varepsilon_{it} + \xi_{it} \end{aligned} \quad (19)$$

The capital stock at t no longer appears, as we know from the law of motion that capital investment and capital fully determine the next period's capital stock, i.e. $k_{it} = (1 - \delta)k_{it-1} + i_{it-1}$. In order to estimate the markup in this specification we need one extra step. The current specification would lead to a biased estimator for the markup since $E(\Delta x_{it} \xi_{it}) \neq 0$, since

$$E(l_{it} \xi_{it}) \neq 0 \quad (20)$$

$$E(m_{it} \xi_{it}) \neq 0 \quad (21)$$

This is exactly what causes the simultaneity bias when estimating a production function since $\omega_{it} = g(\omega_{it-1}, \underline{\omega}_{it}) + \xi_{it}$. This clearly shows that the labor decision depends on current productivity and therefore reacts to the news term in the productivity Markov process. However, given the assumption that labor and materials are essentially freely chosen variables and have no adjustment costs, we can rely on the following instruments l_{it-1} and m_{it-1}

$$E(l_{it-1} \xi_{it}) = 0 \quad (22)$$

$$E(m_{it-1} \xi_{it}) = 0 \quad (23)$$

and estimate the markup (μ) consistently using equation (18).

3.3 Returns to Scale and the User Cost of Capital

Before we turn to alternative proxy estimators we want to stress that the use of the control function has two major advantages in addition to correcting for unobserved productivity shocks in the production function framework. We are not required to measure the capital share ($\alpha_{Kit} = \frac{r_{it} K_{it}}{P_{it} Q_{it}}$) and assume constant returns to scale in order to estimate the

markup parameter. The standard Hall approach for instance had to rely on constant returns to scale to step away from the heroic task of measuring a firm-level user cost of capital r_{it} .¹⁶ In order to relax the returns to scale assumption researchers had to take a stand on the user cost of capital which has proven to be a very difficult job. The constant returns to scale assumption is also key in the approach of Roeger (1995) in order to eliminate unobserved productivity shocks using the primal and dual representation of the model, in addition to needing a measure for r_{it} as well.

The use of the control function in our simple approach collects all the terms depending on capital and investment and does not require any assumption on the returns to scale and the user cost of capital. Obviously, these advantages do not come without any other assumptions. It is clear that we are able to eliminate them by relying on the result that we can proxy for unobserved productivity shocks using a non parametric function in the firm's state variables, in this case capital and investment. But as we will show below, we can accommodate more state variables and therefore relax some of the assumptions that the original Olley and Pakes (1996) framework rely on.

3.4 Alternative Proxy Estimators

In this section we briefly discuss the use of other proxy estimators that have been introduced in the literature building on the insight of Olley and Pakes (1996). In turn we discuss the LP and the ACF proxy estimators in the context of our interest in estimating markups. We show how our estimator suggested in approach 1 can be extended to allow for different proxy variables and additional state variables.

3.4.1 Intermediate input proxy estimator

Levinsohn and Petrin (2003), hereafter LP, suggest the use of intermediate inputs instead of investment as to control for unobserved productivity shocks. Therefore, the basis of their estimation procedure is to write productivity as a function of m_{it} and k_{it} , $\omega_{it} = h_{it}(m_{it}, k_{it})$.

The rest of the estimation therefore proceeds in a similar way. However, the control function will now include capital at t as there is still independent variation in capital between time t and $t - 1$ as investment is not used as a proxy in LP. The estimating equation now becomes

$$\Delta q_{it} = \mu_{it} \alpha_{Lit} \Delta l_{it} + \Delta \phi_t(m_{it}, k_{it}) + \Delta \varepsilon_{it} \quad (24)$$

¹⁶See Hall (1990) however, as already noted in footnote 4, who suggested a simple way to jointly estimate the returns to scale parameter and the markup.

where

$$\Delta\phi_t(m_{it}, k_{it}) = \mu(\alpha_{Mit}\Delta m_{it} + \alpha_{Kit}\Delta k_{it}) + h_t(m_{it}, k_{it}) - h_{t-1}(m_{it-1}, k_{it-1}) \quad (25)$$

However, one has to be careful with using this proxy estimator especially in the context of our setup. Here we are explicit about the notion of competition in the output market, i.e. we allow for imperfect competition. As it turns out this has implications for the validity of the LP estimator. Essentially, the LP estimator relies on the inversion of the intermediate input demand function - just as OP - which assumes perfect competition in the output market. Therefore more assumptions are needed to still allow for the monotonic relationship of intermediates in productivity conditional on the capital stock. Essentially, we have to assume that more productive firms do not set disproportionately higher markups. See De Loecker (2007b) for a detailed discussion on this.

3.4.2 A more flexible approach

Akerberg, Caves and Frazier (2006), ACF hereafter, discuss the underlying data generating process of OP and LP. They show that the suggested framework can be generalized to allow for more flexible production technologies and timing assumptions of the inputs of the production process. For our purpose, it is sufficient to note that the OP method delivers a consistent estimate of the freely chosen variables under a plausible DGP. However, in this section we briefly show that one can relax these by using the argument raised in ACF: include all inputs into the non parametric function $\phi(\cdot)$ in a first stage and use the relevant timing assumptions in the second stage to estimate the parameters of interest. Remember that, in our setup, a crucial difference is that the input shares (input elasticities) are computed from data rather than estimates that we wish to obtain. However, if we believe that, for instance, labor cannot be hired without adjustment costs and similarly for intermediate inputs, therefore lagged labor and materials constitute additional state variables of the firm's problem. Essentially our model then looks like follows

$$\Delta q_{it} = \Delta\phi_t(i_{it}, k_{it}, l_{it}, m_{it}) + \Delta\varepsilon_{it}^* \quad (26)$$

where $\Delta\phi_t(i_{it}, k_{it}, l_{it}, m_{it}) = \mu(\alpha_{Lit}\Delta l_{it} + \alpha_{Mit}\Delta m_{it} + \alpha_{Kit}\Delta k_{it}) + \Delta h_t(i_{it}, k_{it}, l_{it}, m_{it})$ and the markup parameter is not identified in a first stage. As in ACF the first stage gets rid off all *i.i.d.* shocks, like measurement error. Our second stage, however, only requires one moment condition to identify μ . Given the underlying productivity process and the law of motion on capital, we can rely on several moments and test our model for overidentifying restrictions. More specifically, we can construct moment conditions using our estimate for $\widehat{\Delta\phi_{it}}$ out of the first stage.

$$E(\Delta\omega_{it}Z_{it}) = 0 \quad (27)$$

where $\Delta\omega_{it} = \widehat{\Delta\phi}_{it} - \mu\Delta x_{it}^{all}$.¹⁷ Given the underlying productivity process as described in (16), natural candidates for Z_{it} are l_{it-2} and k_{it-2} .¹⁸

Although the GMM approach is more general, it does substantially reduce the number of observations since we require $t - 2$ lags. Alternatively, we can restrict the first stage by observing that when firms do not face adjustment costs for material inputs, we can estimate the markup in a first stage as the coefficient on $\alpha_M\Delta m_{it}$. Formally, we have the following investment function $i_{it} = i_t(k_{it}, \omega_{it}, l_{it})$, and therefore can rely on $\omega_{it} = h_t(i_{it}, k_{it}, l_{it})$ as a proxy for unobserved productivity. This implies that the control function for productivity growth will include labor at t and $t - 1$.

$$\Delta q_{it} = \mu\alpha_{Mit}\Delta m_{it} + \Delta\phi_t(i_{it}, k_{it}, l_{it}) + \Delta\varepsilon_{it}^* \quad (28)$$

In fact, this is often a reasonable assumption we can take to the data: firms face hiring/firing costs for employees but can freely adjust their demand for intermediate inputs. We will estimate this specification and compare it to our general framework. This section shows the flexibility of our approach since we can include additional state variables that potentially further control for unobserved productivity shocks. For instance, in the context of firms in international trade the export status could serve as an important additional state variable to take into account. We will come back to this in detail.

3.5 Identifying markups for exporters

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 simply interact the input growth term Δx_{it} with a firm-time specific export status variable. In the context of sorting out markup differences for exporters and domestic firms, controlling for unobserved productivity shocks is absolutely critical given the strong correlation between export status and productivity. We will further explain our empirical model in detail, once we have introduced the data, and discuss the information we can rely on.

4 Background and Data

We rely on a unique dataset covering all firms active in Slovenian manufacturing during the period 1994-2000.¹⁹ The data are provided by the Slovenian Central Statistical Office

¹⁷Note that now we consider all inputs and denote it by x^{all} . This implies that we either estimate α_k in addition to the markup parameter or need to make an assumption on returns to scale, i.e. a measure of the user cost of capital.

¹⁸This result is quite intuitive and very similar to the final stage of Olley and Pakes (1996). Given our model is already in first differences, the instruments are now at $t - 2$.

¹⁹We refer to Appendix A for more details on the Slovenian data.

and contains the full company accounts for an unbalanced panel of 7,915 firms.²⁰ We also observe market entry and exit, as well as detailed information on firm level export status. 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 use the detailed information on export status to shed some light on markup differences between exporters and domestic producers. 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, 2007a). Therefore, we want to analyze the impact of the increased participation in international markets on the firms' ability to charge prices above marginal cost.

5 Markups and Firm Export Status Dynamics

In this section we use our empirical model to estimate markup parameters for Slovenian manufacturing firms, and more specifically to test whether exporters have, on average,

²⁰The unit of observation is an establishment (plant) level, but we refer to it as a firm.

different markups. In addition, we rely on substantial entry into foreign markets in our data during the sample period to analyze how markups change as a function of export entry and exit compared to domestic producers and continuing exporters. To our knowledge, we are the first to provide robust econometric evidence of this relationship.

5.1 Exporters and Markups

We collect our main results in Table 2 and consider various specifications of our empirical Model: 1) the standard Hall approach, 2) various versions of our control function approach. For the latter we consider 4 different specifications: Control Function I simply introduces the control for productivity growth as introduced in section 3.2. Furthermore, we show the estimates using a second approach (Control Function II) where we estimate the model without and with the selection correction. Finally, we estimate the markup allowing for adjustment cost in labor (Control Function III) which boils down to an ACF approach to correct for productivity (section 3.4.2).

Table 2: Markups in Slovenian Manufacturing

Specification	Estimated Markup	Standard Error
Standard Hall	1.03*	0.004
Control Function I	1.11*	0.007
Control Function II	1.13*	0.006
Control Function II including Selection	1.11*	0.007
Control Function III (labor state)	1.14*	0.008
<i>Exporters versus Domestic Producers</i>		
Standard Hall		
	average markup	1.0279*
	exporter effect	0.0155
Control Function I		
	average markup	1.0543*
	exporter effect	0.1263*

All regressions include time and industry dummies.

A robust finding is that the estimated markup is higher when we rely on the control function to proxy for unobserved productivity growth and the non random exit of firms. This is consistent with the transition process where firms scaled down employment after long periods of labor hoarding, as well as the entry of *de novo* firms who enter at a much smaller scale.

In the lower panel we verify whether exporting firms (on average) have higher markups (given that exporters tend to produce at lower marginal costs) and compare our results

with the standard Hall approach.²¹ In order to estimate the markup for exporters we extend our main estimating equation and interact the relevant term, Δx_{it} , with an exporter dummy EXP_{it} .

$$\Delta q_{it} = \mu_D \Delta x_{it} + \mu_E \Delta x_{it} EXP_{it} + \delta_E EXP_{it} + \Delta \phi_t(i_{it}, k_{it}) + \Delta \varepsilon_{it} \quad (29)$$

When we use the standard Hall specification, we cannot find significantly different markups for exporting firms²². On the contrary, our approach is better suited to analyze markup differences between exporters and non-exporters, since we can explicitly control for the export-productivity correlation in addition to the standard input growth-productivity growth correlation. Both correlations need to be controlled for in order to estimate a markup for domestic producers and exporters consistently. Indeed, when we control for unobserved productivity shocks, we find a significant higher markup for exporters.

These results can be related to the well established empirical fact that exporters are more productive. In the case of Slovenia, De Loecker (2007a) finds significant productivity differences between exporters and domestic producers. In addition, he finds that export entry further leads to productivity gains - often referred to as learning by exporting - in addition to the more productive firms self selecting into export markets. In the context of our model it is clear that, if we do not control for unobserved productivity shocks, the estimated interaction effect of export status and input growth - and therefore markups for exporters - is biased.²³

This result 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,

²¹All the coefficients are robust to considering firms with positive investment only and therefore the difference between the uncorrected and corrected estimates are not driven by specific sample of firms. In Appendix C we report the estimated markups for the various industries.

²²A few papers analyzed this relationship using the Roeger method (Görg and Warzynski, 2003; Bellone et al., 2007) and find higher markups for exporters as well. As mentioned before, we provide a more flexible approach that does not rely on the assumption of constant returns to scale.

²³In the case where export status is a state variable in the underlying model we cannot identify the interaction term in a first stage. This would imply that export status is part of the non parametric function $\phi(\cdot)$. For a discussion on this see De Loecker (2007a).

given that measured productivity is a simple residual of a sales generating production function, it is well known that it contains market power effects broadly defined.²⁴ 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 shed further light on the measured productivity trajectories upon export entry.

5.2 Markups and Export Entry

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. To capture the relationship between how markups change as a firm enters or exits an export market, we run a similar regression interacting the markup with a firm-time specific export status variable, defined as a set of dummies, $status_{it}$, as follows

$$\begin{aligned}\Delta q_{it} &= \mu \Delta x_{it} + status_{it} * \Delta x_{it} + \Delta \phi_t(i_{it}, k_{it}) + \Delta \varepsilon_{it} \\ status_{it} &= (\mu_{s,b} B_{it}^{st} + \mu_{s,a} A_{it}^{st} + \mu_{al} AL_{it} + \mu_{q,b} B_{it}^q + \mu_{q,a} A_{it}^q)\end{aligned}\tag{30}$$

In equation (30) B_{it}^{st} is a dummy equal to 1 if the firm starts exporting (we call these firms ‘starters’) during our period of analysis, say at time t_0^{Start} , and the observation takes place before it starts exporting ($t < t_0^{Start}$), and equal to 0 otherwise; A_{it}^{st} is equal to 1 if the firm starts exporting and we observe it after it started exporting ($t \geq t_0^{Start}$), and equal to 0 otherwise; AL_{it} is equal to 1 if the firm is always exporting during our period of analysis, and 0 otherwise; B_{it}^q is equal to 1 if the firm stopped exporting during the period (we refer to these firms as ‘quitters’), but is observed while it was still an exporter, and equal to 0 otherwise; A_{it}^q is equal to 1 if the firm stopped exporting and is observed

²⁴In 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.

after it stopped exporting, and equal to 0 otherwise. The default category consists of firms producing only for the domestic market.

Table 3: Markups and export dynamics (Control Function)

		Coefficient	s.e.
Baseline (domestic)		1.04*	0.012
Starters	Before Entering	0.08**	0.033
	After Entering	0.15*	0.021
Always exporters		0.14*	0.020
Stopper	Before Exiting	0.03	0.020
	After Exiting	-0.11*	0.030

Regression includes industry and year dummies in addition to separate dummy variables.

Table 3 shows the results and we clearly see that firms which are always exporting have a larger markup than firms that sell only on the domestic market, consistent with the evidence reported above.

A new set of results emerges in the rows two to six. Firms entering export markets have a larger markup even before they start exporting than their domestic counterparts. The latter is consistent with the self-selection hypothesis whereby more efficient firms find it productive to pay the fixed cost of entering an export market. Here more efficient can mean that a domestic firm might simply produce at a higher cost while charging the same price.

Interestingly, markups increase very substantially, on average, after export entry and the average markup increases to a level slightly above the markup of firms that continue exporting. The difference, however, is not significant.

For firms that stop exporting, their markup did not deviate from the level of non-exporting firms when they were still exporting, but after they stop exporting, the markup drops dramatically.²⁵ It is important to note that these patterns are not found when we do not control for unobserved productivity shocks, in fact markups are either insignificant or much lower in magnitude. The latter shows again the importance of controlling for the correlation between export status and productivity shocks.

It is striking to see that the markup-export patterns are identical to the productivity-export patterns found in De Loecker (2007a). He finds that productivity increases upon export entry and that exporters are more productive than their domestic counterparts. These results are suggestive of changes in performance of new exporters due to higher markups.

Our evidence suggests that the gap between the notion of (physical) productivity in

²⁵This could suggest that these firms were exporting poor quality products to Eastern European countries.

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. An exception is the recent work by Melitz and Ottaviano (2008) who provide a theoretical analysis of the relationship between firm export status and (market specific) markups. We therefore see our results as opening up the *black box* of how exporting affects firm performance.

5.3 Implications for productivity growth

Finally, given our framework, we can back out estimates for productivity growth after we estimated the markup parameter.²⁶ However, now we have to take a stand on the returns to scale - or implicitly on the user cost of capital - under which firms produce.²⁷ It is clear from equation (6) that we can only compute implied productivity growth after imputing values for α_{Kit} . Let us return to the main estimating equation before introducing the use of the control function and consider productivity growth

$$\Delta q_{it} - \hat{\mu} (\alpha_{Lit} \Delta l_{it} + \alpha_{Mit} \Delta m_{it} + (\lambda_{it} - \alpha_{Lit} - \alpha_{Mit}) \Delta k_{it}) = \widehat{\Delta \omega}_{it} \quad (31)$$

We rely on our estimates of the markup $\hat{\mu}$ and impose various values for the returns to scale parameter λ_{it} . We consider three different cases where λ_{it} will take values of 1, 1.1 and 0.9 or constant, increasing and decreasing returns to scale. In this way we can compare the productivity growth estimates between the uncorrected approach (*column I*) and our control function approach (*column II*) under the three different cases. 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. Table 4 shows implied productivity growth under the various scenarios for both approaches.

We report productivity growth as simple average across all firms in Slovenian manufacturing (A), as an average of industry specific sales weighted productivity (B) and as an average obtained from regression (30) averaged over all firms (C). The various comparisons in table 4 clearly show that productivity growth is overestimated without controlling for endogeneity of inputs and markup differences (column I). Indeed, productivity growth is roughly only half of what we obtain when we ignore these two effects (column II). The

²⁶This is ruled out when relying on the Roeger (1995) method.

²⁷Note that we do not have to make any assumptions on returns to scale when estimating the markup parameter.

Table 4: Implied Productivity Growth (Annual Averages in percentages)

	CRS		IRS		DRS	
	I	II	I	II	I	II
A) Manufacturing	3.52	2.16	3.01	1.58	4.03	2.75
B) Industry (weighted)	3.21	1.57	2.77	1.03	3.73	2.11
C) Manufacturing (status)	<i>3.52</i>	2.45	<i>3.01</i>	1.87	<i>4.03</i>	3.07

I is standard model without correction, II is control function approach.

bias is not specific to the returns to scale we assume, however, the implied productivity estimates do depend on the values for λ .

The last row shows productivity growth under our specification (30) where we allow for markups to change with a change in a firm’s export status. These effects are not present when we do not control for unobserved productivity shocks, and therefore the productivity growth estimates are exactly the same as in row (A). 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.

5.4 Robustness and final remarks

Implicitly we have treated deflated output as a measure of physical quantity, and therefore our approach is potentially subject to the same concern as the estimation of production function where deflated revenue is used to proxy for output. However, in our context the bias in the markup parameter is reduced to the extent that unobserved growth in firm-level price deviations away from the average price are correlated with input growth. Moreover, our estimating routine already incorporates full interaction of industry and year dummies which controls for unobserved demand shocks in the spirit of Klette and Griliches (1996), Katayama, Liu and Tybout (2009) and De Loecker (2007b) shows that not observing prices is mostly severe for obtaining reliable measures for productivity, which is not our main objective.²⁸

To see how our main estimating equation is affected by not observing firm-level prices, we explicitly introduce deflated revenue Δr_{it} to proxy for output growth and verify how it potentially biases the markup parameter.

$$\Delta r_{it} = \mu \Delta x_{it} + \Delta \phi_t(i_{it}, k_{it}) + \Delta(p_{it} - p_t) + \Delta \varepsilon_{it} \tag{32}$$

²⁸The coefficients on the inputs do hardly change when controlling for unobserved prices and demand shocks. Klette and Griliches (1996) document similar findings using U.S. manufacturing data.

The main concern is the correlation between Δx_{it} and $\Delta(p_{it} - p_t)$. We expect this correlation 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 higher input will lead to higher output and push prices down. This is an important observation for evaluating our results. This implies that if anything we are underestimating markups. The significantly higher estimated markups, while controlling for productivity shocks through the control function, are in fact consistent with this. More specifically, as shown in De Loecker (2007b) the control function $\Delta\phi_t(i_{it}, k_{it})$ fully controls for unobserved demand shocks following the same process as the productivity unobservable ω_{it} . This observation together with the inclusion of full interaction of industry and year dummies, further eliminates the potential correlation between Δx_{it} and $\Delta(p_{it} - p_t)$. In terms of our main set of results, where we estimate different markups for exporters, and how markups change with firms' export status, we further potentially control for unobserved prices growing differently for exporters and non exporters, or more precisely for firms switching their particular export status.

Finally, we tested whether exporters' (average) markup are different in the domestic ($\mu_{E,D}$) and foreign market ($\mu_{E,E}$) by decomposing $\mu_E \Delta x_{it} EXP_{it}$ into $(\mu_{E,D} s_{it}^D + \mu_{E,E} s_{it}^E) \Delta x_{it} EXP_{it}$, where s_{it}^D and s_{it}^E are the share of domestic and foreign sales in total sales, respectively. We find only a slightly lower domestic markup (0.126), but not statistically different from the foreign market's markup (0.132). In fact, using the firm specific shares, the average total export markup parameter is 0.131, compared to 0.1263 in Table 2.²⁹

6 Discussion and Conclusion

This paper investigates the link between markups and exporting behavior. We find that markups differ between exporters and non exporters. 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 explicitly consider the selection process in the estimation and do not rely on the assumption of constant returns to scale and the need to compute 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

²⁹This test rests on an implicit assumption that the share of domestic (export) sales in total sales are the correct weights, and implies that inputs are used proportional to sales. Without more detailed data on inputs by product or market, it is an open question how strong this assumption is.

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 the non random exit of firms and 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 estimate significant higher markups for firms entering 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 Constantini and Melitz (forthcoming) 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.

References

- [1] Akerberg, D., Benkard, L., Berry, S. and Pakes, A., 2007. "Econometric Tools for Analyzing Market Outcomes". in Handbook of Econometrics, Volume 6, 4173-4276.
- [2] Akerberg, D., Caves, K., and Frazer, G., 2007. Structural Identification of Production Functions, mimeo, UCLA.
- [3] Berry, S., Levinsohn, L. and Pakes, A. 1995. Automobile Prices in Market Equilibrium, *Econometrica*, 63, 841-890.
- [4] Berry, S., Levinsohn, J. and Pakes, A. 2004, Estimating Differentiated Product Demand Systems from a Combination of Micro and Macro Data: The Market for New Vehicles, *Journal of Political Economy*, vol. 112, no. 1,1, pp. 68-105.
- [5] Basu, S., Fernald, J.G., 1997. Returns to Scale in U.S. Production: Estimates and Implications, *Journal of Political Economy*, 105, 249-83.
- [6] Bellone, F., Musso, P., Nesta, L. and Warzynski, F., 2008. Endogenous Markups, Firm Productivity and International Trade, mimeo, OFCE.
- [7] Clerides, S., Lach, S. and Tybout, J. 1998. Is 'Learning-by-Exporting' Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco, *Quarterly Journal of Economics*, Vol. 113, pp. 903-47.
- [8] Constantini, J. and Melitz, M. Forthcoming. The Dynamics of Firm-Level Adjustment to Trade Liberalization, in Helpman, E., D. Marin, and T. Verdier, The Organization of Firms in a Global Economy, Harvard University Press, 2008.
- [9] De Loecker, J. and Konings, J. 2006, Job Reallocation and Productivity Growth in an Emerging Economy, *European Journal of Political Economy*, vol 22, pp. 388-408.
- [10] De Loecker, J. 2007a. Do Export Generate Higher Productivity? Evidence from Slovenia. *Journal of International Economics*, 73, 69-98.
- [11] De Loecker, J. 2007b. Production Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity, NBER WP # 13155.
- [12] Domowitz, I. Hubbard, R.G. and Petersen, B.C. 1988. Market Structure and Cyclical Fluctuations in U.S. Manufacturing, *The Review of Economics and Statistics*, Vol. 70, No. 1., pp. 55-66.

- [13] Foster, L., Haltiwanger, J. and Syverson, C., 2008. Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review*, 98 (1), 394-425.
- [14] Goldberg, P. 1995. Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry, *Econometrica*, Vol. 63, No. 4, pp. 891-951.
- [15] Görg, H. and Warzynski, F., 2003. The Dynamics of Price Cost Margins and Exporting Behaviour: Evidence from the UK. LICOS Discussion Paper # 133.
- [16] Hall, R.E., 1986. Market Structure and Macroeconomic Fluctuations. *Brookings Papers on Economic Activity* 2, 285-322.
- [17] Hall, R. E., 1988. The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy* 96 (5), 921-947.
- [18] Hall, R. E., 1990. Invariance Properties of Solow's Productivity Residual, in Diamond, P. (ed.), *Growth, productivity, Unemployment: Essays to celebrate Bob Solow's Birthday*, Cambridge, MA: MIT Press, 71-112.
- [19] Halpern, L., Koren, M. and Szeidl, A. 2006. Imports and Productivity, mimeo CEU, Budapest.
- [20] Harrison, A., 1994. Productivity, Imperfect Competition, and Trade Reform: Theory and Evidence, *Journal of International Economics* 36, 53-73.
- [21] Kasahara, H. and Rodrigue, J., 2008. Does the use of imported intermediates increase productivity? Plant-level evidence, *Journal of Development Economics*, 87, 106-118.
- [22] Katayama, H., Lu, S. and Tybout, J. 2009. Why Plant-Level Productivity Studies are Often Misleading, and an Alternative Approach to Inference, *International Journal of Industrial Organization*, Volume 27 (3), 403-413.
- [23] Klette, T. J. , 1999. Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data. *Journal of Industrial Economics* 47 (4), 451-476.
- [24] Klette, T. J. and Griliches, Z., 1996. The Inconsistency of Common Scale Estimators When Output prices Are Unobserved and Endogenous, *Journal of Applied Econometrics* 11 (4), 343-361.
- [25] Konings, J., Van Cayseele, P. and Warzynski, F. 2005. The Effect of Privatization and Competitive Pressure on Firms' Price-Cost Margins: Micro Evidence from Emerging Economies. *The Review of Economics and Statistics* 87 (1), 124-134.

- [26] Konings, J. and Vandenbussche, H., 2005. Antidumping protection and markups of domestic firms, *Journal of International Economics*, 65 (1), 151-165.
- [27] Levinsohn, J., 1993. Testing the imports-as-market-discipline hypothesis, *Journal of International Economics*, 35, 1-21.
- [28] Levinsohn, J. and Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economics Studies* 70, 317-340.
- [29] Lööf, H. and Andersson, M., 2008. Imports, productivity and the origin markets - the role of knowledge-intensive economies, working paper, CESIS.
- [30] Melitz, M. 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity, *Econometrica*, Vol. 71, November 2003, pp. 1695-1725.
- [31] Melitz, M. and Ottaviano, G. 2008. Market Size, Trade, and Productivity, *Review of Economic Studies*, Vol. 75, January 2008, pp.295-316.
- [32] Morrison, C.J. 1992. Unraveling the Productivity Growth Slowdown in the United States, Canada and Japan: The Effects of Subequilibrium, Scale Economies and Markups, *The Review of Economics and Statistics*, Vol. 74, No. 3. (Aug., 1992), pp. 381-393.
- [33] Norrbin, S. C., 1993. The Relation between Price and Marginal Cost in U.S. Industry: A Contradiction, *Journal of Political Economy* 101, 1149-1164.
- [34] Olley, S. G. and Pakes, A, 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica* 64 (6), 1263-1297.
- [35] Petrin, A. 2002. Quantifying the Benefits of New Products: The Case of the Minivan, *Journal of Political Economy* , 110, 705-729.
- [36] Roeger, W., 1995. Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for U.S. Manufacturing. *Journal of Political Economy* 103(2), 316-330.
- [37] Shapiro, M., 1987. Measuring Market Power in US Industry. NBER WP # 2212.
- [38] Van Biesebroeck, J., 2005. Exporting Raises Productivity in sub-Saharan African Manufacturing Firms, *Journal of International Economics*, 67 (2), 373-391
- [39] Waldmann, R. J., 1991. Implausible Results or Implausible Data? Anomalies in the Construction of Value-Added Data and Implications for Estimates of Price-Cost Markups *Journal of Political Economy* 99, 1315-1328

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 (2007b) 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.

All monetary variables are deflated by the appropriate two digit NACE industry deflators and investment is deflated using a one digit NACE investment deflator. 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

We observe all variables every year in nominal values, however, 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 . The variables used in the analysis are: sales in thousands of Tolars, Employment: Number of full-time equivalent employees in a given year, Capital: Total fixed assets in book value in thousands of Tolars. 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: Multi-Product Firm Bertrand Price Setting and Markups

Suppose as in Berry, Levinsohn and Pakes (1995) that there are F firms in a specific industries, producing differentiated products. Each firm produces a subset Γ_f of the J products available on the market. To understand what our markup estimates refer to in the context of this model, let us look at the *short run* profit function of firm f :

$$\begin{aligned}\Pi_f &= \sum_{j \in \Gamma_f} (p_j - mc_j) q_j \\ &= \sum_{j \in \Gamma_f} (p_j - mc_j) M s_j(p, x, \xi; \vartheta)\end{aligned}$$

where M is the size of the market and s is market share, that depends on the price vector, as well as observed (x) and unobserved characteristics (ξ) of the products (ϑ is the vector of parameters to be estimated).

Maximizing profits with respect to price, we get the following FOC:

$$s_j(p, x, \xi; \vartheta) + \sum_{j \in \Gamma_f} (p_j - mc_j) \frac{\partial s_j(p, x, \xi; \vartheta)}{\partial p_j} = 0$$

In vector notations, this yields a product-specific markup:

$$\beta_f = \frac{p - mc}{p} = \frac{s(p, x, \xi; \vartheta)}{p} \frac{1}{\Delta(p, x, \xi; \vartheta)}$$

where Δ_{rj} is a $J \times J$ matrix whose (j,r) element is defined by:

$$\Delta_{rj} = \begin{cases} \frac{\partial s_j(p, x, \xi; \vartheta)}{\partial p_j} & \text{if } r \text{ and } j \text{ are produced by the same firm} \\ 0 & \text{otherwise} \end{cases}$$

In other words, 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.

Appendix C: Industry Markups and Export Dynamics

We report the estimated markup coefficients for the various industries of the Slovenian manufacturing sector. These coefficients are obtained after running the exact same regression as in Table 2 (upper panel) by industry to free up the markup parameter. This robustness check shows that our results are not specific to certain sectors or aggregation.

Table 5: Estimated Industry Markups

Industry (2 digit NACE)	Estimated Markup (μ)
15	1.1525
17	0.9868
18	1.0764
19	1.0612
20	1.0517
21	1.1037
22	1.0726
24	1.0837
25	1.1279
26	1.0765
27	1.0457
28	1.1099
29	1.1683
31	1.1806
32	1.1996
33	1.0850
34	1.2525
36	1.1627