Imported Capital Input, Absorptive Capacity, and Productivity: Evidence from Firm-Level Data

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Abstract
Importing foreign capital inputs has been recognized in economics literature as a critical channel for technology transfer across countries, particularly in the context of developing countries. In this study, we examine whether and to what extent the productive impact of imported capital varies with manufacturing firms’ abilities to absorb new technologies using OLS, IV, and recently developed endogenous threshold regression estimates of a production function specification. We find that firms with higher absorptive capacity gain significantly more from importing foreign capital input. Our results also suggest a threshold for such benefits. Furthermore, the productive contribution of skilled labor is significantly higher in firms that import foreign capital input. Thus, developing policies to augment human capital to match international standards will help firms in developing countries to realize benefits associated with imported capital inputs.

Keywords: Imported Capital Input, Absorptive Capacity, Productivity, Skill Intensity, Threshold Regression

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**Introduction**

The importance of productivity growth as a primary determinant of the underlying difference in income across countries is now a well established empirical proposition (Hall and Jones, 1999). The question of interest is how the productivity of firms can be enhanced in developing countries in order to narrow the income gap from more developed countries. The endogenous growth theory suggests that innovation is the main source of productivity growth (Grossman and Helpman, 1991). However, the creation of new products and technologies is concentrated mostly in the developed countries (Eaton and Kortum, 2001). Developing countries rely mostly on technology and knowledge produced by high-income countries rather than direct investment in research and development. A crucial question for developing economies is therefore whether, how, and to what extent importing foreign technology can enhance the productivity of their firms to narrow the income gap between developed and developing countries.

In this paper, we examine the productivity impact of imported capital input by emphasizing on its interaction with the absorptive capacity of manufacturing firms. The importing of foreign capital inputs, which embody technology and knowledge, has been recognized in the economics literature as a significant conduit for technology transfer across countries (Coe and Helpman, 1995; Eaton and Kortum, 1996, 1999, 2001; Grossman and Helpman, 1991; Xu and Wang, 1999).\(^1\) Coe and Helpman (1995), for example, find significant productivity impact at the country level from importing intermediate products and capital inputs, and Keller (2002a,b) supports this finding with industry-level data. In the firm-level studies conducted, it was observed that the productive impact of the imported capital input varies across countries both in terms of

\(^1\) See Keller (2002b) for a detailed discussion of international technology diffusion.
statistical significance and magnitude. Kraay et al. (2001), Keller and Yeaple (2003), and Vogel and Wagner (2008) find weak evidence of productivity effects of importing at the firm level, but Amiti and Konings (2007), Fernandez (2007), Gorg and Hanley (2005), Gorg et al. (2007), Halpern et al. (2006), Jabbour (2007), Kasahara and Rodrigue (2008), Lopez (2006), Lopez and Yadav (2009) and Yasar and Paul (2007, 2008) find statistically significant but highly varying effects. Overall, the findings of this literature suggest that the productive impact of imported capital input varies across countries studied; in some countries it is strong while in others it is weak or statistically insignificant. These differences across the countries may stem in part from the fact that countries at different stages of development have differences in some firm characteristics that help create mechanisms through which productivity gains are realized. Thus, this relationship might be expected to be different in developing countries than it is in relatively more developed countries. This calls for further study of the productive contributions of imported capital in various countries, at different stages of development, by emphasizing its linkages with some other firm characteristics. For example, the productive contributions of imported capital input may also depend on firms characteristics that vary across countries, industries and firms such as input composition, skill intensity or absorptive capacity.

In most cases, the productive effects of importing are examined using standard least squares techniques by including a dummy variable to indicate the import of intermediate inputs in a production function or a productivity equation. The constant

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2 Trade liberalization may increase the firm productivity not only because of the imported capital input but also because of the reallocation of resources across products within firms (Bernard et al., 2006; Goldberg et al., 2009). Our data does not allow us to study the relationship between importing and firms’ product mix changes over time.
coefficient on the imported input variable therefore represents the increase in productivity due to the imported capital inputs. Such a method assumes homogeneity in the productive impact of the imported capital input across the firms by imposing a linearity restriction on the outcome equation. It is expected that the importing capital from countries with higher levels of accumulated technical knowledge will improve the productivity of the firms in a developing host-country through R&D embodied in the capital and learning associated with their use. However, a shortage of absorptive capacity (such as human capital) could potentially limit the ability of the firms to utilize these new technologies effectively.

The relationship may not be linear since the degree to which knowledge spillovers can be effectively utilized in the host-country will depend on the skill intensity or absorptive capability of firms in the host-country, as well as some other firm, industry or country characteristics. In fact, Nelson and Phelps (1966) emphasize the importance of absorptive capability: “...We suggest that, in a technologically progressive or dynamic economy, production management is a function requiring adaptation to change and that the more educated a manager is, the quicker will he be to introduce new techniques of production. To put the hypothesis simply, educated people make good innovators, so that education speeds the process of technological diffusion.” They argue that the adoption of

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3 See Feenstra (1998) and Head and Ries (2002).
4 By developing a dynamic structural model, for instance, Aw, Roberts and Xu (2008, 2009) thoroughly examined such relations for exporting firms in the Taiwanese electronics industry and found significant interactions between R&D, exporting, and productivity for exporting firms in the Taiwanese electronics industry.
5 Absorptive capacity in this context means that firms in the host-country must have a certain proficiency level to use the imported technology to enhance productivity.
6 In a more general context, it is now well established that higher quality institutional arrangements are necessary in order for trade liberalization to enhance countries’ productivity and thus income (Rodrik, 2000 and 2006). For instance, labor market reforms are needed to allow worker mobility across firms and industries so that the firms can have access to skilled labor. Firms in a country with higher quality institutions and industrial policy are more likely to utilize the imported technology more efficiently than the firms in a country which does not have such arrangements and policies that reward the higher productivity activities.
new technologies requires a threshold stock of human capital in the host-country, and the extent to which the gap between the technology frontier and current productivity can be closed depends on the level of this stock.\textsuperscript{7} Spillover productivity effects from importing technology would thus be expected to occur when human capital in a host-country firm is above a certain threshold level. If labor skill levels fall short of this threshold host-country firms are unlikely to be able to exploit the productive power of the foreign technology.\textsuperscript{8}

In this paper, our goal is to examine the productivity impact of imported capital input on a sample of Chinese manufacturing firms, with a focus on the interaction between import of capital input and absorptive capacity. More specifically, we empirically assess the theoretical predictions of the studies highlighted above, by investigating whether the successful adoption of new technologies requires a threshold level of labor force skills in the host-country, and whether a higher level of skilled labor enhances productivity improvements from importing capital. We recognize that the parameter estimates may fail to distinguish between productivity differences from imported technology and those emerging from unobserved firm-specific characteristics.

\textsuperscript{7} Benhabib and Spiegel (1994) use country-level data to test the Nelson-Phelps hypothesis and conclude that the flow rate of technology spillovers from leaders to followers depends on human capital levels. Cohen and Levinthal (1990) further show that the skills required to benefit from knowledge spillovers are usually the same as those required to create knowledge; benefiting from spillovers and creating knowledge are closely related processes.

\textsuperscript{8} The literature on the productivity impacts of foreign direct investment (FDI) and exporting on domestic firms provides support for these predictions. For example, using data on manufacturing firms in Uruguay, Kokko et al. (1996) find that spillover productivity effects are largest for host-country firms that have sufficient human capital to effectively utilize the foreign technology. Tan and Batra (1995) finds that joint ventures with foreign companies can also facilitate the transfer of technology because they are implemented by foreign management and accompanied by training. Aw, Roberts and Winston (2007) finds that firm investments in R&D and worker training can bolster their ability to internalize the benefits associated with the export market. See also Pavcnik (2003) and Bustos (2007) for the significant relationship between trade and skill upgrading.
that may have caused firms to choose to import capital inputs, and that the productive impact may be heterogeneous across firms. Thus, we estimate our model using two alternative econometric methods to OLS: an instrumental variable ("IV") estimator to control for the potential endogeneity; and newly developed threshold regression techniques (Hansen (2000) and Caner and Hansen (2004)) that employ an endogenous search algorithm to determine a threshold level of the absorptive capacity and its statistical significance without and with endogenous explanatory variables. We use the share of skilled workers (technicians, engineers and managers) as a proxy for the absorptive capacity of the Chinese manufacturing firms for new technologies, and examine the effect of the interaction of the human capital variable with imported technology on firm productivity.

Our study contributes to the literature on the imported capital-productivity nexus by: 1) exploring the productive contributions of imported capital input by emphasizing its interaction with absorptive capacity; 2) employing the instrumental variable technique that allows to control for potential endogeneity of the imported capital input; and 3) implementing a newly developed endogenous threshold regression method that allows the data to endogenously select a sample split and simultaneously test the presence of the threshold level of skilled labor share to provide empirical evidence of the productivity effects caused by imported capital input for firms in a developing economy.

After controlling for a number of firm characteristics that affect productivity and the potential endogeneity, we find that importing capital input is associated with significantly higher productivity in the Chinese manufacturing firms and those firms with higher absorptive capacity gain significantly more from importing foreign technology,
implying that the productive contribution of imported capital is significantly skilled-labor-using. These productivity gains also depend on a threshold level of human capital; the productivity differential for importing capital becomes statistically significant when the share of managers and engineers in total employment is about 38 percent, with a confidence interval of 28 percent to 44 percent. Furthermore, our results indicate that the productive contribution of skilled labor is significantly higher in firms that import foreign capital input.

**Empirical Model**

In order to examine whether and to what extent the productive impact of imported capital varies with the ability of the Chinese manufacturing firms to absorb new technologies, we use OLS, IV, and a recently developed endogenous threshold regression estimate of a production function specification. We assume that the production process is represented by a Cobb-Douglas production function, written as:

\[
\ln Y_i = \alpha_0 + \beta_1 \ln L_i + \beta_2 \ln K_i + \beta_3 \ln IMP_i + \beta_4 \ln SH_i + \beta_5 \ln IMP_i \ln SH_i + \sum_{m} \beta_m R_{m,i} + u_i,
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where \(i\) is a firm subscript; \(\ln Y\) is the log of value added; \(\ln L\) and \(\ln K\) are the log values of labor and capital input, respectively; \(IMP = 1\) if the firm imported any machinery and

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9 Although our data is cross section, and thus most questions in the survey intend to obtain info in 2002, the input and sales variables were available for previous two years for some firms in the sample. Thus, we also used a two-step approach, where we first estimated the total factor productivity using both OLS and a semi-parametric technique introduced by Olley and Pakes (1996), which allows to control for simultaneity bias when estimating a production function and thus to obtain consistent parameter estimates and reliable productivity estimates (Yasar et al., 2008). The results from this specification were similar to the ones reported in the paper but since we lose observations and the data is actually cross-section we did not pursue this further.

10 We have also estimated our model using a translog production function, which allows for a full range of substitution among inputs and thus captures differential productivity patterns for firms with heterogeneous input composition. The coefficients for the variables of the interest were similar to those obtained using the Cobb-Douglas production function.

11 We have also used gross output formulation. The results were consistent. For instance, the coefficient on the interaction term was 0.673 in the IV model, which was statistically significant at 0.01 conventional significance level. The results are available upon request.
otherwise; \( SH \) represents share of technicians, engineers and managers in total employment\(^{12}\); and \( u \) is a stochastic error term.\(^{13}\) \( R_m \) includes the variables for internal firm characteristics, which are age of the firm (\( AGE \)); whether or not the firm’s products have been granted ISO900 certification (\( ISO \)); capacity utilization (\( CU \), defined as the amount of output actually produced relative to the maximum amount that could be produced with existing machinery and regular shifts); and size (\( SD \))\(^{14}\), industry\(^{15} \) (\( ID \)) and region (\( CD \)) dummies.\(^{16}\)

In this model, our main variable of interest is the interaction of the imported machinery variable (\( IMP \)) with the variable representing the share of technicians, engineers and managers in total employment (\( SH \)). Based on the insights from theoretical studies, we expect highly skilled workers to use imported capital input more effectively. The coefficient on the interaction term \( \beta \), thus represents the extent to which human capital augments the productive benefits of imported machinery. Since this coefficient represents the impact of imported machinery on the productive contribution of skilled labor or on the productive contribution of imported machinery of more skilled labor, a

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\(^{12}\) We alternatively used a dummy variable that is equal to one if the average education level of the workers corresponds to a college degree or higher, and zero otherwise to check the robustness of using \( SH \). The results were similar, but note that \( SH \) was available for more firms. Thus, we reported the results of the models with \( SH \).

\(^{13}\) As shown by two recent influential papers, Katayama, Lu and Tybout (2009) and DeLoecker (2006), measured plant-level productivity may confound true plant-level productivity and differences in mark-ups across plants. The data on unit prices are not available for our firm-level data in order to be able to tackle this issue. Using concentration ratios does not change the results (Amiti and Konings (2007).

\(^{14}\) The size dummy for estimation (\( SD \)) is created using the number of workers.

\(^{15}\) One may reasonably argue that firms belonging to different industries in the sample will use different imported capital that embodies a different kind of technology. In order to capture this heterogeneity across the industries, we have also interacted the industry dummies with the import variable, but the coefficients on the interacted terms were neither individually nor jointly significant. The results are available upon request.

\(^{16}\) We have also interacted the import variable with the capital input, the foreign ownership and export variables, but the magnitude and the significance of the variables of interest were similar to those obtained without these interactions. The results are available upon request.
significantly positive (negative) estimate of this coefficient implies complementarity (substitutability) between imported machinery and skilled labor.

The coefficient on IMP alone, $\beta_3$, represents the direct impact of imported machinery on the productivity of firms; if $SH_i=0$ the productivity differential between the importers and non-importers is $\beta_3$. The coefficient on $SH_i$, $\beta_4$, similarly represents the productivity impact of skilled labor share for non-importers. The productivity impact of importing capital for firm $i$ including the impact of human capital is thus $\partial \ln Y_i / \partial IMP = \beta_3 + \beta_5 \ast SH_i$, and the productivity impact of human capital including the contribution of importing capital is $\partial \ln Y_i / \partial SH_i = \beta_4 + \beta_5 \ast IMP$. We expect the impact of the simultaneous increase in skilled labor share and imported capital input on the productivity of firms to be positive. This requires $\beta_5$ to be positive and statistically significant.

The other firm-specific characteristics accommodate heterogeneity across firms. $AGE$ is included because more experience would be expected to enhance productivity. It also represents the reputation of a firm. Whether or not the firm’s products have been granted ISO9000 certification ($ISO$) is included to capture the firm’s managerial or product quality. Capacity utilization ($CU$) is included to control for the average utilization of a firm’s fixed inputs. The remaining explanatory variables are firm-specific controls for size, industry, and region.

**Data**

To estimate the productive impact of imported technology associated with skilled labor intensity, we use cross-section survey data from the *Investment Climate Survey* conducted by the World Bank in 2003 for a sample of Chinese manufacturing firms. The World
Bank’s Enterprise Surveys use either simple random sampling or random stratified sampling to ensure randomness of their sample. Face-to-face interviews were conducted with firms’ managers and bookkeepers or accountants, using a sampling method designed to ensure adequate representation of firms by industry, size, ownership, export orientation, and location. The firms in the survey are from 18 Chinese cities: Benxi, Changchun, Changsha, Chongqing, Dalian, Guiyang, Haerbin, Hangzhou, Jiangmen, Kunming, Lanzhou, Nanchang, Nanning, Shenzhen, Wenzhou, Wuhan, Xian, and Zhengzhou. The industries represented are Food Processing, Garment and Leather Products, Electronics Equipment, Electronics Parts Making, Household Electronics, Auto and Auto Parts, Chemical Products and Medicine, Biotech Products and Chinese Medicine, and Metallurgical Products.

Summary statistics of the data are presented Table 1. Although the survey was conducted for firms in both service and manufacturing industries, we dropped the firms in service industries because information on inputs and sales was not available for many firms in this sector. Furthermore, we dropped observations that were clearly erroneous, such as negative values of age, output and labor. After dropping erroneous observations and the missing observations for the variables included in our model, 1161 observations remained. Of these 1161 firms, about 33 percent reported that they imported foreign capital (machinery) and the remaining 67 percent did not. The average skilled labor share in our sample is about 27 percent. As shown in Table 2, none of the variables of interest for our model exhibit a very high degree of correlation, mitigating inference problems due to multicollinearity. Multicollinearity tests based on variance inflation factors (VIFs) and tolerance levels (presented in Table 2) illustrate that relying on the variables in (1) is
justified. None of the variables had VIFs greater than 10 and tolerance levels less than 0.1, which are generally accepted thresholds to identify multicollinearity problems.

**Results and Discussion**

The OLS parameter estimates for our model are presented in Table 3 for the Chinese manufacturing firms in our data. The statistically significant estimates are identified by asterisks.\(^{17}\) The parameter estimates show a positive productive contribution of skilled labor associated with imported machinery and the productive contribution of imported machinery associated with more highly skilled labor.

More specifically, the productive impact of additional skilled labor for non-importers \((IMP=0)\) is \(\beta_4=0.918\), whereas that for importers \((IMP=1)\) is \(\beta_4 + \beta_5 \cdot IMP = 0.918 + 0.885 = 1.803\), so \(\beta_5=0.885\) indicates how much importing capital augments the productive contribution of more human capital (a greater share of managerial, engineering and technical labor). Conversely, the productive contribution of importing capital for a firm with no skilled labor is insignificantly different than zero \((\beta_3 = -0.006)\), but skilled labor augments the productivity of importing as \(\beta_5 = 0.885\) is significantly different than zero. For example, for a firm with the mean skilled labor share of 0.271, the productivity enhancement associated with importing capital is \(\beta_3 + \beta_5 \cdot SH = -0.006 + 0.885 \cdot (0.271) = 0.235\) – about 23.5 percent. The productive effect of importing capital is thus driven by a strongly positive skilled labor bias; importing capital is skilled-labor intensive in the sense that the productive differential for importers increases with additional human capital.

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\(^{17}\) Three asterisks mean statistical significance at the 1 percent level, two at the 5 percent level, and one at the 10 percent level.
The significantly positive estimated coefficient on the interaction between imported machinery and skilled labor share means that they are complements—sometimes referred to as the technology-skill complementarity. This finding is consistent with the theoretical studies that predict the productivity of importing machinery to be positively related to a more highly skilled workforce because effective adoption or absorption of new technology requires human capital. Thus, firms wishing to obtain new technology by importing machinery need to hire skilled workers to utilize this technology effectively. Moreover, the magnitude of the technology spillover effect from importing is larger for firms with more human capital.

In fact, the productive impact of importing capital with no skilled labor is essentially zero but increases significantly with more human capital. It can thus be surmised that a threshold share of skilled labor is required to exploit the imported technology. To test this hypothesis, we estimated the productivity impact of imported machinery at various percentiles of skilled labor share, as reported in Table 4. This table presents the percentage difference in productivity between importers and non-importers at different percentiles\textsuperscript{18} of the skilled labour share. The first column of Table 4 shows the skilled labor share, the second column shows the differential impact of a higher skill share on the productivity effect of importing capital based on the OLS results, and the third column presents the differential based on the IV estimator, which will be highlighted in the next section. The corresponding standard errors obtained from the

\textsuperscript{18} For instance, 50\textsuperscript{th} percentile indicates that 50 percent of the firms had a skilled-labor share of 23.1 percent or less and 50 percent of the firms in the sample had a skilled labor share equal to or higher than 23.1 percent of the total employment.
Delta Method are presented in parenthesis. The productive differential for importers is positive at all percentiles of the skilled labor shares. However, the differential does not become statistically significant at 5 percent conventional significance level until the share reaches about 23 percent, which corresponds to the 50th percentile of the skilled labor share. At this percentile the productivity of importing capital becomes $-0.06 + 0.885*(0.231) = 0.199$ – a productivity premium of about 19.9 percent for importers. An increase in the skilled labor share to 50 percent implies a productivity differential of nearly 43 percent. In other words, an importer is predicted to have 43 percent higher productivity than a comparable non-importer when the skilled labor share is 50 percent. These results are consistent with the suggestions in the literature that absorptive capability of domestic firms is the main factor affecting the degree to which knowledge spillovers can be utilized in the host economy, and that a threshold level of human capital must be attained to exploit such spillovers (Kokko et al., 1996).

Further, our other coefficient estimates suggest that total factor productivity is significantly related to the control variables. The statistically significant positive coefficient on ISO9000 indicates that certified firms are about 28 percent more productive than those that are not, and the statistically significant positive coefficient on

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19 The Delta method is a generalization of Central Limit Theorem, which is useful when one is interested in some function of a random variable rather than the random variable itself (see Gallant and Holly, 1980). It uses the parameter estimates from our model and their corresponding variance covariance matrix to evaluate the productivity differential between importers and non-importers at different values of skilled labor share. We have also used nonparametric bootstrap methods introduced by Efron (1979) that obtain the sampling distribution of the statistic of interest by recycling the information in the sample. The results were very similar.

20 Originally, we have also included the exports and foreign direct investment as explanatory variables in our model but it did not change the results discussed here. The parameter estimate for exporting was not statistically significant, but the coefficient on the foreign direct investment variable indicated that the firms with foreign shares are more productive. As we will discuss in the next section, we use the past values of these variables in our IV model.
CU indicates that productivity increases with average capacity utilization. Finally, age seems to have a negative linear impact on firm productivity.

**Endogeneity**

We used OLS with interaction terms to empirically examine the productive impact of imported technology by emphasizing its interaction with skill intensity for firms in the Chinese manufacturing industry. Overall, the OLS results presented in the first column of the Table 3 illustrate significant association between productivity and imported technology conditional on the skilled labor share; firms differ in their stock of skilled labor and the productive impact of imported machinery depend to a large extent on these stocks. However, this can not be interpreted as a causal relationship because of a few reasons. First, firms with better performance might choose to import foreign technology. It may be that only the most productive firms are able to enter the import markets. In other words, importing firms may be more productive at the outset and not as a result of enjoying benefits associated with imported capital inputs. In addition to this self-selection, there may be some omitted determinants of productivity that will inherently be correlated with the import variable. In these cases, the error term will be correlated with the imported capital variable and the OLS estimates will be biased and inconsistent. Thus, to evaluate potential endogeneity issues that may affect the robustness of our model, we alternatively employ an IV estimator.

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21 One may also expect the firms with high productivity to hire more skilled labor. Thus, we have also used whether or not the firms has a contractual relationship with the universities or research institutions as an instrument for the skilled labor share. The results are consistent with those presented in the paper, but this instrument is not strong enough. Note, however, that we use instruments for the interaction of the skilled labor share with the imported machinery in our IV model.

22 Another way of controlling for the endogeneity is to jointly estimate an import status equation with the production function (Clerides et al., 1998; Van Biesebroeck, 2005). We have tried this also and obtained consistent results. However, since we are also interested in the interaction of the import variable with the skilled labor share, we do not report the results from this approach. Few studies, such as Van Biesebroeck
We assume that we are interested in estimating $y_i = \chi' \beta + u_i$. When endogeneity is present, one must control for potential estimation biases by identifying $J$ instruments in an associated vector $z_i$. For $\beta$ to be a consistent estimator, the population moment condition $E[(y_i - \chi' \beta)z_i] = 0$ must hold. The IV estimator solves the corresponding sample moment condition $\frac{1}{N} \sum_{i} (y_i - \chi' \beta)z_i = 0$ by choosing values of $\beta$ that drive this condition as close to zero as possible by minimizing:

$$Q_N(\beta) = \left[ \frac{1}{N} \sum_{i} (y_i - \chi' \beta)z_i \right] \Omega_N \left[ \frac{1}{N} \sum_{i} (y_i - \chi' \beta)z_i \right]$$

where $\Omega_N$ is a weighting matrix.

Valid instruments ($z_i$) must not be correlated with the error term, i.e. the instruments used must have an impact on productivity only through the endogenous import variable and its interaction with the skilled labor share. We assume that the following variables meet this requirement and use them as instruments to control for resulting potential endogeneity: the ethnicity of the manager or whether or not the general manager of the firm is from an industrialized country (MN); whether the firm is a subsidiary or a joint venture of a multinational firm (FO); whether the firm is an exporter in the previous year (EXP); and the percentage of firm owned by the state/provincial government (SO).

The intuition for using these variables as instruments is simple: If the manager is from an industrialized foreign country, the firm is more likely to import. Firms with some

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(2005) and Yasar and Paul (2007), show that measures controlling for endogeneity of international linkage variables for other data are robust to estimation methods accommodating potential endogeneity.

23 See Cameron and Trivedi (2005) for more detailed information.

24 Similar instruments were used by Van Biesebroeck (2005) to examine the relationship between exports and productivity for the sub-Saharan African Manufacturing Firms.

25 To check the sensitivity of the results to the specification of these instruments, we alternatively used the state ownership and the ethnicity of the general manager as instruments, which produce similar results.
state ownership are less likely to import. A firm that is an exporter or a subsidiary/joint venture of a multinational firm is more likely to import. We assume that these variables affect the firm productivity through import and its interaction with the skill intensity of the firm. These variables intuitively satisfy the conditions for valid instruments.

To evaluate the correlation between the instruments and the error term, we use the Sargan test of overidentifying restrictions. The null hypothesis is that the instruments and the error terms are independent, so failure to reject this hypothesis validates the use of the instruments. To assess whether our instruments are sufficiently related to the endogenous variable, we use an F-test of the joint significance of the instruments in reduced form. We estimate two reduced form equations: one for the imported capital input variable by a logit estimator and one for the interaction of the imported capital input with the skill share variable by a fractional logit model. We then obtain the fitted values for imported capital input and its interaction with the skilled labor share to form estimates of these two reduced form equations, and replace the imported capital input (IMP) and its interaction with the skilled labor share (IMP*SH) in the original model by its fitted values, and estimate the resulting model by least squares.

*IV Results*

The parameter estimates using the IV estimator are presented in the third column of Tables 3, with robust standard errors in parentheses. The results denoted IV, in the third column of the table, are based on the instrument set explained above, which includes variables EXP, FO, MN, and SO. Using the Sargan test of overidentifying restrictions to test for correlation between the instruments and error term gives the P-Value of 0.406, which validates the use of these instruments. We also use an F-test to examine whether
these instruments are sufficiently related to the endogenous variables by estimating their joint significance in reduced form equations. F-tests show that these instruments are sufficiently correlated to the endogenous variables to be valid instruments.

Our IV parameter estimates based on these instruments are presented in the third column of Tables 3.\textsuperscript{26} Controlling for potential endogeneity by IV estimation increases productive impact of importing. The parameter estimates show a positive productive contribution of skilled labor associated with imported machinery and the productive contribution of imported machinery associated with more highly skilled labor. The productive impact of additional skilled labor for non-importers ($IMP=0$) is $\beta_4 = 0.721$, while that for importers ($IMP=1$) is $\beta_4 + \beta_5 * IMP = 0.721 + 1.449 = 2.170$, so $\beta_5 = 1.449$ indicates how much importing capital augments the productive contribution of a greater share of managerial, engineering and technical labor. Conversely, the productive contribution of importing capital for a firm with no skilled labor is insignificantly different than zero ($\beta_3 = 0.051$), but skilled labor enhances the productivity of importing as $\beta_5 = 1.449$ is significantly different than zero. For a firm with a median skilled labor share of 0.231, the productivity boost associated with importing capital is about 38.7 percent. This finding is consistent with the OLS results but the parameter estimates obtained by the IV estimator are higher, indicating that OLS biases the parameter estimates downward. Overall, these results also verify the previous results and the theoretical predictions that the productivity of importing machinery is positively related to a more highly skilled work-force because effective adoption or absorption of new technology requires human capital. This suggests that the firms that obtain new

\textsuperscript{26} The statistically significant estimates are identified by asterisks; three asterisks mean statistical significance at the 1 percent level, two at the 5 percent level, and one at the 10 percent level.
technology by importing machinery may need to hire skilled workers to utilize this technology effectively.

Furthermore, as illustrated in the third column of the Table 4, although there is no significant productivity differential between the importers and non-importers when the skilled labor is essentially zero, the gap increases significantly with more human capital. It is apparent that a threshold share of skilled labor is required to exploit the imported technology. The productive differential for importers is positive at all percentiles of the skilled labor shares. However, the differential does not become statistically significant at the 5 percent conventional significance level until the skilled labor share reaches about 31 percent. At this percentile the productivity premium is about 50 percent for importers.

The coefficients for the remaining independent variables are similar in terms of both their magnitude and significance for the IV estimation.

Robustness: Least Squares and IV Threshold Regression

The main objective of this article is to examine the impact of imported machinery on the productivity of firms in China and to determine if the effect differs with the level of the skilled labor share. In the previous sections, an interaction term between imported technology and skilled labor share is estimated using both OLS and IV estimators to accomplish this objective. In order to check the robustness of our results obtained by the interaction effects, we use an alternative method that allows the data to endogenously select a sample split and simultaneously test the presence of the threshold level of skilled labor share. As explained earlier, the productive impact of imported technology may be heterogeneous in the sense that it may vary at different levels of skilled labor share, indicating that the relationship is not monotonic but rather nonlinear. The failure to
account for these potential threshold effect non-linearities can potentially result in biased results. Standard threshold models assume that one knows the break points with certainty. However, a prior knowledge on how the impact of imported capital on productivity varies with the threshold variable is not available with certainty. Hansen (2000) introduced a threshold regression technique that treats the threshold as an unknown parameter and estimates it endogenously using the data, instead of assuming it arbitrarily. It also allows us to test the existence of this threshold.

We implement this approach to endogenously search for regime changes in the data by using the skilled-labor share as a threshold variable. This endogenous threshold analysis allows the impact of the imported technology on productivity to vary with skilled labor share. When there is a single threshold, which seems to be the case for our data, the regression model can be rewritten as follows.27

\[ Y_i = \beta X_i + \delta_1 I(SH_i \leq \gamma)IMP + \delta_2 I(SH_i > \gamma)IMP + u_i, \]

where \( Y_i \) is the dependent variable, \( SH_i \) is a threshold variable, corresponding to the skilled labor share, \( X_i \) is a vector of control variables explained in the previous section, \( I \) is an indicator function, and \( \gamma \) is the estimated threshold value. This method allows the division of the impact of import into two regimes, conditional on whether the skilled labor share is smaller or greater than the estimated threshold level \( \gamma \). In other words, it allows the regression parameters to differ depending on the value of the threshold.

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27 Papageorgiou (2002), and Khoury and Savvides (2006) use this method to examine the relationship between openness to trade and growth.

28 Because of convergence issues the region and industry dummies are not included in the base model. We have, however, included the region and industry dummies that were not highly collinear with other variables in the threshold model that allows an endogenous regressor. The resulting threshold parameter estimate was 0.385, with a confidence interval of [0.380, 0.413]. Thus, including these dummy variables does not change the threshold parameter, but results in a narrower confidence interval.
variable. For instance, $\delta_1$ is the impact of imported technology on productivity when $q_i \leq \gamma$ and $\delta_2$ is the impact of imported technology on productivity when $q_i > \gamma$. This method estimates $\gamma$ and the parameters using least squares estimator and obtains reliable confidence intervals for $\gamma$. The estimation strategy includes three main steps.\(^{29}\) First, we estimate the threshold value $\gamma$ (a value that minimizes the concentrated sum of squared errors). Second, we test the statistical significance of the threshold effects. More specifically, we test the null hypothesis of no threshold (i.e. $H_0 : \delta_1 = \delta_2$) against the alternative hypothesis of a threshold regression model (i.e. $H_A : \delta_1 \neq \delta_2$) by using a bootstrap procedure that allows us to obtain critical values for the test statistic. Finally, if the null hypothesis is rejected, we construct confidence intervals for the threshold ($\gamma$) variable. We expect to obtain a more exact productive impact of import by using this methodology than those obtained by traditional monotonic approaches.\(^{30}\)

*Threshold Model Results*

The results from the threshold regression model are reported in the first column of Table 5. Using the skilled labor share as the potential threshold variable, Hansen’s (2000) endogenous search technique identifies a statistically significant threshold, which corresponds to a skilled labor share of $\hat{\gamma} = 0.427$ with 95% confidence interval [0.289, 0.466]. The corresponding bootstrapped p-value, which is obtained by using a Lagrange Multiplier test for a threshold with 1000 replications as explained in Hansen (1996), is 0.041. Thus, the null hypothesis is rejected at the five percent conventional significance level, indicating that the productive impact of imported capital varies across the two

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\(^{29}\) We estimated the threshold models using the Gauss programs written by Bruce Hansen.

regimes, i.e. there is a sample split based on our threshold variable skilled labor share. While import is significantly associated with the firm productivity in the first regime only at the 10 percent conventional level, it becomes statistically significant at the 1 percent level when the skilled labor share is above the threshold level of 0.427, which is the threshold endogenously determined by the data. In the first regime, where the skilled labor share is less than the threshold of 42.7 percent, the importing firms are only 16.2 percent more productive than the non-importing firms. This productive difference is not significant at 0.05 or 0.01 conventional significance levels. However, in the second regime the productivity premium for the importing firms is 49.9 percent and significant at 1 percent conventional significance level. The threshold level divides the sample of 1161 into two subsamples of 996 and 165 firms; 996 firms in the sample have a skilled labor share that is less than \( \hat{\gamma} \), while 165 firms have a skilled labor share that is higher than \( \hat{\gamma} \).

The normalized likelihood ratio sequence \( LR_n(\gamma) \) statistic as a function of our threshold variable is also illustrated in Graph 1. The least-squares estimate of \( \gamma \) is the value that minimizes the function \( LR_n(\gamma) \) which occurs at \( \hat{\gamma} = 0.427 \). The asymptotic 95% critical value for the threshold estimates is shown by the portion of the curve in the graph that lies below the dotted line that is drawn at the critical value. As illustrated in the graph, the 95% confidence set is [0.289, 0.466].

**IV Threshold Regression**

The threshold model employed in the previous section assumes that all right-hand-side variables are exogenous. Caner and Hansen (2004) introduced a technique that allows us to estimate the threshold models with endogenous variables but an exogenous threshold variable. First, a threshold reduced form model is estimated by least squares, and then the
fitted values of the endogenous variable are obtained based on this reduced form estimates. Finally, these fitted values are used in place of the endogenous variables in a structural equation that is estimated by least squares. While the threshold parameter is estimated by using a two-stage least squares estimator, the slope parameters are estimated by employing a generalized method of moment estimator.

We have also estimated the threshold parameter by using this method. As illustrated in the third column of Table 3 and Graph 2, this method identifies a threshold that corresponds to a skilled labor share of 0.380, with 95% confidence intervals of [0.289, 0.443]. These results are consistent with those obtained by using the threshold regression technique that treats all the explanatory variables exogenous.

**Conclusion**

Recent studies have suggested that importing capital is an important channel for firms in developing countries to transfer new technologies from developed countries. However, the empirical literature does not clearly establish the importance of some firm characteristics (such as the firm’s absorptive capacity) on the productive impact of this capital input, which involves the mechanisms through which these productivity gains are realized. In particular, firms’ internal conditions such as a lack of human capital, or skilled labor intensity, might limit a host-country firm’s ability to exploit the potential productive benefits from imported technology embodied in imported capital inputs. In fact, some of the differences found by the previous studies in the productive impact of imported capital input across countries that are at different stages of development may stem in part from the differences in these firm characteristics. This study focuses on the role played by the firms’ absorptive capacity in the link between imported technology
and firm productivity. To capture this capacity, the share of skilled workers for a sample of Chinese manufacturing firms is interacted with a variable representing the imported machinery in a Cobb-Douglas production function specification. Examining the productive impact of imports associated with human capital in this manner provides insights about the mechanisms through which imported technology enhances the productivity of firms. In addition to standard least squares (OLS) estimator with interaction effects, two alternative econometric methods have been used to estimate the parameters of production function: IV estimator and the endogenous threshold regression technique. These alternative estimation approaches allow us to recognize endogeneity and heterogeneity in the relationship between imported capital and firm productivity. These are important extensions of the existing empirical treatments of imported technology in the literature.

Our results are in line with the theoretical studies which suggest that the adoption of new technologies requires a threshold stock of human capital in the host-country, and that the extent to which the gap between the technology frontier and current productivity can be closed depends on the level of this stock. After controlling for observable variables that represent heterogeneity across firms and potential endogeneity, our empirical results suggest that importing machinery plays an important role in enhancing firm productivity, but that the level of human capital determines the level of positive effects attained. Importing new machinery and equipment has a greater productivity impact on firms with a relatively high share of skilled workers. Conversely, importing machinery more significantly increases the productivity of firms with higher skill shares. This gap widens as the skill share increases. This finding that greater human capital
shares are associated with increasingly greater productivity impacts from importing capital implies capital-skill or technology-skill complementarity. It can thus be concluded that the simultaneous increase in both imported capital input and skilled labor is necessary for the productivity improvements in a developing country.

In contrast to the results obtained from previous empirical research, and in keeping with the theoretical predictions of existing literature, this study finds that the productive impact of the import does not increase monotonically and that such impact is more profound when the level of skilled labor is higher than a certain threshold level, indicating that firms need to attain a minimum level of human capital skill before purchasing foreign technology to generate productive benefits. A higher absorptive capacity through skilled worker intensity can allow firms to maximize benefits associated with new technologies and manufacturing techniques transferred from high-income countries. Hence, policies to help firms improve workers’ skills to match international standards will help to enhance productivity through foreign technology transfer. Enhancing firm productivity will involve simultaneously encouraging capital deepening and augmenting the skill level of labor force. Evidently, the productive impact of the imported technology may vary with the country’s stage of development and over time. Thus, further research is needed to analyze the effects of temporal changes on firms’ performance across various countries by utilizing plant-level panel data.
References


Table 1. Descriptive statistics (No. of Obs. = 1161)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log value added of firm (lnY)</td>
<td>8.760</td>
<td>2.239</td>
</tr>
<tr>
<td>Log capital input (lnK)</td>
<td>9.106</td>
<td>2.249</td>
</tr>
<tr>
<td>Log labor input (lnL)</td>
<td>5.185</td>
<td>1.360</td>
</tr>
<tr>
<td>Whether or not firm imported any machinery (IMP)¹</td>
<td>0.334</td>
<td>0.472</td>
</tr>
<tr>
<td>Share of managers, engineers and technical workers in total employment (SH)²</td>
<td>0.270</td>
<td>0.171</td>
</tr>
<tr>
<td>Age of the Firm (AGE)³</td>
<td>16.310</td>
<td>13.753</td>
</tr>
<tr>
<td>Capacity utilization (CU)⁴</td>
<td>72.112</td>
<td>24.146</td>
</tr>
<tr>
<td>Whether or not firm’s products have been certified by ISO900 certification (ISO)⁵</td>
<td>0.508</td>
<td>0.500</td>
</tr>
</tbody>
</table>

Instrumental Variables

| Whether or not the firm is a subsidiary or a joint venture of a multinational firm (FO)⁶ | 0.115  | 0.320              |
| Whether or not the firm is an exporter in the previous year (EXP)⁷                     | 0.242  | 0.429              |
| Whether or not the General Manager is from an industrialized country (MN)⁸            | 0.396  | 0.195              |
| Percentage of firm owned by the state/provincial government (SO)⁹                      | 0.043  | 0.196              |

Notes:

¹ IMP: In the survey managers were asked whether they imported any machinery. We use a dummy variable that is equal to 1 if firms imported any machinery, and 0 otherwise.
² SH: Share of managerial, engineering, and technical workers in total employment.
³ AGE: Managers were asked in what year their firm began operations.
⁴ CU: Capacity utilization is the amount of output actually produced relative to the maximum amount that could be produced with existing machinery and equipment and regular shifts.
⁵ ISO: Managers were asked whether firms’ products have been certified by ISO900 certification. We use a dummy variable that is equal to 1 if the firm has a certified product, and 0 otherwise.
⁶ FO: Managers were asked whether the firm is a subsidiary or a joint venture of a multinational firm. We use a dummy variable that is equal to 1 if the firm has a foreign partner, and 0 otherwise.
⁷ EXP: Managers were asked what percent of sales are exported. We use a dummy variable that is equal to 1 if firms reported positive shares, and 0 otherwise.
⁸ In the survey managers were asked about the nationality of the general manager. We use a dummy variable that is equal to 1 if firms have a general manager who is from an industrialized country, and 0 otherwise.
⁹ Managers were asked what percent of the firm is owned by the state or provincial government.
¹⁰ Total number of observations: 1161.
¹¹ The summary statistics for size, industry, and region dummy variables are not reported here in the interest of space. They are available from the authors upon request.
Table 2. Tests of Multicollinearity: Variance Inflation Factors (VIF) and Tolerance

<table>
<thead>
<tr>
<th>Variable</th>
<th>VIF</th>
<th>Tolerance</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnK</td>
<td>3.510</td>
<td>0.285</td>
</tr>
<tr>
<td>lnL</td>
<td>4.900</td>
<td>0.204</td>
</tr>
<tr>
<td>IMP</td>
<td>4.390</td>
<td>0.228</td>
</tr>
<tr>
<td>SH</td>
<td>1.860</td>
<td>0.538</td>
</tr>
<tr>
<td>IMP*SH</td>
<td>4.250</td>
<td>0.235</td>
</tr>
<tr>
<td>AGE</td>
<td>4.000</td>
<td>0.250</td>
</tr>
<tr>
<td>AGE^2</td>
<td>3.740</td>
<td>0.268</td>
</tr>
<tr>
<td>CU</td>
<td>1.180</td>
<td>0.849</td>
</tr>
<tr>
<td>ISO</td>
<td>1.470</td>
<td>0.682</td>
</tr>
</tbody>
</table>

Mean VIF 3.420

Note: The “rule of thumb” in the econometric literature is that a VIF > 10 or a Tolerance level < 0.1 are signs of severe multicollinearity problems. Age variable is mean adjusted.
### Table 3: Parameter Estimates

(\textbf{Dependent Variable=Natural log of value added})

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Ordinary Least Squares (OLS) Estimates</th>
<th>Instrumental Variable (IV) Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>IMP</strong></td>
<td>-0.006 (0.146)</td>
<td>0.051 (0.283)</td>
</tr>
<tr>
<td><strong>SH</strong></td>
<td>0.918 (0.262)**</td>
<td>0.721 (0.294)**</td>
</tr>
<tr>
<td><strong>IMP*SH</strong></td>
<td>0.885 (0.415)**</td>
<td>1.449 (0.577)**</td>
</tr>
<tr>
<td><strong>lnK</strong></td>
<td>0.355 (0.027)**</td>
<td>0.3336 (0.033)**</td>
</tr>
<tr>
<td><strong>lnL</strong></td>
<td>0.706 (0.053)**</td>
<td>0.708 (0.054)**</td>
</tr>
<tr>
<td><strong>AGE</strong></td>
<td>-0.022 (0.011)*</td>
<td>-0.021 (0.011)*</td>
</tr>
<tr>
<td><strong>AGE^2</strong></td>
<td>0.000 (0.000)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td><strong>CU</strong></td>
<td>0.015 (0.001)**</td>
<td>0.015 (0.001)**</td>
</tr>
<tr>
<td><strong>ISO</strong></td>
<td>0.278 (0.079)**</td>
<td>0.258 (0.083)**</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1161</td>
<td>1161</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.759</td>
<td>0.758</td>
</tr>
<tr>
<td>Sargan Test (P-value)</td>
<td>0.406</td>
<td></td>
</tr>
</tbody>
</table>

**NOTES:**

1) Robust standard errors in parentheses *Significant at the 10% level. **Significant at the 5% level.
***Significant at the 1% level. The standard errors clustered by industry and region are much smaller.

2) The regression run in this table includes dummy variables that control for size, industry and region characteristics. However, they are not reported here in the interest of space. They are available from the authors upon request.
Table 4: Skilled Labor Share and Productive Impact Differential between Importers and Non-Importers

<table>
<thead>
<tr>
<th>Percentiles of Share of Managers, Engineers and Technicians in Total Employment</th>
<th>Productive Impact Differential Between Importers and Non-Importers (Based on OLS regressions)</th>
<th>Productive Impact Differential Between Importers and Non-Importers (Based on IV regressions)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; percentile of SH = 0.036</td>
<td>0.026 (0.134)</td>
<td>0.103 (0.271)</td>
</tr>
<tr>
<td>5&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.073</td>
<td>0.059 (0.123)</td>
<td>0.157 (0.261)</td>
</tr>
<tr>
<td>10&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.092</td>
<td>0.076 (0.117)</td>
<td>0.184 (0.256)</td>
</tr>
<tr>
<td>20&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.132</td>
<td>0.111 (0.107)</td>
<td>0.243 (0.248)</td>
</tr>
<tr>
<td>30&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.169</td>
<td>0.144 (0.098)</td>
<td>0.296 (0.241)</td>
</tr>
<tr>
<td>40&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.200</td>
<td>0.171 (0.093)*</td>
<td>0.341 (0.237)</td>
</tr>
<tr>
<td>50&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.231</td>
<td>0.199 (0.089)***</td>
<td>0.387* (0.235)</td>
</tr>
<tr>
<td>60&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.271</td>
<td>0.234 (0.086)***</td>
<td>0.444* (0.233)</td>
</tr>
<tr>
<td>70&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.310</td>
<td>0.269 (0.087)***</td>
<td>0.501** (0.234)</td>
</tr>
<tr>
<td>80&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.378</td>
<td>0.329 (0.095)***</td>
<td>0.599 (0.241)***</td>
</tr>
<tr>
<td>90&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.500</td>
<td>0.437 (0.125)***</td>
<td>0.776 (0.267)***</td>
</tr>
<tr>
<td>95&lt;sup&gt;th&lt;/sup&gt; percentile of SH = 0.644</td>
<td>0.564 (0.173)***</td>
<td>0.985 (0.315)***</td>
</tr>
<tr>
<td>Mean of SH = 0.271</td>
<td>0.235 (0.086)***</td>
<td>0.445 (0.233)*</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses, which are obtained by using the Delta Method. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Table 5: IV Threshold Model Statistics

<table>
<thead>
<tr>
<th>Statistics</th>
<th>TR Model</th>
<th>IV TR Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold Value ($\gamma$)</td>
<td>0.427</td>
<td>0.380</td>
</tr>
<tr>
<td>95% Confidence Interval-White correction for Heteroskedasticity</td>
<td>[0.289, 0.466]</td>
<td></td>
</tr>
<tr>
<td>Confidence Interval – Heteroskedasticity is corrected by using quadratic variance estimate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Confidence Interval – Heteroskedasticity is Corrected by using nonparametric kernel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LM-test for no threshold</td>
<td>24.512</td>
<td></td>
</tr>
<tr>
<td>LM-test for no threshold (P-value)</td>
<td>0.041</td>
<td></td>
</tr>
<tr>
<td>$\hat{\delta}_1$</td>
<td>0.162(0.093)*</td>
<td></td>
</tr>
<tr>
<td>$\hat{\delta}_2$</td>
<td>0.499(0.190)**</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1161</td>
<td>1161</td>
</tr>
<tr>
<td>Number of observations with a SH&lt; $\gamma$</td>
<td>996</td>
<td>936</td>
</tr>
<tr>
<td>Number of observations with a SH&gt; $\gamma$</td>
<td>165</td>
<td>225</td>
</tr>
</tbody>
</table>

Notes: The Lagrange Multiplier (LM) is used to obtain the statistical significance of sample split in the threshold regression model.
Figure 1: Confidence Interval Construction for Threshold using TR Model
Figure 2: Confidence Interval Construction for Threshold using IV TR Model

Confidence Interval Construction for Threshold

Likelihood Ratio Sequence in $\gamma$

Threshold Variable

- $LR_\gamma(\gamma)$
- 90% Critical
- Hetero Corrected - 1
- Hetero Corrected - 2