Does the Use of Imported Intermediates Increase Productivity? Plant-Level Evidence*

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Abstract

This paper examines whether importing intermediate goods improves plant performance. While addressing the issue of simultaneous productivity shocks and decisions to import intermediates, we estimate the impact foreign intermediates have on plants' productivity using plant-level Chilean manufacturing panel data. Across different estimators, we find evidence that becoming an importer of foreign intermediates improves productivity.

KEYWORDS: productivity, imported intermediates, plant-level dynamic decisions

JEL: F10, D21, D24

1 Introduction

International trade is one of the primary avenues for the diffusion and adoption of new technologies worldwide. This is particularly true and important for developing nations where it is believed that importing new technologies is a significant source of productivity and economic growth. Through adoption and imitation of imported technologies, countries can take advantage of research and development (R&D) abroad to improve the efficiency of domestic production.

Previous empirical work using aggregate cross-country data shows that importing intermediate goods that embody R&D from an industrial country can significantly boost a country's

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productivity (cf., Coe and Helpman, 1995; Coe, Helpman and Hoffmaister, 1997). Countries that are more open to trade benefit more from foreign R&D because they are better able to access improvements in technology by importing intermediate goods.[1] Aggregated data, however, do not capture heterogeneity across different plants in the economy. As empirically shown by Baily, Hulten, and David (1992) and Pavcnik (2002), it is vital to examine plant-level changes in order to understand changes in aggregate productivity levels. Furthermore, recent developments in trade theory suggest that understanding the plant-level response to trade policy is a crucial factor in understanding its impact on aggregate productivity and welfare (e.g., Melitz, 2003; Bernard, Eaton, Jensen and Kortum, 2003).

The goal of this paper is to test whether the use of foreign intermediate goods increases plant productivity, using a detailed panel data set on Chilean manufacturing plants from 1979-1996. The data set captures heterogeneity in terms of import status across plants and across time: some plants import most of their intermediate goods, some change their import status, others do not import at all. While importers are larger and more productive than non-importers in the data, the direction of causality between importing foreign intermediates and plant's performance is not immediately obvious.

Does the use of foreign intermediate goods directly increase productivity or do inherently high productivity plants tend to use foreign intermediate goods? To answer these questions, we estimate both the immediate and long-run effects from the use of imported intermediates on plant's productivity while addressing the important econometric issues of simultaneity and endogenous selection using the Within-Group estimator, the System GMM estimator (cf., Blundell and Bond, 1998), and the estimator developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) (OP/LP Proxy estimator, hereafter).

The results across different estimators indicate a statistically significant, often substantial, positive impact from the use of imported intermediates on plant productivity. The System GMM and the OP/LP Proxy point estimates suggest a positive impact from the use of imported intermediates on productivity ranging from 12.9 to 22.0 percent. There exists substantial uncertainty over the different estimators in regards to the precise magnitude of the positive effect from importing. However, even the Within-Groups estimates—which are likely to be biased downward due to measurement errors in imported intermediates (cf., Griliches and Hausman, 1986)—show

[1] Keller (2001) provides the industry-level empirical evidence for the role of R&D spillovers through imports.

that the use of imported intermediates leads to an immediate increase in productivity by 2.6 percent. In addition, we find some evidence for a positive *dynamic* effect from the use of imported intermediates; the evidence suggests that past import status has a positive impact on current productivity (i.e., "learning by importing"). We also examine the sensitivity of our results to export status and time-varying industry-specific effects. Overall, the results indicate the robustness of the effect of intermediate imports on output across various estimation methods.

Among recent papers discussing the impact of foreign intermediate inputs on productivity at the micro-level are Biesebroeck (2003), Muendler (2004), Amiti and Koenings (2005), and Halpern, Koren, and Szeidl (2006). The empirical findings in the literature are mixed. Biesebroeck (2003) finds that productivity improvements do not happen through more advanced inputs in Columbia and, similarly, Muendler (2004) shows only a small contribution of foreign materials and investment goods on output for Brazil. In contrast, Amiti and Koenings (2005) find that the productivity gains arise from reducing inputs tariffs especially for importing firms during a trade reform for Indonesia, which is consistent with the findings of this paper. Halpern, Koren, and Szeidl (2006) use a panel of Hungarian firms to examine two different mechanisms, a quality and a variety channel, through which imports can affect firm productivity and find that importing inputs increase firm productivity by 14 percent, of which about two thirds is attributed to an increase in the variety of intermediates used in production.

The paper is organized as follows. The next section proceeds to describe the analytical framework used to study the relationship between productivity and imported intermediates. Section three outlines the empirical specification, while sections four and five explain the estimation procedure and data set, respectively. The sixth section presents the results. The last section concludes.

2 The Theoretical Framework

2.1 Production Function

For each period t, the i^{th} plant's production, Y_{it}, is given by:

$$Y_{it} = e^{\omega_{it}} K_{it}^{\beta_k} L_{it}^{s\beta_s} L_{it}^{u\beta_u} E_{it}^{\beta_e} \left[\int_0^{N(d_{it})} x(j)^{\frac{\theta-1}{\theta}} dj \right]^{\frac{\beta_x \theta}{\theta-1}}, \tag{1}$$

where ω_{it} represents a serially correlated productivity shock, K_{it} is capital input, L^s_{it} is skilled labor input, L^u_{it} is unskilled labor input, E_{it} is energy input, and intermediate materials are horizontally differentiated. The elasticity of substitution between any two material inputs is given by $\theta > 1$. The variable $N(d_{it})$ denotes the range of intermediate inputs which are employed in the i^{th} plant; it is a function of a plant's discrete choice, denoted by $d_{it} \in \{0, 1\}$, to import from abroad or not: $N(d_{it})(1 - d_{it})N_{h,t} + d_{it}N_{f,t}$, where $N_{h,t}$ is the range of intermediate inputs produced in this country and $N_{f,t}$ is the range of intermediate inputs available in the world. There are a range of intermediate inputs that are not produced domestically in this country but are produced in foreign countries and thus available through imports.

Horizontally differentiated materials in the production function is a common specification used to analyze a change in the total factor productivity in the international trade and the growth literatures (e.g., Ethier (1982), Romer (1990), and chapter 3 of Grossman and Helpman (1991)). An alternative approach would include vertically differentiated inputs with foreign inputs of higher quality (e.g., chapter 4 of Grossman and Helpman (1991)). Given that our data set does not contain any information on firm-specific product price nor the range of the variety of intermediate inputs a firm uses, it is difficult to empirically differentiate between the quality or variety effect of foreign intermediates on productivity. For tractability we employ the former model here but our estimates are likely to capture both the variety and the quality effects.

Consider the equilibrium in which all intermediate goods are symmetrically produced at level $\bar{x}$. Substituting $x(j)\bar{x}$ into equation (1) leads to

$$Y_{it} = e^{\omega_{it}} N(d_{it})^{\frac{\beta_x}{\theta-1}} K_{it}^{\beta_k} L_{it}^{s\beta_s} L_{it}^{u\beta_u} E_{it}^{\beta_e} X_{it}^{\beta_x}, \tag{2}$$

where $X_{it}N(d_{it})\bar{x}$.

Total factor productivity (TFP) is defined as $A_{it}\frac{Y_{it}}{K_{it}^{\beta_k} L_{it}^{s\beta_s} L_{it}^{u\beta_u} E_{it}^{\beta_e} X_{it}^{\beta_x}}$. Then, from (2),

$$\ln A(d_{it}, \omega) = \frac{\beta_x}{\theta - 1} \ln(N(d_{it})) + \omega_{it}. \tag{3}$$

This equation indicates that productivity is positively related to the range of employed intermediate inputs. Plants importing intermediate inputs from abroad employ a larger variety of intermediate inputs and hence exhibit higher productivity than those employing domestic intermediate inputs only; for example, had there been no difference in the value of ω across plants, then $\ln A(1,\omega) - \ln A(0,\omega) = \frac{\beta_x}{\theta-1}\ln(N(1)/N(0)) > 0$.

2.2 Exit, Import, and Learning by Importing

The behavioral framework of Olley and Pakes (1996) is extended by incorporating import-decisions into their dynamic model. Consider a risk-neutral plant that maximizes the expected present value of the sum of net cash flows. At the beginning of every period, after observing the current productivity shock ω_t, the plant makes the following decisions. First, it makes a discrete decision to exit, χ_t, by comparing a sell-off value of Φ with its continuation value. If it continues in operation, it chooses the import status (d_t), and then variable factors (labor, materials, fuels) and investment level ($\imath_t$). Capital is accumulated according to the law of motion $K_{t+1} = (1-\delta)K_t + \imath_t$; it is assumed that this year's investment becomes productive the next year. Denote the logarithm of capital stock by k_t.

The past import status may have an impact on the evolution of productivity; importing materials may bring plants into close contact with foreign suppliers in developed countries, which may lead to the positive dynamic externalities, or "learning by importing". To examine the possibility of "learning by importing", we allow the distribution of ω_{t+1} conditional on information available at t to be dependent not only on the past productivity, ω_t, but also on the past import status, d_t.[2]

Consider a fixed cost for importing materials, which may depend not only on the current import choice but also on the past import status because of a sunk start-up cost of importing materials. We denote the fixed import cost—which we may think as the sum of the per-period fixed cost and the sunk start-up cost—by $\Gamma(d_{t-1}, d_t)$. Since the profit and the value functions depend on the time specific factors, such as factor prices, we index the profit and the value functions by time. The Bellman equation for the plant can be written as

$$V_t(\omega_t, k_t, d_{t-1}) = \max\left\{\Phi_t, \max_{d_t,\imath_t}\{\pi_t(\omega_t,k_t,d_t) - c(\imath_t,k_t) - \Gamma(d_{t-1},d_t) + \beta E[V_{t+1}(\omega_{t+1},k_{t+1},d_t)|J_t]\}\right\},$$

where Φ_t is the sell-off value of the plant, $\pi_t(\cdot)$ is the profit after maximizing out the variable

[2] Ericson and Pakes (1995) consider the model in which the distribution of ω_{t+1} depends on the amount of $R\&D$ investment.

factors, $c(\imath_t, k_t)$ is the cost of investment, $\Gamma(d_{t-1}, d_t)$ is the fixed cost of importing materials, and J_t represents information available at time t. The policy functions associated with the fixed point of the Bellman equation specify an exit rule, a discrete import decision rule, and an investment decision rule. In particular, when the profit function $\pi_t(\cdot)$ is strictly increasing in ω_t, the plant exit rule is characterized by the threshold value $\underline{\omega}_t(k_t, d_{t-1})$ as:

$$\chi_t = \begin{cases} 1, & \text{for } \omega_t \geq \underline{\omega}_t(k_t, d_{t-1}), \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The import decision rule and the investment demand equation are written, respectively, as:

$$d_t = d_t^*(\omega_t, k_t, d_{t-1}) \tag{5}$$

$$\imath_t = \imath_t^*(\omega_t, k_t, d_{t-1}) \tag{6}$$

Note that the decisions to exit, import, and invest crucially depend not only on the capital stock but also the past import status because the past import status is one of the state variables. Accordingly, we will modify the "standard" OP/LP estimation procedure by incorporating the past import status as an additional state variable.

3 Econometric Specification

The equation (2) suggests the following specification of the Cobb-Douglas production function augmented by the term representing the use of imported intermediates:

$$y_{it} = \beta_k k_{it} + \beta_s l_{it}^s + \beta_u l_{it}^u + \beta_e e_{it} + \beta_x x_{it} + \beta_d d_{it} + \omega_{it} + \eta_{it}, \tag{7}$$

where lowercase variables denote log values. A plant's discrete choice to import from abroad is denoted by d_{it} while η_{it} is an i.i.d. shock that is not known to plants at the time of input decisions. To examine the possibility of dynamic effect of import status on productivity through "learning by importing," we consider the following stochastic process of ω_{it}:

$$\omega_{it} = \xi_t + \gamma d_{i,t-1} + \rho \omega_{i,t-1} + u_{it}, \tag{8}$$

where ξ_t is a year-specific productivity shock, u_{it} is independent of $d_{i,t-1}$ and $\omega_{i,t-1}$ with the cumulative distribution $F_u(\cdot)$.

We examine whether the use of imported intermediates leads to higher productivity by testing whether $\beta_d > 0$. A positive estimate of β_d provides plant-level evidence for R&D spillovers through trade in intermediate goods. On the other hand, a positive value of γ in equation (8) is evidence for "learning by importing" and the long-run effect of "learning by importing" is measured by $\frac{\gamma}{1-\rho}$.

The benefit from importing intermediates may differ across plants because the available range of intermediate goods is different across plants.[3] Assuming that all intermediate goods are symmetrically produced at level $\bar{x}$, the ratio of total intermediates to domestic intermediates measures the ratio of the range of intermediate inputs available in the world to the range of domestically produced intermediate inputs since $\frac{X_{it}}{X_{it}^h} = \frac{N_{it}(1)\bar{x}}{N_{it}(0)\bar{x}} = \frac{N_{it}(1)}{N_{it}(0)}$, where X_{it} is total intermediates and X_{it}^h is domestic intermediates. From this viewpoint the productivity effect of importing depends on how much imported intermediates are used relative to domestic intermediates. We examine whether the higher ratio of total intermediates to domestic intermediates leads to higher productivity by considering the following alternative specification:

$$\begin{aligned} y_{it} &= \beta_k k_{it} + \beta_s l_{it}^s + \beta_u l_{it}^u + \beta_e e_{it} + \beta_x x_{it} + \beta_n n_{it} + \omega_{it} + \eta_{it}, \qquad (9) \\ \omega_{it} &= \xi_t + \gamma n_{i,t-1} + \rho \omega_{i,t-1} + u_{it}, \end{aligned}$$

where $n_{it} = \ln \frac{X_{it}}{X_{it}^h}$. From the estimate of β_n and β_x, we may compute the elasticity of substitution across different varieties of intermediate goods, denoted by θ, using $\beta_n = \frac{\beta_x}{\theta - 1}$.

4 Estimation

4.1 The OP/LP Proxy Estimator

One of the main econometric issues in estimating the equations (7)-(9) is the simultaneity of a productivity shock ω_{it} and input decisions. If inputs are chosen on the basis of the productivity shocks, a plant with a higher productivity shock may use more inputs. Since the regressors are

[3] The benefit from importing intermediates may also be different when plants face heterogeneous transportation costs of foreign intermediate goods. Kasahara and Lapham (2007) show that, in such a case, the higher the ratio of total intermediates to domestic intermediates, the larger the productivity effect from importing.

positively correlated with the error term, the coefficients estimated by ordinary least squares (OLS) tend to be upwardly biased for variables that are more responsive to a contemporary productivity shock than other variables.

Endogenous exit decisions may also induce bias in the estimated coefficients due to sample selection. When a profit function is increasing in k_t and d_{t-1}, the threshold value of productivity that induces exiting, $\underline{\omega}_t(k_t, d_{t-1})$, is decreasing in k_t and d_{t-1}. Specifically, plants having larger capital stocks and previous experience importing intermediates expect larger future profits and hence stay in the market for lower realized values of ω_t; the OLS estimates may lead to biases in the coefficients of capital and imported materials.

In order to control for simultaneity and self-selection, we apply the framework developed by Olley and Pakes (1996) and extended by Levinsohn and Petrin (2003).[4] Our specification for production technology differs from theirs in that we have an additional state variable of import status, d_{it}, and that the import status has a dynamic effect on productivity as specified by (8).

Suppose that capital k_{it} and the import decision d_{it} are the state variables but l_{it}, x_{it}, and e_{it} are freely variable inputs. Then, the material's demand function is given as $x_{it} = x_t^*(\omega_{it}, k_{it}, d_{it})$, where the function $x_t^*(\cdot)$ is time-dependent, reflecting its dependence on time-specific common shocks in productivity and relative prices. Assuming that $x_t^*(\cdot)$ is strictly increasing in ω_{it}, we can invert this function to obtain the productivity shock ω_{it} as a function of (x_{it}, k_{it}, d_{it}):

$$\omega_{it} = \omega_t^*(x_{it}, k_{it}, d_{it}). \tag{10}$$

Replacing $\omega_t^*(x_{it}, k_{it}, d_{it})$ for ω_{it} in the equation (7) leads to a partial linear function:

$$y_{it} = \beta_s l_{it}^s + \beta_u l_{it}^u + \beta_e e_{it} + \phi_t(x_{it}, k_{it}, d_{it}) + \eta_{it}, \tag{11}$$

where $\phi_t(x_{it}, k_{it}, d_{it}) = \beta_k k_{it} + \beta_x x_{it} + \beta_d d_{it} + \omega_t^*(x_{it}, k_{it}, d_{it})$. In the first stage, following Levinsohn and Petrin (2003), we consistently estimate β_s, β_u, and β_e from (11).

[4] Levinsohn and Petrin's estimator is developed based on the investment proxy estimator of Olley and Pakes (1996). In the Chilean data, there are a substantial number of zero investment observations (perhaps due to the presence of fixed investment cost). For these observations, the investment proxy estimator of Olley and Pakes cannot be used because they do not satisfy the monotonicity condition (and thus the investment function is not invertible with respect to shocks). Given this feature of the Chilean data, we choose to use the Levinsohn and Petrin intermediate proxy estimator rather than the Olley and Pakes investment proxy estimator while we address the selection bias using the method suggested by Olley and Pakes.

In the second stage, the rest of the parameters β_k, β_x, and β_d are estimated as follows. Define the innovations in productivity conditional on last year's productivity, last year's import status, *and* survival:

$$\nu_{it} = \omega_{it} - E[\omega_{it}|\omega_{i,t-1}, d_{i,t-1}, \chi_{it} = 1], \tag{12}$$

where $\chi_{it} = 1$ if the i^{th} plant continues in operation at t and $\chi_{it} = 0$ if it exits. The productivity innovations ν_{it} in (12) are orthogonal to all information available at time $t-1$ and, together with η_{it} in (11), can be used to construct the orthogonality conditions. In fact, for each candidate parameter vector $\beta^* = (\beta_x^*, \beta_k^*, \beta_d^*)$, we may construct an estimate for the residual as:

$$(\nu_{it} \hat{+} \eta_{it})(\beta^*) = y_{it} - \hat{\beta}_s l_{it}^s - \hat{\beta}_u l_{it}^u - \hat{\beta}_e e_{it} - \beta_k^* k_{it} - \beta_x^* x_{it} - \beta_d^* d_{it} - \hat{E}[\omega_{it}|\omega_{i,t-1}, d_{i,t-1}, \chi_{it} = 1], \tag{13}$$

where the estimate of $E[\omega_{it}|\omega_{i,t-1}, d_{i,t-1}, \chi_{it} = 1]$ is obtained using the procedure suggested by Olley and Pakes (1996); in particular, we control for selection bias by considering the expectation conditional on the survival $\chi_{it} = 1$.[5] The parameters $\beta^* = (\beta_x, \beta_k, \beta_d)$ are estimated by minimizing the GMM criterion function that is based on nine orthogonality conditions using the predetermined variables $(k_{it}, k_{i,t-1}, d_{it-1}, d_{i,t-2}, x_{it-1}, x_{i,t-2}, l_{i,t-1}^s, l_{i,t-1}^u, e_{i,t-1})$ as instruments for the residual $\nu_{it} + \eta_{it}$. The standard errors are obtained by the bootstrap.

5 Data

The data set is based on an annual census of Chilean manufacturing plants, which covers all plants with more than 10 workers, by Chile's Instituto Nacional de Estadistica (INE) for 1979-1996.[6] Previous empirical studies using (a subset of) this data set includes Lui (1993), Pavcnik (2002), and Levinsohn and Petrin (2003). The data set includes gross revenue, the number of blue- and white-collar workers, various types of investment, imported materials, total materials, electricity and fuels. Each variable is deflated by using the corresponding annual price deflater to real 1980 Chilean pesos.

[5]The supplemental appendix, which is available from the authors upon request, discusses how exactly the selection issue is addressed in the context of the LP approach. While our approach controls for selection bias, Levinsohn and Petrin (2003) find that selection is unimportant when using an unbalanced panel.

[6]The unit of observation in our empirical analysis is "plant" rather than "firm." This is due to limitations of our data set. Firm-level analysis might be particularly important to address the issue of "learning-by-importing"; the dynamic learning through importing might be more important at firm-level than at plant-level.

We exclude plants for which any of the data for capital stocks, unskilled labor, skilled labor, energy, and domestic intermediates are either not available or reported as zero values. In particular, plants that do not report book values of their capital stocks in any year are initially excluded since constructing capital stocks for these plants is impossible.[7] After cleaning the data, the unbalanced panel data set contains 3598 plants. A substantial number of plants are eliminated from the sample due to a missing initial capital stock. Because this may lead to a sample selection problem, we also report the results under the extended sample of 4508 plants in which the capital stock in 1980, if it is missing, is imputed by a projected capital stock based on other reported plant observables.[8] Hereafter, the sample that excludes the plants missing book values of their capital stocks is called the "Basic Sample" while the sample with imputed capital stocks is called the "Extended Sample." Since the main features of the descriptive statistics of these two samples are similar, we focus on the statistics of the Basic Sample in this section.

Output is total revenue adjusted for inventory change. Real output (Y) is constructed by deflating nominal output using an industry output price deflater. Real domestic material (X^h) is constructed by subtracting the nominal value of imported materials from the total materials and then deflated using an industry price deflater.[9] Real imported materials is constructed by deflating the nominal imported materials by the import price index (in Chilean peso) reported in International Financial Statistics. The real value of total materials (X) is the sum of the real domestic materials and the real imported materials. The number of blue- and white-collar workers are used for skilled and unskilled labor input (L^s and L^u). The energy input (E) is the sum of the real purchased value of electricity and that of fuels. The value of imported materials is reported separately from the total value of materials.

The capital stock is constructed separately for buildings, machinery and equipment, and

[7]The book values of capital are only reported, if any, in 1980 and 1981. Some plants did not report the book values of capital in either 1980 or 1981. Since it is not possible to construct capital stock without these reports, the plants missing their book values of capital were excluded from the sample. Notably, plants enter into the market after 1982 are not included in the sample. We focus on the sample of plants that operated in both 1979 and 1980 so that we may use the variables that are two period lagged in our regression analysis.

[8]Three types of capital (i.e., machinery, transportation, and buildings) are available in the data. We first impute a missing capital stock separately across types and then combine three types of imputed capital stock into one. We use 4-digit industry dummies, location dummies, and business-type dummies (e.g., corporation vs. public) to do projection.

[9]For both the output price deflater and the intermediate price deflater, we have used a 3-digit industry deflater for 1979-1986, which is contained in the original data set as described in Lui (1993), and a 2-digit industry deflater for 1987-1996 obtained from Yearbook of National Accounts by the Central Bank of Chile. As far as we know, the material price deflater at 3-digit levels are not available after 1987.

Table 1: Descriptive Statistics in 1980

	Output	Capital	Labor	Energy	Interme-diates	Import Ratios	Output/ Workers	No. of Plants
All Plants	95.58	45.20	54.45	3.35	49.36	0.08	1.16	3598
	(437.46)	(253.38)	(105.09)	(26.13)	(221.81)	(0.18)	(1.63)	—
Importing Plants	445.64	194.32	177.17	11.20	201.87	0.37	2.56	273
	(1021.01)	(431.44)	(256.26)	(34.72)	(407.35)	(0.25)	(3.73)	—
Non-Importing Plants	20.84	9.08	26.18	0.66	12.60	—	0.74	2017
	(38.29)	(51.95)	(29.51)	(5.52)	(25.28)	—	(0.72)	—
Switchers	137.77	69.78	72.44	5.86	74.23	0.13	1.50	1308
	(521.03)	(355.70)	(103.35)	(39.38)	(303.84)	(0.22)	(1.68)	—
Survivors	170.97	76.44	77.74	6.28	84.93	0.11	1.50	1348
	(79.34)	(376.54)	(139.50)	(40.20)	(338.10)	(0.21)	(1.96)	—
Quitters	50.41	26.48	40.50	1.60	28.05	0.05	0.95	2250
	(155.63)	(129.72)	(74.09)	(10.77)	(94.93)	(0.16)	(1.36)	—

Notes: Standard errors are in parentheses. The statistics are based on the "Basic Sample" that excludes plants for which the initial capital stock are not reported. "Importing Plants" are plants that continuously imported foreign intermediates in the sample. "Non-Importing Plants" are plants that never imported foreign intermediates in the sample. "Switchers" are plants that switched their import status in the sample. "Survivors" are plants that did not exit during the sample period (1980-1996) while "Quitters" exit during the sample period. "Output," "Capital," "Energy," and "Intermediates" are measured in millions of 1980 pesos. "Labor" is the number of workers. "Import Ratios" are the ratios of imported intermediate materials to total intermediate materials.

vehicles from the 1980 book value of capital (the 1981 book value if the 1980 book value is not available) using perpetual inventory method.[10] The nominal net investment variable is constructed, separately for buildings, machinery and equipment, and vehicles, and then deflated using the construction deflater for buildings and the machinery deflater for machinery and equipment, and vehicles to obtain the real net investment ($\imath$).[11] Buildings are likely to be rented rather than owned by plants, since zero values are found frequently for buildings, especially for small plants. We add the capitalized rental value measured at plant level to current year capital stock.[12] The total capital stock (K) is the sum of the real capital stock for building, machinery and equipment, and vehicles, and the capitalized rental value. Note that the capital stock in year t does not include the investment in year t.

[10]Since the reported book values are evaluated at the end of year t, the book values of capital are deflated by the (geometric) average deflater of machinery and equipment for years t and t+1. Depreciation rates are set to 5 % for building, 10 % for machinery and equipment, and 20% for vehicles.

[11]The data contains information on five types of investments: (i) purchases of new capital, (ii) purchases of used capital, (iii) production of capital for own use, (iv) improvements in own capital by third parties, and (v) sales of capital. The net investment is the sum of (i)-(iv) minus (v).

[12]The data on rental rate is not available. To obtain a crude measure of rental rate, assuming the aggregate Cobb-Douglas production, we compute (rental rate)=(the share of capital)$\times$ GDP/(Capital Stock)-(depreciation rate)$\approx$ 0.15 on average for 1980-1996 using the data on Chilean GDP and Capital Stock constructed from the Chilean national accounting data with (the share of capital)=0.3 and (depreciation rate)=0.05. The capitalized rental value is computed as (rental value)/0.15 using rental value reported at plant level.

Table 2: Transition Probability of Import Status and Exit

Year t status	No Imports			Imports		
Year $t+1$ status	No Imports	Imports	Exit	No Imports	Imports	Exit
1981-1985 ave.	0.844	0.054	0.102	0.170	0.788	0.042
1986-1990 ave.	0.885	0.055	0.061	0.173	0.805	0.023
1991-1995 ave.	0.874	0.067	0.058	0.119	0.860	0.021
1981-1995 ave.	0.868	0.059	0.074	0.154	0.818	0.028

Notes: The statistics are based on the "Basic Sample" that excludes plants for which the initial capital stock are not reported.

Table 1 reports descriptive statistics for variables in the year of 1980. A comparison between "Importing Plants," 'Non-Importing Plants," and "Switchers" in Table 1 reveals substantial differences between the three types of plants. Importing plants are substantially larger and have higher labor productivity while 'Non-Importing Plants" are smaller and least productive among those three types of plants, although the direction of causality is not clear. On the other hand, as shown in the last two rows of Table 1, "Survivors" which do not exit before 1996 are larger, more productive, and tend to import more in 1980 than "Quitters" that exit within the sample period of 1980-1996.

Out of 3598 plants, 273 plants (7.6%) continuously import foreign intermediates throughout the sample period (i.e., "Importing Plants" in Table 1), while 2017 plants (56.1%) are "Non-Importing Plants" that never import intermediates from abroad. This suggests that plant import status is persistent over time. There are, nevertheless, 1308 plants (36.4%) that switch between importing and not importing over the period and, among them, 757 plants switch import status more than once. This within-plant variation of import status is, thus, an important source of identification of the import variable coefficient.

Table 2 presents transition rates across import status together with exit rates. The last row indicates the average transition rates for 1981-1995. The persistence in import status is also clear here; among the plants that did not import in year t, more than 85 percent of them did not import in year $t+1$, while, among the plants that did import in year t, about 82 percent of them did import in year $t+1$. Comparing plants across import status in year t, we notice that importers are more likely to survive than non-importers.

6 Results

Tables 3 and 4 present the results from various estimators using the discrete choice import variable; columns (1)-(5) of Table 3 and Table 4 report the results of the Basic Sample while columns (6)-(8) of Table 3 and Table 4 report those of the Extended Sample. To address the simultaneity issue, we also consider the Within-groups estimator and the system GMM estimator (Blundell and Bond, 2000). The results from the OLS and the Within-groups estimators for the Extended Sample are omitted because they are very similar to those for the Basic Sample.

The most important finding is the significance and often large size of the current discrete import variable coefficient across different estimators. The OLS point estimate implies that a plant only using domestic intermediates can increase its productivity by 11.1 percent if it starts importing intermediates. The OLS estimate is, however, likely to be biased due to correlation between an unobserved plant productivity shock and inputs.

The within-estimator is robust against the simultaneity between a permanent plant-specific shock and input decisions. Column (2) of Table 3 demonstrates that although estimate of β_d is smaller using the within-estimator relative to OLS, at 2.6 percent, it is still positive and significant. The smaller estimate of β_d may be due to the downward bias induced by classification error in discrete import variable d_t.

While the within-estimator controls for correlation between inputs and a permanent shock, it does not address the simultaneity between inputs and the persistent shock that varies within-plant over time. To correct for such simultaneity in panel data, we further provide the results from two alternative estimators: the system GMM estimator and the OP/LP Proxy estimator. The system GMM estimates in columns (3) of Table 3 also indicate that imports have a strong, positive effect on plant productivity. The model finds 18.0 percent increases in productivity from a switch to imports for the Basic Sample.

Columns (4)-(5) of Table 3 provide the results of the OP/LP Proxy estimator which controls for both selection and correlation between inputs and an unobserved productivity shock by using intermediate inputs as proxies for unobserved productivity shocks.[13] The over-identification restrictions are not rejected for all four cases.[14] Column (4) reports the OP/LP estimates under

[13]Since both the investment and the import policy functions (5)-(6) may differ across years, due to the macroeconomic cycles and the changes in trade policies, we allow for $\phi(\cdot)$ to differ across the following six periods: 1979-1981, 1982-1983, 1984-1986, 1987-1989, 1990-1992, and 1993-1996.

[14]In addition to the over-identification test, we conducted two other specification tests suggested by Levinsohn

Table 3: Estimates of Production Function: Discrete Import Variable

The Data Set	Basic Sample					Extended Sample		
Estimators	OLS	Within	GMM	OP/LP Proxy		GMM	OP/LP Proxy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skilled labor	0.139	0.062	0.034	0.137		0.038	0.127	
	(0.003)	(0.004)	(0.031)	(0.006)		(0.027)	(0.008)	
Unskilled labor	0.143	0.175	0.251	0.145		0.243	0.142	
	(0.004)	(0.006)	(0.032)	(0.008)		(0.028)	(0.008)	
Energy	0.052	0.062	0.092	0.043		0.002	0.057	
	(0.002)	(0.003)	(0.025)	(0.005)		(0.002)	(0.006)	
Capital	0.091	0.054	0.108	0.058	0.064	0.139	0.065	0.076
	(0.002)	(0.003)	(0.019)	(0.009)	(0.010)	(0.016)	(0.011)	(0.012)
Materials	0.647	0.581	0.612	0.549	0.509	0.655	0.575	0.525
	(0.003)	(0.005)	(0.023)	(0.025)	(0.029)	(0.020)	(0.024)	(0.037)
Disc. Import (β_d)	0.111	0.026	0.180	0.214	0.220	0.161	0.139	0.129
	(0.005)	(0.005)	(0.049)	(0.035)	(0.067)	(0.045)	(0.032)	(0.039)
γ	—	—	0.009	0.041	—	0.008	0.024	—
			(0.013)	(0.011)		(0.011)	(0.009)	
ρ	—	—	0.245	0.892	—	0.271	0.900	—
			(0.022)	(0.027)		(0.016)	(0.116)	
Implied $\frac{\gamma}{1-\rho}$	—	—	0.012	0.379	—	0.011	0.235	—
P-value for over-identification test				0.593	0.759		0.874	0.427
No. of Obs.			33200				45518	

Notes: Standard errors are in parentheses. Columns (1)-(5) use the "Basic Sample" that excludes plants for which the initial capital stock are not reported. Columns (6)-(8) use the "Extended Sample" in which a missing initial capital stock is imputed by a projected initial capital stock based on other reported plant observables. The System GMM estimator in columns (3) and (6) use a lag length of 2 and 3 for instruments in the first-differenced equations and a lag length of 1 in the level equations. The OP/LP estimators in columns (4) and (7) specify the stochastic process of ω_t of the equation (8), while the OP/LP estimators in columns (5) and (8) uses the third order polynomials in (ω_{t-1}, d_{t-1}).

the AR(1) specification for the ω_{it} process using the Basic Sample. It indicates a large productivity effect (21.4 percent) arising from the usage of imported intermediate goods. To examine the robustness of the results with respect to the specification of the productivity process, we report the OP/LP estimates under the flexible specification for ω_t using a third-order polynomial in (ω_{t-1}, d_{t-1}) with selection. The results are reported in column (5) of Table 3. Once again, it indicates a large productivity effect (22.0 percent for the Basic Sample) from the usage of imported intermediates. We also estimate the production function using the technique proposed by Ackerberg, Caves and Frazer (2005) and find that the results on the effect from using imports are robust with respect to the potential identification issues they raise in respect to the OP/LP estimation technique.[15]

Comparing columns (3)-(5) with columns (6)-(8) in Table 3, we notice that controlling for sample selection due to missing capital stocks may be potentially important; the estimates of import coefficient from the Extended Sample—which deals with the sample selection due to missing capital stocks—range from 12.9 to 16.1 percent, which is smaller and perhaps more reasonable than those from the Basic Sample.

One might wonder why the estimates for import coefficient from the GMM and OP/LP estimators are substantially larger than the OLS estimates. In a multivariate context, however, even if import variables are positively correlated with contemporary shocks, the OLS estimates for import variables could be *downwardly* biased when import decisions are *less* responsive to a shock than other inputs (cf., Levinsohn and Petrin, 2003).[16] This is potentially the case as import status is persistent over time in the data. It might be also surprising that the capital coefficient from the OP/LP estimation are lower than the OLS estimates given that a reason for the development of the OP/LP estimators was to remove a suspected downward bias in OLS capital coefficients. However, relative to the "standard" specification, our specification includes an additional persistent variable—import status—which is positively correlated with

and Petrin (2003). First, to be consistent with the model, productivity shock should be monotonically increasing in the materials, holding state variables (i.e., capital and import status) constant. By plotting the productivity proxy ω_{it} as a function of capital and intermediate inputs separately for importers and non-importers, we found that this is indeed the case. Second, we use the energy variable in place of the materials as an input proxy and found that the estimated impact of imported materials on productivity is even larger under the energy proxy.

[15]The result is available from the authors upon request.

[16]Other possible explanation for the downward OLS bias is the presence of measurement (or classification) errors in import variables. Using the past import variables as instruments may correct for the bias due to measurement errors. This could be an explanation for the difference between the OLS and the GMM estimates. On the other hand, the implication of measurement errors for the OP/LP estimator is not well understood in the literature.

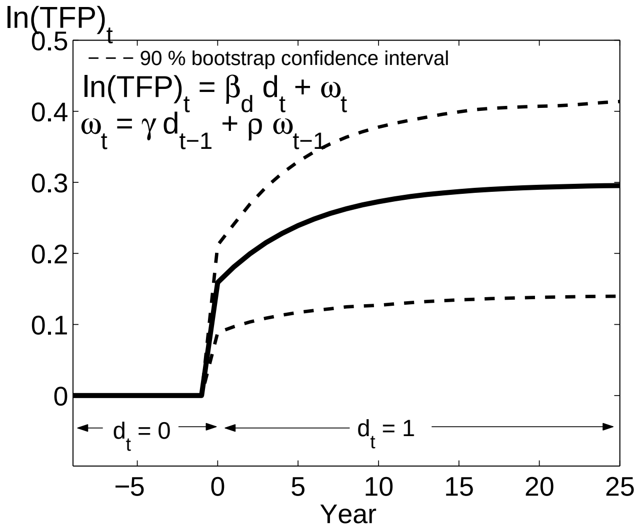

Figure 1: Productivity Dynamics and Import Status

capital and, consequently, it is difficult to assess ex ante the direction of OLS bias on capital coefficient in our case.[17]

Although we cannot be as certain about the magnitude of the effect given the wide range of estimates across different estimators, even the within-estimator—which is likely to be downwardly biased—suggests that the productivity gain from importing is 2.6 percent. Overall, the results reported in Table 3 suggest a positive static effect from importing on productivity since the estimates are quantitatively important even at the lower bound.[18]

Another interesting finding is that, throughout columns (3)-(4) and (6)-(7) of Table 3, the estimated values of γ are positive and often significant. This suggests a positive *dynamic* effect of the use of imported materials (i.e., "learning by importing") although the evidence is not as strong as the case for the static effect given the small and insignificant estimates of γ for the GMM estimator as reported in columns (3) and (6).

Figure 1 shows what would happen to the total factor productivity, defined as $\beta_d d_{it} + \omega_{it}$,

[17]When we estimate the production function without the import variable using the Basic Sample, the OLS estimate of capital coefficient becomes 0.050 while the OP/LP estimate for capital becomes 0.086. Comparing them with the corresponding estimates in Table 3, we notice that the exclusion of import variable substantially decreases the OLS estimate of capital coefficient while it increases the OP/LP estimates.

[18]There are caveats regarding the validity of the GMM estimator as well as the OP/LP estimator, however. The GMM estimator may potentially suffer from weak instruments problem while the maintained assumptions for the OP/LP estimator might be violated in reality. To the extent that the validity of the assumptions underlying these estimators is uncertain, we should take the results from the GMM and the OP/LP estimators with caution.

for a plant that is not importing at the steady state (i.e., $d_{i0} = 0$) before Year 0 and, for some exogenous reason, starts importing intermediates at Year 0.[19] The figure is produced using the estimates from the extended sample reported in column (7) of Table 3. The solid line indicates the dynamic path of productivity implied by the point estimates reported in column (4) while the dashed lines represent a 90 percentile bootstrap confidence interval.[20] At Year 0, a plant starts importing foreign intermediates, leading to an immediate increase in productivity by 13.9 percent (static effect). After Year 0, a plant gradually achieves additional 23.5 percent productivity increase (dynamic effect). Note, however, that a 90 percent bootstrap confidence interval suggests that there exists substantial uncertainty regarding the precise magnitude of the dynamic effect of importing materials.

Table 4 presents estimates using the continuous measure of import usage, measured by the ratio of total intermediates to domestic intermediates. In the table, the estimated coefficients for skilled labor, unskilled labor, energy, capital, and materials are all significant and similar to those reported in corresponding columns of Table 3; that is, the use of the continuous import variable in place of the discrete import variable leads to the similar estimates for these variables.

Across various estimators, the coefficients for the continuous import variable are often significant and of large size across different estimators, indicating the importance of foreign intermediates in explaining productivity differences across plants and over time. The system GMM estimates in columns (3) and (6) imply that a 100 percent decrease in the share of domestic intermediates in total intermediates could increase productivity between 5.8 and 7.2 percent although the estimate from the Basic Sample in column (3) is not significant. The OP/LP estimates reported in columns (4)-(5) and (7)-(8) again support a substantial impact of an increase in the share of imported intermediates on productivity, finding that a 100 percent decrease in the share of domestic intermediates increases productivity by 17.7 to 27.0 percent.

The positive estimates of γ throughout all columns in Table 4 are suggestive of the positive dynamic effect of an increase in the usage of imported intermediates although, as in the case of the discrete import variable, the estimates from GMM estimator are insignificant. The OP/LP

[19] Idiosyncratic shocks, u_{it}, are set to zero for all periods. Or, alternatively, we may interpret the solid line as the path of "average" productivity among plants that start importing at Year 0 and keep importing after Year 0 for some exogenous reason.

[20] To construct a 90 percentile bootstrap confidence interval, we repeatedly compute the dynamic path of productivity under different bootstrap estimates for (β_d, γ, ρ) and take a 5 and a 95 percentile of $\beta_d d_{it} + \omega_{it}$ for each year.

Table 4: Estimates of Production Function: Continuous Import Variable

The Data Set	Basic Sample					Extended Sample		
Estimators	OLS	Within	GMM	OP/LP Proxy		GMM	OP/LP Proxy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skilled labor	0.147	0.062	0.056	0.138		0.046	0.128	
	(0.003)	(0.004)	(0.031)	(0.006)		(0.026)	(0.008)	
Unskilled labor	0.144	0.174	0.278	0.148		0.253	0.145	
	(0.004)	(0.006)	(0.033)	(0.008)		(0.028)	(0.009)	
Energy	0.051	0.062	0.074	0.044		0.002	0.056	
	(0.002)	(0.003)	(0.025)	(0.005)		(0.002)	(0.006)	
Capital	0.094	0.054	0.121	0.066	0.074	0.145	0.074	0.089
	(0.002)	(0.003)	(0.019)	(0.009)	(0.010)	(0.016)	(0.009)	(0.016)
Materials	0.651	0.582	0.603	0.616	0.577	0.653	0.608	0.548
	(0.003)	(0.005)	(0.024)	(0.021)	(0.027)	(0.020)	(0.023)	(0.026)
Cont. Import (β_n)	0.096	0.034	0.058	0.246	0.270	0.072	0.177	0.182
	(0.006)	(0.007)	(0.042)	(0.052)	(0.061)	(0.032)	(0.043)	(0.062)
γ	—	—	0.004	0.030	—	0.001	0.026	—
			(0.016)	(0.010)		(0.014)	(0.008)	
ρ	—	—	0.241	0.822	—	0.271	0.871	—
			(0.023)	(0.031)		(0.016)	(0.027)	
Implied $\frac{\gamma}{1-\rho}$	—	—	0.005	0.169	—	0.001	0.199	—
Implied θ	7.78	18.12	11.40	3.50	3.14	10.07	4.44	4.01
P-value for over-identification test				0.824	0.759		0.834	0.995
No. of Obs.			33200				45518	

Notes: Standard errors are in parentheses. Columns (1)-(5) use the "Basic Sample" that excludes plants for which the initial capital stock are not reported. Columns (6)-(8) use the "Extended Sample" in which a missing initial capital stock is imputed by a projected initial capital stock based on other reported plant observables. The System GMM estimator in columns (3) and (6) use a lag length of 2 and 3 for instruments in the first-differenced equations and a lag length of 1 in the level equations. The OP/LP estimators in column (5) and (8) specify the stochastic process of ω_t using the third order polynomials in (ω_{t-1}, n_{t-1}).

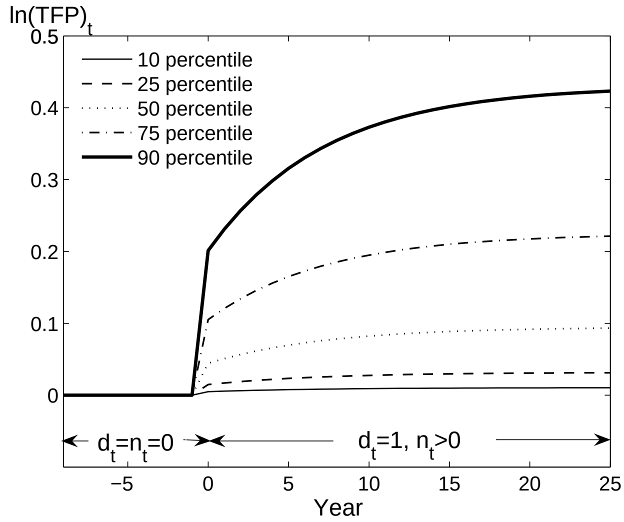

Figure 2: Productivity Dynamics Heterogeneity across Different Import Shares

estimates of $\frac{\gamma}{1-\rho}$ in columns (4) and (7) indicate that the long-run dynamic effect of a 100 percent decrease in the share of domestic intermediates are 16.9 and 19.9 percent, respectively. From the estimated coefficients of materials and continuous import variable, we can also compute an estimate of the elasticity of substitution as $\hat{\theta} = 1 + \frac{\hat{\beta}_x}{\hat{\beta}_n}$. Using the OP/LP estimates in Table 4, we obtain point estimates of θ of 3.14 to 4.44 which are in line with those found by Feenstra, Markusen, and Zeile (1992).

Even among importing plants, there exists substantial heterogeneity in the use of imported intermediates; the share of imported intermediates in total intermediates for the bottom 10 percentile of importing plants is only 2.8 percent while the share of imported intermediates for the 90 percentile importing plants is as high as 67.9 percent. In the view of specification for continuous import variable (9), when plants are heterogeneous in the use of imported intermediates, they will experience different productivity dynamics when they start importing intermediates.

Figure 2 plots the dynamic paths of total factor productivity before and after plants start importing intermediates at Year 0 for five hypothetical plants with different import shares.[21] Here, we assume that the import shares when plants import are plant-specific and permanently fixed. The thin line represents the productivity dynamics for the bottom 10 percentile importing plants with 2.8 percent import shares while the thick line corresponds to the dynamics for the

[21]The estimates in column (7) of Table 4 are used to produce the figure.

Table 5: OLS Regression of TFP on Import and Export: Discrete Variables

	Basic Sample			Extended Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Discrete Import	0.153	0.128	0.007	0.098	0.076	0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Discrete Export	0.135	0.111	0.014	0.091	0.072	0.021
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)
Industry-Year Dummies	No	Yes	Yes	No	Yes	Yes
Plant Fixed Effects	No	No	Yes	No	No	Yes
No. of Obs.	11027	11027	1694	12014	12014	3241

Notes: Standard errors are in parentheses. The estimates are based on the observations for the 1990-1996 period since those are the only years for which export behavior is observed. "Industry-Year Dummies" includes a full set of interactions between 4-digit ISIC industry dummies and year dummies. Total factor productivity is calculated as $\hat{E}[\omega_{it}|\omega_{i,t-1}, \chi_{it} = 1]$.

90 percentile importing plants with 67.9 percent import shares; other three lines represent the productivity dynamics for 25, 50, and 75 percentile importing plants.[22] Figure 2 highlights that the productivity effect from importing intermediates may substantially differ across plants because of the difference in import shares. The bottom 10 percentile importing plants hardly benefit from importing intermediates while the 90 percentile importing plants experience an immediate increase in productivity by 20.1 percent at Year 0 (static effect) and gradually achieve additional 22.6 percent productivity increase after Year 0 (dynamic effect).

While the continuous import variable estimates provide important additional evidence for the impact of imported intermediates on plant-level productivity, we also check the sensitivity of the results with respect to the following potentially important controls: export behaviour and industry-year dummies.[23] An omission of export variable from the regressors might lead to an upward bias in the coefficient of imported intermediates since "good" firms often both export and import (cf., Kasahara and Lapham, 2007). On the other hand, the trade environment may change differently across industries over time; for instance, an increase in tariffs in the mid-1980's may have differential impacts across industries. Industry-year dummies may capture time-varying industry-specific trade environment.[24]

To examine the robustness, we first estimate a production function (7) by the OP/LP pro-

[22] The shares of imported intermediates in total intermediates for 25, 50, and 75 percentile importing plants are 8.1, 22.2, and 44.8 percent, respectively.

[23] Although this procedure is common in the international trade literature, unlike the results in Tables 3 and 4, it is not robust to the presence of sunk imports costs. See Biesebroeck (2003) for an example.

[24] Other potentially important controls include foreign investment goods and foreign ownership. Due to data limitations, we cannot examine the robustness against the inclusion of these controls and our estimates of the productivity effect from importing intermediates potentially capture the effect of foreign investment goods or foreign ownership.

Table 6: OLS Regression of TFP on Import and Export: Continuous Variables

	Basic Sample			Extended Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Continuous Import	0.139	0.112	0.012	0.081	0.062	0.005
	(0.008)	(0.007)	(0.003)	(0.005)	(0.004)	(0.003)
Continuous Export	0.008	0.007	0.001	0.006	0.005	0.002
	(0.001)	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Industry-Year Dummies	No	Yes	Yes	No	Yes	Yes
Plant Fixed Effects	No	No	Yes	No	No	Yes
No. of Obs.	11027	11027	1890	12014	12014	3591

Notes: Standard errors are in parentheses. The estimates are based on the observations for the 1990-1996 period since those are the only years for which export behavior is observed. "Industry-Year Dummies" includes a full set of interactions between 4-digit ISIC industry dummies and year dummies. Total factor productivity is calculated as $\hat{E}[\omega_{it}|\omega_{i,t-1}, \chi_{it} = 1]$.

cedure but without including import variable as a regressor and obtain the estimates of total factor productivity. Then we regress the estimated total factor productivity on import variable, export variable, as well as a full set of interactions between 4-digit ISIC industry dummies and year dummies. We also control for the plant fixed effects. For export status, we consider both discrete export variable that takes the value of one for an exporter (and zero for a non-exporter) and continuous export variable measured by the ratio of export sales to total revenues. Since export behavior is observed only for the 1990-1996 period in the data, the estimates are obtained based on the 1990-1996 period sample.

Table 5 presents the results for the discrete import/export variables. As reported in columns (1)-(2) and (4)-(5), the import effect is still positive and significant, ranging from 7.6 to 15.3 percent, even after controlling for export status and industry-year dummies. The estimates controlling for plant fixed effects in columns (3) and (6) are lower, indicating 0.4-0.7 percent positive productivity effect from importing; the estimates for the plant fixed effects may be downwardly biased because of the classification errors and it is not significant in column (6) possibly because there is not enough within-plant variations in import variables given the short nature of the panel data as well as the substantial persistence in import status.[25] On the other hand, the export effect is positive and significant in all cases, indicating a possible productivity effect from becoming an exporter.

Table 6 reports the results for the continuous import/export variables. The results imply that a 100 percent decreases in the share of domestic intermediates increases productivity by

[25]More than 80 percent of plants are dropped from the fixed effects regression because these plants did not change their export/import status throughout the sample period of 1990-1996.

0.5 to 13.9 percent. Thus, not only whether plants import but also how much they import is important in determining plant productivity. In contrast, the results for the continuous export variable suggest a small productivity effect from increasing the share of exports in total output across all estimates. One possible interpretation is that the productivity effect of exporting may work mainly through the extensive margin of whether plants export or not rather than the intensive margin of how much they export.

We also check how the results change across industries by estimating the production functions for two of the largest 3-digit industries, Food and Metals, and find that focusing on one particular industry does not alter the basic finding.[26]

7 Conclusion

The results in this paper demonstrate significant plant-level evidence that imported intermediates improve a plant's productivity. We find that by switching from being a non-importer to an importer of foreign intermediates a plant can immediately improve productivity; although the point estimates substantially differ across different estimators, even the estimate from the Within-Group estimator, which is probably downwardly biased, indicates a 2.6 percent positive productivity effect from importing. We also find some evidence of a positive dynamic effect from the use of imported materials. These results have important implications for both government policy and plant production strategy.

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