The importance of large firms for generating economic value from subsidized technological innovation: a regional perspective[1]

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Abstract: This study investigates the relationship between government subsidies and the commercial value obtained from a region's scientific and technological achievements, and argues that this relationship will depend on the average size of the firms present in that region. Using panel data on the high-tech industry in 27 provinces and autonomous regions in China from 2009 to 2019, we show that government subsidies have a significant double threshold effect on the commercial/economic value obtained from scientific and technological achievements. When the average size of enterprises in a region is small, government subsidies have a negligible effect on the commercial/economic value obtained from technological innovation. As the average firm size reaches a first threshold value, the impact of government subsidies becomes significant and positive. This impact increases further when the average firm size in a region exceeds a second threshold value. These findings improve our understanding of the role of government subsidies for the commercialization stage of the technological innovation process and have important implications for policy makers.

Keywords: Region; Subsidies; Technological innovation; Commercialization; Economic value; Firm size

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1. Introduction

It is generally accepted that technological innovation is crucial for the competitiveness and growth of enterprises, regions and countries (Branstetter and Sakakibara, 2002; Moaniba et al., 2019; Ghazinoory et al., 2020). As the Research and Development (R&D) activities required to develop these technological innovations are typically characterized by market failures (Wu, 2017; Gauthier, 2014), governments of both developed (Kleer, 2010; Mowery and Sampat, 2005; Stevens, 2004) and developing countries and regions (Gupta et al., 2017) have started to subsidize R&D. These government subsidies are supposed to promote scientific and technological achievements, and existing studies suggest that they, at least partially, succeed in raising investments in R&D as well as scientific and technological outputs of R&D, both at the level of the firm and the region/country (e.g. Czarnitzki and Licht, 2006; Doh and Kim, 2014; Guo et al., 2018).

However, although increasing R&D investments and R&D outputs such as patents is important, it is the transformation of these scientific and technological achievements into successful industrial or commercial applications that is crucial for reaping their economic value (Ernst et al., 2016; Ghazinoory et al., 2020). Firms are the core drivers of this transformation process, as they are the main actors that commercialize new products and services and generate economic value through it. Unfortunately, this commercialization process is not straightforward. First, producing and selling technological innovations typically requires time and is risky, and it is therefore difficult to continue without sufficient long-term financing (Xiao et al., 2012). Second, the process is affected by flaws in the Intellectual Property Rights system (Jeong et al., 2019; Gangopadhyay and Mondal, 2012) and other market failures (Choi and Lee, 2017) in a region or country. In particular, commercialization activities characterized by externalities, with knowledge leaking to external actors who then reap part of the benefits, resulting in an insufficient incentive for the focal enterprise to commercialize scientific and technological achievements (Arrow, 1962). As a result, firms will typically underinvest in the commercialization of technological innovation. In China, for example, only 17.8% of all scientific and technological achievements by Chinese companies are transformed into successful industrial or commercial applications (China National Science and Technology Report, 2015), and these transformation rates vary substantially between regions (Guan and Chen, 2010).

Given these market failures, governments across the globe have taken a series of measures, including subsidies, to promote the transformation of scientific and technological achievements into economic results (e.g., The Bayh-Dole Act, 1980, and the Technology Transfer Commercialization Act, 2000, which were passed by the US Congress; the Commercialising Emerging Technologies (COMET) program, provided by the Commonwealth government of Australia; and the China Torch Program and National High-tech R&D (863) Program launched by the Chinese National Economic Council). The current study wants to investigate *to which extent government subsidies can increase the commercial/economic value obtained from the scientific and technological achievements in a region*. It is generally assumed that government subsidies have a positive effect on the transformation of scientific and technological achievements into regional economic value (Decter et al., 2007; Grimaldi et al., 2011; Rasmussen, 2008). However, we know from research at the level of the firm and of the ecosystem, that not all firms and networks of firms have the same potential to commercialize new scientific and technological achievements. Therefore, this study argues that the relationship between government subsidies to firms in a given region and the commercial/economic value obtained from scientific and technological achievements in that region will depend on the regional economic texture, and in particular on the average size of the firms that are located there.

Analyzing panel data on the high-tech sector in 27 provinces and autonomous regions in China through a threshold model, we show that the effect of government subsidies on the economic value obtained from scientific and technological achievements is negligible when the average firm size in a region is small, becomes positive and significant when the average firm size is medium, and increases even further when the average firm size in the region is large. These results reveal the "black hole" of commercialization subsidies, improving our understanding of the phenomenon and having important implications for practitioners.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature and develops the hypotheses of the study. Section 3 discusses the data and variables, including the empirical context, the sample and data sources, and the construction of the variables. Section 4 presents the empirical analyses and results and Section 5 the discussion and limitations.

2. The relationship between subsidies, average firm size, and economic value from technological innovations in a region

In this section, we first explain that the transformation of scientific and technological achievements into commercial/economic value is a crucial part of the technological innovation process. We then argue that at the level of a geographical region, there is a relationship between government subsidies and the commercial/economic value that is obtained from scientific and technological achievements, but that this relationship varies greatly depending on the average size of the firms that are located in the region.

2.1. Obtaining economic value from technological innovations

Technological innovations in firms are achieved through a long and complex process (as presented in Figure 1) that can be divided into two stages: (1) Research and Development (R&D) activities that lead to scientific and technological achievement, and (2) the transformation of these scientific and technological achievements into economic value through commercialization. The R&D stage includes research, development, testing and university-industry collaboration (Guan and Chen, 2010). The inputs for this phase consist mainly of R&D personnel and R&D funding, which are transformed into scientific and technological outputs, such as patents. Some firms are more efficient than others in transforming these R&D inputs into scientific and technological achievements. In the second stage of the technological innovation process, these scientific and technological achievements are commercialized, thereby transforming them into economic value (Fleming, 2001). This transformation stages includes activities like engineering, manufacturing, business planning and marketing. In this paper, we focus on the second stage of the technological innovation process. Given the development of scientific and technological achievements by firms in a region, we investigate to which extent government subsidies affect the commercial/economic value that is obtained from them.

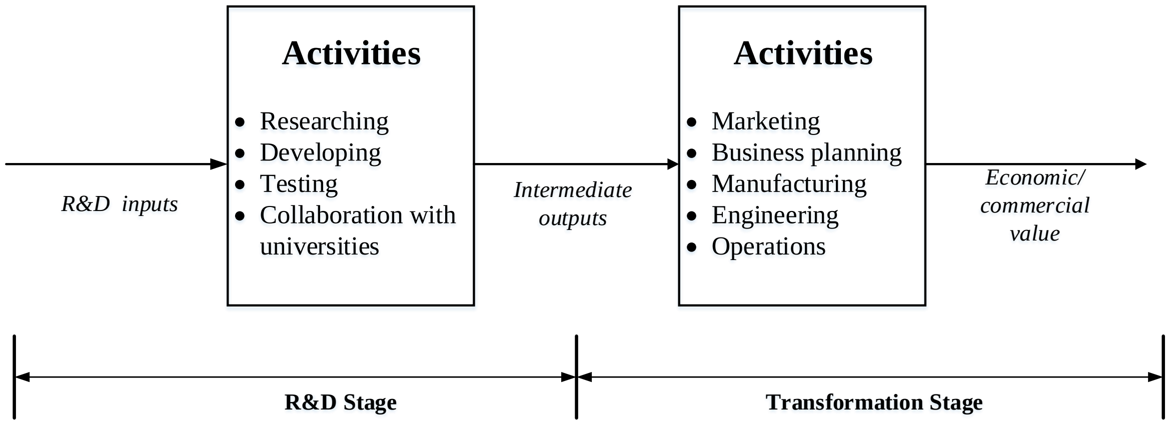

Figure 1. Technological innovation process (based on Guan and Chen, 2010, and Chen and Guan, 2012)

2.2. Subsidies and the regional economic value obtained from technological innovations

The transformation of scientific and technological achievements into commercial/economic value has public goods attributes, as it is difficult for individual investors to obtain all the benefits from commercialization (Arrow, 1962). If resources are allocated through market mechanism, firms' investments in the commercialization of technological innovations will be lower than the optimal level. Governments try to address these market failures by offering subsidies that can be used for commercialization (Decter et al., 2007; Grimaldi et al., 2011; Rasmussen, 2008; Hong et al., 2016; Chen and Yang, 2019), e.g. by subsidizing spin-offs in their region which commercialize the scientific and technological outputs of their university, or by supporting enterprises in commercializing their internal scientific and technological achievements, or by subsidizing collaborations between research institutes and enterprises in the region that aim at transforming the research outputs of these institutes into economic value for the enterprises. Most of these subsidies are targeted at firms, which can be regarded as the main vehicle for transforming scientific and technological outputs into commercial/economic value.

In recent years, scholars have gradually increased their research in this area. Research on the impact of government subsidies on intermediate R&D outputs has been complemented with studies, both at the firm and the regional level, which investigate the effects of subsidies on sales revenue growth and market performance (Xu et al., 2014). Most studies argue that government subsidies can indeed promote the transformation of scientific and technological achievements into commercial/economic value. Firstly, government subsidies can lower the cost of commercialization for the enterprises involved, and can thereby promote the overall commercialization degree of technological innovation projects in a region (Guo et al., 2018; Wallsten, 2000). Secondly, receiving government subsidies has a certification effect, especially when it comes to obtaining long term debt financing necessary for innovation activities (Meuleman and De Maeseneire, 2012). In China, for example, a firm's ability to obtain subsidies signals that is has a good relationship with the government. As it is known that Chinese firms that have a good relationship with the government are likely to receive additional funding if they incur losses during the technological innovation process (Liang et al., 2012), this certification effect of government subsidy programs helps Chinese firms gain other sources of external financial support, and thereby commercialize their inventions (Guo et al., 2018). Therefore, the larger the size of the subsidies in a region, the more likely that enterprises in that region will be able to acquire outside funding to commercialize scientific and technological achievements.

Several empirical studies from diverse countries and regions support the importance of government subsidies to firms for the transformation of scientific and technological achievements into economic value through the commercialization of new products. Almus and Czarnitzki (2013) confirm that the commercialization process of technological innovations in Eastern Germany is heavily fostered by public R&D funds. Similarly, Kang and Park (2012) find that government R&D subsidies have positive impacts on South Korean enterprises' economic results from innovation. Finally, Bai (2011) and Li and Bai (2013) show similar positive effects of Chinese government subsidies on the commercialization of scientific and technological achievements.

In sum, the dominant belief, which is confirmed in several empirical contexts, is that government subsidies play an important role in stimulating the commercialization of scientific and technological achievements in a country or region. From this, the following baseline hypothesis is proposed:

H1. *The higher the government subsidies granted to firms in a certain region, the higher will be the economic value obtained from the technological innovations in that region*.

2.3. The importance of firm size for obtaining regional economic value from subsidized technological innovation

Although the general expectation is that government subsidies will positively impact the economic value obtained from scientific and technological achievements in a region, not all empirical studies observe this positive effect. Hewitt-Dundas and Roper (2010) find that public R&D subsidies for product development do not significantly improve sales revenues from new products. Also Hong et al. (2016) cannot confirm a general positive relationship between subsidies and the degree to which scientific and technological achievements translate into economic value. We advance the economic texture in a region as an important contingency factor in this respect. In particular, we propose that the average size of the enterprises in a region will affect the degree to which subsidies increase the economic value from technological innovation.

Literature studying the effects of government subsidies in the first stage of the technological innovation process (i.e. the R&D stage, see Figure 1), generally assumes that government subsidies granted to smaller firms will have a more positive effect on recipients' scientific and technological output than subsidies granted to larger firms. While government subsidies to firms with sufficient resources may fully or partially "substitute" or "crowd out" the R&D investments these firms were going to make anyways, subsidies to resource-constrained firms are expected to allow additional investments in R&D (Czarnitzki and Hottenrott, 2011). As these financial constraints "*may especially apply to small or young firms that may face higher cost of capital than larger or older firms*" (Czarnitzki and Hottenrott, 2011, pp. 68), the literature generally assumes that subsidizing R&D activities of smaller firms is more effective than subsidizing these activities in larger firms (where substitution effects are expected to be larger; see also Hottenrott and Lopes-Bento, 2014).

However, when it comes to investigating the regional effect of government subsidies on the transformation of scientific and technological achievements into economic value, we expect that firm size may play an opposite role. In particular, although larger firms may be less financially constrained in commercializing new technological achievements and hence more likely to use part of their subsidies as substitutes for investments they were going to make anyways, we expect them to use the additional investments stemming from these subsidies much more effectively than smaller firms when transforming scientific and technological achievements into industrial or commercial applications. Apart from financial inputs, commercializing innovations also requires continuous inputs of human resources and (production) technology (Lee and Yoon, 2015; Lewin et al., 2009). Large-scale enterprises have advantages in terms of their internal talent reserve and technical foundation (Bos-Brouwers, 2010), so that they have scale advantages in gaining resources for their business operations and commercialization activities (Ettlie and Rubenstein, 1987). They are also better able to cooperate with actors inside and outside their industry (Luukkonen, 2005; Kafouros et al., 2020), thereby bringing in external knowledge crucial to the commercialization of technological innovation (Frank et al., 2019; Cassiman and Veugelers, 2006). Moreover, they have stronger market control and a wider business scope, providing them with more opportunities to generate economic benefits from innovation (Blundell et al., 1999). As such, we expect that larger enterprises in a region will have a stronger ability than smaller enterprises to generate economic value from government support.

Moreover, the presence of larger enterprises in a region will also improve the ability of smaller, financially constrained firms in that region to effectively use government subsidies for the development of industrial and commercial applications. According to innovation alliance network theory, the presence of large enterprises in an innovation network can improve the innovation performance of the network as a whole. In particular, large enterprises can take the role of a ‘hub organization’ and ensure the joint creation and extraction of value in the innovation network (Dhanaraj and Parkhe, 2006). They can effectively bring together small and medium-sized enterprises to achieve integration of innovative knowledge, technology, capital and other resources, and thereby promote the transformation of scientific and technological achievements of the whole high-tech industry throughout the region (Schilling and Phelps, 2007; Leten et al., 2013).

These mechanisms can also be expected to play in China, where large companies usually have more resources such as marketing personnel and advanced production processes (Wang et al., 2019; Lin et al., 2020), whereas smaller enterprises typically rely on larger enterprises to form alliances and jointly commercialize technological innovations (Xiang et al., 2019; Mei et al., 2019). Given these direct and indirect effects, we propose the following hypothesis:

H2. *The relationship between the government subsidies granted to firms in a certain region and the economic value obtained from the technological innovations in that region will be stronger when the average size of the firms located in the region is larger.*

3. Data and variables

3.1. Empirical context

The current study uses the context of the Chinese high-tech industry to investigate the relationship between government subsidies in a given region, the average firm size in that region, and the economic value from technological innovations commercialized by firms in that region. In the past two decades, the Chinese government has significantly increased its innovation funding for scientific and technological activities, resulting in a stark increase in the number of Chinese innovation projects and patents (Gang et al., 2016). This top position in terms of scientific and technological achievements, however, does not yet translate fully into economic returns. When looking specifically at the National High-tech R&D (863) Program, we see that only about 10% of the scientific and technological achievements are actually transformed into new products, while only 2.5% produced a significant economic benefit (China National Science and Technology Report, 2015; Qi et al. 2015). This means that the transformation of scientific and technological achievements into economic value in China has great room for improvement. The low conversion rate of scientific and technological achievements in China has several reasons, including overdependence of enterprises on their accumulated knowledge stock, insufficient non-R&D innovation, and market and government failures (Choi and Lee, 2017; Hervas-Oliver et al., 2011).

Given these challenges, China is a particularly interesting context to study the effect of government subsidies to firms in a certain region on the commercial/economic value obtained from technological innovations in that region. The central government as well as the regional governments actively adopt subsidy policies to encourage enterprises to improve both the R&D process and the commercialization of technological innovations, mainly through direct grants. In this process of subsidy allocation, regional governments have strong discretion vis-à-vis the central authorities[2].

3.2. Sample and data sources

This study investigates the relationship between government subsidies, average firm size, and the economic value from technological innovation in a region by focusing on China’s high-tech industry. It is defined as an industry that produces high-tech products with modern cutting-edge technology and it is characterized by intensive knowledge and technology and low energy consumption (Hong et al, 2016). According to the China Statistics Yearbook on High Technology Industry, China's high-tech industrial sector consists of five sub-sectors, namely (1) pharmaceutical industry (2) aircraft and spacecraft, (3) electronic and communication equipment, (4) computer and office equipment, and (5) medical equipment and instrument manufacturing industry. In general, the high-tech industry is one of the main industries in a knowledge-based economy and is the most important force for the transformation of technology patents into economic value (Chen et al., 2018). China's national and local governments are keen to develop its high-tech industry by providing substantial R&D grants and facilitating/improving the commercialization of technological innovations in this sector. As such, we believe it is a relevant context to investigate our research question.

This study uses data on the high-tech industry of 27 provinces and cities in mainland China during 2009-2019. Although there are 31 provinces and autonomous regions in mainland China, China’s regional economic development is unbalanced. Some regions, namely Tibet, Xinjiang, Inner Mongolia and Qinghai have very little high-tech activities and, as a result, the data on these four regions is largely missing. Removing these four regions leads to 27 remaining provinces and cities, distributed in three major regions of China (see Table 1).

Table 1. Distribution of the 27 provinces in China's three regions.

Regions	Provinces and autonomous regions
Eastern	Beijing, Tianjin, Shanghai, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan,
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan,
Western	Sichuan, Chongqing, Guizhou, Shannxi, Gansu, Ningxia, Yunnan, Guangxi

[2] Note that the Chinese government does not provide any specific grants or subsidies for collaborations between industries and/or firms. Instead, it tries to stimulate transformation by subsidizing activities of individual firms.

The panel data used in this study are obtained from three official sources: *China statistics yearbook on high technology industry (2010-2020), China statistical yearbook on science and technology (2010—2020) and China statistical yearbook (2010—2020),* which cover the annual data from 27 provinces and autonomous regions. Data sources for each of the variables are shown in Table 2. In the next section, we will describe the operationalization of the variables in our model.

3.3. Construction of variables

3.3.1. Main variables

Commercial value from innovation($COMV_{it}$*)*: Our dependent variable is measured as the sales revenue from new products of the high-tech industry in a region *i* at time *t* (expressed in million yuan).

Government subsidies ($SUBS_{it}$*)*: The Chinese government is an important provider of R&D subsidies and chiefly uses these funds to support enterprises and institutions in implementing innovation activities (Zhao and Song, 2018). Unlike tax incentives, subsidies are simple and straightforward, and are widely used in China. In fact, there are two main forms of government subsidies for corporate R&D in China. One the one hand, there are fixed/quota subsidies, where the actual costs of the company's R&D activities are not taken into account. On the other hand, there are ratio subsidies, where the government funds a certain ratio of the company’s R&D costs. For both forms of subsidies, companies need to apply with the government and go through a review system. In this study, we use government subsidies for R&D activities by firms in the high-tech industry in province i in period t (expressed in million yuan). These subsidies are considerable and vary widely between provinces, as not all provinces are equally active in the high-tech industries. For example, in 2018, the Chinese government provided about 1224 million yuan (or 191 million dollars) in subsidies to firms in the high-tech industries in Beijing and about 2672 million yuan (or 418 million dollars) to firms in the high-tech industries in Shanghai, but only about 35 million yuan (or 5 million dollars) to their counterparts in the province of Shanxi.

Table 2. Variables and data sources.

Variable	Abbreviation	Regional data used to construct the variable	Data sources
Dependent variable			
Commercial value from innovations	**COMV**	Sales revenue from new products of high-tech industry	China Statistics Yearbook on High Technology Industry: 2010–2020 (covering 2009-2019)
Explanatory variable			
Government subsidies	**SUBS**	Government funding for science and technology innovation activities of high-tech industry	China Statistics Yearbook on High Technology Industry: 2010–2020 (covering 2009-2019)
Threshold variable			
Firm size	**FIRMSIZE**	Sales revenues from principal business of high-tech industry divided by number of enterprises in high-tech industry	China Statistics Yearbook on High Technology Industry: 2010–2020 (covering 2009-2019)
Control variables			
Region size	**REGSIZE**	Number of enterprises in high-tech industry	China Statistics Yearbook on High Technology Industry: 2010–2020 (covering 2009-2019)
Foreign trade	**TRADE**	Total import and export (of all industries) divided by regional GDP	China statistical yearbook on science and technology, China Statistical Yearbook: 2010-2020 (covering 2009-2019)
Education level	**EDU**	Number of individuals with college degree or above divided by total population	China Statistical Yearbook: 2010-2020 (covering 2009-2019)
Unemployment rate	**UNEMP**	Number of unemployed persons divided by total population	China Statistical Yearbook: 2010-2020 (covering 2009-2019)
State-owned share of enterprises	**STATE**	Number of state-owned enterprises in high-tech industry divided by total number of enterprises in high-tech industry	China Statistical Yearbook: 2010-2020 (covering 2009-2019)
R&D efficiency	**RDEFF**	Number of patent applications in high-tech industry divided by total expenditure on R&D of high-tech industry	China Statistics Yearbook on High Technology Industry: 2010–2020 (covering 2009-2019)
Enterprise R&D investment	**EINV**	Enterprise funding for science and technology innovation activities of high-tech industry	China Statistics Yearbook on High Technology Industry: 2010–2020 (covering 2009-2019)

Firm size ($FIRMSIZE_{it}$ *)*: There are several potential measures of firm size, like sales revenues, profits, total assets, and number of employees. Each of these indicators has its advantages and limitations (Scherer, 1965). We use the sales revenues in million yuan from principal business in a region i in period t, i.e. the revenues obtained by all high-tech enterprises in region i in period t in their major production and business activities, and divide it by the total number of all high-tech enterprises in region i in period t. This gives us the average size of the high-tech enterprises in region i in period t (expressed in million yuan).

3.3.2. Control variables

We control for several other characteristics of the region which can be expected to influence its ability to generate commercial/economic value from technological innovation. In particular, we control for general socio-economic indicators, as well as for a region's enterprise-funded R&D expenditures and R&D efficiency (which are important characteristics of the first stage of the technological innovation process).

Region size ($REGSIZE_{it}$): We use the number of enterprises in the high-tech industry in a region *i* at time *t* as an indicator for the size of the region's economy. The higher the number of high-tech enterprises in a region, the more resources available for the development and commercialization of technological innovations.

Foreign trade ($TRADE_{it}$ *):* Technology spillover effects in international trade bring knowledge and advance technology that are valuable in the R&D and commercialization stage of technological innovations. Therefore, the level of foreign trade in a region can be expected to positively affect the commercial/economic value that can be obtained from technological innovations in that region (Zhang et al., 2018). This study uses the total import and export trade of a region (expressed in 100 million yuan) and divides it by regional GDP (expressed in 100 million yuan), which yields a percentage.

Education level (EDU_{it}): The education level of a region reflects the development of science, technology and culture in the region. Especially, the higher the level of higher education, the more high-quality R&D personnel and knowledge is available for the development and commercialization of technological innovations. We measure a region's education level as the share of the total population of the region that has a college degree or above.

Unemployment rate ($UNEMP_{it}$): The regional unemployment reflects the level of economic development in the region, which can be expected to affect the development and commercialization of technological innovations. In order to calculate this measure, we divide the number of unemployed persons by the total population in a region.

State-owned share of enterprises ($STATE_{it}$): State-owned enterprises in China have greater advantages in terms of market power, taxation, and policy support, as well as in obtaining financing for innovation (Liang et al., 2012). We include the number of state-owned enterprises divided by the total number of enterprises in the high-tech industry in a region to account for these effects.

R&D efficiency ($RDEFF_{it}$): We control for a region's efficiency in the first stage of the technological innovation process (cfr. Figure 1) as this stage provides the intermediate outputs that can be commercialized. To measure R&D efficiency, we divide the number of patent applications in the high-tech industry in region i and period t by the total R&D expenditures of the high-tech industry in region i and period t (expressed in million yuan). As our data sources did not contain information on the number of patent applications in the high-tech industry for 15 (or 5%) of the total 297 data points in our sample, we imputed these missing values with an average (in the case of one specific province where only one data point was missing) or we used the trend extrapolation method (in the case of five provinces that had more than one missing data point).

Enterprise R&D investment (EINV). Besides subsidized science and technology innovation activities, also enterprise-funded innovation activities of the high-tech industry will affect the different stages of the technological innovation process (cfr. Figure 1). We therefore control for the enterprise-funded R&D expenditures of the high-tech industry in province i in period t (expressed in million yuan).

Table 3. Descriptive statistics of variables.

Variable	Mean	P50	St. dev	Min	Max	N
lnCOMV	10.472	10.569	1.796	5.037	14.604	297
lnSUBS	5.522	5.706	1.546	0.884	9.057	297
FIRMSIZE	372.882	341.791	179.899	69.919	858.898	297
lnREGSIZE	6.281	6.477	1.254	2.639	9.163	297
TRADE	0.280	0.141	0.294	0.027	1.454	297
EDU	0.030	0.029	0.008	0.010	0.053	297
UNEMP	3.330	3.400	0.672	1.200	4.500	297
STATE	0.205	0.157	0.158	0.011	0.738	297
RDEFF	0.630	0.575	0.336	0.093	2.220	297
EINV	9.632	4.188	18.047	0.360	142.316	297

Descriptive statistics for these variables are shown in Table 3. As the distribution of $COMV_{it}$ $COMV_{it+1}$, $SUBS_{it}$, and $REGSIZE_{it}$ was highly skewed, we logarithmically transformed these variables before including them in our analyses.

4. Empirical analyses and results

4.1. Correlation analysis

The correlation coefficients between variables are shown in Table 4. We see that the commercial/economic value from innovations (*lnCOMV*) has an significant positive correlation with government subsidies (*lnSUBS*) ($\beta = 0.739$, $p < 0.01$). Firm size (*FIRMSIZE*) is significantly positively correlated with the commercial/economic value obtained from innovations and with government subsidies ($\beta = 0.522$, $p < 0.01$; $\beta = 0.354$, $p < 0.01$). These correlation coefficients provide initial support for our hypotheses. Most of the other correlation coefficients are lower than 0.5. Moreover, all variance inflation factors were below the generally accepted threshold of 10 (the maximum being 4.41), which suggests that multicollinearity doesn't pose a problem in our analyses (Hair et al., 2010).

Table 4. Correlation coefficients.

	lnCOMV	lnSUBS	FIRMSIZE	lnREGSIZE	TRADE	EDU	UNEMP	STATE	RDEFF	RDEXP
lnCOMV	1									
lnSUBS	0.739***	1								
FIRMSIZE	0.522***	0.354***	1							
lnREGSIZE	0.801***	0.716***	0.296***	1						
TRADE	0.544***	0.402***	0.382**	0.535***	1					
EDU	0.314***	0.290***	0.403***	0.176***	0.125**	1				
UNEMP	-0.254***	-0.133**	-0.169***	-0.202***	-0.205***	-0.243***	1			
STATE	-0.309***	0.202***	-0.276***	-0.301***	-0.334***	0.084	0.100*	1		
RDEFF	0.190**	0.118**	0.283***	0.134**	0.121**	0.091	-0.349***	-0.132**	1	
EINV	0.633***	0.492***	0.297***	0.611***	0.534***	0.026	-0.310***	-0.246***	0.388***	1

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

4.2. Significance and confidence interval of threshold estimation

We test our hypotheses by using the nonlinear panel data threshold regression model with fixed effects as proposed by Hansen (1999). This model allows the coefficients of (one or more) variables in the model to change when a specific explanatory variable, called the 'threshold variable', crosses a critical value. A great advantage of threshold models is that the threshold value is determined from the sample, and that it is not necessary to pre-specify the form of the nonlinear relationship, and this avoids artificial setting errors (Hansen, 2000). Our objective is to study the effect of government subsidies on the commercial/economic value obtained from technological innovation in a region, using the average firm size in the region as a threshold variable.

In the first step, we examine whether a significant nonlinear relationship exists between government subsidies (*lnSUBS*) and the commercial/economic value obtained from technological innovation in a region (*lnCOMV*) under different levels of our chosen threshold variable *FIRMSIZE*, in order to determine the number of thresholds. In order to determine whether the threshold effects are statistically significant, we perform a Likelihood Ratio test, following the bootstrap procedure described in Hansen (1999). The need to bootstrap arises from the fact that, because the threshold is not identified under the null hypothesis, the test statistic of the hypothesis test that the threshold is statistically significant (F) has a non-standard distribution. In order to obtain the critical values and associated p-values of the test statistic, we thus first need to obtain the asymptotic distribution of the test statistic under the null hypothesis that the threshold effect does not exist. The procedure, described in full in Hansen (1999), uses the residuals of the fixed-effects transformed model, grouped so that bootstrapping occurs on the region level, as the empirical distribution for the bootstrapping. Draws from that distribution are then used to construct bootstrap samples with which the model can be estimated assuming the null and the alternative hypothesis, and the bootstrap value of the likelihood ratio statistic F can be calculated. Repeating this B = 300 times, the associated p-value is then the share of draws for which the bootstrap F-value exceeds the actual F-value, and the critical values are then the values of F for which a given share of the sample is smaller than the associated critical value.

As can be seen in the F-test statistics and threshold values in Table 5, we identify a single-threshold effect of average firm size (*FIRMSIZE*) at the 1% significance level, and a double threshold at the 5% significance level, while the triple threshold is not significant. According to Hansen's threshold model, these results imply that there exists a double threshold of average firm size in the relationship between government subsidies and the commercial/economic value obtained from technological innovations in a region.

Table 5. Identification of threshold effect.

			Critical value		
	F-value	P-value	10%	5%	1%
Single threshold	107.57***	0.000	18.807	22.610	32.405
Double threshold	28.87**	0.013	17.386	20.051	31.315
Triple threshold	9.47	0.630	21.295	26.508	31.293

Note: The p-value and the critical value were obtained by bootstrapping with 300 replications, as suggested by Hansen (1999).
* Significant at 10% level, ** significant at 5% level, *** significant at the 1% level.

Now that self-sampling inspection has pointed to the existence of a double threshold effect, it becomes necessary to evaluate and test the actual threshold values γ. Threshold values were identified using a least squares likelihood ratio statistic LR. The threshold values and the 95% confidence intervals of the double threshold are shown in Table 6. We use the likelihood ratio $LR_n(\gamma)$ to construct the "non-rejection region", which indicates the valid confidence interval of γ. The "non-rejection region" at the confidence level of $1-\alpha$ is a series of γ values that belong to $LR_n(\gamma) \leq \mathrm{c}(\alpha) = -2\ln(1-\sqrt{1-\alpha})$ (Hansen 1999). At the 95%

confidence level, $c(\alpha) = 7.35$, which is represented by the dotted line in Figure 2 and Figure 3.

Going from left to right in the figures, the first point on the horizontal axis for which LR falls below the dotted line, represent the lower bound of the confidence interval around the estimated threshold value. Going from right to left, the first point on the horizontal axis for which LR falls below the dotted line, represent the upper bound of the confidence interval. In the double threshold model, the first threshold is estimated to be 173.232 in the interval of [169.2344, 177.3333] (see Figure 2). The second threshold is estimated to be 396.228 within the range of [387.6805, 400.2193] (see Figure 3). It can be seen that the estimated threshold values are in the corresponding confidence intervals, so the threshold estimates are consistent with the true values.

Therefore, according to these two threshold values, the average firm size in a region can be divided into three ranges: low firm size (*FIRMSIZE<=173.232*), medium firm size (*173.232< FIRMSIZE <=396.228*) and large firm size (*FIRMSIZE >396.228*). Over all the years included in our dataset, approximately 13% of our observations (i.e. 39 observations) have an average firm size that is small (*FIRMSIZE* <= 173.232), 47% (i.e. 139 observations) have an average firm size that is medium (*173.232 <FIRMSIZE <= 396.228*), and about 40% (i.e. 119 observations) have an average firm size that is large (*FIRMSIZE > 396.228*).

Table 6. Threshold estimation and confidence interval

Threshold	Value of threshold estimate	95% confidence interval
Single threshold model	173.232	[168.9713, 177.3333]
Double threshold model		
First threshold	173.232	[169.2344, 177.3333]
Second threshold	396.228	[387.6805, 400.2193]

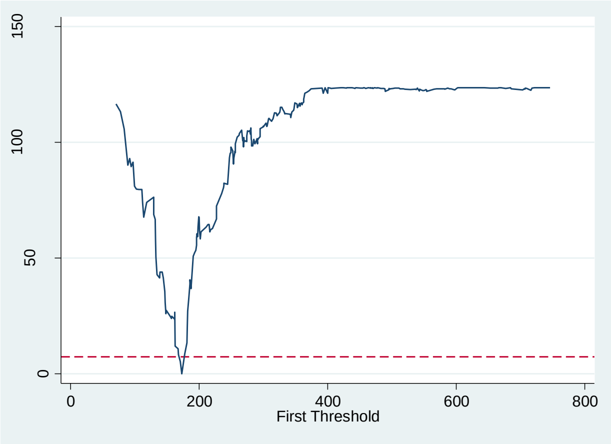

Figure 2. Identification of the first threshold value

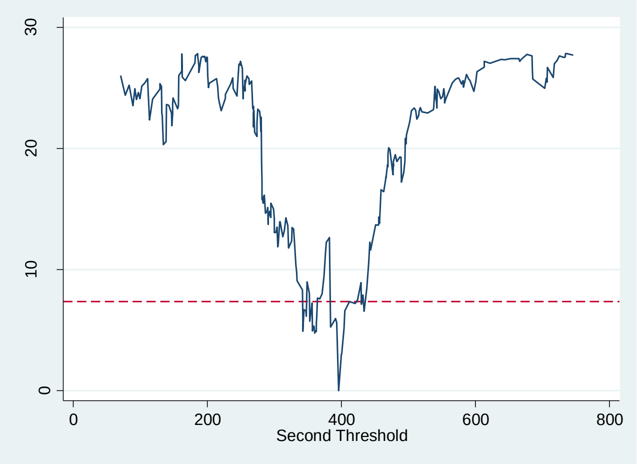

Figure 3. Identification of the second threshold value

4.3. Fixed effects panel model estimation

Once we have identified the threshold values, we incorporate them in our panel regression model. The F-test and the Hausman test show that an individual fixed effects model should be used. Although our previous analyses point to the appropriateness of a double threshold model (see model 2 in Table 8), for reasons of completeness we also provide results for a model that looks at the effect of government subsidies (*lnSUBS*) without controlling for firm size (*FIRMSIZE*) (model 1 in Table 8). The results of model 1 show that the linear regression coefficient of government subsidies (*lnSUBS*) on the commercial/economic value obtained from technological innovations (*lnCOMV*) in a region is positive and significant, suggesting that Hypothesis 1 is supported. As can be seen from the double threshold model 2, which is our main model of interest, the impact of government subsidies (*lnSUBS*) on the commercial/economic value obtained from technological innovation (*lnCOMV*) in a region is positive, but not statistically significant when the average firm size (*FIRMSIZE*) in that region is below 173.232 million yuan (about 26 million U.S. dollars) in revenues. When the average firm size is between 173.232 and 396.228 million yuan (between 26 and 59 million U.S. dollars), the positive influence of subsidies (*lnSUBS*) is increasing and becomes significant at the 5% level; and when the average firm size (*FIRMSIZE*) in the region exceeds 396.228 million yuan (about 59 million U.S. dollars) in revenues, the impact of government subsidies becomes even larger and significantly positive at the 1% confidence level, in line with our Hypothesis 2.

Table 8. Panel estimation results.

Variable		Dependent variable (lnCOMV) Model 1 Fixed effects	Model 2 Threshold
Control variables	lnREGSIZE	0.835***	1.144***
		(3.58)	(5.31)
	TRADE	0.708	0.055
		(1.56)	(0.17)
	EDU	13.716**	9.806**
		(-2.31)	(2.61)
	UNEMP	-0.316**	-0.128
		(-2.43)	(-1.13)
	STATE	-1.269**	0.147
		(-2.34)	(0.23)
	RDEFF	0.417**	0.322***
		(2.74)	(2.84)
	EINV	0.009	0.002
		(1.60)	(0.49)
Independent variables	lnSUBS	0.352***	
		(5.95)	
Double threshold	lnSUBS (FIRMSIZE <=173.232)		-0.013
			(-0.22)
	lnSUBS (173.232< FIRMSIZE <=396.228)		0 .176**
			(3.25)
	lnSUBS (FIRMSIZE >396.228)		0..236***
			（4.96）
Constant		3.717	2.138
		(2.22)	(1.42)
Goodness of fit	R^2	0.887	0.884
	F-value	24.95***	53***
	Number of observations	297	297

Note: t-statistics in parentheses. Standard errors clustered by region. * Significant at 10% level, ** significant at 5% level, *** significant at the 1% level.

4.4. Robustness tests

To verify the robustness of our results, we reran our analyses, using the “Total profit of high-tech industry divided by the number of enterprises in high-tech industry” as an alternative measure of firm size. The results of this analysis are shown in Table 9 and Table 10. We again find a double-threshold, the first threshold being 13.551 (i.e. average profits of about 13.551 million yuan or 2.02 million dollars per enterprise); the second threshold being

25.695 (i.e. average profits of about 25.695 million yuan or 3.84 million dollars per enterprise). The results are in line with those of our main model presented earlier, in the sense that when the average firm size in a region is below the first threshold, the effect of government subsidies is not significant at the 10% level. Subsidies do exert a significant promotion effect when the average firm size in a region is medium, and this effect becomes even larger when the average firm size in a region exceeds the second threshold value.

Table 9. Threshold estimation and confidence interval for alternative measure of firm size

Threshold	Value of threshold estimate	F-value	P-value	95% confidence interval
Double threshold model				
First threshold	13.551	46.50***	0.000	[12.8857, 13.6087]
Second threshold	25.695	35.91***	0.0067	[24.9103, 25.7583]

Note: The p-value and the critical value were obtained by bootstrapping with 300 replications, as suggested by Hansen (1999).
* Significant at 10% level, ** significant at 5% level, *** significant at the 1% level.

We also conducted two robustness test to mitigate endogeneity concerns. First, we included a time lag between the independent and dependent variables in our fixed effects model, which reduces the number of datapoints in the analysis to 270. The results of this analysis were fully in line with those presented above. Second, as running fixed effects models and including time lags do not allow to fully rule out endogeneity issues, we also checked the robustness of our findings using an Arellano-Bond model (Arellano and Bond, 1991). The Arellano–Bond estimator is a generalized method of moments estimator used to estimate dynamic panels with fixed effects. The model takes eliminates individual effects through first differences, and then instruments the lagged dependent variable through lags of the level or difference of the dependent variable. In particular, the results of our main analyses presented above might be inconsistent if subsidies are strategically allocated to regions with the highest potential commercial value of technology. In this case, our results would reflect mere selection effects, and not the causal effect of allocating more subsidies to a region. In order to test this possibility, we estimate an Arellano-Bond model where we (a) allow commercial value of technology to depend on its lag, thus accounting for path dependencies, (b) include region fixed effect to account for unobserved idiosyncrasies, and (c) instrument the dynamic term as well as subsidies with instruments based on their lagged values.

Table 10. Estimation results of model parameters for alternative measure of firm size

Variable		Dependent variable (lnCOMV) Model 1 Threshold
Control variables	lnREGSIZE	1.096*** (5.65)
	TRADE	0.710 (1.36)
	EDU	10.179*** (2.86)
	UNEMP	-0.226* (-1.97)
	STATE	-0.393 (-0.99)
	RDEFF	0.302** (2.69)
	EINV	0.002* (0.68)
Double threshold	lnSUBS (FIRMSIZE-1 <= 13.551)	0.078 (1.21)
	lnSUBS (13.551< FIRMSIZE-1 <=25.695)	0.200*** (3.25)
	lnSUBS (FIRMSIZE-1>=25.695)	0.266*** (4.21)
Constant		2.464 (1.67)
Goodness of fit	R^2	0.894
	F-value	30.80***
	Number of observations	297

Note: t-statistics in parentheses. Standard errors clustered by region. * Significant at 10% level, ** significant at 5% level, *** significant at the 1% level.

We constructed three dummy variables, the first dummy (*SMALL*) taking the value 1 if *FIRMSIZE* <= 173.232 (and 0 otherwise), the second dummy (*MEDIUM*) taking the value 1 if 173.232 < *FIRMSIZE* <= 396.228 (and 0 otherwise), and the third dummy (*LARGE*) taking the value 1 if *FIRMSIZE* > 396.228 (and 0 otherwise). We interact these dummies with *lnSUBS* and include them in the analyses, likewise instrumenting the interactions. The results of our additional analyses show that endogeneity issues do not pose a significant problem in our study. Using the Arellano-Bond estimator, we find that government subsidies have a positive but insignificant effect on the sales revenue from new products in a region when the average firm size in the region in small. This effect turns positive and significant when the average firm size is medium (at the 1% significance level), and becomes even more pronounced and significant at the 1% level when the average firm size in the region is large (see Table 11). Given that the Arellano-Bond approach accounts for endogeneity issues, this result implies that when the average firm size in a region is sufficiently large, government subsidies have an actual, causal effect on the sales revenue from new products in that region (and not merely a substitution effect as discussed by Antonelli, 2020).

Table 11. Estimation results of Arellano-Bond model

Variable		Dependent variable (lnCOMV)
		Model 1
		Arellano-Bond
Control variables	lnREGSIZE	0.770***
		(3.60)
	TRADE	0.028
		(0.12)
	EDU	4.399
		(1.47)
	UNEMP	-0.203
		(-1.56)
	STATE	-0.379
		(-0.81)
	RDEFF	0.153
		(1.51)
	EINV	-0.001
		(-0.23)
	lnSUBS	0.003
		(-0.01)
	LnSUBS*MEDIUM	0.143***
		(6.72)
	LnSUBS*LARGE	0.178***
		(6.16)
Lagged dependent		0.330***
		(5.28)
Goodness of fit	F-value	53.74***
	Hansen test of overidentifying restrictions	17.47
	(p-value)	(1.000)
	Arellano-Bond test for AR(1) in first differences (p-value)	-2.88
		(0.004)
	Arellano-Bond test for AR(2) in first differences (p-value)	-1.38
		(0.168)
	Number of observations	270

Note: t-statistics in parentheses. Standard errors clustered by region. * Significant at 10% level, ** significant at 5% level, *** significant at the 1% level.

5. Discussion and limitations

Our study demonstrates that government subsidies to firms in a given region do not always allow to increase the commercial/economic value obtained from technological innovations in that region. Instead, the effect of government subsidies in a region is affected by the economic texture of that region, and in particular by the average size of the enterprises that are present there. When the size of enterprises in a region is small, government subsidies have a negligible effect on the transformation of scientific and technological achievements into commercial/economic value. For about one quarter of the regions in our study, government subsidies did not have any impact, as these regions did not have sufficiently large firms to lead the commercialization process. Government subsidies only begin exerting a substantial promotion effect when the average firm size in a region is sufficiently high. So, while research by Pavitt et al. (1987) showed that both the smallest and the largest firms are the most efficient in turning R&D inputs into R&D outputs, our study indicates that when it comes to leveraging government subsidies to transform these R&D outputs into economic value, the presence of large firms in a region is essential. This implies that if governments want to increase the economic value resulting from technological innovations, they should not merely provide subsidies, but also try to strengthen the economic texture in the region. On the one hand, efforts should be undertaken to generate and leverage scale economies. On the other hand, interactions between large enterprises and other regional players should be stimulated.

Whereas both economies of scale, as well as the ability of large firms to function as a 'hub organization' in the regional ecosystem are expected to improve the regional potential to leverage subsidies for transformation, we are unable to disentangle which of both aspects is most important. We hope that future research, either at the level of the firm or the region will try to distinguish between economies of scale and network effects in the transformation of scientific and technological achievements into economic value, as this may inform more tailored policy measures. Along the same lines, we hope that future studies will also pay attention to the specific types of government interventions, including distinctions between grants and tax breaks, as these could have different effects.

In this study, we have tried to account for potential issues of endogeneity. First, we used a fixed effects panel regression to control for unobserved heterogeneity. Moreover, we replicated our findings by introducing a time lag between our dependent and independent variables and by using an Arellano-Bond estimator as a robustness test. Nevertheless, future studies may want to verify our findings using more sophisticated methods. It would for example be interesting to identify and include instrumental variables in the fixed effects model; something we were unable to do with the data available.

Finally, it is important to note that care should be taken in transferring our findings to other sectors and regions or countries. China's economy is less market-oriented than developed countries such as Europe and the United States, and China's regional economic development is unbalanced, especially with respect to high-tech industries. Moreover, the Chinese government does not provide subsidies specifically for university-industry collaborations. Future research should therefore verify whether our findings also hold in other, more developed countries and regions, and whether the effects of subsidies for firms differ from those of subsidies for university-industry collaborations. Moreover, specific thresholds in terms of firm size are expected to differ, not only between countries, but also between industries (Hong et al., 2016). The commercialization of technological innovations in low-tech sectors and the subsidizing thereof may be characterized by different thresholds than that in high-tech industries. We sincerely hope that future research will develop a more thorough understanding of these contingencies.

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