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# The impact of China's R&D subsidies on R&D investment, technological upgrading and economic growth

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ABSTRACT

This paper investigates the impact of research and development (R&D) subsidies on R&D inputs and their wider economic effects. The empirical analysis employs a structural vector autoregressive (VAR) model using a panel of Chinese provinces during the 2000–2010 time period. In support of a partial crowding-out view, public R&D subsidies allocated to large and medium-sized enterprises (LMEs) are found to increase total R&D inputs proxied by total R&D personnel, despite reducing privately-financed R&D inputs. Specifically, we find that an increase of R&D subsidies by one standard deviation decreases private R&D expenditures in LMEs by 6.5%, but increases total R&D personnel in LMEs by 2.6%. We also find evidence that the effects of R&D subsidies extend beyond their main effect on corporate R&D, promoting technological upgrading, capital deepening, and economic growth. We further find evidence suggesting some misallocation of research-oriented public funds. The findings help shed important insights into the ongoing debate regarding the role of the state in promoting innovation in a transitioning economy context.

## 1. Introduction

To better harness the growth-enhancing power of innovation,[1] an important question that naturally arises for policy-makers is how deeply should the state intervene in promoting a country's own technological capabilities. Stemming from the failed import substitution policies of the 1970s, conventional wisdom calls for a rather limited role of the government to support indigenous innovation efforts given the public good nature of research and development (R&D) (David et al., 2000) .[2] Yet, the explosion of innovation activities in emerging economies coinciding with periods of rapid economic growth has led to a renewed optimism that state-led innovation can be a major contribution to stimulate regional innovation systems and national competitive advantage (Mazzucato, 2015; Stiglitz et al., 2013).

A key argument in favor of state-intervention relates to the idea that investments in innovation are limited by financial constraints facing firms,[3] especially ones from transitioning economy countries.[4] State financial support can potentially help to mitigate the negative effects of financial constraints due to the significant amount of initial capital infusion necessary to purchase high-tech equipment and pay high-skilled workers (Hall and Lerner, 2010). The main objective of public R&D subsidies is to engender additionality effects on the corporate sector's private investments in innovation.

Despite their intended goal, however, the allocation of R&D

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[1] It is well-known that investments in innovation (i.e. R&D) play an essential role in fostering innovation and economic growth (Romer, 1990).

[2] Market failure may arise due to externalities in knowledge production that are difficult to internalize, resulting in an underinvestment in R&D.

[3] Low access to liquidity potentially prevents profitable R&D investment opportunities from happening, leading to a market failure in innovation that adds to that created by the public good nature of R&D.

[4] Transitioning economy firms typically face financial constraints due to underdeveloped financial markets and discriminatory lending practices that favor state-owned enterprises, thereby preventing them from carrying out potentially lucrative research projects (Brown, Martinsson, and Petersen, 2012; Nee and Opper, 2012).

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subsidies might have the opposite outcome reducing private investments in innovation (i.e.crowding-out or substitution effect).[5] In theory, private R&D investments are expected to increase only if the beneficiaries face more binding financial constraints that hinder investment in innovation (Hall, 2008; Hottenrott and Peters, 2012). In the empirical literature, the findings are quite mixed and sometimes contrasting. Depending on the specific policy of interest, empirical setting and country context, R&D subsidies are found to be associated with null or crowding-out effects as well as crowding-in effects on private innovation investments (for recent reviews, see Zúñiga-Vicente et al., 2014 and Dimos and Pugh, 2016).

Studying the relationship between public R&D subsidies and private innovation investments in the China context offers an interesting case. China's R&D investments as a share of GDP nearly doubled from 0.9% to 1.6% in just one decade from 2000 to 2010, with more than half of these investments coming from large and medium-sized enterprises (LMEs) by 2010 (see Fig. 1).[6] During the same 10-year time period, the amount of R&D subsidies quadrupled (Fig. 2). The unprecedented surge in China's public R&D subsidies is part of a new wave of innovation support policies — initiated by the Mid- to Long-term Science and Technology Development Plan 2006–2020 (MLP)[7] — that aim to increase the effectiveness of government support (Liu et al., 2011).

This paper explores the role of public R&D subsidies in stimulating private R&D inputs of LMEs using a panel of Chinese provinces during the 2000–2010 time period. To this end, we employ a structural vector

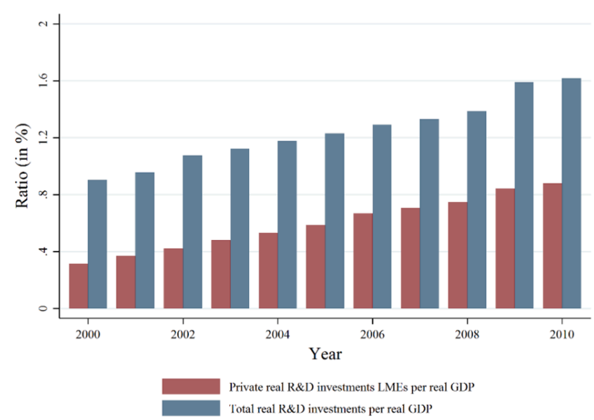


**Fig. 1.** Private real R&D investments in LMEs per real GDP and total real R&D investments per real GDP in China. Notes: Own calculations based on aggregated provincial data (see Table 1). Data on total provincial R&D investments are based on China's statistical yearbook on science and technology activities of industrial enterprises (various years).

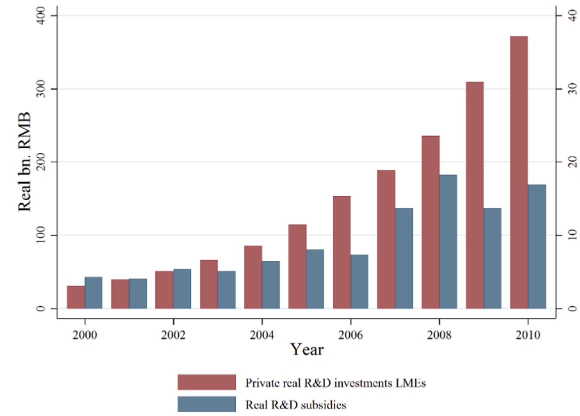


**Fig. 2.** Private real R&D investments in LMEs and real R&D subsidies in China. Notes: Own calculations based on aggregated provincial data (see Table 1).

autoregressive (VAR) model, and corresponding impulse response functions (IRF), to estimate the effect of R&D subsidies respectively on private R&D expenditures and total R&D personnel. The key advantages of our research design are as follows: (i) we rely on aggregate data that are representative of China's R&D subsidy policy[8]; (ii) we estimate the total effect (direct and indirect) of China's R&D subsidy policy defined as the sum of government funds from all R&D programs[9]; and (iii) the total effects of R&D subsidies are not only estimated for R&D inputs of LMEs, but also their potential wider economic impact.

The main finding is that public R&D subsidies increase total R&D inputs despite reducing private R&D investments of LMEs. Specifically, we find that an increase of R&D subsidies by one standard deviation decreases private R&D expenditures in LMEs by 6.5%, while the full time equivalent of total R&D personnel in LMEs increases by 2.6%. The findings imply a partial crowding-out of private funds through public funds, simultaneously rejecting competing views of perfect substitution versus complementarity of public R&D subsidies on private R&D investments in China's corporate sector.

Looking at the effect of R&D subsidies only on R&D inputs potentially obscures the effect of R&D support policies on the broader economy, however. This is because rapidly increasing R&D inputs are associated with decreasing output growth in China, implying a diminishing research productivity (Boeing and Huenermund, 2020). To this end, the VAR model is setup to estimate a set of recursive equations that further permits us to study the potential wider economic effects of R&D subsidies. In general, we find that the increase in total R&D inputs induced by R&D subsidies helps to promote technological progress, capital deepening and economic growth via respective increases in patents, investments in physical capital and GDP-per-capita growth. We also find that R&D subsidies tend to increase the investment rate in residential buildings, suggesting some misallocation of public funds in line with previous studies (Yang et al., 2020).

This paper makes several contributions to the literature. First, most

[5] A firm invests in R&D if and only if the marginal rate of return is larger or equal to the marginal cost of capital. The marginal cost of capital reflects the opportunity costs of investing funds in R&D versus non-R&D projects and thus depends on, among other things, the expected returns to other uses of available funds, such as investment in physical assets, available internal finance, and costs of external capital.

[6] China's current R&D-to-GDP ratio has already overtaken the ratio of the European Union; and, China is second only to the United States in gross R&D expenditures.

[7] The stated goals of MLP is to transform China into a global technology leader before 2050, emphasizing the two main drivers for China's continued progress and development include the persistence to promote opening and reform and heavy reliance on the progress of science and technology. Several major policies — introduced as part of the 10th (2001-2005) or 11th (2006-2011) Five-Year Science and Technology Development Plans, — include the National High-Tech R&D Program (the 863 Program), the National Key Technologies Program, and the State Basic R&D Program (the 973 Program).

[8] Much of the existing literature studying the effects of China's public R&D subsidies increasingly rely on firm-level panel data (Boeing, 2016; Wu, 2017). Despite offering more opportunities to explore underlying firm heterogeneity, these studies are typically limited in geographical scope (i.e. a single province) or in terms of sectoral coverage (i.e. publicly listed firms), neither of which could be considered as representative of China.

[9] Many of the existing micro-based analyses, for instance, focus on the direct effects of (single-program) subsidies, ignoring potential indirect spillover effects that may take place between firms.

evaluations of the effect of public R&D subsidies on private R&D expenditures are conducted for developed rather than for emerging and developing economies. Second, we contribute to the ongoing debate regarding the impact of China's state-led R&D support on private R&D investments.[10] Third, in line with existing studies,[11] we find compelling evidence showing the wider benefits of public R&D subsidies as well as potential misappropriation of public funds.

The remainder of this study is structured as follows. Section 2 briefly provides the theoretical framework. Section 3 introduces our empirical strategy, data and descriptive statistics. Section 4 presents the main results and robustness tests. The final section concludes.

## 2. Theoretical framework

In our theoretical framework, we start with the following production function,

$$Y_i = K_i^{\alpha} H_i^{\beta} (A_i \lambda_i P_i)^{1-\alpha-\beta} \tag{1}$$

where $Y_i$ is output, $K_i$ physical capital and $H_i$ human capital in province $i$.[12] $A_i$ is the level of the provincial technology, $\lambda_i$ is the provincial employment rate, and $P_i$ denotes the provincial resident population. Decreasing returns to scale are imposed by $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$. We specify provincial labor as $L_i = \lambda_i P_i$, with $\lambda_i$ as the long-term fixed provincial employment rate $\left(\frac{L_i}{P_i}\right)$, while provincial population $P_i$ grows at the exogenous rate $n_i$ (Eberle et al., 2019). Dividing Eq. (1) by $P_i$, the provincial per capita production function is

$$y_i = k_i^{\alpha} h_i^{\beta} (A_i \lambda_i)^{1-\alpha-\beta}. \tag{2}$$

In Eq. (2) provincial GDP per capita is the output. Physical and human capital per capita, the level of technology and the employment rate are core production factors. Due to data restrictions, in our empirical analysis we will use the physical capital (fixed assets) investment rate ($s_{k,i}$) instead of the physical capital stock ($k_i$) and the technological growth rate (subsequently labelled as $g_i$) instead of the provincial technological level ($A_i$). As economic development accelerates, the contribution of capital accumulation decreases while the importance of technological progress increases (e.g. Aghion and Howitt, 2009).[13]

Technological progress, i.e. innovation, is a human capital intensive activity (Aghion and Howitt, 2009; Romer, 1990). A substantial share of current R&D expenditures are costs for R&D personnel, hence investments in human capital.[14] According to China's National Bureau of Statistics (NBS), R&D expenditures refer to the real expenditure of surveyed units on their R&D activities including basic research, application study, testing and development. This definition includes direct expenditure on R&D activities, indirect expenditure of management and services on R&D activities. Accounting items not included in the definition are capital construction and material processing by others, expenditure on production activities, loan returns, and transfer fees to other agencies.

Accordingly, R&D subsidies are also considered as a public incentive to support investments in human capital. We formulate the dynamics of per capita human capital as

$$\frac{\dot{h}_i}{h_i} = s_{h,i}\left(k_i^{\alpha} h_i^{\beta-1} (A_i \lambda_i)^{1-\alpha-\beta}\right) - (n_i + \delta). \tag{3}$$

In Eq. (3), $s_{h,i}$ is the investment rate in human capital that depreciates with a constant rate $\delta$ and the province-specific growth rate of the population $n_i$ (Mankiw et al., 1992). With respect to Eq. (3), *R&D investments* are accounted for by the share of private funds in $s_{h,i}$, hence $s_{hprivate,i}$, and the *R&D personnel* is captured by $h_i$ (the stock of private human capital in a given province that is measured by R&D personnel in LMEs, see Table 1 for further information).

The wider economic effects of increasing provincial human capital (triggered by public R&D subsidies) may also affect other economic variables in Eq. (2). First, policy makers allocate R&D subsidies to incentivize corporate R&D investments (in human capital) to promote provincial technological growth (Romer, 1990).[15] We assume that technological growth ($g_i$) is determined by input factors (especially human capital) that are effective in the provincial corporate research sector (e.g. Rivera-Batiz and Romer, 1991; Romer, 1990).[16] We allow public R&D subsidies (temporarily) to incentivize a varying input of human capital in the research sector (according to the accumulation process of human capital in Eq. (3) above), which is assumed to be given in Romer (1990) and Rivera-Batiz and Romer (1991). Thus, public R&D subsidies may support technological progress via increasing human capital input.

Second, the physical capital investment rate is assumed to be constant in the long run and thus, in theory, unaffected by increases in R&D subsidies (e.g. Mankiw et al., 1992). With that said, the empirical model that we estimate explicitly allows for short-term fluctuations in the physical capital investment rate. Third, the employment rate is assumed to be fixed in the long run, but temporary changes may depend on substitution and output effects.[17] R&D subsidies may lower the costs for R&D personnel (given the elastic supply of human capital) and basic labor may become more expensive compared to R&D personnel, which may lead to a substitution effect. Conversely, if R&D subsidies raise

[10] Some studies find that public subsidies lead to a crowding-in effect (Chen and Yang, 2019; Liu et al., 2016; Hu and Deng, 2019; Howell, 2017). Other studies find evidence of a neutral or crowding-out effect (Wang et al., 2017; Boeing, 2016; Chen, 2018), or that the effect depends on the subsidy amount (Zhao et al., 2019).

[11] A number of related studies exist that investigate the effect of various policy instruments including but not limited to R&D subsidies, on patenting and other innovation outcomes (Li, 2009; Li, 2012; Bai, 2013; Fan et al., 2012; Hong et al., 2019; Cheng and Zhang, 2018).

[12] The provincial level analysis helps take into account that China's regions are strongly heterogeneous in terms of economic development (Tsui, 2014) and innovation activities (Li, 2009).

[13] Whereas Mankiw et al. (1992) assume that technological progress is exogenously given and equally distributed across economies, the growth model in Romer (1990) explicitly endogenizes the accumulation processes of technology in a R&D sector. In this R&D sector human capital is the main driver of technological progress. Once a fully industrialized economy has reached the steady state, per capita income and growth is driven by innovation.

[14] The share of labor cost in total business enterprise R&D expenditures decreases from developed to developing economies: 64.5% Germany (in 2011) and 48.7% United Kingdom, 42.8% Japan, 41.0% Korea, and 26.6% China (all in 2009) (OECD Statistics, 2019).

[15] As explained above, we assume that R&D subsidies predominantly foster private human capital (investments) in the research sector (e.g. Romer, 1990) that, in turn, promotes technological progress in a subsequent step. Thus, one could argue that technological progress $g_i$ is a main target of R&D subsidies. However, in our setting private human capital is considered a primary target while provincial technological progress is a secondary effect. In other words, this considers that changes in innovation inputs, i.e. R&D, will precede changes in innovation outputs, i.e. patents.

[16] This assumption is consistent with our flexible empirical panel VAR approach that relates all variables in the economic system among each other. As emphasized by Romer (1990), the role of human capital in the research sector is of particular importance for the accumulation of technology. Please note the distinction at this point between human capital in a one sector model with diminishing returns (e.g. Mankiw et al., 1992) and in a multiple sector model with a distinct role in the research sector (e.g. Romer, 1990), which has different implications of human capital for *long-term* economic growth. In a multiple sector model human capital triggers technological progress that drives long-term economic growth.

[17] See Schalk and Untiedt (2000) for a brief discussion of substitution and output effects on regional employment in the context of physical capital subsidies.

**Table 1**
Variable definitions and data sources.

| Variables | Definition | Data source |
|---|---|---|
| **Core variables VAR model** | | |
| *lgdp (y)* | Real GDP per capita (per resident population). CPIs are used to calculate real values | NBS, online data base |
| *lemp (λ)* | Employment rate (number of employed persons at year-end by province per capita (per resident population)) | NBS, China Statistical Yearbook (various years), available online |
| *linvq* ($s_k$) | Real investments in fixed assets per real GDP | NBS, online data base |
| *lhk (h)* | R&D personnel LMEs per capita (per resident population) | NBS, Statistics on Science and Technology Activities of Industrial Enterprises (various years) |
| *lprdef* ($s_{h\ private}$) | Private real R&D investments in LMEs per real GDP (R&D subsidies subtracted from R&D investments in LMEs) | NBS, Statistics on Science and Technology Activities of Industrial Enterprises (various years) |
| *lpat (g)* | Granted invention patents per 100 million real GDP | CNIPA. online data base |
| *lsub* ($s_{h\ public}$) | Real R&D subsidies to LMEs per real GDP | NBS, Statistics on Science and Technology Activities of Industrial Enterprises (various years) |
| **Control variables added in robustness** tests | | |
| *lcontrol1* | Real non-firm R&D investments per real GDP | NBS, Statistics on Science and Technology Activities of Industrial Enterprises (various years) |
| *lcontrol2* | Ratio private firms to state-owned firm | NBS, online data base |
| *lcontrol3* | Ratio loss making state-owned firms to total state owned firms | NBS, online data base |
| *lcontrol4* | Ratio innovative LMEs to total LMEs | NBS, Statistics on Science and Technology Activities of Industrial Enterprises (various years) |
| *lcontrol5, lcontrol6* | Ratio of valued-added in the primary sector and secondary sector, respectively, to total value-added | NBS, online data base |
| *lcontrol7* | Ratio coal deposit to total coal deposit China. Figures of 2003 used for missing earlier years | NBS, online data base |
| *control8* | Trade specialization index in Li (2009): Exports$_i$ – Imports$_i$) / (Exports$_i$ + Imports$_i$) | NBS, online data base |
| *lcontrol9* | Ratio of foreign to total R&D investments of LMEs | NBS, China Statistical Yearbook on Science and Technology, Statistics on Science and Technology Activities of Industrial Enterprises (various years) |
| *patsub* | Binary indicator that takes the value of 1 if a province provides patent subsidies | Li (2012) |
| *linvq_rb* | Real investments in residential buildings per real GDP | NBS, online data base |

Notes: All variables starting with *l* are in logarithms.

output, they may subsequently also trigger a higher demand for labor (output effect). Shifts in the provincial per capita output then are a function of changes of provincial input factors, expressed as

$$\frac{\dot{y}_i}{y_i} = \alpha\frac{\dot{k}_i}{k_i} + \beta\frac{\dot{h}_i}{h_i} + (1-\alpha-\beta)\frac{\dot{A}_i}{A_i} + (1-\alpha-\beta)\frac{\dot{\lambda}_i}{\lambda_i}. \quad (4)$$

Based on this framework, we expect R&D subsidies to shift the private human capital investment rate $s_{h,i}$ (temporarily) upwards and thus to increase the provincial stock of human capital $h_i$. The increase in the stock of human capital may also lead to wider benefits with respect to the technological growth rate $g_i$, per capita output $y_i$ and employment rate $\lambda_i$.

## 3. Empirical strategy, data and descriptive statistics

### 3.1. Empirical strategy

The VAR system is composed of six equations with six dependent variables (in logarithm *l*) observed at the provincial level: (1) R&D subsidy intensity, *lsub*; (2) human capital, either proxied by private investments in R&D, *lprdef* **or** more directly observed through the full-time equivalent of total R&D personnel, *lhk*; (3) technological growth rate, *lpat*; (4) physical capital investment rate, *linvq*; (5) employment rate, *lemp*; and (6) real GDP per capita, *lgdp*. We estimate a panel VAR, along with the associated IRF analysis, that allows us to determine the effects of an increase in R&D subsidies on all provincial variables. The reduced-form VAR system, both flexible and atheoretical, can be specified compactly in matrix notation (e.g. Love and Zicchino, 2006; Rickman, 2010) as

$$y_t = Ay_{t-1} + \varphi_i + \tau_t + e_t, \quad (5)$$

where $y_t$ denotes a vector of the six endogenous variables *(lsub, lprdef* **or** *lhk, lpat, linvq, lemp, lgdp)*, the matrix $A$ contains reduced-form coefficients, $\varphi_i$ is a vector of provincial fixed effects, $\tau_t$ is a vector of time dummies to capture general shocks, respectively, and the vector $e_t$ comprises (reduced-form) residuals (e.g. Love and Zicchino, 2006; Rickman, 2010).[18] The inclusion of provincial fixed effects take into account all time-invariant confounders at the province level, e.g. the provincial climate, relief, geographical location, sea access and distances to other provinces and the provincial or national capital. Note that we use a bias-corrected fixed-effects estimator as proposed by Everaert and Pozzi (2007) to avoid any dynamic panel bias that may arise due to the inclusion of fixed effects into our recursive set of six equations (Nickell, 1981).

As a response to criticism of the atheoretical reduced-form VAR approach, we employ the structural VAR approach (e.g. Rickman, 2010), expressed as

$$By_t = Cy_{t-1} + \varphi_i + \tau_t + D\varepsilon_t. \quad (6)$$

In Eq. (6), the matrix $B$ includes contemporaneous (structural) parameters, the matrix of polynomials $C$ links contemporaneous variables to time-lagged ones; and, the diagonal matrix $D$ links uncorrelated (exogenous) shocks, $\varepsilon_t$ to the endogenous variables (Keating, 1992; Rickman, 2010).[19] As Rickman (2010) points out, theory-based restrictions in the structural VAR model are set on the matrix $B$. To identify our structural panel VAR approach, we follow Di Giacinto (2010), who advances an approach by Wold (1954) to presume a recursive causal ordering of the included endogenous variables at period $t$ (Choleski decomposition). Based on the theoretical framework in Section 2, we link the theoretical approach to our empirical model and define the causal ordering at time $t$ (see Fig. 3).

Variables to the left (e.g. R&D subsidy intensity) have contemporaneous and delayed effects on the remaining provincial variables more to the right. Conversely, variables on the right have only time lagged (feedback) effects (e.g. GDP per capita).[20] With respect to Eq. (2), GDP per capita is the key outcome variable in the provincial system and thus the most endogenous variable with solely time lagged effects on the remaining provincial economic variables, while the investment rate and

[18] The inclusion of additional lags is restricted by the limited time period and the limited number of observations.

[19] Note that $A = C^*B^{-1}$ and $e_t = \varepsilon_t{}^*B^{-1}$ (Rickman, 2010).

[20] The results of a Granger causality test based on the approach by Dumitrescu and Hurlin (2012) can be found in Table OA1 in the Online Appendix. Note that contemporaneous (indirect) effects between the variables are not covered by the test.

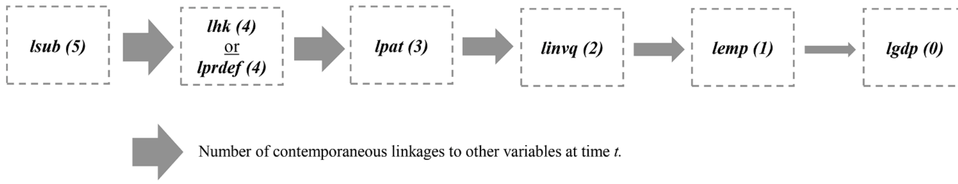


**Fig. 3.** Defined causal ordering across core variables at time *t* (contemporaneous linkages).

the employment rate are ordered on the basis of their flexibility in the short run and thus appear more to the left in Fig. 3 . Following the rational developed in our theoretical framework, R&D subsidy intensity is the most exogenous variable in the provincial economic system. R&D subsidies, *lsub,* are assumed to directly (contemporaneously) affect private R&D investments, *lprdef* **or** total R&D personnel, *lhk*, which again are an important input factor in knowledge production and thus directly affect provincial technological growth as measured by patents, *lpat*. Subsequently ordered variables are the physical capital investment rate (*linvq)*, the employment rate (*lemp)*, and finally real GDP per capita (*lgdp)* as the key outcome variable.

By applying the moving-average (MA) presentation of the VAR, we illustrate the responses (total effects) of the provincial variables to an orthogonal increase in the R&D subsidy intensity (Lütkepohl, 2005). The calculated confidence intervals are based on Monte Carlo simulations (Love and Zicchino, 2006).

### 3.2. Data

The provincial level data covers the time period 2000 to 2010[21] and is obtained from China's NBS and the China National Intellectual Property Administration (CNIPA), i.e. China's patent office.[22] Table 1 details variable definitions and data sources (the variable abbreviations specified in Table 1 are used throughout the paper), and in Online Appendix OA1 we discuss key issues related to China's provincial data. We construct real values for monetary output and investment measures by using the provincial consumer price index (CPI). Summary statistics of the core variables are presented in Table OA2a, followed by results from a correlation analysis presented in Table OA2b.

The correlation coefficients support our initial theoretical intuition and decision to run separated VAR models for: (i) R&D personnel; and (ii) R&D investments. Specifically, the correlation coefficients between the variables R&D personnel and private real R&D investments are very high ($\rho 1 = 0.953$ for all provinces; and $\rho 2 = 0.886$ when Tibet and provincial-status municipalities are excluded). This high correlation is expected because a substantial share of firms' R&D spending is expensed for the wages of R&D personnel and helps motivate the need to run models separately for R&D personnel and R&D investments.

### 3.3. Descriptive statistics

For each core variable in each province, we report the long-term growth rate from 2000 to 2010 in Fig. 4 and the summarized economic activities for the entire period 2000 to 2010 in Table OA3. Beijing, Shanghai, and Tianjin, which are relatively developed provincial-status municipalities, have the highest GDP per capita and the highest patents-to-GDP ratio (Table OA3). However, because municipalities may more strongly benefit from agglomeration effects, a comparison restricted to the remaining provinces provides a more conservative analysis. Developing provinces with lower initial and average GDP per capita show the highest growth in physical capital investments (e.g. Jiangxi, Anhui, or Liaoning; see Fig. 4). More developed provinces, such as Zhejiang and Guangdong, have high growth rates in private R&D investments, R&D personnel, and patenting. In line with our theoretical framework, less developed provinces may exhibit higher marginal returns to physical capital, whereas more developed provinces pursue innovation to substitute capital- with technology-driven growth.

Fig. 5 shows that provinces that allocate higher levels of R&D subsidies also have higher levels of private R&D investments and receive more granted patents between 2000 and 2010 (scaled by real GDP). In the majority of provinces R&D subsidies provided to LMEs amount for up to 0.1% of provincial GDP and private R&D investments of LMEs account for up to 1.15% of provincial GDP. In the next section we perform a more detailed analysis of these patterns.

## 4. Estimation results

This section presents the results of our panel VAR approach and the IRF analysis. To avoid the influence of outliers, the basic model excludes Tibet and the municipalities Beijing, Chongqing, Shanghai, and Tianjin. Due to substantial economic dynamics in Chinese provinces, we apply a panel unit root test (Im et al., 2003) as a pre-estimation check to control for stationarity of the variables. As shown in Table 2, for some variables the test indicates non-stationarity, and we detrend these variables.

### 4.1. Main results

We first investigate to what extent public R&D investments compliment versus substitute for private R&D investments in China's corporate sector and the implications for total R&D employment. To this end, we estimate separately the effect of public R&D subsidies on: (i) private R&D investments; and (ii) total R&D personnel in LMEs, proxying for total R&D inputs. The three main potential outcomes of interest are as follows: (i) an increase in both private R&D investments and total R&D personnel (*crowding-in*); (ii) a decrease in private R&D investments and a null effect, or decrease, on total R&D personnel (*total crowding-out*); or (iii) a decrease in private R&D investments and an increase in total R&D personnel (*partial crowding-out*).

The main results are reported in Fig. 6. Following the VAR literature (e.g. Love and Zicchino, 2006; Mitze et al., 2018), we report the reaction of our core variables to an orthogonal increase in the R&D subsidy intensity in the amount of one standard deviation (multiplied by 100 [in %], y-axis). The figures illustrate the estimated responses by the solid lines and the dashed lines show the calculated 5% and 95% confidence intervals for the various IRFs based on Monte Carlo simulations with 500

[21] In 2011, the NBS survey was amended and the availability of consistent information on R&D investments and R&D personnel of industrial LMEs restricts our analysis until 2010. Industrial LMEs operate in the industries mining, manufacturing and the production and supply of electricity, gas and water. They are defined as firms with at least 300 employees, 30 million RMB sales revenue, and 40 million RMB assets (National Bureau of Statistics of China, 2003).

[22] We regard granted patents as a superior measure compared to patent applications, as granted patents have passed two selections. First, the expected economic value exceeds the cost of patenting (application), and second, the invention has passed examination at the patent office (grant). This two-step selection helps to mitigate the distortion of application-based patent subsidies on patents as an indicator of technological growth in China (Boeing and Mueller 2019).

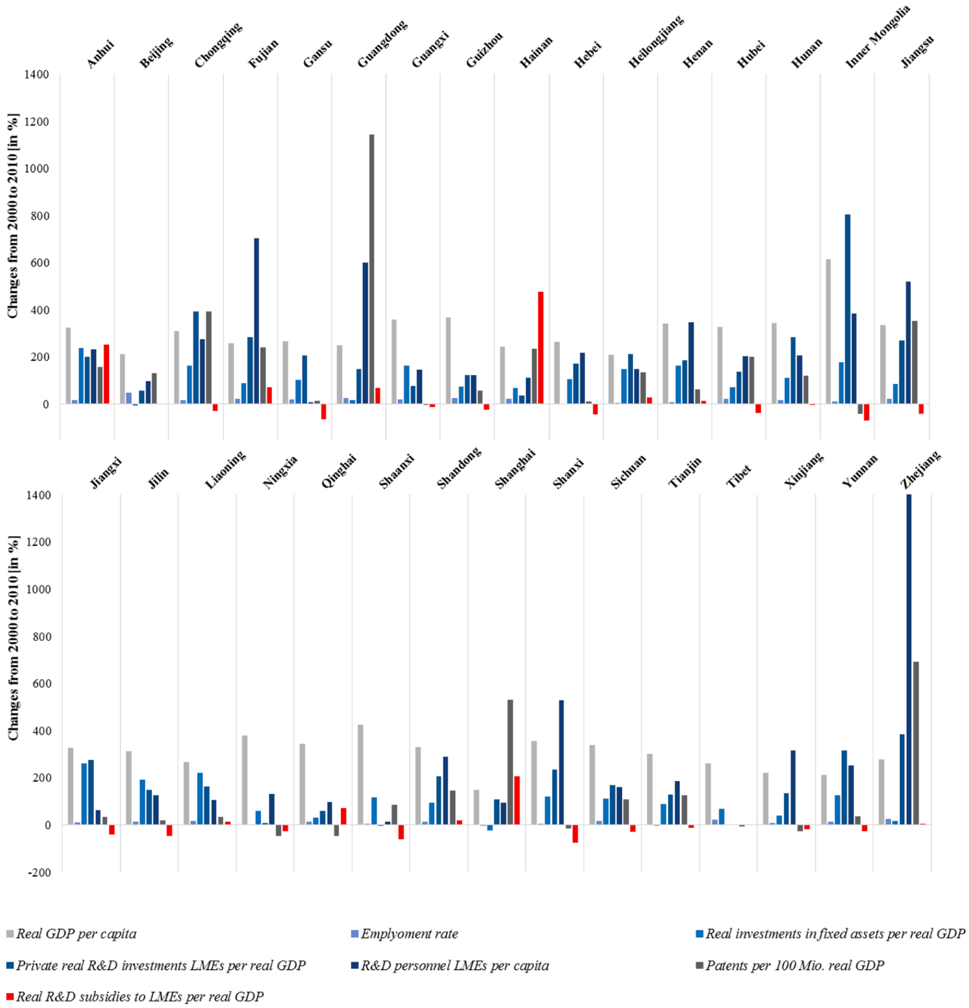


**Fig. 4.** Provincial changes from 2000 to 2010 for core variables (in %). Notes: Own calculations based on provincial data (see Table 1).

repetitions (the x-axis denotes years).

Panel 1 shows that an increase in the R&D subsidy intensity leads to a negative coefficient on the private R&D investment rate (solid line). The estimated error belts (dashed lines) reveal a statistically significant effect in the short run. In the year of the policy shock, an increase in the R&D subsidy intensity by one standard deviation corresponds with a decrease of 6.46% in the private R&D investment rate. Panel 2, by contrast, shows that an increase in the R&D subsidy intensity leads to a positive effect on total R&D personnel, 2.57% in the year of the policy shock, while the confidence intervals suggest that this effect is only significant in the first year.

Together, we interpret the findings as evidence of a contemporaneous partial crowding-out effect: firms substitute some private funds with public funds but total R&D inputs still increase via the expansion of R&D personnel induced by the R&D subsidy. Our interpretation of the findings hinges on the idea that total R&D personnel serves as a proxy for total R&D inputs, including but not limited to private R&D investments. That is, while R&D subsidies decreases private R&D expenditures, the subsidy transfer increases overall the total amount of R&D inputs. A key condition for this assumption is that the share of labor cost for R&D expenditures is stable in the short run,[23] i.e. an increase in R&D personnel is not overcompensated by a simultaneous decrease in other R&D-related current or capital costs. In support of this assumption, the share of labor cost in Chinese business enterprise R&D expenditures is indeed very stable oscillating between 25.6% and 26.7% during the 2008–2011 time period (OECD Statistics 2019).

### *4.2. Wider economic effects of R&D subsidies*

In addition to the effect on R&D inputs, Panels 1 and 2 of Fig. 6 also show that an increase in the R&D subsidy intensity has a significant positive effect on the patent activity (a maximum of 2.2% in Panel 1 and 2.06% in Panel 2 in the year of the policy shock) and the provincial physical capital investment rate (a maximum of 1.11% in Panel 1 and 0.99% in Panel 2 in the second year after the policy shock). Increases in patents may be explained by a preceding increase in total R&D inputs, emphasized by a closely related shape of the two response functions (see Panel 2 of Fig. 6).[24] The effect on physical capital suggests that R&D subsidies have an effect on investments into fixed assets, which may be R&D or non-R&D related, and we will explore this point further in

[23] Using R&D personnel versus total R&D expenditures as a proxy for total R&D inputs has the added benefit of implicitly controlling for policy-induced demand shocks that may increase wages of scientists (Goolsbee, 1998).

[24] Griliches (1990) mentions that the relationship between patents and R&D inputs “is close to contemporaneous with some lag effects which are small and not well estimated” (p. 1674). Empirically, we have to strike a balance between the timeliness of patent applications and the higher accuracy of granted patents. In the Chinese context we regard granted patents as a superior measure because they have passed examination and are less distorted by application-based patent subsidies (Boeing and Mueller 2019).

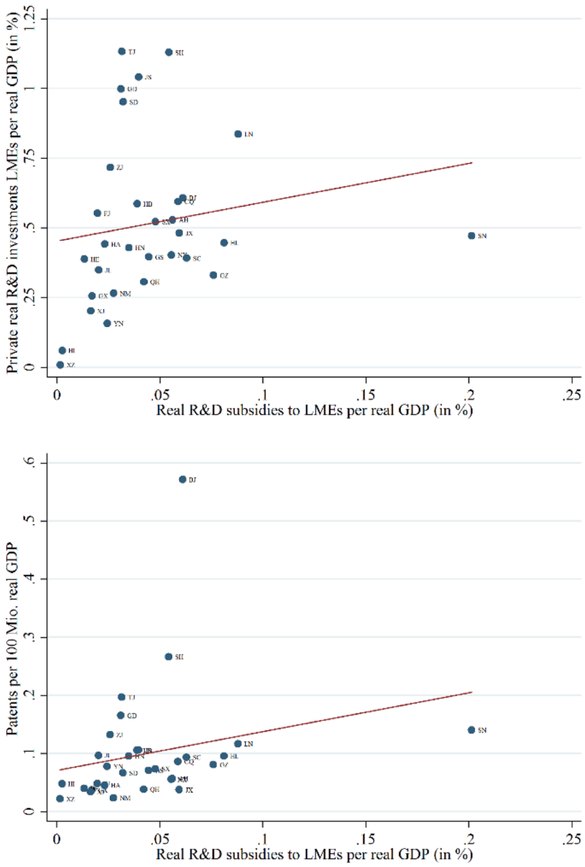


**Fig. 5.** Scatterplot average private real R&D investments in LMEs per real GDP (upper panel) and average patents per 100 million real GDP (lower panel) in relation to average real R&D subsidies provided to LMEs per real GDP (values for the entire period 2000 to 2010). Notes: Abbreviations for provinces are: AH Anhui, BJ Beijing, CQ Chongqing, FJ Fujian, GS Gansu, GD Guangdong, GX Guangxi, GZ Guizhou, HI Hainan, HE Hebei, HL Heilongjiang, HA Henan, HB Hubei, HN Hunan, NM Inner Mongolia, JS Jiangsu, JX Jiangxi, JL Jilin, LN Liaoning, NX Ningxia, QH Qinghai, SN Shaanxi, SD Shandong, SH Shanghai, SX Shanxi, SC Sichuan, TJ Tianjin, XZ Tibet, XJ Xinjiang, YN Yunnan, ZJ Zhejiang.

**Table 2**
Panel unit root tests.

| | Years | IPS test-statistic | *p*-value |
|---|---|---|---|
| *lgdp* | 11 | 2.91 | 0.998 |
| *lgdp_det* | 11 | -2.31 | 0.011 |
| *lemp* | 11 | 0.88 | 0.810 |
| *lemp_det* | 11 | -4.02 | 0.000 |
| *linvq* | 11 | -1.25 | 0.105 |
| *linvq_det* | 11 | -4.76 | 0.000 |
| *lhk* | 11 | -2.10 | 0.018 |
| *lnrdef* | 11 | -3.32 | 0.000 |
| *lpat* | 11 | 1.36 | 0.913 |
| *lpat_det* | 11 | -7.04 | 0.000 |
| *lsub* | 11 | -6.23 | 0.000 |

Notes: Panel unit root tests are based on Im et al. (2003) for the core variables over the time period 2000–2010. The outliers Beijing, Shanghai, Tianjin, Chongqing and Tibet are excluded. The null hypothesis (H0) states that panels comprise unit roots, the alternative hypothesis (HA) states that panels are stationary. We add to the detrended variables the suffix "*_det*". Control variables are also detrended if the unit root test reports non-stationarity.

Section 4.3.

Because the results for employment and output mainly are statistically insignificant in the basic model, we only provide a brief discussion of the economic response patterns (once omitted municipalities are included the results turn statistically significant, see Figure OA5). For the provincial employment rate, we obtain a negative effect in the short run (solid line), potentially through substitution and adjustment effects, but a rather positive effect in the medium run. As for the real provincial GDP per capita, our results also suggest a short-run negative effect; however, the response (solid line) in Panel 1 shows a delayed significant positive effect with a maximum of 0.23% in the 6th year after the policy shock.

### 4.3. Robustness tests

In this subsection, we carry out a number of sensitivity tests and checks for robustness. For brevity, the discussion focuses mainly on interpreting the effect of R&D subsidies on R&D inputs. Results on the other set of outcomes are reported for reference in the Online Appendix.

First, we augment our basic model with nine control variables to address a potential omitted variable bias by capturing time-variant heterogeneity of the provincial innovation and economic production systems. The additional control variables comprise: (1) provincial R&D investments carried outside of LMEs, e.g. mainly by universities and research institutes; (2) the ratio of private to state-owned firms; (3) the ratio of loss-making state-owned firms to control for heterogeneity in financial constraints;[25] (4) the share of innovative LMEs as a measure for the dissemination of knowledge spillovers; (5) the ratio of value added in the primary sector and (6) secondary sector to total value added to control for variation in the sectoral composition; (7) provincial coal resources, as these may absorb short-term oriented investments to the detriment of long-term economic development (i.e. resource curse), which would increase the opportunity cost of R&D; (8) the share of business R&D carried out by foreign invested enterprises; and (9) the trade specialization index proposed by Li (2009), measuring export activities and the absorption of foreign technological knowledge that is embodied in foreign goods. The results in Figure OA1 confirm the robustness of our main findings.

Second, we include provincial patent subsidies in a further robustness test to address potential substitution bias. Figure OA2 again support the robustness of our main findings. Third, we account for changes in China's innovation policy introduced after the seminal 'National Conference on Technological Innovation' in 1999 (Liu et al., 2011). Because the enforcement of national policies at the provincial level takes time, we extend the implementation period by three years and restrict our analysis to the years 2003 to 2010.[26] After adjusting the time period of analysis, the results remain qualitatively similar as before (Figure OA3).

Fourth, instead of physical capital investments we use investments in residential buildings as an indicator for short-term profit maximizing investments, which is unlikely to be complementary to R&D investments. Due to data limitations, this analysis is also restricted to the years 2003 to 2010. The main effects on private R&D investments and R&D personnel remain robust. The corresponding IRFs in Figure OA4 also show that an increase in the R&D subsidy intensity has a significant positive short-run effect on the investment rate in residential buildings. One potential explanation for this result relates to misallocation of public funds (Li et al., 2017), where some R&D subsidies get redirected towards non-R&D investments.

Fifth, after including provincial-status municipalities we fail to see any significant changes on the main results (Figure OA5). Interestingly, the results for employment and output increase in statistical

[25] In comparison to state-owned firms, China's private firms are constrained in access to external finance, and among state-owned firms loss-making ones are more likely to encounter internal financial constraints.

[26] We also apply unit root tests for this time period before estimation. Note that we also detrend the variable *linvq*, although the unit root test reports stationarity for the time period 2003-2010; however, IRF analysis does not work otherwise.

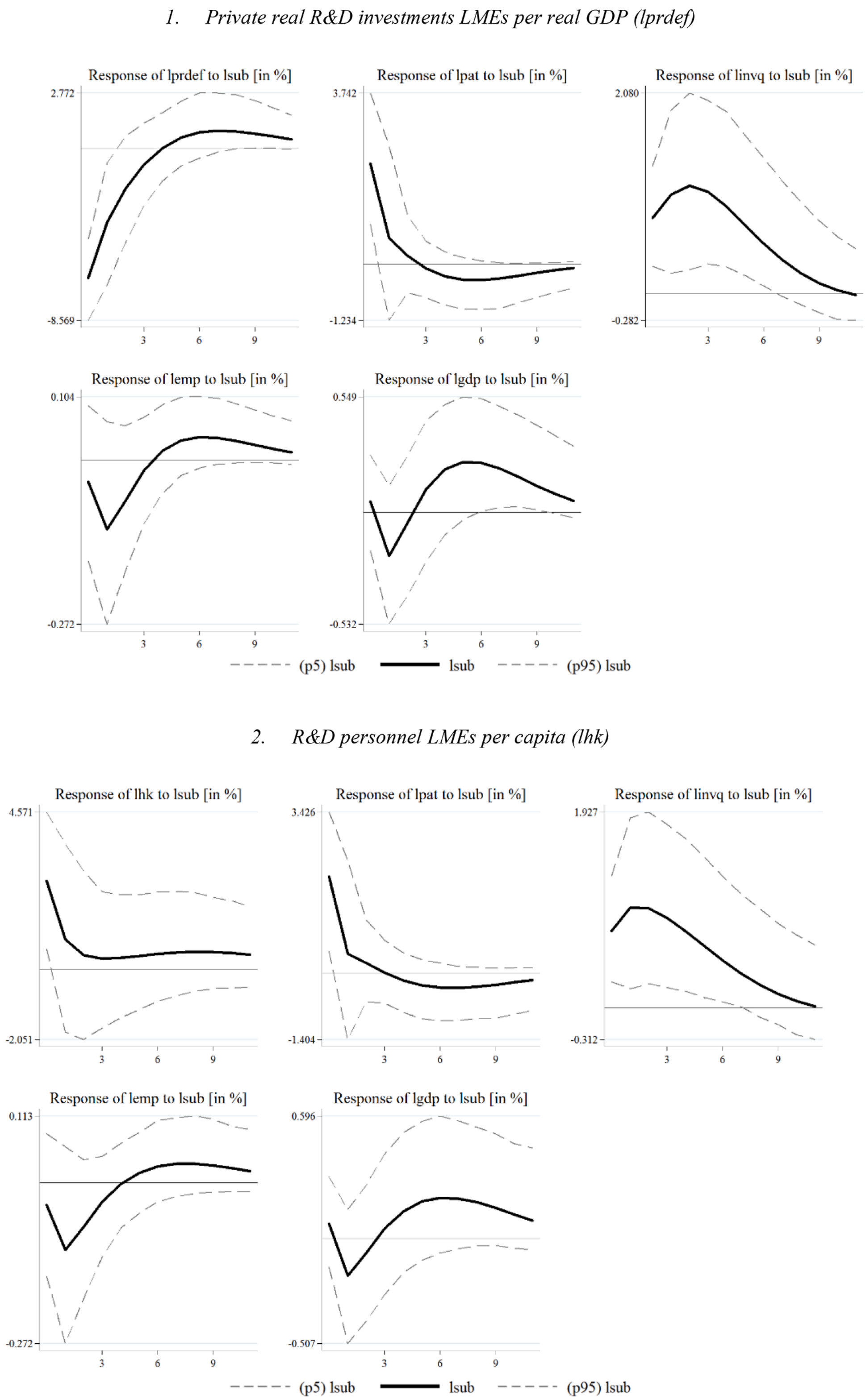


**Fig. 6.** IRF analysis for an increase in R&D subsidy intensity (lsub), 2000–2010. 1. *Private real R&D investments in LMEs per real GDP (lprdef) 2. R&D personnel in LMEs per capita (lhk)* Notes: The solid lines are the estimated IRFs, the dashed lines illustrate the 95% confidence intervals that are calculated by Monte Carlo simulations with 500 repetitions.

significance. As a further sensitivity analysis, we test the inclusion of the four municipalities during the 2003–2010 time period. The significant positive effects on private R&D investments and R&D personnel employed in LMEs remain robust (Figure OA6), whereas the results on the other outcomes of interest become more muted in their statistical significance. These results indicate that the wider economic benefits observed above are driven by the development of municipalities during the early years of our period.

Sixth, we reverse the causal ordering between provincial human capital and R&D subsidies at time *t*. Different to our prior assumption that public funding has a rather exogenous effect on private R&D investments and R&D personnel employed in LMEs, we now assume that R&D personnel and private R&D investments at time *t* endogenously determine the allocation of public funds. Due to the model's empirical specification, this restricts any potential effect of R&D subsidies on R&D inputs at time *t* to zero. Indeed, we find that the effects of R&D subsidies on private R&D investments and R&D personnel disappear in this setting, indicating that they are only of contemporaneous significance (Figure OA7). In other words, this finding confirms our previous main result, namely a contemporaneous effect of R&D subsidies on R&D inputs of firms, while there is no crowding-out effect in subsequent time periods where the R&D activities of LMEs remain constant.

## 5. Conclusion

The dramatic increase in innovation activity coinciding with a rapid period of economic growth in transitioning economy countries like China has drawn a renewed interest among academics and policy makers about the role of the state in promoting a country's own technological capabilities. A small but growing number of empirical studies investigate the relationship between innovation support policies and innovation outcomes in China and other transitioning economy contexts. Yet, it remains controversial what is the effect of public R&D investments made by the state on private R&D investments and their wider economic effects. To help contribute to this ongoing debate, this paper studies the effect of R&D subsidies on private R&D investments of LMEs and the broader implications for technological and economic development in the Chinese context. To this end, we estimate a structural VAR model relying on provincial-level data during the 2000–2010 time period.

The main results are as follows. We find that an increase in the R&D subsidy intensity by one standard deviation corresponds to a decrease of 6.46% in private R&D investments, but an increase of 2.57% in the R&D personnel employed. We interpret this finding as evidence in support of a partial crowding-out effect of R&D subsidies on R&D inputs: public funds partially substitute (i.e. crowd-out) private funds while total R&D inputs still increase via the expansion of R&D personnel induced by the R&D subsidy.

The observed partial substitution effect adds important nuance to existing work that tends to dichotomize the potential effects of public R&D subsidies on private R&D inputs as either perfect substitutes or complimentary. Importantly, despite leading to a partial crowding-out effect on private investment, public R&D subsidies expand total R&D personnel. The expansion of total R&D inputs, in turn, facilitates wider economic benefits (i.e. technological upgrading, capital deepening, and economic growth) despite evidence that some of the public funds become misappropriated. As fodder for future research, more work is needed in terms of optimal policy design that examines more closely the allocation decisions of firms with respect to how R&D subsidies get channeled into R&D vs. non-R&D related uses.

## CRediT authorship contribution statement

**Philipp Boeing:** Conceptualization, Investigation, Resources, Methodology, Writing – original draft, Project administration. **Jonathan Eberle:** Data curation, Methodology, Formal analysis, Writing – original draft, Funding acquisition. **Anthony Howell:** Writing – review & editing.

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## Supplementary materials

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