A Note on Detecting Learning by Exporting *

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Abstract

Learning by exporting refers to the mechanism whereby firms improve their performance (productivity) after entering export markets. Although this mechanism is often mentioned in policy documents, a significant share of econometric studies has not found evidence for this hypothesis. This paper shows that the methods used to come to the latter conclusion suffer from a large internal inconsistency: they rely on an exogenous evolving productivity process. I show how recent proxy estimators can accommodate endogenous productivity processes such as learning by exporting. I rely on my framework to discuss the bias introduced by ignoring such a process, and how adjusting for it can lead to detect significant productivity gains upon export entry. I estimate my model on standard firm-level data and find substantial *additional* productivity gains from entering export markets.

Keywords: Productivity; Learning by Exporting

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1 Introduction

Learning by exporting (LBE) refers to the mechanism whereby firms improve their performance (productivity) after entering export markets. This mechanism is often mentioned in policy documents, based on case-studies, and has recently been confirmed for developing countries.[1] The case-study evidence tends to point to the importance of learning from foreign markets through buyer-seller relationships where exporters can learn from foreign customers and rivals about improving product quality, shipment size, or even more directly by specific investment requirements. All of the above mentioned potential mechanisms are, however, never observed or modelled in our empirical models. In practice, researchers typically rely on a residual of a production function as a measure of productivity and test whether this increases post export entry. In addition to the known problems with estimating production functions to obtain reliable measures of productivity, I focus on the role of exporting in shaping a firm's future productivity draw. In this paper I argue that even when we only observe a firm's export status, LBE can be detected by explicitly allowing the evolution of productivity to depend on previous export experience. In particular, I show that current methods are biased towards rejecting the LBE hypothesis. Moreover, they suffer from a large internal inconsistency by either (implicitly) assuming that productivity is simply an idiosyncratic shock or that productivity at the firm level follows an exogenous (Markov) process over time. In both cases, past export experience is not allowed to impact future productivity in any way. Given that our measures of productivity are typically sales per input measures, we are excluding past export experience to impact both direct technological improvements (process innovation) as well as product innovation or product quality upgrading. I do not want to distinguish between true productivity and measured productivity, because if anything, the implicit assumption in current empirical work is even stronger, i.e. past export experience is not allowed to impact any component.[2]

A significant share of studies has not found evidence for the learning by exporting hypothesis. In a survey article on international trade and technology diffusion, Keller (2004) concludes that "*The analysis has shown that there is no econometric evidence for a strong learning from-exporting effect*", but goes on to say that "*... it is puzzling that the econometric evidence is so strongly at odds with the case-study evidence*.". In a more recent survey Wagner (2007) reports strong evidence in favor of the self-selection mechanism across a wide range of countries and industries, "*while exporting does not necessarily improve productivity*". Finally, Keller (2009) does provide more evidence in favor of learning from exporting and discusses outstanding issues related to measuring the exact channels. This paper is concerned with identifying whether any effects are present, and can augment the arguments made by Keller.

Although evidence is reported for a list of developing countries, the current view is that the

[1]For instance Van Biesebroeck (2005) for Africa and De Loecker (2007) for Slovenia.

[2]I refer to De Loecker (2010) and references herein for a discussion on what measured productivity contains given we use sales (or value added) to proxy for output when estimating production functions.

correlation between firm-level export status and productivity is a result of a self-selection process of more productive firms into becoming exporters. The recent evidence using rich micro datasets should be contrasted to results obtained using aggregate data analyzing the link between trade and various macro aggregates such as output, income, TFP and innovation. For instance Frankel and Romer (1999) conclude that their results on trade and income "bolster the case for the importance of trade and trade promoting policies". However, these type of aggregate studies cannot separate the productivity gains into reallocation effects across producers and within-firm productivity gains. This paper is concerned with estimating the within-firm productivity effect associated with export entry.

The lack of overwhelming evidence from micro data impacted the direction of theoretical work in this field where not much attention is devoted to model possible feedback effects, at the level of a firm, from exporting on productivity.[3] Instead, most models of international trade with heterogeneous firms, as introduced by Melitz (2003), rely on exogenous productivity shocks coupled with a fixed cost of exporting to generate the result that exporters are more productive. These models therefore provide no direct insight in the potential role of export promotion policies often pursued by developing countries.

A recent literature has emphasized the importance of studying the productivity-export relationship while acknowledging that firms often decide to export while making investments simultaneously. I rely on my empirical framework to shed light on the separate effect of exporting on productivity, while controlling for potential joint investment decisions. Although not the focus of this paper, I provide estimates on the productivity effect of export entry while controlling for other firm-level actions such as R&D (as in Aw, Roberts and Xu forthcoming), technology adoption (as in Bustos, forthcoming) and quality upgrading (as in Verhoogen 2008). I briefly discuss such a decomposition at the end of the paper.

I stress that I do not take a stand on whether productivity gains upon export entry are due to passive learning or due to active decisions of firms. In this sense, the term learning by exporting is not rich enough to cover all potential mechanisms that might induce productivity gains when firms start exporting, such as investing in marketing, upgrading product quality, innovation, or dealing with foreign buyers. Although the difference is important and crucial for understanding the underlying mechanism, this paper is about establishing the correct predicted average productivity gain associated with firms entering export markets. Throughout the paper I refer to LBE as the process whereby exporting leads to higher productivity.

This paper is related to earlier work by De Loecker (2007) using the same data, where post export entry productivity gains were found to be important, and to vary with export destinations. This paper, however, deals with a different and new mechanism on how exporting can impact productivity. In particular, I focus on the potential role of export experience in shaping a firm's

[3] An exception is Costantini and Melitz (2007) who model a joint export-innovation decision in a dynamic model of international trade.

future productivity, while allowing other firm-level actions to impact future productivity as well. The point made in this paper extends beyond the export-productivity literature, and is important whenever we want to allow for endogenous productivity processes when evaluating the relationship between firm-level actions - such as technology upgrading, FDI, patenting, merger activity - and productivity.

2 Empirical Models Used to Test LBE

In this section I introduce my empirical model which directly allows past export experience to (potentially) impact current productivity. I show that current techniques rule out any LBE to take place in the data to start with, and hereby bias the productivity estimates in an important way. In what follows I consider the following production function (in logs) for firm i at time t generating output (y_{it}) from labor (l_{it}) and capital (k_{it}) as follows,

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where ω_{it} captures productivity and subsumes the constant term, and ε_{it} is a standard $i.i.d.$ error term capturing unanticipated shocks to production and measurement error. The point made in this paper can easily be extended towards more flexible production functions such as the translog and CES production functions. I stick to the Cobb-Douglas production function to highlight the importance of departing from the standard assumptions on the law of motion of productivity. In addition, most if not all of the empirical literature has relied on the Cobb-Douglas specification and this allows me to compare my results directly to the standard techniques.

2.1 Estimating LBE using proxy estimators

Proxy estimators suggested by Olley and Pakes (1996, OP hereafter) and Levinsohn and Petrin (2003, LP hereafter) quickly became popular in empirical international economics.[4] They provided researchers with an empirical model to estimate production functions using firm-level data and deal with the endogeneity of inputs and the non random exit of firms, as well as allowing for persistence in the unobserved productivity shocks. In particular, these methods were used to obtain firm-specific productivity measures and verify the causal relationship with export status, import status, and other firm-level international trade activities such as FDI.

2.1.1 Dealing with Unobserved Productivity Shocks

The method relies on a control function in firm specific decision variables such as investment, capital and intermediate inputs (in LP), to proxy for unobserved productivity (ω_{it}) in a first stage of the econometric procedure to estimate a production function. The crucial insight of Olley and

[4] An influential paper is this line of research is Pavcnik (2002).

Pakes (1996) is that we can proxy productivity by a function in investment and capital, or in my notation $\omega_{it} = h_t(i_{it}, k_{it})$, provided that investment is monotonically increasing in productivity, whereas Levinsohn and Petrin (2003) suggest the use of a static input, such as intermediate inputs, to control for productivity. The latter has two main advantages over the investment approach. First not all producers in micro data invest in every period, and second proving monotonicity of investment in productivity can be complicated when introducing new state variables, such as export status in my case.[5]

The focus of this paper is on the productivity process in the context of learning by exporting. This law of motion plays a crucial role in the proxy estimator approach and guides the identification of the production function coefficients.[6] Both the OP and LP method crucially rely on an exogenous (first order) Markov process for productivity, where productivity at time $t+1$ consists of expected productivity given a firm's information set, and a productivity shock ξ_{it+1},

$$\omega_{it+1} = g_1(\omega_{it}) + \xi_{it+1} \tag{2}$$

The news term in the Markov process, ξ_{it+1}, is by assumption uncorrelated with any lagged choice variables of the firm because the latter are in the firm's information set. The latter forms the basis for the identification of the capital coefficient in a final stage of the OP/LP procedure. In fact given the assumption that capital is formed by past investment, both current and lagged capital stock should be uncorrelated with shocks to the productivity process, and hence can be used to to identify the capital coefficient. The identification of variable inputs in production, such as labor, require a different strategy. We expect current labor choices to be correlated with shocks to productivity, and can therefore rely on lagged labor choices provided that wages are sufficiently serially correlated over time.

The practice of implicitly relying on such a productivity process is problematic when analyzing potential productivity effects from exporting. In particular, such a procedure does not allow for a firm's productivity to be impacted by whether it exported or not before. This has implications for testing whether exporting impacts future productivity or not and will not be helpful in evaluating the strong export-productivity correlation reported in various datasets across countries and industries. I.e. whether the correlation is generated by a process whereby firms with exogenous high draws from an underlying productivity distribution can incur the fixed cost associated with entering export markets, or whether the correlation is a consequence of exporting impacting future productivity. Note that both channels are not mutually exclusive, and one can rely on various methods to control for a potential self-selection effect, by either matching on observables or by relying on firm specific trade liberalization variables. At a minimum, in order to allow for the learning by exporting hypothesis to be true in the data, we need, at the very least, to include the

[5] I refer to Van Biesebroeck (2005) and De Loecker (2010) for a more detailed discussion.

[6] I abstract away from the additional correction for sample selection. This will lead to the inclusion of an estimated survival probability in the expected productivity component, i.e. the function $g_1(.)$.

export status in $g(.)$.[7]

To highlight the importance of not allowing export status to impact future productivity, I consider a more general model where exporting can potentially impact future productivity, given by the following process for productivity

$$\omega_{it+1} = g_2(\omega_{it}, \mathbf{E}_{it}) + \xi_{it+1} \tag{3}$$

where $\mathbf{E}_{it}$ is a vector of variables capturing a firm's export experience. For what follows I will simply rely on an export dummy variable, e_{it}, but this vector $\mathbf{E}_{it}$ can be extended to capture export intensity as measured by export sales, the number of export markets, how long the firm has been exporting, among others. The point of the paper will be reinforced when we make this specification richer. I will consider various specifications in the empirical analysis, but for the remainder of the paper I stick to the simple export dummy specification.

2.1.2 Estimation Procedure

A recent literature has discussed the ability to identify any parameter in the first stage of the OP/LP procedure. The argument made by Ackerberg, Caves and Frazier (2006) rests on the insight that conditional on a non parametric function of capital and investment (or materials), it is very unlikely that there is any variation left to identify the coefficient on the labor input. The exact specification of the first stage depends on whether a static or dynamic input control is used (material inputs or investment) to proxy for productivity, but the main point is that the first stage produces an estimate of predicted output as a function of the production function's parameters. More specifically, the first stage when relying on a proxy variable z_{it}, either investment or an intermediate input, is given by

$$y_{it} = \phi_t(z_{it}, l_{it}, k_{it}, e_{it}) + \varepsilon_{it} \tag{4}$$

where $\phi_t(z_{it}, l_{it}, k_{it}, e_{it}) = \beta_l l_{it} + \beta_k k_{it} + h_t(z_{it}, k_{it}, e_{it})$. When relying on investment the first stage control function $\phi(.)$ will include e_{it} as well since the export status of a firm impacts future productivity, and therefore constitutes a new state variable.[8] In the case where z_{it} is a static input, the export status variable is included to capture differences in input demand between exporters and domestic producers.

The parameters of interest are identified using GMM by relying on the moment conditions on ξ_{it+1}, for which we need to specify the evolution of productivity. Relying on the endogenous

[7] This is the case even when we include an export dummy as an input into the production function. In fact, the latter is problematic for at least two reasons within this setup. First of all, the impact of exporting on productivity is only deterministic, and implies that all export entrants' productivity will increase by the estimated coefficient on the export dummy. Finally, the Cobb-Doulgas production function implies that a firm can substitute any input with being an exporter at a constant unit elasticity. This remark is also valid in the context of R&D and productivity.

[8] This is distinct from the export status entering the investment policy function through modeling the firm's decision of entering the export market. However, In both cases, e_{it} will become a state variable in the underlying dynamic problem and therefore requires that the investment function includes it as well

productivity process, $\omega_{it+1} = g_2(\omega_{it}, e_{it}) + \xi_{it+1}$, I consider the following moments

$$E\left\{\xi_{it+1}(\beta_l, \beta_k)\left(\begin{array}{c} l_{it} \\ k_{it+s} \end{array}\right)\right\} = 0 \tag{5}$$

where $\xi_{it+1}(\beta_l, \beta_k)$ is obtained by non parametrically regressing $\omega_{it+1}(\beta_l, \beta_k)$ on $(\omega_{it}(\beta_l, \beta_k), e_{it})$, and $\omega_{it+1}(\beta_l, \beta_k) = \widehat{\phi}_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1}$. Note that I can in principal rely on multiple moments for capital, as indicated by $s = \{0, 1\}$, depending on the assumptions made on when a firm's capital stock is determined.

Verifying the bias on the coefficients due to endogenous productivity changes in this framework is straightforward. If $\xi_{it+1}(.)$ is obtained from simply regressing $\omega_{it+1}(.)$ on its lag, the innovation in productivity will contain lagged export status' effect on productivity. The coefficient on capital (and potentially labor) will be biased if e_{it} is correlated with k_{it+s} (l_{it}). From the above it is clear that under LBE the capital coefficient will be biased if a firm export status is correlated with its capital stock. There is overwhelming evidence that exporters are more capital intensive, and therefore will imply an upward bias of the capital coefficient. This arises because too much variation in output (purified from variation in labor) is attributed to variation in the capital stock

This general framework also shows that the labor coefficient is potentially biased as well. However, the first stage of a modified OP approach, where the export status is explicitly treated as a state variable, would control for this potential correlation. Therefore I focus mostly on the role of capital and how it interacts with the productivity process. Finally, it is important to note that this approach allows for both labor and capital to be treated as dynamic inputs.[9] In fact, in the latter case I can rely on l_{it+s} for $s = \{0, 1\}$ as well, and test for overidentifying restrictions in the GMM framework.

2.1.3 Illustration: a special case

I illustrate the potential bias from excluding past export experience in the productivity process using a simplified version of the model discussed above. I consider a simple case where productivity follows an $AR(1)$ process with a coefficient of one, and is simply a linear function of past export status and a shock to productivity which occurs after the investment decision.

$$\omega_{it+1} = \omega_{it} + \gamma e_{it} + \xi_{it+1} \tag{6}$$

The moment conditions used to identify the production coefficients, as given by (5), are constructed by running a simple regression of productivity given parameters, $\omega_{it+1}(\beta_l, \beta_k)$, on its lag and an export dummy as given by (6). If we ignore the effect of past export experience on current productivity, or in other words if we exclude the term γe_{it}, the productivity shock contains variation in export status. The moments used to estimate the coefficients are based on an error term which contains export status variation, i.e. $\xi^*_{it+1} = \xi_{it+1} + \gamma e_{it}$. This will lead to biased estimates

[9] This would require making $h_t(.)$ a function of l_{it} as well. For my purpose the difference is irrelevant.

of the production function coefficients if a firm's capital stock (labor) is correlated with its export status. In this special case the magnitude of the capital coefficient's bias is directly related to γ. It is useful to return to the original OP framework and consider the final stage of their procedure under this specific law of motion (6). It is easy to show that the capital coefficient is obtained after running the following OLS regression

$$\Delta\widetilde{y}_{it+1} = c + \beta_k \Delta k_{it+1} + \gamma e_{it} + \xi_{it} + \varepsilon_{it+1} \tag{7}$$

Output growth purified from variation in labor ($\Delta\widetilde{y}_{it+1}$) is related to capital growth and the firm's lagged export status. Ignoring the export status e_{it} will lead to a biased estimate of β_k if the (percentage) change in capital is correlated with the firm's lagged export status. Note that in this simplified framework the change in capital Δk_{it+1} picks up variation in investment across firms, in addition to a common depreciation factor. If firms that export at time t also invested more at t, our estimate of the capital coefficient will be biased.

In fact, we expect this correlation to be positive if anything, and hereby overestimate the capital coefficient and attribute productivity variation coming from export experience to capital variation. Or in other words if productivity gains from exporting occur simultaneously with investment, this will bias the capital coefficient upward and, as I will show below, will underestimate the actual productivity effect from exporting by attributing it to a growth in capital.

In sum, when excluding the export status in the law of motion of productivity, the model is internally inconsistent if LBE is the true underlying process in the data, if it is not, the relevant coefficients of $g(.)$ will not be significant. In addition, we get a biased estimate of the capital coefficient and therefore of firm-level productivity in a systematic way that biases against finding LBE. This has direct implications for testing the LBE hypothesis, which is mostly tested by comparing productivity trajectories of exporters while entering export markets (during the sample period) with that of non exporters. If firms that become exporters also invest more into capital, the productivity gain from exporting will be underestimated and might lead to the false conclusion that being an exporter does not impact future productivity. Again, I do not take a stand whether investing in capital is a source of LBE. In this paper I want to correctly predict the future productivity path of exporters.

2.2 Alternatives to proxy estimators

Although the focus of this paper is on using proxy estimators to detect LBE, it is important to note that the same critique applies to other empirical methods used in the literature. For instance, one of the earliest studies by Bernard and Jensen (1999) using US plant-level data relied on *OLS* based production function residuals to test for LBE effects, and found no strong evidence. First of all, the use of *OLS* is problematic when it comes to obtaining consistent estimates of the production function coefficients. In addition, using *OLS* assumes that a firm's productivity shock is independent of any activity or decision made by the firm in the past, including export behavior.

Relying on *OLS* implies that productivity is not correlated with any input choice and in addition that it is not correlated over time (within firms). The latter implies that past export experience is not allowed to influence future productivity outcomes. The productivity residuals obtained using *OLS* are therefore not suited to test the LBE hypothesis as they are obtained under the assumption that "learning effects" are not present. An often used alternative is the use of firm fixed effects, which implies that productivity only moves over time due to idiosyncratic shocks (υ_{it}), $\omega_{it} = \omega_i + \upsilon_{it}$, which clearly does not allow for LBE either. In fact, for firms that enter export markets during the sample period, the export effect will be washed out due to averaging productivity over both the pre and post export years.

2.3 Implications for detecting LBE

The ultimate goal of estimating production functions is to obtain firm-specific estimates for productivity or performance more broadly. Let me denote the coefficient of the production function obtained with and without explicitly allowing LBE effects by β^e and β, respectively. For now, I assume that the labor coefficient is estimated consistently. The latter is the case when relying on a standard OP/LP setup where lagged export status is incorporated in the control function in the first stage.[10] This implies that the difference in estimated productivity is given by $(\beta_k - \beta_k^e)k_{it}$, and from the discussion above, I expect this to be positive. In other words, productivity is overestimated in levels, no matter whether a firm is an exporter or not (if exporting is not an input into the production function).

I highlight the implications of the biased capital coefficient in a simple difference-in-difference framework. However, the point made here is more general. In particular, let us consider the change in productivity before and after a firm becomes an exporter and compare it to a firm that does not but is identical in any other dimension. If an exporter becomes both more productive and expands its capital stock, too much of the growth in capital ($\beta_k - \beta_k^e$) is subtracted from output growth and will not be attributed to productivity growth upon export entry.

The average productivity effect of export entry after s periods (LBE_s) using non exporters' productivity (ω_{is}^d) as a control group (C) is given by the average difference between productivity growth of export entrants (ω_{is}^e) belonging to the set of starters ($START$) and domestic producers.

$$\begin{aligned} LBE_s &= \frac{1}{N}\left[\sum_{i \in START} \Delta\omega_{is}^e - \sum_{i \in C} \Delta\omega_{is}^d\right] \\ &= \sum_i \left[(\Delta y_{is}^e - \Delta y_{is}) - \beta_l(\Delta l_{is}^e - \Delta l_{is}) - \beta_k(\Delta k_{is}^e - \Delta k_{is})\right] \end{aligned} \tag{8}$$

where $\Delta x_{is} = x_{is} - x_{i,-1}$ and $s = 0$ is the time when a firm enters the export market with $s = \{0, 1, ..., S\}$ and I dropped the relevant summation index. Therefore the impact of underestimating

[10] See Van Biesebroeck (2005) and De Loecker (2007). I focus mostly on the role capital and exporting in shaping the evolution of productivity.

the capital coefficient, interacted with the increase in capital stock at the time of export entry implies that we do not correctly identify the productivity effect of entering foreign markets. Or more formally, I can write the bias of the learning by exporting effect for $s = \{0, 1, .., S\}$ by considering the difference of (8) between the exogenous (LBE_s) and the endogenous productivity process (LBE_s^*)

$$|LBE_s - LBE_s^*| = (\beta_k - \beta_k^e)\frac{1}{N}\sum_i(\Delta k_{is}^e - \Delta k_{is}) \tag{9}$$

The bias is a function of two terms. The first one is due to the different estimate of the capital coefficient by allowing the productivity process to depend on past export status. The second term is the (average) difference in capital stock growth between exporters and non exporters, or a reduced set of the latter when relying on matching techniques. Up to differences in depreciation rates among exporters and domestic producers, the second term captures differences in investment over s periods between exporters and domestic producers.

This last equation clearly demonstrates that we will typically underestimate the LBE effect given that both terms are expected to be positive. The extent to which standard methods will underestimate LBE depends on how much exporters grow disproportional in their capital stock ($\Delta k_{is}^e - \Delta k_{is}$), as well as how strong the role of exporting is in the law of motion on productivity ($\beta_k - \beta_k^e$). It is clear that the bias potentially grows with the time frame used to verify the LBE effect, i.e. for $s = \{0, 1, 2, .., S\}$, as the potential for exporters to further widen the capital stock gap with domestic producers increases. I will empirically quantify (9) using firm-level data where a substantial amount of firms enter the export market during the sample.

3 Data

I rely on a unique dataset covering all firms active in Slovenian manufacturing during the period 1994-2000. I refer the reader to De Loecker (2007) for more details on the Slovenian data. In sum, the data are provided by the Slovenian Central Statistical Office and contains the full company accounts for an unbalanced panel of 7,915 firms. I also observe market entry and exit, as well as detailed information on firm level export status.

Over the time period 1994-2000, 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 the total number of firms, in total sales and total employment. I observe a 42 percent increase in total exports of manufacturing products over the sample period. Furthermore, entry and exit 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.

4 Results

Before I estimate the model with a more general law of motion for productivity I report a number of fundamental correlations in the data. In my sample exporters are clearly more capital intensive and they become even more so (compared to domestic producers in the same industry) upon export entry. Table 1 indicates the importance of incorporating the export status of a firm in law of motion of productivity. In panel A I report the average export premium for capital and investment while controlling for industry and year effects. I consider two partial correlations that directly relate to equation (6), by controlling for employment (I) and employment and output jointly (II). In panel B, I report the percentage capital growth difference between new exporters and domestic producers after export entry ($s = 0$) for various windows ($s = 1, 2, 3, 4$), while controlling for a full set of year and time effects.

The results in panel A indicate that without correcting the standard model, the capital coefficient will be biased given the strong correlation between a firm's export status and its level of capital stock, after controlling for output and employment. Panel B clearly shows that new exporters' capital stock grows faster than their domestic counterparts. For example, four years after export entry the difference in the growth of capital is 37 percent. Both observations directly relate to the two components of the bias in the LBE parameter, as described in equation (9) and imply an underestimation of the LBE effect since both terms are expected to be positive and quite large. In fact, using expression (9), I only need to estimate the capital coefficient under a more general law of motion of productivity to compute the actual LBE parameter by multiplying the difference in the estimates of the capital coefficient ($\beta_k - \beta_k^e$) by the average capital growth difference upon export entry. Under the approach outlined under section 2 the growth differential in labor interacted with the difference in labor coefficients will add to the bias in the LBE parameter.

I first need to estimate the coefficients for each industry in my data separately. I estimate the coefficients under the assumption of a pure exogenous productivity process and compare them with estimates obtained from a more general law of motion of productivity whereby I allow exporting to impact future productivity in a flexible way.[11] I report the estimated coefficients in the Appendix. The results are as expected and hold for every 2 digit industry reported. As expected the capital coefficient is estimated significantly lower when allowing for a more general law of motion on productivity, confirming the positive correlation between a firm's export status and its capital stock. On average, the capital coefficient is estimated 30 percent lower.[12] It is worth mentioning that the bias in the labor coefficients is significantly smaller. This table is at some level sufficient to conclude that taking an endogenous productivity process to the data is important for obtaining the

[11] I rely on a 4th order polynomial in productivity and interact all terms with various variables measuring past export experience such as a simple export dummy, the export share in total sales to capture the intensity of exporting, the number of years exported. The estimated coefficients are robust with respect to the inclusion of these additional variables.

[12] I checked whether ($\beta_k - \beta_k^e$) is significantly different from zero for each industry using the bootstrapped standard errors of both estimators.

correct LBE parameter. However, in order to compute the additional productivity effects from export entry, I need to compute the input growth differentials between starters and their domestic counterparts.

Table 2 reports the bias in the LBE parameter using (9) for $s = \{0, 1, 2, 3\}$, or the additional productivity gain after $s + 1$ years of exporting. The additional productivity gain (or the bias) is reported for each industry, and for the manufacturing sector at large. The columns consider different windows (s) and I expect, if anything, the bias to increase with s. The results in Table 2 show that across the various industries of the manufacturing sector, the bias in the LBE parameter is substantial. Taking stock of the differences in the production function coefficients reported in the Appendix, this table reflects that exporters' input usage grows faster compared to their domestic counterparts. Both effects imply that one would underestimate the importance of export entry of future productivity, as suggested in equation (9).

For instance, in the Chemical industry (sector 24), an additional 7.35 percent productivity growth effect upon export entry is found when relying on a more general law of motion for productivity. The bias in the LBE parameter is considerable in magnitude ranging from 1.08 to 7.38 percent additional productivity after four years of exporting. The additional productivity effects need to added to the productivity effects potentially obtained using standard methods. Finally, I do find substantial heterogeneity across sectors, which can be traced back to either heterogeneity in input growth differences between exporters and domestic producers, or to heterogeneity in the impact of exporting on future productivity across sectors.

5 Identifying the separate effect of exporting

Although this paper is focussed on correctly predicting the productivity effect of exporting, my framework can help shed light on the separate role of exporting when firms jointly decide on exporting and investments broadly defined. A recent literature has emphasized the importance of studying the productivity-export relationship while acknowledging that firms often decide to export while making investments simultaneously. Therefore, we might overstate the effect of exporting on productivity if becoming an exporter was jointly decided with other productivity enhancing actions.

I briefly show how my empirical framework can single out the impact of exporting, while holding "investments" fixed. As I will argue below, given the data constraints I face I do not pursue a precise decomposition of the role of exporting, technology adoption and other firm-level actions that potentially raise future productivity. However, I do show that my framework is a natural setting to study this.

Given the above, I assume that the data on firm-level investment (i_{it}) contains expenditure on new technologies, and upgrading of existing production processes. Obviously, it also captures the standard capital expansion expenditures. It is important to understand that in this way I attribute future productivity effects to a wide range of firm-level actions and I can therefore isolate the role of exporting. The matched treatment estimator does control for those firm-level actions, by comparing firms who only differ in their export status. However, that approach cannot verify the additional impact of jointly entering export markets and investing. The law of motion on productivity is then given by $\omega_{it+1} = g(\omega_{it}, i_{it}, e_{it}) + \xi_{it+1}$,where I now explicitly allow future productivity gains to come from either exporting or investing, or both. Note that the same arguments apply on the importance of incorporating lagged investment expenditures to obtain consistent estimates of the production function.

For the empirical analysis I consider the following parametric form for the productivity process which is similar to Aw, Roberts and Xu (forthcoming), only that in addition I allow for interactions between the level of productivity and firm level actions, exporting and investing.

$$\omega_{it+1} = \sum_{j=0}^{3} \theta_j \omega_{it}^j + \theta_4 i_{it} + \theta_5 e_{it} + \theta_6 e_{it} i_{it} + \theta_7 i_{it} \omega_{it} + \theta_8 e_{it} \omega_{it} + \theta_9 e_{it} i_{it} \omega_{it} + \xi_{it+1} \quad (10)$$

Table 3 shows the results of running this procedure on the Slovenian manufacturing sectors. I rely on materials to proxy for productivity and use the moments described in section 2. In addition to the estimates of of θ, I also present the result of a F-test on the joint significance of all θ_k for $k = \{4, ..., 9\}$ which implies testing whether productivity follows an exogenous process.

Table 3 shows the importance of incorporating the relevant firm-level actions that can plausibly affect future productivity to obtain correct estimates of the production function coefficients, and consequently productivity. The additional effect of investing, while having the same export status and productivity level is less of interest to me given my aggregate measure of investment, which contains replacement investment, capital expansion, in addition to investing in new technologies.[13]

I can now compute the additional effect from joint exporting and investing, while holding the level of productivity fixed. In this way I can compare predicted productivity effect from joint exporting and investing. Using my estimates I can compute this for each firm using $\widehat{\theta}_6 i_{it} e_{it} + \widehat{\theta}_9 i_{it} e_{it} \omega_{it}$. I report the average predicted additional productivity effect from the joint decision to export and invest for the manufacturing sector and the various industries in the Appendix. Across all sectors exporting and investing raises future productivity, and the average ranges from 1 to 8 percent. The standard deviation within industries is substantial and reflects the large variation in investment and productivity among firms who jointly export and invest.

Finally, while I am comparing firms with the same level of productivity, I still allow for a magnifying effect as measured by θ_9. When comparing two firms who both jointly enter the export market and invest the same dollar amount, θ_9 captures the additional productivity effect for the more productive firm. Similarly, θ_8 captures the idea that the productivity effect from exporting last period depends on the firm's productivity level. The results indicate that the productivity gains are lower when firms are already very productive.

[13]My results do support the hypothesis that investing raises (expected) future productivity, as assumed by various theoretical frameworks in industry dynamic models.

6 Conclusion

In this note I show how current methods that are used to test for learning by exporting are biased towards rejecting this hypothesis. I address the large inconsistency in current empirical approaches by allowing exporting to affect a firm's future productivity. I show that recent proxy estimators of production functions are a natural framework to accomplish this by allowing for an endogenous productivity process. I provide a simple way to sign the importance of the bias and apply it to a firm-level dataset. I find substantial additional productivity gains associated with export entry, ranging up to 7.35 percent.

These results indicate the importance of export participation for productivity growth and warrant further investigation of the exact underlying mechanisms and its potential policy implications. I reported results for the case of Slovenia to show the importance of my correction. Slovenia is good case to study this since there was substantial export entry during the sample period and at the same time LBE is plausible given that exporting opened new possibilities for domestic firms . In doing so I make a simple point that in order to test the learning by exporting hypothesis in the data we need at the very least an empirical model that allows future productivity to depend on past export participation, to estimate the correct productivity effects from export participation. The methodology discussed in this paper extends naturally to cases where firm level actions impact future productivity, such as technology adoption, R&D, product quality upgrading, and investment more broadly defined.

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Appendix. Production Function and Exporting-Investment Results

1. *Production Function Coefficients.*

I present the estimated coefficients of the production function under the standard exogenous productivity process assumption, and compare it to my endogenous process, where exporting is allowed to impact future productivity. I list the percentage difference between both estimates.

Table A.1 Production function coefficients

Industry	Capital Coefficients			Labor Coefficients		
	Exog.	Endog.	Diff.	Exog	Endog	Diff.
15	0.181	0.131	38	0.863	0.810	7
17	0.190	0.165	15	0.774	0.562	38
18	0.175	0.152	15	0.844	0.833	1
19	0.373	0.356	5	0.599	0.542	11
20	0.088	0.063	40	0.908	0.885	3
22	0.361	0.337	7	0.662	0.603	10
24	0.373	0.274	36	0.681	0.601	13
25	0.201	0.142	42	0.768	0.669	15
26	0.321	0.255	26	0.687	0.614	12
27	0.058	0.042	39	0.910	0.751	21
28	0.250	0.194	28	0.714	0.666	7
29	0.237	0.199	19	0.669	0.700	-4
31	0.254	0.223	14	0.742	0.558	33
32	0.268	0.155	73	0.759	0.732	4
33	0.179	0.120	50	0.862	0.797	8
36	0.194	0.146	33	0.781	0.709	10

All Coefficients are significant at the 1 percent. Standard errors are obtained by block bootstrapping.

The industry classification NACE rev. 1 is similar to the ISIC industry classification in the U.S.A. and the various industries with corresponding code are: Food Products (15), Textiles (17), Wearing Apparel (18), Leather and Leather Products (19), Wood and Wood Products (20), Pulp, Paper and Paper Products (21), Chemicals (24), Rubber and Plastic Products (25), Other non-Metallic Mineral Products (26), Basic Metals (27), Fabricated Metal Products (28), Machinery and Equipment n.e.c. (29), Electrical Machinery (31), RTv and Communication (32), Medical, Precision and Optical Instruments (33), Other Transport Equipment (35), Furniture and Manufacturing n.e.c. (36).

2. Joint Export-Investment Productivity Effects.

I report the average, by industry and across all manufacturing sectors, joint export-investment productivity effect. These numbers should be interpreted as the average additional percentage predicted productivity effect from jointly entering export markets and investing, compared to a domestic firm who does not invest.[14] The variation across firms within a sector comes from the variation in actual investment expenditures.

[14] Alternatively, I can rely on a fixed replacement investment rate and consider a threshold percentage to consider a smaller sample of investing firms, or equivalently a large share of non investing firms.

Table A.2. Joint export-investment productivity effects

Industry (Nace 2)	Additional Effect (%)
15	1.5
17	5.4
18	2.4
19	5.6
20	2.1
22	1.1
24	7.8
25	3.3
26	3.5
27	7.7
28	2.5
29	4.7
31	5.8
32	5.0
33	4.6
36	2.4
Manufacturing	3.69

Table 1: Capital stock and export status

	A: Correlation Export		B: Capital Growth	
	I	II	Window (s)	$\sum_i(\Delta k_{is}^e - \Delta k_{is})$
Capital	0.38	0.21	1	0.21 (0.02)
	(0.02)	(0.02)	2	0.25 (0.04)
Investment	0.39	0.18	3	0.37 (0.05)
	(0.03)	(0.03)	4	0.35 (0.07)

Table 2: Additional Productivity Gains (bias LBE)

Industry	$s=0$	$s=1$	$s=2$	$s=3$
15	1.52	2.77	3.11	4.06
17	0.21	2.60	4.46	5.92
18	0.57	1.05	1.11	1.47
19	0.93	1.63	2.02	2.57
20	0.73	1.33	1.48	1.93
22	1.07	1.89	2.29	2.92
24	2.79	5.09	5.60	7.35
25	2.18	3.91	4.58	5.90
26	2.07	3.75	4.23	5.51
27	1.91	3.27	4.37	5.44
28	1.60	2.91	3.23	4.22
29	0.47	0.96	0.733	1.08
31	2.45	4.24	5.51	6.90
32	2.56	4.77	4.92	6.58
33	1.85	3.36	3.79	4.94
36	1.69	3.04	3.52	4.55
Manufacturing	1.52	2.73	3.14	4.07

The Appendix lists the industry classification codes with their corresponding descriptions.

Table 3: Estimates of Productivity Process

Parameter	Estimate	Standard Error
θ_1	0.853	0.025
θ_2	0.074	0.017
θ_3	-0.015	0.004
θ_4	0.020	0.003
θ_5	0.172	0.044
θ_6	-0.038	0.011
θ_7	-0.007	0.002
θ_8	-0.111	0.026
θ_9	0.024	0.004
#Obs	5,203	
F-test	$F(6, 5203) = 38.61$	