Innovation, External Technological Environment and the Total Factor Productivity of Enterprises

Zumian Xiao: School of Finance, Shandong University of Finance and Economics, Jinan, Shandong, China. Email: xiaozumian@sdufe.edu.cn

Hongfeng Peng (Corresponding Author): School of Finance, Shandong University of Finance and Economics, Jinan, Shandong, China. Email: fhpeng@whu.edu.cn

Zheyao Pan: Department of Applied Finance, Macquarie University, Sydney, Austrila. Email: terry.pan@mq.edu.au

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Abstract

In this paper, we study the impact of endogenous innovation and the external technological environment on total factor productivity. We first develop an endogenous growth model and derive a testable empirical model. We then estimate the empirical model based on the World Bank's worldwide enterprise survey data for 119 countries spanning 2007-2017. Our results suggest that: (i) enterprises' R&D activity increases their total factor productivity; (ii) a higher level of external technology weakens the impact of the R&D activity on total factor productivity; and (iii) enterprises located in low- and middle- income countries often lack continuous innovation.

Key words: R&D; Innovation; Technological Environment; Total Factor Productivity

JEL classification: D24; O31; O32

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1. Introduction

Total factor productivity (hereafter TFP) measures the total output per unit of total inputs, in other words, the ratio of total output to total factor inputs. The TFP growth rate is often regarded as a key indicator of technological improvement, which drives the potential space for a society to increase the welfare of its people (Isaksson, 2007). It is therefore pivotal to explore the driving forces behind TFP to understand its common trend as well as its divergence across different nations. Various factors from micro, sectoral and macro dimensions have been proposed and studied in the literature,[1] a key message is that innovation is the intrinsic driver of firm productivity improvement and long-term economic growth (Kung and Schmid, 2015).

There are two potential channels through which innovation could boost TFP growth. The first is to raise the level of production technology by upgrading a firm's own innovation capacity. The second is to increase productivity by absorbing advanced external technology through technology spillover effects. However, the relation between innovation and TFP is still inconclusive from the perspectives of both theoretical mechanism and empirical evidence. Specifically, according to our understanding, there are two major questions remaining to be addressed: (1) Does R&D innovation necessarily increase the level of TFP in enterprises; and (2) Can technology spillovers from outside enhance the TFP of an enterprise? Regarding the first question, prior studies generally document a significant positive association between innovation and TFP growth rate (Isaksson, 2007). However, this relation may vary across firms due to their heterogeneities in different dimensions (e.g., Costantini and Melitz, 2008; Atkeson and Burstein, 2010). In the meanwhile, excessive or misallocated R&D investment may also negatively affect productivity at the firm level (e.g., Lööf and Heshmati, 2006; Van Leeuwen and Klomp, 2006; Ayerst, 2020).[2] To answer the second question, we need to realize that the effect of technology spillovers can be influenced by a number of factors, such as the enterprise's ability to absorb external technology,

[1] For comprehensive literature reviews on the determinants of TFP, we refer readers to Isaksson (2007), Hopenhayn (2014), and Ugur et al. (2020), among others.
[2] The literature suggests that resources might be misallocated and results in low TFP (e.g., Hsieh and Klenow, 2009).

and the distance between the firm's production technology and the technological frontier, etc. Moreover, reliance on external technology may in turn lead to a loss of incentive for independent R&D activity and innovation, making technology spillovers counterproductive (Ugur et al., 2020).

The answers to these questions cannot only help understand how the endogenous innovation and technology environment affect the TFP of enterprises, but also shed light on the formation of industrial policies aiming at enhancing TFP. In order to better understand the impact of internal and external technological factors on enterprise-level productivity, we first extend the classical endogenous growth models of Romer (1990), Grossman and Helpman (1991a, b) and Aghion and Howitt (1992) by incorporating both endogenous innovation and external technology environment. By solving the model, we find that both the enterprise's own R&D and the external technology environment are the core influencing factors of TFP. At the same time, our model implies that there is no deterministic prediction on how firm-level TFP would react to changes in endogenous R&D and external technology environment, and the interaction between these two factors is a key driver of TFP.

To understand how innovation influences the TFP of micro enterprises, we derive a testable empirical model based on our theoretical model. We then estimate the empirical model with a large global sample based on the World Bank's enterprise survey data for 119 countries spanning 2007 to 2017. Our empirical analysis reveals three key findings as summarized below. First, in line with the existing literature, we find that on average TFP is positively associated with an enterprise's R&D input. Second, consistent with our model prediction, the interaction between R&D investment and external technology environment is significantly related with TFP. More importantly, we find that a higher level of external technology weakens the impact of the R&D activity on TFP. Third, we show that enterprises located in low- and middle-income countries often lack continuous innovation.

To mitigate the impact of the endogeneity nature of R&D investment on casual inference, we first conduct an instrumental variable (IV) analysis by using quality certification of the firm's product as the IV for R&D investment. The results of our IV analysis confirm the causative effect of R&D investment on TFP. We also find that the productivity enhancing effect of R&D investment increases after the introduction of the Patent Cooperation Treaty/Patent Prosecution Highway (PCT/PPH) pilot program in early 2010. This result also provides supporting evidence on our casual inference. Finally, we show that our main results are insensitive to an alternative measurement approach of TFP.

Our contribution to the literature is twofold. Theoretically, we extend the classical endogenous growth model to incorporate the external technological environment factor. Through this model, we contribute to the existing literature by providing an analytical framework that clarifies mechanisms through which R&D investment, external technological environment, and their interaction drive TFP. Empirically, by using the global enterprise survey dataset from World Bank, we provide a large-scale analysis on TFP and its determinants. To the best of our knowledge, we are the first in the literature to identify the fact that external technological environment reduces the efficiency of R&D investment globally.

The remainder of this paper is structured as follows. Section 2 briefly reviews existing studies. Section 3 develops a conceptual framework in which endogenous innovation and external technological environment are incorporated. Section 4 presents and discusses our empirical results. The final section concludes the paper.

2. Literature review

A large body of literature has examined the factors that influence total product productivity. The most important driving forces include R&D innovation, technology spillovers, and the external technology environment that firms face. In this section, we combine the prior literature from these three perspectives.

2.1 R&D activity and TFP

R&D activities have both direct and indirect effects on TFP, with direct effects promoting endogenous technological innovation, and indirect effects promoting technology absorption and imitation, leading to technological innovation.

R&D and innovation activities are important drivers of overall economic development. At the macro level, the theoretical studies of Acemoglu et al. (2006) and Benhabib et al. (2013) emphasize the importance of R&D activities for enhancing productivity growth. In the meanwhile, the empirical analysis conducted by Tientao et al. (2016), Lee (2016), and Huang et al. (2019) shows that R&D investment plays an important role in increasing TFP both globally and regionally (Korea and China).

At the micro level, Qi et al. (2009) explore the effect of local R&D on TFP of Chinese firms based on micro data from 2003 to 2006. Their empirical results suggest that R&D plays a significant positive role in firm-level TFP growth. Cui and Yang (2018) shows that firms subjecting to the IPO suspension are more likely to reduce their investments in R&D. Xu et al. (2019) suggests that it is the market rather than the government that enhances corporate R&D investment. Zhao and Wang (2019) finds that pay gap could lead inventor innovation and improve technology innovation. Bond and Guceri (2017) study the large UK firms and their results indicate that firms with large R&D expenditures have an average TFP increase of 14% compared to firms without any R&D input.

2.2 Technology spillovers and TFP

Apart from R&D investment, technology spillover is also proposed to be a key determinant of TFP. First, at the macro level, technology spillovers change the level of aggregate TFP in the economy. Literature has suggested that technology spillovers facilitate the transfer of advanced technology and management experience from foreign countries, thus contributing to productivity and efficiency (Fujimori and Sato, 2015; Liu, Agbola and Dzator, 2016; Huang et al. 2019). At the same time, however, some studies point out that the impact of foreign technology spillovers on the productivity and efficiency is uncertain and depends on economic circumstances (e.g. Qi et al., 2009; Newman et. al., 2015).

Second, at the micro level, scholars have not reached a consistent conclusion on whether technology spillovers significantly change firm TFP or not. Hu and Tan (2016) note that export participation is positively correlated with TFP growth using data from large firms in the Chinese manufacturing sector. Du et al. (2012) find that when exports increase, domestic firm productivity increases significantly, but foreign subsidiary productivity does not change significantly. Ugur et al. (2020) also find that technology spillovers generally have a positive effect on TFP, but with a large degree of heterogeneity and in some cases this effect is not significant.

Finally, the literature suggests that human capital can increase the rate of technology diffusion and lead to better acceptance and use of new technologies in latecomer countries, thus contributing to economic growth. Su and Liu (2016) find that firms' human capital endowment can increase the impact of FDI on productivity growth based on the 1991-2010 Chinese city panel data set. Bengoa et al. (2017) have confirmed a direct positive effect of social capital on TFP growth.

2.3 External technological environment and TFP

Taking the literature on technology spillovers as a starting point, researchers begin to investigate the issue from a more general perspective. They see technological upgrading beyond endogenous innovation as the effect of the overall external technological environment. For example, Bengoa et al. (2017) estimate the long-term impact of peripheral R&D activities on local TFP based on Spanish regional panel data. Their empirical results show that R&D has a significant positive impact on local TFP. Notably, Badinger and Egger's (2016) empirical analysis with panel data covering 12 OECD countries and 15 manufacturing industries over the period 1995-2005 suggests that public R&D expenditures have a significant impact on productivity only within or across similar industries.

The mechanism on how aggregate TFP would be affected by innovation and technology spillovers has been covered in extant literature. However, much less attention has been paid on the productivity at the firm level. More importantly, existing literature has not adequately taken the interaction between R&D investments and external technological environment and its impact on firm-level TFP into consideration. To fill this gap, this paper focuses on the impact of innovation and technological environment on total factor productivity of enterprises. Our theoretical reasoning is based on a model including both endogenous innovation and external technological environment, which is illustrated in detail as below.

3. Theoretical model and econometrical specification

Schumpeter first introduced the concept of “creative destruction” in 1934 (Schumpeter, 1934), a cornerstone of the theoretical model of innovation and economic growth, in his attempt to build a theory of endogenous economic growth with innovation as an intrinsic driver. Romer (1990) proposes an endogenous growth model with technological change as the key driver of growth. Similar to Romer (1990), in this section, we assume that the technological improvement can be represented as an increase in product variety, and technological advances manifest themselves in quality improvements to existing products (see Grossman and Helpman, 1991b; Aghion and Howitt, 1992). Enterprises improve their own production technology through endogenous R&D activity or technology introduction and absorption.

3.1 Production function

We assume that the final product market is completely competitive. A firm i in this market employs labor L_i and acquires intermediate products labeled by a continuous real number $\varepsilon \in \left[0, N_i(t)\right]$ to produce the final product Y_i, where $N_i(t)$ represents the types of intermediate products. Following Broda (2006), the production function is defined as:

$$Y_i(t) = \left(A_i(t) L_i(t)\right)^{1-\alpha} \left[\int_0^{N_i(t)} M_{i,\varepsilon}^{\theta}(t) d\varepsilon\right]^{\alpha/\theta} \tag{1}$$

where $A_i(t)$ is a heterogeneous parameter that captures a firm’s productivity level at time t. $\alpha \in [0,1]$ represents the ratio of 1 minus the labor share, and $\theta \in [0,1]$ measures the elasticity of substitution between different types of intermediate input $M_{i,\varepsilon}(t)$. All intermediate products are taken into production homogenously at the same price. Following Grossman and Helpman (1991a, b), when the economy achieves its equilibrium, the demand for each intermediate product is the same. Therefore, we have $M_i(t) = M_{i,\theta}(t)$, and equation (1) can be simplified to:

$$Y_i(t) = \left(A_i(t) L_i(t)\right)^{1-\alpha} N_i(t)^{\alpha/\theta} M_i^{\alpha}(t) \tag{2}$$

The model sets each intermediate product to be produced one-on-one with the final product as the input. Thus, the total capital stock can be defined as $K_i(t) = N_i(t) M_i(t)$ and the production function can be rewritten as:

$$Y_i(t) = A_i(t)^{1-\alpha} L_i(t)^{1-\alpha} N_i(t)^{((1-\theta)/\theta)\alpha} K_i(t)^{\alpha} \tag{3}$$

We define enterprise total factor productivity (TFP) as:

$$Z_i(t) = \frac{Y_i(t)}{L_i(t)^{1-\alpha} K_i(t)^{\alpha}} \tag{4}$$

Bringing (3) into (4) gives:

$$Z_i(t) = A_i(t)^{1-\alpha} N_i(t)^{((1-\theta)/\theta)\alpha} \tag{5}$$

In this way, a firm's TFP consists of two components: product type ($N_i(t)^{((1-\theta)/\theta)\alpha}$) and product quality ($A_i(t)^{1-\alpha}$).

3.2 Innovation and the external technological environment

We define $A_i(t)^{1-\alpha}$ in line with Ertur and Koch (2011) and Tientao et al. (2016) as:

$$A_i(t)^{1-\alpha} = \Upsilon\left(\frac{Z_i^{'}(t)}{Z_i(t)}\right)^{\mu_i} \tag{6}$$

The technological frontier faced by enterprise i is referred to as $Z_i^{'}$. The parameter $\mu_i \in [-1,1]$ captures the degree of technology diffusion and represents the rate at which the level of production technology of firm i changes as a result of external technology absorption. In fact, the closer a firm is to the technological frontier, the more productive it will be. Combining equations (5) and (6) yields:

$$Z_i(t) = \Upsilon\left(\frac{Z_i^{'}(t)}{Z_i(t)}\right)^{\mu_i} N_i(t))^{((1-\theta)/\theta)\alpha} \tag{7}$$

We follow Grossman and Helpman (1991a, b), and argue that a firm's innovation (as measured by the number of product categories) is related to its endogenous R&D activity, human capital accumulation, and external technological conditions (both external R&D and human capital). The specific expression of $N_i(t)$ is as follows:

$$N_i(t)^{((1-\theta)/\theta)\alpha} = R_i^{\theta}(t) H_i^{\vartheta}(t) \left(\bar{R}_i^{\theta}(t) \bar{H}_i^{\vartheta}(t)\right)^{\mu_i} \tag{8}$$

Where θ and ϑ represent the elasticity of the firm's R&D and human capital stock, respectively. We denote the firm's R&D expenditure and human capital stock as $R_i(t)$

and $H_i(t)$ respectively. $R_i^{\theta}(t)H_i^{\vartheta}(t)$ captures the technological innovation achieved by the firm's employees with endogenous R&D. $\bar{R}_i^{\theta}(t)\bar{H}_i^{\vartheta}(t)$ is the external technological condition corresponding to the level of R&D activity of other firms, by which depends on the level of external R&D inputs and human capital.

Thus, in combination with equation (7) and (8), it is obvious that the TFP of the enterprise satisfies the following equation:

$$Z_i(t) = \Upsilon\left(\frac{Z_i^{'}(t)}{Z_i(t)}\right)^{\mu_i} R_i^{\theta}(t)H_i^{\vartheta}(t)\left(\bar{R}_i^{\theta}(t)\bar{H}_i^{\vartheta}(t)\right)^{\mu_i} \tag{9}$$

From the above equation, both the enterprise's own R&D and the external technology environment are the core variables influencing factors of TFP. The external technology environment includes the given exogenous technology frontier and the external technology conditions determined by the R&D level of other enterprises. Equation (9) also suggests that the interaction between R&D and the external technology environment determines the level of TFP.

Since the technology diffusion parameter μ_i falls into the interval $[-1,1]$, we are unable to simply infer from the theoretical model how firm TFP would react to changes in endogenous R&D and external technology environment. Therefore, it is necessary to estimate the parameters and perform statistical inference based on observable data.

3.3 Econometrical specification

By deriving the equivalence transformation of the results from the theoretical model, we are able to obtain the regression equation for empirical analysis.

Taking the logarithm of both sides of equation (9), we get:

$$\begin{aligned}\ln Z_i(t) = \ln \Upsilon + \mu_i\left(\ln Z_i^{'}(t) - \ln Z_i(t)\right) + \theta \ln R_i(t) + \vartheta \ln H_i(t) \\ + \theta\mu_i \ln \bar{R}_i(t) + \vartheta\mu_i \ln \bar{H}_i(t)\end{aligned} \tag{10}$$

After simple algebra, we have:

$$\ln Z_i(t) = \beta_0 + \beta_1 \ln R_i(t) + \beta_2 \ln H_i(t) + \beta_3 \ln Z_i^{'}(t) + \beta_4 \ln \bar{R}_i(t) + \beta_5 \ln \bar{H}_i(t) \tag{11}$$

where the coefficients are substitutions for the relevant parameters in equation (10). The equation draws the relationship between the two core explanatory variables —— endogenous innovation and external technological environment—— and the firm TFP.

The empirical regression model is obtained by focusing on the R&D investments and adding other control variables and an error term:

$$TFP_{imn} = \alpha_0 + \alpha_1 R\&D_{imn} + \boldsymbol{\beta}'\boldsymbol{X}_{imn} + \delta_{year\_m} + \delta_{city\_n} + \xi_{imn} \quad (12)$$

Where the explained variable TFP represents the total factor productivity level of the surveyed firm in year m and country n. $R\&D_{imn}$ is the core explanatory variable, representing the firm's R&D investments. $\mathbf{X}_{imn}$ is the vector of the other control variables, and δ_{year_m} and δ_{city_n} denote the year and city fixed effects respectively[3]. ε_{imn} is the random error term.

4. Empirical analysis

In this section, we first define main variables of interest and elaborate further on the data employed. We then present and discuss the estimates of the baseline regression and its extensions. In the last part, we conduct several tests to address endogeneity problems and ensure robustness of our results.

4.1 Data and variables

4.1.1 Explained variable

This paper closely follows the official World Bank guidelines to estimate firm level total factor productivity (see Saliola and Seker, 2011). Prior studies have pointed out that without intermediary input, the calculation of TFP would be biased and inaccurate (e.g., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Van Beveren, 2012). Therefore, following Saliola and Seker (2011) among others, we introduce the intermediate input into the calculation of firm TFP to obtain more reliable productivity estimation. To ensure the consistency of TFP calculation, our empirical analysis excludes firms from industries that usually lack intermediary input or R&D activity, such as the agriculture and service sectors, and focuses on manufacturing firms only.

TFPs are estimated for each industry within the manufacturing sector separately. We also allow parameters that represent output elasticity of inputs to vary across different income groups of economies. Subsequently, to control for an average economy-level and time effects, dummy variables for each economy and year are included. The regression of firm output (Y_{sci}) on capital (K_{sci}), labor (L_{sci}) and intermediate inputs (M_{sci}) is carried out according to the following equation:

[3] We use city instead of country fixed effect because within a country, TFP can vary significantly across different cities. See Su and Liu (2016) for such evidence in China.

$$\ln\left(Y_{sci}\right)=c_s+\beta_1\ln\left(K_{sci}\right)+\beta_2\ln\left(L_{sci}\right)+\beta_3\ln\left(M_{sci}\right)+\beta_4\ln\left(K_{sci}\right)\cdot I_c \\ +\beta_5\ln\left(L_{sci}\right)\cdot I_c+\beta_6\ln\left(M_{sci}\right)\cdot I_c+F_c+F_y+u_{sci} \tag{13}$$

where s denotes the industry which the firm belongs to, and c denotes the country in which the firm is located. I_c is a dummy variable that proxies the income level of the country in which the firm is located (This dummy equals 1 for high income country according to the World Bank classification as of the survey year; it equals 0 other wise)[4]. F_c and F_y denote country and year fixed effects, respectively.

Based on the parameter estimates, the TFP for each firm in each year can be calculated as:

$$TFP_{sci}=\hat{u}_{sci}+\hat{c}_s+\hat{F}_c+\hat{F}_y \tag{14}$$

4.1.2 Explanatory variables

First, the core explanatory variables include endogenous innovation and external technological environment. For the endogenous innovation, we use R&D investments as the primary proxy. In addition, referring to Bengoa et al. (2017), we calculate the proportion of firms with independent R&D capabilities in each country in each year as the measure of the external technological environment.

Second, we rely on the existing literature in the field of total factor productivity to select firm-level control variables, such as firm size, location of the firm, and ownership identity (see e.g., Lileeva and Trefler, 2010; Yang and Chen, 2012). Moreover, owing to the richness of the World Bank survey data, we are able to incorporate variables refer to constraints in different dimensions faced by firms, such as, financial constraint, illegal activity (see Chen and Guariglia, 2013; Liu and Li, 2017; Caggese, 2019; and Besley and Mueller, 2018 et al.) and the time that senior management spent on dealing with government regulations (see Xie et al., 2020 and Li et al., 2021). In addition, we also control for new products, which is a commonly used indicator for product innovation, to compare its impact on TFP with that of R&D investments.

Finally, we control for the macroeconomic factors that might affect firm TFP, including aggregate investment ratio, population growth and trade openness.

[4] See detailed information on the classification rules at: https://datatopics.worldbank.org/world-development-indicators/stories/the-classification-of-countries-by-income.html.

4.2 Data description and descriptive statistics

The data is from the World Bank's Global Enterprise Survey Database (ESD) and the World Development Indicators (WDI) database. After merging these two databases together, we exclude the observations that do not meet the basic accounting standards, and the observations with missing values that are necessary to calculate the TFP. Observations with obvious recording errors are eliminated as well.[5] Eventually, we are left with 37,065 firm-year observations for 119 countries spanning 2007-2017. The description of variables and data sources are presented in Table 1.

[Insert Table 1 about here]

We report the descriptive statistics for the variables mentioned above in Table 2. We find significant differences in TFP across firms in the sample, as well as remarkable differences in firm characteristics. At the same time, there is a significant gap between the proportion of enterprises that invest in R&D and the proportion of enterprises that actually launch new products, indicating that the technology used by enterprises to produce new products does not necessarily originate from endogenous research and development activities.

[Insert Table 2 about here]

4.3 Empirical analysis

4.3.1 Baseline regression results

Because the World Bank did not achieve continuous tracking on firms being surveyed, we adopt a pooled OLS regression approach to estimate our baseline regression model as specified in Eq. (12). In column (1) of Table 3, we present the estimation results of the regression including *R&D*, firm level control variables, and the year and city fixed effects. The year fixed effects capture the global macro factors that are relate to firm-level TFP in each year, and the city fixed effects control the impact of local unobservable factors on firm TFP level, reducing the concern that time-invariant omitted factors might bias the estimation. In column (2), we further control for the

[5] Specifically, we exclude observations with sales loss due to crime being 100% or more of annual sales and observations with percentage of senior management time spent in dealing with government regulation being 100% or above.

annual country-level macro variables.

It is evident that the coefficient of R&D investment is positive at the 1% or 5% significance level across all the columns with close magnitudes, suggesting that a higher level of R&D investment is robustly associated with an increase in TFP. This result is in line with prior studies on global markets (e.g., Tientao et al., 2016). In the literature, there are two types of innovation: process innovation and product innovation. The positive coefficient of R&D activity confirms the productivity enhancing role of process innovation. We further analyze the impact of production innovation on TFP by using the launch of new products as a proxy[6]. According to estimates in columns (1) and (2), new product launch within past three years leads to a significant decrease in firm TFP level for the current year. This indicates that the launch of new product may weaken the enterprises' incentive to continue to innovate and to upgrade its production technology, resulting in the reduction of firm TFP. This may be explained by the fact that most of the sample firms in our study are located in the low- and middle- income countries, where firms may not have a sustained incentive to innovate, and that the introduction of new products is accompanied by a decline in productivity.

Estimates for the control variables reported in Table 3 show that there exhibits a significant economies of scale effect. Our estimates suggest an increase in firm size could push up firm TFP, and the effects are significant at 1% level. This is consistent with the assertion made by Klette (1996) that there are significant spillovers in R&D across lines of business within a firm. Therefore, larger firms are more productive. The results in Table 3 also indicate that financial constraint and illegal activity constitute significant obstacles to increase in firm productivity. The underlying mechanisms behind the results are well documented in the literature. Financial constraint will hinder the growth of firm productivity by amplifying cash-flow shocks (Chen and Guariglia, 2013), forcing firms to exit and eroding market selection (Liu and Li, 2017) and acting as barriers to entry that reduce radical innovation, which is very risky but potentially very productive. (Caggese, 2019). And illegal activities negatively affect firm

[6] Using launch of new product as a proxy of production innovation is widely used in the literature (e.g. Haneda and Ito, 2018; Hullova et al., 2019).

productivity by directly reducing output and indirectly causing misallocation of labor from production to protection (Besley and Mueller, 2018).

[Insert Table 3 about here]

4.3.2 Extension of the baseline regression with external technical environment

As discussed in the theoretical model development part in Section 3, external technology environment may also contribute to TFP itself and through its interaction with R&D activities. To test this prediction, we add the external technology environment measure (*Tech*) and its interaction with *R&D* (*R&D * Tech*) into our baseline regression in Eq. (12). As shown in columns (1) and (2) of Table 4, the coefficient estimates for external technical environment are significantly negative. It suggests that the improvement in technical environment suppress the TFP of enterprises. This justifies the point made earlier that firms may not have the tradition and motivation for continuous and independent innovation. When external technology is more accessible, they are more inclined to technology introduction rather than independent research and development.

In columns (1), it is shown that the coefficient of the interaction term negative at 5% significance level. In column (2), we find similar results when we add country-level control variables into the regression. This indicates that the interaction between R&D investments and external technology environment is a significant driver of TFP.
Furthermore, the negative sign suggests that the external technology environment weakens the TFP enhancing effect of R&D investments. Put it in another way, the efficiency of R&D activities in improving firm-level productivity is less pronounced when firms are more accessible to external technology. One possible explanation is that when external technology is available, firms may use more R&D activities for technology absorption and *imitation* rather than *innovation*. This is especially the case in our framework that firms in low- and middle- income countries are not close to the technology frontier yet, and they can still enjoy the benefit of imitating other firms.

[Insert Table 4 about here]

4.3.3 Heterogeneity

To check whether the heterogeneity among firms matter for the consistency of previously reported results, we divide the full sample into subsamples according to country income level and firm ownership heterogeneity and re-estimate our baseline regression model as specified in Eq. (12).

First, the full sample is divided into three groups according to the income level of the country where the firms are located[7], and the regression results are shown in Table 5. Since the sample size of firms located in low-income countries is too small to justify the statistical inference, we focus only on the firms in middle- and high-income countries. For middle-income countries, R&D investment leads to an increase in TFP, while new product is related with a decrease in TFP, confirming the distinct roles of process innovation and product innovation on TFP as discussed in Section 4.3.1. The coefficients for these two variables are not statistically significant for the high-income countries. It is possible due to the limited sample size. An alternative explanation is that firms in high-income countries are closer to the technology frontier, making them harder to improve TFP with the same amount of R&D compared to their counterparties in the middle-income countries; in the meanwhile, firms in the high-income countries have a stronger incentive to continue innovation, and therefore product innovation exhibits no inhibiting effect on TFP.

[Insert Table 5 about here]

Second, we divide the sample into three subsamples according to the ownership of the firms. The estimates are reported in Table 6. The small sample size does not permit meaningful statistical inference for state-owned and foreign enterprises. And for the private firms, regression results are quite similar to those from Table 3. This also

[7] The income level of the country where the enterprise is located, according to the World Bank classification. The World Bank assigns the world's economies to four income groups—low, lower-middle, upper-middle, and high-income countries. The classifications are based on the GNI per Capital & Income thresholds (see more details at: https://datatopics.worldbank.org/world-development-indicators/stories/the-classification-of-countries-by-income.html).

suggests that our empirical analysis primarily reflects how the TFP of private firms is affected by innovative activity and technological environment.

[Insert Table 6 about here]

4.4 Addressing endogeneity and future robustness checks

Research on the relation between R&D investments and TFP is plagued by the concern that endogeneity can undermine the credibility of casual inferences due to the endogenous nature of innovation. It is quite plausible that firms with a higher level of productivity have more resources to support R&D investments. Endogeneity problems in our setting can also arise from omitted variables, although the inclusion of city and year fixed effects has mitigated this concern to some extent. As outlined and discussed below, we address such endogeneity issues using two empirical strategies: instrumental variable analysis and testing of the economic mechanism.

4.4.1 Instrumental variable analysis

To address the endogeneity concern as discussed above, we adopt the quality certification of the firm's product as the instrumental variable for R&D investments[8] and re-estimate the empirical model using two-stage least squares (2SLS) method. In the first stage, we regress *R&D* on *Quality Cert*, a dummy variable that equals to 1 if an enterprise has achieved quality certification in the last three years and 0 otherwise, and alternative control variables and fixed effects as described in Table 3. As shown in columns (1) and (2) in Table 7, *Quality Cert* is positively associated with *R&D* in different model settings at the 1% significance level in two different model settings. After confirming the relevance of the instrument, in the second stage, we regress *TFP* on the fitted values of *R&D*, which is denoted by *HatR&D*. As reported in Table 8, we

[8] Quality certification is a valid instrumental variable for R&D investments. First, the quality certification for products will facilitate process innovation through the formalization of structure and the enabling of cooperation and communication across departments within the enterprise and therefore lead to a higher level of R&D investment (Terziovski and Guerrero, 2014). As a result, the quality certification fits the relevance assumption well. Second, in the World Bank Global Enterprise Survey database, the value of the product quality certification variable is assigned based on data within past three years, such that, the TFP in current year does not affect this variable reversely, satisfying the exclusion condition.

find the coefficients of *HatR&D* are positive and statistically significant at 1% level across two different model settings in columns (1) and (2). In addition, the weak identification test (Kleibergen- Paap rk Wald F-statistic) results are statistically significant, indicating that the instrument variable is not weak. Overall, the two-stage instrumental variable analysis suggests that our main results are unlikely to be driven by potential endogeneity.

[Insert Table 7 about here]

[Insert Table 8 about here]

4.4.2 The impact of a global intellectual property rights protection program

As pointed out by Bedford et al. (2020), the patenting activity captures a significant portion of firm innovative originality. It is necessary to further examine the effect of patent protection policy. Innovation inputs such as R&D investments do not necessarily lead to a desirable increase in innovation outputs, i.e., TFP. One key determinant of the innovation efficiency is entrepreneurs' incentives to innovate, which ultimately depends on the protection of intellectual property rights (IPR) (Fang et al., 2017). Based on this argument, we expect that enhanced IPR protection will increase the investment efficiency of R&D investments. We test this conjecture using the launch of a global intellectual property rights protection program as an indicator of increased IPR.[9]

A Patent Cooperation Treaty/Patent Prosecution Highway (PCT/PPH) pilot program was started on 29 January 2010 for a planned period of two years. This pilot program enables fast-track patent examination procedures for PCT applications that have received a positive written opinion of either the International Searching Authority or the International Preliminary Examining Authority, or an international preliminary examination report from the European Patent Office (EPO), the Japan Patent Office (JPO) or the United States Patent and Trademark Office (USPTO). It is the start of the

[9] One benefit of using global IPR protection policy instead of country-level ones is that country-level IPR protection is more likely to be an endogenous outcome of local innovative activities, especially for small economies.

growing global multilateral PPH network. It is of great significance to the promotion of intellectual property protection around the world.

We create a dummy variable to represent such a global institutional change and add its interaction term with R&D to the baseline regression[10]. Table 9 shows that the coefficient of the interaction term is positive and statistically significant. This finding suggests that for firms with R&D activity, development of global PPH network can improve their innovation productivity. The supporting evidence of our prediction also helps alleviates the endogeneity concern to some extent. Our proposed mechanism is economically plausible, and we can therefore claim greater confidence that causality rather than correlation explains our results.[11]

[Insert Table 9 about here]

4.4.3 Robustness check: An Alternative measure of TFP

As discussed in Section 4.1.1, we include the intermediate inputs in the calculation of TFP. Some of the previous studies do not involve intermediate input in the calculation of TFP. To check if our results are sensitive to the method of TFP calculation, we replace the explained variable with the new measurement which uses only capital and labor as inputs. Estimates in Table 10 are quite similar to our baseline results, suggesting that our baseline regression results are robust.

[Insert Table 10 about here]

5. Conclusion

In this paper, we extend the classical endogenous growth models of Romer (1990), Grossman and Helpman (1991a, b) and Aghion and Howitt (1992) by incorporating both endogenous innovation and external technology environment. Our theoretical

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[10] The dummy variable takes the value 0 if the sample firm was surveyed before 2010, and it takes the value 1 otherwise. The dummy variable is dropped from the regression because we control for the year fixed effects. For more details, please refer to "Pilot of Patent Prosecution Highway Program to use PCT Work Products", PCT Newsletter No. 12/2009 (http://www.wipo.int/edocs/pctndocs/en/2009/pct_news_2009_12.pdf).

[11] We are aware of the concern that there are other global events around 2010 other than the launch of the global IPR contributing to our results. This concern is partially weakened by the fact that we rely on the interaction term to test our conjecture and we have also controlled the year fixed effects. Therefore, any global event that is only related to TFP but not the TFP-RD intensity will have no impact on our inference. We also claim the result as suggestive evidence only.

model implies that there is no deterministic prediction on how firm-level TFP would react to changes in R&D activities, but the interaction between R&D activities and external technological environment is a key driver of TFP.

We test these predictions based on the World Bank Global Enterprise Survey data for 119 countries. We find that R&D activities of enterprises will significantly increase the TFP level, but this effect will be mitigated by the external technology environment. We also find that the product innovation leads to a decrease in TFP, suggesting that firms may lack of the incentives to innovate continuously. The heterogeneity analysis suggests that our results are concentrated in middle-income countries and domestic private firms. Finally, we show that our results are robust with an instrumental variable analysis and the TFP enhancing effect of R&D investments increases with stronger intellectual property rights protection.

Our empirical results imply the following inspirations: (1) Endogenous innovation is the key to the improvement of total factor productivity of enterprises, and therefore improvement in the financing facilitation for R&D investment is crucial to fully guarantee the development of innovating firms; (2) Minimizing the inhibiting effect of upgrading of the external technology environment on the endogenous innovation is critical to stimulate the innovating incentive of enterprises, and to realize the optimization of production efficiency, especially for the firms located in middle-income countries; (3) To achieve sustained productivity growth with industrial policies, how to motive enterprises to continually innovate after the release of new products is a key factor which needs to be considered by policy makers.

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Table 1 Variable Description and Data Sources

Variable type	Variable	Variable description	Data Sources
Explained variable	*TFP*	Total factor productivity	ESD
Explanatory variables	*R&D*	Whether the company has independent research and development (dummy variable)	ESD
	New Product	Whether the company has developed new products within three years (dummy variable)	ESD
	Tech	External technical environment	WDI
Control variables	*Size*	Size of the enterprise, as measured by the number of employees	ESD
	Ownership	Ownership identity of enterprises (state-owned, private, or foreign)	ESD
	Financial Constraint	Financial constraint faced by firms	ESD
	Loss Crime	Sales loss due to crime activity (%)	ESD
	Mtime	Senior management time spent in dealing with government regulation (%)	ESD
	Tope	Top executives' experience in the industry	ESD
	Investment	Investment ratio (proportion of capital formation to GDP) (%)	WDI
	Popg	Population growth rate (%)	WDI
	Trade Open	Trade openness (the proportion of exports and imports to GDP) (%)	WDI

Note: ESD stands for Enterprise Survey Data, and World Development Indicators data provided by Word Bank. The external technology environment is measured by the share of firms with R&D inputs in the country. The size of the enterprise is measured by the number of employees. When the number of employees is less than 20 for small enterprises, the variable takes the value of 1; when the number of employees between 20-90 for medium-sized enterprises, the variable takes the value of 2; when the number of employees more than 100 for large enterprises, the variable takes the value of 3. The ownership identity has three values, 1 for state-owned enterprises, 2 for private enterprises, and 3 for foreign enterprises. The level of financial constraint is measured by the degree to which is finance access an obstacle to the operations of enterprises. This variable is valued from 0 to 4, referring to the state of varying degrees of financing constraints ranging from loose to tight. The sales loss due to crime activity is measured by the percentage of total annual sales that be damaged or lost because of crime activity. Top executives' experience is measured by years worked in the industry.

Table 2 Descriptive Statistics

Variable	Mean	Min	Max	S.D.	Skewness	Kurtosis	Obs.
TFP	1.6540	-1.5019	5.0781	0.6619	0.7226	4.8596	37,065
R&D	0.2784	0.0000	1.0000	0.4482	0.9889	1.9779	25,041
New Product	0.4439	0.0000	1.0000	0.4969	0.2258	1.0510	25,077
Tech	22.8561	0.0000	57.8000	15.8296	0.4086	2.2496	25,173
size	1.8207	1.0000	3.0000	0.7694	0.3181	1.7486	37,065
Ownership	2.0635	1.0000	3.0000	0.2638	2.7235	12.2306	36,582
Financial Constraint	1.5645	0.0000	4.0000	1.3411	0.3289	1.9010	35,763
Loss Crime	0.6451	0.0000	99.0000	3.4372	11.3774	186.1449	36,737
Mtime	2.6847	0.0000	4.7005	0.7453	-0.7753	7.3074	37,049
Tope	18.4545	0.0000	75.0000	11.2782	0.8088	3.3773	36,758
Investment	23.6813	9.8078	54.2726	7.3578	0.9441	4.3735	36,362
Popg	1.4454	-1.7452	6.5680	1.0270	0.5571	4.9197	37,065
Trade Open	64.2752	19.4588	183.4055	29.9916	1.4455	4.9845	36,822

Note: This table reports the summary statistics of all the key variables used in this study. The variable definitions are introduced in Table 1.

Table 3 Firm R&D and TFP

Variable	(1)	(2)
R&D	0.0325***	0.0331***
	(0.0111)	(0.0112)
New Product	-0.0279***	-0.0246**
	(0.0099)	(0.0100)
Size	0.0959***	0.0961***
	(0.0060)	(0.0061)
Ownership	0.0391**	0.0409**
	(0.0189)	(0.0191)
Financial Constraint	-0.0231***	-0.0230***
	(0.0037)	(0.0037)
Loss Crime	-0.0040***	-0.0040***
	(0.0014)	(0.0014)
Mtime	0.0083	0.0097
	(0.0072)	(0.0072)
Tope	-0.0015***	-0.0016***
	(0.0004)	(0.0004)
Investment		-0.0186***
		(0.0025)
Popg		0.0488***
		(0.0161)
Trade Open		0.0056***
		(0.0007)
Constant	0.0562	-0.1572
	(0.7122)	(0.7157)
Year	Yes	Yes
City	Yes	Yes
Obs.	24,263	23,965
R^2	0.1048	0.1097

Note: This table presents the regression results of estimating the impact of *R&D* on *TFP*. In columns (1) and (2), we report the regression results of excluding and including the country-level macro variables, respectively. Robust standard errors are in parentheses. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.

Table 4 The interaction between R&D and external technology environment

Variables	(1)	(2)
R&D	0.0816***	0.0818***
	(0.0242)	(0.0244)
Tech	-0.0273***	-0.0247**
	(0.0099)	(0.0100)
R&D Tech*	-0.0016**	-0.0016**
	(0.0007)	(0.0007)
New Product	-0.0063***	-0.0053***
	(0.0013)	(0.0014)
Size	0.0953***	0.0957***
	-0.006	-0.0061
Ownership	0.0416**	0.0423**
	-0.0188	-0.0191
Financial Constraint	-0.0235***	-0.0234***
	(0.0036)	(0.0037)
Loss Crime	-0.0039***	-0.0040***
	(0.0014)	(0.0014)
Mtime	0.0085	0.0098
	(0.0072)	(0.0072)
Tope	-0.0014***	-0.0016***
	(0.0004)	(0.0004)
Investment		-0.0189***
		(0.0025)
Popg		0.0540***
		(0.0161)
Trade Open		0.0052***
		(0.0007)
Constant	0.2365	-0.0054
	(0.7229)	(0.7266)
Year	Yes	Yes
City	Yes	Yes
Obs.	24,263	23,965
R^2	0.1060	0.1106

Note: In this table, we report the results of extending the baseline regression to incorporate external technology environment (denoted by *Tech*) and its interaction with R&D investment (denoted by *R&D* Tech*). In columns (1) and (2), we report the regression results of excluding and including the country-level macro variables, respectively. Robust standard errors are in parentheses. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.

Table 5 Heterogeneity Analysis: Firms in Countries with Different Income Level

Variable	Low-income Countries		Middle-income Countries		High-income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D	-0.0409	-0.0471	0.0352***	0.0368***	0.0513	0.0361
	(0.0508)	(0.0543)	(0.0118)	(0.0119)	(0.0414)	(0.0410)
New Product	-0.0459	-0.0568	-0.0289***	-0.0250**	0.0103	-0.0013
	(0.0454)	(0.0498)	(0.0108)	(0.0109)	(0.0305)	(0.0300)
Size	-0.0119	-0.0196	0.0944***	0.0926***	0.1444***	0.1585***
	(0.0282)	(0.0305)	(0.0065)	(0.0065)	(0.0199)	(0.0199)
Ownership	0.0253	0.0227	0.0356*	0.0403**	0.1078	0.0833
	(0.0743)	(0.0778)	(0.0200)	(0.0202)	(0.0730)	(0.0736)
Financial Constraint	-0.0076	0.0001	-0.0227***	-0.0227***	-0.0273**	-0.0295**
	(0.0160)	(0.0168)	(0.0039)	(0.0040)	(0.0122)	(0.0120)
Loss Crime	-0.0027	-0.0030	-0.0037**	-0.0035**	-0.0061**	-0.0077***
	(0.0095)	(0.0098)	(0.0015)	(0.0015)	(0.0027)	(0.0026)
Mtime	-0.0065	-0.0118	0.0094	0.0112	0.0061	0.0084
	(0.0329)	(0.0332)	(0.0077)	(0.0077)	(0.0268)	(0.0262)
Tope	-0.0007	-0.0014	-0.0014***	-0.0015***	-0.0019	-0.0022
	(0.0018)	(0.0020)	(0.0004)	(0.0004)	(0.0014)	(0.0014)
Investment		-0.0310		-0.0161***		-0.2435
		(0.0223)		(0.0026)		(0.5241)
Popg		0.4055*		-0.0458**		0.0104
		(0.2190)		(0.0214)		(0.4514)
Trade Open		0.0105**		0.0056***		0.0119
		(0.0050)		(0.0007)		(0.0410)
Constant	1.5173***	0.9838**	-0.0651	0.1082	1.2392***	8.4827
	(0.2025)	(0.4141)	(0.7138)	(0.7187)	(0.2565)	(16.1517)
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,106	1,020	20,714	20,502	2,443	2,443
R^2	0.2075	0.2181	0.0982	0.1023	0.1036	0.1235

Note: This table presents the baseline regression results of estimating the impact of *R&D* on *TFP* in different subsamples divided by country income levels. Robust standard errors are in parentheses. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.

Table 6 Heterogeneity Analysis: Firms with Different Ownership

Variable	State-owned Firms		Private Firms		Foreign Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D	-0.3479	-0.5297	0.0377***	0.0380***	0.0014	0.0072
	(0.4701)	(0.4859)	(0.0115)	(0.0115)	(0.0514)	(0.0525)
New	-0.5230	-0.8430*	-0.0301***	-0.0268***	0.0291	0.0350
Product	(0.4535)	(0.4656)	(0.0102)	(0.0103)	(0.0506)	(0.0519)
Size	0.0649	0.0733	0.0941***	0.0943***	0.1080***	0.1090***
	(0.1655)	(0.1683)	(0.0062)	(0.0062)	(0.0315)	(0.0323)
Financial	0.0002	-0.0343	-0.0227***	-0.0225***	-0.0183	-0.0195
Constraint	(0.1509)	(0.1592)	(0.0037)	(0.0038)	(0.0183)	(0.0188)
Loss Crime	0.2260***	0.1964***	-0.0038***	-0.0038***	-0.0143*	-0.0137*
	(0.0632)	(0.0631)	(0.0014)	(0.0014)	(0.0081)	(0.0081)
Mtime	-0.2564	-0.0788	0.0060	0.0074	0.0430	0.0453
	(0.3742)	(0.3859)	(0.0075)	(0.0075)	(0.0314)	(0.0317)
Tope	0.0131	0.0151	-0.0015***	-0.0017***	-0.0011	-0.0014
	(0.0110)	(0.0113)	(0.0004)	(0.0004)	(0.0020)	(0.0021)
Investment		0.0390		-0.0185***		-0.0235*
		(0.0912)		(0.0025)		(0.0139)
Popg		-0.0786		0.0475***		0.0912
		(0.8314)		(0.0166)		(0.0793)
Trade Open		-0.0360		0.0058***		0.0054*
		(0.0342)		(0.0007)		(0.0028)
Constant	2.5704*	4.9313	0.1380	-0.0758	1.4654***	1.4525***
	(1.3969)	(3.0133)	(0.7126)	(0.7161)	(0.3244)	(0.5545)
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	107	107	22,807	22,533	1,349	1,325
R^2	0.6875	0.6925	0.1008	0.1060	0.3060	0.3094

Note: This table presents the regression results of estimating the impact of *R&D* on *TFP* in different subsamples divided by corporate ownership types. Robust standard errors are in parentheses. * and *** denote statistical significance at the 10 and 1 percent levels, respectively.

Table 7 Instrumental Variable Analysis: First-stage Regression Results

Variable	(1)	(2)
Quality Cert	0.1085***	0.1091***
	(0.0072)	(0.0072)
New Product	0.2478***	0.2483***
	(0.0061)	(0.0062)
Size	0.0748***	0.0744***
	(0.0038)	(0.0039)
Ownership	0.0247**	0.0242**
	(0.0121)	(0.0122)
Financial Constraint	0.0029	0.0027
	(0.0022)	(0.0022)
Loss Crime	0.0024***	0.0024***
	(0.0008)	(0.0008)
Mtime	0.0119***	0.0121***
	(0.0041)	(0.0041)
Tope	0.0005**	0.0005**
	(0.0002)	(0.0002)
Investment		-0.0022
		(0.0014)
Popg		0.0041
		(0.0083)
Trade Open		-0.0001
		(0.0003)
Constant	0.2122	0.2150
	(0.3514)	(0.3526)
Year	Yes	Yes
City	Yes	Yes
Obs.	23,675	23,381
R^2	0.3032	0.3039

Note: This table reports the first-stage regression results. The dependent variable is *R&D* and the instrumental variable is *Quality Cert*, which is a dummy variable that equals to 1 if an enterprise has achieved quality certification in the last three years and 0 otherwise. We also include the same control variables in our baseline regression. In columns (1) and (2), we report the regression results of excluding and including the country-level macro variables, respectively. Robust standard errors are in parentheses. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.

Table 8 Instrumental Variable Analysis: Second-stage Regression Results

Variable	(1)	(2)
HatR&D	0.6898***	0.6692***
	(0.1123)	(0.1119)
New Product	-0.1947***	-0.1866***
	(0.0304)	(0.0304)
Size	0.0339***	0.0361***
	(0.0125)	(0.0125)
Ownership	0.0158	0.0191
	(0.0213)	(0.0215)
Financial Constraint	-0.0237***	-0.0233***
	(0.0039)	(0.0040)
Loss Crime	-0.0057***	-0.0056***
	(0.0014)	(0.0014)
Mtime	0.0002	0.0017
	(0.0078)	(0.0077)
Tope	-0.0019***	-0.0021***
	(0.0004)	(0.0004)
Investment		-0.0173***
		(0.0027)
Popg		0.0396**
		(0.0171)
Trade Open		0.0056***
		(0.0007)
Constant	-0.0306	-0.2204
	(0.9323)	(0.9280)
Year	Yes	Yes
City	Yes	Yes
Obs.	23,675	23,381
Weak Identification	229.773***	229.159***
Under Identification	228.491***	227.686***

Note: This table reports the second-stage regression results. The dependent variable is *TFP*, and the key independent variable, *HatR&D,* denotes the fitted value of *R&D* based on the first-stage regression results. In columns (1) and (2), we report the regression results of excluding and including the country-level macro variables, respectively. For the weak identification test, a Kleibergen-Paap Wald F statistic is reported. For the under identification test, a Kleibergen-Paap Wald LM statistic is reported. Robust standard errors are in parentheses. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.

Table 9 Regressions with PCT/PPH Policy Dummy

Variable	(1)	(2)
R&D	0.0331***	0.0151
	(0.0112)	(0.0145)
*Policy Dummy**		0.0360*
R&D		(0.0210)
New Product	-0.0246**	-0.0248**
	(0.0100)	(0.0100)
Size	0.0961***	0.0962***
	(0.0061)	(0.0061)
Ownership	0.0409**	0.0413**
	(0.0191)	(0.0191)
Financial	-0.0230***	-0.0230***
Constraint	(0.0037)	(0.0037)
Loss Crime	-0.0040***	-0.0040***
	(0.0014)	(0.0014)
Mtime	0.0097	0.0096
	(0.0072)	(0.0072)
Tope	-0.0016***	-0.0016***
	(0.0004)	(0.0004)
Investment	-0.0186***	-0.0187***
	(0.0025)	(0.0025)
Popg	0.0488***	0.0482***
	(0.0161)	(0.0161)
Trade Open	0.0056***	0.0056***
	(0.0007)	(0.0007)
Constant	-0.1572	-0.1516
	(0.7157)	(0.7220)
Year	Yes	Yes
City	Yes	Yes
Obs.	23,965	23,965
R^2	0.1097	0.1098

Note: This table reports the regression results of counting the impact of the PCT/PPH Policy. *Policy Dummy* is a dummy variable that takes the value 0 when the sample firm was surveyed before 2010, and it takes the value 1 otherwise, which is constructed according to the document "Pilot of Patent Prosecution Highway Program to use PCT Work Products", PCT Newsletter No. 12/2009 (http://www.wipo.int/edocs/pctndocs/en/2009/pct_news_2009_12.pdf). In column (1), we replicate the column (2) in Table 3 for comparison. In column (2), we report the results of incorporating the interaction term between *Policy Dummy* and *R&D*. Robust standard errors are in parentheses, *, ** and *** denote statistical significance at the 10, 5 and 1 percent levels, respectively.

Table 10 Robustness check: Alternative measure for *TFP*

Variable	(1)	(2)
R&D	0.0930***	0.0955***
	(0.0159)	(0.0161)
New Product	-0.0124	-0.0107
	(0.0139)	(0.0141)
Size	0.1190***	0.1179***
	(0.0086)	(0.0087)
Ownership	0.0993***	0.1022***
	(0.0278)	(0.0281)
Financial	-0.0384***	-0.0387***
Constraint	(0.0051)	(0.0052)
Loss Crime	-0.0081***	-0.0079***
	(0.0016)	(0.0016)
Mtime	0.0132	0.0137
	(0.0097)	(0.0097)
Tope	-0.0014**	-0.0014**
	(0.0006)	(0.0006)
Investment		0.0021
		(0.0033)
Popg		-0.0054
		(0.0198)
Trade Open		0.0029***
		(0.0009)
constant	0.1077	0.0238
	(0.9683)	(0.9716)
Year	Yes	Yes
City	Yes	Yes
Obs.	24,263	23,965
R^2	0.1347	0.1351

Note: This table reports the results of using an alternative TFP calculation approach, in which TFP is calculated with only capital and labor as inputs. In columns (1) and (2), we report the regression results of excluding and including the country-level macro variables, respectively. Robust standard errors are in parentheses. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.