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# Does Exporting Lead to Productivity Spillovers in Horizontal or Vertical Industries? Evidence from Indonesia

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# Does Exporting Lead to Productivity Spillovers in Horizontal or Vertical Industries? Evidence from Indonesia

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**Abstract**

*This paper investigates the presence of productivity spillovers due to exporting. In particular, it examines whether productivity gains from exporting spill over upstream (to suppliers), downstream (to customers) or horizontally (to competitors). Using plant-level data on Indonesian manufacturing sectors, we find productivity gains to downstream firms of approximately 2.5-3.5% during the period 1990-1996. We do not find the presence of spillovers upstream or horizontally.*

Keywords: Exporting, spillovers, productivity, linkages, Indonesia

JEL Classifications: F13, O12, O19

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## Motivation & Overview

The success of East Asia over the last half-century has garnered significant discussion for the topic of export orientation, in both the policy and the academic worlds. Specifically, understanding the link between exports, productivity, and growth has been a source of much examination in the literature. Empirical studies have observed a correlation: exporting plants are more efficient than their non-exporting counterparts. See Roberts and Tybout (1997), Clerides, Lach, and Tybout (1998), Bernard and Jensen (1999), Van Biesebroeck (2005), Alvarez and Lopez (2004), De Loecker (2005). But this correlation could work in two ways and the empirical evidence is mixed, in my opinion. First, the presence of some fixed-costs of exporting could dictate that only the most productive firms in the economy are able to enter the export market - a selection effect. Clerides, Lach, and Tybout for Colombia, Mexico and Morocco (1998), and Bernard and Jensen for the United States (1999) demonstrate evidence of the selection effect and Melitz (2003) offers the theoretical underpinnings for this mechanism. Second, there is the possibility of learning from exporting where firms could gain access to new technologies, learn better business practices and marketing strategies, etc., which enables these firms to become more productive. Clerides, Lach, and Tybout, in their paper, acknowledge the possibility of learning by exporting in certain industries in Morocco. Further, Blalock and Gertler (2004), Van Biesebroeck (2005), Alvarez and Lopez (2004), and De Loecker (2005) demonstrate learning by exporting in Indonesia, Sub-Saharan Africa, Chile, and Slovenia, respectively. While the evidence does not perfectly separate along income lines, it does seem that learning by exporting is more present in developing countries where firms are furthest behind the international production frontier and stand to gain the most in terms of technology and knowledge capital from exposure through exporting. In the case of Indonesia, Blalock and Gertler examine the period 1990-1996 and found a 2-5% increase in productivity attributed to learning by exporting.

This paper attempts to extend the current empirical literature on exporting to determine whether the learning effects from exporting spill over to domestic firms. In extending Blalock and Gertler's work in Indonesia, we investigate the presence of spillovers to firms in horizontal and vertical industries. The literature on learning spillovers has primarily focused on the effects of foreign ownership and multinational enterprises (MNEs) rather than exporting behavior. Aitken and Harrison (1999) find that FDI has a negative spillover effect to horizontal firms, perhaps demonstrating a business-stealing effect. On the other hand, Javorcik (2004) concludes that FDI has a positive effect on upstream sectors.

This paper aims to fill the gap in our knowledge of learning spillovers from exporting.[1] Using plant-level panel data on Indonesian manufacturing plants, we find the presence of spillovers from exporting plants downstream to customer plants. The presence of these spillovers underlines the importance of exporting and demonstrates the presence of learning linkages allowing us to interject in the debate on export orientation.

## Background

The modern phase of Indonesian economic growth began in 1966, the year after a bloody coup eliminated the communist party (PKI). As Indonesia entered the 1980s, it began to move away from high trade and capital controls that were prevalent in the economy during the late 60s and 70s. The period from 1985 to

[1] Subsequent to the circulation of the first draft of this paper, I became aware of a working paper by Alvarez et al (2006) that looks at spillovers from exporting in Chilean manufacturing. In the results section, I have contrasted my papers with theirs with regards to findings, methodologies, and implications.

1990 was highly characterized by policies of export promotion, lowering of trade barriers, and reduction of regulations in investment. Particularly important in the export drive was the drawback scheme in 1986 that provided refunds to exporters on their imported inputs. Additionally, a 50% currency devaluation later that year, customs reform, a new, liberalized foreign investment code, and banking reforms were also key initiatives. Consequently, the late 80s witnessed the beginning of a manufacturing export boom that carried over into the 90s; manufacturing exports grew approximately 35% annually from 1986 to 1992. Though there was a dip in the growth of exports in 1993, perhaps due to a worldwide fall in demand, export growth returned to about 35% from 1994 to 1996, until the financial crisis hit in 1997[2].

Initially, there were a few reasons to doubt that the export boom actually represented increased international competitiveness of Indonesian manufacturing industries. First, one item, plywood, dominated the export picture so much that it constituted nearly 50% of Indonesian exports in the mid to late 1980s. This was due in part to an export substitution policy as a means of keeping more value-added within Indonesia. The government banned log exports in the mid 80s in order to develop the nascent plywood industry (plywood is an engineered wood that takes certain types of logs as inputs). Plywood's share in exports peaked at around 50% before declining to below 20% by the mid 90s. Hence, the growth in exports cannot be attributed to the development of the plywood industry alone. Also, a proliferating array of labor-intensive industries became increasingly important; this groups share rose from 38% of exports in 1988 to nearly 70% by the mid-90s. In particular, sectors such as clothing and apparel and electronics fueled both labor-intensive export growth as well as overall export growth. Exports of electronics, in particu-

[2]See 19: Hill (1996)

lar, had an interesting time-path. They were significant in the early 80s but then dropped off dramatically during the late 80s. In 1990, exports of electronics stood at approximately $204 million, similar to the 1984 level of $214 million. Then, in 1992, these exports grew to $935 million, the sharpest increase by far of any sector in the economy during that time period[2].

Second, there was the possibility that the rise in exports from Indonesia was due to quota thresholds; under the MFA[3], Indonesia was guaranteed an export quota in garment and textiles. However, the garment and textile exports continued to grow quickly even after Indonesia had hit quota limits under the MFA. Apart from generally modest quota increases, most of the growth came from expanding to non-MFA markets outside the governance of quotas. The fact that Indonesias exports of these items continued to grow quickly in the 90s was a testament to its growing international competitiveness.

## Data

To pursue this research, I have gained access to a rich, plant-level data set gathered by Indonesias Central Bureau of Statistics (BPS). Blalock and Gertler (2004) discuss the data gathering process, which I detail below. The annual survey is taken from manufacturing establishments with more than 20 employees from 1979 to 2000. Depending on the year, there are up to 160 variables including sector classification, type of ownership, exports, assets, asset changes, electricity, fuels, income, sales, unit output, expenses, investment, labor, wages, raw material use, machinery, etc. Each of the years has approximately 285 different manufacturing

[2]See 19: Hill (1996)

[3]The Multifibre Agreement (MFA) contains a series of bilaterally negotiated quota restrictions covering trade in both textiles and clothing between individual developed countries and developing countries.

industries and 17,000 firms. Industry classification is very disaggregated; it is a five digit ISIC code that is consistent during my time period of interest. Some summary statistics for key variables are stated in Table 1. One striking feature is the low percentage of plants that actually export - less than 16%. The concentration of exports to a few plants/firms has been noted in many different developing country cases.

The BPS submits a questionnaire annually to all registered manufacturing establishments, and field agents are dispatched to follow up with each non-respondent or to confirm that operations have ceased. Because field office budgets are partly determined by the number of reporting establishments, agents have incentives to register all establishments. So, while selection bias may not be a problem, BPS officials do mention that some establishments intentionally misreport financial data out of concern that tax authorities or competitors may gain access to the data. However, if under-reporting or over-reporting is consistent over time, the results would be unbiased in a fixed-effects estimation.

A thorough cleaning process is performed in three stages, to address the problem of missing data and obvious erroneous responses that is inherent in any dataset, especially one from a developing country. First, observations, which are missing key variables are dropped from the sample. Next, a small number of observations with clearly erroneous data (for example, with export share greater than 100%) are dropped. Finally, if years are missing, the establishment is dropped from the dataset. This final cleaning stage removes approximately 15% of the sample. It is also assumed that keystroke mistakes are random and hence this type of measurement error should not bias the estimations.

After the cleaning, the sample is further narrowed based on two conditions. First, we focus our attention on the time period 1990-1996 for several reasons: (1)

the dataset contains data on export shares only beginning in 1990; (2) to avoid complications from the Indonesian financial crisis and the broader East Asian financial crisis that began in 1997. Second, because foreign-owned firms are more likely to export than domestic firms, it would be easy to confuse export spillovers with foreign ownership spillovers. Thus, all of the results in this paper are based on a sample limited to wholly domestically-owned establishments, which only removes about 5% of the data. However, as a robustness check, we re-ran all of the specifications including firms with foreign ownership and none of the results changed materially.

For information on vertical sectors, we use the 1995 Input-Output (I-O) table. The I-O tables are compiled approximately every five years by the Indonesian Central Bureau of Statistics. Ideally we would have liked to use both the 1990 and 1995 tables, but we were not able to get access to the 1990 table. The I-O table is a square matrix that describes the input from and output to 172 sectors: row $i$ specifies the rupiah value of outputs from sector $i$ to 172 sectors; column $j$ details the rupiah value of inputs to sector $j$ from 172 sectors. Then, with a concordance table, we are able to translate ISIC codes found in the panel data to sector numbers in the I-O table. The analysis focuses on 91 sectors (sector numbers 49-139) in the I-O table, which are the manufacturing sectors. Having described the preparation of our unbalanced panel, we now discuss the methodology.

## Methodology

Our goal is to estimate the effect of exposure to exporting on productivity and this analysis is performed over two stages. In the first stage, total factor productivity (TFP) is estimated, separately for each industry. To this end, we aggregate the 91 sectors into 17 industries and TFP is estimated through the following production function:

$$y_{ist} = \beta_0 + \phi_1 k_{ist} + \phi_2 l_{ist} + \phi_3 m_{ist} + \varepsilon_{ist} \tag{1}$$

$y_{it}$ is log sales for firm $i$ in sector $s$ at time $t$; the right hand-side variables are inputs: capital, labor, and materials, respectively. All variables are in rupiah terms and are deflated using industry-level price indices[4].

It has been shown that OLS leads to biased results when estimating a production function due to simultaneity and selection issues. For example, labor and intermediate materials are flexible inputs that depend on productivity. When a firm observes a productivity decline it tends to reduce its labor force and conversely, firms tend to increase their workforce when productivity is trending upwards. Since labor is an input in equation (1), but is also determined by productivity, we have a simultaneity problem. Selection bias arises from the fact that some firms may go out of business during the time-period of interest due to low productivity. Olley and Pakes (1996) argue that firms with higher capital are less likely to exit due to a random negative productivity shock. To correct for these biases, Olley-Pakes introduce a semi-parametric estimation technique, which is used in this paper - see the appendix for a more detailed discussion on the Olley-Pakes methodology in estimating the production function. Table A.1 in the appendix shows the coefficients on capital, labor, and materials from estimating equation (1), separately for each of the 17 industries, using both OLS and the Olley-Pakes methodologies. From the table, we can see that for 14 out of 17 industries, the coefficient on capital rises for the Olley-Pakes estimation. Further, under the Olley-Pakes estimation, the coefficient on labor falls for all industries, and the coefficient on materials falls for most industries. This is reassuring considering that, as discussed in the appendix, OLS is predicted to have an upward bias on the coefficients of labor and materials, and a downward bias on

[4] Industry-level price indices were obtained from Arnold and Javorcik (2005). See 10.

the capital coefficient.

Having estimated the production function, we can solve for TFP through the following equation, where $\hat{\phi_1}$, $\hat{\phi_2}$, and $\hat{\phi_3}$ come from the Olley-Pakes estimation of equation (1).

$$TFP_{ist} = y_{ist} - \hat{\phi_1}k_{ist} - \hat{\phi_2}l_{ist} - \hat{\phi_3}m_{ist} - \beta_0 \tag{2}$$

Having estimated plant-level productivity, we turn to testing the main question: does an increase in exposure to exporting in vertical or horizontal industries cause an increase in TFP? In the theoretical literature, productivity is generally assumed to evolve according to a Markov process: $TFP_{ist} = \alpha TFP_{ist-1} + \beta X_{ist} + \epsilon_{ist}$. To this end, the following equation is estimated:

$$\begin{aligned} TPF_{ist} = \delta_0 + \delta_1 TFP_{ist-1} + \delta_2 ExportStatus_{ist} + \delta_3 Horizontal_{st} + \\ \delta_4 Upstream_{st} + \delta_5 Downstream_{st} + \gamma_t + \mu_i + \epsilon_{ist} \end{aligned} \tag{3}$$

$ExportStatus_{ist}$, can be defined in two ways: first as a dummy for whether the plant became an exporter in the previous period; second as a continuous variable that captures the share of output that the plant exports in the previous period. In the next section, I present the results and discuss the implications of the results from the two different definitions of $ExportStatus_{ist}$. $Horizontal_{st}$ is an index that measures the degree of exporting in sector $s$ at time $t$. $Upstream_{st}$ and $Downstream_{st}$ are indices that proxy the exposure of firm $s$ to exporting through its vertical relationships. These indices are defined below:

$$Horizontal_{st} = \sum_{i \epsilon s} (\alpha_{1ist} ExportShare_{ist}) \tag{4}$$

$$Upstream_{st} = \sum_{p} (\alpha_{2pst} Horizontal_{pt}) \tag{5}$$

$$Downstream_{st} = \sum_p (\alpha_{3spt} Horizontal_{pt}) \tag{6}$$

$\alpha_{1ist}$ is defined as the share of output of firm $i$ in sector $s$ at time $t$. $\alpha_{2pst}$ is defined as the share of inputs that sector $p$ supplies to sector $s$. $\alpha_{3spt}$ is the share of output that sector $s$ sells to sector $p$. $\alpha_{2pst}$ and $\alpha_{3spt}$ are easily derived from the I-O table. $\gamma_t$ are year dummies to control for time trends. The spillover variables of interest in this analysis are the three indices: *Horizontal*, *Upstream*, and *Downstream*. At this time, a clarificatory note is in order - from the definitions above, we that a significant coefficient on the *Upstream* index is evidence of spillovers downstream and conversely, a significant coefficient on the *Downstream* index corresponds with spillovers to upstream firms. Summary statistics for exporting and spillover indices are given in Tables 2 and 3. From the tables, we see that exporting and exposure to exporting generally increased over the period 1990-1996 (though there was a dip in 1993, perhaps associated with a slight global recession). Further, from Table 2, we see that export share tended to increase via the extensive margin rather than the intensive margin. That is, export share increased as new plants entered the export market rather than through existing plants increasing their own export share. In fact, the data seems to indicates that for the average exporting pant, its export share changes very little over the 1990-96 time period. Also, from Table 2, we clearly see that the majority of plants are not players in the export market. Another interesting feature is illustrated in Graph 1: the distribution of export share conditional on plants exporting is fairly uniform except near 100%, which ostensibly indicates that some plants are being built specifically for the export market. Such a feature would be consistent with export processing zones, which were part of Indonesia's export promotion push in the late 80s and 90s.

Turning back to the estimation equation, $\mu_i$ are plant-level fixed effects, which are added to control for unobservable time-invariant plant characteristics that are endogenous. For example, the quality of management is fairly time-invariant feature at the plant-level, which is correlated with both productivity and the degree of exporting and exposure to exporting.

Equation (3) above is a dynamic panel with fixed effects and "short T" (T = 7 here). Further, the explanatory variables are endogenous: exposure to exporting can lead to productivity gains or more productive plants can be selected as suppliers or customers of exporting plants. Hence, this estimation suffers from several biases, which have been the source of much work (see Roodman 2006 for a summary). Refer to the appendix for a more detailed exposition on the Arellano-Bond systems GMM estimation strategy, which seeks to resolve these endogeneity concerns and is the technique used in this paper to estimate equation (3).

## Hypothesis and Results

We hypothesize that spillovers will be positive for all three relationships through two primary channels: learning transfers and quality upgrading. For example, assuming the existence of learning by exporting, the exporting firm will have incorporated new technologies and better business practices. Under economies of agglomeration, this knowledge could easily spill over to other firms in the same industry (horizontal spillovers). Furthermore, knowledge transfer could occur as rival firms hire workers away from the exporting firm. Next, exporting firms competing on the international markets would likely quality upgrade as Verhoogen (2007) demonstrated in Mexico. In order to quality upgrade, these firms would also demand higher quality inputs from their suppliers, which could result in knowledge and technology sharing. Similarly, there could be knowledge and technology sharing with downstream firms due to long-lasting relationships or labor movements. Additionally, the quality angle could play a role here as well as the exporting firm's improved productivity could lead to higher quality input for its downstream partners, which in turn could have a positive effect on downstream productivity. One can imagine a scenario where an exporting firm significantly improves its product, such as capital equipment. The newer, more technologically advanced capital equipment could substantially improve the productivity of downstream firms who use the equipment in their operations. Unfortunately, in this paper, due to a lack of data on quality or unit prices, it is difficult to disentangle the channels described above and conclusively attribute the productivity spillovers to either the learning or quality mechanism.

The first results are presented in Table 4 - note that $ExportStatus_{ist}$ is defined as a dummy for whether the plant became an exporter in the previous period. Our main estimation, equation (3), is shown in column (1). Column (3) is similar to column (1) except that the explanatory variables are lagged one period as we may expect that the spillover variables may affect productivity with some time lag. Specifications (2) and (4) add an additional TFP lag over columns (1) and (3), respectively, to address the fact that serial correlation cannot be rejected in columns (1) and (3) at the 95% confidence level. First, we notice some strong results across all the specifications. We observe that TFP is near a unit root process and hence the use of the system GMM technique extension by Blundell and Bond (1996) as discussed in the appendix is warranted. Second, the coefficients on the dummy for entering the export market in the previous period are statistically significant across the four specifications and indicate a gain of approximately 4-6% in productivity. Comparably, Blalock and Gertler found a 2-5% gain to productivity due to an entry into the export market. Additionally, we find that there is evidence of spillovers as the coefficient on the $Upstream$ variable is statistically significant at the 99% confidence level over all specifications. A one unit increase in the exposure to upstream exporting leads to approximately a 0.5% increase in productivity. This could be explained by better inputs from upstream suppliers as previously discussed. A one unit increase is the average year-over-year increase (excluding 1993) that the *Upstream* variable demonstrates in the data. A one unit increase in *Upstream* to plant $x$ can also be viewed in the following way: a supplier who provides 10% of plant $x's$ inputs, went from not exporting to exporting 10% of their output. Significant coefficients are present for the *Horizontal* and *Downstream* variables, but are not robust across all of the specifications.

We extend the above analysis by further relaxing our assumptions about how long it takes the spillover variables to affect productivity. In Table 5, we see the results of this analysis. Column (1) has 0, 1, and 2 lags of the spillover variables while column (2) has 1, 2, and 3 lags of the spillover variables. Under both specifications, assumptions of strong instruments and no serial correlation cannot be rejected (see Hansen over-identification test and second order auto-correlation test, respectively). Under these two specifications, joining the exporting market leads to a one-time productivity gain of slightly more than 6%. Further, Wald tests on the combined effects of the lags indicate that the *Upstream* variable is significant at the 95% level under both specifications. The cumulative effect of the *Upstream* lags is approximately 0.7%. Hence, from Tables 2 and 3, we surmise that a one unit increase in the *Upstream* variable translates into a 0.5-0.7% increase in downstream productivity, which means that downstream plants experienced a 2.5-3.5% productivity increase due to spillovers during the period 1990-1996[5]. It is arguable whether or not such productivity gains are economically significant but compared to productivity gains found in other studies, it seems reasonably significant. The corresponding Wald tests for the *Horizontal* and *Downstream* variables indicate

[5]From Table 3, we see that the *Upstream* variable increased about 5 units during the period 1990-96. Multiplying by the 0.5-0.7% range gives us the overall effect of 2.5-3.5%.

no statistically significant effects.

To summarize, we have observed statistically significant affects that are robust over all six specifications, for productivity gains from entering the export market and spillovers from exporting firms to downstream firms.

We also repeat these six specifications using export share for $ExportStatus_{ist}$. In this scenario, all of the results for $Horizontal$, $Upstream$, and $Downstream$ are essentially the same. However, the coefficients on export share are insignificant across all the specifications in contrast to the 4.5-6% gain we observed before. See Tables A.2 and A.3 in the appendix for these results. We interpret this difference in the following way: entering the export market leads to a one-time gain in productivity but once a firm has entered the export market, further increases in export share do no lead to more learning.

At this point, it would be useful to contrast our methodologies and results with that of Alvarez and Lopez. They use plant-level data from Chile to estimate the following relationship:

$$TFP_{isrt} = \alpha_0 - \beta_1 Horizontal_{st} - \beta_2 Upstream_{st} - \beta_3 Downstream_{st} + \epsilon_{isrt} \quad (7)$$

Their model also includes sector, year, region and plant fixed effects and TFP is constructed using the Olley-Pakes technique. Their spillover variables are constructed as they are in this paper and they also add geographic concentration of an industry as a control variable. Noticeably absent from their model is the presence of lagged TFP on the right-hand side, meaning TFP is not modeled as a dynamic Markov process, which we think is more realistic. Second, the presence of plant-level entry into the exporting market is omitted. A plant's decision to export is both correlated with the spillover variables and productivity and this endogeneity is not solved through their instruments. They instrument the spillover variables using exports-weighted sector level exchange rates. The exclusion restriction that underlies their instruments assumes that sector level exchange rates affect plant-level productivity only through exposure to exporting through the spillover variables. While this is a clever instrument, we see potentially two problems here. First, sector level exchange rates would affect a plant's decision to export, which is an omitted variable as just mentioned. Second, sector level exchange rates could affect the degree of import competition as an appreciation would increase import competition and a depreciation would conversely decrease import competition. It is not necessarily clear in which way import competition would affect plant-level productivity: (1) increased competition could cause domestic plant to "shape-up" and allocate their resources more efficiently or (2) increased competition could lead to some degree of de-industrialization and business stealing as domestic plants are unable to compete. However, in either case, import competition would affect plant-level productivity, meaning a failure in the exclusion restriction.

Their paper finds that spillovers are present to upstream suppliers: a 1% increase in exposure to exporting downstream causes approximately a 0.5% increase in the upstream supplier's productivity. This is a different finding than in our paper, which finds productivity spillovers to downstream firms. Finally, while Chile is a fairly small country (60th and 46th in world population and PPP GDP rankings as of 2006, respectively), Indonesia is one of the largest developing countries in the world (4th and 15th, respectively), allowing us to more credibly consider the external validity of the findings here.

## Conclusion

This paper seeks to fill a gap in the literature in determining the existence of productivity spillovers from exporting. The success of East Asia's growth has brought attention to policies of export orientation and questions of export promotion. Under old trade theory, export promotion, especially subsidies, were viewed as welfare reducing because they worsen the terms of trade and act as a transfer from the domestic to the foreign country. However, in the more recent literature, Brander and Spencer (1985) and Krugman (1984) have argued that export subsidies may be welfare enhancing under imperfect markets in the form of international oligopolistic competition or increasing returns to scale, respectively. Increasing returns to scale could arise if there were some positive learning effects and spillovers as demonstrated in this paper.

The results from this paper confirm the presence of learning by exporting and additionally find productivity spillovers external to the firm. This finding has important policy implications and the presence of externalities lends weight in favor of export promotion policies pursued by Indonesia during the 80s and 90s. Further, Indonesia, as one of the largest developing countries in the world, is a good test case because the results found here potentially have implications to the rest of the developing world. Using detailed plant-level data in the manufacturing sector in Indonesia, we find the presence of productivity spillovers to downstream firms. In fact, from 1990-96, plant-level productivity increased 2.5-3.5% as a result productivity spillovers from upstream suppliers who learned on the exporting market. We do not find spillovers to horizontal plants and in contrast to the Alvarez and Lopez working paper, we do not find spillovers to upstream plants. This paper is able to solve many econometric issues of endogeneity and dynamic panel bias. However, further work needs to be done to better understand the mechanism of these spillovers.

# Appendix

TFP Construction

In this paper, we estimate the following production function separately for each sector (hence no $s$ subscript in the equation below):

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_2 m_{it} + \epsilon_{it} \tag{8}$$

where $y, k, l, m$ represent log sales, log capital, log labor, and log materials, respectively. All values are in local currency rupiah terms and have been deflated using industry specific deflators. Now, a simple OLS estimation of this production function is susceptible to two forms of endogeneity bias. First, there is simultaneity bias between fully flexible inputs, such as labor and materials, and productivity ($\omega_{it}$): these inputs affect the plant's productivity and at the same time, labor and materials are a function of plant productivity. Hence, OLS generally over-estimates the coefficients on the flexible inputs. Olley-Pakes propose investment as a proxy for productivity: $i_{it} = f(k_{it}, \omega_{it})$. Assuming that $f$ is a strictly monotonic increasing function, we can invert $f$ to recover $\omega_{it} = f^{-1}(k_{it}, i_{it})$. Now, the above equation becomes:

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_2 m_{it} + \omega_{it} + \epsilon_{it} \tag{9}$$

The terms with capital can be combined: $\phi(i, k) = \beta_0 + \beta_1 k_{it} + \omega_{it}$. Using a third order polynomial expansion in $i$ and $k$ for $\phi(i, k)$, equation (9) can be estimated to determine the coefficients on the flexible inputs - labor and capital. However, the coefficient on capital is yet to be identified and we have a second endogeneity concern to address. Plants that drop out of business (and hence out of sample) due to negative productivity shocks are likely to be firms with low levels of capital. Hence, a simple OLS estimate will under-estimate the coefficient on capital. Following the first-stage estimation, we have:

$$y_{it} - \hat{\beta}_2 l_{it} - \hat{\beta}_2 m_{it} = \phi(i,k) + \epsilon_{it} \tag{10}$$

$$y_{it} - \hat{\beta}_2 l_{it} - \hat{\beta}_2 m_{it} = \beta_0 + \beta_1 k_{it} + \omega_{it} + \epsilon_{it} \tag{11}$$

$$y_{it} - \hat{\beta}_2 l_{it} - \hat{\beta}_2 m_{it} = \beta_0 + \beta_1 k_{it} + g(\widehat{P_{it-1}}, \omega_{it-1}) + \epsilon_{it} \tag{12}$$

Moving from equation (11) to equation (12), productivity ($\omega_{it}$) is a function of the previous period's productivity and ($\hat{P}$) the probability that the firm survives some random productivity shock. $\hat{P}$ is estimated via a separate probit on the level of capital in the previous period. Equation (12) is estimated via non-linear least squares to recover a consistent estimate of the coefficient on capital.

Arellano-Bond Systems GMM Estimator

Assume that we want to estimate the following equation, which is a dynamic panel model with fixed effects, "small T", and endogenous explanatory variables.

$$y_{it} = \beta_1 y_{it-1} + \beta_2 x_{it} + \beta_3 \mu_i + \epsilon_{it} \tag{13}$$

This formulation possesses an interesting set of econometric problems that have inspired numerous solutions in the econometrics literature. Generally, to remove the individual fixed effects, all of the variables are de-meaned resulting in the following equation:

$$y^*_{it} = \beta_1 y^*_{it-1} + \beta_2 x^*_{it} + \epsilon^*_{it} \tag{14}$$

where $y^*_{it-1} = y_{it-1} - \frac{1}{T-1}(\overline{y_i}) = y_{it-1} - \frac{1}{T-1}(y_{i2} + ... + y_{iT})$; and $\epsilon^*_{it} = \epsilon_{it} - \frac{1}{T-1}(\overline{\epsilon_i} = \epsilon_{it} - \frac{1}{T-1}(\epsilon_{i2} + ... + \epsilon_{iT})$. Notice that the $y_{it-1}$ term in $y^*_{it-1}$ is correlated negatively with the $-\frac{1}{T-1}(\epsilon_{it-1})$ term in $\epsilon^*_{it}$. As $T \to \infty$, this correlation goes to zero, but in panels with small T, this correlation could be quite substantial. Further, this endogeneity cannot be solved by using lags of $y_{it-1}$ since the lags are correlated with their respective counterparts in the transformed error term, $\epsilon^*_{it}$. Kiviet (1995) argues that the best way to handle this dynamic panel bias is to perform regular Least Squares Dummy Variable (LSDV) to remove the fixed effects and then correct the results for the bias. However, his method works only for balanced panels and does not address the potential endogeneity from other regressors. Another way to approach the problem is to perform first-differencing on the original equation. First-differencing still removes the fixed-effect: $\Delta y_{it} = \beta_1 \Delta y_{it-1} + \beta_2 \Delta x_{it} + \Delta \epsilon_{it}$ but now we can use $\Delta y_{it-2}$ or $y_{it-2}$ to instrument for the correlation between $\Delta y_{it-1}$ and $\Delta \epsilon_{it}$ (assuming no serial correlation). This is the Anderson-Hsiao (1982) estimator. Arellano and Bond (1991) improve the efficiency of this estimator by using deeper lags of the endogenous variables as additional instruments. This is known as the Arellano-Bond difference estimator. However, in further work, Blundell and Bond (1998) demonstrate that if $y$ is close to a unit root process, past levels are weak instruments for future changes (i.e. $y_{it-2}$ is a weak instrument for $\Delta y_{it-1}$ if $y$ approaches an unit-root process). Blundell and Bond develop an alternative strategy. Instead of differencing the original equation to remove the fixed effects, they difference the instruments and assume they are exogenous to the fixed effects: $E(\Delta y_{it-2}\mu_i) = 0$ for all $i$ and all $t$. The technique that combines the Arellano-Bond and the Blundell-Bond methods is known as the Arellano-Bond systems GMM estimator. Finally, two more points need to be addressed. First, the techniques discussed above only work under the assumption that there is no serial correlation in the error terms. Going back to equation (4), since there is a mechanical correlation between $\Delta\epsilon_{it}$ and $\Delta\epsilon_{it-1}$ through the shared $\epsilon_{it-1}$ term, Arellano-Bond propose a test for second order autocorrelation in differences. Second, a standard Hansen/Sargan over-identification test can be used for testing the validity of the instruments.

**Table A.1 - Coefficients of the Production Function**

| Industry | Capital | | Labor | | Materials | |
|---|---|---|---|---|---|---|
| | OLS | OP | OLS | OP | OLS | OP |
| 1 - Meats, fruits, vegetables | 0.04 | 0.01 | 0.34 | 0.30 | 0.66 | 0.67 |
| 2 - Oils, grains, beans, other | 0.11 | 0.15 | 0.44 | 0.37 | 0.51 | 0.51 |
| 3 - Alcohol, tobacco | 0.12 | 0.20 | 0.48 | 0.43 | 0.48 | 0.45 |
| 4 - Textiles and apparel (non-leather) | 0.07 | 0.09 | 0.44 | 0.36 | 0.53 | 0.57 |
| 5 - Leather products and footwear | 0.07 | 0.11 | 0.35 | 0.29 | 0.59 | 0.60 |
| 6 - Paper and wood products | 0.07 | 0.09 | 0.37 | 0.36 | 0.59 | 0.56 |
| 7 - Chemicals, paints, fertilizers | 0.11 | 0.07 | 0.46 | 0.42 | 0.48 | 0.48 |
| 8 - Cosmetics, medicines | 0.07 | 0.12 | 0.51 | 0.43 | 0.49 | 0.47 |
| 9 - Other chemicals, petroleum | 0.12 | 0.00 | 0.29 | 0.23 | 0.61 | 0.68 |
| 10 - Rubber, plastic products | 0.05 | 0.07 | 0.34 | 0.30 | 0.64 | 0.65 |
| 11 - Ceramic, glass, clay | 0.06 | 0.09 | 0.58 | 0.57 | 0.39 | 0.37 |
| 12 - Metal industries | 0.09 | 0.14 | 0.52 | 0.47 | 0.45 | 0.43 |
| 13 - Metal products | 0.08 | 0.09 | 0.38 | 0.32 | 0.57 | 0.58 |
| 14 - Machinery, equipment, appliances | 0.06 | 0.11 | 0.44 | 0.36 | 0.55 | 0.55 |
| 15 - Transport equipment, repair | 0.05 | 0.08 | 0.54 | 0.54 | 0.50 | 0.47 |
| 16 - Jewelry, sporting goods, other | 0.04 | 0.09 | 0.61 | 0.57 | 0.40 | 0.37 |
| 17 - Printing and publishing | 0.04 | 0.08 | 0.49 | 0.43 | 0.50 | 0.49 |

Note: Production function estimated separately for 17 industries using both OLS and Olley-Pakes methodology

**Table A.2 - Dependent Variable is TFP estimated from Olley-Pakes in First Stage**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| L(1).TFP | 0.9030*** | 0.6614*** | 0.9022*** | 0.7951*** |
| | (0.0243) | (0.1746) | (0.0265) | (0.1961) |
| L(2).TFP | | 0.2336 | | 0.1121 |
| | | (0.1663) | | (0.1943) |
| L(0).Export share | -0.0003 | -0.0006 | | |
| | (0.0009) | (0.0009) | | |
| L(1).Export share | | | -0.0001 | -0.0003 |
| | | | (0.0011) | (0.0011) |
| L(0).Horizontal | 0.0011 | 0.0014* | | |
| | (0.0007) | (0.0007) | | |
| L(1).Horizontal | | | 0.0018** | 0.0018** |
| | | | (0.0008) | (0.0008) |
| L(0).Upstream | 0.0044*** | 0.0051*** | | |
| | (0.0016) | (0.0017) | | |
| L(1).Upstream | | | 0.0048*** | 0.0045** |
| | | | (0.0019) | (0.0019) |
| L(0).Downstream | -0.0016** | -0.0017** | | |
| | (0.0008) | (0.0007) | | |
| L(1).Downstream | | | -0.0008 | -0.0008 |
| | | | (0.0011) | (0.0010) |
| Number of Observations | 64,935 | 47,018 | 64,935 | 47,018 |
| Number of Years | 6 | 5 | 6 | 5 |
| Specification Tests (p-values) | | | | |
| - Hansen Over-Identification Test | 0.51 | 0.40 | 0.16 | 0.07 |
| - 2nd Order Autocorrelation | 0.00 | 0.24 | 0.00 | 0.64 |

* statistically significant at 10% level
** statistically significant at 5% level
*** statistically significant at 1% level

*Estimation Method: GMM-IV System Estimator (Arellano & Bover, 1995; Blundell & Bond, 1998)*
*Robust standard errors in parentheses*
*Time period dummies are included though their coefficients are not shown here*

**Table A.3 - Dependent Variable is TFP estimated from Olley-Pakes in First Stage**

| | (1) | (2) |
|---|---|---|
| L(1).TFP | 0.9008*** | 0.9014*** |
| | (0.0373) | (0.0295) |
| L(0).Export share | 0.0024 | |
| | (0.0024) | |
| L(1).Export share | -0.0042 | 0.0026 |
| | (0.0035) | (0.0040) |
| L(2).Export share | 0.0011 | -0.0020 |
| | (0.0025) | (0.0035) |
| L(3).Export share | | -0.0005 |
| | | (0.0028) |
| L(0).Horizontal | -0.0007 | |
| | (0.0025) | |
| L(1).Horizontal | -0.0019 | -0.0013 |
| | (0.0033) | (0.0031) |
| L(2).Horizontal | 0.0035 | 0.0051** |
| | (0.0022) | (0.0024) |
| L(3).Horizontal | | -0.0025 |
| | | (0.0029) |
| L(0).Upstream | 0.0014 | |
| | (0.0027) | |
| L(1).Upstream | -0.0021 | -0.0049 |
| | (0.0058) | (0.0047) |
| L(2).Upstream | 0.0080* | 0.0075* |
| | (0.0048) | (0.0043) |
| L(3).Upstream | | 0.0028 |
| | | (0.0048) |
| L(0).Downstream | -0.0046 | |
| | (0.0029) | |
| L(1).Downstream | -0.0013 | -0.0024 |
| | (0.0043) | (0.0049) |
| L(2).Downstream | 0.0064 | -0.0003 |
| | (0.0066) | (0.0054) |
| L(3).Downstream | | 0.0026 |
| | | (0.0054) |
| Number of Observations | 47,018 | 33,136 |
| Number of Years | 5 | 4 |
| Specification Tests (p-values) | | |
| - Hansen Over-Identification Test | 0.64 | 0.47 |
| - 2nd Order Autocorrelation | 0.74 | 0.62 |
| - Test: L(0/1).Exp share + L(1/2).Exp share + L(2/3).Exp share = 0 | 0.50 | 0.95 |
| - Test: L(0/1).Hor + L(1/2).Hor + L(2/3).Hor = 0 | 0.52 | 0.19 |
| - Test: L(0/1).Up + L(1/2).Up + L(2/3).Up = 0 | 0.02** | 0.02** |
| - Test: L(0/1).Down + L(1/2).Down + L(2/3).down = 0 | 0.69 | 0.90 |

* statistically significant at 10% level
** statistically significant at 5% level
*** statistically significant at 1% level

*Estimation Method: GMM-IV System Estimator (Arellano & Bover, 1995; Blundell & Bond, 1998)*
*Robust standard errors in parentheses*
*Time period dummies are included though their coefficients are not shown here*

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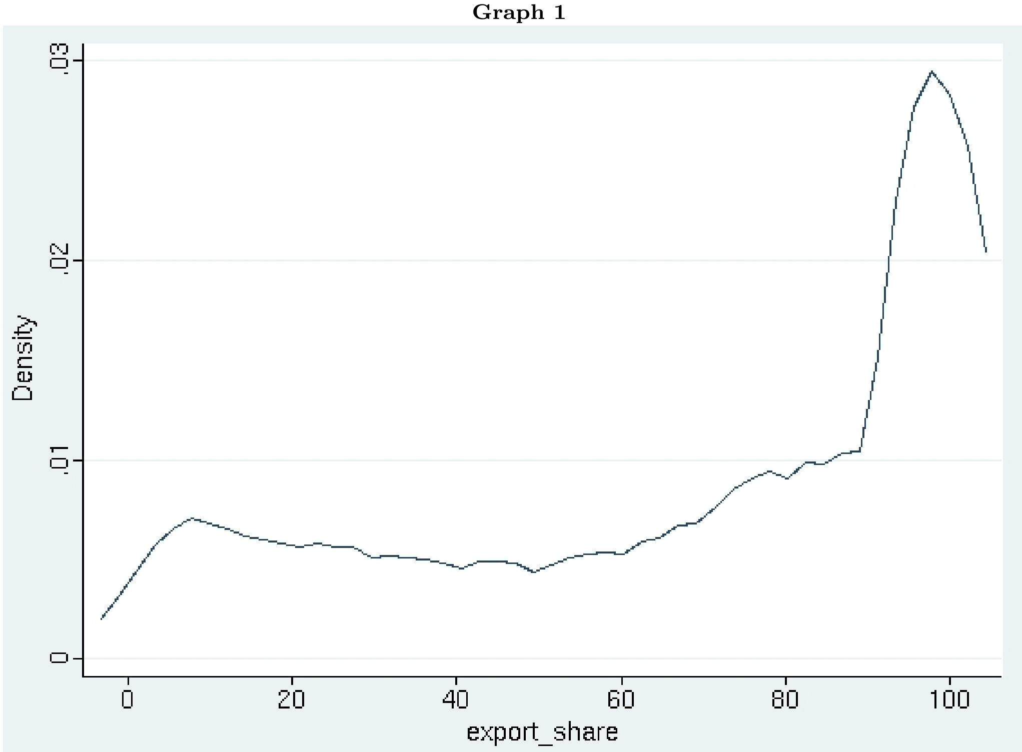
# Tables and Graphs

**Graph 1**




This graph depicts a kernel density plot of the export share of plants conditional on the plant being an exporter

**Table 1 - Summary Statistics**

| | | Levels | |
|---|---|---|---|
| Variable | Num. Obs. | Mean | Std. deviation |
| ln Y | 90,431 | 12.42 | 1.95 |
| ln K | 90,431 | 11.65 | 2.18 |
| ln L | 90,431 | 10.45 | 1.65 |
| ln M | 90,431 | 10.84 | 2.22 |
| ln TFP (OP) | 90,431 | -2.04 | 1.60 |
| % of Plants Exporting | 90,431 | 15.96 | 36.62 |
| $ExportShare^1$ | 90,431 | 11.02 | 28.53 |
| $ExportShare^2$ | 14,433 | 69.05 | 33.09 |
| Horizontal | 90,431 | 25.14 | 22.26 |
| Upstream | 90,431 | 8.50 | 9.29 |
| Downstream | 90,431 | 6.24 | 9.32 |

(1) All plants in the sample
(2) Conditional on plants which export
Output, Capital, Labor, Materials are in 000s of rupiahs
TFP is calculated using the Olley-Pakes methodology
Horizontal, Upstream, Downstream variables are defined on page 9, 10

**Table 2 - Additional Summary Stats for Exporting Variables**

| | | $ExportShare^1$ | | $ExportShare^2$ | | % of Plants, Exporting | |
|---|---|---|---|---|---|---|---|
| Year | Num. Obs. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| 1990 | 11,452 | 7.70 | 24.05 | 67.14 | 32.48 | 11.47 | 31.86 |
| 1991 | 11,500 | 9.77 | 26.82 | 67.22 | 33.00 | 14.53 | 35.24 |
| 1992 | 12,387 | 12.14 | 29.85 | 68.91 | 33.82 | 17.62 | 38.10 |
| 1993 | 12,796 | 12.16 | 29.92 | 70.39 | 32.94 | 17.27 | 37.80 |
| 1994 | 13,365 | 11.91 | 29.75 | 71.53 | 32.39 | 16.66 | 37.26 |
| 1995 | 15,275 | 10.89 | 28.23 | 68.67 | 32.51 | 15.86 | 36.53 |
| 1996 | 13,656 | 12.04 | 29.69 | 68.32 | 34.00 | 17.63 | 38.11 |

(1) All plants in the sample
(2) Conditional on plants which export. Number of plants which export can be determined as the total number of observations times the % of exporting plants

**Table 3 - Additional Summary Stats for Spillover Variables**

| | | Horizontal | | Upstream | | Downstream | |
|---|---|---|---|---|---|---|---|
| Year | Num. Obs. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| 1990 | 11,452 | 17.48 | 17.53 | 6.46 | 6.22 | 4.72 | 7.52 |
| 1991 | 11,500 | 21.08 | 20.97 | 7.28 | 7.81 | 5.61 | 8.40 |
| 1992 | 12,387 | 26.13 | 22.51 | 8.15 | 8.79 | 6.52 | 9.37 |
| 1993 | 12,796 | 24.23 | 22.47 | 7.39 | 9.42 | 5.82 | 8.51 |
| 1994 | 13,365 | 26.84 | 23.31 | 8.41 | 8.72 | 6.44 | 9.49 |
| 1995 | 15,275 | 27.33 | 20.86 | 9.66 | 9.78 | 7.32 | 10.53 |
| 1996 | 13,656 | 30.83 | 24.44 | 11.35 | 11.71 | 6.79 | 10.24 |

**Table 4 - Dependent Variable is TFP estimated from Olley-Pakes in First Stage**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| L(1).TFP | 0.9008*** | 0.5616*** | 0.9012*** | 0.6786*** |
| | (0.0232) | (0.1771) | (0.0263) | (0.1978) |
| L(2).TFP | | 0.3243* | | 0.2244 |
| | | (0.1675) | | (0.1942) |
| Dummy: Became Exporter in Previous Period | 0.0437*** | 0.0599*** | 0.0443*** | 0.0612*** |
| | (0.0162) | (0.0156) | (0.0163) | (0.0167) |
| L(0).Horizontal | 0.0009 | 0.0012* | | |
| | (0.0006) | (0.0006) | | |
| L(1).Horizontal | | | 0.0018*** | 0.0019*** |
| | | | (0.0007) | (0.0008) |
| L(0).Upstream | 0.0044*** | 0.0055*** | | |
| | (0.0016) | (0.0017) | | |
| L(1).Upstream | | | 0.0049*** | 0.0046*** |
| | | | (0.0019) | (0.0018) |
| L(0).Downstream | -0.0015** | -0.0015** | | |
| | (0.0007) | (0.0007) | | |
| L(1).Downstream | | | -0.0007 | -0.0007 |
| | | | (0.0010) | (0.0010) |
| Number of Observations | 64,935 | 47,018 | 64,935 | 47,018 |
| Number of Years | 6 | 5 | 6 | 5 |
| Specification Tests (p-values) | | | | |
| - Hansen Over-Identification Test | 0.38 | 0.31 | 0.11 | 0.04 |
| - 2nd Order Autocorrelation | 0.00 | 0.09 | 0.00 | 0.32 |

* statistically significant at 10% level
** statistically significant at 5% level
*** statistically significant at 1% level

*Estimation Method: GMM-IV System Estimator (Arellano & Bover, 1995; Blundell & Bond, 1998)*
*Robust standard errors in parentheses*
*Time period dummies are included though their coefficients are not shown here*

**Table 5 - Dependent Variable is TFP estimated from Olley-Pakes in First Stage**

| | (1) | (2) |
|---|---|---|
| L(1).TFP | 0.8898*** | 0.9052*** |
| | (0.0403) | (0.0292) |
| Dummy: Became Exporter in Previous Period | 0.0620*** | 0.0607*** |
| | (0.0199) | (0.0222) |
| L(0).Horizontal | -0.0011 | |
| | (0.0028) | |
| L(1).Horizontal | -0.0020 | -0.0003 |
| | (0.0035) | (0.0026) |
| L(2).Horizontal | 0.0040* | 0.0054** |
| | (0.0022) | (0.0024) |
| L(3).Horizontal | | -0.0039 |
| | | (0.0027) |
| L(0).Upstream | 0.0026 | |
| | (0.0027) | |
| L(1).Upstream | -0.0010 | -0.0044 |
| | (0.0063) | (0.0041) |
| L(2).Upstream | 0.0057 | 0.0082* |
| | (0.0051) | (0.0043) |
| L(3).Upstream | | 0.0018 |
| | | (0.0042) |
| L(0).Downstream | -0.0036 | |
| | (0.0029) | |
| L(1).Downstream | -0.0011 | -0.0004 |
| | (0.0045) | (0.0045) |
| L(2).Downstream | 0.0054 | -0.0010 |
| | (0.0071) | (0.0052) |
| L(3).Downstream | | 0.0010 |
| | | (0.0054) |
| Number of Observations | 47,018 | 33,136 |
| Number of Years | 5 | 4 |
| Specification Tests (p-values) | | |
| - Hansen Over-Identification Test | 0.55 | 0.52 |
| - 2nd Order Autocorrelation | 0.82 | 0.67 |
| - Test: L(0/1).Hor + L(1/2).Hor + L(2/3).Hor = 0 | 0.50 | 0.18 |
| - Test: L(0/1).Up + L(1/2).Up + L(2/3).Up = 0 | 0.03** | 0.01*** |
| - Test: L(0/1).Down + L(1/2).Down + L(2/3).down = 0 | 0.66 | 0.80 |

* statistically significant at 10% level
** statistically significant at 5% level
*** statistically significant at 1% level

*Estimation Method: GMM-IV System Estimator (Arellano & Bover, 1995; Blundell & Bond, 1998)*
*Robust standard errors in parentheses*
*Time period dummies are included though their coefficients are not shown here*