

## Detecting Learning by Exporting<sup>†</sup>

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*Learning by exporting refers to the mechanism whereby a firm's performance improves after entering export markets. This mechanism is often mentioned in policy documents, but many econometric studies have not found corroborating evidence. I show that the econometric methods rely on an assumption that productivity evolves exogenously. I show how to accommodate endogenous productivity processes, such as learning by exporting. I discuss the bias introduced by ignoring such a process, and show that adjusting for it can lead to different conclusions. Using micro data from Slovenia, I find evidence of substantial productivity gains from entering export markets. (JEL D22, D24, D83, F14, L25)*

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. The case study evidence points to the importance of learning from foreign markets both directly, through buyer-seller relationships, and indirectly, through increased competition from foreign producers. In particular, exporters can learn from foreign customers and rivals by improving product quality, shipment size, or, even more directly, by undertaking specific investments. All of the above mechanisms are, however, never observed or modeled in our empirical models. In practice, researchers typically rely on a residual of a production function as a measure of productivity, and they test whether this increases post-export entry.

In this paper, I focus on the role of exporting in shaping a firm's future productivity. I argue that LBE can be detected by explicitly allowing the evolution of productivity to depend on previous export experience. I show that currently used econometric methods rely on the assumption that productivity evolves exogenously. I show how to accommodate endogenous productivity processes, such as learning by exporting, and depart from the standard assumption that export experience does not impact a firm's future performance.

Most, if not all, empirical work relies on measures of productivity that reflect sales per input at the firm level. Therefore, an exogenous productivity process implies that past export experience has no impact on direct technological improvements (process innovation), or on sales through product innovation or product quality upgrading.

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<sup>†</sup>Go to <http://dx.doi.org/10.1257/mic.5.3.1> to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

Learning by exporting refers to a variety of mechanisms that might induce productivity gains when firms start exporting, such as investing in marketing, upgrading product quality, innovating, or dealing with foreign buyers.

Although this paper is not concerned with separating the various components of measured productivity, I highlight that the implicit assumption in current empirical work is even stronger: export experience is not allowed to impact any component. The difference is important and crucial for understanding the underlying mechanism; however, this paper is about establishing the correct predicted productivity gain associated with firms entering export markets. Throughout the paper, I refer to LBE as the process whereby exporting leads to higher productivity.

A number of studies have not found evidence for the learning by exporting hypothesis. In a survey article on international trade and technology diffusion, Keller (2004) concludes that there is very little evidence from econometric studies, while there is substantial evidence from case studies. Wagner (2007) reports strong evidence in favor of the self-selection mechanism across a wide range of countries and industries, while exporting does not enhance productivity. Keller (2010) provides evidence supporting 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 augments Keller's (2004, 2010) arguments.

The recent evidence using rich micro datasets should be contrasted with 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 types of aggregate studies cannot separate the productivity gains into reallocation effects across producers and within-firm productivity gains. This paper aims to estimate the within-firm productivity effect associated with export entry. Of course, in order to obtain the correct aggregate effects, we again require the correct estimates at the micro level.

A recent literature has emphasized the importance of studying the productivity effects of exporting, while acknowledging that firms often simultaneously undertake substantial investments to improve their performance. I rely on my empirical framework to shed light on the separate effect of exporting on productivity, while controlling for potential joint investment decisions. 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 2011), technology adoption (as in Bustos 2011 and Lileeva and Trefler 2010), and quality upgrading (as in Verhoogen 2008). These papers rely on specific underlying theoretical mechanisms that generate a correlation between export status and productivity, through a separate productivity-enhancing activity.

My approach is silent on the exact theoretical mechanism. However, my empirical framework nests these approaches by allowing for a general process for productivity, whereby past export activities are flexibly allowed to affect a firm's productivity. This flexible approach is particularly important because it allows the effects of exporting to be heterogeneous across producers.

The identification strategy is based on a general class of models, with the important feature that firms cannot immediately adjust their export status in light of a productivity or demand shock.

After having discussed the potential bias of ignoring a firm's export experience in the underlying productivity process, I demonstrate the importance of this bias using data on Slovenian manufacturing firms. It is ultimately an empirical question whether this bias is important in other data and settings. At a minimum, though, we need more work on other countries before we can know whether there is learning from exporting, and whether developing countries can rely on export promotion to improve the performance of the domestic economy.

This paper is related to earlier work by Van Biesebroeck (2005) and De Loecker (2007) in which exporting is introduced in the estimation of production functions. This paper, however, deals with a different mechanism whereby exporting can impact productivity. In particular, I focus on the potential role of export experience in shaping a firm's future productivity, while allowing other firm-level actions to impact future productivity. The point made in this paper extends beyond the export-productivity literature: it 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.<sup>1</sup>

## I. Empirical Framework

In this section, I introduce my empirical model, which allows past export experience to (potentially) impact current productivity. I show that current techniques rule out any LBE, thus, biasing the productivity estimates in an important way.

I consider the following production function (in logs) for firm  $i$  at time  $t$  generating output ( $y_{it}$ ) from labor ( $l_{it}$ ) and capital ( $k_{it}$ ):

$$(1) \quad y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it},$$

where  $\omega_{it}$  captures productivity and subsumes the constant term, and  $\epsilon_{it}$  is a standard i.i.d. error term capturing unanticipated shocks to production and measurement error. The point made in this paper extends directly to 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.<sup>2</sup>

I focus on the process of productivity while relying on a set of standard assumptions used throughout the literature.<sup>3</sup> One important assumption is that productivity enters in a Hicks-neutral fashion.<sup>4</sup>

<sup>1</sup> See Doraszelski and Jaumandreu (2011) for a discussion in the context of estimating the productivity effects of R&D activities.

<sup>2</sup> 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 those obtained with standard techniques. I refer to De Loecker and Warzynski (2012) for more details on how this approach can be used to identify more general production functions.

<sup>3</sup> See Akerberg, Caves, and Frazer (2006) for an overview.

<sup>4</sup> This is the main assumption I rely on to identify the parameters of interest. All of the results in this paper go through using a production function of the form:  $y_{it} = f(l_{it}, k_{it}) + \omega_{it} + \epsilon_{it}$ .

### A. Estimating LBE

Estimating production functions using *proxy estimators*, as suggested by Olley and Pakes (1996)—henceforth, OP—and Levinsohn and Petrin (2003)—henceforth, LP—quickly became popular in the field of empirical international economics.<sup>5</sup> This approach provides a framework for estimating production functions using firm-level data and explicitly corrects for the well-known simultaneity and selection biases. In particular, these methods are used to obtain firm-specific productivity measures and verify the causal effect of participating in international trade on productivity, through exporting, importing, and other firm-level activities such as direct foreign investment.<sup>6</sup>

*Dealing with Unobserved Productivity Shocks.*—To proxy for unobserved productivity to estimate a production function, the method relies on a control function in firm-specific decision variables such as investment, capital, and intermediate inputs (in LP). The crucial insight of OP is that we can proxy productivity by a function of investment and capital, whereas LP suggest the use of a static input, such as intermediate inputs, to control for productivity.<sup>7</sup>

This paper focuses on the productivity process in the context of learning by exporting. 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  $\xi_{it+1}$ :

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

This law of motion plays a crucial role in the proxy estimator approach and guides the identification of the production function coefficients.<sup>8</sup>

This specification (2) nests other, more traditional approaches used in the literature such as OLS and fixed effect, where the productivity process is given by  $g(\omega_{it}) = 0$  and  $g(\omega_{it}) = \omega_{it}$ , respectively, and  $\xi_{it}$  is an i.i.d. shock to output across firms and time in both cases. Therefore the point made in this paper also extends to these methods.<sup>9</sup>

<sup>5</sup> An influential paper in this line of research is Pavcnik (2002).

<sup>6</sup> See, for example Van Biesebroeck (2005), De Loecker (2007), Halpern, Koren, and Szeidl (2011), and Amiti and Konings (2007) for applications of this approach, where, in particular, measures of international participation at the firm level (such as exporting and importing), are included.

<sup>7</sup> There is a trade-off between both approaches. In this context, the intermediate input proxy approach, LP, has two main advantages over the investment approach. First not all producers in micro data invest in every period, and second showing monotonicity of investment in productivity can be complicated when introducing new state variables, such as export status in my case. I refer to Van Biesebroeck (2005) and De Loecker (2007, re2011) for a more detailed discussion.

<sup>8</sup> 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.

<sup>9</sup> In this context, both approaches are problematic. 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, including past export behavior. Using firm fixed effects does not allow for LBE either.

The term  $\xi_{it+1}$  is by assumption uncorrelated with any lagged choice variables of the firm because the latter are in the firm's information set. This forms the basis for the identification of the capital coefficient in a final stage of the OP/LP procedure. Furthermore, using the standard assumption that capital is formed by past investments, both current and lagged capital stock should be uncorrelated with shocks to the productivity process, and can be used to identify the capital coefficient.<sup>10</sup>

The practice of (implicitly) relying on a productivity process given by (2) is problematic if the objective is to estimate the productivity effects from exporting. Moreover, it cannot help in distinguishing various data-generating processes that all lead to a strong export-productivity correlation, as reported in various datasets across countries and industries. In particular, it is important to know whether the correlation is due to an underlying process whereby firms with exogenously high productivity incur the fixed cost of entering export markets; or whether the correlation is a consequence of export activities directly affecting productivity.

These 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, as in De Loecker (2007), or by relying on firm-specific trade liberalization variables as suggested by Lileeva and Trefler (2010). However, at a minimum, we need to allow for LBE to take place or, more formally, include export information in the productivity process ( $g(\cdot)$ ).<sup>11</sup>

I consider a general model in which exporting is allowed to impact future productivity as given by

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

where  $\mathbf{E}_{it}$  is a vector measuring a firm's export experience.<sup>12</sup> For notational convenience, I assume that  $\mathbf{E}_{it}$  is simply an export dummy,  $e_{it}$ , but the vector  $\mathbf{E}_{it}$  can be extended to capture export intensity, as measured by export sales, the number of export markets, and how long the firm has been exporting, among others. The point made in this paper remains valid when including more information.<sup>13</sup>

It is important to re-emphasize that I explicitly rely on a sales-generating production function. This implies that  $\omega_{it}$  is meant to capture differences in both firm-level cost and demand factors. The productivity process then suggests that firms entering exporting markets do expect an impact on their future revenue through either

<sup>10</sup> 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.

<sup>11</sup> This is the case even when we include an export dummy as an input into the production function, or if  $y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_e e_{it} + \omega_{it}$ . In fact, the latter is problematic for at least two reasons within this setup. First, 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. Second, the Cobb-Douglas 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.

<sup>12</sup> This law of motion for productivity is similar to the one used by Doraszelski and Jaumandreu (2011), except that they include lagged R&D expenditures instead of a firm's export status.

<sup>13</sup> I will consider various specifications in the empirical analysis, but for the remainder of the paper, I stick to the simple export dummy specification.

increased demand and/or decreased cost of production. Unexpected effects from exporting, which materialize in higher output, are captured by  $\xi_{it+1}$ .

*Estimation Procedure.*—The parameters of interest are identified using moment conditions of the productivity shock  $\xi_{it+1}$ , for which we need to specify the evolution of productivity. Given the endogenous productivity process (3), I rely on the following moment conditions:

$$(4) \quad E \left\{ \xi_{it+1} (\beta_l, \beta_k) \begin{pmatrix} l_{it} \\ k_{it+1} \end{pmatrix} \right\} = 0,$$

where  $\xi_{it+1}(\beta_l, \beta_k)$  is obtained by nonparametrically regressing  $\omega_{it+1}(\beta_l, \beta_k)$  on  $(\omega_{it}(\beta_l, \beta_k), e_{it})$ , and  $\omega_{it+1}(\beta_l, \beta_k) = \hat{\phi}_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1}$ . Predicted output,  $\hat{\phi}_{it+1}$ , is obtained from a first-stage regression of output ( $y_{it}$ ) on all the inputs ( $l_{it}, k_{it}$ ) and the proxy variables including either intermediate inputs or investment, capital, and the firm's export status.<sup>14</sup>

If we now incorrectly assume an exogenous productivity process, the productivity shock ( $\xi_{it+1}$ ) contains the productivity effect of exporting. The coefficient on capital (and potentially labor) will, therefore, be biased if  $e_{it}$  is correlated with  $k_{it+1}$  ( $l_{it}$ ). From the above, it is clear that under LBE, the capital coefficient will be biased if a firm's export status is correlated with its (future and current) capital stock. In the latter, the capital coefficient will be biased upwards. This arises because too much variation in output (purified from variation in labor) is attributed to variation in the capital stock.<sup>15</sup>

### B. Illustration: A Special Case

Using a simplified version of the model discussed above, I illustrate the potential bias from excluding past export experience in the productivity process. I consider a simple case in which 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 that occurs after the investment decision:

$$(5) \quad \omega_{it+1} = \omega_{it} + \gamma e_{it} + \xi_{it+1}.$$

<sup>14</sup> A recent literature has discussed the ability to identify any parameter in the first stage of the OP/LP procedure. The argument made by Akerberg, Caves, and Frazier (2006) rests on the insight that, conditional on a nonparametric 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  $y_{it} = \phi_t(z_{it}, l_{it}, k_{it}, e_{it}) + \epsilon_{it}$ , where  $\phi_t(z_{it}, l_{it}, k_{it}, e_{it}) = \beta_l l_{it} + \beta_k k_{it} + h_t(z_{it}, k_{it}, e_{it})$  where  $\omega_{it} = h(\cdot)$  is the proxy for productivity, which is obtained after inverting the intermediate input (or investment) equation as discussed in OP and LP.

<sup>15</sup> This general framework also shows that the labor coefficient is potentially biased. However, the first stage of a modified OP approach, where the export status is explicitly treated as a state variable, can, in principal, 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.



The moment conditions used to identify the production coefficients, as given by (4), 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 (5). If we ignore the effect of past export experience on current productivity, or if we exclude the term  $\gamma e_{it}$ , the productivity shock contains variation in export status. The moments used to estimate the coefficients are based on an error term that contains export variation—i.e.,  $\xi_{it+1}^* = \xi_{it+1} + \gamma e_{it}$ . This will lead to biased estimates 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  $\gamma$ . It is useful to return to the original OP framework and consider the final stage of their procedure under this specific law of motion (5). It is easy to show that the capital coefficient is obtained after running the following OLS regression:<sup>16</sup>

$$(6) \quad \Delta \tilde{y}_{it+1} = c + \beta_k \Delta k_{it+1} + \gamma e_{it} + \xi_{it} + \epsilon_{it+1}.$$

Defining  $\Delta x_{is} = x_{is} - x_{i,s-1}$ , output growth purified from variation in labor ( $\Delta \tilde{y}_{it+1}$ ) 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  $\beta_k$  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  $\Delta k_{it+1}$  picks up variation in investment across firms, in addition to depreciated capital. If firms that export at time  $t$  also invested more at  $t$ , our estimate of the capital coefficient would be biased.

In fact, we expect this correlation to be positive, if anything, and thereby overestimate the capital coefficient and attribute productivity variation coming from export experience to capital variation. 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 LBE.

### C. Implications for Detecting LBE

Relying on a misspecified productivity process leads to biased estimates of the production function and of productivity in a systematic way. This has direct implications for testing the LBE hypothesis, which is tested mainly by comparing productivity trajectories of new exporters to *similar* domestic producers using difference-in-difference techniques (DID). I revisit the DID approach and compare it to my nonparametric estimate of LBE.

*A Nonparametric Estimate of LBE.*—A nonparametric estimate of the function  $g_2(\cdot)$ , or expected productivity given past productivity and the firm's export status, is obtained alongside the production function coefficients. Therefore, when including the correctly specified productivity process, given by equation (3), an estimate of LBE is directly obtained. The standard approach in the literature, however, is to obtain an estimate of productivity without allowing exporting to affect

<sup>16</sup> See Appendix B for an explicit derivation. In the original OP approach, the productivity process is not linear, and, therefore, NLLS is used to estimate  $\beta_k$ .

productivity, only in a second step to analyze the relationship between productivity and exporting.<sup>17</sup>

It is useful to revisit the productivity process and make explicit that the function  $g_2(\cdot)$  is to be estimated, where  $\beta_g$  refers to the vector of coefficients:<sup>18</sup>

$$(7) \quad \omega_{it+1} = g_2(\omega_{it}, e_{it}; \beta_g) + \xi_{it+1}.$$

The timing assumption on the arrival of the productivity shock,  $\xi_{it+1}$ , is what gives identification of the LBE effect: the decision to export was made prior to the firm receiving the productivity shock.<sup>19</sup> This implies that unexpected shocks to the firm's production process are orthogonal to its export decision or, formally, that  $E(\xi_{it+1} e_{it}) = 0$ . This condition is largely supported by both theoretical and empirical work in international trade. Entering export markets is a very costly undertaking for a firm. The (sunk) entry cost associated with starting to export prevents firms from adjusting their export status instantaneously upon receiving shocks to their underlying productivity.<sup>20</sup> Predicted productivity given a firm's past export experience is, thus, identified by the difference in current productivity between firms that *did* and *did not* export at period  $t$ , while holding their input use constant. Furthermore, conditioning on productivity at time  $t$  controls for unobserved time-varying differences among firms. In addition, the standard OP control for selection can be used to further control for exporters' higher propensity to survive in a marketplace.<sup>21</sup>

It is well known that more-productive firms self-select into export markets. This potential self-selection into export markets is controlled for by the inclusion of lagged productivity. The concern is that when we compare an exporter to a nonexporter, we would attribute the future productivity differences to the act of exporting, although it merely reflects that the more-productive firms become exporters. However, by including  $\omega_{it}$ , this potential selection process is accounted for.<sup>22</sup>

To verify whether past export experience impacts a firm's future productivity, we then rely on  $\frac{\partial g_2}{\partial e_{it}}$ , which depends on the firm's past productivity level.<sup>23</sup> The nonparametric specification of the expected productivity term is very useful in this context. It allows for an estimate of the effect of exporting on future productivity to vary with the firm's own productivity level. The heterogeneous response to exporting is directly built into  $g_2(\cdot)$  and is similar, although using a very different

<sup>17</sup> See De Loecker (2011) for a discussion of this so-called two-stage approach.

<sup>18</sup> In practice, this function is approximated using polynomial approximations  $\sum_{sm} \beta_{sm} \omega_{it}^s e_{it}^m$  and, hence, the coefficients  $\beta_{sm}$  are estimated alongside  $\beta_l, \beta_k$ .

<sup>19</sup> It is well known that a small share of firms go in and out of exporting. In my empirical analysis, I define entry into exporting as the first time a firm becomes an exporter, and similarly for exiting of export markets.

<sup>20</sup> See, for instance, Roberts and Tybout (2007) for an empirical analysis of the importance of entry and fixed costs of exporting using micro data.

<sup>21</sup> This would lead to the inclusion of the estimated survival probability  $P_{it+1}$  in the nonparametric function  $g_2(\cdot)$ . See Olley and Pakes (1996) and De Loecker (2007) for an application to exporting.

<sup>22</sup> To see this, consider the probability of starting to export at time  $t$ :  $\Pr\{e_{it} = 1\} = \Phi(\omega_{it-1}, z_{it-1})$ , where  $z_{it-1}$  captures other variables impacting the export decision. Using the productivity process, I can rewrite  $\omega_{it+1} = g_2(g_2(\omega_{it-1}, e_{it-1}) + \xi_{it}, e_{it}) + \xi_{it+1}$ . Under the model's structure,  $\omega_{it-1}$  is accounted for, and the identification is based on the variation in output at  $t + 1$ , holding inputs at time  $t + 1$  fixed in addition to controlling for productivity differences at time  $t$  and at time  $t - 1$  that might have existed prior to the entry into export markets.

<sup>23</sup> Additional variables can be included, and I refer the reader to Section V of this paper for an explicit discussion of this.



methodology, to Lileeva and Trefler's (2010) analysis of exporting and productivity using Canadian plant-level data.

*A Difference-in-Difference Approach.*—In order to compare the results in this paper directly to the current literature I recast the problem of relying on an exogenous productivity process in a difference-in-difference framework. This framework will turn out to be useful to write the bias into different components that directly relate to simple correlations and patterns in the data.

Let me denote the coefficient of the production function obtained with and without explicitly allowing LBE effects by  $\beta^e$  and  $\beta$ , respectively. For now, I assume that the labor coefficient is estimated consistently.<sup>24</sup>

Let us now consider the difference in a firm's productivity before and after starting to export, and compare it to the case where it did not start exporting. Using biased estimates of the capital coefficient, we will find that if an exporter both becomes 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 ( $\omega_{is}^d$ ) as a control group ( $C$ ) is given by the average difference between productivity growth of export entrants ( $\omega_{is}^e$ ) belonging to the set of starters ( $START$ ) and domestic producers:

$$(8) \quad LBE_s = \frac{1}{N} \left[ \sum_{i \in START} \Delta \omega_{is}^e - \sum_{i \in C} \Delta \omega_{is}^d \right]$$

$$= \sum_i [(\Delta y_{is}^e - \Delta y_{is}) - \beta_l (\Delta l_{is}^e - \Delta l_{is}) - \beta_k (\Delta k_{is}^e - \Delta k_{is})],$$

where  $\Delta x_{is} = x_{is} - x_{i,s-1}$  and  $s = 0$  is the time when a firm enters the export market with  $s = \{0, 1, \dots, S\}$ , and I dropped the relevant summation index. Therefore, the impact of underestimating 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. I can write the bias of the LBE effect for  $s = \{0, 1, \dots, S\}$  by considering the difference of (8) between the exogenous ( $LBE_s$ ) and the endogenous productivity process ( $LBE_s^*$ ):

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

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

<sup>24</sup> 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. See De Loecker (2007).

exporters and nonexporters, 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 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 disproportionate 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 ( $\beta_k - \beta_k^e$ ). I will empirically quantify (9) using firm-level data where a substantial number of firms enter the export market during the sample period.

*Comparing the Nonparametric and the DID Approaches.*—The nonparametric estimate of the LBE effect is obtained jointly with the production function coefficients, whereas the DID approach relies on estimated productivity after having estimated the production function first—i.e., in a two-stage procedure. The two approaches are related but are different in an important way. The DID approach will generate the same estimate for the LBE effect only if the productivity process is specified as in equation (6)—that is only if the export dummy enters in a linear fashion and if productivity follows an  $AR(1)$  with a coefficient of 1.

To see this, consider productivity growth using equation (6), and take expectations over all firms and time periods conditional on a firm's information set at time  $t$ . The productivity effect of exporting is then  $\gamma$  since  $E(\xi_{it+1}) = 0$ . The exact same estimate is obtained when relying on the approach illustrated in equation (9), where productivity growth is compared between exporters and domestic producers.<sup>25</sup> It is important to underscore that the LBE estimate should theoretically be zero, or at least not significantly different from zero, if an exogenous process for productivity is employed. The bias term in equation (9) then measures the full extent to which there are productivity effects associated with exporting.<sup>26</sup>

The nonparametric and DID approaches are thus expected to generate the same estimate for LBE only under a restrictive productivity process. The advantage of the nonparametric approach is that it does not restrict the LBE effect to be common to all firms. In fact, the interaction between a firm's export status and its productivity will generate an entire distribution of LBE effects, potentially different for each firm. The LBE effect is estimated allowing for a heterogeneous response to exporting. An average treatment estimate of LBE using the DID framework would still be valid to produce an estimate of the average effect. However, Lileeva and Trefler (2010) have found the heterogeneous response of productivity to exporting to be important empirically.

The more general treatment of the productivity process will also rely on the correct level of persistence in the exogenous part of the productivity process. Therefore,

<sup>25</sup> The standard errors on both estimates will be different since the two-stage approach relies on estimated productivity to compute the LBE estimate. The DID approach has the potential to rely on a set of matched firms to control for pre-export differences among firms.

<sup>26</sup> In fact, the analog of equation (9) for the nonparametric case reduces to the LBE nonparametric estimate since, under the exogenous process, there is no LBE by construction.

a firm's export experience will explain different variations in productivity growth. In contrast, the approach used in (5) relies on the entire first difference in productivity.<sup>27</sup>

I will produce estimates of the LBE effect in my data using both the nonparametric and the DID frameworks, while allowing for various specifications of the productivity process. In this way, I can verify both whether LBE is present in the data and whether it varies across firms.

## II. Application

I demonstrate my approach using standard firm-level data. I observe firms in the Slovenian manufacturing sector during the period 1994–2000. (See De Loecker 2007 for more details on the Slovenian data.) The data, which come from the Slovenian Central Statistical Office, contain 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.

An attractive feature of using data on Slovenian firms during the period 1994–2000 is the reorientation of trade flows due to the transition process and the increased integration with the European Union. We can, therefore, expect exporting to affect the performance of firms in this setting.

### A. Diagnostics

Before I estimate the model with a more general law of motion for productivity, I report a number of correlations in the data. In Table 1, I list two partial correlations that directly relate to equation (9) and underscore the importance of incorporating export information into the productivity process.

In panel A of Table 1, I report the average difference in the conditional mean of capital and investment, while controlling for employment (column 1) and employment and output jointly (column 2). In panel B, I report the percentage capital growth difference between new exporters and domestic producers after export entry ( $s = 0$ ) for various windows ( $s = 1, 2, 3, 4$ ). I control for a full set of year and industry effects in every specification.

The results in panel A indicate that, after controlling for output and employment, the capital coefficient is expected to be biased given the strong correlation between a firm's export status and its level of capital stock. Panel B clearly shows that new exporters' capital stock grows faster than, otherwise equal, nonexporting firms. 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 positive. In fact, using expression (9), I only need to estimate the capital coefficient under a more general law of motion of productivity

<sup>27</sup> It is useful to revisit equation (5) and now allow for a persistence parameter  $\rho$ , such that  $\omega_{it+1} = \rho\omega_{it} + \gamma e_{it} + \xi_{it+1}$ , where  $\rho \leq 1$ . Relying on  $\rho = 1$  would lead to an estimate for LBE, under the nonparametric approach, given by  $E(\omega_{it+1} - \rho\omega_{it}) = \gamma$ . In this case, the DID estimate for LBE will be biased in this setting by  $(\rho - 1)E(\omega_{it} | e_{it} = 1)$ .

TABLE 1—CAPITAL STOCK AND EXPORT STATUS

	Panel A. Correlation export		Panel B. Capital growth	
	(1)	(2)	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)

Notes: The numbers in column 1 are obtained after running a regression of log capital on an export dummy while controlling for the firm's labor use ( $l_{it}$ ) and a full set of year and industry effects, and column 2 further conditions on log output.  $s$  refers to the number of periods upon export entry. Standard errors are in parentheses.

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 in Section II, the growth differential in labor interacted with the difference in labor coefficients will add to the bias in the LBE parameter.

I compare the production function coefficients, by industry, across two specifications of the productivity process: the standard exogenous and an endogenous process allowing exporting to impact future productivity in a flexible way.<sup>28</sup> I report the estimated coefficients in Table A1 in Appendix A. As expected, the estimated capital coefficient is 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 estimated capital coefficient is 30 percent lower.<sup>29</sup> It is worth mentioning that the bias in the labor coefficients is significantly smaller.

The difference in the estimated production function coefficients already suggest that it is imperative to allow for an endogenous productivity process to obtain the correct LBE parameter.

### B. Measuring the Bias under a DID Approach

Under the DID approach, I can directly compute the extent to which the estimated (average) LBE effects are biased, by multiplying the difference in estimated coefficients by the corresponding growth rates of the inputs, as suggested in equation (9). In the theoretical discussion in Section IC, the potential bias of the labor coefficient was assumed away. However, in all the results, I include both inputs in the calculation of the bias using  $\sum_x (\beta_x - \beta_x^e) \frac{1}{N} \sum_i (\Delta x_{is}^e - \Delta x_{is})$  with  $x = \{l, k\}$ .

The estimates obtained in Table 2 are not the full extent to which exporting raises future productivity. In fact, the numbers have to be interpreted as the additional effect of exporting on productivity since I compare the LBE average effect under

<sup>28</sup> I rely on a fourth-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, and the number of years exported. The estimated coefficients are robust with respect to the inclusion of these additional variables. The exogenous process is not restricted to be linear and follows (2).

<sup>29</sup> I checked whether  $(\beta_k - \beta_k^e)$  is significantly different from zero for each industry using the bootstrapped standard errors of both estimators.

TABLE 2—DIFF-IN-DIFF (*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

Notes: Appendix A lists the industry classification codes with their corresponding descriptions.  $s$  refers to the time between the entry into export markets and when the productivity effect is estimated, with  $s = 0$  the effect from entry at  $t - 1$  to  $t$ .

the exogenous and endogenous productivity process specification. Strictly speaking, under an exogenous productivity process, there should be no systematic relationship between exporting and future productivity, conditional on input use. In the next subsection, I rely on my nonparametric estimates to discuss the total effect.

Table 2 reports the bias in the LBE parameter after  $s + 1$  years of exporting, where  $s = \{0, 1, 2, 3\}$ . The additional productivity gain (or the bias) is reported for each industry and for the manufacturing sector as a whole. 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 Appendix A, this table reflects that exporters' inputs grow faster. Both effects imply that one would underestimate the importance of export entry on future productivity.

The bias in the LBE parameter is considerable in magnitude, ranging from 1.08 to 7.38 percent additional productivity growth after four years of exporting. Finally, I find substantial heterogeneity across sectors, which can be traced back to either heterogeneity in input growth or heterogeneity in the impact of exporting on future productivity across sectors.

### C. Nonparametric Estimates of LBE

I present the nonparametric estimates of LBE, using the approach outlined in Section IC. In panel A of Table 3, I list the average LBE effect for the entire manufacturing sector, where I compare the estimates of the linear model with those of the general model. It is useful to consider the linear model, as it directly compares to the (additional) estimates produced in Table 2, where an average LBE estimate of 1.52 was obtained. There are three important results.

TABLE 3—NONPARAMETRIC ESTIMATES OF EXPORTING ON PRODUCTIVITY (*in percent*)

Linear model		General model	
Parameter	Estimate (SE)	Moment	Estimate
<i>Panel A. Manufacturing</i>			
Average effect ( $\gamma$ )	4.10 (0.014)	25th pct	2.03
Persistence ( $\rho$ )	0.87 (0.006)	50th pct	2.96
		75th pct	4.87
Industry	Average	Median	
<i>Panel B. Industry: Nonparametric results</i>			
15	2.71	2.28	
17	2.54	1.98	
18	1.72	1.66	
19	1.93	1.83	
20	2.40	1.92	
22	6.45	4.88	
24	4.44	3.93	
25	6.63	4.50	
26	3.32	2.73	
27	3.97	3.19	
28	4.50	3.32	
29	4.50	3.45	
31	6.14	4.64	
32	5.36	4.60	
33	6.27	5.04	
36	2.38	1.99	

Notes: The linear model is given by  $(g(\cdot) = \rho\omega_{it} + \gamma e_{it})$  and the general model  $(g(\omega_{it}, e_{it}))$ . Appendix A lists the description of the industry codes.

First of all, the average productivity premium from exporting is 4.1 percent and indicates that the bias is substantial. Second, the persistence parameter is significantly different from one, and implies that the DID approach will produce incorrect estimates of the LBE effect, regardless of whether the lagged export status is included in the law of motion of productivity. Third, the estimates indicate that there is an important difference in the estimated LBE effect along the productivity distribution. In the third and fourth columns of panel A in Table 3, I list the twenty-fifth, fiftieth, and seventy-fifth percentiles of the LBE effect to highlight that the gains from exporting differ substantially among the set of exporters. To highlight the degree of heterogeneity in the effect of exporting on productivity, I plot the kernel density of the predicted productivity effect from exporting in Figure 1, using the estimated productivity process.

Panel B of Table 3 produces the same results for the various industries, and, as expected, we see substantial variation across industries in terms of magnitudes. One consistent picture does emerge: all sectors have positive average LBE effects, and the average effect is always bigger than the median, suggesting the importance of recovering the nonparametric effect of exporting on productivity. My results echo the finding of Lileeva and Trefler (2010), who document that exporting affects firms differently, depending on their initial productivity level.

Using my estimate of  $g(\cdot)$ , I find that the productivity effect of exporting is U-shaped in initial productivity. This suggests that starting to export raises productivity both more for less-productive and very productive firms. Given that my productivity



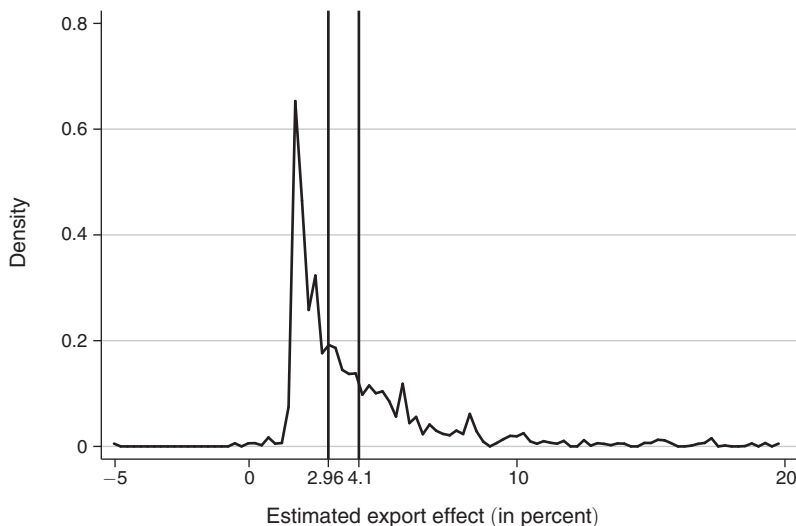


FIGURE 1. KERNEL DENSITY ESTIMATE OF THE EXPECTED PRODUCTIVITY EFFECT FROM EXPORTING

*Notes:* I plot the kernel density estimate of the estimated productivity effect for firms exporting at  $t$ . The two vertical lines indicate the median and average estimate, respectively. These numbers correspond to Table 3, panel A.

measures, purposely, contain both efficiency and demand, I do not engage in a detailed analysis of these heterogeneous effects. This would, in fact, require more structure on the underlying demand system and how firms compete in the product market.

Comparing the results in Table 2 (column 2 for  $s = 0$ ), to the average estimates, reported in Table 3, indicates that the bias is economically important. For instance, the average effect of exporting in the manufacturing sector is 4.1, while the bias is 1.52, suggesting that we would underestimate the LBE effect substantially. As discussed in Section II, the estimated effect under the DID approach will be exactly equal to the one obtained with the nonparametric approach when restricting the specification of the productivity process to the one described in equation (6). The DID approach is, therefore, further subject to a bias due to imposing a persistence parameter of one, which was rejected in all the specifications. However, the main point of comparing the two approaches is to put the bias into context.

The literature has, in various ways, relied on modifications of the linear specification of productivity; therefore these results help separate out the role of persistence in productivity, and whether firm-level decision variables such as exporting belong in the law of motion of productivity. My results show that both concerns are first-order, and that there is value in incorporating a richer specification of the productivity process into the analysis.

### III. Identifying the Separate Effect of Exporting

Although this paper's focus is on correctly predicting the productivity effect of exporting, my framework is a natural setting in which to separately identify the

productivity effect of exporting when firms jointly invest and export. A recent literature has emphasized the importance of studying the productivity-export relationship, while acknowledging that firms often simultaneously decide to export and invest substantially. See, for example, Costantini and Melitz (2007) and Aw, Roberts, and Xu (2011) for recent theoretical and empirical work underscoring this importance. Therefore, we might overstate the effect of exporting on productivity if firms become exporters while also engaging in other productivity-enhancing actions.

I briefly show how my empirical framework can single out the impact of exporting, while holding *investment* fixed, using the following process for productivity:  $\omega_{it+1} = g(\omega_{it}, i_{it}, e_{it}) + \xi_{it+1}$ . I observe data on firm-level investment ( $i_{it}$ ), capturing expenditures on new technologies and upgrading of existing production processes. However, it also captures the standard capital expansion expenditures and, therefore, attributes future productivity effects to a wide range of firm-level actions that are picked up by this investment variable. Given these data constraints, I do not pursue a precise decomposition of the role of exporting, technology adoption, and other firm-level actions that potentially raise future productivity.

I consider the following parametric form for the productivity process:

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

This specification is similar to that of Aw, Roberts, and Xu (2011). In contrast, I do, however, add interaction terms between the level of productivity and firm-level actions, exporting, and investing. Table 4 shows the results for the Slovenian manufacturing sectors.

In addition to the estimates of  $\theta$ , I also present the result of a  $F$ -test on the joint significance of all  $\theta_k$  for  $k = \{4, \dots, 9\}$ , or I test whether productivity follows an exogenous process.

Table 4 shows that, to obtain correct estimates of the production function coefficients and, consequently, productivity, it is important to incorporate the relevant firm-level actions that can plausibly affect future productivity. The additional effect of investing, while having the same export status and productivity level, is not of direct interest here given the aggregate measure of investment. My results do support the hypothesis that investing raises (expected) future productivity, as assumed by various theoretical frameworks in industry dynamic models.

Two results directly speak to the LBE hypothesis. First, when holding fixed productivity and investment (broadly defined), I find that exporting has a positive effect of 4.7 percent and is very close to the average effect reported in Table 3, panel A (i.e., 4.1 percent). Second, the effects of exporting, holding investment fixed, differ substantially with the firm's productivity. The latter confirms the importance of allowing for heterogeneous effects of exporting. The results from Table 4 confirm the U-shaped relationship between productivity and the future productivity effects due to exporting.

After having estimated (10), the additional effect from joint exporting and investing can be computed, while holding the level of productivity fixed. In particular, I compute the average predicted additional productivity effect from the joint

TABLE 4—ESTIMATES OF ENDOGENOUS PRODUCTIVITY PROCESS

Variable	Parameter	Estimate	Standard error
Productivity	$\theta_1$	0.853	0.025
Productivity <sup>2</sup>	$\theta_2$	0.074	0.017
Productivity <sup>3</sup>	$\theta_3$	−0.015	0.004
Invest	$\theta_4$	0.020	0.003
Export	$\theta_5$	0.172	0.044
Invest × export	$\theta_6$	−0.038	0.011
Invest × productivity	$\theta_7$	−0.007	0.002
Export × productivity	$\theta_8$	−0.111	0.026
Export × invest × productivity	$\theta_9$	0.024	0.004
Observations	5,203	<i>F</i> -test:	$F(6, 5203) = 38.61$

*Notes:* The estimates are obtained after running my estimation procedure on the data and using the specification of the productivity process given by (10). The *F*-test is on the joint significance of the coefficients corresponding to the decision variables (investment and exporting), or  $\{\theta_4, \dots, \theta_9\}$ .

decision to export and invest and list them in Table A2 in Appendix A. Across all sectors exporting and investing raises future productivity, and the estimates range from 1 to 8 percent. The standard deviation within industries is substantial and reflects the large variation in investment and productivity among firms that jointly export and invest.

I can compare firms with the same level of productivity but still allow for a magnifying effect as measured by  $\theta_9$ . When comparing two firms that both jointly enter the export market and invest the same dollar amount,  $\theta_9$  captures the additional productivity effect for the more productive firm. Similarly,  $\theta_8$  captures the idea that the productivity effect from exporting depends on the firm's initial productivity level. The results indicate that the productivity gains are lower when firms are already very productive.

#### IV. Conclusion

In this paper, I show that current methods used to test for learning by exporting are biased towards rejecting this hypothesis. I allow exporting to affect a firm's future productivity and show that recent proxy estimators of production functions are a natural framework, as they allow an endogenous productivity process. I provide a simple way to sign the importance of the bias and apply it to a dataset of Slovenian manufacturing firms.

I find substantial productivity gains associated with export entry. Furthermore, using my nonparametric estimate of LBE, I find that the effect of exporting on productivity differs substantially across producers, and points to heterogeneity in the impact of exporting on firm performance.

These results suggest an important role for export participation in productivity growth and warrant further investigation of the underlying mechanisms and their potential policy implications. I reported results for Slovenia to show the importance of my correction. Slovenia is a good case study 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. The clear conclusion is: to test learning by exporting, we need an empirical model that allows productivity to depend on export participation.

It is ultimately an empirical question whether this bias is important in other settings, but we need more work on other countries before we can know whether developing countries can rely on export-promotion policies to improve the performance of domestic producers, and spur economic growth.

The methodology discussed in this paper extends naturally to cases in which firm-level actions impact future productivity, such as technology adoption, R&D, product-quality upgrading, and investment.

## APPENDIX A: DATA AND ADDITIONAL RESULTS

### A. Data

As mentioned in the main text, I refer to De Loecker (2007) for a detailed discussion of the data. It is important for this setting to note that the data contain standard information on firm-level production and that similar data have been used throughout the literature. See, for example, Olley and Pakes (1996) and Levinsohn and Petrin (2003).

In particular, and as mentioned in the paper, the data represent the population of producers of manufacturing products over the period 1994–2000. The estimation of the production function requires information on plant-level output (revenues deflated with detailed producer price indices), (deflated) value added, and input use: labor as measured by full-time equivalent production workers, raw materials, and a measure of the capital stock. The latter is constructed from the balance sheet information on total fixed assets broken down into (i) machinery and equipment, (ii) land and buildings, and (iii) furniture and vehicles. Appropriate depreciation rates (based on actual depreciation rates) are used to construct a firm-level capital stock series using standard techniques. See, for example, the data Appendix in Olley and Pakes (1996).

In addition, the data report investment and provide detailed information on ownership, firm entry, and exit. Finally, the export status and export revenues—at every point in time—provide information whether a firm is a domestic producer, an export entrant, or a continuing exporter.

### B. 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.

The industry classification NACE rev. 1 is similar to the ISIC industry classification in the United States, and the various industries with corresponding codes 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),

TABLE A1—PRODUCTION FUNCTION COEFFICIENTS

Industry	Capital coefficients			Labor coefficients		
	Exogenous	Endogenous	Difference	Exogenous	Endogenous	Difference
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

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

TABLE A2—JOINT EXPORT-INVESTMENT PRODUCTIVITY EFFECTS

Industry (NACE 2)	Additional effect (percent)
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

Chemicals (24), Rubber and Plastic Products (25), Other Nonmetallic 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), and Furniture and Manufacturing n.e.c. (36).

### C. Joint Export-Investment Productivity Effects

I report the average joint export-investment productivity effect, by industry and across all manufacturing sectors, using  $\hat{\theta}_6 i_{it} e_{it} + \hat{\theta}_9 i_{it} e_{it} \omega_{it}$ . 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 that does not invest. 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 noninvesting firms. The variation across firms within a sector comes from the variation in actual investment expenditures.

## APPENDIX B: DERIVING EQUATION (6)

To obtain equation (6), start from the production function given by (1). The first stage of the OP approach is given by

$$(B1) \quad y_{it} = \beta_l l_{it} + \phi_t(l_{it}, k_{it}, i_{it}) + \epsilon_{it},$$

where  $\phi_t(\cdot) = \beta_k k_{it} + h_t(k_{it}, i_{it})$  and  $h_t(\cdot)$  comes from the investment proxy for productivity—i.e.,  $\omega_{it} = h_t(k_{it}, i_{it})$ .

Now consider the production function one period ahead,  $t + 1$ , and use the specific law of motion for productivity given by (5) and use the fact that we have an estimate of the labor coefficient from the first stage,  $\hat{\beta}_l$ :

$$(B2) \quad y_{it+1} = \hat{\beta}_l l_{it+1} + \beta_k k_{it+1} + \omega_{it} + \gamma e_{it} + \xi_{it+1} + \epsilon_{it+1}$$

$$(B3) \quad y_{it+1} - \hat{\beta}_l l_{it+1} = \phi_{it} + \beta_k \Delta k_{it+1} + \gamma e_{it} + \xi_{it+1} + \epsilon_{it+1},$$

where the second line uses that  $\omega_{it} = \phi_{it} - \beta_k k_{it}$  and let  $\Delta$  be the first difference operator, such that  $\Delta k_{it+1} = k_{it+1} - k_{it}$ .

The final step is to observe that  $\phi_{it} = y_{it} - \hat{\beta}_l l_{it}$ , and, therefore, we can rearrange terms and collect the output growth net from labor variation on the LHS:

$$(B4) \quad \Delta(y_{it+1} - \hat{\beta}_l l_{it+1}) = \beta_k \Delta k_{it+1} + \gamma e_{it} + \xi_{it+1} + \epsilon_{it+1}.$$

Now define  $\Delta(y_{it+1} - \hat{\beta}_l l_{it+1}) \equiv \Delta \tilde{y}_{it+1}$  to obtain equation (6). Under the capital formation process of OP, we then get that  $\Delta k_{it+1} = i_{it} + \delta k_{it}$ .

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