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Abstract

This paper investigates the relationship between the foreign technical measures and the input of firm’s R&D investment and firm’s technical progress with the Chinese Manufacturing Firm Survey database and the official annual survey of the Chinese export technical measures. To tackle the problem of selection bias, we employed the PSM-DID method controlling for observed heterogeneity. Our result suggests that both the standard DID method and the PSM-DID method show that the coefficient of technical effect is significantly positive for R&D investment. It reviews that technical measures induced firms to increase their R&D investment. However, the threshold regression model shows that the technical measures that induce the firms to increase its R&D investment only be established under low loss ratio which is 31.864%. By using the TFP as a proxy variable for technical progress, it shows that the effect of technical measures on firm’s technical progress is not significant.

Key words: Technical Measures, R&D Investment, Technical Progress
1. Introduction

Free trade gives global citizens the economic freedom to maximize their economic interests as consumers, distributors and producers without government intervention. Hence, the globalization of commerce creates entrepreneurship, economic growth, and innovation within a global society.

In the early 1990s, as the historic Uruguay Round struggled toward a successful conclusion, a panel established under the General Agreement on Tariffs and Trade (GATT), which had governed international trade for the previous half century. After the GATT, the traditional forms of trade restrictions like tariff, licensing and trade quotas had been diminished, but trade protectionism has not stopped. It just changed to other forms like technical standards, technical laws, and qualified evaluation procedure.

In recent years, nontariff barriers have increased as tariffs have fallen worldwide (Beghin, 2008). According to the WTO annual report, the number of sanitary and phytosanitary (SPS) notifications increased from 855 in 2005 to 1681 in 2015 (see Figure 1) and the number of technical barriers to trade (TBT) notifications increased from 894 in 2005 to 1989 in 2015 (see Figure 2). In total, the number of TBT/SPS notification increased from 1749 to 3670 during this decade. Additionally, the increasing technical barriers have caused increasing lost for the exporting countries. Take China for example, according to the Chinese TBT/SPS annual report, in 2006, about 30% Chinese exporters were affected by the foreign TBT/SPS with a total loss 28.8 billion dollars, while in 2015, more than 40% of the Chinese exporters were affected by the foreign TBT/SPS with a total lost 93.4 billion dollars.

[Insert Figure 1-2 here]

The research on technical measures is mainly focused on the macroeconomic level,
which examines the impact of technical measures on the international trade volume. Most of the research suggested that technical measures had a negative impact on the trade volume. However, the truth is that exporters suffered the greatest from these technical measures, and that is why we should put more attention to the effect of technical measures on the microeconomic level. Even though most research suggest that technical barriers had a negative impact on the total trade volume, it reviews different impact to exporters. Some exporter may decrease their export after they have encountered the technical measures, but some may not. We can see that some exporters could still increase their export market share even though they had encountered the foreign technical measures. One reason to explain this situation is that those exporters were able to overcome the technical measures imposed on them by improving their technical input. It shows that the foreign technical measures would force exporters to improve their technical level to some extent. Our question is whether the foreign technical measures would increase exporters’ R&D investment which would make the technical progress.

Therefore, this paper examines the impact of foreign technical measures on Chinese exporters’ R&D investment and technical progress. The paper is organized as follows. Section 2 presents a literature review. Section 3 presents the effect of foreign technical measures on Chinese exporters. Section 4 describes the conceptual model. Section 5 explains the method and introduces the model and variables. Section 6 discusses the empirical results with interpretations. Section 7 presents the conclusion.

2. Literature review

2.1 The measurements of technical measures

Unlike tariff, anti-dumping, and anti-subsidy, technical measures have different kinds, like technical standards, technical regulations, and standard procedures. Therefore, before analysing the technical measures, we have to know how to quantify them. It is
common to use the proxy variable to quantify technical measures, like the number of technical standards, TBT/SPS notifications, maximum residue limits (MRLs) and the method of dummy variables.

The number of technical standards is one of the most widely used measurements for TBT/SPS (Swann et al. 1996, Moenius 2004, 2006, Czubala 2007, Schlueter et al. 2009, Jayasinghe et al 2009, Bao 2011, Yang 2013). Swann et al. (1996) combined data on British and German standards with the British trade performance in 3-digi sectors to explore the effects of standards on trade performance. The result revealed that higher standards would improve the UK trade balance. Czubala (2009) constructed the database of European Union (EU) product standards to examine the impact of EU standards on African textiles and clothing exports. Bao(2011) used the number of technical standards as a proxy variable of TBT to examine the impact of international food safety standard on China’s grain export.

Some would like to use the TBT/SPS notification from WTO as the proxy variable of TBT. Bao(2005) used the total and classified TBT/SPS notification to differentiate the technical measures between developed countries and developing countries. Qin, Ni (2013) used the TBT notification as the proxy variable of technical measures to examine the impact of TBT on international trade.

Some would like to use the MRL as the proxy variable of TBT (Otsuke et al., 2001; Wilson & Otsuki, 2001; Chen, Yang and Findlay, 2006; Bao, 2011). MRL refers to maximum residue limit which is the maximum amount of pesticide residue that is expected to remain on food products. More and more countries are now strictly controlling the MRL of import food products. To some extent, the MRL can represent the technical measures for the country. Chen (2006) used a gravity model of agricultural product trade to test the effect of the residue standards on China’s export of vegetables (Chlorpyrifos MRL) and aquatic products (Oxytetracycline MRL).
Some would like to use the method of dummy variable to be the proxy variable of technical measures (Leamer, 1990; Harrigan, 1993; Disdier et al., 2008, Karov et al., 2009; Jiang, 2012). Cao & Johnson (2006) used the dummy variable to analyse the effect of the New Zealand regulation system, which 0 means the time before the implementation of the new regulation system and 1 means the time after the implementation of the new regulation system. Diasdier et al. (2008) and Karov et al. (2009) used the dummy variable to present whether one product was affected by the SPS. Jiang (2012) used the dummy variable as the proxy variable of technical regulations to analyse the technical regulation effect on the Sino-Japan trade.

2.2 The technical effect of technical measures

The technical effect of technical measures means the effect of technical measures on exporters’ technical input and technical progress. Flam and Helpman (1987) studied the theoretical impact of product quality on international trade. They developed a model to incorporate differentiation in product quality. Their model predicted a pattern of trade dynamics, i.e., the appearance of new and high-quality products, and the disappearance of old and low-quality products. Based on their model, they predicted that richer countries export higher quality goods. Frederick and Ganeshan (2004) presented a case study of the effects of technical measures on Indian pharmaceutical exports. The study highlighted differing perceptions as to the significance of technical measures, the importance of firm-level research, lessons for other low-income economies and the need for enterprises to adopt offensive technological strategies. It showed that 70% Indian pharmaceutical exporters would try to promote their technology level after encountering the foreign technical measures. Based on Melitz (2003) new-new trade theory, Felbermayr & Jung (2008) analyzed the relationship between TBT and industry productivity. They realized that with lower TBT technology requirement, there would be more small scale and low technological level exporters in the market, therefore, it
would lower the industry productivity. Li and Liu (2006) realized that under the constrain of foreign TBT, exporters which try to improve their technical level may overcome the foreign TBT and had more export. Crowley(2006) explored how the country-breadth of tariff protection affected technology adoption decision of both domestic import-competing and foreign exporting firms. It showed that a country-specific tariff like an antidumping duty induces both domestic import-competing firms and foreign exporting firms to adopt a new technology earlier than they would under free trade. In contrast, a broadly-applied tariff, like a safeguard can accelerate technology adoption by a domestic import-competing firm, but will slow-down technology adoption by foreign exporting firms. Du, Cai and Zhou (2009) find that Chinese domestic enterprises manifested prominent innovation intention when facing trade barriers, and they were prominent foreign demand oriented. Market share affected innovation intensity of domestic enterprises, and the industry structure among bilateral countries would engender different promoting degree. Furthermore they found that monopolization and control of technology would restrain domestic innovation intention.

3. The effect of foreign technical measures on Chinese exporters

China’s export has exploded since joining the WTO. According to the WTO database, Chinese exports was 266.1 billion dollars in 2001 before joining the WTO, and it increased to 2.1 trillion dollars in 2016 which it had increased almost 10 times in 15 years.

[Insert Figure 3 here]

Meanwhile, more and more Chinese exporters suffered from foreign technical measures during this time. According to the Chinese technical measures annual survey conducted by the General Administration of Quality Supervision, Inspection and Quarantine of the People’s Republic of China (AQSIQ), more than 30% of those surveyed exporters encountered foreign technical measures in the past decade with the
total loss of 59.4 billion dollars in 2016. Technical measures are now second only to currency issues in exporters’ evaluation of obstacles to their industry. The situation can be seen in Figure-4.

[Insert Figure 4 here]

The top 5 industries affected by foreign technical measures in 2016 were:
1. Mechanical & Electrical Industry; 2. Mining & Metals Industry; 3. Textile & Garment Industry; 4. Toy & Furniture Industry; 5. Food & Agricultural Products Industry. More than 34% of the affected-exporters were from the Mechanical & Electrical Industry; 18% of them were from Mining & Metals Industry; 10% of them were from Textile & Garment Industry; 7% of them were from the Toy & Furniture Industry; 4% of them were from Food & Agricultural Products Industry.

[Insert Figure 5 here]

More specifically, the technical measures that affect industrial goods the most were: Certification Requirement, Technical Requirement, Labeling and Documentation, Packaging Material Requirement, and Restriction of Hazardous Substance. Also, for the food and agricultural products, the technical measures that most affect them were: Maximum Resident Limits, Microbiological Indicators, Standard of the Permissible Limits of Toxic Heavy Metals, Food Labeling Requirement and Food Processing Plant Requirement.

The top 5 export markets with the strictest technical measures that impact Chinese exporters the most were: 1. The European Union; 2. The United States of America; 3. Japan; 4. The Association of Southeast Asian Nations; 5. Korea. 34% of the affected-exporters reported that they have encounter the EU technical measures, 31% of the affected-exporters suffered from the USA technical measure, and 5% of them suffered from Canada, Africa and ASEAN seperately.
4. Conceptual Model

Suppose there are two countries, country E and country F.

Country E is a large open economy with perfectly competitive market and its domestic producers always sell at home. The price of good Z in country E is $P_z$.

In country F, the production function of good Z is:

\[ y_z = Af(L) \]

While $A$ represents the technology; $L$ represents the labor input.

Suppose $q$ is the most important factor of $A$, and $q$ represents the R&D investment which $A = A(q), A'(q) > 0, A''(q) < 0, A(0) = k > 0$.

Each firm has the same function of $A(q)$, which means with the same input of $q$, they can have the same $A$.

However, different firms have the different cost function of $q$, which means when $i \neq j, c_i(q) \neq c_j(q)$, and $c'_i(q) > 0, c''_i(q) > 0, c_i(0) = 0$ for each firm.

There is a $q_i^*$ which $A(q_i^*) = c_i(q_i^*)$, and

\[ A(q) > c_i(q), 0 < q < q_i^* \]
\[ A(q) < c_i(q), q > q_i^* \]

The relationship between $A(q)$ and $c_i(q)$ can be seen in Figure 7.

And for labor input, we have $f'(L) > 0, f''(L) < 0$ and there is a $L^*$ which

\[ f'(L) = w \quad \text{and} \quad f'(L) > w, 0 < L < L^* \]
\[ f'(L) \leq w, L \geq L^* \]

The relationship between $f(L)$ and $wL$ can be seen in Figure 8.
To sum up, the production function of good Z for firms in country F is
\[ y_z = A(q) f(L), \] while the total cost function of good Z is \[ C_i(z) = wL + c_i(q). \]

If country F’s firms want to sell good Z to country E, there will be two additional costs they have to bear: a fixed entry cost \( W \) and a tariff cost \( t \). To enter country E, firms from country F must first make an initial investment, modeled as a fixed entry cost \( W \), which is thereafter sunk.

Since the tariff and the fixed entry cost are so high that the imports from country F to country E would not be unlimited. Meanwhile, the country E’s market is so large that the imports would not affect the market price.

Firms from country F can set their own price when selling the good Z to country E. Since all good Z are same to customers, if they set the price higher than \( P_z \), customers in country E would not buy their products. There is no need to set the price less than \( P_z \) as the market in country E is so large that they can sell as many as they can at the price of \( P \). So each firm would set the price as \( P_z \).

Profit for any firms in country F which export to country E is:
\[ \pi_i = (P_z - t) A(q) f(L) - wL - c_i(q) \]

And we have \[ \pi_i'(L) = (P_z - t) A(q) f'(L) - w = 0 \]
\[ \pi_i'(q) = (P_z - t) A'(q) f(k, l) - c_i'(q) = 0 \]

The relationship between \( \pi_i \) and \( q \), we have:
\[ \pi_i'(q) = (P_z - t) A'(q) f(k, l) - c_i'(q) \]
\[ q = 0, \pi_i'(q) = k(P_z - t) f(L) > 0 \]
\[ q \to +\infty, A'(q) \ll c_i'(q), \pi_i'(q) = (P_z - t) A'(q) f(L) - c_i(q) < 0 \]

And \[ \pi_i''(q) = (P_z - t) A''(q) f(L) - c_i''(q) < 0 \]
So there is only $q_i^{**}$ for each firm $i$ that $\pi_i'(q_i^{**})=0$

Since $\pi_i''(q)<0$, $\pi_i(q_i^{**})$ would be Firm $i$’s maximum profit.

In order to export to country E, $\pi_i(q_i^{**}) \geq W$ so that it can cover the original fixed entry cost.

The relationship between $\pi_i$ and $q$ can be seen in figure 5.

[Insert Figure 9 here]

Suppose country E is setting a technical standard (TBT) for good Z, which can be seen as technical measures. In order to meet the standard TBT, each firm will need to at least input $\overline{q}$ to produce.

[Insert Figure 10 here]

As you can see in the figure 6, to Firm 3 and Firm 4, because their input of $q_i$ were $q_3^{**}$ and $q_4^{**}$, which were more than $\overline{q}$, that means the new standard would not affect their producing process. So for Firm 3 and Firm 4, they can easily overcome the new standard TBT.

To Firm 2, even though its input of $q_i$ was $q_2^{**}$ which was less than the minimal requirement $\overline{q}$, when it increases its input $q_i$ from $q_2^{**}$ to $\overline{q}$, its profit will be still larger than W. So Firm 2 would increase its input to $\overline{q}$ though its profit would decrease.

To Firm 1, its input of $q_i$ was $q_1^{**}$ which was less than the minimal requirement $\overline{q}$. When it increases its input $q_i$ from $q_1^{**}$ to $\overline{q}$, its profit will be lower than W. So it would just quit the country E.
To sum up, those company (like Firm 3 and Firm 4), which their maximum profit input of $q$ was more than minimal requirement $\bar{q}$, would keep on exporting to the country. They would not effected by the new standard.

Those firms (like Firm 2) which their maximum profit input of $q$ were less than the minimal requirement $\bar{q}$, but when they increase input to $\bar{q}$, their profit would be still more than W, then they would increase their input to $\bar{q}$. Since they have to input more $q$, and with the input of $q$ increase then the $A_i$ increase, they would improve their technical level.

[Insert Figure 11 here]

Those firms (like Firm 1), which their maximum profit input of $q$ were less than the minimal requirement $\bar{q}$, and when they increase the input to $\bar{q}$, their profit would be lower than W. They would be forced to quit the export market.

Since no one would decrease their $q$ input but those company, like Firm 2, would input more $q$, which it would improve their technical level. Therefore, it seems the new standard would increase the total technical level.

4 Methodology and Data

4.1 Technical measures and R&D input

Difference-in-difference (DID) methods for estimating the effect of policy interventions have become very popular in economics. These methods are used in problems with multiple subpopulations-some subject to a policy intervention or treatment and others not-and outcomes that are measured in each group before and after the policy intervention (although not necessarily for the same individuals). To account
for time trends unrelated to the intervention, the change experienced by the group subject to the intervention (referred to as the treatment group) is adjusted by the change experienced by the group not subject to treatment (the control group). DID evaluation of the effectiveness of policy uses the first difference to eliminate the fixed effect, and then uses the second difference to show the policy effect. This paper analyzes nonparametric identification, estimation, and inference for the average effect of the treatment for setting where repeated cross sections of individuals are observed in a treatment group and a control group, before and after the treatment.

The standard model for the DID design is as follows. Firm $i$ belongs to a group $TBT_i \in \{0,1\}$ (where group 1 is the treatment group which means those firms which had been affected by the foreign technical measures) and is observed in time period $T_i \in \{0,1\}$ (which $T_i = 0$ means time in 2009 and $T_i = 1$ means time in 2010). Firm $i$’s group identity and time period can be treated as random variables. Let $R&D_i$ denote the R&D investment for firm $i$, then in the standard DID model, the R&D investment for firm $i$ in the absence of the intervention satisfies

$$R&D_i = \beta_0 + \beta_1 T_i + \beta_2 TBT_i + \beta_3 TBT_i \cdot T_i + \epsilon_i$$

The second coefficient, $\beta_1$, represents the time effect. The third coefficient, $\beta_2$, represents the group effect. The third term, $\epsilon_i$, represents unobservable characteristics of the firm.

From the equation, we can have different formulas for different firms. For those firm who had not been affected by the foreign technical measures (also seen as control group), we have $TBT=0$, So we can have the equation like $Y_i = \beta_0 + \beta_1 T_i + \epsilon_i$, and in different years we have:

$$R&D_{control} = \beta_0, t = 0$$
$$R&D_{control} = \beta_0 + \beta_1, t = 1$$

The change to those exporters which had not affected by the TBT,

$$\text{diff}_{control} = (\beta_0 + \beta_1) - \beta_0 = \beta_1$$
To those firms which had affected by the foreign technical measures (also seen as treated group), we have TBT=1, so the equation can be simplified as 

\[ R & D_t = \beta_0 + \beta_1 t + \beta_2 + \beta_3 t + \epsilon_t, \]

and in different years we have:

\[
R & D_{t, 0} = \beta_0 + \beta_3, t = 0 \\
R & D_{t, 1} = \beta_0 + \beta_1 + \beta_2 + \beta_3, t = 1 
\]

The change to those firms which had affected by the foreign technical measures,

\[
diff_{t, treated} = (\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_2) = \beta_1 + \beta_3 
\]

So the technical measures net effect should be :

\[
diff_{t, treated} - diff_{t, control} = (\beta_1 + \beta_3) - \beta_1 = \beta_3 
\]

[Insert Table 1 here]

One problem with estimating the technical effect of the foreign technical measures is the possible endogeneity of firms being affected. It is not likely to be random which firms would encounter foreign technical measures and those affected firms might exhibit characteristics that systematically differ from non-affected firms. The selection of the control group can be subjective and arbitrary, and does not have a strong conviction. We do not have sufficient reasons to rule out the endogeneity of technical measures, so the direct use of DID to assess the results of technical measures can be biased.

To correct the selection bias, we follow the methodology used by Gorg and Strobl (2007) and Aerts and Schmidt (2008), and introduce the matching procedures and the difference-in-differences estimation, which is propensity score matching (PSM) combined with the more general difference-in-difference (DID) technique. The aim of the matching procedure is to find a group of non-affected firms by the foreign technical measures that display the same characteristics as the group of foreign technical measures affected firms. The propensity scores are calculated according to observed characteristics influencing the foreign technical measures operation, for the purpose of controlling selection bias (Rosenbaum and Rubin, 1983; Lechner, 2002).
The selection bias here refers to a situation that, due to inference from the observable characteristics of the exporters, the foreign technical measures implementation may be deemed non-random. That is to say, the input of technology may be attributed to not only the foreign technical measures but also other characteristics, such as firms’ production level and firm structure. Consequently, the PSM is employed to prevent such bias, by selecting non-affected exporters similar to those exporters, rather than the raw sample.

The matching procedure can be described as follows. Let $A \in \{T, C\}$ be a foreign technical measures affected indicator equal to T for firms being affected by foreign technical measures (the treatment group) and equal to C for firms that are not affected (the control group). $R & D_{k,t+s}^T$ denotes the R&D input at time $t+s$ for a firm that has been affected at time $t$, and $R & D_{k,t+s}^C$ is the R&D input that would have been observed if the firm had not been affected. Obviously, no firm can be observed in two different states at the same time, so either $R & D_{k,t+s}^T$ or $R & D_{k,t+s}^C$ is missing for each firm $k$. This fundamental problem of causal inference is sometimes described as the evaluation problem of missing data. However, under certain assumptions, the average treatment effect on the treated can be identified as:

$$E \{ R & D_{t+s}^T - R & D_{t+s}^C | A = T \} = E \{ R & D_{t+s}^T | A = T \} - E \{ R & D_{t+s}^C | A = T \}$$

Matching techniques can be used to construct a sample of non-affected twin firms to acquired firms and, thus, approximate the non-observed counterfactual event in the last term.

The underlying identifying assumption behind the matching is that treatment participation and treatment outcome is independent, conditional on a set of observable characteristics. This assumption is called conditional independence (CIA), also known as “selection on characteristics”. The CIA implies that treatment status is random conditional on a set of observed attributes X. In our notation, the CIA is given by
\((R & D^C, R & D^T) \perp A|X\). The plausibility of the non-testable CIA depends on the richness of the available data.

To identify the treatment effect, the so-called balancing property of the propensity score must also be fulfilled. This assumption is given by \(A|X \perp p(X)\), where \(p(X)\) is the propensity score. This means that observation with the same propensity score must have the same distribution of characteristics, independently of treatment status.

The matching procedure in this paper uses the algorithms as the Nearest-Neighbor without replacement method. In the first step, we calculate the probability of a firm affected by foreign technical measures, using a number of observable characteristics. Each affected firm will be matched by an “identical” but non-affected firm. Then the ATT for the R&D input variable before and after the effect can be formally specified as follows:

\[
ATT = [E(R & D_{treatment}\mid t = 1) - E(R & D_{treatment}\mid t = 0)] - [E(R & D_{control}\mid t = 1) - E(R & D_{control}\mid t = 0)]
\]

4.2 The Threshold Regression Model

Hansen (2000) set the form of “threshold regression model” as

\[
y_i = \alpha_1 x_i + e_i, q_i \leq \gamma
\]

\[
y_i = \alpha_2 x_i + e_i, q_i > \gamma
\]

Where \(y_i\) and \(q_i\) are real-valued and \(x_i\) is an m-vector. \(q_i\) is called the threshold variable, and is used to split the sample into two groups, which we may call “regimes”, depending on the context. It may be an element of \(x_i\), and is assumed to have a continuous distribution. The random variable \(e_i\) is a regression error.

To write the model in a single equation, define the dummy variable \(d_i(\gamma) = \{q_i \leq \gamma\}\)

where \(\{\cdot\}\) is the indicator function and set \(x_i(\gamma) = x_i d_i(\gamma)\), so that (1)-(2) equal
\[ y_i = \alpha'x_i + \delta'_n(x_i(\gamma)) + e_i \]

Where \( \theta = \theta_2 \). Equation (3) allows all of the regression parameters to switch between the regimes, but this is not essential to the analysis. The results generalize to the case where only a subset of parameters switch between regimes and to the case where some regressors only enter in one of the two regimes.

To express the model in matrix notation, define the \( n \times 1 \) vectors \( Y \) and \( e \) by stacking the variables \( y_i \) and \( e_i \), and the \( n \times m \) matrices \( X \) and \( X_{\gamma} \) by stacking the vectors \( x_i' \) and \( x_i(\gamma)' \). Then (3) can be written as:

\[ Y_i = X\alpha + X_{\gamma}\delta_n + e \]

The regression parameters are \( (\theta, \delta_n, \gamma) \), and the natural estimator is least squares (LS). Let \( S_n(\alpha, \delta, \gamma) = (Y - X\alpha - X_{\gamma}\delta)'(Y - X\alpha - X_{\gamma}\delta) \) be the sum of squared errors function. Then by definition the LS estimators \( \hat{\theta}, \hat{\delta}, \hat{\gamma} \) jointly minimize (5). For this minimization, \( \gamma \) is assumed to be restricted to a bounded set \( [\gamma, \bar{\gamma}] = \Gamma \). Note that the LS estimator is also the MLE when \( e_i \) is iid \( N(0, \sigma^2) \).

The computationally easiest method to obtain the LS estimates is through concentration. Conditional on \( \gamma \), (4) is linear in \( \theta \) and \( \delta_n \), yielding the conditional OLS estimators \( \hat{\theta}(\gamma) \) and \( \hat{\delta}(\gamma) \) by regression of \( Y \) on \( X_{\gamma}^* = [XX_{\gamma}] \). The concentrated sum of squared errors function is

\[ S_n(\gamma) = S_n(\hat{\alpha}(\gamma), \hat{\delta}(\gamma), \gamma) = YY - YY_{\gamma}^*(XX_{\gamma}^*{XX}_{\gamma}^*)^{-1}XX_{\gamma}^*Y \]

And \( \hat{\gamma} \) is the value that minimizes \( S_n(\gamma) \). Since \( S_n(\gamma) \) takes on less than \( n \) distinct values, \( \hat{\gamma} \) can be defined uniquely as

\[ \hat{\gamma} = \arg \min_{\gamma \in \Gamma_n} S_n(\gamma) \]

Where \( \Gamma_n = \Gamma \cap \{q_1, q_2, \ldots, q_n\} \), which requires less than \( n \) function evaluations. The slope estimates can be computed via \( \hat{\theta} = \hat{\theta}(\hat{\gamma}) \) and \( \hat{\delta} = \hat{\delta}(\hat{\gamma}) \).
We need to verify that there is indeed evidence for a threshold effect. We do so by employing the heteroskedasticity-consistent Lagrange multiplier (LM) test for a threshold of Hansen (1996). Since the threshold $\gamma$ is not identified under the null hypothesis of no threshold effect, the $p$-values are computed by a bootstrap analog, fixing the regressors from the right-hand side of (12) and generating the bootstrap dependent variable from the distribution $N(0, \hat{\sigma}^2)$, where $\hat{e}_i$ is the OLS residual from the estimated threshold model. Hansen (1996) show that this bootstrap analog produces asymptotically correct $p$-values.

To test the hypothesis $H_0 : \gamma = \gamma_0$, a standard approach is to use the likelihood ratio statistic under the auxiliary assumption that $e_i$ is iid $N(0, \sigma^2)$.

### 4.3 Technical Measures and Technical Progress

Since TFP is now often used as the proxy variable for technical progress, this paper will also use it as the proxy variable of technical progress to see whether technical measures would induce the firm’s technical progress.

As we know, there several ways to calculate the firm’s TFP including OLS, fix-effects, the Olley-Pakes investment proxy estimator and the Levinsohn-Petrin input proxy estimator. The OLS estimates of production functions would yield biased parameter estimates when there are potential correlation between input levels and the unobserved firm-specific productivity shocks in the estimation of production function parameters, and biased estimates of productivity. The fix-effects mainly focus on the difference between firms, not the differences from time to time. The Olley-Pakes investment proxy estimator needs positive investment, but there are some zero-investment or even
negative investment in our data which we need to drop a portion of data. The Levinsohn-Petrin input proxy estimator uses intermediate input proxies instead of investment to avoid such problem. Firms in our data always report positive use of intermediate, so we decide to use the Levinsohn-Petrin input proxy estimator to calculate firms’ TFP.

Levinsohn and Petrin (2003) add a second freely variable input, \( \iota \), which call the intermediate input. The log of output is a function of the log of inputs and the shocks:

\[
y_i = \beta_0 + \beta_{\iota} \cdot \iota_i + \beta_k \cdot k_i + \beta_i \cdot t_i + \omega_i + \varepsilon_i
\]

The intermediate input’s demand function is given as

\[
t_i = t_i(\omega_i,k_i)
\]

Assuming monotonicity holds one can invert the input demand function to obtain

\[
\omega_i = \omega_i(t_i,k_i).
\]

Thus, the intermediate input replaces investment, with \( \phi(.) \) now given as a function of the intermediate input and capital, or

\[
\phi(t_i,k_i) = \beta_0 + \beta_k \cdot k_i + \beta_t \cdot t_i + \omega_i(t_i,k_i)
\]

That we can have:

\[
y_i = \beta_{\iota} \cdot \iota_i + \phi(t_i,k_i) + \varepsilon_i
\]

\[
TFP_i = \ln y_i - \ln \hat{y}_i
\]

### 4.4 Data description

The empirical analysis combines two data sources from China’s National Bureau of Statistics (CNBS) and the general administration of quality supervision, inspection and quarantine of the people’s republic of China (AQSIQ). The first data set is the Chinese Manufacturing Firm Survey Database (CMFSD), which is compiled by China’s National Bureau of Statistics (CNBS) covering the period 2005-2011. CMFSD includes almost all of Chinese manufacturing firms of the SOEs and non-SOEs with annual sales no less than 5 million RMB (equivalent to about 700,000 dollar). CMFSD is a major firm-level data source for researchers and policy-makers to investigate various economic and social topics in current China (e.g. Brandt, Van
Biesebroeck, and Zhang 2014). The second data base is from the official annual survey of the Chinese export technical measures, which is copiled by the AQSIQ. The annual survey begins from 2006 and randomly search more than 2000 companies every year all around the country to get the information about their facing the foreign TBT. This annual survey is one of the most authoritative survey about the TBT in China.

From the Chinese Manufacturing Firm Survey Database (CMFSD), we can have details of the company in the year of 2009 and 2010 like its total asset, its production. And from the 2010 survey of Chinese export technical measures, we can see whether those sample exporters had encountered the foreign technical measures or not in the year of 2009. Combined these two database, we have 1132 companies which show up in both two databases at the same time.

5 Results and discussion
5.1 Technical measures and R&D based on PSM-DID analysis

In order to apply the PSM-DID estimator, we need to identify a good matching group from the sample of those firms which affected by the foreign technical measures. It needs to estimate propensity score matching models. The key of propensity score matching is to construct a control group from the group of unaffected exporters and to ensure that the control group is as similar as possible to the treatment group with respect to available observable characteristics. In our case, the treatment is affected by foreign technical measures and we study its effect on R&D investment. To implement the propensity score matching estimation, the first step would be estimating a logit model on affecting by the foreign technical measures. We estimate the likelihood of affecting by the foreign technical measures with a micro dataset of the Chinese manufacturing firms as follows:
\[ \Pr(Treatment = 1 | X = x_j, t) = \beta_0 + \beta_1 \text{age}_j + \beta_2 \ln(\text{employee}_j) + \beta_3 \ln(\text{asset}_j) + \beta_4 \ln(\text{output}_j) + \beta_5 \gamma_{\text{coastal}} + \beta_6 \gamma_{\text{foreign}} + \varepsilon_{it} \]

Where \( X \) is a vector of the observable characteristics of the exporter samples we choose in the year of 2010. The exporter encounter the foreign technical measures is denoted by a dummy variable (Treated) indicating whether the firm encountered the foreign technical measures in 2010. As estimated from our sample, 1132 Chinese firms had encountered the foreign technical measures in 2010. The other explanatory variables include age, number of employee, asset, output, a dummy for being in a coastal city, and a dummy for being owned by foreign capital. The variable \( \text{age} \) represents the time which the firm had established until 2010. The variable \( \ln(\text{employee}) \) is the log of firm’s employee amount in 2010. \( \ln(\text{asset}) \) represents the total asset of the firm. \( \ln(\text{output}) \) represents the gross output of the exporter in 2010. The dummy variable \( \text{coastal} \) indicating that whether the firm is located in the coastal province in China. The dummy variable \( \text{foreign} \) indicating that whether the firm is owned by foreign capital.

Table 2 shows the estimates for the probit model of being affected by foreign technical measures. As expected, exporters in the coastal province have higher probability of being affected by foreign technical measures, and exporters with more employee and more output are also more likely to be affected by foreign technical measures. However, exporters with more asset and owned by foreign capital have lower probability of being affected by foreign technical measures.

[Insert Table 2 here]

Table 3 shows that there are significant differences in the individual characteristic variables before matching between technical measures affected exporters and non-affected exporters. For example, before applying the NN matching, the mean difference of asset between affected exporters and non-affected exporters is significant, which
there exists sample selection bias; however, after the NN matching, their differences are not significant, which is verified by the T-test.

[Insert Table 3 here]

Figure 12 plots the distributions of the propensity scores before and after the matching. The figure shows that the gap of the propensity scores’ density between affected exporters and non-affected exporters are closer after the matching.

[Insert Figure 12 here]

Table 4 shows the result of sample comparison before and after using the PSM method. As a whole, the standardized difference of the sample with the PSM is smaller than that without PSM. It reflects that the systematic difference between the affected exporters and matched non-affected exporters is effectively diminished, rather than completely eliminated: the P-value of the LR test is greater than 10%, which manifests that no significant differences between the affected exporters and matched non-affected exporters after applying the PSM which means the sample is supposed to be appropriate.

[Insert Table 4 here]

Based on the propensity score computed from the probit model, propensity score matching are performed. In estimating the ATT using PSM-DID, the effects are measured by the variable of ln(1+R&D). The equation of PSM-DID method is:

\[
ATT = [E(ln(1 + R \& D_{\text{treatment}}) \mid t = 1) - E(ln(1 + R \& D_{\text{treatment}}) \mid t = 0)] - [E(ln(1 + R \& D_{\text{control}}) \mid t = 1) - E(ln(1 + R \& D_{\text{control}}) \mid t = 0)]
\]

The standard errors of PSM-DID are obtained by bootstrapping with 500 replications.

To compare the results with PSM-DID, we also estimate the treatment effects through DID method without controlling for sample selection bias. The equation of DID method is:

\[
ln(1 + R \& D_i) = \beta_0 + \beta_1 \cdot T_i + \beta_2 \cdot TBT_i + \beta_3 \cdot TBT_i \times T_i + \beta_4 \cdot X_{it} + \epsilon_i
\]
Furthermore, to examine the differences in the technical effects of the technical measures in different industries, we divide the sample into 4 industries, including Mechanical & Electrical Industry, Mining & Metals Industry, Textile & Garment Industry, and Food & Agricultural Products Industry.

The estimated results for DID and PSM-DID are shown in Table 5. It reveals that the technical effect of technical measures on all exporters are positive and statistically significant in both DID and PSM-DID. The result indicates that the foreign technical measures have significant impact on exports’ R&D investment, which means the foreign technical measures affected exporters are more willing to increase their R&D investment. In addition, on the industry-level analysis, the technical effect of technical measures on the exporters from the Mechanical & Electrical Industry and the Food & Agricultural Products Industry are positive and statistically significant in both DID and PSM-DID, while the coefficients of ATT for the exporters from the Mining & Metals Industry and the Textile & Garment Industry are positive, but not statistically different from 0 at the 10% level from PSM-DID estimation. It shows that the foreign technical measures affected exporters from the Mechanical & Electrical Industry and the Food & Agricultural Products Industry are more willing to increase their R&D investment compared with those foreign technical measures affected exporters from the Mining & Metals Industry and the Textile & Garment Industry.

[Insert Table 5 here]

5.2 The relationship between the loss caused by technical Measures and the change of R&D investment

Based on the previous conceptual model, we know that not all the foreign technical measures affected firms would increase their R&D investment. Firms like Firm 1, which their input of \( q_i \) were less than the minimal requirement \( \bar{q} \). When they
increase their input of \( q_i \) from \( q_i^* \) to \( \bar{q} \), their profit would be less than the fix entry cost. So they would just quit the export market which they won’t increase their R&D investment. Only firms like **Firm 2** which their maximum profit input of \( q \) were less than the minimal requirement \( \bar{q} \), but when they increase input to \( \bar{q} \), their profit would be still more than the fix entry cost, then they would increase their input input of \( q \) to \( \bar{q} \) which means they would increase their R&D investment. The difference between firms like Firm 1 and firms like firm 2 is their loss due to the new technical measures which Firm 1’s loss is more than firm 2. It reminds us that there may be a non-linear relationship between the increased R&D investment and the firm’s loss due to the new technical measures. So we will use the threshold model to examine the relationship between the increased R&D investment and the firm’s loss. According to Hansen (2000), we can have the relationship between R&D input and the loss due to the new technical measures:

\[
\Delta \ln(1 + R & D_i) = \alpha_i + \beta_1 \ln(1 + L_i) \cdot I( LR_i > \lambda) + \beta_2 \ln(1 + L_i) \cdot I( LR_i \leq \lambda) + \beta_3 X_i + \nu_i
\]

Where \( \Delta \ln(1 + R & D_i) = \ln(1 + R & D_{i+1}) - \ln(1 + R & D_{i-1}) \) is the change of Firm i’s R&D investment. \( L_i \) is the Firm i’s loss due to the foreign technical measures. \( LR_i \) is the loss ratio, which is the percentage of Firm i’s loss due to the foreign technical measures and its output. \( I(\cdot) \) represents an indicator function, indicating whether leverage measure of firm i is less than or greater than a threshold parameter \( \lambda \); \( \lambda \) is the endogenous threshold value to be estimated from the model. Depending on whether the loss share is smaller or larger than the threshold value (\( \lambda \)) to be estimated, observations are divided into two “regimes” where the regimes are distinguished by differing regression slopes, \( \beta_1 \) and \( \beta_2 \). In addition, we include initial values of a number of other variables \( X_i \), namely, firm asset, firm output, firm age, firm employee, and ownership (foreign).
Before applying the threshold regression model, we apply a test for the existence of threshold effect between firm’s loss due to the technical measures and the change of firm’s R&D investment. This paper uses the bootstrap method to approximate the F statistic, and then calculates the bootstrap p-value. Table 6 presents the empirical results of the test for a single threshold, multiple threshold and triple threshold effects. The test statistic for a single threshold is highly significant, with a bootstrap p-value of 0.031, but the test statistic for a double threshold and a triple threshold are statistically insignificant, with a p-value of 0.183 and 0.276. Thus, we may conclude that there is strong evidence that there is a threshold in the relationship between firm’s loss and the change of its R&D investment. And it implies that the threshold value is 31.864%. As a result, the data on the loss ratio for the technical measures affected exporters can be divided into low and high ratio group.

[Insert Table 6 here]

Figure 21 shows the threshold estimates from plots of the concentrated likelihood ration function, LR(), corresponding to the estimate of

[Insert Figure 12 here]

Once the search for the loss ratio threshold effects, we proceed to investigate the relationship between firm’s loss caused by foreign technical measures and the change of its R&D investment under different loss ratio regimes for those technical measures affected exporters.

Table 7 summarizes the estimation results of the relationship between between firm’s loss caused by foreign technical measures and the change of its R&D investment. It reveals that when the loss ratio is below 31.864%, which means the percentage of loss caused by foreign technical measures with the firm’s output, the loss has a positive significant impact on the firm’s R&D investment, which the coefficient is 0.432. However, when the loss ratio above that threshold value, the loss does not have any
significant impact on the firm’s R&D investment. As a result, the technical measures that induce the firm to increase its R&D investment only be established under low loss ratio.

[Insert Table 7 here]

5.3 Technical Measures and Technical Progress

We set the production function as two-factors Cobb-Douglas function:

\[ y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} \]

\[ \ln y_{it} = A_{it} + \beta_k K_{it} + \beta_l L_{it} + \varepsilon_{it} \]

We use the the Levinsohn-Petrin input proxy estimator to calculate each firm’s TFP, which is based on the Cobb-Douglas function. In addition, we add three control variables, including firm age, firm region and time:

\[ \ln y_{it} = \alpha_{it} + \beta_k K_{it} + \beta_l L_{it} + \beta_A Age_{it} + \beta_R Region_{it} + \beta_Y Year_{it} + \varepsilon_{it} \]

Table 8 shows the descriptive statistics of firms’ TFP. As you can see, according to Levinsohn-Petrin input proxy estimator method, firms’ average TFP is 8.23. Figure 14 is the scatter of the firms’ TFP from 2005 to 2011.

[Insert Table 8 here]

After calculating firms’ TFP, we use DID method to measure the technical effect of technical measures on firms’ TFP.

\[ \Delta TFP_{it} = \alpha_0 + \alpha_1 t + \alpha_2 T + \alpha_3 \cdot T * T + \beta_1 X_{it} + \varepsilon_{it} \]

Table 9 shows that the coefficient \( \alpha_3 \) is positive, but not significant, thus the technical effect of technical measures on firms’ TFP is not significant.

[Insert Table 9 here]
6  Concluding Remarks

This paper investigated the relationship between the foreign technical measures and the input of firm’s R&D investment and firm’s technical progress with the Chinese Manufacturing Firm Survey database and the official annual survey of the Chinese export technical measures. To tackle the problem of selection bias, we employed the PSM-DID method controlling for observed heterogeneity. Our result suggests that both the standard DID method and the PSM-DID method show that the coefficient of technical effect is significantly positive for R&D investment. It reviews that technical measures induced firms to increase their R&D investment. However, the threshold regression model shows that the technical measures that induce the firms to increase its R&D investment only be established under low loss ratio which is 31.864%. By using the TFP as a proxy variable for technical progress, it shows that the effect of technical measures on firm’s technical progress is not significant.

References

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Moenius, J. Information versus product adaptation: the role of standards in trade [R].
Moenius, J. The good, the bad and the ambiguous: standards and trade in agricultural product [R]. IATRC Summer Symposium, 2006.

Figure 1. Number of SPS notification per year from 2000 to 2015

Source: World Trade Organization
Figure 2. Number of TBT notification per year from 2000 to 2015

Source: World Trade Organization
Figure 3. Chinese Export from 2001 to 2016

Source: World Trade Organization
Figure 4. The Chinese Technical Measures Annual Survey

Source: The Chinese Technical Measures Annual Survey
Figure 5. Top 5 Industries Affected by Foreign Technical Measures

Source: The Chinese Technical Measures Annual Survey
Figure 6. Top 5 export market that affected Chinese exporters

Source: The Chinese Technical Measures Annual Survey
Figure 7. Relationship between $A(q)$ and $c_i(q)$
Figure 8. Relationship between $f(L)$ and $w_L$
Figure 9. relationship between $\pi_i$ and $q$
Figure 10. TBT and $q$
Figure 11. Firms with new standards
Figure 12. Density Before Matching and After Matching
Figure 13. Confidence Interval Construction for Single Threshold
Figure 14. The scatter of the firms’ TFP from 2005 to 2011
Table 1. The coefficient of DID method

<table>
<thead>
<tr>
<th></th>
<th>Before change</th>
<th>After change</th>
<th>Time-difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment group (TBT-affected)</td>
<td>$\beta_0 + \beta_2$</td>
<td>$\beta_0 + \beta_1 + \beta_2 + \beta_3$</td>
<td>$\beta_1 + \beta_3$</td>
</tr>
<tr>
<td>Control group (non-affected)</td>
<td>$\beta_0$</td>
<td>$\beta_0 + \beta_1$</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td>Group-difference</td>
<td>$\beta_2$</td>
<td>$\beta_2 + \beta_3$</td>
<td>$\beta_3$</td>
</tr>
</tbody>
</table>
Table 2. Logit estimation

<table>
<thead>
<tr>
<th>Treat</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>z</th>
<th>P&gt;(z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coastal</td>
<td>0.272391</td>
<td>0.0925629</td>
<td>2.94</td>
<td>0.003</td>
</tr>
<tr>
<td>lnemployee</td>
<td>0.096243</td>
<td>0.00454949</td>
<td>2.12</td>
<td>0.034</td>
</tr>
<tr>
<td>Foreign</td>
<td>-0.295403</td>
<td>0.0818567</td>
<td>-3.61</td>
<td>0.000</td>
</tr>
<tr>
<td>lnasset</td>
<td>-0.0949938</td>
<td>0.0552293</td>
<td>-1.72</td>
<td>0.085</td>
</tr>
<tr>
<td>lnproduction2</td>
<td>0.1448474</td>
<td>0.0589025</td>
<td>2.46</td>
<td>0.014</td>
</tr>
<tr>
<td>con</td>
<td>-1.424107</td>
<td>0.2028428</td>
<td>-7.02</td>
<td>0.000</td>
</tr>
</tbody>
</table>
Table 3. Comparison between variables before and after the NN matching

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unmatched Matched</th>
<th>Mean Treated</th>
<th>Mean Control</th>
<th>%bias</th>
<th>%reduct bias</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coastal</td>
<td>U</td>
<td>.77949</td>
<td>.71429</td>
<td>15.0</td>
<td>2.37***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>.77749</td>
<td>.80256</td>
<td>-5.3</td>
<td>-0.79</td>
<td></td>
</tr>
<tr>
<td>ln employee</td>
<td>U</td>
<td>6.1263</td>
<td>5.7913</td>
<td>25.2</td>
<td>4.09***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>6.1263</td>
<td>6.0241</td>
<td>7.7</td>
<td>1.05</td>
<td></td>
</tr>
<tr>
<td>Foreign</td>
<td>U</td>
<td>.45641</td>
<td>.531</td>
<td>-14.9</td>
<td>-2.39***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>.45641</td>
<td>.47179</td>
<td>-3.1</td>
<td>-0.43</td>
<td></td>
</tr>
<tr>
<td>ln asset</td>
<td>U</td>
<td>6.8912</td>
<td>6.5759</td>
<td>18.1</td>
<td>2.91***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>6.8912</td>
<td>6.8772</td>
<td>0.8</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>ln output</td>
<td>U</td>
<td>7.3561</td>
<td>6.9417</td>
<td>25.5</td>
<td>4.08***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>7.3561</td>
<td>7.4</td>
<td>-2.7</td>
<td>-0.34</td>
<td></td>
</tr>
</tbody>
</table>

***, **, * denote significance at the 1%, 5% and 10% levels, respectively
Table 4. Comparison between samples before and after employing the PSM

<table>
<thead>
<tr>
<th>Sample</th>
<th>Pseudo R</th>
<th>LR test</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmatched</td>
<td>0.027</td>
<td>39.73</td>
<td>0.000</td>
</tr>
<tr>
<td>Matched</td>
<td>0.008</td>
<td>8.32</td>
<td>0.503</td>
</tr>
</tbody>
</table>
Table 5. The result of DID and PSM-DID method

<table>
<thead>
<tr>
<th>Sample</th>
<th>Outcome</th>
<th>DID</th>
<th>S.E.</th>
<th>ATT</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>ln(1 + R &amp; D)</td>
<td>(\beta_3)</td>
<td>1.7643**</td>
<td>0.5718</td>
<td>1.4978*</td>
</tr>
<tr>
<td>Mechanical &amp; Electrical Industry</td>
<td>ln(1 + R &amp; D)</td>
<td>(\beta_3)</td>
<td>1.8434***</td>
<td>0.6763</td>
<td>1.5872**</td>
</tr>
<tr>
<td>Mining &amp; Metals Industry</td>
<td>ln(1 + R &amp; D)</td>
<td>(\beta_3)</td>
<td>1.1343*</td>
<td>0.6352</td>
<td>1.0394</td>
</tr>
<tr>
<td>Textile &amp; Garment Industry</td>
<td>ln(1 + R &amp; D)</td>
<td>(\beta_3)</td>
<td>1.4873*</td>
<td>0.8231</td>
<td>1.3453</td>
</tr>
<tr>
<td>Food &amp; Agricultural Products Industry</td>
<td>ln(1 + R &amp; D)</td>
<td>(\beta_3)</td>
<td>1.5893**</td>
<td>0.7585</td>
<td>1.4232*</td>
</tr>
</tbody>
</table>

***, **, * denote significance at the 1%, 5% and 10% levels, respectively
Table 6. Test for Threshold Effects

<table>
<thead>
<tr>
<th>Test</th>
<th>F statistics</th>
<th>Bootstrap p value</th>
<th>10%</th>
<th>5%</th>
<th>1%</th>
<th>Estimate threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Threshold</td>
<td>23.4055**</td>
<td>0.0362</td>
<td>13.4295</td>
<td>17.9914</td>
<td>31.5974</td>
<td></td>
</tr>
<tr>
<td>Double Threshold</td>
<td>13.1857</td>
<td>0.16430</td>
<td>16.2184</td>
<td>20.5159</td>
<td>101.1189</td>
<td>31.864%</td>
</tr>
<tr>
<td>Triple Threshold</td>
<td>10.3423</td>
<td>0.1943</td>
<td>14.0185</td>
<td>22.3348</td>
<td>38.9662</td>
<td></td>
</tr>
</tbody>
</table>

***,**,* denote significance at the 1%, 5% and 10% levels, respectively
Table 7. Result of The Threshold Regression Model

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>Low loss ratio</th>
<th>High loss ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold Value</td>
<td>≤ 31.864%</td>
<td>&gt; 31.864%</td>
</tr>
<tr>
<td>( \ln(1 + L_i) )</td>
<td>0.432**</td>
<td>-0.232</td>
</tr>
<tr>
<td>Foreign</td>
<td>0.014*</td>
<td>0.012*</td>
</tr>
<tr>
<td>Age</td>
<td>-0.023</td>
<td>-0.018</td>
</tr>
<tr>
<td>( \ln(\text{asset}_i) )</td>
<td>1.342*</td>
<td>1.213*</td>
</tr>
<tr>
<td>Coastal</td>
<td>0.008*</td>
<td>0.004</td>
</tr>
<tr>
<td>( \ln(\text{employee}_i) )</td>
<td>-0.242**</td>
<td>-0.362</td>
</tr>
<tr>
<td>( \ln(\text{outcome}) )</td>
<td>0.984*</td>
<td>1.043*</td>
</tr>
<tr>
<td>Con</td>
<td>0.018</td>
<td>0.032</td>
</tr>
</tbody>
</table>

***, **, * denote significance at the 1%, 5% and 10% levels, respectively
Table 8. The TFP calculation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observation</th>
<th>Means</th>
<th>S.E.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>5950</td>
<td>8.23</td>
<td>1.69</td>
<td>2.43</td>
<td>12.86</td>
</tr>
</tbody>
</table>
Table 9. Technical Measures and Technical Progress

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standard DID (1)</th>
<th>Standard DID (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_i$</td>
<td>0.0051</td>
<td>0.0056*</td>
</tr>
<tr>
<td>$Treat_i$</td>
<td>0.0452</td>
<td>0.0419</td>
</tr>
<tr>
<td>$Treat_i \times T$</td>
<td>0.0126</td>
<td>0.0103</td>
</tr>
<tr>
<td>$Foreign$</td>
<td></td>
<td>0.0032*</td>
</tr>
<tr>
<td>$Coastal$</td>
<td></td>
<td>0.0018*</td>
</tr>
</tbody>
</table>

***, * denote significance at the 5% and 10% levels, respectively