The Japanese Economic Review
The Journal of the Japanese Economic Association

The Japanese Economic Review
Vol. 65, No. 2, June 2014

doi: 10.1111/jere.12041

IMPORTED INTERMEDIATE INPUTS, FIRM PRODUCTIVITY AND PRODUCT COMPLEXITY*

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This paper takes product complexity into account to study the impact of imported intermediate inputs on firms. Highly disaggregated Chinese transaction-level trade data and firm-level production data from 2002 to 2006 are used to construct firm-level imported intermediate inputs. After controlling for the endogeneity of imported intermediate inputs and taking industrial imports of final goods into account, the analysis finds that firm productivity increases with increased imported intermediate inputs. The impact of imported intermediate inputs on firm productivity is weaker as firms produce more complex products.
JEL Classification Numbers: F10, F13.

1. Introduction

The use of imported intermediate inputs is one of the most important topics in empirical trade research, especially in recent years. Initially, trade economists primarily focused on the effect of a firm's exports on firm productivity (Bernard and Jensen, 2004; Park *et al*., 2010; Yang and Mallick, 2010). However, research interest has gradually shifted to the exploration of the effect of firm imports, which are playing an increasingly important role in raising firm productivity (Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Halpern *et al*., 2011). Amiti and Konings (2007) analyse Indonesian firm-level data, including plant-level information on imported inputs, and find that firms gain at least twice as much from input tariff reductions as from output tariff reductions. Halpern *et al*. (2011) find that during 1993–2002, one-third of the productivity growth in Hungary was attributable to imported inputs.

The present paper uses Chinese firm-level data to confirm the positive effect of imported intermediate goods on firm productivity. The results are primarily attributable to spillover and competition effects from imported goods. However, the present paper finds that the impact of imported intermediate inputs on firm productivity becomes weaker as firms produce more complex products. Differentiated products, which account for four-fifths of total products, to some extent bear less pressure from severe competition but enjoy fewer benefits from foreign imports penetrating the domestic market compared with homogeneous products. However, the growth in productivity of firms that produce heterogeneous goods is slower than that of firms that produce homogeneous goods when product complexity requires more imported intermediate goods. If a homogeneous intermediate input is imported, firms will find it easier to adopt its up-to-date technology because homogeneous products are less technology-specific than heterogeneous products.

* We thank Taiji Furusawa and Ryuhei Wakasugi for initiating this project. We also thank Tomohiko Inui, Naohiko Ijiri, an anonymous referee and conference participants at the Yokohama Conference of Empirical International Trade (2012) for their very helpful comments.

The present paper contributes to the literature in at least three important ways. First, based on Chinese firm-level data, it confirms the positive effects of both imported intermediate inputs and final imports on firm productivity. Compared with some research based on Chinese provincial data or industry-level data, our findings are more micro-grounded and, hence, are more reliable. A few recent papers based on Chinese firm-level data have found strong evidence of the positive effect of imports on firm productivity. However, those papers focus on imports of either intermediate inputs or final goods, but not both. We analyse Chinese firm-level data to examine the effects of imported intermediate inputs and final imports. Although the effects of tariffs on firm productivity have been widely considered in the literature, our paper extends the related analysis by incorporating the effects of both tariffs and nontariff barriers.

Second, the paper enriches our understanding of product heterogeneity, which could help us to understand the phenomenon of "home market bias" in the sense that a larger market will produce more and be a net exporter of differentiated goods. This phenomenon is described in Krugman (1980), although the empirical support is mixed (see e.g. Davis and Weinstein, 1999; Feenstra *et al*. (2001). Different from previous studies that have directly tested home market effects, the present paper examines the effects of two categories of imported intermediate inputs on firm productivity: homogeneous products and heterogeneous products. Following Rauch (1999), all products are divided into homogeneous products and heterogeneous products. Homogeneous goods are made up of goods whose prices are quoted on organized exchanges and those whose reference prices are quoted only in trade publications. By contrast, heterogeneous goods, for example, shoes (No. 851 in the SITC standard), may include many complex units, such as hiking shoes, sandals, leather shoes, and so on, with no reference price. We find that firms that produce homogeneous goods benefit more from foreign imports. Furthermore, the impact of imported intermediate inputs on firm productivity is weaker as more heterogeneous intermediate products are imported.

Third, to explore the nexus among imported intermediate inputs, firm productivity and product complexity, we follow the standard procedure to investigate the relationship in three steps. First, we use the augmented Olley and Pakes (1996) methodology to construct measures of Chinese firm-level total factor productivity (TFP). Olley and Pakes (1996) provide a semi-parametric approach to address the two estimation biases in the measured TFP that arise when the ordinary least squares (OLS) approach is used: simultaneity bias and selection bias. We adopt this approach with some necessary modifications to fit the case of China, as suggested by Yu (forthcoming). Second, to examine the impact of imported intermediate inputs and final imports on firm productivity, we use fixed-effects estimates for our panel data. Third, we introduce product complexity by merging the data obtained from Rauch (1999) with Chinese firm-level data.

The heterogeneous productivity gains from imports between complex products and simple products are identified by the own coefficients of the import variables and their interactions with product complexity. Because a firm's imported intermediate inputs could foster firm productivity through spillover effects and firms with high-level productivity might also import more intermediate inputs to produce more, our benchmark estimates face a reverse causality problem. To address this, we employ a firm-specific input tariff index as the instrument. Our instrumental variables (IV) estimates show that the impact of imported intermediate inputs on firm productivity is weaker as more heterogeneous intermediate products are imported.

This study joins a growing literature on trade and firm productivity, including Amiti and Konings (2007), Topalova and Khandelwal (2011), Ge *et al*. (2011), Feng *et al*. (2012) and

Yu (forthcoming). Amiti and Konings (2007) use Indonesian manufacturing firm-level data and find that firm productivity increases by 1% (3%) when output tariffs (input tariffs) drop by 10%. Similar to their findings, we also find that firm productivity benefits from both imported intermediate inputs and imports of final goods. Different from their work, we focus on the impact of imports rather than tariffs. As trade protection in many countries today is via nontariff barriers but not import tariffs, our findings have broader implications.

Ge *et al*. (2011) investigate the channels of productivity gains from trade liberalization and further show improvement in firm performance caused by changes in imports. By way of comparison, we take both imported intermediate inputs and final imports into account and further calculate a firm's productivity gain when more products with different complexity are imported. Yu (forthcoming) finds that the effect of input tariff reductions on productivity improvement is weaker than that of output tariff reductions, as processing imports are already duty free. In this paper, we mainly focus on imports and product complexity. Tariffs are adopted as the IV to address possible endogeneity problems. To this end, our analysis coincides with that of Feng *et al*. (2012), who also use Chinese tariffs as the IV of imported intermediate inputs. However, their analysis abstracts the role of product complexity.

The remainder of the paper is organized as follows. Section 2 describes the data used in the regressions. Section 3 discusses the estimation results. Section 4 concludes.

2. Data

To calculate the impact of imports on firm productivity taking product complexity into account, we rely on three disaggregated, large panel data sets: firm-level production data, product-level trade data and product complexity data.

Firm production data are derived from a rich panel of data from an annual industrial firm survey from 2002 to 2006, covering all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed 5 million yuan (equivalent to US$833,000). Following Cai and Liu (2009), we use the following criteria to clean the sample and omit outliers. First, observations with missing key financial variables are excluded. Second, we drop firms with fewer than eight workers because they fall under a different legal regime, as suggested by Brandt *et al*. (2012). Third, following Feenstra *et al*. (forthcoming), we delete observations according to the basic rules of generally accepted accounting principles (GAAP) if any of the following are true: (i) liquid assets are greater than total assets; (ii) total fixed assets are greater than total assets; (iii) the net value of fixed assets is greater than total assets; (iv) the firm's identification number is missing; or (v) an invalid established time exists.

The import data are obtained from China's General Administration of Customs, which records a variety of information for each trading firm's product list, including trading price, quantity and values at the Harmonized System (HS) eight-digit level. More importantly, this rich data set allows us to calculate the value of imported intermediate inputs and firm-level tariffs, which are the main variables in our regressions.

The product complexity data come from Rauch (1999), who follows two approaches, a conservative approach and a liberal approach, to classify traded commodities. The conservative classification is generated by minimizing the number of commodities that are classified as either organized exchange or reference priced commodities (we refer to these as homogeneous products). The liberal classification is obtained by maximizing those

TABLE 1
Summary statistics

Variables	Mean	Standard deviation
Firm productivity	1.30	0.29
Final goods import (in log)	17.58	2.37
Intermediate goods import (in log)	−3.96	2.86
Product heterogeneity (conservative method)	0.82	0.38
Product heterogeneity (liberal method)	0.80	0.40
State-owned enterprise indicator	0.01	0.11
Foreign indicator	0.72	0.45
Firm labour (in log)	5.50	1.15
Firm input tariffs	2.58	3.97

numbers.[1] For each approach, the traded goods are classified into three categories: heterogeneous products, homogeneous products traded in organized exchanges, and homogeneous products with guiding prices. As our paper focuses mainly on heterogeneous goods, we combine homogeneous products traded in organized exchanges and homogeneous products with guiding prices and refer to them as homogeneous goods.

Firm-level production data are crucial in measuring TFP, while product-level customs data are non-substitutable in calculating the value of imported intermediate inputs. However, there are some technical challenges in merging the two data sets. Although the data sets share a common variable (i.e. the firm's identification number), the coding system in each data set is completely different.[2] To address this challenge, strictly following Yu and Tian (2012), we use two methods and other common variables to match the two data sets. (See Appendix I for details.) First, we use each firm's Chinese name and year to match the two data sets. That is, if a firm has an exact Chinese name in both data sets in a particular year, it should be the same firm.[3] Second, we use another matching technique to serve as a supplement. Namely, we rely on two other common variables to identify the firms: the zip code and the last seven digits of the firm's phone number. The rationale is that firms should have a unique phone number within a postal district. Although this method seems straightforward, there are subtle technical and practical difficulties.[4] We merge the product complexity data with the other two data sets. The customs data, the firm-level trade data and the product complexity data are compiled using different international standards. To merge all the data sets together, we benefit from the United Nations concordance, which successfully links product heterogeneity to HS eight-digit products. (See Feenstra *et al*., (2001) for a detailed discussion.)

Table 1 reports the summary statistics for the key variables used in the regressions. We exclude trading companies from our data set and calculate firms' imported intermediate inputs based on firm imports that are reported in the transaction-level trade data set. (See

[1] See Rauch (1999) for a more detailed description of the definition of the conservative and liberal classifications.

[2] In particular, the firm codes in the product-level trade data are at the ten-digit level, whereas those in the firm-level production data are at the nine-digit level, with no common elements.

[3] The year variable is necessary as an auxiliary identification variable because some firms could change their name in different years and newcomers could possibly take their original name.

[4] For example, the phone numbers in the product-level trade data include both area phone codes and a hyphen, whereas those in the firm-level production data do not.

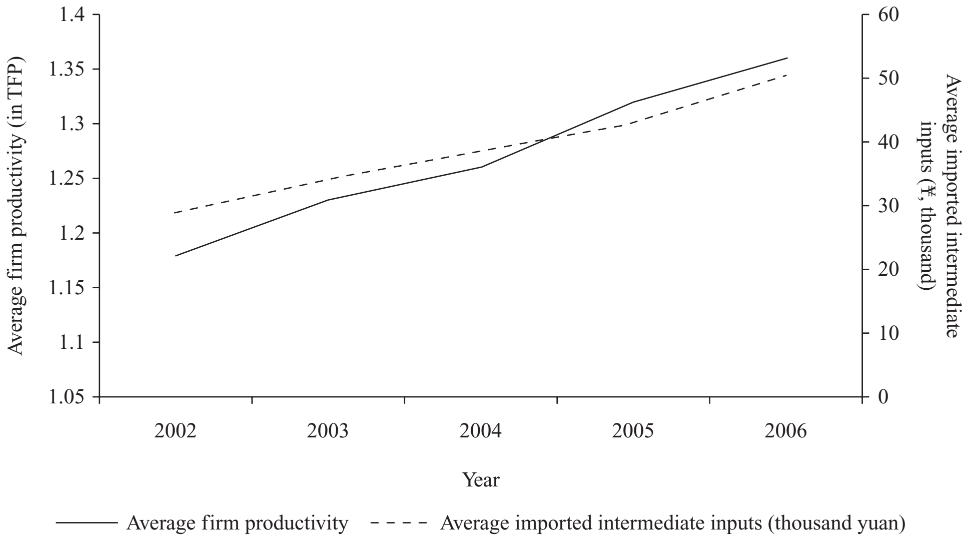

FIGURE 1. Firm productivity and imported intermediate inputs
Sources: Customs trade data (2002–2006) and authors' calculations.

Ahn *et al*. (2011) for a detailed discussion on the behaviour of trading companies.) The rationale is straightforward. The products imported by a manufacturing firm could serve as imported intermediate goods or capital goods, such as machinery for production. Because our main interest is to explore the role of imported intermediate inputs, we first merge the data based on the United Nations Classification by Broad Economic Categories and then drop those goods that are classified as capital goods. Thus, the remaining data in the sample cover only imported intermediate inputs.

By contrast, there is no way for researchers to extract firm imports of final goods from either the firm-level production data set or the product-level trade data set. The firm-level production data set reports firms' exports but not imports. The production-level trade data set only reports each firm's imported intermediate inputs. However, the firm-level data set explicitly reports the four-digit Chinese industrial classification (CIC) level for each firm. Therefore, imports of final goods are calculated based on total industry imports at the four-digit CIC level minus the goods in the same industry that are imported by firms. By measuring firm productivity as the augmented Olley and Pakes (1996) TFP (see Appendix II for a detailed discussion), Figures 1 and 2 show that firm productivity is positively correlated with imported intermediate inputs and imports of final goods, respectively, during the post-World Trade Organization (WTO) period (2002–2006), given that China joined the WTO in 2001.

3. Measures, empirics and the results

3.1 Empirical specifications

To investigate the impacts of imported intermediate inputs and final goods imports on firm productivity, we consider the following empirical framework:

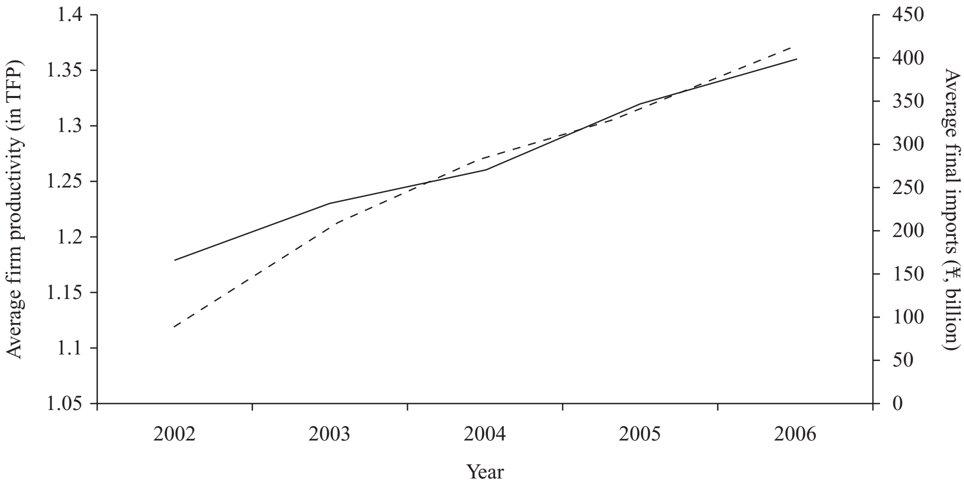

FIGURE 2. Firm productivity and imports of final goods
Sources: *China Statistical Yearbook*, customs trade data (2002–2006) and authors' calculations.

$$TFP_{ijt}^{OP} = \alpha_0 + \alpha_1 FIM_{jt} + \alpha_2 IIM_{it} + \boldsymbol{\theta}\mathbf{X}_{it} + \varpi_i + \eta_t + \mu_{it}, \tag{1}$$

where the explained variable TFP_{ijt}^{OP} is the logarithm of firm i's measured TFP in industry j in year t, based on the augmented Olley and Pakes (1996) approach, as in Yu (forthcoming). IIM_{it} denotes the imported intermediate inputs of firm i in year t. FIM_{jt} denotes the imports of final goods by industry j in year t. $\mathbf{X}_{it}$ denotes other firm characteristics, such as type of ownership (i.e. SOEs or foreign-invested firms).

State-owned enterprises are traditionally considered to have relatively low economic efficiency and, hence, low productivity (Hsieh and Klenow, 2009). By comparison, foreign-invested firms have higher productivity, partially as a result of international technology spillovers (Keller and Yeaple, 2009) or fewer financial constraints (Manova *et al*., 2009). We include the two indicators in the empirical specification to measure the roles of SOEs and foreign-invested firms. In particular, if a firm has any investments from other countries (regimes), it is classified as a foreign-invested firm. The majority of the inflow of foreign investment comes from Hong Kong, Macao and Taiwan; therefore, these investments are considered in the construction of the indicators.[5] Similarly, we construct an indicator for SOEs, which is one if a firm has any investment from the government and zero

[5] Specifically, foreign-invested enterprises include the following firms: foreign-invested joint-stork corporations (code: 310), foreign-invested joint venture enterprises (320), fully foreign-invested enterprises (330), foreign-invested limited corporations (340), Hong Kong/Macao/Taiwan joint-stock corporations (210), Hong Kong/Macao/Taiwan joint venture enterprises (220), fully Hong Kong/Macao/Taiwan-invested enterprises (230) and Hong Kong/Macao/Taiwan-invested limited corporations (240).

TABLE 2
Benchmark estimates

Regressand: $\ln TFP_{ijt}^{OP}$	OLS (1)	OLS (2)	OLS (3)	FE (4)
Log of imported intermediate inputs	0.013*** (29.81)	0.012*** (25.65)	0.012*** (26.26)	0.012*** (19.23)
Log of final imports	—	0.015*** (28.96)	0.013*** (24.03)	0.013*** (9.98)
State-owned enterprise indicator	—	−0.097*** (−8.36)	−0.067*** (−5.92)	−0.075*** (−5.05)
Foreign indicator	—	−0.017*** (−5.69)	−0.012*** (−4.01)	−0.012*** (−3.24)
Log of labour	—	0.000 (0.08)	0.000 (0.88)	0.001 (0.95)
Firm-specific fixed effects	No	No	No	Yes
Year-specific fixed effects	No	No	Yes	Yes
Observations	60,209	59,323	59,323	59,323
Probability > F	0.000	0.000	0.000	0.000
R^2	0.02	0.04	0.07	0.06

Notes: *** represents significance at the 1% level. Numbers in parentheses are *t*-values. The regression in column (1) describes the basic relationship between imported intermediate inputs and firm productivity. The regressions in columns (2)–(4) use imported intermediate inputs and final imports as described in Equation (1). FE, fixed effects; OLS, ordinary least squares.

otherwise.[6] Following Eaton *et al*. (2011). We use the logarithm of total employment to represent the scale of the firm, which serves as an additional control variable, Still, there are some other explanatory variables that we do not control, which are absorbed into the error terms: (i) firm-specific fixed effects, ϖ_i, to control for time-invariant but unobservable factors; (ii) year-specific fixed effects, η_t, to control for firm-invariant factors; and (iii) an idiosyncratic effect, μ_{it}, with normal distribution $\mu_{it} \sim N\left(0, \sigma_i^2\right)$ to control for other unspecified factors.

Several studies use firm-level data to examine the impact of imports in various countries, such as Chile, India and Indonesia. Our baseline regressions are displayed in Table 2. Column (1) presents the results of the regression that includes only the imported intermediate inputs as the regressor, without controlling for firm-specific or year-specific fixed effects. It turns out that imported intermediate inputs are positively and statistically significantly correlated with firm productivity, which is consistent with the results of other studies. Moving forward, we add imports of final goods, the firm's type of ownership and firm size (i.e. log of labour) to the regression in column (2). Column (3) takes one step forward to control for the year-specific fixed effects. The coefficient of imported intermediate inputs is still positive and significant. We find positive effects of final imports on firm productivity in columns (2) and (3). Finally, after controlling for both the firm-specific fixed effects and the year-specific fixed effects, column (4) confirms our previous findings of significant and positive correlation between imports and firm productivity.

The imported intermediate inputs could foster firm productivity as a result of technological spillovers or quality effects, as suggested by Amiti and Konings (2007). In addition, imports of final goods induce tougher competition for firms within the same industry, so that firms will have to try their best to boost their productivity to survive.

[6] By the official definition reported in the *China City Statistical Yearbook* (2006), SOEs include firms such as domestic SOEs (code: 110), state-owned joint venture enterprises (141) and state-owned and collective joint venture enterprises (143), but exclude state-owned limited corporations (151).

3.2 Role of product complexity

Thus far, we have found a positive nexus between imports and firm productivity. However, Equation (1) is a relatively crude specification because imports could be quite different when products with different levels of complexity are imported. For example, on the one hand, if a homogeneous product is introduced to the domestic market, firms will have more incentive to improve their productivity given that the competition in the market is more intense. On the other hand, if a homogeneous intermediate input is imported, firms may find it easier to adopt its up-to-date technology because homogeneous products are less technology-specific than heterogeneous products.

To confirm this, we introduce a product complexity indicator, following Rauch (1999), as explained above. That is, we construct an indicator "N_i" of product complexity, which is zero if a product has a reference price and is thus a homogeneous good, and one otherwise. Taking the complexity indicator into account, we use the following specification for our main estimations:

$$TFP_{ijt}^{OP} = \beta_0 + \beta_1 FIM_{jt} + \beta_2 IIM_{it} + \beta_3 FIM_{jt} \times N_i + \beta_4 IIM_{it} \times N_i + \delta X_{it} + \varpi_i + \eta_t + \mu_{it}. \quad (2)$$

In addition to all the regressors listed in Equation (1), the new regressors in Equation (2) are the complexity indicator (N_i) and its interactions. The interaction term between imported intermediate inputs (and final imports) and the complexity indicator is included to capture possibly heterogeneous productivity gains from imports caused by different product complexity. Following previous studies, such as Yu *et al*. (2013), we use the conservative method as a default measure of the complexity indicator.

Column (1) in Table 3 includes the interaction terms for product complexity and imported intermediate inputs and final imports. The coefficients of imported intermediate inputs and final imports are still positive and significant, whereas their interaction terms with the complexity indicator are negative and significant. This suggests that imports have greater impact on the productivity of firms that produce homogeneous goods. In column (2), we control for the firm's type of ownership, firm size and year dummies. The results remain almost the same as those in column (1), except that the coefficient of the interaction term between imported intermediate inputs and the complexity indicator is insignificant. It could be that this result is caused by the measure of the complexity indicator.

To confirm this, we use the liberal method as an alternative measure of the complexity indicator. Results when the liberal approach is used to define the complexity indicator are displayed in column (3), but the results are similar to as those in column (2). Controlling for firm-specific and year-specific fixed effects with either the liberal measure in column (4) or the conservative measure in column (5) does not change the insignificance of the interaction term of imported intermediate inputs and the complexity indicator. We suspect that this is because of the lack of control for the endogeneity of imported intermediate inputs. We now turn to address this issue.

3.3 Endogeneity issues

The specifications in Tables 2 and 3 face possible endogeneity problems. Previous studies, such as Krugman (1980), Melitz (2003), Alcala and Ciccone (2004) and Kasahara and Lapham (2013), have recognized that the firm's imports and exports largely depend on the

TABLE 3
Estimates with different measures of product complexity

Regressand: $\ln TFP_{ijt}^{OP}$	OLS (1) conservative	OLS (2) conservative	OLS (3) liberal	FE (4) conservative	FE (5) liberal
Log of imported intermediate inputs	0.013*** (12.99)	0.013*** (12.96)	0.013*** (12.17)	0.006*** (3.16)	0.004** (2.18)
Log of final imports	0.018*** (32.40)	0.015*** (26.95)	0.015*** (26.93)	0.007*** (3.73)	0.006*** (3.49)
Log of imported intermediate inputs × Complexity indicator	−0.002*** (−2.02)	−0.001 (−1.52)	−0.001 (−1.32)	−0.001 (−0.61)	0.001 (0.64)
Log of final Imports × Complexity indicator	−0.003*** (−10.83)	−0.003*** (−10.81)	−0.003*** (−10.72)	−0.001** (−2.21)	−0.001 (−1.20)
State-owned enterprise indicator	—	−0.068*** (−6.01)	−0.068*** (−6.00)	0.02 (0.85)	0.02 (0.82)
Foreign indicator	—	−0.009*** (−2.99)	−0.009*** (−2.96)	0.016 (1.25)	0.016 (1.24)
Log of labour	—	0.002 (1.59)	0.002 (1.62)	0.000 (0.08)	0.000 (0.07)
Firm-specific fixed effects	No	No	No	Yes	Yes
Year-specific fixed effects	No	Yes	Yes	Yes	Yes
Observations	60,209	59,323	54,323	59,323	59,323
R^2	0.03	0.07	0.07	0.10	0.11

Notes: *** and ** represent significance at the 1 and 5% level, respectively. Numbers in parentheses are *t*-values. The regressions in columns (1)–(5) use product heterogeneity data, which can be derived using the conservative method or the liberal method as described in Equation (2). Columns (1)–(2) and (4) use the conservative method whereas columns (3) and (5) use the liberal method, as discussed in the text. FE, fixed effects; OLS, ordinary least squares.

firm's productivity. On the one hand, imported intermediate inputs will increase firm productivity because of spillover effects; on the other hand, firms with high productivity tend to import more intermediate inputs to produce more. We thus use an IV to address the potential endogeneity issue.

China was committed to set its tariffs at the designated levels set by the WTO after its accession in 2001. Hence, tariffs can be treated as an exogenous IV. When tariffs are higher, firms import fewer intermediate inputs, suggesting that the two variables are highly correlated. Thus, the input tariff is a good IV for imported intermediate inputs.

Because the imported intermediate inputs are measured at the firm level, we use firm-specific input tariffs to avoid possible aggregation bias. In China, firms' imports are divided into ordinary imports and processing imports. Processing trade usually means processing with imported materials and processing with supplied materials. Since processing imports are duty free, given that a firm could engage in both processing imports (P) and non-processing imports (O), following Yu *et al*. (2013), we construct a firm-specific input tariff index (FIT_{it}) as follows:

$$FIT_{it} = \sum_{k\in O}\left(m^k_{i,initial\_year}\Big/\sum_{k\in M} m^k_{i,initial\_year}\right)\tau^k_t,$$

where $m^k_{i,initial\_year}$ is firm i's imports of product k in the first year the firm appears in the sample. Note that $O \cup P = M$, where M is the set of the firm's total imports.

Table 4 lists the results using IV to mitigate the endogeneity problem. Columns (1)–(3) use the conservative complexity measure, whereas column (4) adopts the liberal complexity measure as a robustness check. Columns (1)–(4) in Table 4 present two-stage least squares (2SLS) fixed-effects estimates for the input tariff and its interaction with the product complexity indicator as the instruments. As shown in column (1), after controlling for reverse causality, imported intermediate inputs boost firm productivity, although the coefficient is statistically insignificant. The coefficient of imported intermediate inputs turns out to be significant after adding more control variables in columns (2)–(4). Once again, with more imported intermediate inputs, firm productivity is higher. More importantly, the impact becomes weaker as firms produce more complex products.

The economic rationale is as follows. A firm could realize productivity gains from importing because imported intermediate inputs involve better technology, which, in turn, fosters firm productivity, as suggested by Amiti and Konings (2007). Compared with heterogeneous products, the advanced technology in homogeneous goods is less product-specific and, hence, easier for firms to absorb. Therefore, we see that there is greater improvement in the productivity of firms with homogeneous products than in firms with heterogeneous products.

To check whether final imports have similar effects, column (2) in Table 4 includes imports of final goods and their interactions with the complexity indicator. The results are similar to those for imported intermediate inputs. Column (3) includes the firm's ownership type and firm size in the estimates and yields similar results for the key coefficients as in column (2). Finally, when a similar regression is run with the liberal measure of complexity to capture the role of product complexity (see column 4), close results are found.

Several tests are performed to verify the quality of the instruments. First, we use the Kleibergen–Paap Lagrange multiplier χ^2-statistic to check whether the excluded

TABLE 4
Instrumental variable estimates

Regressand: $\ln TFP_{ijt}^{OP}$	(1) Conservative	(2) Conservative	(3) Conservative	(4) Liberal
Log of imported intermediate inputs	0.013 (1.17)	0.072** (2.43)	0.077** (2.45)	0.051** (2.48)
Log of final imports	—	0.019*** (−3.73)	0.020*** (3.74)	0.015*** (4.16)
Log of imported intermediate inputs × Complexity indicator	−0.010** (−1.98)	−0.075*** (−2.73)	−0.080*** (−2.75)	−0.050*** (−2.96)
Log of final imports × Complexity indicator	—	−0.016*** (−2.92)	−0.017*** (−2.93)	−0.010*** (−3.24)
State-owned enterprise indicator indicator	—	—	0.041 (1.52)	0.034 (1.40)
Foreign indicator	—	—	0.021 (1.44)	0.018 (1.28)
Log of labour	—	—	−0.001 (−0.20)	−0.002 (−0.35)
Kleibergen–Paap rk Lagrange multiplier χ^2 statistic	109.6	21.7	20.2	42.4
Kleibergen–Paap rk Lagrange multiplier Wald F-statistic	50.6	10.0	9.0	18.2
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes
Observations	46083	46083	44976	44976
R^2	0.1008	0.0534	0.0465	0.0757
First-stage regressions				
IV1: Firm input tariffs	−0.024*** (−2.96)	−0.024*** (−2.84)	−0.021** (−2.53)	−0.022*** (−2.74)
	[68.41]	[66.75]	[62.84]	[62.25]
IV2: Firm input tariffs × Product complexity	−0.219*** (−21.07)	−0.081*** (−10.00)	−0.081*** (−10.02)	−0.102*** (−12.09)
	[239.03]	[74.85]	[71.63]	[91.15]

Notes: *** and ** represent significance at the 1 and 5% level, respectively. Numbers in parentheses are *t*-values, whereas those in brackets are F-statistics. In the first-stage regressions, IV1 reports the coefficient of firm-specific input tariffs, using imported intermediate inputs as the regressand. IV2 reports the coefficient of the interaction between firm-specific input tariffs and the product complexity indicator, using the interaction between imported intermediate inputs and the product complexity indicator as the regressand.

instruments are correlated with the endogenous regressors. Second, the Kleibergen and Paap (2006) F-statistics provide strong evidence for rejecting the null hypothesis that the first stage is weakly identified at a highly significant level. Finally, the first-stage estimates offer strong evidence to justify such instruments. In particular, all the t-values of the instruments are significant.

Our final task is to provide some economic intuition for our findings. From Table 4, we see that more imported intermediate inputs lead to higher firm productivity, which is consistent with previous studies. More importantly, the impact of imports on firm productivity is weaker as firms produce more complex products. This result is intuitive. If firms produce complex final products, they face less severe competition in the final goods market because the final goods are more differentiated. Therefore, the firms have less incentive to improve their productivity compared with firms producing homogeneous products. Meanwhile, the spillover effects of imported intermediate inputs might help firms increase their productivity, which would encourage firms to produce more or higher-quality products. Therefore, if firms import more intermediate inputs, producers of less complex commodities would tend to produce more or higher-quality products, which could help them to realize greater productivity gains.

4. Concluding remarks

This paper explores the nexus among imports, firm productivity and product complexity. Using a Chinese firm-level production data set and a transaction-level trade data set, we find that imports boost firm productivity. First, if there are more imported intermediate inputs, the firm's productivity gain will be higher. This is possibly because of technology spillovers and learning from imports. Second, manufacturing firms would enjoy productivity gains from the imports of final goods in their own industry through competition effects.

More importantly, we find that the impact of imported intermediate inputs on firm productivity becomes weaker as firms produce more complex products. By separating products into homogeneous products and heterogeneous products, our empirical analysis shows that firms with homogeneous products realize more productivity gains, possibly because the competition and learning effects for such firms would be greater.

Our findings have the following policy implications. If imports boost firm productivity, it is a good development strategy for the government of China (and perhaps some other developing countries) to import more from the rest of the world. In this way, countries can approach a balanced trade position and, more importantly, increase their firms' productivity and, hence, national welfare.

Appendix I

Matched statistics–number of firms

	Trade data		Production data		Matched data			
Year # of	Transactions (1)	Firms (2)	Raw Firms (3)	Filtered Firms (4)	With raw Firms (5)	With filtered Firms (6)	With raw Firms (7)	With filtered Firms (8)
2000	10,586,696	80,232	162,883	83,628	18,580	12,842	21,425	15,748
2001	12,667,685	87,404	169,031	100,100	21,583	15,645	24,959	19,091
2002	14,032,675	95,579	181,557	110,530	24,696	18,140	28,759	22,291
2003	18,069,404	113,147	196,222	129,508	28,898	21,837	33,901	26,930
2004	21,402,355	134,895	277,004	199,927	44,338	35,007	49,891	40,711
2005	24,889,639	136,604	271,835	198,302	44,387	34,958	49,891	40,387
2006	26,685,377	197,806	301,960	224,854	53,748	42,833	49,680	47,591
All years	128,333,831	286,819	615,951	438,165	83,679	69,623	91,299	76,823

Notes: Column (1) reports the number of observations of Harmonized System eight-digit monthly transaction-level trade data from China's General Administration of Customs by year. Column (2) reports the number of firms covered in the transaction-level trade data by year. Column (3) reports the number of firms covered in the firm-level production data set compiled by China's National Bureau of Statistics without any filter or cleaning. By contrast, column (4) presents the number of firms covered in the firm-level production data set with careful filtering according to the requirements of GAAP. Accordingly, column (5) reports the number of matched firms using exactly identical company names in both the trade data set and the raw production data set. By contrast, column (6) reports the number of matched firms using exactly identical company names in both the trade data set and the filtered production data set. Finally, column (7) reports the number of matched firms using exactly identical company names and exactly identical zip codes and phone numbers in both the trade data set and the raw production data set. By contrast, column (8) reports the number of matched firms using exactly identical company names and exactly identical zip codes and phone numbers in both the trade data set and the filtered production data set.

Appendix II

Estimates of Olley–Pakes TFP by processing and ordinary firms separately

Chinese	Ordinary firms			Processing firms		
Industry	Labour	Materials	Capital	Labour	Materials	Capital
13	0.051	0.875	0.247	0.116	0.884	0.066
14	0.048	0.928	0.027	0.037	0.925	0.074
15	0.298	0.500	0.193	0.243	0.505	0.088
17	0.059	0.884	0.017	0.089	0.834	0.041
18	0.076	0.858	0.054	0.177	0.669	0.142
19	0.044	0.925	0.040	0.118	0.808	0.000
20	0.023	0.895	0.126	0.044	0.913	0.003
21	0.042	0.917	0.055	0.101	0.873	0.103
22	0.008	0.907	0.111	0.027	0.896	0.063
23	0.039	0.821	0.023	0.105	0.836	0.025
24	0.123	0.764	0.068	0.104	0.863	0.036
26	0.049	0.800	0.107	0.007	0.927	0.024
27	0.040	0.865	0.059	0.038	0.860	0.038
28	0.011	0.795	0.045	0.016	0.837	0.041
29	0.177	0.545	0.090	0.073	0.938	0.032
30	0.172	0.624	0.158	0.125	0.696	0.114
31	0.044	0.853	0.059	0.050	0.870	0.035

Appendix II
(*continued*)

Chinese Industry	Ordinary firms Labour	Ordinary firms Materials	Ordinary firms Capital	Processing firms Labour	Processing firms Materials	Processing firms Capital
32	0.028	0.985	0.018	0.038	0.961	0.010
33	0.081	0.820	0.051	0.055	0.850	0.076
34	0.046	0.870	0.040	0.044	0.883	0.026
35	0.017	0.875	0.066	0.032	0.917	0.026
36	0.061	0.832	0.043	0.038	0.869	0.111
37	0.043	0.891	0.044	0.054	0.924	0.029
39	0.101	0.834	0.018	0.102	0.826	0.000
40	0.067	0.836	0.078	0.086	0.878	0.086
41	0.000	0.927	0.082	0.139	0.567	0.168
42	0.044	0.918	0.004	0.142	0.818	0.094

Notes: This table reports the estimated log of Olley–Pakes total factor productivity (TFP) by separating ordinary and processing firms. The Chinese industries and associated codes are classified as follows: Processing of foods (13), Manufacture of foods (14), Beverages (15), Textiles (17), Apparel (18), Leather (19), Timber (20), Furniture (21), Paper (22), Printing (23), Articles for culture and sports (24), Petroleum (25), Raw chemicals (26), Medicines (27), Chemical fibers (28), Rubber (29), Plastics (30), Non-metallic minerals (31), Smelting of ferrous metals (32), Smelting of non-ferrous metals (33), Metal (34), General machinery (35), Special machinery (36), Transport equipment (37), Electrical machinery (39), Communication equipment (40), Measuring instruments (41) and Manufacture of artwork (42). We do not report standard errors for each estimated coefficient to save space, although standard errors are available upon request.

Final version accepted 19 March 2014.

REFERENCES

Ahn, J., A. K. Khandelwal and S. J. Wei (2011) "The Role of Intermediaries in Facilitating Trade", *Journal of International Economics*, Vol. 84, No. 1, pp. 73–85.

Alcala, F. and A. Ciccone (2004) "Trade and Productivity", *Quarterly Journal of Economics*, Vol. 119, No. 2, pp. 613–646.

Amiti, M. and J. Konings (2007) "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia", *American Economic Review*, Vol. 97, No. 5, pp. 1611–1638.

Bernard, A. and B. Jensen (2004) "Why Some Firms Export?", *Review of Economics and Statistics*, Vol. 86, No. 2, pp. 561–569.

Brandt, L., J. V. Biesebroeck and Y. Zhang (2012) "Creative Accounting Or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing", *Journal of Development Economics*, Vol. 97, No. 2, pp. 339–351.

Cai, H. and Q. Liu (2009) "Does Competition Encourage Unethical Behavior? The Case of Corporate Profit Hiding in China", *Economic Journal*, Vol. 119, pp. 764–795.

Davis, D. R. and D. E. Weinstein (1999) "Economic Geography and Regional Production Structure: An Empirical Investigation", *European Economic Review*, Vol. 43, No. 2, pp. 379–407.

Eaton, J., S. Kortum and F. Kramarz (2011) "An Anatomy of International Trade: Evidence from French Firms", *Econometrica*, Vol. 79, No. 5, pp. 1453–1498.

Feenstra, R. C., Z. Li and M. Yu (forthcoming) "Export and Credit Constraints under Incomplete Information: Theory and Empirical Investigation from China", *Review of Economics and Statistic*.

——, J. R. Markusen and A. K. Rose (2001) "Using the Gravity Equation to Differentiate among Alternative Theories of Trade", *Canadian Journal of Economics*, Vol. 34, No. 2, pp. 430–447.

Feng, L., Z. Li and D. L. Swensen (2012) "The Connection between Imported Intermediate Inputs and Exports: Evidence from Chinese Firms", National Bureau of Economic Research, No. 18260.

Ge, Y., H. Lai and S. C. Zhu (2011) "Intermediates Import and Gains from Trade Liberalization", University of International Business. Mimeo.

Halpern, L., M. Korenand and A. Szeidl (2011) "Imported Inputs and Productivity", University of California, Berkeley. Mimeo.

Hsieh, C. T. and P. Klenow (2009) "Misallocation and Manufacturing TFP in China and India", *Quarterly Journal of Economics*, Vol. 124, No. 4, pp. 1403–1448.

Kasahara, H. and B. Lapham (2013) "Productivity and the Decision to Import and Export: Theory and Evidence", *Journal of International Economics*, Vol. 89, No. 2, pp. 297–316.

—— and J. Rodrigue (2008) "Does the Use of Imported Intermediates Increase Productivity? Plant-Level Evidence", *Journal of Development Economics*, Vol. 87, No. 1, pp. 106–118.

Keller, W. and S. R. Yeaple (2009) "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States", *Review of Economics and Statistics*, Vol. 91, No. 4, pp. 821–831.

Kleibergen, F. and R. Paap (2006) "Generalized Reduced Rank Tests Using the Singular Value Decomposition", *Journal of Econometrics*, Vol. 133, No. 1, pp. 97–126.

Krugman, P. (1980) "Scale Economies, Product Differentiation, and the Pattern of Trade", *The American Economic Review*, Vol. 70, No. 5, pp. 950–959.

Manova, K., S. J. Wei and Z. Zhang (2009) "Firm Exports and Multinational Activity under Credit Constraints", National Bureau of Economic Research, No. 16905.

Melitz, M. J. (2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity", *Econometrica*, Vol. 71, No. 6, pp. 1695–1725.

Olley, S. and A. Pakes (1996) "The Dynamics of Productivity in the Telecommunications Equipment Industry", *Econometrica*, Vol. 64, No. 6, pp. 1263–1297.

Park, A., D. Yang, X. Shi and Y. Jiang (2010) "Exporting and Firm Performance: Chinese Exporters and the Asian Financial Crisis", *Review of Economics and Statistics*, Vol. 92, No. 4, pp. 822–842.

Rauch, J. E. (1999) "Networks Versus Markets in International Trade", *Journal of International Economics*, Vol. 48, No. 1, pp. 7–35.

Topalova, P. and A. Khandelwal (2011) "Trade Liberalization and Firm Productivity: The Case of India", *Review of Economics and Statistics*, Vol. 93, No. 3, pp. 995–1009.

Yang, Y. and S. Mallick (2010) "Export Premium, Self-Selection and Learning-by-Exporting: Evidence from Chinese Matched Firms", *The World Economy*, Vol. 33, No. 10, pp. 1218–1240.

Yu, M. (forthcoming) "Processing Trade, Tariff Reductions, and Firm Productivity: Evidence from Chinese Firms", *Economic Journal*, doi: 10.1111/ecoj.12127.

—— and W. Tian (2012) "China's Processing Trade: A Firm-Level Analysis", in H. McMay and L. Song, eds, *Rebalancing and Sustaining Growth in China*, Canberra: Australian National University E-press, pp. 111–148.

——, G. Ye and B. Qu (2013) "Trade Liberalization, Product Complexity and Productivity Improvement: Evidence from Chinese Firms", *The World Economy*, Vol. 36, No. 7, pp. 912–934.