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Technological relatedness and asymmetrical firm productivity gains under market reforms in China

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This article employs fixed effect quantile regression techniques to study the effects of technological relatedness on firm productivity and to investigate whether the size of those effects varies for low and high performing firms. Next, we consider how changes in the local industrial mix brought about by China's market reforms influence the ability of different types of firms to benefit from technological-related spillovers. The findings highlight the important role that technological relatedness has on increasing firm productivity, providing some support for the idea that regions should pursue a strategy of 'regional branching' to evolve the local industrial mix into related economic activities. The findings also reveal, however, that increasing technological relatedness may asymmetrically harm underperforming firms and widen disparities in productivity between local firms.

Keywords: firm productivity, relatedness, quantile regression, China
JEL Classification: C31, O18, L25, R30

Introduction

The geographical clustering of firms is expected to lead to externalities or agglomeration economies, which in turn, have important implications for firm performance, and in aggregate, regional competitiveness and development (Marshall, 1920; Porter, 1990). The linkages between agglomeration and firm performance is strongly rooted in micro-economic theory (Fujita et al., 1999; Krugman, 1991), although both the theoretical and empirical work are overwhelmingly applied to advanced market economies, operating under the following assumptions: factors move freely across cities, no barriers to entry or exit and limited government intervention. Such theoretical assumptions may not necessarily be generalizable to transitioning economies where the state remains largely responsible for steering the location, direction and intensity of the production of goods.

In China, the state designation of special economic zones and development of industrial clusters are recognized as being two important engines of its extraordinary growth over the past three decades (Fan and Scott, 2003). For instance, more than 100 clusters were created across 60 Chinese cities since 1995, accounting for 14% of China's productivity growth between 1998 and 2007 (Hu et al., 2015). In spite of the rapid pace of agglomeration in certain areas, other areas face an insufficient level of agglomeration due to the implementation of uneven market reforms, inter-regional competition and distortionary activities of local policies (Au and Henderson, 2006).

While economic reforms have helped to restructure Chinese social, economic and political institutions, their gradual and spatially uneven implementation have led to considerable variation in time and space (He and Pan, 2009). In less reformed areas, for instance, large SOEs dominate the local economy and are likely to obstruct the main mechanisms that promote agglomeration economies, mainly inter-firm competition and inter-firm cooperation. In more reformed areas, the reduction in local state dominance may either increase the supply of agglomeration economies or give rise to negative externalities such as hyper-competition, or both. Due to the potential mediating effects of changes in China's local industrial mix brought about by market-oriented reforms, it is unclear who benefits from agglomeration economies during times of economic transition.

This article therefore studies empirically the relationship between two important dimensions of agglomeration, mainly technological relatedness and specialization, and firm productivity in a transitioning Chinese economy context. We attempt to address the following three questions. First, what are the effects of agglomeration economies on firm productivity? Second, do agglomeration economies generate asymmetrical productivity gains that depend, in part, on the firm's own internal productivity capabilities? Third, do changes to the local industrial structure brought about by market reforms influence the ability of different firms to benefit from agglomeration economies?

To answer these questions, this study relies on a sample of over 165,000 Chinese firms located in 255 Chinese cities for the 1998–2007 period. Conventional panel models are first employed to study the effects of technological relatedness on the 'average' firm. Next, fixed effect quantile regression models are used to track how the effect of technological relatedness is conditioned by the firm's internal production capabilities. Lastly, we develop an identification strategy that relies on propensity score matching and difference-in-difference estimation to investigate the causal effects of market reforms on firm productivity given different existing industrial structures.

Our article makes the following two contributions to the literature. First, we link empirically the firm's own internal production capacity to its ability to benefit from technological relatedness using a quantile regression framework. Existing studies tend to rely on conventional regression through the mean estimation strategies that are only capable of revealing the average effect of agglomeration on the 'average' firm. By contrast, quantile regression techniques provide a more complete picture of agglomeration benefits by computing several regression curves that correspond to various percentage points along the productivity distribution. Second, our study is applied to a transitioning economy context in order to better understand how market-oriented reforms impact the ability of different types of firms to benefit from technological relatedness.

The structure of this article is as follows. The subsequent section provides a brief literature review followed by an overview of China's economic reforms in Section 3. Section 4 introduces the data and main variables. Section 5 describes the model estimation strategy and the identification strategy. Section 6 presents the empirical results and Section 7 concludes.

Literature review

Traditional agglomeration studies tend to emphasize exclusively the role of geographical proximity, differentiating agglomerations along three dimensions: localization economies that arise due to specialization, Jacobs externalities that arise due to industrial diversity and urbanization economies that arise due to spillovers that take place between industries. The evidence from this body of research indicates that firms tend to benefit from their geographical proximity due to externalities on input–output markets, labour markets, access to public goods and knowledge spillovers (Glaeser et al., 1992; Henderson, 2003; Marshall, 1920). Although some studies also point to the potential for negative externalities to arise due to increased competition or the need to pay higher rents (Staber, 1998).

Moving beyond the traditional agglomeration literature, new perspectives emanating out of evolutionary economic geography instead highlight the importance of knowledge, cognitive or technological relatedness between industries as an important compliment to geographical proximity (Boschma, 2005; Boschma and Frenken, 2006; Frenken et al., 2007). The notion of technological relatedness builds on the idea championed by Jacobs (1969), where the co-agglomeration of many diverse industries facilitates inter-industry spillovers, which in turn, enhances firm productivity (Glaeser et al., 1992). Frenken et al. (2007) further extend this idea by showing that firms are more likely to benefit from inter-industry spillovers given the industries engage in similar types of economic activities.

Recent studies positively link the role of technological relatedness to various economic indicators, including firm survival, firm innovation and economic growth. In their study of local industry dynamics, for instance, Neffke et al. (2011) show that regional growth in Spain is positively related with industry relatedness but not localization economies. In another article, Neffke et al. (2012) find that technological relatedness rather than localization economies improve the chances of firm survival.

The findings by Neffke et al. (2011, 2012) and others have helped to reinvigorate a longstanding debate over whether regions should specialize or diversify industrial activity. Based on the new evidence, proponents of evolutionary economic geography support a process they term as 'regional branching,' the idea that regions are path-dependent and tend to evolve into new diverse areas according to their existing capabilities. The policy implications suggest that policy supports should be aimed at attracting and developing new firms and industries that share a close technological proximity to local existing industry leaders, as opposed to using policies to support the region's leading firms and industries that are already doing well.

There are two important reasons why technological relatedness may have a stronger positive effect on firm productivity than specialization. First, firms will try harder to protect their knowledge from direct competitors within the same industry than if the firm is in another (related) industry. Second, firms within the same industry may share a large overlap in competencies, and may therefore be unable to benefit from one another, leading to a cognitive lock-in (Nooteboom, 2000), whereas spillovers that occur between related industries are expected to lead to the recombination of new ideas and eventually to new innovations, which in turn, promote firm performance (Boschma and Frenken, 2006).

While technological relatedness has been linked to promoting economic growth and development, it is unlikely that all firms will benefit equally from technological related spillovers. In the existing literature, the ability of the firm to seek out and exploit externalities has been shown to depend, in part, on the firm's own characteristics such as its size, age, internal knowledge capacity and production capabilities (McCann and Folta, 2011; Rigby and Brown, 2015).

Rigby and Brown (2015), for instance, find that firms with a smaller pool of internal resources—i.e. smaller, older, domestic and single-plant businesses—asymmetrically benefit from agglomeration economies. The main reason for this is because firms with fewer endowments have higher incentives to seek out and rely on externalities to achieve competitiveness. On the other hand, McCann and Folta (2011) argue that it is the firms that possess a larger pool of internal resources—i.e. internal knowledge stocks—that are better able to benefit from spillovers due to their higher stocks of existing knowledge.

China's economic reforms

The introduction of market reforms in China was initially enacted in the late 1970s. The intensification of state enterprise reforms in the late 1990s and early 2000s led to the large-scale dismantling of inefficient state-owned enterprises (SOEs) and an influx of new indigenous entrepreneurial firms and foreign-invested enterprises (FIEs). As a result of these reforms, China has evolved from a transitioning economy rife with economic and political uncertainties to one that is more favourable to entrepreneurial activities.

Coinciding with its reforms, the importance of the institutional dimensions are becoming supplanted by market-based mechanisms that emphasize firm efficiency over political connections. For instance, economic reforms have led to the legalization of private firms and the relaxation of bankruptcy procedures for SOEs. Entrepreneurial firms are now increasingly able to raise venture capital, and access intermediaries for legal, accounting and information services in order to compete with foreign firms.

Due to the gradual nature of China's economic reforms, the depth of transition varies across heterogeneous provinces and cities leading to large regional differences in terms of local levels of marketization. In a World Bank study, for instance, Chinese firms spent 36 days per year interacting with government bureaucracies in the top 10 percentile of cities compared to 87 days per year for firms in the bottom 10 percentile of cities (World Bank, 2008). Firms located in regions still in the earlier stages of transition therefore face higher institutional barriers, which in turn, directly harms firm performance as excessive regulatory compliance occupies valuable firm resources. As regions experience deepening reforms, firms are expected to operate more efficiently.

Linking China's economic reforms to the local industrial mix and firm productivity

China's economic reforms are likely to also have an indirect effect on firm performance by influencing the ability of firms to benefit from agglomeration economies. Economic reforms are expected to moderate the relationship between agglomeration economies and firm productivity via changes that take place in the local industrial structure. Chinitz (1961) was the first to link industrial structure to externalities, arguing that changes in the local industrial mix influence the level of inter-firm cooperation and inter-firm competition within an agglomerated region. Both of which are essential components of a healthy functioning agglomeration and serve as key drivers of firm innovation and technological upgrading (Staber, 1998).

Regions at the comparatively earlier stages of market reforms are often dominated by one or a few large SOEs, which reduces inter-firm competition since SOEs often lack strong incentives to develop their firm-specific advantages. A state-dominated local economy may also reduce inter-firm cooperation by impeding the ability of private firms to take advantage of Marshallian sources of agglomeration that are expected to take place within the same or related industries for the following reasons. First, entrepreneurial firms' access to independent specialized suppliers providing intermediate inputs may be obstructed.

There are two possible reasons why this obstruction may occur. The size of the local market for independent specialized suppliers will contract as large SOEs are more likely to source inputs from non-local suppliers, either via internal supply (vertical integration) or national contracts. Also, the local suppliers that do exist are more likely to seek out contracts with the SOEs and therefore may be less likely to work with smaller entrepreneurial firms.

Second, workers with the most specialized skill-sets and experience may seek out employment with SOEs for prestige and stability as well as for higher pay. As a result, non-state-owned entrepreneurial firms' access to a quality labour pool is diminished. Lastly, a few dominant SOEs in the local economy may hinder the flow of tacit information by reducing social interactions, thereby disrupting the creation of and access to knowledge spillovers in the region (Glaeser et al., 1992).

As economic reforms are gradually implemented across different areas, the proportion of SOEs in the local industrial mix decreases. In turn, it is expected that the reduction in local SOE dominance in more reformed regions will improve opportunities for greater local inter-firm cooperation and lead to better market integration, giving rise to agglomeration economies. At the same time, firms in these reformed areas may also be impacted by the rise of negative externalities such as hyper-competition, as market reforms also led to rapid influx of new private and foreign firms. The net effect of agglomeration economies following market reforms thus depends on whether the new supply of positive externalities outweighs the rise of new types of negative externalities.

Data and variable development

The empirical portion of this article relies on the Annual Report of Industrial Enterprise Statistics compiled by the State Statistical Bureau of China for the years 1998 through 2007. The data includes all firms with an annual turnover over 5 million Renminbi, ~$600,000. In total, the sample of firms accounts for 90–95% of industrial output in China (Brandt et al., 2012). Our sample includes a semi-balanced panel of more than 165,000 entrepreneurial firms operating across 255 Chinese cities for the 1998–2007 period.

Variable development

Firm productivity

While labour productivity is generally the most widely used measure of firm performance, it does not take into account capital intensity. This is a key disadvantage, especially in the case of China where the share of labour earnings in GDP accounts for less than one half of Chinese manufacturing. Instead, we derive the firm's total factor productivity (TFP). In order to obtain TFP estimates, the firm's value added, capital stock and investment must first be developed.

The real value added is constructed by separately deflating output, net of goods purchased for resale and indirect taxes and material inputs, where the input deflators are calculated using the output deflators and information from China's 2002 National Input–Output (IO) table. Next, the real capital stock for 1998 is developed using the perpetual inventory method, assuming a depreciation rate of 9% and deflating annual investment using the Brandt–Rawski deflator. Following 1998, the observed change in the firm's nominal capital stock at original purchase prices is used as the estimate for the nominal fixed investment using the same rate of depreciation and deflator to roll the real capital stock estimates forward. Relying on the construction of these variables, TFP estimates are derived for Chinese firms using the Olley and Pakes (1996) semi-parametric method.

Measuring technological relatedness

Following Hidalgo et al. (2007), we rely on a co-occurrence indicator to measure technological proximity, expressed as,

$$\phi_{jm} = min(Prob(\mathrm{RCA}_j^r \mid \mathrm{RCA}_m^r), Prob(\mathrm{RCA}_m^r \mid \mathrm{RCA}_j^r)) \quad (1)$$

where the proximity ϕ between industry j and industry m is equal to the minimum between the pairwise probability that industry j has a local revealed comparative advantage (RCA) conditional on industry m also having a local RCA.[1] A higher ϕ_{jm} indicates a higher probability that two industries with RCA co-agglomerate in the same region, and are therefore more likely to have higher relatedness with each other. Note that RCA is included as our proxy for specialization.

Unlike existing proxies that rely on traditional sector classifications to define industrial relatedness, ϕ is more comprehensive and captures the technological or cognitive similarity between any two subsectors irrespective of their official industry classification. Table 1 confirms that there is a lack of perfect overlap between sector classifications. The measure of proximity decreases at higher levels of industry aggregation, while the means and medians at the three and two digit classification remain quite close.

To quantify technological relatedness across Chinese regions, we employ the *density* measure, expressed as:

$$w_{it}^{r} = \frac{\sum_j x_{jt}^{r}\phi_{ij}}{\sum_j \phi_{ij}} \quad (2)$$

where w_{it}^{r} is the density around industry i for region r in year t, $x_{jt}^{r} = 1$ if RCA > 1 and 0 otherwise. The density measure essentially combines information on the intrinsic relatedness of a product with that of the local pattern of specialization. A higher w_{it}^{r} indicates that sector i is closer to the productive advantage of city r in time t. Note that our regional unit of k is measured at both the province level and at the city level.

Indicator for market reforms

We measure China's economic transition using the marketization index developed by the National Economic Research Institute (NERI).[2] The marketization index is constructed annually from 1998 to 2007 and includes 23 sub-indices divided into 5 major dimensions related to the marketization progress in each of the 31 provinces. The general NERI index will capture the changes brought about by marketization across various dimensions that may not necessarily impact the local industrial mix.

In order to isolate the institutional changes brought about by the reforms that are expected to directly impact the local industrial mix, we rely on the NERI sub-index (2c)—the proportion of non-state sectors in urban employment—as our preferred proxy. The NERI sub-index (2c) is a provincial level variable and may therefore hide spatial variations that may exist at the city level. We therefore rely on the ASIF data to calculate the same measure—the proportion of non-state sectors in urban employment—but at the city level.

Model specification

Based on Koenker et al. (1978), the standard linear conditional quantile function takes the following form:

$$y_{it}(\tau_k \mid X = x) = x_{it}'\beta(\tau_k) \quad (3)$$

where y_{it} is the productivity of firm i in year t. X is a vector of control variables, and k is the index for the chosen quantiles. In line with the literature, we estimate the 10th, 25th, 50th, 75th and 90th quantiles, τ_k.

Table 1. *Technological proximity values within china industrial classification (CIC) codes.*

	Mean	Median	SD	Min	Max
Across all products	0.135	0.127	0.084	0.000	0.667
Within the same two-digit industry	0.194	0.194	0.054	0.091	0.321
Among different two-digit industry	0.131	0.131	0.038	0.045	0.243
Within the same three-digit industry	0.198	0.200	0.097	0.000	0.449
Among different three-digit industry	0.141	0.135	0.061	0.005	0.545

One main drawback of the standard quantile regression approach is that it fails to take into account firm heterogeneity—i.e. firm's management skills, size, knowledge, technology and location—and as a result may produce biased estimates. The conditional QR estimation procedure can be extended to include individual fixed effects (FEQR) that capture time-invariant firm characteristics.

The fixed effects quantile regression (FEQR) is expressed as,

$$\begin{aligned} &y_{it}(\tau \mid x_{it}) = \alpha_i + x_{it}'\beta(\tau) \\ &i = 1,\ldots,N, \quad t = 1,\ldots,T. \end{aligned} \tag{4}$$

where the α's are the unobservable time-invariant individual fixed effects and is a pure location shift effect on the conditional quantiles of the response. x_{it} are the control variables and include the lagged-dependent variable to account for possible dynamics. The covariates, x_{it} are assumed to depend on the quantile, τ, of interest, but the α's do not.

To estimate Equation (4) for several quantiles simultaneously, we perform the following minimization algorithm for the τth regression quantile,

$$\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T} \xi_k \rho_{\tau_k}(y_{it} - \alpha_i - x_i'\beta) + \lambda \sum_{i=1}^{n} |\alpha_i| \tag{5}$$

The weights, ξ_k, set to equal unity, control for the relative influence of the τ quantiles on the estimation of α_i's parameters. We assume that the α's are constant across quantiles, which works to reduce the number of parameters to be estimated, and permits each chosen quantile, ρ_k to be estimated simultaneously. A penalty term, $\lambda\sum_{i=1}^{n} |\alpha_i|$, is added to the minimization algorithm to account for the computational problem arising from estimating a large number of individual fixed effects for the τ quantiles. λ describes the importance of the penalty term in the minimization formula.

Identification strategy

Throughout China's economic transitioning process, the designation of which areas were chosen to undergo more intensive market reforms was not at random. Many coastal cities were first chosen to undergo various economic reforms after the opening-up of the Chinese economy, leaving many of the inland cities less impacted by economic reforms at least initially. Coastal cities were chosen first due to their geographical advantages and close proximity to shipping ports. Firms in these areas may have been initially more productive than those firms located elsewhere, which makes it difficult to identify the causal effects of market reforms on firm productivity given different existing industrial structures.

To address this problem, we use propensity score matching combined with difference-in-difference (PSM DID) estimation to confirm the causal effect of market reforms on firm productivity given different existing industrial structures. We use China's entry into the WTO in 2001 as the policy treatment. Following its entry into the WTO, China intensified the pace of its market reforms, leading to a reduction in the share of local SOE employees, particularly in downstream industries. The treatment group includes the firms that are located in areas that have undergone more intensive market reforms following China's 2001 WTO entry, proxied by the share of SOE employees in the local industrial mix.

The identification strategy consists of two stages. In the first stage, a non-linear propensity score matching technique is used to construct a control group of firms that match most closely to treated firms based on observable characteristics. A list of covariates is linked to market reforms in order to identify the most appropriate control group. We select the following covariates—firm's region, labour productivity, capital intensity, size, age and TFP—so that firms in the control group are matched to the treatment group on the basis of the pre-treatment (1998–2001) mean of these variables.

In the second stage, difference-in-difference estimation is used to help remove the time-invariant unobserved heterogeneity across firms, such as location specific effects and managerial skill. The dependent variable, firm TFP, is first differenced by calculating the difference between the post-treatment (2002–2007) and pre-treatment (1998–2001) means, meaning that we only keep a balanced sample of firms are observed both before and after China entered the WTO in 2001.

FEQR results: technological relatedness, specialization and firm productivity

We begin by first estimating the effect of technological relatedness and specialization on the 'average' firm using conventional panel model methods. As our regional unit of analysis, we use both province level and city level proxies for our variables. All standard errors are robust and are clustered at the corresponding regional unit to adjust for the potential correlation of errors between firms found in the same region. Note that the measures for technological relatedness and specialization are standardized for comparison purposes.

Columns (1)–(2) and (4)–(5) in Table 2 show the model results in levels using OLS with firm and year fixed effects. Columns (3) and (6) include a lagged dependent variable to account for possible dynamics. Following Anderson and Hsiao (1982), the dynamic models are estimated in first differences using the 2-year lagged levels of the variables as instruments. Our instruments pass the relevant tests for under-identification and weak instruments as indicated by the Anderson–Hsiao specifications. The results reveal that all of the coefficients are highly statistically significant and are similar across each model specification. In regards to the firm characteristics, the findings show that older firms and smaller firms respectively have higher TFP levels, although both effects are found to be non-linear.

The coefficients on density and RCA are both positive in each model. Controlling for the firm's TFP in the previous year, the positive coefficients on density and RCA in the dynamic models indicate a genuine learning effect for firms that locate in regions with a higher density of relatedness or that are more specialized. Thus, the results from the fixed effects models do not appear to be driven by issues related to firm sorting. These findings support earlier work by Au and Henderson (2006) who argue that the restrictions on migration prevent workers from migrating within and between industries, thereby reducing some of the usual problems with self-selection of higher skilled individuals and firms into certain areas.

In terms of economic impact, the coefficient on density is larger than the one on RCA, implying that firms benefit more in terms of higher productivity from technological relatedness than by specialization. One reason for this finding is because specialization implies excessive overlap in firm competencies which may lead to a cognitive 'lock-in' (Nooteboom, 2000). By contrast, spillovers that take place between related industries help to promote the recombination of new ideas and, which in turn, is expected to facilitate more innovation and larger productivity gains (Boschma and Frenken, 2006).

Next, we study whether the size of the coefficients on technological relatedness and specialization changes depending on the location of the firm along the productivity distribution. The main goal here is to see whether or not all firms equally benefit from technological related spillovers and localization economies. We rely on the fixed effect quantile regression (FEQR) models to test whether the size of the coefficients is conditioned by the firm's own production capabilities. If there is a pure location shift effect, as is implicitly assumed in the mean

Table 2. *Panel model results: technological relatedness, specialization and firm productivity.*

	OLS estimation levels	OLS estimation levels	Dynamic estimation first differences	OLS estimation levels	Dynamic estimation first differences
	(1)	(2)	(3)	(4)	(5)
Firm-level controls					
Firm age	0.306***	0.292***	0.245***	0.299***	0.228***
	(0.010)	(0.010)	(0.016)	(0.010)	(0.016)
Firm age^2	−0.050***	−0.048***	−0.053***	−0.049***	−0.050***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm size	−0.760***	−0.766***	−0.433***	−0.761***	−0.448***
	(0.013)	(0.013)	(0.016)	(0.013)	(0.016)
Firm size^2	0.059***	0.060***	0.039***	0.059***	0.039***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Lagged TFP			0.467***		0.465***
			(0.005)		(0.005)
Province-level controls					
Density		0.061***	0.015***		
		(0.002)	(0.002)		
RCA		0.031***	0.010***		
		(0.003)	(0.002)		
Local share of SOE employees		0.257***	0.289***		
		(0.027)	(0.011)		
City-level controls					
Density				0.081***	0.021***
				(0.003)	(0.003)
RCA				0.040***	0.017***
				(0.004)	(0.003)
Local share of SOE employees				0.102***	0.060***
				(0.003)	(0.002)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Num. obs.	404,796	404,796	69,339	404,796	69,339
Anderson Canon. Corr. LM statistic p value (Under-identification test)			0.000		0.000
Cragg–Donald Wald F-statistic (Weak identification test)			478		606

The dynamic estimations in Columns (3) and (5), the Anderson–Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for under-identification and the Cragg–Donald Wald F statistic test for weak identification test. See Appendix A for a description of variables.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

regression models, then the coefficients at each of the estimated quantiles will be the same as the mean effect.

Table 3 reports the results from the quantile regression model. All of the coefficients for technological relatedness and specialization are highly statistically significant at each quantile of interest. The signs on the coefficients for both RCA and Density are negative for firms at the 10th percentile, but become positive and monotonically increase moving along the TFP distribution for both the province and city level estimations.

Table 3. *FEQR results: technological relatedness, specialization and firm productivity.*

	Quantile					
	0.1	0.25	0.5	0.75	0.90	Mean
Province level						
Density	–0.007***	0.005***	0.013***	0.029***	0.039***	0.015***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)
RCA	–0.006***	0.002***	0.014***	0.023***	0.036***	0.010***
	(0.001)	(0.000)	(0.002)	(0.004)	(0.002)	(0.002)
City level						
Density	–0.012***	0.006***	0.025***	0.046***	0.060***	0.021***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.009)	(0.003)
RCA	–0.018***	0.004***	0.019***	0.042***	0.051***	0.017***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)

Models are estimated using fixed effects quantile regression (FEQR) models and include all control variables from Table 2 above. The standard errors for the quantile regression are obtained after 1000 bootstrap repetitions. From left to right, columns represent the 10th, 25th, 50th, 75th and 90th percentiles of the TFP distribution, respectively, followed by the conventional regression through the mean model. See Appendix A for a description of variables.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The findings from Table 3 indicate that the nature of the relationship between technological relatedness (and specialization) and firm productivity hinges critically upon the internal production capabilities of the firm. While firms at the lower end of the productivity distribution have the most incentives to seek out place-based economies in order to achieve competitiveness (Rigby and Brown, 2015), our results align more with the findings in McCann and Folta (2011). That is, only those firms that possess a sufficient set of internal resources, in this case productivity capabilities, are able to benefit from place-based economies. In other words, despite sharing close and even excessive technological proximity, the least performing firms are unable to successfully exploit and benefit from either technological related spillovers or localization economies.

As described above, market reforms have been gradually implemented in China in both time and space. If the least performing firms tend to be located in areas that have not undergone market transition, then one of the reasons why they may be unable to benefit from place-based economies could be due to the domination by SOEs in the local industrial mix, which could obstruct the ability of firms, especially the least performing ones from benefiting from the Marshallian sources of agglomeration. The next section turns to explore this question, and in general, whether market reforms help to mitigate or moderate the ability of different firms to benefit from placed-based economies.

FEQR results: moderating effects of market reforms on the agglomeration–firm productivity relationship

We examine how changes in the local industrial mix brought about by economic reforms influences the ability of different firms to benefit from technological relatedness and specialization. The FEQR model is re-estimated in Table 4 by splitting firms into mutually exclusive groups according to whether the firm is located within a region that has comparatively higher value of density (and RCA, respectively) and is in a region that has a larger versus smaller share of SOE employment. A larger share of local SOE employment indicates that the region has undergone comparatively less market reforms, while a smaller share of local SOE employment indicates that the region has undergone comparatively more market reforms. A simple test of equality (*t*-test) is used to

Table 4. *FEQR results: technological relatedness, specialization and firm productivity with market reforms.*

	Quantile					
	0.1	0.25	0.5	0.75	0.90	Mean
Panel A: province level						
Higher density						
× Less market reforms	0.070***	0.042***	0.028***	0.016***	0.012***	0.031***
	(0.014)	(0.010)	(0.007)	(0.005)	(0.003)	(0.008)
× More market reforms	−0.151***	−0.091***	0.077***	0.081***	0.096***	0.070***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.009)	(0.005)
Difference (*p* value)	−***	−***	+***	+***	+***	+***
Higher RCA						
× Less market reforms	0.133***	0.127***	0.120***	0.083***	0.031***	0.101***
	(0.009)	(0.007)	(0.006)	(0.007)	(0.009)	(0.005)
× More market reforms	0.160***	0.134***	0.115***	0.022***	−0.037***	0.112***
	(0.007)	(0.005)	(0.005)	(0.005)	(0.007)	(0.004)
Difference (*p* value)	+***	+***	−***	−***	−***	+***
Panel B: city level						
Higher density						
× Less market reforms	0.119***	0.098***	0.068***	0.055***	0.039***	0.078***
	(0.021)	(0.013)	(0.017)	(0.010)	(0.016)	(0.021)
× More market reforms	−0.151***	0.029***	0.082***	0.135***	0.169***	0.126***
	(0.028)	(0.007)	(0.018)	(0.015)	(0.029)	(0.018)
Difference (*p* value)	−***	−***	+***	+***	+***	+***
Higher RCA						
× Less Market Reforms	0.081***	0.062***	0.039***	0.031***	0.024***	0.061***
	(0.024)	(0.017)	(0.010)	(0.009)	(0.005)	(0.013)
× More Market Reforms	0.141***	0.126**	0.111***	−0.036***	−0.068***	0.108***
	(0.011)	(0.019)	(0.021)	(0.015)	(0.024)	(0.013)
Difference (*p* value)	+***	+***	+***	−***	−***	+***

Models are estimated using fixed effects quantile regression (FEQR) models and include all control variables from Table 2 above. The standard errors for the quantile regression are obtained after 1000 bootstrap repetitions. From left to right, columns represent the 10th, 25th, 50th, 75th and 90th percentiles of the TFP distribution, respectively, followed by the conventional regression through the mean model. The p value shown in each column tests the null hypothesis that the difference in the coefficients is statistically insignificant. See Appendix A for a description of variables.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

compare the value of the coefficient for agglomerated firms located in areas that underwent deeper reforms to the value of the coefficient obtained for regions at earlier stages of reforms.

The coefficients for firms in areas that have undergone *less* intense market reforms given a comparatively higher Density value are positive at the 10th percentile and monotonically decrease, but remain positive moving along the firm productivity distribution. By contrast, the coefficients in areas that have undergone *more* intense market reforms given a comparatively higher Density value are negative at the 10th percentile and monotonically increase and turn positive moving along the firm productivity distribution. The effect on the 'average' firm in areas given a higher Density value is positive at both the comparatively earlier and later stages of market reforms. These results are similar at both the province and city levels.

The coefficients for firms in areas that have undergone *less* intense reforms given a comparatively higher RCA value are positive at the 10th percentile, but monotonically decrease moving along the firm productivity distribution. The same relationship exists for firms in areas that have undergone *more* intense market reforms, with the coefficient turning negative at the higher end of the firm's productivity distribution. The effect on the 'average' firm in areas given a higher RCA value is positive at both the comparatively earlier and later stages of market reforms. These results are similar at both the province and city levels.

Results from the *t*-test indicate that the shift from a high to low share of local SOE employment (e.g. the change in market reforms) has a net negative mediating effect in areas with a high density value for lower performing firms. The mediating effect eventually turns positive moving along the firm productivity distribution. In terms of specialization, results from the *t*-test indicate that the shift from a high to low share of local SOE employment has a net positive mediating effect in areas with a high RCA value for lower performing firms, but eventually turns negative moving along the firm productivity distribution.

To keep a clear focus, Table 5 summarizes these findings by showing how technological relatedness and specialization influence firm productivity for the least performing, best performing and the 'average' following the implementation of more intense market reforms. The coefficient signs show how the shift from earlier to later stages of economic transition moderates the ability of low [high] performing firms and average performing firms to benefit from the technological relatedness and specialization, respectively.

The negative sign in the first row in column (1) shows that deepening market reforms mitigates the ability of the lowest performing firms to benefit from technological relatedness. In contrast, a moderating effect is observed for the top performing firms (column 3) and the 'average' firm (column 5). In row 2, the effects of RCA have the opposite effects. Deepening market reforms help enable the least performing firms to benefit from localization economies, yet have a mitigating effect for the top performing firms.

The results indicate that deepening economic reforms influence the ability of the firm to benefit from both technological relatedness and specialization, and that the size of the effects is conditioned by the firm's own internal production capabilities. One potential explanation for the findings in regards to technological relatedness is that the least performing firms do not posses sufficient internal resources to seek out and benefit from existing knowledge created in other industries despite sharing a closer technological proximity. Rather, they are only capable of capturing spillovers within their own industry due to the greater overlap in their core competences. By contrast, in terms

Table 5. *Summary of the main findings.*

	Bottom 10% firms		Top 10% firms		Average (mean) firm	
	Province	City	Province	City	Province	City
	(1)	(2)	(3)	(4)	(5)	(6)
Higher density × Δ market reforms	–***	–***	+***	+***	+***	+***
Higher RCA × Δ market reforms	+***	+***	–***	–***	+***	+***

The summary of findings are based on the results from the quantile regressions estimated in Table 4. The signs (±) correspond to the direction of the moderating effect of deepening market reforms on the ability of the firm to benefit from Density (technological relatedness) and specialization (RCA). A positive sign indicates that the shift from earlier to later stages of market reforms intensifies the moderating effect, whereas a negative sign indicates a mitigating effect. Statistical significance stars are based on *t*-tests (*p* values) and test whether the Δ *Market Reforms*, that is from less intense to more intense market reforms, leads to a statistically different mediating effect.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

of specialization, the top performing firms are leaders in their industries, and may be unable to learn anything new from spillovers within their own industry, and are instead harmed by the negative competition effects.

Robustness check: propensity score matching and difference-in-difference estimation results

Next, we carry out a robustness check using a PSM DID identification strategy to address concerns related to the non-random assignment of China's market reforms. Table 6 reports the results from the estimation of the probit model. The dependent variable is a dummy variable that takes a value of 1 if the firm is in the treatment group—that is, following China's entry into the WTO in 2001 the firm is located in a region that was exposed to more intensive market reforms, proxied by the share of local SOE employees—and 0 otherwise. The objective here is to first check whether the selected covariates are important determinants of the policy treatment. All covariates are measured by the mean before the policy treatment.

The results show that the covariates are indeed statistically significant. Firms are more likely to receive policy treatment if they have higher labour productivity, capital intensity and TFP, and are smaller in size and younger. These results are consistent with our expectations that regions more likely to undergo more intense economic reforms tend to be in areas where firms are more advanced.

Based on the above determinants of policy treatment, we construct a matched control group to compare with treated firms. Table 7 shows the pre-treatment means of the policy determinants between the treated and matched groups. The results from the *t*-test reveal that there is no significant difference in the covariates we chose between treated and matched samples, an indication that the matching procedure is valid.

Having shown that the matching procedure is valid, we next re-estimate a quantile regression model using the difference-in-difference matching estimation. The model is re-estimated in Table 8 by splitting firms into mutually exclusive groups according to whether the firm is

Table 6. *Determinants of market reforms.*

	Dependent variable: market reforms (0 = less market reforms, 1 = more market reform)
Labour productivity	0.076***
	(0.001)
Capital intensity	0.034***
	(0.010)
Size	−0.009***
	(0.002)
Age	−0.003***
	(0.0001)
TFP	0.159***
	(0.025)
Region dummies	Yes
Observations	404,796
Adjusted R^2	0.111

Notes: This table tests whether the variables used for propensity score matching are important determinants of the policy treatment. The binary-dependent variable equals 1 if the share of SOE employees in the local city is less than the median value for all cities, and 0 otherwise. A value of 1 indicates the implementation of more intense local market reforms. See Appendix A for a description of variables.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7. *Balancing tests for propensity score matching.*

	Mean		*t*-test	
	Treated	Matched	*t*-statistic	*p* value
Labour productivity	5.124	5.124	0.032	0.975
Capital intensity	5.042	5.041	0.138	0.890
Size	5.044	5.043	0.057	0.954
Age	2.080	2.079	0.268	0.789
TFP	1.358	1.357	0.297	0.767
RCA	0.897	0.897	0.186	0.853
Density	0.528	0.527	0.223	0.823

Propensity score matching method using nearest neighbour is applied to test whether there is a significant difference between the treated and matched groups on potential determinants of China's market reforms. See Appendix A for a description of variables.

Table 8. *PSM DID robustness check: technological relatedness, specialization and firm productivity with market reforms (correcting for selection).*

	Quantile					
	0.1	0.25	0.5	0.75	0.90	Mean
Higher density						
× less market reforms	0.016**	0.014***	0.006**	0.004	0.001	0.008***
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
× more market reforms	–0.024***	–0.009*	0.009**	0.017***	0.024***	0.012***
	(0.006)	(0.004)	(0.003)	(0.005)	(0.007)	(0.002)
Difference (*p* value)	–***	–***	+***	+***	+***	+***
Higher RCA						
× less market reforms	0.049***	0.040***	0.031**	0.026**	0.021***	0.031**
(control group)	(0.015)	(0.013)	(0.013)	(0.011)	(0.009)	(0.012)
× more market reforms	0.118***	0.075***	0.044***	0.016***	–0.014***	0.042***
(treatment group)	(0.004)	(0.009)	(0.005)	(0.004)	(0.002)	(0.013)
Difference (*p* value)	+***	+***	+***	–***	–***	+***

Models are estimated using PSM DID estimation strategy within the quantile regression framework. The standard errors for the quantile regression are obtained after 1000 bootstrap repetitions. From left to right, columns represent the 10th, 25th, 50th, 75th and 90th percentiles of the TFP distribution, respectively, followed by the conventional regression through the mean model. The p value shown in each column tests the null hypothesis that the difference in the coefficients is statistically insignificant. See Appendix A for a description of variables.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

located within a region that has comparatively higher value of density (RCA) and is in the treatment group versus the control group. The objective here is to better identify the causal effects of market reforms on firm productivity given different existing industrial structures.

The results are largely robust to the initial findings presented in Table 4 and summarized in Table 5. The impact of market reforms leads to a reduction in firm productivity for lower performing firms given higher density negative productivity, although this impact changes and helps to increase firm productivity as we move along the firm productivity distribution. By contrast, the impact of market reforms leads to an improvement in firm productivity for lower performing firms, but leads to a reduction in productivity as we move along the firm productivity distribution.

Conclusion

This article studies the effects of place-based economies, mainly technological relatedness and specialization, on firm productivity and explores whether the agglomeration benefits are distributed equally across all firms. Taking China's economic transition into consideration, we also explore whether changes in the local industrial mix brought about by market reforms moderate the ability of different firms to benefit from place-based economies. The findings reveal that a delicate balance exists between the costs and benefits of place-based economies that depends, in part, on the technological relatedness between industries, the production capabilities of the firm and the extent of market reforms.

The findings show that the average geographical welfare will be higher via larger productivity gains if regions pursue technological relatedness as opposed to specialization. These findings support recent perspectives emanating out of evolutionary economic geography that advocate cities pursuing a strategy of regional branching. That is, use policy incentives to attract new firms that are related to the productivity advantage of the region instead of supporting new firms that belong to local industry leaders that are already doing well.

Our results also offer a cautionary tale for lower performing firms who may be disproportionately harmed by pursuing a regional policy emphasizing regional branching. While technological related spillovers have a positive effect on the ‘average’ firm and the higher performing firms, they have a net negative effect on the least performing firms. These results suggest that the least performing firms ultimately lack the necessary internal resources to sufficiently exploit the local supplier/buyer networks, attract similar workers or absorb knowledge spillovers from related industries, yet are simultaneously exposed to increasing negative externalities, such as unfair competition and increasing rents.

Lastly, changes in the industrial mix brought about by China’s market reforms resulted in an overall increase in average geographical welfare. At the same time, market reforms also intensify the negative (positive) effects of technological relatedness on the least (top) performing firms, thereby increasing productivity disparities between lower and higher performing firms. A challenge for future research will be to examine whether local state interventions help protect under-performing firms in areas that pursue regional branching strategies.

Endnotes

[1] The revealed comparative advantage (RCA) is expressed as $\frac{e_{jt} / e_t}{E_{jt} / E_t}$, where e_{jt} is local employment in industry j in year t, e_t is total local employment, E_{jt} is national employment in industry j, and E_t is total national employment. A value of greater than one indicates a local industry leader.

[2] http://www.neri.org.cn/en.asp.

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Appendix A. Variable summaries and definitions

Table A1. *Variable definitions and summary statistics.*

	Definition	Mean	St. Dev.
Firm productivity	TFP of firm i in year t, constructed using the Olley and Pakes (1996) method. See Appendix A for description	3.19	1.11
Firm age [age^2]	Logarithm age of the number of years the firm has been in operation	2.18 [5.21]	0.66 [3.14]
Firm size [size^2]	Logarithm number of firm employees	4.85 [24.48]	0.976 [9.74]
Regional variables			
City [Province] density	Proxy introduced by Hidalgo et al. (2007) to capture technological relatedness—'proximity' of sector i to the productive advantage of region k for each year	0.156 [0.103]	0.031 [0.022]
City [Province] RCA	Measures specialization of industry i in region k for each year	1.20 [1.03]	2.25 [1.34]
City [Province] local share of SOE employees	Proportion of employees in state-owned enterprises (SOEs) in industry i in region k for each year. Note, the city level proxy is calculated using the ASIF data source, and the provincial level proxy is obtained from the marketization subindex (2c) constructed by the National Economic Research Institute (NERI) in each year for each of the 31 provinces	0.375 [0.354]	0.382 [0.322]
Interaction terms-province level			
Higher density × more [less] market reforms	Variable equals 1 if density is above the median value across all local industries for each province and the local share of SOE employees is above [below] the median value across all local industries for each province, and 0 otherwise	0.134 [0.027]	0.191 [0.045]
Higher RCA × more [less] market reforms	Variable equals 1 if RCA is above the median value across all local industries for each province and the local share of SOE employees is above [below] the median value across all local industries for each province, and 0 otherwise	0.015 [0.014]	0.046 [0.031]
Interaction terms-city level			
Higher density × more [less] market reforms	Variable equals 1 if density is above the median value across all local industries for each city and the local share of SOE employees is above [below] the median value across all local industries for each city, and 0 otherwise	0.114 [0.023]	0.261 [0.052]
Higher RCA × more [less] market reforms	Variable equals 1 if RCA is above the median value across all local industries for each city and the local share of SOE employees is above [below] the median value across all local industries for each city, and 0 otherwise	0.011 [0.004]	0.062 [0.043]