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Effects of R&D subsidies on regional economic dynamics: Evidence from Chinese provinces

Jonathan Eberle and Philipp Boeing

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Keywords: China, R&D subsidies, regional economic growth, panel VAR, impulse response functions

JEL Classification: C33, R11, R58, O38, O47

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1. Introduction

In recent years, China has been shifting from a capital-led towards a more innovation-led growth model. Although China reached outstanding output growth of more than 8% annually between 1978 and 2007 (Zhu, 2012), more recently the pace of output and productivity growth has been slowing down in the overall economy and manufacturing industries (Bai and Zhang, 2017; Brandt et al., 2017). This slowdown may be attributed to diminishing returns to higher levels of physical and human capital and a deterioration in the efficiency of resource allocation (Wei et al. 2017). As China moves closer to the global technology frontier, the creation of domestic innovation is seen not only as an important complement to the absorption of technologies developed elsewhere, but also as a main driver of productivity and economic growth. The government comprehensively supports China's transformation towards more innovation-led growth with numerous targets and policies (Cao et al., 2013).

A first-order policy target is to increase research and development (R&D) inputs in firms. To this end, the government quadrupled annual R&D subsidies allocated to large and medium-sized enterprises (LMEs) between 2000 and 2010, the time period underlying this study. Simultaneously, the relative contribution of private R&D investments[1] and employment of R&D personnel in the business sector increased from around 35% to 54% for investments and 36% to 54% for personnel (own calculations). These figures emphasize the importance of the corporate sector within China's innovation system. Against the background of aggregate dynamics at the national level, a striking feature of China's economic development is persistent provincial disparities (Tsui, 2014), which are also observable for innovation inputs and output. To appropriately consider heterogeneity among provincial production and innovation systems, our evaluation of China's R&D subsidies is conducted at the provincial level.[2]

Although it is well known that market failure in the private production of knowledge may require an adjustment of private R&D by public subsidies (David et al., 2000), the evaluation

[1] Following the standard approach in the literature, private R&D investment is calculated by subtracting R&D subsidies from total firm R&D expenditures (Dimos and Pugh, 2016). Private R&D corresponds to "net," "self-financed," or "own" R&D expenditures and does not discriminate between R&D expenditures by state-owned and non-state-owned firms.

[2] In the Chinese context the Annual Survey of Industrial Enterprises from the National Bureau of Statistics and the Administrative Enterprise Income Tax Records from the Chinese State Administration of Tax are sources of micro data for the quasi-population of LMEs. However, these data are not appropriate for the proposed evaluation because only total subsidies but not R&D subsidies are observed. In contrast, province-level data allows us to observe R&D subsidies.

literature shows that R&D subsidies could function as both complements and substitutes (Zuniga-Vicente et al., 2014; Dimos and Pugh, 2016). Most impact evaluations of public R&D subsidies on private R&D expenditures are conducted for developed economies. Until now, only a few studies provide an evaluation for China and the results are somewhat inconclusive (see Boeing 2016; Boeing and Peters 2019; Hu and Deng 2019; Liu et al., 2016). Chen (2018) is the only study at the provincial level and finds a partial crowding-out effect.

The contribution of our study is at least twofold: First, we estimate not only *direct* but also *indirect* effects of R&D subsidies on R&D inputs, which are unobservable in single equation approaches. Second, we estimate the *total* (*direct* plus *indirect*) effects of R&D subsidies on various economic variables in the provincial production system. In this way, we can detect secondary effects on the provincial capital deepening, technological progress, labor, and output, and thus draw conclusions on the role of R&D subsidies for the development of provincial innovation *and* economic activities. To this end, we are the first to use a panel vector autoregressive (VAR) model and corresponding impulse response function (IRF) analysis to analyze the effects of R&D subsidies on the economic performance of Chinese provinces. This econometric approach explicitly allows for the identification of *total* effects on a defined set of economic variables.

For R&D inputs of LMEs, we find that an increase of R&D subsidies significantly decreases private R&D investments, while there is a significant positive effect on the R&D personnel employed. We interpret these findings as a partial crowding-out effect because firms substitute some private funds with public funds but total R&D inputs still increase. Complementary to this result, we find a positive effect on provincial patents, our measure of technological progress. Interestingly, we also find some evidence for potentially unintended effects because R&D subsidies also increase the investment rate in physical capital and residential buildings. Although investments in physical capital may be complementary to R&D in general, investments in residential buildings more likely suggest some misallocation of R&D subsidies.

The remainder of the paper is set out as follows. In Section 2, we review the institutional setting and prior studies on R&D subsidies in China. Section 3 provides the theoretical framework. In Section 4, we specify our empirical strategy, data and descriptive statistics. In Section 5, we present the main results and robustness tests, and discuss our findings and policy implications. We conclude in Section 6.

2. Institutional setting and prior literature

According to Romer (1990), business R&D plays an essential role in fostering innovation and economic growth. However, market failure in private knowledge production may lead to suboptimal innovation rates and the deceleration of economic growth. Due to externalities in knowledge production that are difficult to internalize, private and social returns to innovation activities differ (Arrow, 1962). In conjunction with moral hazard and risky financing of R&D, this difference in private and social returns may lead to systematic underinvestment in R&D. This market failure may require policy intervention and an upward correction of business R&D activities by the provision of public subsidies (David et al., 2000).

Although governments offer public funding to spur R&D in firms – to incentivize more private R&D investments – R&D subsidies might also crowd out private financing of R&D. A firm invests in R&D if and as long as the marginal rate of return to R&D 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 others, the expected returns to other uses of available funds, such as investment in physical assets, available internal finance, and costs of external capital. Based on a theoretical concept developed by Hall (2008), Hottenrott and Peters (2012) show that optimal R&D investment increases only if grantees were initially financially constrained, implying insufficient internal financial means. The empirical evaluation literature indeed shows that R&D subsidies may function as both complements or substitutes, depending and the specific setting, and might have crowding-out, neutral, or additionality effects on the private R&D investment of firms (see Zuniga-Vicente et al., 2014; Dimos and Pugh, 2016).

2.1 The institutional setting

The Chinese State Council aims to develop China into an innovative country by 2020 and a world leader in science and technology by 2050. Against this target, China's ratio of gross expenditures for R&D to GDP has already overtaken the ratio of the European Union; and in gross R&D expenditures, China is projected to overtake the United States around 2020 (OECD, 2014). In order to stimulate additional business R&D expenditures, the Chinese government invests heavily in innovation policy, e.g. through direct grants and tax incentives. Major national R&D programs 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). In addition, firms receive R&D subsidies from programs administered by sub-national agencies.

During the time period we study, the ratio of total real R&D investments and private real R&D investments by LMEs to real GDP has continuously increased and doubled between 2000 and 2010 (Figure 1). Given China's strong growth in GDP over this time period, the increase in R&D intensity is even more striking.

<<< Figure 1 >>>

The major innovation policies in this period are formulated in the 10th and 11th Five-Year Science and Technology Development Plans (2001-2005 and 2006-2011) and, more importantly, the Mid- to Long-term Science and Technology Development Plan 2006-2020 (MLP). The MLP aims to foster R&D expenditures of domestic firms, as well as to better coordinate the existing R&D policies to increase the effectiveness of government support (Liu et al., 2011). After 2006, a more mission-oriented policy approach was implemented and amendments of major national R&D programs took place, paralleled by substantial increases in government funding. Between 2000 and 2010 annual R&D subsidies to LMEs quadrupled from 4.31 to 16.95 real billion RMB, while the private R&D expenditures of LMEs increased twelvefold from 30.84 to 371.86 real billion RMB (Figure 2).[3] These efforts lead to a continuous increase in the ratio of private firm to total R&D investments as well as the ratio of firm to total R&D personnel in China, emphasizing the increasing relevance of firms for the China's innovation system (Figure 3). However, the key question to ask is whether R&D subsidies have contributed to the rise in private R&D expenditures.

<<< Figures 2 & 3 >>>

2.2 Prior Chinese studies

Most evaluations of the effect of public R&D subsidies on private R&D expenditures are conducted for developed economies. Only a few studies provide an analysis for developing economies. In this section, we focus on the Chinese economy and first discuss prior *firm-level* studies and hereafter *provincial-level* studies. For the early period 2001 to 2006, Boeing (2016) estimates the average treatment effect on the treated (ATT) and finds a partial crowding-out effect. Liu et al. (2016)

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[3] Using the 2005 RMB-EUR year-end exchange rate, this corresponds to an increase from 3.225 billion EUR to 38.888 billion EUR.

observe high-tech manufacturing firms in Jiangsu province based on cross-sectional survey data for the year 2012. They estimate the ATT and find that grantees increase private R&D expenditures by 14.3 %. Hu and Deng (2019) use survey data for private-owned manufacturing firms, observed between 2007 and 2011, and find that treated firms almost double private R&D expenditures compared to the pre-treatment year. Most recently, Boeing and Peters (2019) observe misappropriation of R&D subsidies by firms and separately estimate the intention-to-treat (ITT) and complier-average-causal-effect (CACE). Between 2001 and 2011, they show partial crowding-out for the actual effectiveness of R&D policy, whereas the efficacy among compliers (i.e., non-misappropriating firms) confirms additionality. In summary, these studies suggest heterogeneous effects. Boeing (2016) and Boeing and Peters (2019) fail to reject partial crowding-out for the population of firms, but R&D subsidies have a higher effectiveness for high-tech and private firms, which is similar to the results by Liu et al. (2016) and Hu and Deng (2019). Confirming theoretical predictions, these findings emphasize that higher returns to R&D and financial constraints, as expected for high-tech firms and private firms in China, result in higher effectiveness of R&D subsidies compared to the population effect.

To the best of our knowledge, the only *provincial-level* study that evaluates the effect of R&D subsidies on business R&D expenditures is Chen (2018). For the population of firms, he finds insignificant effects on total R&D expenditures, while the effects on private R&D expenditures are significant negative, which one may interpret as evidence for crowding-out. Other related studies mainly investigate the effect of R&D subsidies, tax allowances, and public R&D investment on provincial patent activity. Sun (2000) shows that patent applications are spatially concentrated on provincial level and public R&D (investments and employment) does not significantly increase provincial patent activities. Li (2009) finds significant positive effects of provincial governments' science and technology expenditures on invention patents, but insignificant effects on utility model patents (in contrast to utility patents, invention patents are more closely related to technological inventions). Fan et al. (2012) show that public R&D investments contribute to provincial inequalities in innovation outputs as measured by patents. The findings by Cheng and Zhang (2018) suggest that public R&D subsidies and tax incentives increase the funds that firms devote to R&D collaborations with universities and research institutes. Moreover, both public R&D support measures increase the joint patent output of firms, universities, and research institutes. In a nutshell, these studies confirm, for the most part, positive effect of public support measures on patent output at the provincial level.

Although prior studies at the *provincial level* investigate the *direct* effects of R&D subsidies on firms' R&D input and provincial patent output, we aim to contribute to the literature by analyzing the *total* (*direct* plus *indirect*) effects of R&D subsidies on a larger set of theory-based economic variables. For this exercise, we follow recent applications of a VAR approach at the regional level (e.g. Ramajo et al., 2017; Mitze et al., 2018; Eberle et al., 2019). In the Section 3, we present a theoretical framework that motivates our subsequent empirical analysis.

3. Theoretical framework

Based on Solow (1956), the theoretical growth literature has emphasized the importance of human and physical capital accumulation for economic growth (e.g. Mankiw et al., 1992). Although capital deepening is essential for growth in developing economies, with accelerating economic development the contribution of capital accumulation decreases while the importance of technological progress increases (e.g. Aghion and Howitt, 2009). This is because innovation offsets the diminishing returns to capital by a continual rise in technology. Thus, innovation drives both technological progress and capital deepening, the two main components of economic growth. Once an economy is fully industrialized and has reached the steady state, per capita income and growth is solely driven by innovation and technological progress.[4] However, in the case of China, provincial economies are strongly heterogeneous and display a high level of variation regarding the general economic development (Tsui, 2014) and innovation activities (Li, 2009). Therefore, we apply a provincial-level analysis to evaluate the outcomes of public R&D subsidies in China.

We assume the following production function for each province *i*

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

[4] Whereas Mankiw et al. (1992) assume that technological process is exogenously given and equally distributed across economies, Romer's (1990) growth model explicitly endogenizes the accumulation processes of technology in a R&D sector.

where Y_i is provincial output, K_i provincial physical and H_i human capital, A_i denotes the level of the provincial technology, λ_i is the provincial employment rate, and P_i denotes provincial resident population. Decreasing returns to scale are imposed by $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$. Following Eberle et al. (2019), we specify provincial labor as $L_i = \lambda_i P_i$, with λ_i as the in long-term fixed provincial employment rate ($\frac{L_i}{P_i}$), while provincial population P_i grows at the exogenous rate n_i. By dividing Equation (1) by P_i, the provincial per capita production function can be expressed as

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

Equation (2) defines the provincial GDP per capita as the output factor, and physical and human capital per capita, and the level of technology and the employment rate as core production factors in the provincial economic system. Note that, due to data limitations, we use the physical capital (fixed assets) investment rate (subsequently labelled as $s_{k,i}$) 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).

R&D is a human capital intensive activity (Romer, 1990; Aghion and Howitt, 2009) and a substantial share of current business R&D cost are labor cost for internal R&D personnel, hence investments in human capital.[5] We formulate the dynamics of per capita human capital (e.g. Mankiw et al., 1992) as

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

In Equation (3), $s_{h,i}$ is the investment rate in human capital that depreciates with a constant rate δ (Mankiw et al., 1992). With respect to Equation (3), *R&D investments* are accounted for by $s_{h,i}$ and the *R&D personnel* is captured by h_i.

To identify the effects of R&D subsidies (labeled by $s_{h\_public,i}$), we augment our model with private R&D investments by LMEs (labeled by $s_{h\_private,i}$). The parameter will be informative whether or not the crowding-out hypothesis can be rejected. Alternatively, we will also augment

[5] In developed economies, this share is usually higher than in developing economies. It was 64.5% for Germany (in 2011) and 52.3% for the United Kingdom, 44.8% for Japan, 44.1% for Korea, and 30.4% for China (all in 2009) (OECD Statistics, 2019). Please note that this is only a theoretical assumption; our flexible empirical approach accounts for alternative transmission channels of R&D investments (Section 4.1).

the model with firms' R&D personnel (h_i).[6] If crowding-out cannot be rejected for private R&D investments, the parameter for firms' R&D personnel will allow us to differentiate the extent of crowding-out: a neutral effect implies full and a positive effect partial crowding-out of private R&D expenditures. Using firms' R&D personnel instead of total R&D investment has the additional advantage that this measure implicitly controls for potential wage-adjustments of R&D personnel as a result of a policy-induced demand shock for scientists.

An increase in the provincial human capital may also affect other economic variables in the provincial system in Equation (2) via economic secondary effects. First, the physical capital investment rate is assumed to be constant and thus unaffected by increases in R&D subsidies (e.g. Mankiw et al., 1992). Second, policy makers allocate R&D subsidies to incentivize corporate R&D investments to promote provincial technological growth.[7] We assume that technological growth (g_i) is determined by input factors that are effective in the provincial corporate research sector (e.g. Romer, 1990; Rivera-Batiz and Romer, 1991).[8] In contrast to Romer (1990) and Rivera-Batiz and Romer (1991), 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 Equation (3)), which is assumed to be given in the original model setups. Third, the provincial employment rate is assumed to be fixed in the long run, temporary effects may depend on substitution and output effects.[9] R&D subsidies to firms may lower the costs for R&D personnel (human capital) and basic labor may become more expensive comparative to R&D personnel,

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[6] The simultaneous inclusion of both variables ($s_{h,i}$ and h_i) would require our model to consider the same information twice and should be avoided. The correlation coefficients between the variables *R&D personnel LMEs per capita* and *private real R&D investments LMEs per real GDP* support this concern: $\rho_1 = 0.8834$ (all provinces), $\rho_2 = 0.88$ (Tibet excluded), $\rho_3 = 0.8707$ (Tibet and provincial-status municipalities excluded). Correlation coefficients for logarithmized variables are even higher.

[7] R&D subsidies may predominantly foster human capital (investments) in the research sector (e.g. Romer, 1990) and thus one may argue that technological growth g_i is a main target variable of R&D subsidies. For the reasons mentioned above, human capital is considered a main target variable (transmission channel) of R&D subsidies; but, in line with the applied flexible empirical model, we do not discriminate between human capital that is either productive in a production or research sector (the dynamics of human capital in Equation (3) are modelled by Mankiw et al. (1992) for the production sector). A potential effect on the provincial patent rate (proxy for technological growth) is interpreted as secondary effect here.

[8] 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 may be 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.

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

which may lead to a substitution effect. Conversely, if R&D subsidies raise provincial output, they may subsequently also trigger a higher demand for labor (output effect). Lastly, shifts in the provincial per capita output can be written as a function of changes of provincial input factors presented in Equation (2)

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

According to our theoretical framework, we expect provincial R&D subsidies to lead to a (temporarily) higher human capital investment rate $s_{h,i}$ and level of human capital h_i, given that firms are financially constrained. Moreover, positive secondary effects may arise especially on the provincial technological growth rate g_i, on the provincial per capita output y_i and employment rate λ_i. Due to substitution effects in the very short run, the latter effect is expected to arise after a phasing-in of several years.

4. Empirical strategy, data and descriptive statistics

4.1 Empirical strategy

The VAR system that we model is composed of six equations with six dependent variables: (1) R&D subsidy intensity **lsub**, (2) human capital **lprdef** and **lhk** (proxied by private R&D investments or R&D personnel of LMEs), (3) technological growth rate **lpat** (provincial patents), (4) physical capital investment rate **linvq** (provincial investments in fixed assets), (5) employment rate **lemp** (provincial employed persons), and (6) real GDP per capita **lgdp** (provincial output). In order to investigate the *total* effects of Chinese R&D subsidies to the provincial corporate research sector, we consider not only *direct* effects (denoted by the estimate in a partial analysis approach) but also mutual *indirect* effects between the defined provincial variables. To this end, we propose a panel VAR and associated IRF analysis that allows us to determine the total effects of an increase in Chinese 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

$$\mathbf{y_t = Ay_{t-1} + f_i + t_t + e_t}. \tag{5}$$

In Equation (5), $\mathbf{y_t}$ denotes a vector of the six provincial endogenous variables [lsub, lprdef/lhk, lpat, linvq, lemp, lgdp], the matrix **A** is containing reduced-form coefficients, $\mathbf{f_i}$ is a vector of provincial fixed effects to capture time constant heterogeneity, and $\mathbf{t_t}$ is a vector of time dummies to capture general external shocks, respectively, while the vector $\mathbf{e_t}$ comprises (reduced-form) residuals (e.g. Love and Zicchino, 2006; Rickman, 2010). From a methodological perspective, the inclusion of provincial fixed effects has the considerable advantage that all time-invariant confounders are controlled for.[10] To account for the influence of additional time-variant confounders, in Section 5.2 we test the robustness of our model after augmenting several time-variant controls.

As a response to criticism of the atheoretical reduced-form VAR approach, the structural VAR approach has been developed (e.g. Rickman, 2010), which can be formulated as

$$\mathbf{By_t = Cy_{t-1} + f_i + t_t + D\boldsymbol{\varepsilon}_t}. \tag{6}$$

In Equation (6), the matrix **B** includes contemporaneous (structural) parameters, the matrix of polynomials **C** is connecting contemporaneous to time-lagged variables, and, eventually, diagonal matrix **D** links uncorrelated (exogenous) shocks $\boldsymbol{\varepsilon}_\mathbf{t}$ to the provincial endogenous variables (e.g. Keating, 1992; Rickman, 2010).[11] As Rickman (2010) points out, theory-based restrictions (see Section 3) in the structural VAR model are set on the matrix **B**. To this end, in order 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 provincial endogenous variables at period *t* (Choleski decomposition). Based on the developed theoretical framework in Section 3, we define the causal ordering at time *t* (see Figure 4).

<<< Figure 4 >>>

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

[10] We are estimating six dynamic panel equations (in the reduced-form specification) incorporating provincial fixed effects, which is why the basic fixed-effects estimator suffers from a dynamic panel bias (Nickell, 1981). To account for this issue and to yield unbiased estimates, we use a bias-corrected fixed-effects estimator that is proposed by Everaert and Pozzi (2007).

[11] Please note that $\mathbf{A = C{*}B^{-1}}$ and $\mathbf{e_t} = \boldsymbol{\varepsilon}_\mathbf{t}\mathbf{{*}B^{-1}}$ (Rickman, 2010).

have only time lagged (feedback) effects (e.g. GDP per capita). With respect to Equation (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 variables, while the investment rate and the employment rate are ordered on the basis of their flexibility in the short run and thus appear more to the left in Figure 4 (e.g. Eberle et al., 2019). We define the R&D subsidy intensity as the most exogenous variable in the provincial economic system. R&D subsidies are assumed to directly (contemporaneously) affect R&D investments and personnel of LMEs, which are seen as important input factor in knowledge production (Romer, 1990) and thus directly affect provincial technological growth g_i (patents), while labor and capital goods are assumed to trigger (delayed) secondary effects on g_i.

An important concern is reverse causality. If human capital determines R&D subsidies and not vice versa, a picking-the-winner strategy would imply a non-random allocation of public funds to firms with more human capital and R&D investments and an upward bias of the estimated effect. Because this corresponds to a different causal ordering, in Section 5.2 we perform a robustness test to control for different effects of R&D subsidies on other variables in the economic system (this corresponds to a change of R&D subsidies and R&D investments and personnel of LMEs in Figure 4).

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), while the calculated confidence intervals are based on Monte Carlo simulations (Love and Zicchino, 2006).

4.2 Data

The data is mainly obtained from China's National Bureau of Statistics (NBS) and contains information at the province-year level observed between 2000 and 2010.[12] Table 1 present's details for the variable definitions and data sources, and in Appendix A1 we discuss some features of China's officially reported data. In the remainder of this paper, we use the variable abbreviations presented in Table 1. Table A1 in the Appendix provides summary statistics of the six economic core variables. We construct real values for monetary output and investment measures by using the

[12] In 2011, the NBS survey was amended and the availability of consistent information on R&D investments and R&D personnel of LMEs restricts our analysis until 2010. LMEs 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)

provincial consumer price index (CPI). Technological growth is measured by granted invention patents obtained from China's patent office (CNIPA).[13]

<<< Table 1 >>>

As a robustness test, we augment several time-variant provincial characteristics that may influence the coefficients of the core VAR variables. First, we control for non-LMEs R&D investments, mainly from universities and research institutes, in order to account for further determinants of technological growth at the province level. R&D personnel and private R&D investments of LMEs are likely to be correlated with non-LMEs R&D investments, and this may lead to omitted variable bias. Second, we include the ratio of private to state-owned firms and the ratio of loss-making state-owned firms. We hereby we aim to control for heterogeneity in financial constraints. 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. Third, we include the ratio of innovative LMEs to total LMEs as a measure for potential knowledge spillovers at the province level, because the expected value of firms' R&D, and hence the decision to perform R&D, is also dependent on the degree of spillovers. Fourth, the ratios of the valued-added of the primary and the secondary sectors to total valued-added are added as indicators for the provincial economic composition. Fifth, provincial coal resources are added because these may absorb short-term oriented investments to the detriment of long-term economic development, also known as *resource curse*, which would increase the opportunity cost of R&D. Finally, we use the trade specialization index proposed by Li (2009) that measures export activities and the absorption of foreign technological knowledge, which is embodied in foreign goods.

4.3 Descriptive statistics

For each core variable in each province, we report the long-term growth rate from 2000 to 2010 in Figure 5 and the summarized economic activities for the entire period 2000 to 2010 in Table A2. Beijing, Shanghai, and Tianjin, which are relatively developed provincial-status municipalities, have the highest GDP per capita, as well as the highest patents-to-GDP ratio (Table A2). However,

[13] In this context, 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 also helps to mitigate the distortion of application-based patent subsidies on patents as an indicator of technological growth in China.

municipalities may benefit from agglomeration effects, and 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 Table 5). More developed provinces, such as Zhejiang and Guangdong, have high growth rates in private R&D investments, R&D personnel, and patenting. As a stylized fact, and confirming theoretical predictions, this suggests that less developed provinces have relatively higher marginal returns to physical capital, whereas more developed provinces pursue innovation to substitute capital- with technology-driven growth.

<<< Figure 5 >>>

R&D subsidies may be an important policy instrument to support the transition towards innovation and technology-led growth. Figure 6 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). The pattern suggests that an increase in the intensity of R&D subsidies to GDP is accompanied by an increase in the private intensity of R&D and patents to GDP. While acknowledging that these figures do not allow for a causal interpretation, in the subsequent section we perform an analysis that addresses identification issues.

<<< Figure 6 >>>

5. Empirical results

In this section we present the results of our panel VAR approach and the IRF analysis. To avoid having our results influenced by outliers, in the basic model we exclude Tibet and the municipalities Beijing, Chongqing, Shanghai, and Tianjin but include the municipalities in a robustness test. 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 thus we detrend these variables.

<<< Table 2 >>>

As noted in Section 4.1, the econometric approach allows us to calculate the total (*direct* plus *indirect*) effects of an increase in public R&D subsidies on all economic variables in Equation (2). The total effects on private R&D investments and personnel of LMEs (captured by human capital in Equation (2)) are considered as primary effect because the human capital variable is seen as primary transmission channel of Chinese R&D subsidies. Moreover, R&D subsidies may have additional (unintended) effects on the remaining variables that are interpreted as economic secondary effects.

5.1 Basic model

In Figure 7, we investigate the total effect of R&D subsidies on the R&D personnel and private R&D investments of LMEs and total effects on our secondary variables. 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 confidence intervals for the various IRFs (x-axis denotes years).

We start with the effect of R&D subsidies on R&D inputs of LMEs. Panel 1 shows that an increase in the R&D subsidy intensity leads to a contemporaneous significant negative effect on the private R&D investment rate. Panel 2 shows that an increase in the R&D subsidy intensity leads to a continuous positive effect on R&D personnel, while the confidence intervals suggest that this effect is only significant in the first year. We interpret these findings as a contemporaneous partial crowding-out effect because firms substitute some private funds with public funds, but total R&D inputs still increase.

In addition to the effect on R&D, Panels 1 and 2 show that an increase in the R&D subsidy intensity has a significant positive effect on the provincial physical capital investment rate and patent activity. The effect on physical capital suggests that R&D subsidies have an effect on investments into assets, which may be research or non-research related, and we will explore this point further in Section 5.2. Increases in patents may be explained by a simultaneous increase in R&D inputs, emphasized by a closely related shape of the two response functions (see Panel 2 of

Figure 7).[14] Moreover, the positive effects on the physical capital investment rate may also emanate positive secondary effects on patents.

For the regional employment rate, we find a negative effect in the short run, potentially through substitution and adjustment effects, but a rather (insignificant) positive effect in the medium run. As for the real provincial GDP per capita, our results also suggests a short-run negative effect; however, the responses in Panels 1 and 2 show a delayed significant positive effect. In conclusion, there is some evidence that R&D subsidies have a positive effect on the provincial economy in the medium run.

<<< Figure 7 >>>

5.2 Robustness Tests

In this section we report five robustness tests. First, we augment our basic model with several control variables to address a potential omitted variable bias (see Table 1 for an overview of variables). The results in Figure A1 confirm the significant negative contemporaneous effect on the private R&D investments of LMEs (Panel 1) and a significant positive contemporaneous effect on R&D personnel (Panel 2). Furthermore, in Panel 2 the effect on the patent activity turns insignificant, while the positive effect on the physical capital investment rate remains robust in both panels. The significant negative effects on the employment rate and GDP per capita are restricted to the short-term perspective, while the significant positive effect on the GDP per capita diminishes in this setting.

Second, we account for changes in China's innovation policy introduced after the *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 (Figure A2).[15] The effect on the private R&D investment rate of firms is still contemporaneously negative but turns insignificant afterwards (Panel 1). The results also show that an increase in the R&D subsidy intensity has a long-lasting significant positive effect on the R&D personnel of LMEs (Panel 2). The estimated response of the

[14] 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).

[15] We also apply unit root tests for this time period before estimation. Please 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.

physical capital investment rate and the provincial patent activity remains significant positive. We do not find a significant effect on the employment rate, nor on the per capita income. These findings largely support our main results and indicate no substantial increase in the effectiveness of R&D subsidies in more recent years.

Third, we return to the question whether the effect of R&D subsidies on the physical capital investment rate suggests the use of R&D subsidies for non-research investments. We use investments in residential buildings as an indicator for short-term profit maximizing investments, which, however, are unlikely to be complementary to R&D. Due to data limitations, this analysis is restricted to the years 2003 to 2010. The corresponding IRFs in Figure A3 show that a shock in the R&D subsidy intensity has a significant positive short-run effect on the investment rate in residential buildings. Thus, the results support that R&D subsidies are partially misallocated to non-research investments.

Fourth, we include provincial-status municipalities. We fail to note changes on the responses of our core variables, except for the employment rate and GDP per capita, which are a significant negative in the short term but convert into positive effects in the medium run (Figure A4). As a further sensitive analysis, we test the inclusion of the four municipalities in the time period 2003 to 2010. The significant positive effect on the R&D personnel employed in firms and the negative effect on the private R&D investments of LMEs remains robust (Figure A5). However, the positive response of the physical capital investment rate is non-significant in the setting where R&D inputs are measured by private R&D investments of firms (Panel 1).

Fifth, different to our prior assumption that public funding has a rather exogenous and contemporaneous effect on firms' R&D personnel and private R&D investments, we now assume that R&D personnel and private R&D investments at time t endogenously determine the allocation of public funds. To this end, the causal ordering between human capital and R&D subsidies at time t in Figure 4 is reversed. In the model, this restricts any potential effect of R&D subsidies on private R&D investments at time t to zero. The findings suggest that the effects of R&D subsidies on R&D personnel and private R&D investments are only of contemporaneous significance, as they disappear in this setting (Figure A6). Firms instantaneously substitute own funds with public funds, while there is no effect in subsequent periods. Accordingly, there are no significant effects on the R&D personnel at all. The results confirm 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 remain constant. The significant positive effect on the patent activity, investment rate as well as partially on the real GDP per capita remains unchanged.

5.3 Discussion

Our main empirical insight is that an increase of R&D subsidies significantly decreases private R&D investments, while there is a significant positive effect on the R&D personnel employed in firms. We interpret these findings as a partial crowding-out effect because public funds substitute some private funds while total R&D inputs still increase. Hence, R&D subsidies have not contributed to a rise in private R&D expenditures but still led to an increase in total R&D inputs. This finding corroborates prior investigations of China's R&D subsidies at the firm (Boeing, 2016) and provincial level (Chen, 2018).

In addition, we find positive secondary effects on the provincial patent activity and the investment rate in physical capital. Through increases in total R&D inputs, provincial economies benefit from technological progress and capital deepening. The former empirical finding especially confirms the prediction of our theoretical framework. What is more, we find some evidence for potentially unintended effects as R&D subsidies also increase the investment rate in residential buildings. Although investments in physical capital may be complementary to R&D in general, investments in residential buildings more likely suggests partial misallocation of R&D subsidies. This finding is in line with the firm-level evidence presented in Boeing and Peters (2019), which show that misappropriated R&D subsidies are partially used for investments in physical capital. In particular, real-estate investments seem to increase the opportunity cost of R&D investment in China. Based on data for manufacturing firms in 35 Chinese cities, Rong et al. (2016) find that housing price appreciation creates opportunities for high earnings of real estate investments. For this reason, manufacturing firms enhance diversification in the real estate sector and thereby decrease investments in innovation, which may provide a possible explanation for the effect of R&D subsidies on the investment rate in residential buildings.

In general, our findings imply that China's R&D subsidies have effectively stimulated R&D activities of firms, as well as further economic activities of provinces, but failed to increase private R&D funding. Although a first-order goal of China's innovation policy is to increase R&D activities in firms, this goal could be reached more efficiently under an additionality rather than partial crowding-out regime. Thus, a crucial question is how to improve China's R&D policy towards a higher effectiveness in stimulating private R&D expenditures. Below we discuss three potential avenues.

First, rigorous monitoring may increase the odds of R&D subsidies being invested in research, instead of non-research, and this is a necessary condition for any effect on R&D activities. Second, selection of financially constrained recipients and strict monitoring of funding contract rules, especially in the case of matching grants, reduces the risk that public funds become a substitute for private funds. Even if grantees fulfilled matching criteria of supported R&D projects by using private funds from non-supported R&D projects, this reallocation does not lead to crowding out of private funds. Third, China's increasing emphasis on mission-oriented R&D programs bears the risk of disproportionally lower marginal returns to supported projects relative to non-supported projects. A strict mission-oriented policy may enhance government failure in the identification of R&D projects with the highest social returns and results in resource misallocation to the detriment of welfare and growth. Rigorous ex-post evaluation will help to identify and adjust ineffective policies in time.

6. Conclusions

In this study we investigate the impact of R&D subsidies on R&D inputs of large- and medium-sized firms in Chinese provinces. A panel VAR model and corresponding IRF analysis allow us to differentiate between direct and indirect effects, which add up to total effects. Based on this approach we can identify the impact of R&D subsidies on additional measures of provincial innovation and economic performance. A main result is that R&D subsidies fail to incentivize private R&D expenditures while firms increase the total employment of R&D personnel. We interpret these findings as a partial crowding-out effect because public funds substitute some private funds while total R&D inputs still increase. Beyond that, we gain novel insights into additional transmission channels of R&D subsidies. Notably, we find positive effects on measures of technological progress, capital deepening, and growth, while there is a negative effect on employment in the short run. Politically unintended effects of R&D subsidies on investments in residential buildings suggests partial misallocation of public funds.

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Tables

Table 1
Variable Descriptions and Data Sources.

Variable abbreviation	Description	Data sources
	Core variables VAR model	
lgdp (y)	Real GDP per capita (per resident population). CPIs are used to calculate real values.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
lemp (λ)	Employment rate (Number of employed persons at year-end by region per capita (per resident population)). Missing data for 2003 and 2006 are calculated on the basis of the formula: (Employed Persons$_{t-1}$ + Employed Personsi$_{t+1}$)/2	National Bureau of Statistics of China, China statistical yearbook (various years), available online (http://www.stats.gov.cn/english/statisticaldata/annualdata/)
linvq (s_k)	Real investments in fixed assets per real GDP.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
lhk (h)	R&D personnel LMEs per capita (per resident population).	Statistics yearbook on science and technology activities of industrial enterprises (various years)
lprdef ($s_{h\_private}$)	Private real R&D investments LMEs per real GDP (R&D subsidies subtracted from R&D investments LMEs).	Statistics yearbook on science and technology activities of industrial enterprises (various years)
lpat (g)	Patents per 100 Mio. real GDP (Granted Patents, Invention).	CNIPA (various years), online available (http://www.sipo.gov.cn/tjxx/jianbao/)
lsub (s_{h_public})	Real R&D subsidies to LMEs per real GDP.	Statistics yearbook on science and technology activities of industrial enterprises (various years)
	Control variables VAR model	
lcontrol1	Real non-firm R&D investments per real GDP.	Statistics yearbook on science and technology activities of industrial enterprises (various years)
lcontrol2	Ratio private firms to state-owned firm.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
lcontrol3	Ratio loss making state-owned firms to total state owned firms.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
lcontrol4	Ratio innovative LMEs to total LMEs.	Statistics yearbook on science and technology activities of industrial enterprises (various years)
lcontrol5 and lcontrol6	Ratio valued-added sector 1 and sector 2, respectively, to total value-added.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
lcontrol7	Ratio coal deposit to total coal deposit China. Figures of 2003 used for missing earlier years.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
control8 (not in ln)	Exports minus imports as share of the sum of ex- and imports: (Exports$_i$ – Imports$_i$) / (Exports$_i$ + Imports$_i$).	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)
linvq_rb	Real investments in residential buildings in the whole Country per real GDP.	National Bureau of Statistics of China, online data base (http://data.stats.gov.cn/english)

Notes: All variables are in logarithm (ln).

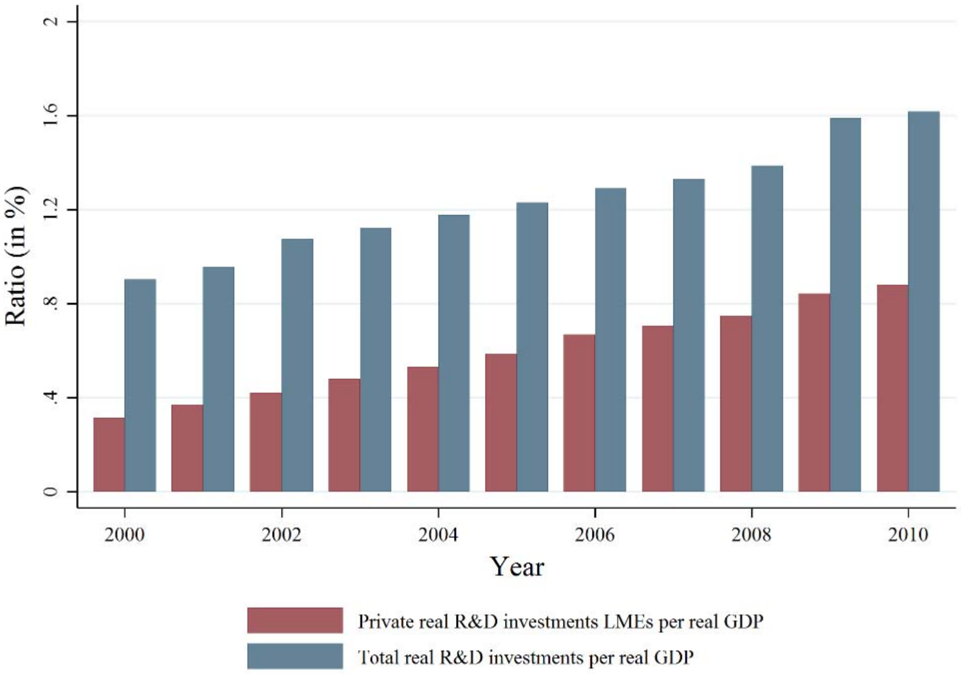
Table 2
Panel Unit Root Tests.

	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

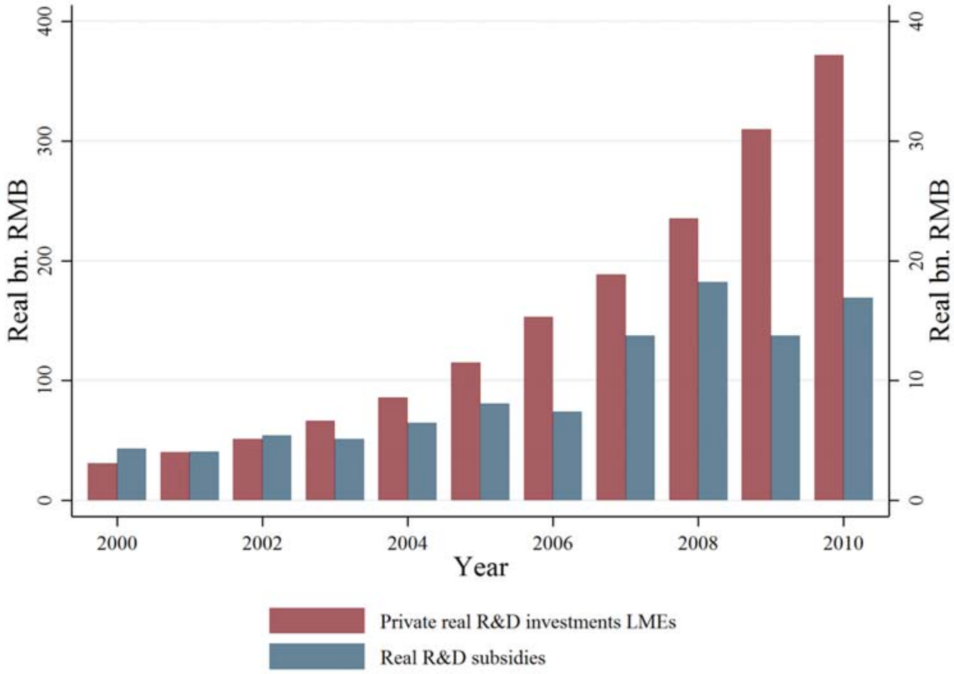
Figures

Figure 1
Dynamics of private real R&D investments LMEs and total real R&D investments per real GDP in China.



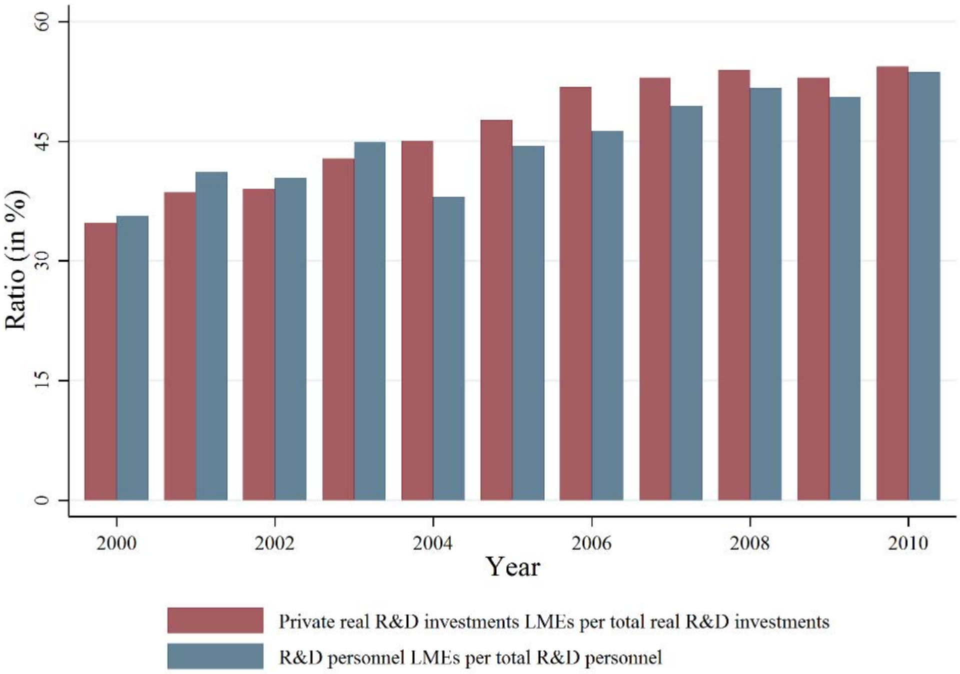
Notes: Own calculations based on aggregated provincial data. Data on total provincial R&D investments are based on China's statistical yearbook on science and technology activities of industrial enterprises (various years). For the remaining variables see Table 1.

Figure 2
Dynamics of private real R&D investments LMEs and real R&D subsidies in China.



Notes: Own calculations based on aggregated provincial data (see Table 1). Absolute values are presented.

Figure 3
Dynamics of innovation activities by LMEs in China.



Notes: Own calculations based on aggregated provincial data. Data on total provincial R&D investments and total provincial R&D personnel are based on China's statistics yearbook on science and technology activities of industrial enterprises (various years). For the remaining variables see Table 1. Ratio per total real R&D investments and ratio per total R&D personnel is presented.

Figure 4
Defined causal ordering across the provincial variables at time *t* (contemporaneous linkages).

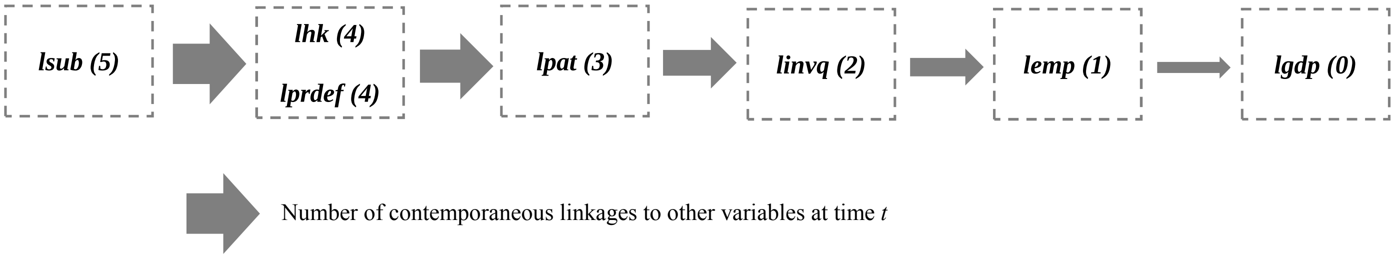
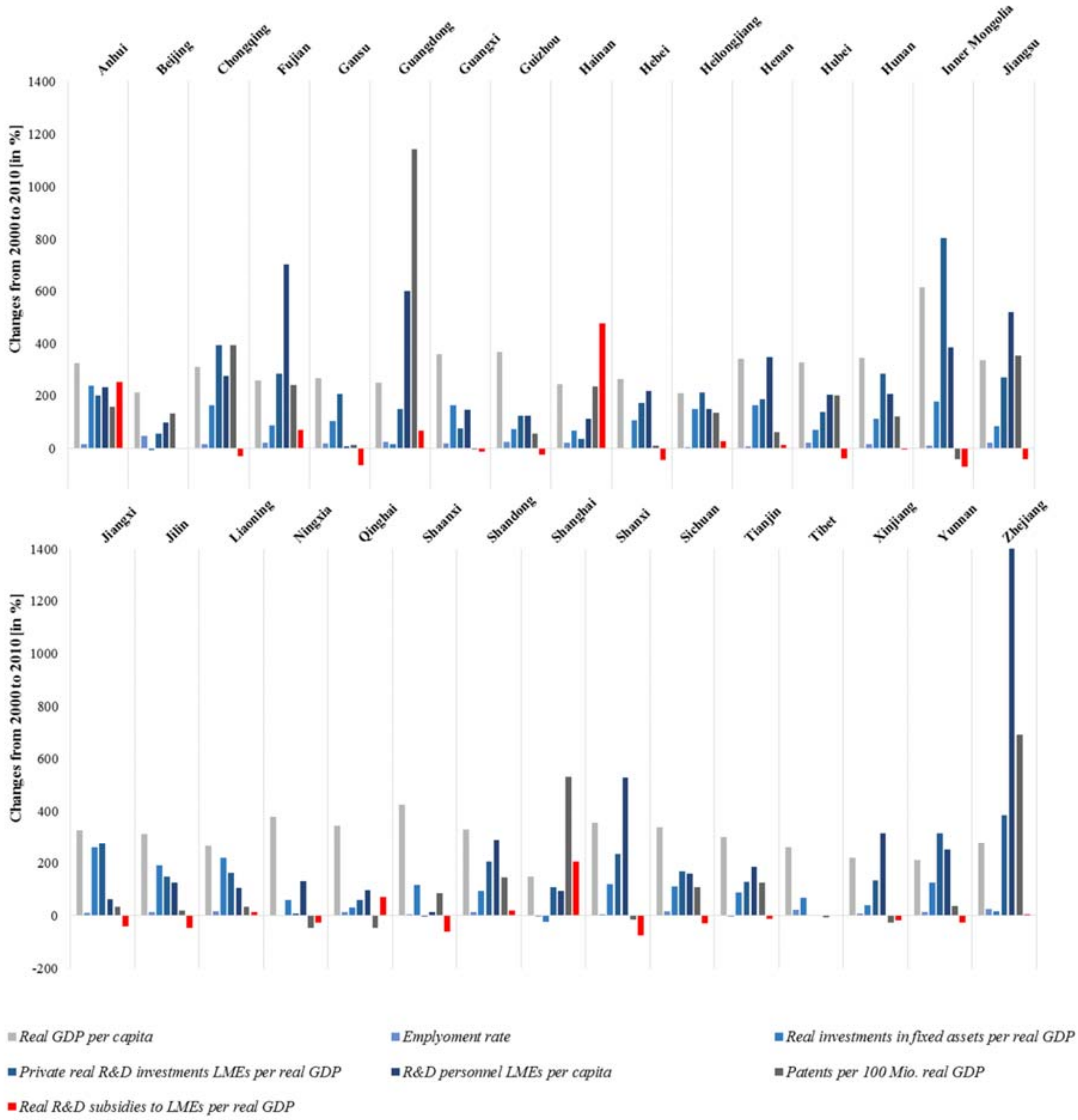
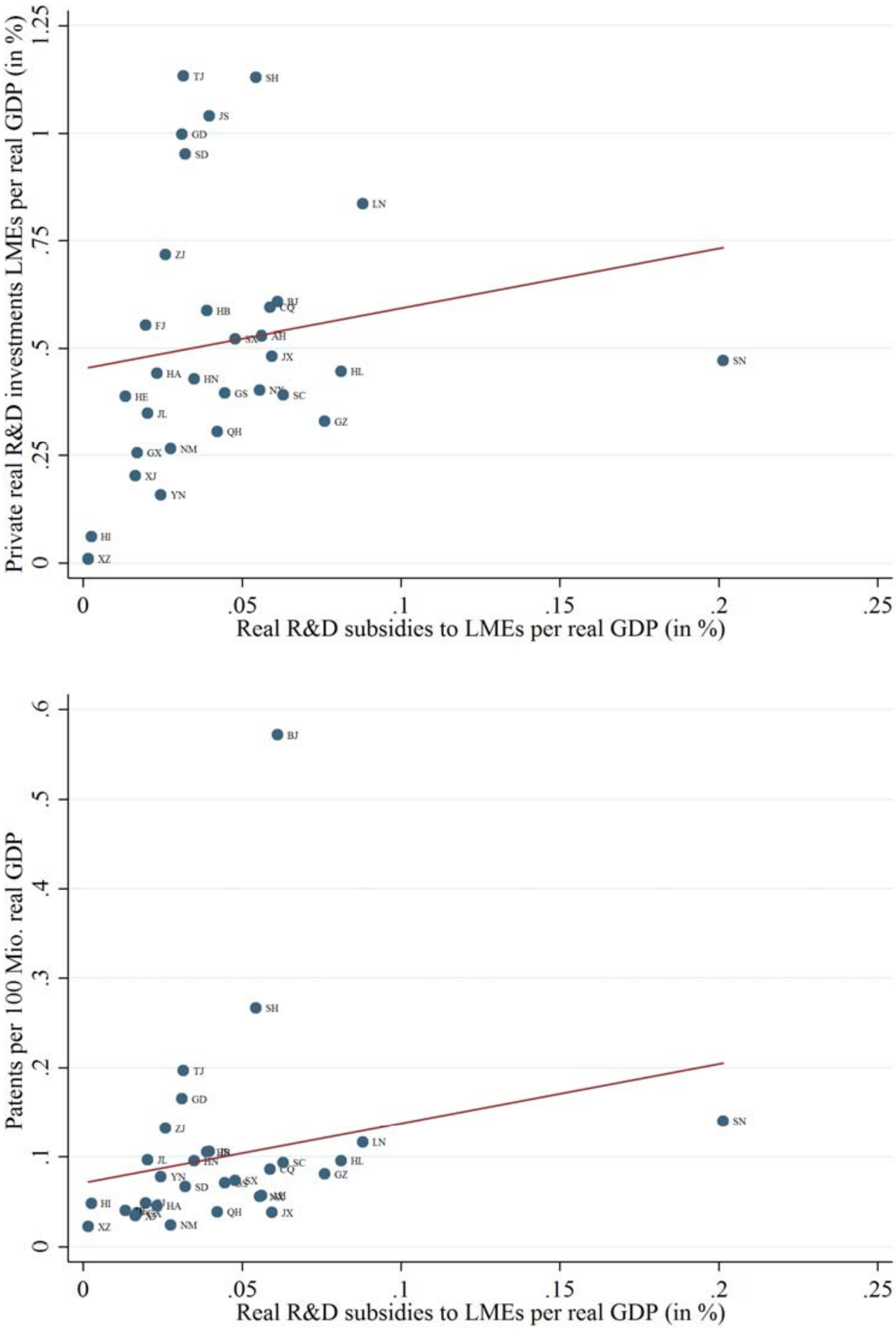


Figure 5
Provincial changes from 2000 to 2010 for various economic indicators (in %).



Notes: Own calculations based on provincial data (see Table 1).

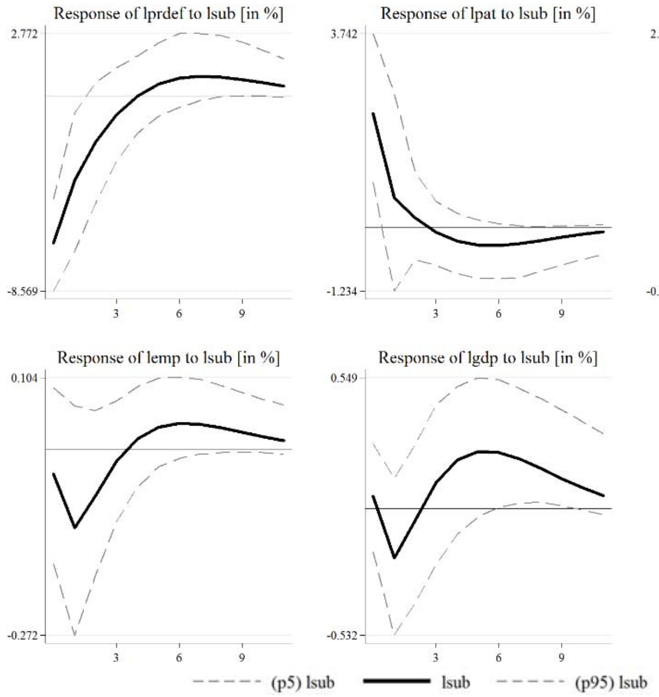
Figure 6
Scatterplot average private real R&D investments LMEs per real GDP (upper panel) and average patents per 100 Mio. real GDP (lower panel) in relation to average real R&D subsidies to LMEs per real GDP (values for the entire period 2000 to 2010).



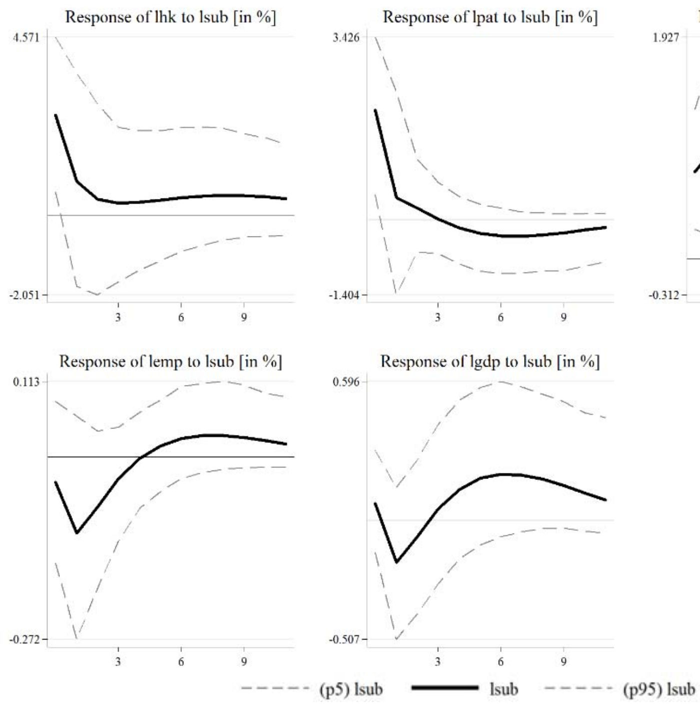
Notes: Own calculations based on provincial data (see Table 1). The shortcuts for the provinces are: AH: Anhui, BJ: Beijing, CQ: Chongqing, FJ: Fujian, GS: Gansu, GD: Guangdong, GX: Guangxi, GZ: Guizhou, HI: Hainan, HE: Hebei, HL: Heilongjiang, HA: Henan, HB: Hubei, HN: Hunan, NM: Inner Mongolia, JS: 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.

Figure 7
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2000-2010.

1. *Private real R&D investments LMEs per real GDP (lprdef)*



2. *R&D personnel LMEs per capita (lhk)*



Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions).

Appendix

Appendix A1

Data properties.

The use of China's provincial data is not without challenges, and in this section we briefly discuss some main issues.

1. Due to a decentralized accounting approach, the sum of *provincial GDP* is not equal to China's national GDP. For example, data on the national GDP is approximately 5.9 % smaller compared to the summed provincial GDP for the year 2010. Differences also applies to employed persons, population, investments in fixed assets and patents in our data.

2. NBS calculates *resident population data* for the years 2000, 2001 and 2010 based on the National Population Census 2000 and 2010, while data for the remaining years is based on annual national sample surveys on population changes. According to the National Population Census in 2010, population data for Beijing (2006 to 2009) as well as for Tibet (2001 to 2009) was corrected in retrospect and we use the corrected data.

3. Data on the *employed persons* by regions is obtained from various issues of China's Statistical Yearbooks. As mentioned in Table 1, there is no data available for the years 2003 and 2006. Until the year 2010, the annual provincial data is based on the National Population Census in 2000, as well as on the annual Sample Survey on Labour Force. Data for the year 2010 is based on the National Population Census 2010 and the annual Sample Survey on Labour Force (similar to the data on resident population). According to the novel Census in 2010, data on the national wide employed persons is also corrected in retrospect for the period 2001 to 2009. However, corrected data on provincial level is, to our knowledge, not available. The modifications on national level show only moderate differences (e.g. modified data on the employed persons on national level is 1.55 % smaller for the year 2005), implying that modified data on provincial level would be slightly smaller than the applied extrapolated provincial data in this study.

4. The data on the *R&D personnel* and *investments of LMEs* was collected from the Statistics yearbook on science and technology activities of industrial enterprises (various years). In order to ensure the consistency of the time series, we calculate the annual sum by aggregating the provincial values. The calculated national value for both variables corresponds in each year to the variables "Full time Equivalent of R&D Personnel" and "Expenditure on R&D" in the category "Basic

Statistics on Science and Technology Activities of Large and Medium-sized Industrial Enterprises" in various Chinese Statistical Yearbooks. This confirms the consistency of our main R&D variables.

5. The *patent data* from China's patent office CNIPA (formally State Intellectual Property Office of China (SIPO)) is equal to the published provincial data by the NBS, only for the provinces Zhejiang and Guangzhou the patent count differs by one patent.

Table A1
Summary statistics, 2000-2010.

	Observations	Mean	Median	Std. Dev.	Min.	Max.
			(1) All Provinces			
gdp	341	17525.02	13130.93	13448.59	2755.85	72296.29
emp	341	0.5128	0.5114	0.0741	0.3637	0.7324
invq	341	0.4909	0.4636	0.1577	0.2576	0.9339
hk	341	0.0005	0.0004	0.0005	0	0.0026
prdef	341	0.0045	0.0039	0.0031	0	0.0147
pat	341	0.0884	0.0614	0.0996	0	0.8133
sub	341	0.0005	0.0004	0.0005	0	0.0039
			(2) Without Tibet			
	Observations	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
gdp	330	17792.19	13483.73	13572.57	2755.85	72296.29
emp	330	0.5127	0.5115	0.0751	0.3637	0.7324
invq	330	0.4826	0.4495	0.1523	0.2576	0.9339
hk	330	0.0005	0.0004	0.0005	0.00001	0.0026
prdef	330	0.0047	0.0039	0.0030	0.0001	0.0147
pat	330	0.0906	0.0636	0.1004	0.0093	0.8133
sub	330	0.0005	0.0004	0.0005	0.0000009	0.0039
			(3) Without municipalities			
	Observations	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
gdp	297	14695.55	12246.18	9398.49	2755.85	50716.66
emp	297	0.5129	0.5116	0.0687	0.3637	0.7324
invq	297	0.4977	0.4752	0.1607	0.2576	0.9339
hk	297	0.0004	0.0003	0.0004	0	0.0026
prdef	297	0.0041	0.0036	0.0028	0	0.0132
pat	297	0.0664	0.0561	0.0429	0	0.3068
sub	297	0.0005	0.0003	0.0005	0	0.0039
			(4) Without municipalities and Tibet			
	Observations	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
gdp	286	14895	12338.08	9492.73	2755.85	50716.66
emp	286	0.5129	0.5116	0.0696	0.3637	0.7324
invq	286	0.4885	0.4704	0.1552	0.2576	0.9339
hk	286	0.0004	0.0003	0.0004	0.00001	0.0026
prdef	286	0.0042	0.0036	0.0027	0.0001	0.0132
pat	286	0.0681	0.0581	0.0426	0.0093	0.3068
sub	286	0.0005	0.0004	0.0005	0.0000009	0.0039

Notes: Own calculations based on provincial data (see Table 1). Summary statistics are shown for the variables before ln-transformation and before detrending.

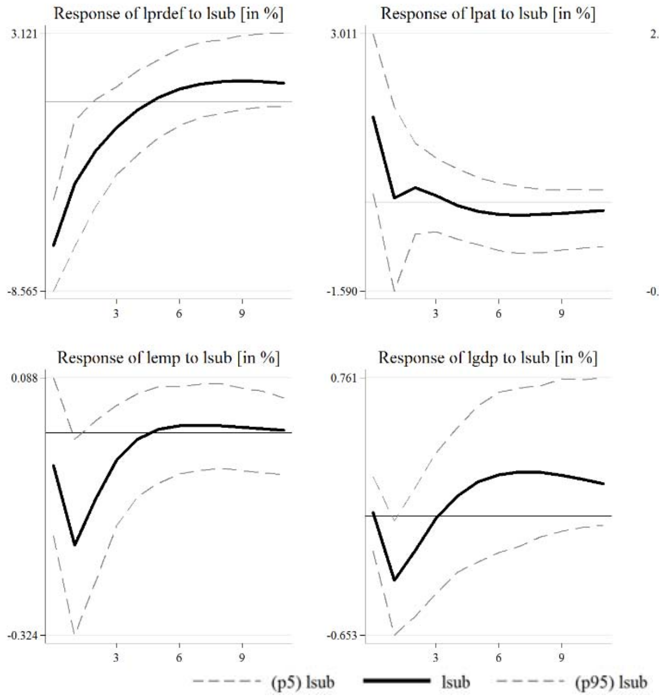
Table A2
Summarized economic activities of Chinese provinces, 2000-2010.

Province	Province code	Real GDP per capita (in RMD)	Employment rate (in %)	Real invest-ments in fixed assets per real GDP (in %)	Private real R&D invest-ments LMEs per real GDP (in %)	R&D personnel LMEs per cap-ita (%)	Patents per 100 Mio. real GDP	Real R&D sub-sidies to LMEs per real GDP (%)
Anhui	AH	9931.11	57.63	64.99	0.53	0.03	0.06	0.06
Beijing	BJ	47487.28	60.40	39.24	0.61	0.12	0.57	0.06
Chongqing	CQ	13838.82	61.58	64.19	0.59	0.05	0.09	0.06
Fujian	FJ	21119.31	53.34	42.87	0.55	0.06	0.05	0.02
Gansu	GS	8355.77	52.03	54.59	0.40	0.03	0.07	0.04
Guangdong	GD	26118.49	50.59	30.95	1.00	0.11	0.17	0.03
Guangxi	GX	9664.27	56.56	51.88	0.26	0.01	0.04	0.02
Guizhou	GZ	6164.53	59.47	55.21	0.33	0.01	0.08	0.08
Hainan	HI	12557.51	46.24	47.12	0.06	0.00	0.05	0.00
Hebei	HE	15589.74	51.48	53.15	0.39	0.03	0.04	0.01
Heilongjiang	HL	15125.84	43.25	42.54	0.45	0.06	0.10	0.08
Henan	HA	12159.59	60.03	52.80	0.44	0.04	0.05	0.02
Hubei	HB	13366.52	47.46	49.68	0.59	0.05	0.11	0.04
Hunan	HN	11743.63	56.40	46.46	0.43	0.03	0.10	0.03
Inner Mongolia	NM	20497.95	44.04	65.77	0.27	0.03	0.02	0.03
Jiangsu	JS	26810.00	52.37	47.31	1.04	0.12	0.11	0.04
Jiangxi	JX	10653.52	48.70	64.57	0.48	0.03	0.04	0.06
Jilin	JL	15600.97	41.25	65.99	0.35	0.03	0.10	0.02
Liaoning	LN	21680.34	46.85	62.56	0.84	0.08	0.12	0.09
Ningxia	NX	12574.28	50.34	72.49	0.40	0.03	0.06	0.06
Qinghai	QH	11595.21	48.95	65.93	0.31	0.02	0.04	0.04
Shaanxi	SN	12436.36	51.15	60.92	0.47	0.06	0.14	0.20
Shandong	SD	21597.89	54.89	49.67	0.95	0.07	0.07	0.03
Shanghai	SH	50526.30	42.75	35.26	1.13	0.15	0.27	0.05
Shanxi	SX	13576.99	44.75	50.49	0.52	0.05	0.07	0.05
Sichuan	SC	10321.21	56.96	58.13	0.39	0.03	0.09	0.06
Tianjin	TJ	39663.56	40.69	50.41	1.13	0.13	0.20	0.03
Tibet	XZ	9682.03	51.59	78.14	0.01	0.00	0.02	0.00
Xinjiang	XJ	13864.87	37.78	54.99	0.20	0.02	0.03	0.02
Yunnan	YN	8664.30	56.43	56.94	0.16	0.01	0.08	0.02
Zhejiang	ZJ	28861.31	65.49	45.65	0.72	0.10	0.13	0.03

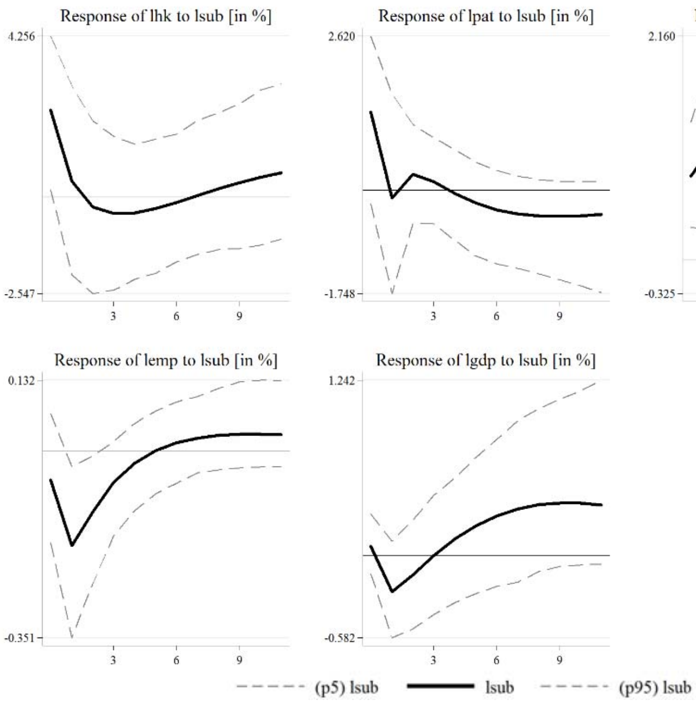
Notes: Own calculations based on provincial data (see Table 1).

Figure A1
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2000-2010 (control variables included).

1. *Private real R&D investments LMEs per real GDP (lprdef)*



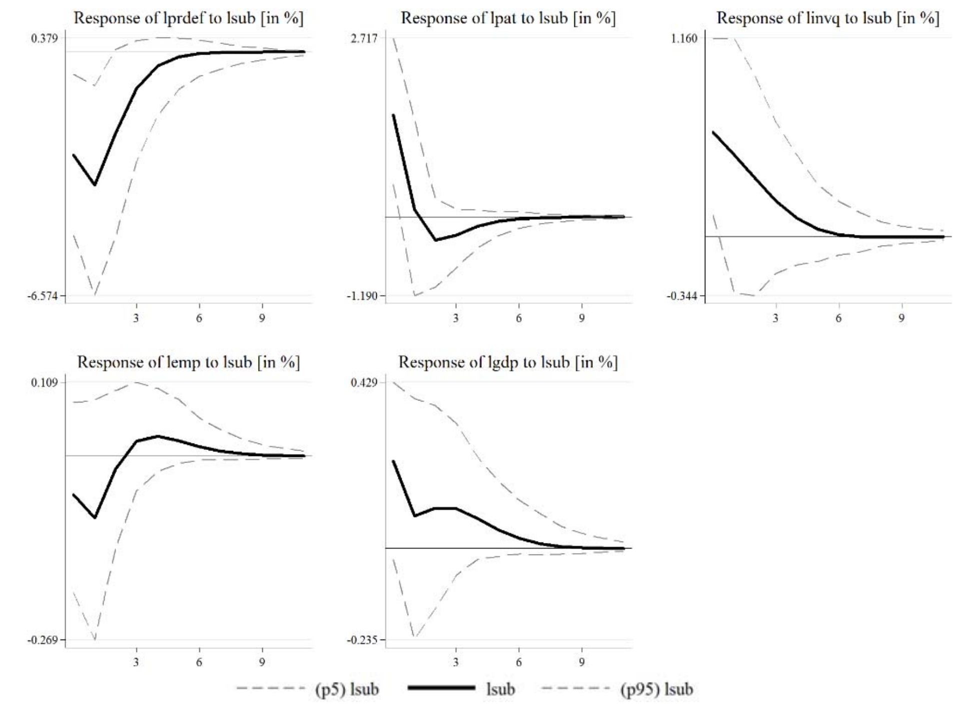
2. *R&D personnel LMEs per capita (lhk)*



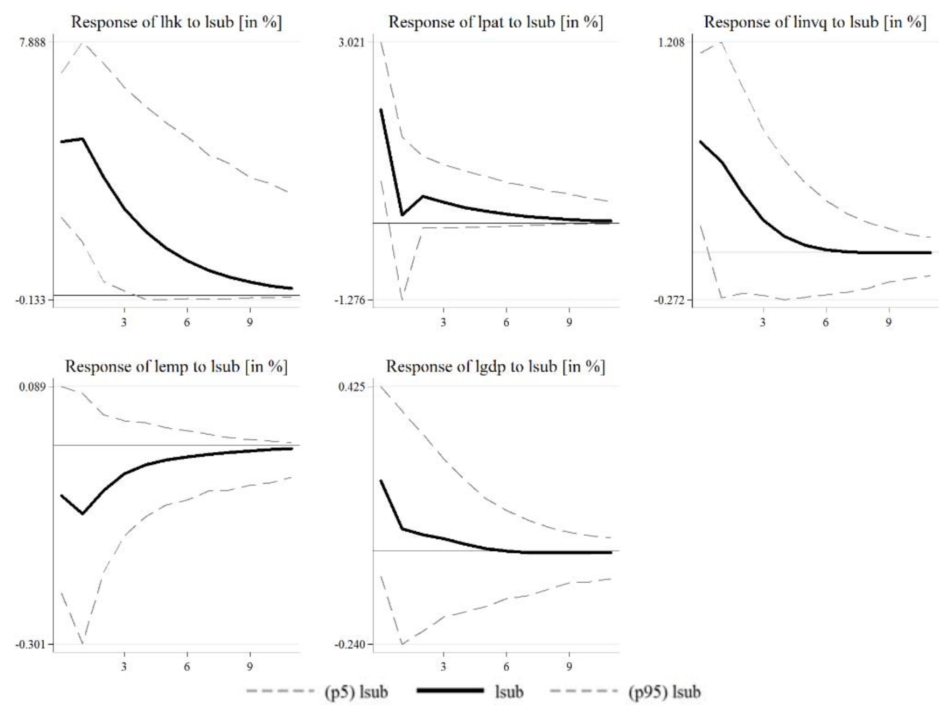
Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions)

Figure A2
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2003-2010.

1. *Private real R&D investments LMEs per real GDP (lprdef)*



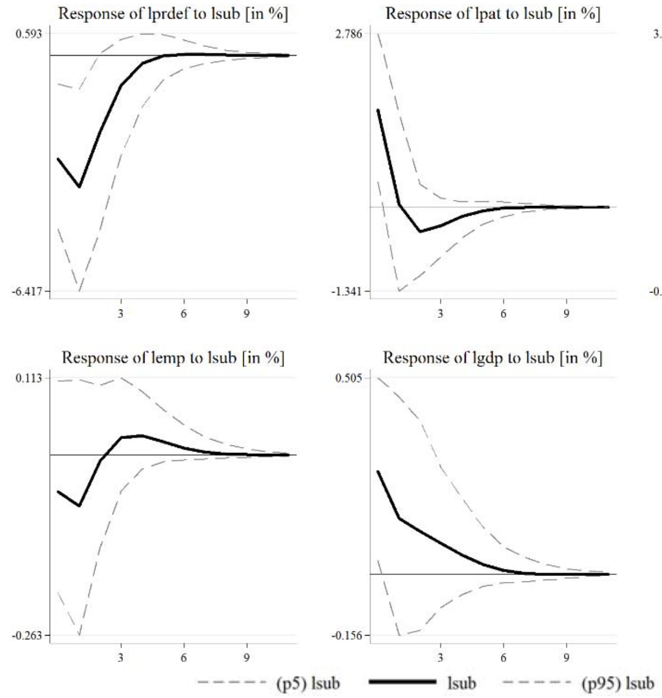
2. *R&D personnel LMEs per capita (lhk)*



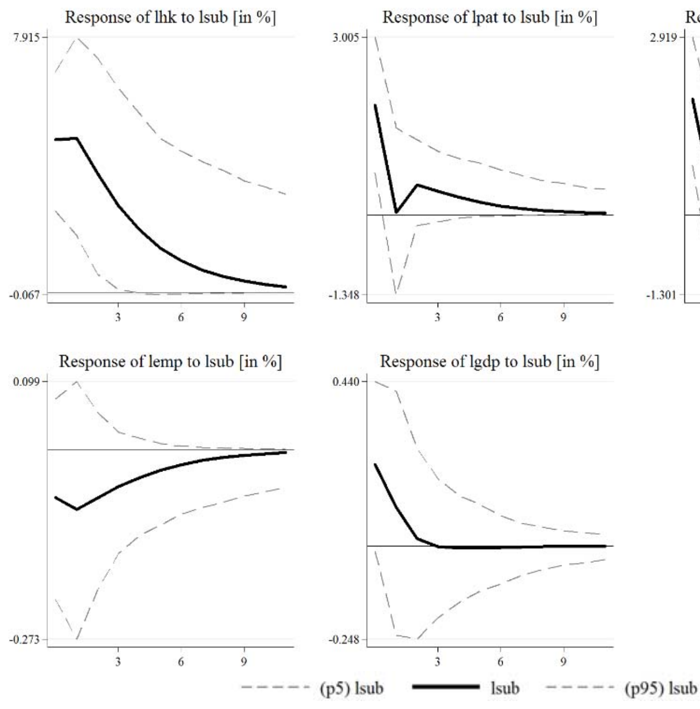
Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions)

Figure A3.
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2003-2010 (*linvq_rb* denotes investment rate in residential buildings).

1. *Private real R&D investments LMEs per real GDP (lprdef)*



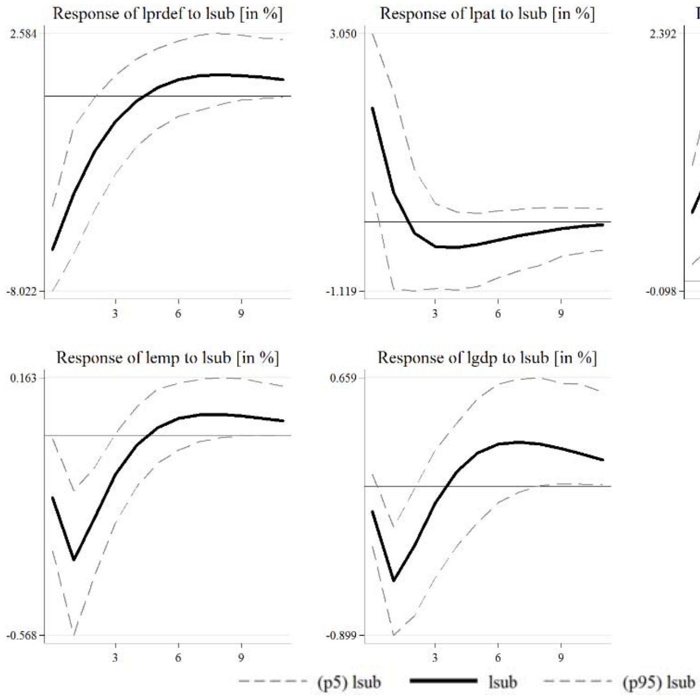
2. *R&D personnel LMEs per capita (lhk)*



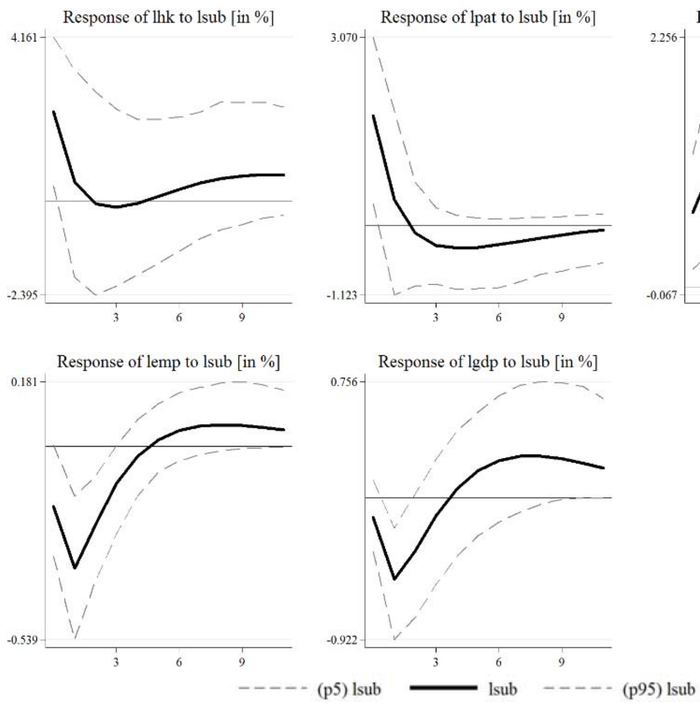
Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions)

Figure A4
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2000-2010 (Beijing, Shanghai, Tianjin and Chongqing included).

1. Private real R&D investments LMEs per real GDP (lprdef)



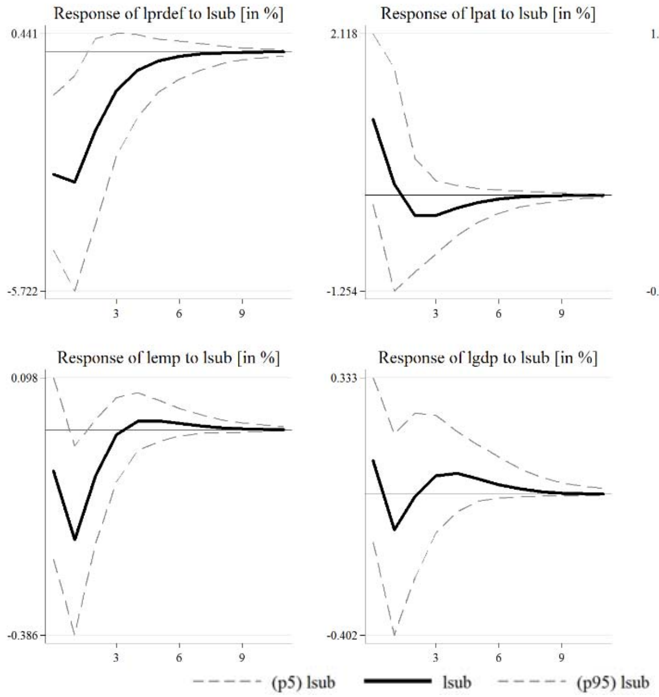
2. R&D personnel LMEs per capita (lhk)



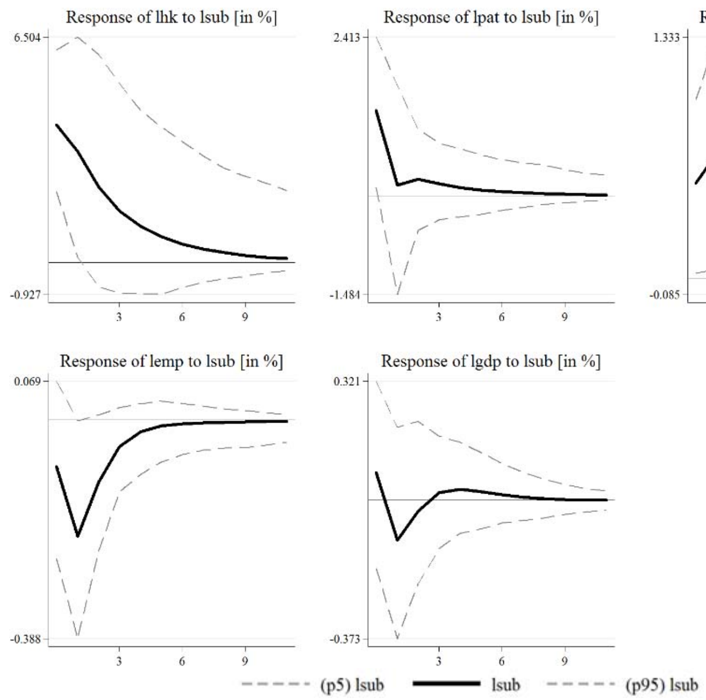
Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions)

Figure A5
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2003-2010 (Beijing, Shanghai, Tianjin and Chongqing included).

1. *Private real R&D investments LMEs per real GDP (lprdef)*



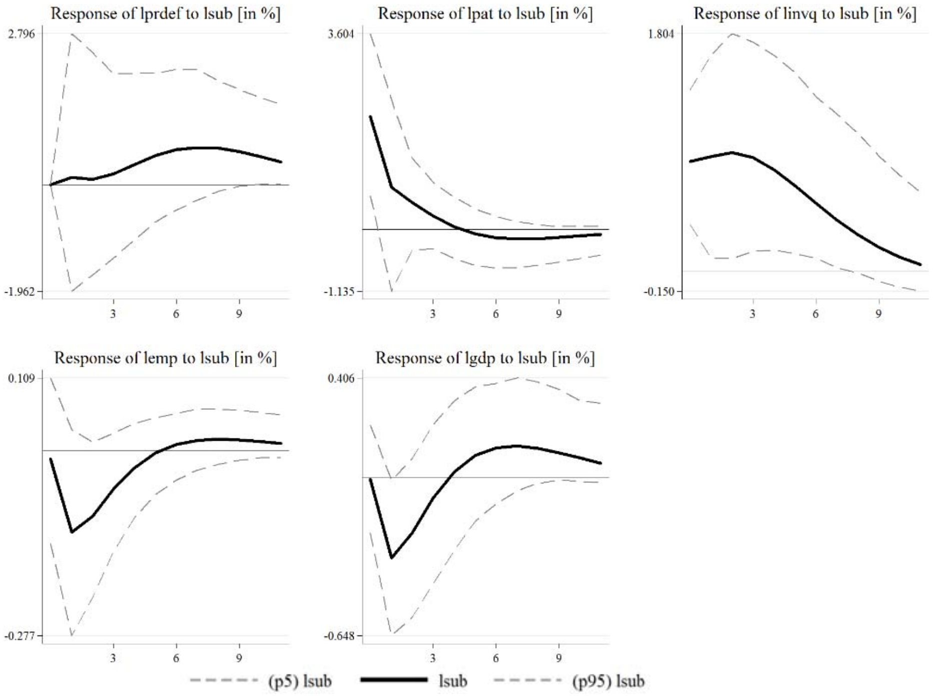
2. *R&D personnel LMEs per capita (lhk)*



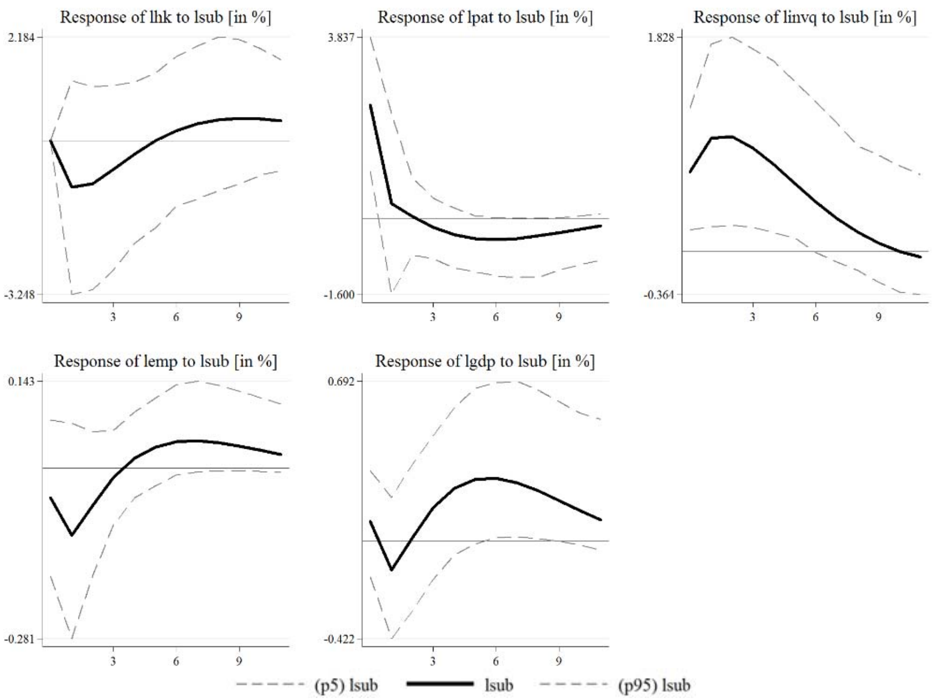
Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions)

Figure A6
IRF analysis for an increase in R&D subsidy intensity (*lsub*), 2000-2010 (Changed causal ordering).

1. *Private real R&D investments LMEs per real GDP (lprdef)*



2. *R&D personnel LMEs per capita (lhk)*



Notes: The solid lines are the estimated IRFs, while the dashed lines illustrate the 95 % confidence intervals that are calculated by conducting Monte Carlo simulations (500 repetitions)