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International Talent Inflow and R&D Investment: Firm-level Evidence from China*

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Abstract: Using firm-level R&D data with regional international talent data, we find that international talent increases the R&D investment of Chinese manufacturing firms, a result that is further confirmed with patent data and under a number of robustness checks. These findings stem from two mechanisms: international talent boosts human capital accumulation and provides a diversified labor force. Further, the R&D promoting effect is stronger if firms are located in eastern China rather than in other regions, of small and medium-sized rather than large-sized, of domestic ownership rather than foreign ownership. The policy implication is, the introduction of international talent can be a new way to promoting R&D investment, especially for skilled-labor constrained countries.

Keywords: International talent inflow, manufacturing firms, R&D, patent application
JEL Classification: F16; F22; O32

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1. Introduction

The international mobility of the labor force is one of the most important elements of globalization [WTO, 2008; *United Nations* (UN), 2013; *Organization for Economic Cooperation and Development* (OECD), 2016]. Riding on this wave, China became an official member of the *International Organization for Migration* (IOM) in 2016, and in recent years, it has experienced a rapid growth of immigration. By the end of 2017, the immigration stock in China reached nearly 1 million, having increased by 2.34% annually from 2010, higher than the global average growth rate of 1.89%.[2] Meanwhile, a substantial literature has documented that immigration can exert multiple economic impacts on the receiving countries, such as on trade (Gould, 1994; Rauch and Trindade, 2002; Bastos and Silva, 2012), on foreign direct investment (FDI) (Cuadros et al., 2016; Tomohara, 2017), and on the labor market (Edo and Toubal, 2017; Martins et al., 2018).

Different from the existing literature, in this paper, we aim to provide some evidence on the impact of international talent inflow (ITI), i.e., skilled or educated immigration, on firms' innovation activities, using both research and development (R&D) data and patent data from China. Globalization has intensified the competition for technology, in which the "*war for talent*" has become a key element. The development of knowledge economies requires a more highly skilled labor force which, due to population aging and declining interest of native youth in the hard sciences, will not be available in sufficient numbers; thus, skilled immigrants are needed to fill the gaps. Possessed with a bilingual background, highly skilled migrants play a vital role in the process of knowledge transfer across borders, and their importance is growing as technology becomes more biased towards skilled labor (UN, 2013; Mallick and Sousa, 2017). Therefore, it is important to focus on a special driver of economic growth, namely innovation, and investigate how international talent affects the R&D investment of Chinese manufacturing firms.

Specifically, we combine firm-level R&D data with regional international talent

[2] The data are derived from IOM, and calculated by the authors. Details of the data can be found at https://migrationdataportal.org.

data from 2004 to 2007, and also longer-term patent data between 2004 and 2013,[3] and examine the impact of ITI on firms' R&D investment in China. The results indicate that ITI increases the R&D investment of Chinese manufacturing firms, and the promoting effect is stronger if the firms are located in eastern China. Further, ITI increases the R&D investment of small and medium-sized firms (SMEs) more than large-sized firms, and increases the R&D investment of domestic firms but not foreign firms. In addition, using patent data, we confirm the positive effect of ITI on firm-level innovation. These findings suggest that the introduction of international talent is a new way to promoting firm-level R&D investment, and it is especially important for SMEs and domestic firms which are more resource constrained.

In the theoretical literature, several mechanisms, such as a human capital accumulation effect and a labor force diversity effect, have been posited to explain the influence of immigration on innovation. On the one hand, the former effect states that ITI increases the number of research workers and enriches the local knowledge base, thereby raising R&D investment (Pholphirul and Rukumnuaykit, 2017, Maré et al., 2014). On the other hand, the latter effect says that ITI may increase the firm's communication costs since the labor force becomes more diverse (Ozgen et al., 2014). Thus we can theoretically expect either a positive or a negative R&D effect, depending on individual characteristics and host country characteristics (Liu et al., 2010; Pholphirul and Rukumnuaykit, 2017).

Meanwhile, the empirical findings on the link between immigration and innovation are mixed, especially in the context of a developing country. Existing studies have largely focused on developed countries, such as the United States (Chellaraj et al., 2008; Akcigit et al., 2017), the European Union (Fassio et al., 2019), the United Kingdom (Gagliardi, 2015), Germany (Jahn and Steinhardt, 2016) or Sweden (Maré et al., 2014; Zheng and Ejermo, 2015). Although most of these studies on have identified a positive effect, some have drawn opposite conclusions (Jahn and Steinhardt, 2016; Bratti and Conti, 2018).

[3] The R&D data is only available up to 2007.

The case of China is especially interesting, because it is surrounded by less developed neighbors and is obviously different from developed countries in terms of the labor market and innovation environment, such as the lack of a skilled labor force and weak intellectual property rights protection, etc. Our study contributes to the literature in three ways: *First*, we focus on the R&D effect of ITI in the context of a developing country—China, thereby complementing the existing studies which mainly investigate the influence of human mobility on patents (Liu et al., 2010; Filatotchev et al., 2011), on knowledge transfer across borders (Liu et al., 2015), and on outward FDI (Gao et al., 2013). *Second*, while the existing studies are based on State-level panel data (Faggian and McCann, 2009; Ozgen et al., 2014; Jahn and Steinhardt, 2016; Bratti and Conti, 2018), industry-level data (Fassio et al., 2019), time-series data (Chellaraj et al., 2008), cross-section survey data (Filatotchev et al., 2011; Liu et al., 2010; Gagliardi, 2015), or individual interview data (Liu et al., 2015; Zheng and Ejermo, 2015), we use a detailed and unbalanced panel database with rich information on 338,242 Chinese manufacturing firms from 2004 to 2007. It not only has a large number of observations, but also includes both the time dimension and the cross-section dimension. Moreover, by using such rich information, we examine comprehensively the R&D effect of ITI from the perspectives of firm heterogeneity as well as regional differences. This allows us to obtain more detailed results that can help to make practical advice for firms and the government. In addition, we confirm the positive innovation effect of ITI, using a longer-term *patent data* between 2004 and 2013. *Third,* to address potential endogeneity, we adopt a "shift-share" instrument variable (IV) approach to overcome the potential bias of endogenous location decisions. The IV is calculated based on the historical distribution of ITI among regions in China and hence is exogenous to the current regional characteristics. *Forth*, the firm-level R&D investment data contain numerous zeros. A logarithmic normalization would lead to potential selection bias, which we tackle with transformed measures following Liu and Qiu (2016). These empirical strategies enable us to obtain more persuasive conclusions.

The rest of this paper is organized as follows. Section 2 is the literature review.

Section 3 presents the theoretical analysis. Section 4 explains our econometric model and data. The empirical results are presented in Section 5. Section 6 provides robustness checks. Section 7 is a further analysis using patent data. Finally, section 8 concludes our main findings and proposes policy suggestions.

2. Literature Review

Since the seminal work of Gould (1994), extensive research has examined the positive relationship between trade, FDI, and international migration (Rauch and Trindade, 2002; Bastos and Silva, 2012; Cuadros et al., 2016; Tomohara, 2017). Most of these studies have focused on the role of immigration in transferring transnational business information. The mechanisms can be summarized as a human capital accumulation effect and a labor force diversity effect.

The former effect includes two specific aspects in increasing the number of research workers and enriching the local knowledge base. *First*, there exists self-selection in that the migrants may be more skilled and less risk-averse (Ozgen et al., 2014). High-skilled immigrants can work as research workers; they are key inputs of innovation (Pholphirul and Rukumnuaykit, 2017). If R&D activities in the host country are constrained by a scarcity of skilled workers, the introduction of international talent might result in an increase in the R&D investment of local firms (Ozgen et al., 2014). That is to say, there is a complementary effect from firms hiring more high-skilled immigrants and investing in high technology (Pholphirul and Rukumnuaykit, 2017). *Second*, immigrants may introduce knowledge and skills that are not otherwise readily accessible locally (Maré et al., 2014). Human capital, such as skills and abilities, provides the basis for a firm's innovative ability (Storz et al., 2014). In the modern knowledge economy, technological change is an endogenous process, in which human resources play a central role in knowledge production (Lucas, 1988). The gains from immigration should be greatest if the immigrants and the local workers have information sets that do not overlap but are relevant to one another, because individuals can learn a great deal from each other (Niebuhr, 2010). Therefore, immigration can not only introduce foreign knowledge and skills to the host country but also generates new knowledge, thus promoting the increase of a firm's R&D investment (Maré et al., 2014; Parrotta et al., 2014; Pholphirul and Rukumnuaykit, 2017).

Regarding the labor force diversification effect, immigration increases the labor diversity and exerts an uncertain impact on firms' R&D investment in the host country. On the one hand, people born in different countries may possess diverse skills because they have been educated in different school systems and exposed to different experiences and cultures (Ozgen et al., 2014). The nature of R&D activity is the interaction between different workers and different ideas and abilities (Niebuhr, 2010). Hence, international talent provides diverse perspectives, valuable ideas, and problem-solving abilities which can enhance the creativity of local firms. Moreover, employees from different ethnic backgrounds may stimulate a firm to either improve or develop new products, as they also possess knowledge about global markets and foreign customers' tastes, resulting in an increase of R&D investment (Parrotta et al., 2014). On the other hand, the labor diversity increases communication costs, hinders the communication between employees, and can even lead to social tensions, thus impeding firms' R&D activities (Ozgen et al., 2014; Niebuhr, 2010).

Also, Gagliardi (2015) holds that immigration not only provides a new way for local firms to acquire tacit knowledge but also creates an external environment conducive to innovation. Ozgen et al. (2014) believe that immigration facilitates the matching between available skills and job requirements in the labor market. Greater complementarity between physical and human capital is beneficial to local innovation (Quigley, 1998). However, the impact of immigration also varies in terms of migration characteristics. For example, Liu et al. (2010), Scellato et al. (2015) and Filatotchev et al. (2011) focus on high-skilled immigrants, such as entrepreneur migrants, migrant scientists, and international students. Their conclusions indicate the importance of occupation in shaping the innovation effect of immigration. In contrast, Pholphirul and Rukumnuaykit (2017) study unskilled immigration from developing countries and find differentiated roles of skilled and unskilled immigration in determining the R&D investment of firms in Thailand.

Finally, firm and industry heterogeneity also plays a role. A few studies examine the role of firm location, size, ownership, and industry characteristics in determining the R&D effect of immigration. Faggian and McCann (2009) explore the relationship between the inter-regional mobility of human capital and the innovation of 36 U.K. areas, and find that human capital inflow has a stronger promoting effect on innovation in high-tech sectors. Maré et al. (2014) examine firms in New Zealand, and show that the R&D promoting effect is stronger on medium-sized firms and firms located in larger urban areas. Pholphirul and Rukumnuaykit (2017) find that unskilled immigration decrease significantly the R&D investment of the textile industry and domestic firms in Thailand.

In summary, existing studies reveal the relationship between international migration and firms' innovation from various perspectives. In contrast, in the present paper we match the micro-data of Chinese manufacturing firms with regional international talent data from 2004 to 2007, and study the impact of ITI on firm-level R&D investment. We also compare the different effects in terms of regional and firm heterogeneity. In addition, we confirm the positive innovation effect of ITI by using firm-level *patent data* from 2004 to 2013.

3. Theoretical Analysis

We refer to Barro and Sala-i-Martin (2004) and Borensztein et al. (1998), and assume there are two sectors in the economy: the final output sector and the R&D sector.

3.1. The final output sector

The economy produces a single final consumption good Y, where the representative firm's production function is

$$Y_t = AL_t^{\alpha} X_t^{1-\alpha} \tag{1}$$

where A is the exogenous state of the 'environment', L_t denotes the skilled labor force at time t, and X_t stands for technology endowment. Borrowing from Borensztein et al. (1998), who decompose physical capital into domestic and foreign physical capital, in this paper we divide the skilled labor force into domestic (denoted as l_t) and foreign skilled workers (denoted as l_t^*), and $L_t = l_t + l_t^*$.

The technology endowment consists of an aggregate of different varieties of technical inputs, which can be interpreted as new types of machines;

$$X_t = \left(\int_0^{N_t} x_t(j)^{1-\alpha} dj \right)^{\frac{1}{1-\alpha}} \tag{2}$$

In formula (2), N_t is the total number of machine varieties, $x_t(j)$ is demand for each variety. A higher X_t indicates more R&D investment for the representative firm.

3.2. The R&D sector

The specialized R&D sector conducts innovation activities, which requires a constant cost F in producing a new type of machine. When a new machine is produced, it is licensed to the final production sector, following the optimal condition that the rental price equals the marginal productivity;

$$m_t(j) = A(1-\alpha)L_t^{\alpha} x_t(j)^{-\alpha} \tag{3}$$

Also, once a new machine is introduced, the owner must spend a constant maintenance cost, which is assumed to be 1 for simplicity. At time t, the profit stream of the R&D sector from developing each variety of machine can be expressed as

$$\Pi(j)_t = \int_t^{\infty} [m_t(j) - 1] x_t(j) e^{-r(s-t)} ds - F \tag{4}$$

where r is the interest rate, and $e^{-r(s-t)}$ refers to a present-value factor that converts a unit of income at time s to an equivalent unit of income at time t.

Maximizing (4) subject to (3), we derive the equilibrium level of each variety of machines $x_t(j)$:

$$x_t(j) = L_t A^{1/\alpha} (1-\alpha)^{2/\alpha} \tag{5}$$

Plugging (5) into (2), we obtain the optimal input of technology endowment:

$$X_t = L_t A^{1/\alpha} (1-\alpha)^{2/\alpha} N_t^{\frac{1}{1-\alpha}} = (l_t + l_t^*) A^{1/\alpha} (1-\alpha)^{2/\alpha} N_t^{\frac{1}{1-\alpha}} \tag{6}$$

From Eq. (6), we find that the optimal input of technology endowments (X_t) depends positively on the amount of international talent (l_t^*). This indicates that the more international talent in the local firm, the greater its effect on its R&D investment. That is to say, even if the number of domestic skilled workers (l_t) remains unchanged, the ITI increases the total number of skilled workers (L), thus promoting the R&D investment of the local firms.

While an increase in domestic skilled workers is also conducive to R&D investment, we focus on international talent (l_t^*) for the following two reasons: *First*, from the reality of China, the amount of domestic skilled labor may not satisfy the needs for innovative firms. A knowledge-based society relies on a highly qualified labor force not only in high-tech sectors, but also increasingly in all sectors of the economy and society. However, the loss of skilled people engenders concerns about shortages and brain drain, particularly in developing countries (OECD, 2017). This problem may be more serious in China whose working-age population is shrinking, and the elderly, dependent population is growing fast. In this case, China may increasingly compete for particular skills to fill gaps in its labor market (OECD, 2019). Therefore, it is reasonable to assume that the amount of domestic skilled labor force is given and may be lower than the demand from Chinese firms.

Second, ITI plays an irreplaceable role in promoting firms' R&D investment in the host countries, by bringing in knowledge, skills, and personal networks that are different from local workers. Diversified perspectives, valuable ideas and problem-solving abilities encourage firms to invest in R&D activities (Niebuhr, 2010; Ozgen et al., 2014). Due to their uniqueness, domestic firms may prefer to hire ITI rather than increases continuously domestic employment.

4. Econometric Model and Data

4.1. Related definitions

We focus on the effect of ITI on the R&D investment of Chinese manufacturing firms. Talent is a very broad concept that can be divided into five categories (Mahroum, 2000; Wei, 2013); they are: (1) managers & executives, (2) engineers & technicians, (3) academics & scientists, (4) entrepreneurs, and (5) students. For our purpose, ideally it would be best to use the employment data of foreign workers in

China. But because this data is unavailable, we use a proxy instead--international students with a college level of education. In fact, some international organizations and economists also use international students to represent international talent (OECD, 2009; Haupt et al., 2016). Further detailed reasons are as follows:

First, international students are the main component of ITI in China. On the one hand, the number of entrepreneur migrants and migrant scientists introduced by China is rather small. Before 2008, there were only a handful of outstanding foreign scholars who worked in China. In 2008, China proposed the *Recruitment Program of Global Experts* (1000 Scholars Plan). It is the most important special project designed to attract overseas high-end talent. Since then, China has experienced rapid growth of global “sophisticated” talent inflow. By the end of 2017, the Chinese government had successfully introduced 7,016 overseas high-level talented workers through the plan. However, migrant entrepreneurs and migrant scientists still constitute a small part of the international talent in China. If we average over the “province-year” dimension, the figure would be even smaller. On the other hand, compared with international students, the number of foreign teachers is also relatively small. They account for about 1/10 of international students in each year. As such, international students constitute the major part of international talent in China.

Second, besides international students, there is no other official data on international talent in China. At present, China has not yet published official statistics on ITI at the provincial level. In addition, there is no regional international talent data from the official databases of international organizations, such as IOM, OECD, and UN. Due to these data limitations, we cannot study empirically the impact of other types of international talent on Chinese firms’ R&D investment.

Third, in practice, it is common for international students in China to participate in the local labor market by taking part-time jobs, despite some employment restrictions. A survey in Beijing shows that approximately 58% of international students have sought a part-time job (Han, 2014), among whom approximately 79% are engaged in skilled white-collar occupations. Some even participate in management activities of Chinese firms. According to another survey in 2017, approximately 86.1% of international students plan to have a short-term internship in China, and approximately 95% of international students show a desire to work in China after graduation.[4] Thus it seems that most international students participate in the business activities of Chinese firms by taking part-time jobs, and this phenomenon is becoming more and more common.

4.2. Econometric model

We draw upon Gagliardi (2015) and Baumann and Kritikos (2016), and set up the following econometric model,

$$RD_{it} = \delta_0 + \delta_1 \ln student_{kt} + \varphi Z_{it} + \theta P_{kt} + \gamma_j + \gamma_k + \gamma_t + \varepsilon_{it} \tag{7}$$

where Z_{it} stands for a set of control variables at the firm-level; P_{kt} stands for controls at the province-level; γ_j, γ_k, γ_t, respectively, stand for industry, region and year fixed effects; and ε_{it} is the error term. The specification of variables follows.

(1) *Dependent variable*. Our dependent variable is the R&D investment of firm *i* in year *t*. However, most Chinese manufacturing firms do not conduct R&D activities, resulting in a zero-inflated explanatory variable. To deal with this issue, we follow Liu and Qiu (2016) and use a transformed measure as our dependent variable: $\ln RD_{it} = \ln[RD_{it} + (RD_{it}{}^2 + 1)^{1/2}]$. This transformation allows us to keep all observations of zero R&D investment. Also, as a robustness check, we use another log-like transformation to test our results, $\ln(RD_{it} + 1)$.

(2) *Independent variable* ($\ln talent_{kt}$). Following Wei (2013), we use the international students in province *k* in year *t* to measure the regional amount of ITI.

(3) *Control variables*. R&D activities can be affected by the firm-level characteristics and geographical characteristics (Gagliardi, 2015). We thus choose controlled variables from two perspectives: firm characteristics and regional labor market characteristics.

(*i*) *Variables of firm characteristics*

(*a*) Firm size ($size_{it}$). We use the logarithm of net fixed assets to measure the firm size. While firm size has an ambiguous impact on R&D in the literature (Cohen and

[4] People's Daily (Overseas Edition), Overseas students in China: "Working in China is a good choice," 4/28/ 2017.

Klepper, 1996; Acs and Audrestch, 1990), we examine it using Chinese data.

(*b*) Firm age (*age*$_{it}$). The firm age is calculated by the difference between the year of establishment and the statistical year. Older firms have more experience in production and management activities. They tend to spend more on R&D activities than younger firms (Pholphirul and Rukumnuaykit, 2017).

(*c*) Firm profitability (*profit*$_{it}$). We measure the profitability of a firm as the ratio of operating profits to its gross sales. A higher profitability may encourage the firm to engage in more R&D activities.

(*d*) Export (*export*$_{it}$). We use a dummy variable to control the impact of export on a firm's R&D investment. If a firm's export value is greater than zero, the dummy variable takes a value of 1; otherwise, it is 0. On average, export firms have a shorter distance to the technological frontier (Bournakis and Mallick, 2018).

(*e*) Relationship with the government (*subsidy*$_{it}$). We use a dummy variable, whether a firm can acquire a subsidized income, to reflect its contact with the government. If the subsidy is greater than zero, the dummy variable takes the value of 1; otherwise, it is 0. Government incentives and the access to financing seem to be effective tools in promoting R&D activities (Pholphirul and Rukumnuaykit, 2017).

(*f*) Financial constraints (*interest*$_{it}$). We use a dummy variable, whether a firm pays for an interest, to reflect its financial constraints. If the interest expenditure is bigger than zero, the dummy takes the value of 1; otherwise, it is 0. Innovation requires a large amount of upfront investment. External financing is increasingly becoming an important source of R&D investment.

(*ii*) *Variables of regional labor market characteristics*

Referring to Maré et al. (2014), Gagliardi (2015), and Pholphirul and Rukumnuaykit (2017), we choose the following control variables to reflect the characteristics of the local labor market.

(a) Human capital stock (*human*$_{kt}$). Following Barro and Lee (2013), we choose the educational attainment of the local labor force to measure the human capital stock in each province. We assign the education years of primary school, junior high school, senior high school, college and above as being 6, 9, 12, and 16, respectively. Each of these is multiplied by its proportion (denoted as H_1, H_2, H_3, H_4, respectively) in the total labor force. The formula is expressed as $human = 6H_1 + 9H_2 + 12H_3 + 16H_4$.

(*b*) Unemployment rate (*unemployment*$_{kt}$). We use the long-term unemployment rate to reflect the employment level of the local labor market. It reflects the possibility of obtaining new information and human resources through the employment mechanism, which can affect firms' R&D activities (Faggian and McCann, 2009).

(*c*) Population density (*density*$_{kt}$). We measure the local population density by the ratio of total population to the land area. The population density is closely related to the diversity of the workforce. A high degree of heterogeneity among workers can be a source of creativity, while it can also induce misunderstanding and uncooperative behaviors within workplaces (Parrotta et al., 2014).

4.3. Endogeneity issues

The main challenge of our baseline econometric model is related to the endogeneity problem. *First*, the ITI may be correlated with other regional factors which are related to firms' R&D investment, such as initial knowledge base of a region (Faggian and McCann, 2009). If these factors are omitted, their effects on firms' R&D investment are included in the error term, causing an endogenous problem. To address this, we include region fixed effects in all regressions (Gagliardi, 2015; Chen et al., 2017).

Second, there may be a reverse causality relationship between ITI and R&D investment. A large literature explores the economic impacts of immigration based on their location choice. However, immigrants do not choose their destinations randomly, rather, they are attracted to areas with more favorable conditions (Jaeger, 2007). For this reason, the baseline econometric model may suffer from the endogenous problem (Altonji and Card, 1991; Card, 2001). In our paper, international talent may be attracted to regions with considerable R&D activities, since the return on their higher education is higher than in other areas. To deal with this bias, we use the "*shift-share*" IV, which is a common approach used widely for the study of international migration (Card, 2001; Jaeger et al., 2018).

The "*shift-share*" IV is calculated as:

$$\hat{ITI}_{kt} = \frac{ITI_{k2003}}{\sum_{k} ITI_{k2003}} \times ITI_t \tag{8}$$

In formula (8), ITI_{k2003} refers to the amount of ITI in province k in 2003. ITI_t is the total amount of ITI in China in year t. $\hat{ITI}_{kt}$ is the calculated ITI in province k in year t, referring to the regional distribution of ITI.

The main intuition behind this approach is as follows: on the one hand, the initial share of ITI in each province is relevant to subsequent arrivals because international talent tends to be attracted by former immigrants (Hunt and Gauthier-Loiselle; 2010). On the other hand, the regional distribution is determined by the historical pattern, and is exogenous to the current regional characteristics (Card, 2001; Gagliardi, 2015).

4.4. Data description

There are two main sources of our data. First, the firm-level data come from the *Annual Survey of Industrial Firms* (ASIF). This annual survey is conducted by the *National Bureau of Statistics of China* (NBS). It surveys all State-owned firms and non-State-owned firms whose sales are above five million RMB. Our database covers 338,242 manufacturing firms from 2004 to 2007.[5] Second, the international student data are from the *Educational Statistics Yearbook of China*, published by the China Ministry of Education. Other data are derived from the *China Labor Statistical Yearbook*, the *China Statistical Yearbook for Regional Economy*, and the *China Statistical Yearbook*. Table 1 provides the summary statistics of the major variables.

Table 1 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln*RD*	927356	0.9262	2.3692	0	9.7574
ln*talent*	927356	7.6847	0.9920	3.9318	10.1780
size	927356	8.2593	1.6622	3.5835	12.6088
age	927356	9.1540	8.9278	1	51
export	927356	0.2875	0.4526	0	1
subsidiary	927356	0.1368	0.3436	0	1
interest	927356	0.6636	0.4725	0	1

[5] Our R&D data end in 2007 due to missing data in other years.

profit	927356	0.0570	0.0643	0	0.3277
human	927356	8.7676	0.9274	4.006	11.8936
unemployment	927356	3.6072	0.7111	1.3	6.5
density	927356	0.0583	0.0521	0.0002	0.2930

5. Empirical Results and Analysis

5.1. Baseline regression results

We start by estimating the model on the full sample, and then conduct a number of further analysis and robustness checks. Columns (1) and (3) in Table 2 report the OLS estimation results for the effect of ITI on firms' R&D investment. In column (3), the estimated coefficient is positive and statistically significant at the 1% level. However, the OLS estimation is biased due to endogeneity. Then, columns (2) and (4) report the 2SLS estimation results, where the coefficient of ITI remains significantly positive, implying ITI significantly increases the firm R&D investment. On average, a 1% increase in ITI leads to a 0.079% increase in investment.

These results are in line with the literature that ITI increases the number of research workers, enriches the local knowledge base and provides differentiated skills, and thus boosting the R&D investment in the host country (Ozgen et al., 2014; Maré et al., 2014), and they also indicate that the R&D effect is not dominated by the negative effect of labor diversity. On the one hand, as China's working age population shrinks, the supply of local skilled workers cannot satisfy the demand of Chinese firms for their R&D activities (OECD, 2019). Furthermore, international talent often belongs to the well-off and well-educated classes from the origin countries (Murat, 2014), and communication costs that arise due to language barriers might be lower among employees with a university degree (Niebuhr, 2011). Therefore, the negative effect resulting from labor diversity tend to be weaker on firms' R&D investment.

Table 2: Baseline results of ITI on firms' R&D investment

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
ln*talent*	0.09810^{***}	0.09534^{***}	0.07606^{***}	0.07933^{***}
	(35.72)	(33.99)	(19.02)	(18.94)

size	0.28428***	0.28423***	0.28822***	0.28824***
	(166.54)	(166.52)	(167.09)	(167.12)
age	0.02123***	0.02123***	0.02153***	0.02153***
	(65.09)	(65.10)	(65.54)	(65.54)
export	0.33842***	0.33863***	0.33083***	0.33082***
	(57.99)	(58.03)	(56.04)	(56.04)
subsidy	0.74166***	0.74180***	0.74173***	0.74185***
	(87.02)	(87.04)	(85.50)	(85.51)
interest	0.28171***	0.28146***	0.27512***	0.27506***
	(65.68)	(65.62)	(63.42)	(63.40)
profit	0.82937***	0.82913***	0.85746***	0.85735***
	(28.54)	(28.54)	(29.06)	(29.06)
human			0.25041***	0.24735***
			(29.46)	(29.41)
unemployment			0.07964***	0.08044***
			(14.66)	(14.70)
density			-3.74778***	-3.74075***
			(-31.11)	(-31.17)
Constant	-1.57882***	-1.56174***	-3.62852***	-3.62854***
	(-44.35)	(-43.68)	(-46.66)	(-46.67)
Industry fixed effects	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	940699	940699	927356	927356
R square	0.16488	0.16488	0.16609	0.16609

Notes: The asterisks, *, **, and ***, indicate that the coefficients are significant at the 10%, 5% and 1% levels, respectively. *t* values are in parentheses. Unless otherwise explained, the following tables use the same notation.

5.2. Geographical distribution and the R&D effect of ITI

As in many countries, ITI is also concentrated geographically in specific regions within China, resulting in significant variations in the workers and skills available to firms. Here we estimate the model separately for firms in eastern, central, and western China to allow for heterogeneous effects among regions.[6]

Table 3 presents the results. In columns (1) and (3), the OLS estimation results show that the coefficients are positive and statistically significant; but in column (5), the coefficient turns significantly negative. To avoid the endogeneity problem, we also

[6] Eastern China includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan. Central China includes 8 provinces: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan. Western China includes 12 provinces: Inner Mongolia, Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Tibet, Shaanxi, Gansu, Ningxia, Qinghai and Xinjiang.

report the results of 2SLS estimation, which show that the coefficients are all positive in each sub-sample but are statistically significant in only column (2). Based on the 2SLS regression result in column (2), on average, a 1% increase in ITI leads to a 0.167% increase in firms' R&D investment in eastern China.

Some explanations follow. The R&D effect is stronger on firms that are located in eastern China where the international talent is concentrated, about 70% of the total in the whole country. Innovation is the outcome of interaction between human capital and knowledge spillovers, which tends to be more obvious in eastern China than in other areas. On the one hand, ITI concentration provides eastern firms with more talent. On the other hand, the spillover effect of knowledge is constrained spatially due to the time delay and distortion in spreading (Baptista and Swann, 1998). The agglomeration of Chinese firms in eastern China creates an external environment that is conducive to R&D activities (Faggian and McCann, 2009), providing more opportunities for innovation through face-to-face contacts, which can facilitate the spread of knowledge among firms.

Table 3: Geographical distribution and heterogeneous effects of ITI

	Eastern		Central		Western	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln*talent*	0.24600***	0.16703***	0.02299*	0.01490	-0.03981***	0.00167
	(22.31)	(11.80)	(1.95)	(1.17)	(-3.66)	(0.13)
size	0.27626***	0.27616***	0.31968***	0.31975***	0.35263***	0.35235***
	(139.27)	(139.24)	(70.59)	(70.62)	(63.77)	(63.72)
age	0.02128***	0.02133***	0.01810***	0.01810***	0.02126***	0.02118***
	(50.96)	(51.12)	(26.71)	(26.70)	(25.28)	(25.17)
export	0.29838***	0.29777***	0.54553***	0.54523***	1.06801***	1.06713***
	(47.10)	(47.00)	(27.82)	(27.80)	(30.01)	(29.99)
subsidy	0.73980***	0.73730***	0.84218***	0.84235***	0.54106***	0.54560***
	(73.65)	(73.37)	(34.20)	(34.22)	(22.61)	(22.81)
interest	0.27690***	0.27678***	0.21828***	0.21820***	0.20012***	0.19975***
	(56.07)	(56.05)	(19.22)	(19.21)	(12.66)	(12.64)
profit	0.84128***	0.83388***	0.86697***	0.86333***	1.23261***	1.22206***
	(23.03)	(22.84)	(12.43)	(12.36)	(16.27)	(16.12)
human	0.28922***	0.33538***	0.02656	0.02108	0.19915***	0.14654***
	(22.39)	(24.73)	(0.60)	(0.47)	(7.49)	(5.14)

unemployment	0.13712***	0.08365***	0.38801***	0.38490***	-0.05782	-0.08919*
	(11.90)	(6.07)	(10.38)	(10.27)	(-1.12)	(-1.74)
density	-5.57807***	-5.40572***	-1.74127	-1.79535	-8.80753***	-5.25506**
	(-33.96)	(-32.23)	(-1.47)	(-1.52)	(-3.62)	(-2.12)
Constant	-6.18576***	-5.85949***	-3.64357***	-3.54815***	-2.06276***	-1.89712***
	(-50.32)	(-44.24)	(-6.57)	(-6.32)	(-11.05)	(-10.05)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	704926	704926	134790	134790	87640	87640
R square	0.15962	0.15954	0.17586	0.17586	0.23973	0.23959

5.3. Firm heterogeneity and the R&D effect of ITI

In addition to regional difference, the R&D investment varies according to firm-level characteristics, such as firm ownership and size and industry characteristics.

5.3.1. Firm ownership

Foreign firms may have more chances to cooperate with a foreign partner (Pholphirul and Rukumnuaykit, 2017). By contrast, domestic firms rely more on the diversified knowledge and ideas brought by ITI. In this regard, we now compare the R&D effect of ITI on firms under different ownership. We classify the sample into State-owned (SOEs), private-owned (POEs), Hong Kong, Macao, & Taiwan-owned (HMTs) and foreign-owned firms (FOEs). The criterion is that the paid-in capital received from each type of investors accounts for more than 50% of the total capital.

The empirical results are shown in Table 4. In the 2SLS regressions, the coefficients of ITI are positive and statistically significant in all sub-samples, except for column (8). There are obvious differences in the impacts on firms of different ownership: on average, a 1% increase in ITI leads to, respectively, a 0.10%, 0.090% and 0.172% increase in R&D investment of SOEs, POEs, and HMTs. In contrast, no evidence is found of any significant effect on the R&D investment of FOEs.

These findings indicate that ITI can help to relax the resource constraints (such as technology and skilled workers) of domestic firms (i.e. SOEs, POEs, and HMTs), thus increasing firms' R&D investment. The shortage of R&D resources and the lack of foreign cooperation chances hinder domestic firms to invest in innovative activities. As such, ITI induces domestic firms to engage more in innovative activities by providing extra R&D resources. In contrast, the effect is negative or not obvious on foreign firms. For most foreign firms in China, the production technology is generally imported from abroad rather than developed locally. Foreign firms aim mainly at exploring the Chinese consumer market and making use of China's production advantages for mass production. That is, China acts as a processing and assembling center and also a sales center, rather than an R&D center.

Table 4: Firm ownership and heterogeneous effects of ITI

	State-owned		Private-owned		HMT-owned		Foreign-owned	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln*talent*	0.09925***	0.09959***	0.08563***	0.08970***	0.13564***	0.17268***	0.04361**	-0.00066
	(6.34)	(5.92)	(15.87)	(15.85)	(6.23)	(7.64)	(2.11)	(-0.03)
size	0.47180***	0.47180***	0.21822***	0.21826***	0.24551***	0.24542***	0.27818***	0.27854***
	(55.24)	(55.28)	(88.79)	(88.81)	(41.96)	(41.96)	(49.51)	(49.58)
age	0.00732***	0.00732***	0.01817***	0.01816***	0.00960***	0.00957***	0.03136***	0.03135***
	(7.77)	(7.78)	(35.75)	(35.73)	(5.56)	(5.54)	(16.40)	(16.39)
export	1.29093***	1.29089***	0.34748***	0.34758***	0.09026***	0.08999***	0.13550***	0.13681***
	(25.59)	(25.60)	(39.88)	(39.90)	(5.13)	(5.11)	(7.29)	(7.36)
subsidy	0.77107***	0.77109***	0.74229***	0.74250***	0.64281***	0.64433***	0.66220***	0.65946***
	(18.52)	(18.54)	(59.58)	(59.60)	(20.38)	(20.44)	(21.51)	(21.43)
interest	0.42804***	0.42802***	0.18030***	0.18027***	0.32080***	0.31971***	0.42958***	0.43040***
	(14.09)	(14.10)	(31.82)	(31.81)	(20.66)	(20.59)	(24.94)	(25.00)
profit	1.49423***	1.49420***	1.07691***	1.07758***	0.83942***	0.83895***	0.85736***	0.85909***
	(16.02)	(16.03)	(22.65)	(22.67)	(9.11)	(9.11)	(10.74)	(10.77)
human	0.37367***	0.37327***	0.18976***	0.18624***	0.35124***	0.33455***	0.34846***	0.38363***
	(9.57)	(9.43)	(16.24)	(16.20)	(7.11)	(6.91)	(8.72)	(9.68)
unemployment	0.07649***	0.07650***	0.03143***	0.03258***	0.23633***	0.25449***	0.14976***	0.13483***
	(2.86)	(2.86)	(4.15)	(4.27)	(8.22)	(8.59)	(6.21)	(5.46)
density	-5.47032***	-5.46962***	-3.49748***	-3.49518***	-6.11492***	-6.25020***	-4.86520***	-4.94160***
	(-8.24)	(-8.26)	(-21.38)	(-21.39)	(-9.08)	(-9.15)	(-9.11)	(-9.29)
Constant	-5.32058***	-5.31958***	-2.77969***	-2.78252***	-3.41379***	-3.58351***	-3.58729***	-3.52411***
	(-14.87)	(-14.85)	(-26.38)	(-26.36)	(-6.28)	(-6.48)	(-9.28)	(-9.08)
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	37411	37411	443964	443964	74172	74172	79164	79164

R^2	0.29324	0.29324	0.12291	0.12291	0.15314	0.15310	0.17579	0.17574

5.3.2. Firm size

Larger firms seem to involve more frequently in R&D activities than smaller ones due to economies of scale (Cohen and Klepper, 1996). However, some researchers suggest that the R&D investment is led increasingly by small firms, due to the organizational flexibility afforded by smallness (Acs and Audrestch, 1990). To test this effect, we divide Chinese manufacturing firms into large-sized, medium-sized, and small-sized according to the information from the ASIF database.

As shown in column (2) of Table 5, the coefficient is negative and statistically insignificant, but in columns (4) and (6), the coefficients are significantly positive. Based on the 2SLS results, on average, a 1% increase in ITI leads to a 0.067% and 0.075% increase in the R&D of medium-sized and small-sized firms, respectively.

While the effect for large firms is insignificant, ITI plays an important role in promoting R&D investment of SMEs. Because of the size constraint, SMEs generally lack sufficient capital and technical resources, and are not closely connected with external organizations, such as government and banks (Zhang and Li, 2010). For these reasons, SMEs depend more on the resources provided by international talent. In addition, SMEs have many advantages, such as flexible organizations, a simple decision-making process, and quick response to the changing international market (Faggian and McCann, 2009), which enable SMEs to adjust their traditional employment systems in time and employ ITI for R&D activities.

Table 5: Firm size and heterogeneous effects of ITI

	Large		Medium		Small	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
ln*talent*	-0.02170	-0.00146	0.08414***	0.06735***	0.07146***	0.07530***
	(-0.34)	(-0.02)	(4.88)	(3.63)	(19.14)	(19.53)
size	0.51395***	0.51381***	0.40009***	0.40034***	0.15632***	0.15634***
	(4.75)	(4.77)	(38.06)	(38.08)	(95.35)	(95.37)
age	0.03519***	0.03520***	0.03076***	0.03078***	0.00902***	0.00902***
	(12.43)	(12.47)	(31.42)	(31.45)	(30.14)	(30.14)

export	1.34584***	1.34502***	0.45895***	0.45944***	0.15486***	0.15487***
	(11.79)	(11.82)	(18.29)	(18.31)	(27.99)	(28.00)
subsidy	1.08662***	1.08726***	0.95688***	0.95605***	0.54109***	0.54123***
	(11.17)	(11.21)	(36.44)	(36.42)	(63.40)	(63.41)
interest	1.66493***	1.66573***	0.87048***	0.87095***	0.23828***	0.23821***
	(8.75)	(8.79)	(31.61)	(31.64)	(57.60)	(57.58)
profit	0.64859	0.64851	1.75772***	1.75955***	0.37990***	0.37981***
	(1.04)	(1.05)	(13.93)	(13.95)	(13.08)	(13.07)
human	0.58568***	0.56365***	0.51834***	0.53502***	0.23036***	0.22680***
	(3.94)	(3.70)	(13.41)	(13.76)	(28.41)	(28.52)
unemployment	0.54943***	0.55073***	0.32988***	0.32720***	0.05286***	0.05385***
	(5.67)	(5.70)	(12.68)	(12.56)	(10.33)	(10.43)
density	-1.1e+01***	-1.0e+01***	-7.67333***	-7.72502***	-3.26878***	-3.26105***
	(-4.62)	(-4.60)	(-13.63)	(-13.75)	(-28.52)	(-28.59)
Constant	-9.96927***	-9.93209***	-7.24245***	-7.25843***	-2.39893***	-2.39940***
	(-5.52)	(-5.51)	(-20.00)	(-20.07)	(-32.62)	(-32.62)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	7797	7797	93090	93090	826469	826469
R^2	0.20085	0.20084	0.19339	0.19338	0.10578	0.10578

5.3.3. Industry characteristics

High-tech firms are regarded generally as being at the technological frontier. For them, introducing ITI can be a necessary strategy to encourage R&D investment. Here we test whether the effect is greater on firms in high-tech sectors.

We divide Chinese manufacturing firms into four categories using the following steps: First, according to ASIF, we get the 4-digit level of *Industrial Classification for China Economic Activities* (GB classification). Second, based on the conversion table published by NBS, we correlate the GB classification with the *International Standard Industrial Classification of All Economic Activities* (ISIC classification). Then, we obtain the 4-digit level of ISIC classification. Last, using the industrial classification of OECD (2003), we classify our sample firms into four categories based on their 4-digit ISIC: high-tech, med-high-tech, med-low-tech and low-tech. The classification of manufacturing industries into categories is the R&D intensity index.[7]

[7] For detailed information, please see https://www.oecd.org/sti/ind/48350231.pdf.

Table 6 reports the empirical results. In all sub-samples, 2SLS results show that the coefficients of ITI are positive and statistically significant, indicating that ITI plays a critical role in stimulating the R&D investment of firms in all manufacturing sectors. However, in columns (2) and (6), the 2SLS estimated coefficients are approximately 0.065 and 0.093, respectively. This comparison demonstrates that the R&D effect is stronger on firms in med-high-tech sectors but relatively weaker on firms in high-tech sectors.

The intuition is, China is still a developing country that is surrounded mainly by developing neighbors, where most ITI comes due to either geographical proximity or cultural similarity. Employing a foreign labor force from these countries may be not beneficial to the investment of high-end labor-saving technology, and may even impede technology improvements in the long-term (Pholphirul and Rukumnuaykit, 2017). In this case, the R&D promoting effect is weaker on firms in high-tech sectors. This implies, developing diversified ITI from different countries is conducive to enhancing the R&D effect, especially those from developed countries.

Table 6: Industry characteristics and heterogeneous effects of ITI

	High-tech		Med-high-tech		Med-low-tech		Low-tech	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln*talent*	0.04372^{***}	0.06525^{***}	0.07783^{***}	0.07672^{***}	0.09200^{***}	0.09322^{***}	0.07394^{***}	0.07674^{***}
	(2.61)	(3.58)	(9.55)	(8.96)	(13.78)	(13.58)	(10.39)	(10.27)
size	0.38037^{***}	0.38038^{***}	0.36646^{***}	0.36645^{***}	0.23469^{***}	0.23471^{***}	0.21391^{***}	0.21391^{***}
	(66.36)	(66.36)	(107.27)	(107.27)	(66.93)	(66.95)	(76.00)	(76.01)
age	0.03191^{***}	0.03189^{***}	0.02306^{***}	0.02306^{***}	0.02153^{***}	0.02153^{***}	0.01403^{***}	0.01403^{***}
	(27.07)	(27.05)	(41.10)	(41.10)	(30.10)	(30.10)	(24.00)	(24.00)
export	0.19565^{***}	0.19548^{***}	0.52787^{***}	0.52786^{***}	0.53427^{***}	0.53427^{***}	0.17108^{***}	0.17105^{***}
	(9.89)	(9.88)	(43.19)	(43.19)	(36.59)	(36.59)	(20.96)	(20.95)
subsidy	1.37107^{***}	1.37190^{***}	0.88835^{***}	0.88829^{***}	0.42439^{***}	0.42438^{***}	0.49631^{***}	0.49642^{***}
	(48.00)	(48.04)	(52.37)	(52.37)	(25.21)	(25.21)	(34.56)	(34.57)
interest	0.51602^{***}	0.51606^{***}	0.29755^{***}	0.29755^{***}	0.22028^{***}	0.22025^{***}	0.16902^{***}	0.16894^{***}
	(29.78)	(29.79)	(34.78)	(34.78)	(26.24)	(26.23)	(26.32)	(26.30)
profit	1.53038^{***}	1.52989^{***}	0.74576^{***}	0.74586^{***}	0.63181^{***}	0.63164^{***}	0.40207^{***}	0.40229^{***}
	(16.55)	(16.54)	(13.42)	(13.42)	(10.90)	(10.90)	(8.23)	(8.23)
human	0.57306^{***}	0.55333^{***}	0.28378^{***}	0.28485^{***}	0.12213^{***}	0.12089^{***}	0.10311^{***}	0.10094^{***}
	(17.25)	(16.49)	(16.97)	(17.11)	(7.72)	(7.76)	(7.34)	(7.33)

unemployment	0.08406***	0.09000***	0.10199***	0.10170***	0.06276***	0.06295***	0.05009***	0.05100***
	(3.96)	(4.21)	(9.43)	(9.35)	(5.95)	(5.95)	(5.44)	(5.45)
density	-7.72587***	-7.67402***	-4.28612***	-4.28933***	-1.96248***	-1.95963***	-2.07818***	-2.07834***
	(-16.71)	(-16.62)	(-18.17)	(-18.24)	(-8.41)	(-8.43)	(-10.65)	(-10.65)
Constant	-5.90574***	-5.91041***	-4.08528***	-4.08539***	-2.10347***	-2.10202***	-1.38845***	-1.39247***
	(-19.30)	(-19.31)	(-27.32)	(-27.33)	(-14.12)	(-14.14)	(-10.32)	(-10.29)
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	109523	109523	278776	278776	183035	183035	271535	271535
R^2	0.16307	0.16306	0.18221	0.18221	0.14369	0.14369	0.13418	0.13418

6. Robustness Checks

In this section, we perform several additional checks to ensure the robustness of our main conclusions.

6.1. Alternative log-like transformation

First, referring to Liu and Qiu (2016), we use $\ln(RD_{it}+1)$ to deal with zero values of the dependent variable. The 2SLS estimation results are contained in Panel A of Tables 7 and 8, which show that our baseline results are robust.

6.2. R&D intensity

Second, instead of taking R&D investment as an expense, we construct the R&D intensity to conduct another robustness check, which is the total amount of investment in R&D divided by total sales (both in RMB). It shows the contribution of R&D per unit of output (Nemlioglu and Mallick, 2017; Bournakis et al., 2018) and is helpful to avoid selection bias caused by zeros (Egger et al., 2019). The 2SLS estimation results are shown in Panel B of Tables 7 and 8, confirming our earlier results.

6.3. Panel fixed effects model

Third, we use the panel fixed effects model to make another robustness check. Here, firm fixed effects are added in all regressions to control the effects of time-invariant firm attributes, including the location of firms, on R&D investment. As such, the regional fixed effects are omitted to avoid collinearity. The results are shown in Panel C of Tables 7 and 8, which are basically in line with previous findings.

Therefore, our conclusions are robust.

Table 7: Robustness check result I

	Location		Firm ownership		
	Full sample	Eastern	State-owned	Private-owned	HMT-owned
	(1)	(2)	(3)	(4)	(5)
Panel A Dependent variables: ln(R&D investment+1)					
ln*talent*	0.07210***	0.15099***	0.00060***	0.00048***	0.00064***
	(19.03)	(11.78)	(4.36)	(13.73)	(5.21)
Constant	-3.32934***	-5.33364***	-0.0173***	-0.01149***	-0.01803***
	(-47.25)	(-44.42)	(-5.47)	(-15.49)	(-5.45)
Control variables	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	927356	704926	37412	443968	74172
R^2	0.16708	0.16044	0.15304	0.05869	0.06227
Panel B Dependent variables: R&D intensity					
ln*talent*	0.00037***	0.00074***	0.00051***	0.00053***	0.00077***
	(13.02)	(7.20)	(3.55)	(14.78)	(6.19)
Constant	-0.01331***	-0.02668***	-0.01760***	-0.01152***	-0.01862***
	(-24.08)	(-27.04)	(-5.57)	(-15.47)	(-5.48)
Control variables	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	927365	704928	37412	443968	74172
R^2	0.07691	0.07755	0.15303	0.05869	0.06226
Panel C Panel fixed effects model					
ln*talent*	0.06099***	0.09013***	0.02262	0.03709*	0.49947***
	(5.10)	(4.21)	(0.54)	(1.93)	(6.74)
Constant	-0.44065*	1.46004***	-1.44808	-2.03516***	-9.60801***
	(-1.80)	(4.26)	(-0.97)	(-5.66)	(-6.99)
Control variables	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	927356	704926	37411	443964	74172
R square	0.06974	0.07051	0.19104	0.04545	0.12212

Table 8: Robustness check result II

	Firm size		Industry characteristics			
	Medium	Small	High	Med-high	Med-low	Low

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Dependent variables: ln(1+R&D investment)						
ln*talent*	0.06324***	0.06806***	0.05984***	0.07021***	0.08469***	0.06863***
	(3.73)	(19.69)	(3.63)	(9.06)	(13.62)	(10.22)
Constant	-6.74479***	-2.18709***	-5.49911***	-3.74306***	-1.92855***	-1.27320***
	(-20.33)	(-33.04)	(-19.76)	(-27.62)	(-14.30)	(-10.45)
Control variables	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	93090	826469	109523	278776	183035	271535
R square	0.19389	0.10548	0.16498	0.18378	0.14476	0.13462
Panel B Dependent variables: R&D intensity						
ln*talent*	0.00053***	0.00034***	0.00031***	0.00028***	0.00040***	0.00021***
	(5.17)	(11.67)	(2.70)	(4.84)	(8.56)	(4.15)
Constant	-0.01827***	-0.01225***	-0.03274***	-0.01298***	-0.00630***	-0.00058
	(-8.54)	(-21.58)	(-14.72)	(-12.06)	(-6.28)	(-0.63)
Control variables	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	93097	826471	109523	278776	183035	271535
R square	0.11658	0.06533	0.06829	0.08332	0.06984	0.06929
Panel C Panel fixed effects model						
ln*talent*	0.11682**	0.04310***	-0.00215	0.06241***	0.05485***	0.12161***
	(2.45)	(3.61)	(-0.05)	(2.61)	(2.68)	(5.72)
Constant	-1.59244	-0.36658	2.83758***	1.56350***	-0.63599	-1.79152***
	(-1.26)	(-1.52)	(3.88)	(3.74)	(-1.59)	(-4.93)
Control variables	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	93090	826469	109523	278776	183035	271535
R square	0.09944	0.06890	0.02419	0.07793	0.09533	0.10166

7. Further Analysis Using Patent Data

In general, innovation activities can be measured by using either innovation input (i.e., *R&D investment*) or innovation output (i.e., *patent application*). So far in this paper we have used the former approach to examine the innovation effect of international talent, because R&D investment measures firms' independent innovation investment and is thus regarded as a more representative indicator. It is especially true in the case of China since Chinese firms are reluctant to apply for patents due to weak intellectual property rights protection (Chen et al., 2017). However, there is a shortcoming, namely, the unavailability of R&D data--the time range of our study so far is from 2004 to 2007. In this section, we try to provide a remedy, by further investigating the impact of ITI on firms' *patent application*, where we have data between 2004 and 2013, derived from the State Intellectual Property Office of China (SIPO).

We match the data of SIPO and ASIF by firm code. SIPO provides the information on three types of patents: invention, utility model and design. To be specific, invention patents refer to technical innovations on products or/and methods. Utility model patents refer to technical proposals on the shape or/and structure of a product. Design patents refer to changes in the shape or/and color of a product. The requirements for applying an invention patent is the most difficult, while those for a design patent are the easiest. In this regard, the increase of invention patents is generally regarded as the quality improvement of patent application. However, a large number of firms do not apply for a patent, resulting in zero-inflated explanatory variables. We thus follow Liu and Qiu (2016) and construct two log-transformed measures, namely $\ln[patent+(patent^2+1)^{1/2}]$ and $\ln(1+patent)$, in order to keep all observations of zero patent applications.

Table 9 reports the 2SLS estimation results. Column (1) in Panel A shows that ITI significantly increases Chinese firms' patent application, confirming the results found earlier using R&D data. Further study shows that, as listed in columns (2) and (4), the positive impact is mainly through the increase of invention patents and utility model patents, while the impact on design patents is not significant. Robustness checks based on alternative log-transformed explanatory variables also confirm the above findings (as shown in Panel B of Table 9). To conclude, we find that ITI can improve both the "quantity" and the "quality" of firms' patent application.

Table 9: Effects of ITI on firm-level patent application

	All	Invention	Utility	Design
	(1)	(2)	(3)	(4)

Panel A	Dependent variables: ln[*patent*+(*patent*^{2}+1)$^{1/2}$]			
ln*talent*	0.00254***	0.00120***	0.00118***	0.00010
	(5.16)	(5.09)	(3.53)	(0.78)
Control variables	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	2351238	2351238	2351238	2351238
R^2	0.06108	0.04061	0.05408	0.01954
Panel B	Dependent variables: ln(*patent*+1)			
ln*talent*	0.00196***	0.00092***	0.00091***	0.00008
	(5.10)	(5.10)	(3.54)	(0.78)
Control variables	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	2351238	2351238	2351238	2351238
R^2	0.06102	0.04071	0.05419	0.01954

8. Conclusions and policy implications

In this paper we have matched firm-level micro data with regional international talent data from 2004 to 2007, and found that ITI significantly increases the R&D investment of Chinese manufacturing firms. This result is confirmed with longer-term patent data for the period 2004 and 2013, which further shows that ITI can not only increase the quantity but also the quality of firms' patent application. In addition, we found that it is crucial to consider firm heterogeneity. Firms in eastern China where international talent is concentrated tend to invest more on R&D, and ITI increases the R&D investment of small-and medium-sized firms rather than large-sized firms, of domestic firms rather than foreign firms.

Our paper highlights the fact that the introduction of international talent can be a new way to encourage firms to increase R&D investments; but there are limitations. For one, due to data limitation, we use regional international student data as a proxy for international talent. International students are just one type of international talent. Other types, such as immigrant entrepreneurs and scientists, may also promote innovation activities in the host countries but with greatly varying effects due to the various types of talents (Vissak and Zhang, 2014; Scellato et al., 2015). We hope that more detailed data on China's ITI can be obtained in the near future, and conduct further studies on the heterogeneous effects of other types of international talent. Also, we'd like to extend our study on ITI and compare the results with those only with domestic talent. However, the employer-employee data of Chinese firms are not available at present. These remain interesting studies for the future with data availability.

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