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Effects of knowledge capital on total factor productivity in China: A spatial econometric perspective

Thomas Scherngell[1], Martin Borowiecki[1] and Yuanjia Hu[2]

[1]Foresight and Policy Development Department,
Austrian Institute of Technology (AIT), Vienna, Austria

[2]Institute for Chinese Medical Sciences,
University of Macau, China

Abstract. The transformation of China into a knowledge based economy is currently one of the most intensively debated research issues in Economic Geography and Regional Science. The focus of this study is on the effects of knowledge production and knowledge spillovers on manufacturing total factor productivity (TFP) in China – at the level of Chinese regions – through the lens of the regional knowledge capital model (KCM). The objective is to estimate the impact of region-internal and region-external knowledge capital on TFP in manufacturing industries across Chinese regions, and, by this, providing evidence on the crucial question whether TFP in China is increasingly based on knowledge production and diffusion. Relying on the regional KCM as theoretical framework, we derive a Spatial Durbin Model (SDM) relationship that can be used for empirical testing. The Chinese coverage is achieved by using regional data on 29 Chinese provinces for the years 1988-2007. The dependent variable denotes regional TFP, describing how efficiently each province transforms physical capital and labour into gross value added in manufacturing industries. We explain TFP – starting from the regional KCM – by region-internal and region-external knowledge stocks, the latter referred to as the inter-regional knowledge spillover pool. We measure regional knowledge stocks in terms of patents granted by the Chinese patent office. In estimating the effects, we implement a panel version of the standard SDM that controls for spatial autocorrelation as well as individual heterogeneity across regions. The specification incorporates a spatial lag of the dependent variable as well as spatial lags of the independent variables, allowing for the endogenous estimation of TFP effects resulting from region-external knowledge stocks. In order to identify the point in time of China shifting towards a knowledge-based economy, we employ a panel LM unit root test, providing empirical evidence for structural breaks in the time dimension of the data. By this, the study has the potential to break new ground in providing systematic statistical evidence on the transformation of China into a knowledge-based economy.

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1 Introduction

The tremendous growth performance and catching-up process of the Chinese economy over the past three decades is – undisputedly – unique since the industrial revolution commencing in Europe in the beginning of the 18th century (see, e.g., Wu 2011). The average annual growth in Gross Domestic Product (GDP) since the opening up of the Chinese economy back in 1978 has been maintained at 9.7 percent until 2008 (see, e.g., Tian and Yu 2012), sometimes referred to as the Chinese growth miracle (see Gilboy 2004, among others). During the late 1970s and early 1980s, Chinese government – recognising the failure of the *Great Leap Forward* policy and the cultural revolution in terms of economic development (see Huang 2010) – launched a series of reforms leading to an internationalisation and opening of the country to the outside of the world (see, e.g., OECD 2008). These reforms clearly constitute the landmark as starting point for the transition of China from a centrally planned to a market-based economy, and, subsequently, to the extensive growth of the manufacturing sector, in the earlier phases mostly driven by Foreign Direct Investments (FDIs), accompanied by massive urbanisation (Guo et al. 2013). Growth of the Chinese manufacturing sector has until today represented by far the most important component of overall GDP growth (see Guo et al. 2013, among others).

The characterisation of the sources of this tremendous growth performance have attracted burst of attention in the scientific domain over the past decades (see, e.g., Chow 2008, Chow and Li 2002, Bosworth and Collins 2008, Ozyurt 2009, Zhang and Stough 2013), and is still one of the most interesting research issues, given the fact that opinions on the sustainability of Chinese growth are diverse and have hardly reached consensus. From a New Economic Geography (NEG) perspective (see Krugman 1991), the Chinese growth performance fits very well to theoretical models of NEG, explaining how low transportation costs in combination with the spatial concentration and specialisation of economic activities – referred to as agglomeration effects – increase economies of scale (see Huang 2010). In fact, during the opening up period, China´s entry into the world market was mainly defined by its role as major supplier of quite labour-intensive products, such as textiles and clothes, based on the massive pool of cheap labour providing an immense competitive advantage in an increasingly globalised economy. In this sense, it may be assumed that the Chinese growth dynamics will be levelled out when, on the one hand, the supply of cheap labour is absorbed and, on the other hand, productivity-driven growth – mainly based on new technological knowledge and, generally speaking, innovation – is not becoming a more prominent factor in the Chinese growth nexus (see Krugman 1994, Wu 2011, Zhang and Stough 2013).

Thus, the focus of the current study is on investigating the link between productivity in the manufacturing sector, and knowledge capital, including knowledge spillovers, in China. The last decade has seen the development of a significant body of empirical research in this direction, mainly for the US and Europe, but also for China. Generally speaking, this research has shown that the productivity of firms or industries is related to their R&D productivity, and also to the R&D spending of other firms or other industries (see, e.g., Mairesse and Sassenou 1991). Fischer et al. (2009) characterise the relation between productivity and knowledge capital at a regional level for the European case by spatial econometric methods, showing that a region's Total Factor Productivity (TFP) depends on its own knowledge capital, but – as suggested by theory – also on inter-regional knowledge spillovers. Robbins (2006) finds similar evidence for the US. While also for the Chinese case different determinants of economic growth and productivity have been widely investigated in previous empirical works, there is only scarce evidence on effects of knowledge capital and knowledge spillovers. One notable exception is the study of Kuo and Yang (2008) that relates knowledge capital and knowledge spillovers to regional economic growth in China. The study indeed provides statistically significant evidence for the positive impact of knowledge capital on Chinese economic growth and suggests the existence of knowledge spillovers.

The current study follows this research tradition by investigating effects of knowledge capital on Chinese economic growth from a regional perspective. In doing so, we focus – in contrast to Kuo and Yang (2008) – on total factor productivity (TFP) at the level of Chinese regions through the lens of the regional knowledge capital model (KCM) as, e.g., used for the European case by Fischer et al. (2009) and LeSage and Fischer (2012). The objective is to estimate the impact of region-internal and region-external knowledge on TFP in the manufacturing sector across Chinese regions, and, by this, providing evidence on the crucial question whether TFP in China is increasingly based on knowledge capital. Relying on the regional KCM as theoretical framework, we derive a Spatial Durbin Model (SDM) relationship that is used for empirical testing. The Chinese coverage is achieved using regional data on 29 Chinese provinces for the years 1988-2007. The dependent variable denotes regional TFP, describing how efficiently each province transforms physical capital and labour into gross value added. We explain TFP – starting from the regional KCM – by region-internal and region-external knowledge stocks, the latter referred to as the inter-regional knowledge spillover pool. We measure regional knowledge stocks in terms of patents granted by the Chinese patent office.

Methodologically, we implement a panel version of the standard SDM that controls for spatial autocorrelation as well as individual heterogeneity across regions. The specification incorporates a spatial lag of the dependent variable as well as spatial lags of the independent variables, allowing for the endogenous estimation of TFP effects resulting from region-external knowledge stocks. In order to identify the point in time of China shifting towards a knowledge-based economy, we employ panel LM unit root tests, providing empirical evidence for structural breaks in the time dimension of the data.

By this, the study departs from previous research for the Chinese case in at least four major aspects (see, e.g., Kuo and Yang 2008, Wu 2011, Guo et al. 2013). *First*, we use – following LeSage and Fischer (2012), Fischer et al. (2009) and Robbins (2006) – patent stocks to proxy regional knowledge capital stocks using an extended data set on regional patent applications across Chinese provinces for the years 1988-2007. *Second*, the study accounts directly for spatial knowledge spillovers by adding a spatially discounted knowledge spillover variable to the regional KCM framework. *Third*, we employ a spatial econometric perspective in specifying a panel version of the SDM relationship. This allows us to elegantly trace knowledge diffusion in geographical space using manifestations of the Chinese regional configuration in form of spatial weight matrices. *Fourth*, by focusing on an extended time period from 1988-2007, we are able to disentangle different phases of Chinas transition into a knowledge economy using unit root tests. These are utilised to split our panel data set into different time periods and to estimate separate models for these time periods. This will provide important insights into whether the impact of knowledge capital on Chinese TFP has increased over time.

The remainder of the study is organised as follows. The section that follows characterises China´s way to a knowledge economy, providing information on different phases of Chinese growth between 1978 and 2010, laying special emphasis on policy measures to foster science and technology. Section 3 sets forth the theoretical framework in presenting the regional KCM, before Section 4 describes the data. Section 5 introduces the panel version of the SDM relationship that is used for empirical testing, while Section 6 presents and discusses the estimation results. The final section concludes with a summary of the main results, some policy implications as well as ideas for a future research agenda.

2 China on the way to a knowledge economy?

China´s emerging economy has – without doubt – drawn increasing attention worldwide, not only in the scientific domain, but also in the general public and the policy arena. Since policy reforms and initiatives were introduced back in 1978, the Chinese economy has boosted, reflected by an average annual economic growth in Gross Domestic Product (GDP) on an unprecedented scale of 9.8% for more than 30 years (see, e.g., Tian and Yu 2012). The most important component of this growth miracle represents the manufacturing sector, resulting from the government's development strategy that has focused on this sector since 1978 (see Guo et al. 2013).

The so-called 'open-door policy', declared by Deng Xiaoping in the late 1970s, constitutes the introduction of three cornerstones for the tremendous catching-up process: *First*, the unleash of modern entrepreneurship by allowing private business (see Li 2013) which was practically eliminated in the pre-reform era before 1978. By the end of 1997, the share of State-Owned Enterprises (SOE) in output of the industry sector decreased to 30%, and the market determined the prices of more than 95% of goods (see Bao et al. 2002). *Second*, the transformation into a market-based economy was accompanied by the opening up to the rest of the world, characterised by an extensive increase of Foreign Direct Investments (FDIs). By 2002, China was the world´s largest recipient of FDIs (see Criscuolo and Martin 2004)[1]. *Third*, early initiatives in the farming sector have lead to a considerable decentralisation of agriculture. Collective farming has been replaced by individual household cultivation, meaning that farmers have got the possibility to earn additional benefits for extra efforts. Therefore, on the one hand, productivity in the agricultural sector has increased dramatically,

[1] It is worth noting in this context that FDI activities are highly concentrated in the coastal regions. In general, spatial concentration of economic activities in certain regions across China is striking, though measures have been taken by the Chinese government to decrease regional economic disparities (see, e.g., OECD 2008, Scherngell and Hu 2011).

while, on the other hand – given technological progress in form of new machinery and cultivation techniques – millions of workers from the rural areas began looking for outside employment, providing the developing manufacturing sector in the large cities with cheap labour (see Perkins and Rawski 2008).

The extraordinary growth dynamics of China has lead to an increasing interest in the scientific domain worldwide, aiming at explaining the growth performance and more systematically investigating the sources of growth. Given the considerations from above, it seems quite obvious that the growth miracle (see Krugman 1994, Gilboy 2004) may be mainly based on the massive accumulation and concentration of cheap labour and physical capital. This led many scholars in the late 1990s and early 2000s to question, whether Chinese growth dynamics are sustainable (see, e.g., Wu 2000), assuming a lack of productivity-driven growth due to a low innovative capability, relatively slow technological progress and insufficient development of the high-tech sector. However, the Chinese government has been obviously aware that a second transformation – after the first transformation from a centrally planned to a market-based economy – is necessary to achieve sustainable economic prosperity which can be broadly summarised as transformation from a factor-driven to a knowledge-based, productivity driven economy.

In this context, the government has taken a number of measures in its quest to jump to a knowledge economy in the mid-1990s. The country's development policy was increasingly focused toward science, technology, and, in particular education, resulting in the establishment of the Ministry of Science & Technology (MOST) in 1998, and including landmarks setting the political direction by enacting the law for promoting commercialisation of science and technology, or the newly introduced and continuously improved patent law (see Song 2008, Rongping and Wan 2008, Ratchford and Blanpied, 2008). Concerning higher education and basic research, essential and influential initiatives include the *Project 211* and the *Project 985* initiatives. The former has been established back in 1996 aiming at strengthening and financially supporting more than 1,700 institutions of higher education, mainly universities but also the Chinese Academy of Sciences and State Key Laboratories. The *Project 985* initiative has been announced in 1998, aiming to support certain universities to catch-up to the leading universities worldwide, most prominently *Beijing University* and *Tsinghua University*, receiving large amounts of both national and local funding.

Indeed these policies seem to work; the performance of certain science and technology indicators in the late 1990s and early 2000s is even comparable with the tremendous economic growth performance (see. e.g., Crescenzi et al. 2012)[2]. China's spending on R&D as a percentage of GDP has more than doubled from 0.6 percent in 1995 to over 1.2 percent in 2004, with a private share of R&D expenditures of about two thirds which is comparable to ‘developed’ Western countries. Further, China faced considerable growth of the number of researchers and the number of PhD students, in particular PhD students that have conducted their PhD in foreign countries (see Criscuolo and Martin 2004, for further details). Concerning R&D output, China´s share in world scientific publications has increased from 2% to 6.5% between 1994 and 2004. The same trend for this time period – though a little bit less pronounced – is found for patent applications, both taking grants at the Chinese patent office as well as at international patent offices (see Crescenzi et al. 2012). Until today, Chinese government follows this path by further shifting considerable attention on science and technology investment. The most recent milestone is the 2006 “Medium- to Long-Term Strategic Plan for the Development of Science and Technology”, highlighting key objectives and priorities in science and technology development. The overarching goal is to further transform China into a knowledge-based economy, emphasising the need to develop capabilities for “indigenous” or “home-grown innovation” (Zhu 2006). Tremendous investments in information infrastructure have been another essential element of this policy shift (see Roberts et al. 2011).

Given these political interventions and empirical observations on the science and technology development of China over the past decades, the question that arises is whether these efforts can be absorbed by the Chinese economy, and, indeed constitute the crucial stimulus for the transformation from a non-sustainable factor-driven (see Gilboy 2004) to a sustainable knowledge-driven economy. A potential hampering factor may, for instance, be a lack of integration and knowledge diffusion in the Chinese innovation system, related to fragmented regional policies and protectionism (see, for instance, Crescenzi et al. 2012, Scherngell and Hu 2011, OECD 2008). These considerations induced a number of empirical studies shifting attention to productivity growth of the Chinese economy, usually focusing on Total Factor

[2] However, concerning the territorial dynamics of innovation, it is empirically demonstrated, for instance in the study of Crescenzi et al. (2012), that innovative activity is highly concentrated in geographical space, even more than economic activity, with Guangdong showing a share of nearly half of total patenting activity in China in 2007, and the top three regions (Guongdong, Shanghai and Beijing) accounting for 73% of total patenting activity.

Productivity (TFP) that is viewed as the growth in output not explained by the growth of conventional production factors labour and capital (see Wu 2000, among others). Tian and Yu (2012) and Wu (2011) provide valuable literature overviews and meta-analyses of the remarkable number of empirical studies investigating Chinese TFP development over the past decades, coming to the conclusion that estimates of TFP contribution to Chinese growth are rather diverse in these different contributions[3]. While some works point to rather low contributions of TFP to overall growth (see, e.g., Woo et al. 1994, Woo 1998, Liang 2000, Wang 2000, Young 2003), and, by this, underpinning scepticism about sustainability of Chinese growth, other studies are more positive about TFP contribution (see Borensztein and Ostry 1996), or even claim that TFP is the key in China´s rapid economic growth, estimating TFP growth rates of more than 3% per year (see, e.g. Bosworth and Collins 2008, Chow and Li 2002, Hu and Khan 1997, Zhang and Shi 2003).

However, while there exists a large number of studies on TFP growth, there are only very few studies that explain TFP by knowledge capital and knowledge spillovers, and even fewer studies that take a spatial perspective in analysing Chinese TFP[4]. While *knowledge capital* refers to the technological knowledge stock available within a firm, *knowledge spillovers* denote the benefits of knowledge to firms not responsible for the original investment in the creation of this knowledge[5] (see, e.g., Fischer et al. 2009). Theoretical considerations on the impact of knowledge capital and knowledge spillovers on productivity have been widely reflected in the literature (see, for instance, Romer 1990, Grossman and Helpman 1991), followed by empirical studies testing the relationship between knowledge capital and productivity at the firm level (see, e.g., Mairesse and Sassenou 1991), across industries (see, e.g., Scherer 1993, Branstetter 2001), across countries (see, e.g., Park 1995), or across regions (see, e.g., Robbins 2006, Döring and Schellenbach 2006, Fischer et al. 2009, LeSage and Fischer 2012). For China, Kuo and Yang (2008) are – to our knowledge – the only study estimating the impact of knowledge capital and knowledge spillovers on Chinese economic

[3] An additional comprehensive review of all these works would go beyond the scope of the current study. Thus, the interested reader is referred to Tian and Yu (2012) and Wu (2011) for a detailed overview.

[4] Note that geography and spatial processes are obviously one of the most crucial elements to be taken into account when investigating Chinese economic growth (see, e.g., Bao et al. 2002) and, in particular, Chinese TFP may be related to intra- and inter-national spatial spillovers of knowledge.

[5] Such spillovers may occur when some components of new knowledge cannot be fully appropriated by the producer because it cannot be kept secret entirely, or because property rights do not guarantee full protection from imitation

growth from a regional perspective. However, Kuo and Yang (2008) do not use the rich spatial econometric toolset to detect and estimate spatial spillovers, as used in Fischer et al. (2009), LeSage and Fischer (2012) for the European case, or in Guo et al. (2013) for estimating the leading role of manufacturing for China´s regional economic growth.

Thus, in the current study, we aim to fill this research gap and estimate the role of knowledge capital and knowledge spillovers at the level of Chinese regions through the lens of the regional version of the Knowledge Capital Model (KCM) introduced by Griliches (1979), augmented with a spatially discounted inter-regional knowledge spillover pool variable, estimated by means of a spatial econometric approach. In contrast to Kuo and Yang (2008), we use patent stocks to proxy a region's knowledge capital, providing the most direct evidence for measuring regional knowledge stocks (see Fischer et al. 2009). Further, we aim to identify structural breaks in the development of TFP in China, and, by this, provide novel insights into the Chinese growth nexus and its transformation to a productivity-driven growth model.

3 Theoretical framework

We follow the research tradition that finds thinking in terms of a regional Knowledge Capital Model (KCM) congenial in describing the link between productivity and knowledge capital, including inter-regional knowledge spillovers, at the regional level. Though the regional KCM view is based on various simplifications, the importance and extend of inter-regional knowledge spillovers can be best discussed in the context of an extended version of the regional KCM (see, e.g., Fischer et al. 2009, LeSage and Fischer 2012). In contrast to the standard version of the Cobb-Douglas production, the extended version treats knowledge capital as another type of capital that is added to conventional aggregate production function variables (for a discussion see Griliches 1979, Mairesse and Sassenou 1991). At the regional level, assuming a N-region world with i = 1, ..., N, and denoting time periods by t = 1, ..., T, the regional KCM relationship may be written as

$$Q_{it} = Q(X_{it}, A_{it}) \tag{1}$$

with

$$X_{it} = g\,(L_{it}, C_{it}) \tag{2}$$

$$A_{it} = A(K_{it}, K^{*}_{it}) \tag{3}$$

where Q denotes value added, X the set of conventional capital inputs, comprising L the stock of labour and C the stock of physical capital, with $g(.,.)$ denoting a function assumed to be homogeneous of degree one which exhibits diminishing marginal returns to the accumulation of each factor alone. A is an index of the technical efficiency of production, with K and K^{*} denoting the stocks of region-internal and region-external knowledge capital, also referred to as the inter-regional knowledge spillover pool.

Assuming a Cobb-Douglas production technology for region i at time t gives

$$Q_{it} = L_{it}^{\alpha}\ C_{it}^{1-\alpha}\ K_{it}^{\beta_1}\ K_{it}^{*\beta_2}\ \exp(\tau t + \varepsilon_{it}) \tag{4}$$

that connects output to conventional inputs augmented with knowledge capital. τt represent the trend components of all other influences on final output and productivity, and ε is the error term reflecting remaining unmeasured determinants of output. α is the output elasticity with respect to conventional capital inputs, labour and physical capital, assuming constant returns to scale, while our focus of interest is on the parameters β_1 and β_2 representing output elasticities of region-internal and region-external knowledge capital.

If total factor productivity P is defined as

$$P_{it} = Q_{it}\ /\ L_{it}^{\alpha}\ C_{it}^{1-\alpha}\ , \tag{5}$$

Equation (4) leads to

$$P_{it} = K_{it}^{\beta_1}\ K_{it}^{*\beta_2}\ \exp(\tau t + \varepsilon_{it}) \tag{6}$$

which relates knowledge capital to productivity in a reduced-form framework. In that reduced form, β_1 is the output elasticity of TFP with respect to region-internal knowledge, while β_2

determines the strength of the external knowledge effect on productivity. Note that a positive and significant β_2 is interpreted as evidence of cross-region knowledge spillovers (see Mairesse and Sassenou 1991).

Our theoretical assumptions on regional knowledge capital stocks are another crucial element of the theoretical framework. We view regional stocks of knowledge capital as proxies for the state of knowledge (Fischer et al. 2009)[6], created by private or public agents. Knowledge is assumed to accumulate over time and to depreciate from period to period at a constant rate r_K[7] using the perpetual inventory method so that (ignoring region indices)

$$K_t = (1 - r_K)\ K_{t-1} + S_{t-1} \tag{7}$$

implying that knowledge production activities S undertaken in period t–1 become productive in period t. Given this law of motion, for region i, K_{it} represents its own knowledge capital stock in period t based and previous knowledge production activities, while K_{it}^{*} is the relevant pool of knowledge spillovers (Fischer et al. 2009). However, since not all knowledge capital will necessarily spill over from one region to another in geographical space, it seems appropriate to define K_{it}^{*} as a spatially discounted knowledge spillovers pool, given by

$$K_{it}^{*} = \sum_{j \neq i}^{N} w_{ij}\ K_{jt-q} \tag{8}$$

where w_{ij} represents the spatial discount in region's i general ability to internalise external pieces of knowledge of region j at time t–q. The empirical implications and specification for the knowledge stocks variables and the overall derivation of the empirical model from Equation (6) will be described in Section 5.

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6 The knowledge created by a private or public agent is added to the pool of the existing knowledge capital stock to which other agents have access. Note that even if the benefits of R&D activities are fully appropriated by an agent, in the sense that an agent acquires a monopoly right by patent protection, some portion of the knowledge that has led to the patent may diffuse across regions through various communication channels such as publications, seminars, personal contacts, reverse engineering, (informal) exchange in networks, transfer of human capital and other means (Park 1995).

7 A constant 12 percent depreciation rate was applied for each year to the stock of patents created in earlier years. The assumption of a depreciation rate of 12 percent for the obsolescence of technological knowledge follows former empirical studies (see, among others, Robbins 2006).

4 Data, variables and spatial configuration

In this section we discuss the empirical setting of the study and the data used. Our data set covers 29 regions of Mainland China, including the 21 provinces, five autonomous regions and three municipalities[8] from 1988 to 2007 and thus encompasses a balanced panel data set of 580 observations (29 regions, 20 time periods). In line with the stated research objectives, the dependent variable is industrial TFP at the regional level. In order to observe the impact of knowledge capital stocks and knowledge spillovers on TFP, the independent variables are regional knowledge capital stocks and the interregional knowledge spillover pool as described in the theoretical framework (see Section 3).

The calculation of TFP indices requires data on regional gross industrial output, labour, and physical capital formation (investment in fixed assets), as well as the respective deflators, which is collected from the National Bureau of Statistics of China. Gross industrial output data in Renminbi (constant prices of 2000, deflated) has been used as measure of output Q. Gross industrial output is the preferable concept over value-added, as it simultaneously treats intermediate inputs and primary factor inputs. Information on physical capital stocks is measured in terms of gross fixed investment at constant prices of 2000. We construct the stocks of physical capital for each region by using the perpetual inventory method $C_{it} = (1 - r)\, C_{it-1} + I_{it-1}$, where C_{it} is the stock of physical capital of region i at time t, I_{it-1} is the flow of gross investment in period $t-1$ that becomes productive in period t, and r is the constant depreciation rate[9]. The annual flows of fixed investments were deflated by gross fixed capital formation deflators. The mean annual rate of growth for the period 1988 to 2007 is used to estimate the initial regional capital stocks.

We follow the methodology of Caves et al. (1982) and calculate regional TFP p_{it} of region i and time t using the logarithm of regional real gross industrial output q_{it}, the logarithm of labour l_{it}, the logarithm of regional physical capital stocks c_{it}, and labour compensation shares s_{it} for each region i and period t. Formally, the index is defined by

[8] The province of Hainan was established in 1988 and the municipality of Chongqing was created in 1997. In order to avoid time series inconsistencies, data for Hainan province from 1988 onward is counted together with data for Guangdong and data for Chongqing was added to data of Sichuan province from 1997 onwards.

[9] We apply a constant depreciation rate of 10%.

$$p_{it} = \left(q_{it} - \overline{q}_t\right) - s_{it}\left(l_{it} - \overline{l}_t\right) - \left(1 - s_{it}\right)\left(c_{it} - \overline{c}_t\right) \tag{9}$$

where an upper bar above a variable denotes a geometric mean. It is worth noting that region-level TFP comparisons are a classical index number problem and, thus, TFP indices have no unique optimal form (see Fischer et al. 2009). The choice of the index used here is well justified because, *first*, the index is superlative, meaning that it is exact for the flexible translog functional form. A "flexible" functional form is one that can provide a second order approximation to an arbitrary function. *Second*, the index satisfies the circularity test which is often referred to as transitivity. This property makes the choice of the base region and year inconsequential. *Third*, the index is multilateral rather than bilateral, and thus appropriate for time series and cross section comparisons as well as for combinations of both.

Corporate patent counts[10] are used as a proxy for knowledge capital stocks and patent stocks are derived from the Chinese Patent Statistic Database. Patents are direct outcomes of R&D processes. A patentable invention must be new, must involve an inventive step and must be capable of industrial application. In line with Robbins (2006), we argue that an aggregation of patents is more closely related to the regional knowledge capital stock than an aggregation of R&D expenditures. To create regional patent stocks for 1988-2007, the patents are transformed by, *first*, sorting based on the year that a patent was applied for, and, *second*, by the region where the inventor resides. In order to trace the specific region of an author, the zip codes of the author's address has been used.

5 The empirical model

At this point, we are interested in estimating the impact of region-internal and region-external knowledge capital on regional TFP in China. In this sense, we need to derive a measurable empirical model from our theoretical framework that can be estimated in a way that is

[10] Patent documents provide information on the technological, geographical and temporal location (that is, their technological class, the geocoded location of the inventor(s) and the date of application). All patent applications are assigned to the region of the address of the inventor, rather than the address of the assignee, for tracing inventive activities back to the region of knowledge production. Assignment is done by using a concordance scheme between postal codes and regions. In the case of multiple inventors the standard procedure of proportionate assignment is followed.

appropriate in light of our research questions. A first tempting approach is to take the log form of Equation (6), in matrix notation leading for $i, j = 1, ..., N = 31$ and $t = 1, ..., T = 25$ to

$$p = \beta_1 k + \beta_2 k^* + u \qquad (10)$$

with

$$u = \mu + \tau + \varepsilon \qquad (11)$$

where all variables are expressed in logarithms. p is the NT-by-1 vector consisting of observations p_{it} corresponding to the TFP of region i at time t, while k is the NT-by-1 vector consisting of observations on k_{it} corresponding to the own knowledge capital of region i at time t, and k^* the NT-by-1 vector consisting of observations on k^*_{it} corresponding to the region's i external knowledge capital at time t. u is a random component that comprises the N-by-1 vector μ capturing region-specific effects accounting for all space-specific time-invariant variables whose omission could bias the estimates, the T-by-1 vector τ capturing time-period fixed effects[11], and the NT-by-1 ε vector of the residual terms varying across i and t with zero mean and variance σ^2. Given this specification, model (11) is referred to as the two-way error component model (see Baltagi 2008).

However, the assumptions on the error term u are crucial. As we are dealing with a multiregional setting, spatial dependence between our spatial units may bias our parameter estimates. Further, given our definition of k^* from Equation (8), it can be seen that we can simply formulate model (10) in form of a Spatial Durbin Model (SDM) relationship since k^* represents a spatial lag of k. Following Elhorst (2012), we can re-formulate model (10) introducing a spatial lag of the dependent variable, leading to

[11] Note that we can treat spatial and/or time-period effects as fixed or random (see Baltagi 2008). First, in order to determine which effects to include, we investigated the null hypothesis that spatial and time-period fixed effects are jointly insignificant using a likelihood ratio test. The results indicate that the hypothesis of joint insignificance of spatial effects (646.90, 29 df, $p < 0.01$) as well as time-period effects (66.56, 19 df, $p < 0.01$) must be rejected. We follow a spatial random effects and time-period fixed specification based on a Hausman's specification test that is used to test the spatial random effects against the spatial fixed effects specification. The results (9.25, 3 df, $p = 0.026$) indicate that the spatial random effects and time-period fixed effects specification cannot be rejected against a fixed-effects specification.

$$p = \rho Wp + \beta_1 k + \beta_2 Wk + u \tag{12}$$

with

$$W = W^{*} \otimes \boldsymbol{I}_T , \tag{13}$$

where W is NT-by-NT, and W^* is the N-by-N non-stochastic, time-invariant spatial weights matrix reflecting the spatial configuration of the set of regions with weights w_{ij}, so that Wp is the NT-by-1 vector representing the average of the spatially lagged TFP values in neighbouring regions of i, with ρ being the corresponding spatial autoregressive coefficient measuring the strength of the spatial autoregressive relation between neighbouring regions. Wk is the spatially discounted knowledge spillovers pool[12]. We define $w_{ij} = d_{ij}^{-2}$ assuming an inverse power relationship where d_{ij} denotes geographic distance between the spilling region j and the receiving region i. Our spatial weight matrix specification implies that spatial spillovers of region-external knowledge capital influence all other regions, but the spillover effects are subject to a spatial decay[13].

The SDM offers great analytical opportunities in the context of our research focus given the possibility to measure the scale of intra- and inter-regional spillovers, or so-called direct and indirect effects (LeSage and Pace 2009). Besides direct impacts of a change of k on TFP (direct effects), we can directly observe the effect of changes in these variables in other regions j on region i which we have expressed by Equation (8) in theoretical terms. Such partial derivatives represent possible spillover impacts from all other N-1 regions. Since we consider changes in each $j = 1, ..., N-1$ region, these partial derivatives can be expressed by means of N-by-N matrices for k given by

$$S_k\left(W\right) = \partial p / \partial k = (I_N - \rho W)^{-1}(I_N \beta_1 + W \beta_2) \tag{14}$$

[12]Inclusion of lags of both dependent and independent variables allows to account for spatially autocorrelated omitted variables that are likely to be correlated with the included explanatory variables (LeSage and Pace 2009).

[13]This assumption seems reasonable given the size of Chinese regions and empirical observations that disembodied knowledge spillovers diminish after a distance of about 300 km (see, for instance, Fischer et al. 2009, Scherngell and Hu 2011).

The matrix S_k (W) of all partial derivatives are correct measures of local (direct) and spillover (indirect) impacts arising from changes in k of region i on p of the respective region and all other regions (LeSage and Pace 2009, Elhorst 2010). The off-diagonal elements represent cross-partial derivatives, which can be summarised into scalar measures representing indirect impacts using the average of either the row-sums or column-sums of the matrix elements excluding the diagonal. The average summary measure of direct effects is defined as the average of the sum of the own partial derivatives on the main diagonal of the matrices. The average total scalar measure is represented by the sum of direct and indirect effect averages (see LeSage and Pace 2009 for further details).

Given our interest in providing evidence on the transition of the Chinese economy into an increasingly knowledge based one, we need to split our sample into different time periods. For this purpose, we apply a panel LM unit root test that may identify these different phases of China's transition as indicated by structural breaks in the time series of TFP. In doing so, we implement the panel LM unit root test with up to two breaks of Im et al. (2010) for the period 1988 to 2007. We have opted for the panel LM unit root test of Im et al. (2010) since it corrects for the presence of spatial autocorrelation across our regional TFP observations. Our hypothesis of at least one structural break around the year 2000 is supported by the panel LM test statistics[14]. Accordingly, we split our panel data set into the time periods 1988-1997 and 1998-2007 and estimate separate models for these time periods. In this context, it deserves special mention that the structural break coincides with the aftermath of the Asian crisis of 1998 that was a major a macroeconomic shock to China.

6 Estimation results

In Table 1 we present the spatial Durbin specification of the econometric reduced-form relationship between TFP and knowledge capital. Its results are reported in column (1) for the period 1988 to 1997 and in column (2) for the period 1998 to 2007, which is before and after the structural break in the year 1998 that was identified by the panel LM unit root test. The first column shows that the coefficient β_1 of the knowledge capital stock variable is

[14]The panel LM test statistics for the demeaned series of regional TFP data associated with one break in the slope of each cross-section unit in the panel is -3.139 and thus higher than the 1% critical value (-2.326). In this, the results indicate a structural break in the year 1998. Likewise, the panel LM unit root test statistics associated with two breaks in the slope is -1.398 and higher than the 10% critical value (-1.282). Thus, the structural breaks are located in the years 1998 and 2001.

significantly different from zero and has the expected positive sign. For the period 1988 to 1997, higher regional-internal knowledge capital has a positive effect on regional TFP. In the same line, the results in column (2) confirm that the coefficient of the regional knowledge capital stock variable is significantly different from zero and positive in magnitude for the period 1998 to 2007.

Table 1: Estimation results of TFP: Pooled SDM with spatially lagged dependent variable, spatial random effects and time-period fixed effects

Variable	1988-1997	1998-2007
W*ln p $(\boldsymbol{\rho})$	0.110 (0.084)	0.042 (0.085)
ln k $(\boldsymbol{\beta_1})$	0.188*** (0.061)	0.302*** (0.049)
W*ln k $(\boldsymbol{\beta_2})$	-0.006 (0.092)	0.211** (0.098)
σ^2	0.032	0.022
R^2	0.705	0.861
Corrected R^2	0.029	0.242
Log Likelihood	41.773	85.063

Notes: Standard errors in parentheses. Wald test for spatial lag (1988-2007) yields a value of16.791 ($p < 0.01$); Wald test for spatial error (1988-2007) yields a value of 18.724 ($p < 0.01$). Corrected R^2 is R^2 without the contribution of fixed effects. ***, ** and * denote significance at the 1, 5, and 10% levels, respectively.

However, the coefficients of the SDM do not represent the marginal effects of a change in the knowledge capital stock on productivity. Therefore, we need to consider the average scalar summary measures derived from Equation (14). Table 2 reports these measures in column (1) for the period 1988 to 1997 and in column (2) for the period 1998 to 2007. In column (1) we see that the direct impact of knowledge capital corresponds in sign and magnitude to the coefficient estimate. However, in column (2) the direct impact estimate of knowledge capital is already different from its coefficient estimate. This result indicates the presence of feedback effects in the period 1998-2007 which are due to the coefficient of the spatially lagged explanatory variable *Wk*, which turns out to be positive and significant. Specifically, the direct impact estimate of the knowledge capital variable is 0.304. Since the coefficient of knowledge capital is 0.302, the feedback effect of knowledge capital amounts to 0.002 which corresponds to 1% of the direct effect. This seems small, but is significant and positive as compared to the feedback effect in the period 1988-1997. Similarly, in column (2) we see that the indirect effect of a change in the explanatory variable appears to be significant and positive and to amount to 76% of the direct effect for the period 1998 to 2007. This is higher than the coefficient of the knowledge spillover variable *Wk* in column (1) of Table 1, which was found to be not significantly different from zero.

Table 2: Average scalar summary measures from the SDM

Variable	1988-1997	1998-2007
ln k		
Direct impact	0.188*** (0.063)	0.304*** (0.050)
Indirect impact	0.018 (0.105)	0.231** (0.101)
Total impact	0.206 (0.140)	0.535*** (0.115)

Notes: Standard errors in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels, respectively.

Table 2 further reports the findings for total impacts on TFP that arise due to regional-internal and regional-external knowledge production. Whereas the total impact has the expected sign but is not significantly different from zero for the period 1988-1997, the total impact becomes bigger in magnitude and is significant for the period 1998-2007. In other words, we do indeed observe and statistically confirm a shift in Chinese TFP towards a more knowledge-based growth for the period since 1998 as opposed to TFP growth in the 1990s. Even more specifically, the results provide evidence that this shift is based on both region-internal knowledge capital stocks as well as on inter-regional knowledge spillovers.

Our finding that regional knowledge capital has a positive and significant impact on regional productivity is consistent with Kuo and Yang (2008). They found that an increase of 1% in regional knowledge capital as measured by regional in-house R&D activities is associated with a 4.3% increase in regional growth for the period 1996 to 2004. Further, our results illustrate that if localised regional knowledge capital increases across China, not only does regional TFP increase but we can also observe an increase in feedback effects that arise as a result of impacts passing through neighbouring regions and back to the regions themselves. The observed spatial dependence in TFP seems to be explained by knowledge spillovers. In other words, if knowledge capital in a particular region increases, not only TFP in that region but also TFP in its neighbouring regions will increase. The indirect effect estimate for 1998-

2007 suggests that the change in neighbouring regions' TFP relative to the change in the region's TFP itself is approximately 1 to 1.3 in case of a change in the knowledge capital stock.

7 Summary and concluding remarks

China's tremendous economic growth during the last three decades has attracted burst of studies on the sources of growth. However, the role of knowledge capital and cross-regional knowledge spillovers for promoting growth in China is not well understood yet. This question is of uttermost importance for China given its strategic goal of transforming from an input-driven growth model towards productivity-driven growth. Utilising a panel data set for 29 Chinese provinces over the reform period 1988 to 2007 and employing spatial panel data modelling techniques, the present study set out to empirically assess the impact of region-internal and region-external knowledge capital on TFP across Chinese regions, and, by this, provide evidence on the crucial question whether TFP in China is increasingly based on knowledge production and diffusion.

The empirical findings can be summarised as follows: First, and in line with many previous studies on Endogenous Technological Change in developed nations, knowledge capital does have a significantly positive impact on productivity across Chinese provinces. Second, the total impact of regional knowledge capital on TFP was found to be larger for the period 1998 to 2007 than that for the period 1988 to 1997, which implies that the impact of knowledge capital on Chinese TFP has increased over time. This is supported by our finding of a structural break in the time series of TFP around 1998. Third, the findings confirm the presence of feedback effects across Chinese regions in the period 1998-2007. These feedback effects are due to cross-regional knowledge spillovers which turn out to be positive and significant. Finally, regional heterogeneity in TFP was found to be significantly influenced by knowledge spillovers, with an effect on regional productivity that is positive in sign. Taken together, these findings suggest a positive and significant role of knowledge capital as well as knowledge spillovers in promoting productivity at the regional level in China, which supports the hypothesis of China's transformation towards a knowledge-based economy.

Some key policy implication can be derived from the results. Given the finding that regional knowledge production and cross-regional productivity spillovers are driving forces for productivity growth across Chinese provinces, investment in technological change will continue to be a key strategy by Chinese firms as well as by national and local governments to promote growth for the next years to come. As stated in previous studies, a potential hampering factor for the transition towards a knowledge-based economy may be a lack of integration and knowledge diffusion in the Chinese innovation system, which might be related to fragmented regional policies and protectionism (see, for instance, Crescenzi et al. 2012, Scherngell and Hu 2011, OECD 2008). Given our finding of positive knowledge spillover effects on productivity in the 2000s as opposed to the 1990s, one may conclude that policies to reduce regional barriers to knowledge diffusion have had a positive effect, Nonetheless, such policies that help to attract knowledge spillovers towards less developed inland provinces and instruments that allocate knowledge resources to inland regions are crucial to further reduce the disparities across Chinese provinces.

However, with the provincial data set used in this study, caution must be applied, as the findings might not be transferable to a lower spatial aggregation level. In this, further work needs to be done to establish whether knowledge spillover effects change in magnitude and significance when considering a lower level spatial division of Chinese regions, such as at the prefecture and city level. In the same line, the use of dynamic spatial panel data models with higher temporal dependence might be considered to study knowledge spillover effects across Chinese provinces.

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