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WORKER TRAINING, FIRM PRODUCTIVITY, AND TRADE LIBERALIZATION: EVIDENCE FROM CHINESE FIRMS

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This paper discusses a novel mechanism—worker training—in relation to the effect of output trade liberalization on firm productivity. Using disaggregated Chinese firm-level production data from 2004 to 2006, we find strong evidence that output trade liberalization boosts firm productivity. More importantly, after controlling for the firm's self-selection in regards to investment in worker training, our extensive empirical research suggests the following findings. First, with fiercer import competition, firms experience a decrease in profitability and hence are less likely to invest in worker training. Second, less productive firms are more likely to train their workers, as otherwise they would collapse and exit from the market. The lower the firm productivity, the more is invested in the firm's worker training. Finally, the effect of output trade liberalization on firm productivity is more pronounced for firms with more training investment. Such results are robust regardless of various empirical specifications and different measures.

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I. INTRODUCTION

FIRM productivity and trade liberalization is an important research topic in international trade and economic development. A growing body of

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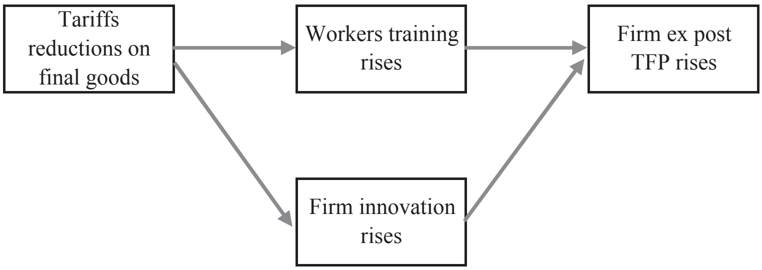
Fig. 1. The Mechanism



empirical research using firm-level micro data finds evidence that trade liberalization from both input goods and final goods fosters firm productivity. Amiti and Konings (2007) use Indonesian firm-level data to find that firms' gains from reduction of input tariffs are at least twice as much as those from reduction of output tariffs. Similarly, Topalova and Khandelwal (2011) find evidence for Indian firms. Using Chinese firm-level dataset, Yu (2015) finds that, overall, the impact of input tariff reductions on productivity improvement is weaker than that of output tariff reductions since processing imports is already free of duty in China. Both tariff reductions are found to contribute at least 14.5% to economy-wide productivity growth in China.

However, as noted by Bernard and Jensen (2004), a key important but unanswered question is "how firms obtain the characteristics that allow them to easily enter the export market." Or equivalently, through what mechanisms do trade policy changes affect welfare gains from trade? Inspired by Melitz (2003), Lileeva and Trefler (2010) and Melitz and Trefler (2012) forcefully argue that foreign market access matters for firm innovation and hence for firm productivity. This paper argues that worker training is another important mechanism, in addition to firm innovation, through which productivity improvement and hence export growth are realized. With tariff reductions on final goods, Chinese domestic firms face tougher import competition. The competitive effect is stronger for low ex ante productive firms, which in turn input more on labor training to boost their ex post productivity. With realized productivity growth, firms are able to maintain their international competitive advantage and export more. This concept is illustrated in Figure 1.

Trade liberalization can affect firm productivity via two channels as Figure 1 shows. The first is the innovation channel, which is already documented by previous studies, such as Lileeva and Trefler (2010). Different from the channel of firm innovation, a new channel—labor training— is introduced in Figure 1, which shows that trade liberalization affects firm productivity. Using Chinese firm-level production data from 2004 to 2006, we find strong evidence for such a mechanism. Our extensive empirical research supports the following novel findings.

First, we find strong evidence that output trade liberalization fosters firm productivity as before. Second, with fiercer import competition, firms experience a decrease in profitability and hence are less likely to invest in firm training. Third, less productive firms are more likely to train their workers, as otherwise they would collapse and exit from the market. The lower the firm productivity, the higher the firm's worker training expenses. Finally, the effect of output trade liberalization on firm productivity is more pronounced for firms with more training investment.

Note that our first finding is already well documented in the literature. Our findings echo the widely accepted firm heterogeneity theory, consistent with previous works. However, our other empirical predictions are novel. To emphasize the role of import competition, in this paper we focus on trade liberalization on final goods. As robustness checks, we include foreign trade liberalization as control variables in our estimates and discuss the case in the context of an input tariff cut.

We make the following three contributions to the literature. First, we identify a new mechanism through which trade liberalization affects firm productivity. The literature on trade strongly emphasizes the role of investment on research and development (R&D) for firms' exposure to global competition but neglects the role of investment in labor training, with only a few exceptions (e.g., Aw, Roberts, and Xu 2011; Helpman, Itskhoki, and Redding 2010). But the importance of worker training is recognized in development economics. For instance, Acemoglu and Pischke (1999) emphasize that firms invest in the general skills of workers when labor market frictions compress the structure of wages. This theoretical concept is evident in reality.[1]

Second, we provide evidence on the nexus between trade liberalization, worker training and productivity for China, the second largest economy and the largest trading country in the world. Due to increasing labor costs in recent years (Cai 2010), Chinese firms try their very best to boost firm productivity to maintain international competitiveness. In addition to increasing input on R&D, Chinese manufacturing firms invest a significant amount in worker training, as illustrated in the next section, by using Chinese firm-level production data. However, previous firm-level research on China mainly focused on firm productivity and exports but was silent on the role of firm's training behavior. Our paper also aims to fill in this gap.

[1] For example, the UK and Italian Governments thought that one of the key factors behind the loss of competitiveness of their firms in the global economy was the lack of training compared with other countries like Germany and Japan. Thus they initiated large training programs in their countries. See Brunello, Garibaldi, and Wasmer (2007) for detailed discussions.

Third, we make contributions to the related identification problem. The econometric challenges of this paper stem from the following empirical issues. In particular, we need to empirically distinguish the difference between ex ante total factor productivity (TFP) and ex post TFP. However, typical empirical research uses the Solow residual to proxy firm TFP, which by definition is an ex post measure. The semi-parametric techniques developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), or even the generalized method of moments (GMM), cannot solve this challenge. Inspired by Feenstra, Li, and Yu (2014), we first estimate and calculate an ex ante TFP measure in the estimates.

Our paper joins the two strands of the growing literature. The first strand is on the nexus between trade liberalization and labor training. Baldwin (1992) was one of the pioneering works to emphasize the dynamic effect of trade liberalization on human capital accumulation. However, not many empirical works directly investigate the importance of the specific channel—labor training. One outstanding exception is Li (2009), who investigates the effect of the import penetration ratio on firm training using American household-level data from the National Longitudinal Survey of Youth (NLSY). He finds that import competition has a negative impact on training provision. Some theoretical papers, such as Deardorff (2000) and Long, Riezman, and Soubeyran (2007), also look at how trade liberalization affects workers' skill acquisition/accumulation decision and thus affects wage inequality. Lai and Ng (2014) use a subjective measure of market competition and find that increased product market competition is strongly associated with more training provision. Görlitz and Stiebale (2011) also find no impact of competition on firm training provision.

The second strand of literature is to examine the nexus between labor training and firm productivity but with no conclusive results (see a review by Blundell et al. 1999). Early works like Blundell, Dearden, and Meghir (1996) generally use wage rates to proxy firm productivity to study the effect of training on productivity due to the unavailability of direct productivity measure. Some studies like Conti (2005) and Dearden, Reed, and Van Reenen (2006) have made efforts to construct industry-level panel data to test the nexus between labor training and firm productivity. Finally, there is a small but growing body of papers, like Black and Lynch (2001) and Almeida and Carneiro (2009), which rely on firm-level panel data to investigate the effect of training on firm productivity. However, the results in these papers are constrained by the limited representativeness of the small sample size of the data.

Still, two points merit special discussions. First, the present paper finds that low productivity firms self-select to provide more training for their workers. It is natural to ask why such firms would not hire well-trained workers from outside by offering more attractive wages (Verhoogen 2008). One possible reason is due to the high cost of searching for skilled workers in a wide geographic area. Today, regional migration is still fairly intense in China, as is evident in the implication of the *hukou* or registered residence system (Cai 2010). Second, this paper cannot distinguish the difference between on-the-job training and off-the-job training because our firm-level data is compiled and collected according to the requirements of the balance sheet of accounting, which does not provide detailed information on the type of labor training. Due to data limitation, we cannot explore this issue further, although it deserves further research in the future.

The rest of the paper is organized as follows. Section II describes Chinese firm-level data. Section III sketches the framework for our empirical specification. Section IV presents our estimation results. Section V briefly discusses policy implications and concludes.

II. DATA

Our sample is derived from a rich firm-level panel dataset that covers between 162,885 firms (in 2000) and 336,768 firms (in 2006). The data are collected and maintained by China's National Bureau of Statistics in an annual survey of manufacturing enterprises (Chinese Manufacturing Firms Survey, CMS). Complete information on the three major accounting statements (i.e., balance sheet, profit and loss account, and cash flow statement) is available. In brief, the dataset covers two types of manufacturing firms—all state-owned enterprises (SOEs) and non-SOEs, the annual sales of which exceed RMB 5 million (or equivalently, US$770,000, under current exchange rates).[2] The dataset includes more than 100 financial variables listed in the main accounting statements of these firms.

Although the dataset contains rich information, some samples are still noisy and are therefore misleading, largely because of misreporting by some firms.[3] Following Yu (2015), we clean the sample and omit outliers by using the following criteria. First, observations with missing key financial variables (such as total assets, net value of fixed assets, sales, and gross value of the firm's output productivity) are excluded. Second, we drop firms with fewer than eight workers since they fall under a different legal regime, as mentioned in Brandt, Van Biesebroeck, and Zhang (2012). Third, we delete observations according to the basic

[2] Aggregated data on the industrial sector in the annual *China Statistical Yearbook* by the National Bureau of Statistics are compiled from this dataset.

[3] For example, information on some family-based firms, which usually have no formal accounting system in place, is based on a unit of RMB 1, whereas the official requirement is a unit of RMB 1000.

TABLE 1

Total Factor Productivity (TFP), Tariffs, and Firm's Training Expenses

	TFP		Training Dummy		Log Training		Industrial Output Tariffs	
Year	Mean (1)	Std. Dev. (2)	Mean (3)	Std. Dev. (4)	Mean (5)	Std. Dev. (6)	Mean (7)	Std. Dev. (8)
2004	1.055	0.317	0.437	0.496	4.244	4.920	8.321	1.863
2005	1.033	0.334	0.408	0.491	4.037	4.960	7.944	1.966
2006	1.046	0.342	0.409	0.492	4.054	4.981	7.582	1.583

Source: Data compiled by the authors.

rules of the generally accepted accounting principles.[4] After applying such a stringent filter to guarantee the quality of the production data, the filtered firm data are reduced by about 50% in each year. Since the CMS data provides information on worker training after 2004, our panel is shortened to cover the period during 2004–6. As shown in Table 1, firm's worker training expenses increase during 2005–6.[5] Table 1 also shows that firm's training investment increases over the sample period.[6]

Tariff data can be accessed directly from the WTO and the trade analysis and information system (TRAINS).[7] China's tariff data are available at the Harmonized System (HS) six-digit disaggregated level for 2000–2006. Given that the product-level trade data are at the HS eight-digit level, the product-level trade data is aggregated to the HS six-digit level to correspond with the ad valorem tariff data. Table 2 provides the basic statistical information for key variables used in the estimations.

[4] For example, observations are dropped if any of the following are true: (1) liquid assets are greater than total assets; (2) total fixed assets are greater than total assets; (3) the net value of fixed assets is greater than total assets; (4) the firm's identification number is missing; or (5) an invalid established time exists (e.g., the opening month is later than December or earlier than January).

[5] A firm's worker training expenses decrease from 2004 whereas their variance increases over years, suggesting that worker training is more skewed over years.

[6] By separating firms into pure exporter (i.e., firms export all of their products), non-pure exporters (i.e., firms at most export some products), and non-exporters (i.e., firms do not export any products), we see that exporters spend more on worker training than non-exporters. Simultaneously, non-pure exporters have larger worker training expenses than pure exporters. Such results are not reported in the text but available upon request.

[7] The data are from the WTO webpage (http://tariffdata.wto.org/ReportersAndProducts.aspx). Note that TRAINS data generally suffers from missing values problems, particularly regarding the tariffs imposed by other countries for Chinese exports. The product–destination–year combinations that have missing tariffs are hence dropped.

TABLE 2

Summary Statistics (2004–6)

Key Variables	Mean	Standard Deviation
Log of export (RMB)	16.460	1.69
Training dummy	0.412	0.492
Log of training expenses (RMB)	4.110	4.950
Log of training expenses per capita (RMB)	1.990	2.530
Industry-level output tariffs	0.090	3.660
Industry-level input tariffs	0.004	0.808
Firm-level external tariffs	0.009	11.300
State-owned enterprises indicator	0.035	0.185
Foreign ownership indicator	0.131	0.338

Note: US$1 is equivalent to RMB 8.05 during the period.

III. EMPIRICAL SPECIFICATION

To investigate the effects of input and output tariff reductions on firm productivity, we consider the following empirical framework:

$$\ln TFP_{ijt}^{OP} = \beta_0 + \beta_1 OT_{jt} + \beta_2 TrainDummy_{it} + \theta \mathbf{X}_{it} + \varpi_i + \eta_t + \mu_{it}, \qquad (1)$$

where $\ln TFP_{ijt}^{op}$ is the logarithm of firm i's TFP in industry j in year t whereas OT_{jt} denotes industry-level output tariffs. The variable $TrainDummy_{it}$ is a firm's training indicator, which equals one if a firm has any expenses on worker training and zero otherwise. The vector $\mathbf{X}_{it}$ denotes other firm characteristics, such as type of ownership (i.e., state-owned enterprises or multinational firms). State-owned enterprises (SOEs) are usually less productive and hence export less (Hsieh and Klenow 2009). By contrast, multinational firms have higher productivity due in part to fewer financial constraints (Feenstra, Li, and Yu 2014) or more international technology spillover (Keller and Yeaple 2009), and hence export more. Therefore, we construct two indicators to measure the roles of SOEs and multinational firms. In particular, a firm is classified as a foreign firm if it has any investments from other countries (regimes). A large proportion of the inflow of foreign investment comes from Hong Kong, Macao, and Taiwan, so these investments are considered in the construction of such an indicator.[8]

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

Similarly, we construct an indicator for SOEs, which is one if a firm has any investment from the Government, and zero otherwise.[9] Finally, the error term is divided into three components: (1) firm-specific fixed effects ϖ_i to control for time-invariant but unobservable factors such as managerial ability (Qiu and Yu 2014); (2) year-specific fixed effects η_t to control for firm-invariant factors such as an appreciation of the renminbi; and (3) an idiosyncratic effect μ_{it} with normal distribution $\mu_{it} \sim N\left(0, \sigma_i^2\right)$ to control for other unspecified factors.

However, the training indicator in the specification above is relatively crude. If a firm only spends a very small amount in worker training, it is still identified as a training firm though it is very unlikely that the small amount of worker training can boost firm productivity. Hence, we use a firm's actual training expenses to capture firm's training activity with the following specification:

$$\ln TFP_{ijt}^{OP} = \beta_0 + \beta_1 OT_{jt} + \beta_2 \ln Train_{it} + \theta \mathbf{X}_{it} + \varpi_i + \eta_t + \mu_{it}. \tag{2}$$

A. *Type-2 Tobit Selection Model*

Thus far our estimates use firm's log of training expenses as a key variable, but such a variable is endogenous. First, it is possible that low productive firms self-select to provide more training since otherwise those firms would collapse and exit from the market. By the same token, tougher import competition raised by lower import tariffs would force firms to raise training to avoid being swept out of the market. To control for this, we introduce a type-2 Tobit model, or equivalently, a bivariate sample selection model (Cameron and Trivedi 2005). The type-2 Tobit specification includes: (1) a training participation equation,

$$TrainDummy_{ijt} = \begin{cases} 0 & \text{if } U_{ijt} < 0, \\ 1 & \text{if } U_{ijt} \geq 0, \end{cases} \tag{3}$$

where U_{ijt} denotes a latent variable faced by firm i in industry j; and (2) an "outcome" equation whereby the firm's training expenses are modeled as a linear function of other variables.

[9] According to 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).

In particular, we estimate the following selection equation using the probit model:

$$\Pr\left(Training_{ijt}=1\right)=\Pr\left(U_{ijt}\geq 0\right)$$
$$=\Phi(\alpha_0+\alpha_1\ln TFP2_{it-1}+\alpha_2 OT_{jt-1}$$
$$+\alpha_3 FE_{it-1}+\alpha_3 SOE_{it-1}+\alpha_4 FIE_{it-1}+\alpha_5\,\mathrm{lg}L_{it-1}$$
$$+\alpha_6 Tenure_{it-1}+\lambda_j+\varsigma_t), \tag{4}$$

where $\Phi(\bullet)$ is the cumulative density function of the normal distribution. In addition to the logarithm of the firm's productivity, a firm's decision to invest in training is also affected by other factors, such as its ownership (whether it is a SOE or a multinational firm) and output tariffs level. Note that the bivariate sample selection estimations require an excluded variable that affects the firm's training decision but does not appear in the level of training expenses (Cameron and Trivedi 2005). Here the firm's age ($Tenure_{it-1}$) serves this purpose, since previous studies have found that older firms are more likely to invest in training (OECD 1993). All regressors in the type-2 Tobit selection model are of a one-period lag since it usually takes time for such factors to affect a firm's training decision. Finally, we include the three-digit China Industrial Classification (CIC) industrial dummies λ_j and year dummies ς_t to control for other unspecified factors.

In addition, productivity is also an important factor to determine a firm's training decisions. We hence shall include it in the regressions in these binary estimates. However, an empirical identification challenge arises. The conventional TFP measure is a Solow residual, which is an ex post measure, whereas our model suggests that productivity is an ex ante measure. Inspired by Feenstra, Li, and Yu (2014), we construct an ex ante productivity measure (*TFP*2), which differs from the standard ex post productivity measure (*TFP*1) but is closer to the framework of Melitz (2003). We hence modify and tailor the standard Olley and Pakes's (1996) TFP to construct the ex ante *TFP*2. The detailed discussion and method to construct this measure will be included in the Appendix. Finally, from the first-step probit estimates (4), we obtain the estimation results for the type-2 Tobit selection model. Thus, after controlling for the endogenous selection of firm's expenses of worker training, we obtain the fitted value of the expenses of worker training, which shall be used in the related estimates.

IV. ESTIMATION RESULTS

A. *Baseline Results*

We start off the estimations in Table 3 by using a firm's training dummy. The positive coefficient of training dummy in column (1) is as expected: training firms are more productive. Similarly, the coefficient of the industry output tariffs also has an anticipated negative sign. However, two such variables are insignificant statistically. We suspect this is due the coarse measure of firm training variable as it cannot measure the extent of firm's training expenses.

To overcome such a pitfall, from now on we use firm's log training to capture a firm's training activity. The two-way fixed-effects estimates in column (2) abstract away the role of firm's training expenses and still find that industry output tariffs have significant negative impact on firm productivity, indicating that firms overall are more productive when they face tougher import competition due to output tariff reductions. Such findings are consistent with previous findings (Amiti and Konings 2007). We then include log firm training in estimates of column (3). The coefficient of firm training is positive and significant, suggesting that the more the firm invests in worker training, the more productive the firm. In addition, exporters are more productive.

However, in reality, trade liberalization usually happens bilaterally. When China reduces its import tariffs, its trading partners are also likely to reduce their tariffs due to the WTO commitment. We hence include a simple un-weighted industry external tariff in column (4). The negative but insignificant coefficient of external tariffs suggests that the lower foreign trade barrier is helpful to boost firm productivity.

It is interesting to ask whether output trade liberalization boosts firm productivity through the channel of firm training. To check this out, we also include an interaction term between output tariffs and firm training in column (4). The coefficient of such a variable has an anticipated negative sign, although it is insignificant. We suspect this is possibly due to the lack of considering firm size since usually larger firms have more training expenses.

To accurately capture the impact of firm training on firm productivity, it is important to take firm's size into account. We hence replace total log training with log per capita training as an additional regressor in column (5). However, the measure of the log per capita training has a potential drawback. For example, firms' per capita training expenses are still increasing when firms fire workers but remain at the same level of total training expenses. To avoid this possible pitfall, we thus also include number of employees (in log) as another control variable in column (5). The coefficient of firm's log per capita training is still positive and significant, confirming that the higher the firm's training expenses, the higher the firm's TFP. Equally importantly, the negative and significant sign of the

TABLE 3
Benchmark Estimates of Worker Training

Regressand: *Firm TFP*	(1)	(2)	(3)	(4)	(5)	(6)
Firm training dummy	0.002					
	(1.01)					
Log *firm training*			0.001**	0.001		
			(2.24)	(1.50)		
Log *firm training per capita*					0.004***	0.003**
					(4.08)	(1.99)
Industry output tariffs	−0.001	−0.002***	−0.001	−0.000	0.001	0.006*
	(−0.66)	(−4.67)	(−0.65)	(−0.24)	(0.14)	(1.80)
Industry output tariffs × log *firm training*				−0.000	−0.000***	−0.000
				(−0.87)	(−3.04)	(−1.28)
Export indicator	0.015***	0.015***	0.015***	0.016***	0.016***	0.011***
	(5.86)	(6.93)	(5.84)	(6.31)	(6.31)	(2.52)
Foreign indicator	0.008	0.007	0.008	0.009	0.009	0.003
	(0.85)	(1.15)	(0.84)	(0.98)	(0.97)	(0.28)
State-owned enterprises indicator	0.020**	−0.009	0.020*	0.022**	0.022**	0.013
	(1.97)	(−1.62)	(1.96)	(2.15)	(2.17)	(0.90)
Log *firm size*				−0.023***	−0.022***	−0.032***
				(−12.27)	(−11.55)	(−10.82)
Industry external tariffs				−0.000	−0.000	0.001***
				(−1.29)	(−1.27)	(3.11)
Log *R&D expenses*						0.002***
						(3.14)
Firm-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	226,513	335,681	226,513	226,513	226,513	147,548
R^2	0.01	0.01	0.01	0.01	0.01	0.01

Note: Robust *t*-values clustered at two-digit Chinese industry level are in parentheses. Regressions in columns (1)–(4) use log firm's total training expenses as a proxy of firm training whereas those in columns (5)–(6) uses log firm's per capita training expenses as a proxy of firm training.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

interaction term between output tariffs and firm training suggests that the effect of trade liberalization on firm productivity is more pronounced for firms with more training investment.

Finally, Figure 1 also suggests that firm training and firm innovation are two possible substitutable channels to boost firm productivity. Therefore, it is important to see whether worker training still plays an important role once firm innovation is controlled in our regression (see column (6) of Table 3). After controlling for firm's R&D expenses, a widely accepted measure of firm innovation, we see that more productive firms have higher per capita training expenses, which is consistent with our previous findings.[10] Since the R&D data are only available in two years in our sample (i.e., 2005 and 2006), we thus drop the variable of R&D in our later regressions to avoid missing too many observations.

B. *Self-Selection of Training*

Table 3 uses firm's per capita training expenses and total training expense to measure training activity, and shows that training firms are highly productive. However, less productive firms may reduce their workerforce more than highly productive firms in response to tougher import competition. Thus, our estimation results may be contaminated by using per capita training expenses as a key measure. To avoid this possible concern, we use total training expense to measure the extent of firm training.

Regardless, a firm's total training variable is endogenous as the less productive firms may self-select to provide worker training. To control for this, we introduce a bivariate sample selection model, or equivalently, a type-2 Tobit model (Cameron and Trivedi 2005). As introduced above, the model includes two steps. The first step is to estimate a training participation equation—equation (3), and the second step is a training extent function—equation (4), which model a firm's training expenses as a linear function of other variables conditional on firm's participation on worker training.

Table 4 reports our type-2 Tobit estimation results. We first include one-period lag of log TFP in the first-step regression to see whether low-productive firms self-select to provide worker training. To be consistent with the theoretical presumption that firm productivity is exogenous, we therefore distinguish the difference between ex ante measured TFP and standard ex post measured TFP. The ex ante measured TFP, *TFP*2, has identical mean but different variance from the standard TFP as introduced above and reported in Appendix Table 1.

As reported in the first-stage estimations, low productive firms are more likely to engage in training behavior. The negative and significant coefficient of output trade liberalization seems striking at first glance. However, such a finding is reasonable. The tougher import competition caused by output trade liberalization results in lower firm profitability, which in turn means less investment in firm training. Meanwhile, exporters and SOEs are more likely to invest in firm training. Similarly, large firms are more likely to engage in worker

[10] However, the variable of industry external tariffs has a striking positive coefficient. We suspect this is due to the endogenous nexus among foreign market access, firm innovation, and firm productivity, as discussed in Lileeva and Trefler (2010) and Trefler and Yu (2017).

TABLE 4

The Heckman Two-Step Estimates of Bivariate Selection Model

	Heckman Two-Step Estimates			
	First Step Training Indicator		Second Step Log Training Expenses	
One-period lag of log *TFP2* ($TFP2^{OP}_{ijt}$)	−0.549***	(−25.69)	−2.157***	(−18.57)
One-period lag of *industry output tariffs*	0.016***	(3.27)	0.056***	(2.96)
One-period lag of *export indicator*	0.110***	(15.92)	0.388***	(12.50)
One-period lag of *state-owned enterprises indicator*	0.236***	(13.74)	1.283***	(18.97)
One-period lag of *foreign ownership indicator*	−0.193***	(−25.05)	−0.754***	(−17.49)
One-period lag of log *firm size*	0.203***	(68.49)	1.028***	(29.55)
One-period lag of *firm tenure*	−0.012***	(−11.05)	−0.045***	(−10.45)
Inverse mills ratio			−0.991***	(−4.12)
Year-specific fixed effects	Yes		Yes	
Three-digit industry-specific fixed effects	Yes		Yes	
Observations	228,288		228,288	

Note: Robust t-values corrected for clustering at the two-digit industry level are in parentheses. The sample selection model is presented in equations (participation) (3) in the text. The regressand in the first step is firms training dummy (training indicator) whereas that in the second step is firms log training expenses. The augmented Olley–Pakes TFP2 is adopted as a measure of firm productivity. Firm tenure is used as an exclusion variable that appeared in the first step but not in the second step. The three-digit Chinese industry-specific fixed effects and year-specific fixed effects are also included in the estimations.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

training. By contrast, foreign firms are found to be less likely to invest in training. A possible reason is that multinational firms are more likely to maintain their training investment in their foreign headquarters and less likely to have much training expenses in foreign affiliates. Finally, older firms are found to have less training expenses.

Once the inverse mills ratio obtained in the first-step probit estimates with three-digit industry-level fixed effects are calculated, we are ready to estimate the second step of the bivariate selection model by including the inverse Mills ratio as an additional regressor. All the coefficients have identical signs as their counterparts in the first stage and highly significant at the conventional statistical level.

C. *Different Measures of TFP*

To further check whether our main findings are sensitive to the measure of firm TFP and the empirical specifications, columns (1) and (2) of Table 5 use Levinsohn and Petrin's (2003) TFP as the regressand and while columns (3) and

TABLE 5

Further Estimates using Different Total Factor Productivity (TFP) Measures

Regressand: *Firm TFP*	TFP (Levinsohn–Petrin)		TFP (Olley–Pakes, Value-Added)	
	(1)	(2)	(3)	(4)
Log *firm fitted training*	0.028***	0.028***	0.013***	0.015***
	(7.00)	(6.85)	(3.11)	(3.46)
Industry output tariffs	−0.002	−0.001	−0.001	−0.001
	(−0.57)	(−0.52)	(−0.19)	(−0.25)
Export indicator	0.083***	0.086***	0.050***	0.052***
	(8.02)	(8.23)	(4.49)	(4.64)
Foreign indicator	0.040	0.049	−0.011	−0.005
	(1.29)	(1.55)	(−0.33)	(−0.13)
State-owned enterprises indicator	−0.069***	−0.069***	−0.098***	−0.097***
	(−2.72)	(−2.70)	(−3.44)	(−3.41)
Industry external tariffs	0.000	0.000	0.002***	0.002***
	(0.09)	(0.14)	(3.35)	(3.23)
Pure exporters dropped	No	Yes	No	Yes
Firm-specific fixed effects	Yes	Yes	Yes	Yes
Year-specific fixed effects	Yes	Yes	Yes	Yes
Observations	126,757	125,614	151,063	148,894
R^2	0.05	0.05	0.09	0.09

Note: *t*-values are in parentheses. All regressions include firm-level fixed effects and year fixed effects. Pure exporters are dropped in columns (2) and (4).
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

(4) use the value-added TFP. After controlling for a firm's self-selection of training and both firm-specific fixed effects and year-specific fixed effects, estimates in column (1) ascertain that the effect of training on firm productivity is positive and significant. Exporters are found to be more productive and SOEs are found to be less productive.

Previous works have recognized that processing firms are less productive (Dai, Maitra, and Yu 2016) since processing firms are usually pure exporters that sell all their products abroad. To make sure that our results are not driven by processing firms, we drop all pure exporters in column (2), and still find all similar results as in column (1).

Thus far, our measured productivity is gross function TFP. It is interesting to see whether our results are robust when measured by value-added TFP. Estimates in the last two columns of Table 5 thus pick up this task by using the value-added Olley–Pakes TFP. Precisely, the value-added TFP is measured by using value added as the output of the production function and estimating the output elasticity with respect to capital and labor, respectively. Estimates in column (3) include pure exporters whereas those in column (4) drop pure exporters from the sample. It turns out that the results are insensitive to the adoption of using value-added TFP as the regressand.

D. *Further Robustness Checks*

It is widely recognized that today China has engaged to a great extent in the global supply chain. In previous estimates we abstract away firm's input tariffs from the regressions because imported intermediate inputs for processing trade may be already free of duty (Yu 2015). Still, non-processing firms bear some amount of input tariffs. One solution is to adopt the firm-level input tariffs as constructed in Yu (2015). However, such an approach is at the expense of losing a large number of observations since the construction of firm-specific input tariffs requires merging of the dataset for firm-level production data (which is used to estimate TFP) and production-level trade dataset (which is used to calculate firm-specific input tariffs). As input tariff reduction is not the key variable in the present paper, we hence abstract it away and allow it to be captured in the error term.[11]

Instead, we consider another interesting case. A firm's imported intermediate goods are not necessarily used as intermediate inputs; it is possible for firms to import capital goods that could in turn boost firm productivity from channels other than firm training. To rule out this case, we drop industries which include mostly intermediate inputs. According to the description of the Broad Economic Classification (BEC) and China's industrial classification, industries like machinery (code 36 and 37) belong to capital goods. We hence drop these two industries in column (1) of Table 6. It turns out that higher firm training still leads to higher firm productivity. Column (2) drops pure exporters and yields similar results. Thus, our finding remains robust even when capital goods are dropped.

Our last exercise is to drop industries that are exposed to various non-tariff barriers, such as import quota, as our main objective is to check whether trade liberalization boosts firm productivity through the channel of firm training. Since exports of textile and garments are restricted by the Multi-Fiber Agreement, which was in place for the decade from 1994 to 2004 (Khandelwal, Schott, and Wei 2013), we hence drop textile and garment from the estimations in columns (3) with the Olley–Pakes TFP as the regressand and (4) with the Levinsohn–Petrin TFP as the regressand. Once again, both estimates suggest that output trade liberalization boosts firm productivity. More importantly, output trade liberalization affects a firm's probability of investing in worker training, which in turn boosts firm productivity.

[11] See details of China's input tariff reduction in Liu and Qiu (2016), which investigates the innovation activities of Chinese firms.

TABLE 6

Further Robust Estimates

Regressand: *Firm TFP*	Specifications			
	No Capital Goods		No Quota Imposed	
	TFP^{OP} (1)	TFP^{OP} (2)	TFP^{OP} (3)	TFP^{LP} (4)
Log *firm fitted training*	0.007***	0.007***	0.007***	0.018***
	(5.41)	(5.28)	(5.77)	(4.37)
Industry output tariffs	−0.008***	−0.008***	−0.007***	−0.012***
	(−8.63)	(−8.75)	(−5.30)	(−2.84)
Export indicator	0.008**	0.008**	0.010***	0.065***
	(2.27)	(2.36)	(2.99)	(6.07)
Foreign indicator	0.000	0.002	0.008	0.054*
	(0.03)	(0.24)	(0.74)	(1.65)
State-owned enterprises indicator	−0.001	−0.001	−0.002	−0.068***
	(−0.11)	(−0.09)	(−0.24)	(−2.58)
Log *firm size*	−0.027***	−0.027***	−0.025***	0.204***
	(−10.91)	(−10.97)	(−10.30)	(26.67)
Industry external tariffs	−0.001***	−0.001***	−0.001***	−0.000
	(−3.72)	(−4.01)	(−4.49)	(−0.15)
Pure exporters dropped	No	Yes	Yes	Yes
Firm-specific fixed Effects	Yes	Yes	Yes	Yes
Year-specific fixed Effects	Yes	Yes	Yes	Yes
Observations	135,377	133,324	135,596	113,132
R^2	0.02	0.02	0.01	0.07

Note: *t*-values are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

V. CONCLUDING REMARKS

In this paper we find that trade liberalization increases firms' training investment, which in turn boosts firm productivity and increases firm exports. We are thus able to identify a new mechanism through which trade liberalization affects firm productivity. Our paper has strong policy implications as well as academic contributions. The competitiveness of Chinese firms is shrinking due in large part to increasing labor costs in recent years. To overcome such a challenge, the Chinese Government is working hard to facilitate the macro-environment for firm R&D. Meanwhile, the Government helps firms in labor-intensive industries to invest in other lower labor-cost African countries (see Tian and Yu 2014 for detailed discussions). Our empirical findings in this paper suggest that, in addition to on-the-job training provided by firms themselves, China's Government may provide more training by having more technical schools and initiating more training programs to increase worker productivity and hence boost firm productivity.

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APPENDIX

MEASURING EX ANTE TFP (*TFP*2)

This section draws heavily from Qiu and Yu (2014) to discuss how we construct and measure TFP using two different approaches: ex post TFP (*TFP*1) and ex ante TFP (*TFP*2) inspired by Feenstra, Li, and Yu (2014).

We extend the approach by Olley and Pakes (1996) to fit with China's reality in the following ways. First, given that the measure of TFP requires real terms of firm's inputs (labor and capital) and output, we adopt different price deflators for inputs and outputs from Brandt, Van Biesebroeck, and Zhang (2012) in which the output deflators are constructed using "reference price" information from China Statistical Yearbooks, whereas input deflators are constructed based on output deflators and Input–Output Tables of China (2002).

Second, we take China's WTO accession in 2001 into account since such a positive demand shock would push Chinese firms to expand their economic scales, which in turn can exaggerate the simultaneous bias of their measured TFP. Third, it is essential to construct the real investment variable when using the Olley–Pakes approach. As usual, we adopt the perpetual inventory method to investigate the law of motion for real capital and real investment. Rather than assigning an arbitrary number for the depreciation ratio, we use the exact firm's real depreciation provided by the Chinese firm-level dataset.

Finally, we also consider firm's processing behavior in the TFP realization by constructing a processing export indicator (one denotes processing export and zero otherwise). The idea is that processing firms may use different technology from non-processing firms (Feenstra and Hanson 2005).

Thus, a firm's investment function is $V_{it} = g_1(x_{it}, \ln K_{it}, EX_{it}, PE_{it}, WTO_t)$ where EX_{it} (PE_{it}) is the export (processing export) indicator to measure whether firm i exports (engages in processing exports) in year t, and WTO_t is an indicator that equals one if the WTO agreement has occurred after 2001 and zero before that. Therefore, inverting the investment function with respect to its first argument we obtain:[12] $x_{it} = g_1^{-1}(V_{it}, \ln K_{it}, EX_{it}, PE_{it}, WTO_t)$.

Given the gross production function $\ln Y_{it} = \alpha_k \ln K_{it} + \alpha_l \ln L_{it} + \alpha_m \ln M_{it} + x_{it} + \varepsilon_{it}$, and defining the function $g_2(\cdot)$ as $\alpha_k \ln K_{jt} + g_1^{-1}(V_{it}, \ln K_{it}, EX_{it}, PE_{it}, WTO_t)$, the estimation of the labor (materials) coefficients $\alpha_l(\alpha_m)$ are obtained as: $\ln Y_{it} = \alpha_l \ln L_{it} + \alpha_m \ln M_{it} + g_2(V_{it}, \ln K_{it}, EX_{it}, PE_{it}, WTO_t) + \varepsilon_{it}$.

The next step is to obtain an unbiased estimated coefficient of α_k. Olley and Pakes (1996) use the following specification:

$$\ln Y_{it} - \hat{\alpha}_l \ln L_{it} - \hat{\alpha}_m \ln M_{it} = \alpha_k \ln K_{it} + E(x_{it} | x_{it-1}, pr_{it}) + [x_{it} - E(x_{it} | x_{it-1}, pr_{it})] + \varepsilon_{it},$$

where the estimated values of the labor coefficient and materials coefficient are used on the left. The expectation of productivity appearing (in two-step) is modeled as a fourth-order polynomial function of lagged productivity, which can be obtained as $(g_{2i,t-1} - \alpha_k \ln K_{i,t-1})$, and also the predicted probability of the firm's survival into the year t, pr_{it}, based on year $t-1$ information. The predicted probability is obtained from probit estimation.[13] The term $[x_{it} - E(x_{it}| x_{it-1}, pr_{it})]$ is the productivity shock for surviving firms, but does not affect the investment or exit choice so it is treated as an error.

Once the coefficient of capital $\hat{\alpha}_k$ is estimated in equation (two-step), it is ready to obtain the standard ex post TFP:

$$TFP1_{it} \equiv x_{it} = \ln Y_{it} - \hat{\alpha}_k \ln K_{it} - \hat{\alpha}_l \ln L_{it} - \hat{\alpha}_m \ln M_{it}.$$

In this way, *TFP*1 includes both true productivity and managerial efficiency. By contrast, the ex ante productivity (*TFP*2), which only capture true productivity, is given by:

$$TFP2_{it} = g_1^{-1}(V_{it}, \ln K_{it}, EX_{it}, PE_{it}, WTO_t).$$

Appendix Table 1 reports the estimated coefficients of labor, capital, materials, *TFP*1, and *TFP*2.

[12] Olley and Pakes (1996) show that the investment demand function is monotonically increasing in the productivity shockx_{it}, by making some mild assumptions about the firm's production technology.

[13] Note that here the nonlinear least squares approach is adopted to estimate (two-step) since it requires the estimated coefficients of the log-capital in the first and second term to be identical (Pavcnik 2002).

APPENDIX TABLE 1

Total Factor Productivity (TFP) of Chinese Firms (2000–2006)

Census Industrial Classification	Labor	Capital	Materials	Variance in	
				*TFP*1	*TFP*2
13	0.077	0.060	0.814	0.322	0.148
14	0.055	0.071	0.857	0.300	0.172
15	0.094	0.113	0.799	0.381	0.235
16	0.020	0.270	0.783	0.631	0.479
17	0.066	0.044	0.868	0.218	0.103
18	0.110	0.039	0.798	0.310	0.093
19	0.084	0.041	0.857	0.276	0.098
20	0.099	0.071	0.841	0.300	0.167
21	0.103	0.055	0.814	0.218	0.119
22	0.063	0.053	0.867	0.234	0.127
23	0.065	0.068	0.815	0.215	0.210
24	0.091	0.039	0.823	0.223	0.113
25	0.014	0.069	0.865	0.324	0.327
26	0.063	0.058	0.820	0.318	0.175
27	0.062	0.064	0.790	0.360	0.219
28	0.040	0.060	0.889	0.313	0.169
29	0.087	0.081	0.769	0.333	0.186
30	0.069	0.046	0.836	0.288	0.180
31	0.046	0.059	0.844	0.287	0.145
32	0.061	0.029	0.891	0.249	0.116
33	0.080	0.079	0.850	0.278	0.322
34	0.062	0.037	0.841	0.311	0.093
35	0.061	0.055	0.837	0.247	0.188
36	0.053	0.049	0.841	0.326	0.123
37	0.063	0.045	0.835	0.283	0.160
39	0.077	0.066	0.836	0.303	0.135
40	0.109	0.075	0.806	0.358	0.194
41	0.049	0.054	0.806	0.386	0.208
42	0.091	0.039	0.857	0.271	0.092

Note: We do not report standard errors for each coefficient to save space though available upon request. The logarithm of firm productivity for Chinese firms (*TFP*1 and *TFP*2) is estimated by industry by the augmented Olley–Pakes approach introduced in the text. Coefficients of labor, capital, and materials are calculated at the sectorial average whereas *TFP*1 and *TFP*2 are measured at firm level using firm-level sales, capital, materials, and labor, respectively.