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# Technological Relatedness and Firm Productivity: Do low and high performing firms benefit equally from agglomeration economies in China?

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**Abstract**

Building on the evolutionary economic geography literature, we employ the density measure introduced by **?** to dynamically track the impact of technological relatedness on firm productivity. We rely on advanced quantile regression techniques to determine whether technological relatedness stimulates productivity and whether the size of the effect varies for low and high performing firms. Lastly, taking China's economic transition into account, we test whether changes in the local industrial mix brought about by China's market reforms enable or inhibit performance-enhancing spillovers.

We show that a dynamic tradeoff exists between agglomeration costs and benefits that depends, in part, on the firm's placement along the productivity distribution: the effect of technological relatedness reduces productivity for the least performing firms, but enhances it for better performing firms. As a result, spillovers via technological relatedness lead to improvements in the geographical welfare by intensifying the learning effect for the vast majority of co-located firms, in spite of increasing productivity disparities between the bottom and top performing firms.

*Keywords:* Firm Productivity, Relatedness, Agglomeration Economies, Firm Heterogeneity, China
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## 1. Introduction

The state designation of special economic zones and development of industrial clusters are recognized as being two important engines of China's extraordinary growth (Fan and Scott, 2003; He and Pan, 2009; Roberts and Goh, 2011). In spite of the rapid pace of agglomeration in certain areas, other areas face an insufficient level of agglomeration due to the implementation of spatially uneven market reforms, inter-regional competition and distortionary activities of local policies (Au and Henderson, 2006). As a result, it is unclear which firms, if any, will be best positioned to capture agglomeration economies in China.

This paper sets out to answer the following three questions related to the nature of agglomeration in China. Do firms located in areas with a denser network of related industries enjoy a productivity premium or face a productivity penalty? Are the agglomeration benefits (or costs) shared equally across all firms? In times of rapid economic transition, deepening reforms influence dynamically the local industrial mix: do such changes to the local industrial structure influence the firm's ability to seek out and benefit from agglomeration economies?

Our paper makes the following three contributions. First, cognitive or technological relatedness is now recognized as having an important role in facilitating performance-enhancing spillovers between related industries (Frenken et al., 2007; Boschma et al., 2012). Building on recent advancements in evolutionary economic geography, we employ the density measure introduced by Hidalgo et al. (2007) to dynamically track the impact of technological relatedness on firm productivity.

For our second contribution, we link empirically the firm's own internal production capacity to its ability to benefit from agglomeration economies using a quantile regression framework. While a growing number of recent studies integrate perspectives of firm heterogeneity (McCann and Folta, 2008, 2011), they typically rely on conventional regression though the mean estimation strategies that are only capable of revealing the average effect of agglomeration on the 'average firm.' 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.

Third, the brunt of the empirical literature on agglomeration focuses on advanced market economies with relatively stable institutions. Since the potency of the agglomeration effect depends on how well the market is integrated, the theoretical assumptions and empirical findings are not necessarily valid in transitioning economies where the state remains largely responsible for steering the location, direction and intensity of the production of goods. To address our concerns, we employ a quasi-experimental design to investigate whether deepening market reforms impede or facilitate firms' ability to benefit from spatial externalities.

The structure of this paper is as follows. The subsequent section presents a general overview on recent trends in the literature pertaining to technological relatedness. Section 3 introduces our Chinese case study. Section 4 outlines the key hypotheses, introduces the data and describes the indicator for our main set of variables. Section 5 describes the model estimation strategy. Section 6 presents the empirical results and section 7 concludes.

**2. Agglomeration and Technological Relatedness**

The role of agglomeration economies are thought to be essential in facilitating the process of mutual learning and knowledge spillovers, which in turn, spur growth, innovation and productivity (Fujita et al., 1999). At the micro-level, firms face a set of potential costs and benefits associated with being located in denser areas. On the one hand, firms are thought to benefit by co-locating with other firms as a result of greater access to buyer-supplier linkages, labor market pooling, sharing of public goods, and knowledge spillovers (Marshall, 1890; Duranton and Puga, 2004). On the other hand, negative externalities may also arise due to increased competition or the need to pay higher rents (Staber, 1998).

The net effect of agglomeration on firm performance likely depends on the type of agglomeration under scrutiny. Traditional studies tend to differentiate agglomerations along two dimensions: spillovers that take place within an industry (localization economies) and between-industries (urbanization economies). These studies often exclusively emphasize the role of geographical proximity, showing that the scope of externalities is limited to spatially proximate firms (Audretsch and Feldman, 1996).

Fresh perspectives emanating out of evolutionary economic geography now argue that geographical proximity in and of itself may not be a sufficient condition in fostering the flow of tacit knowledge between firms (Boschma, 2005; Boschma and Frenken, 2006). Recent research instead highlights the role of knowledge, cognitive or technological relatedness between industries as an important compliment to geographical proximity (Frenken et al., 2007; Boschma et al., 2012; Kogler et al., 2013).

The notion of technological relatedness builds on the idea championed by Jacobs (1969) where the co-agglomeration of many diverse industries (industrial diversity) facilitates inter-industry spillovers, which in turn, enhance 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 (related variety). Recent studies positively link the role of technological relatedness on various economic indicators, including firm survival, firm innovation, and economic growth (Neffke et al., 2011, 2012).

In their study of local industry dynamics, Neffke et al. (2011) show that regional growth is spurred by a process of 'regional branching,' the idea that regions are path-dependent and tend to evolve into new diverse areas according to their existing capabilities. The authors' findings have helped to reinvigorate a long-standing debate over whether regions should specialize or diversify industrial activity. The policy implications of Neffke and others' work is that support should be directed towards the development of new industries that share a close technological proximity to local existing industry leaders, in order to take advantage of knowledge spillovers, as opposed to supporting leading industries that are already doing well.

*2.1. China's Economic Reforms*

The introduction of market reforms in China were 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 favorable 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 (Chang and Wu, 2014). 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.

While economic reforms have helped to restructure Chinese social, economic and political institutions, the process and implementation of reforms have been gradual and spatially uneven (He et al., 2008). As a result, 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, harms firm performance as excessive regulatory compliance occupies valuable firm resources. The direct effects of deepening economic reforms are therefore expected to operate more efficiently. Moving beyond the direct effects, the next section (see Hypothesis 3) argues that economic reforms also indirectly affect firm performance by influencing the ability of firms to benefit from agglomeration economies.

## 3. Hypotheses, Data and Variable Development

*Hypothesis (1): The role of technological relatedness is important for firm performance and may potentially play a stronger role than localization economies.*

Technological relatedness is expected to generate performance-enhancing spillovers (Frenken et al., 2007). We suspect that the role of technological relatedness may play a more important role for firm productivity than localization economies for two reasons. First, firms will try harder to protect their knowledge from direct competitors than if the firm is in another (related) industry. Second, firms within the same industry may share a large overlap in competencies, and therefore be unable to benefit from one another. Instead, spillovers that occur between related industries are expected to lead to the recombination of new ideas, leading to new products.

We do acknowledge, however, the possibility that firms may be unable to benefit from between (related) industry spillovers, due perhaps to an insufficient set of existing resources. In which case, technological relatedness may conversely lead to a negative effect or a smaller effect relative to localization economies on firm performance, due to increasing land costs, congestion costs and higher costs of living and doing business.

*Hypothesis (2): The size of the agglomeration effect will vary for lower and higher performing firms.*

A growing number of agglomeration studies show that the size of the agglomeration effect is conditioned by the characteristics of the firm. The literature identifies various such characteristics including the firm's size, age, internal knowledge capacity, and production capabilities (McCann and Folta, 2008, 2011; Rigby and Brown, 2015).

A nuanced debate exists, however, over which characteristics enable (or impede) the firm's ability to benefit from place-based economies. On the one hand, in line with the resource view of the firm, less endowed firms may be more likely to develop a survival strategy that depends on local economies. In support of this view, Rigby and Brown (2015) find that Canadian firms with a smaller pool of internal resources – i.e. smaller, older, domestic, and single-plant businesses – tend to benefit more from clustering relative to their respective counterparts.

On the other hand, more skilled firms may be better positioned to benefit from spillovers due to their higher stocks of existing knowledge. In support of this latter view, McCann and Folta (2011) show that biotech firms in the U.S. with a larger pool of internal resources – i.e. internal knowledge stocks – asymmetrically gain from agglomeration economies. In another study, *Hypothesis (3): Market-oriented reforms influence different firms' ability to benefit from agglomeration economies via changes in the local industrial mix.*

China's process of marketization is expected to indirectly influence 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 spillovers 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[1]. Second, if workers with the most specialized skill-sets and experience seek out employment with the SOEs for prestige and stability, then entrepreneurial firms' access to a quality labour pool

[1] There are two possible reasons why this obstruction may occur. First, the size of the local market for independent specialized suppliers will contract as large SOEs are more likely to source inputs from nonlocal suppliers, either via internal supply (vertical integration) or national contracts. Second, 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.

will be diminished. Lastly, a few dominant SOEs in the local economy may hinder the flow of tacit information by reducing social interactions, thereby preventing the creation of and access to knowledge spillovers in the region (Glaeser et al., 1992).

Our basic claim therefore is rather straightforward. Areas that have undergone greater market reforms are more conducive to generating agglomeration economies. Whether the net effect of market reforms enable or impede the ability of different firms to benefit from agglomeration economies, however, depends on whether the increasing supply of positive externalities outweighs the negative effects of increasing competition and higher rents associated with denser regions.

### *3.1. Data*

The empirical portion of this paper 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 five million Renminbi, approximately $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.

### *3.2. 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, estimates of the firm's total factory productivity (TFP) are obtained following the semi-parametric approach developed by Olley and Pakes (1996). All relevant variables to estimate TFP are deflated using a price index developed by Brandt et al. (2012). We relegate the discussion of the TFP estimation procedure to the Appendix.

**Measuring Specialization and Technological Relatedness:** To proxy for specialization, we use revealed comparative advantage (RCA), expressed as,

$$RCA_{jt}^{k} = \frac{Emp_{jt}^{k} / \sum_{j} Emp_{jt}^{k}}{\sum_{k} Emp_{jt}^{k} / \sum_{k}\sum_{j} Emp_{jt}^{k}} \tag{1}$$

where $Emp_{jt}^{k}$ is the employment in industry $j$ in region $k$ in year $t$. A value of greater than one indicates a local industry leader.

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

$$\phi_{ij} = min(Prob(RCA_{i}^{k}|RCA_{j}^{k}), Prob(RCA_{j}^{k}|RCA_{i}^{k})) \tag{2}$$

where the proximity $\phi$ between industry $i$ and industry $j$ is equal to the minimum between the pairwise probability that industry $i$ has a local RCA conditional on industry $j$ also having a local RCA. A higher $\phi_{ij}$ 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.

Unlike existing proxies that rely on traditional sector classifications to define industrial relatedness, $\phi$ is more comprehensive and captures the technological or cognitive similarity between any two subsectors irrespective of their official industry classification. Table 1 confirms that the 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.

**Please Place Table 1 Approximately Here**

Figure 1 maps China's product space based on the proximity indicator for the years 1999 to 2007. The nodes represent China's 424 industries at the 4-digit level and the edges show the strength of relatedness between industry pairs. Note the size of the nodes refers to the industry sales, which are standardized to compare over time. To better capture and visualize actual relatedness between industries, a threshold of 0.35 is applied to the network. We opt for a more conservative threshold than in Boschma et al. (2012), since the values of relatedness is comparatively lower in China, with only 1% of ties sharing a value of 0.35 or above.

**Please Place Figure 1 Approximately Here**

We find evidence of path-dependency behavior, particularly for the electronics and telecommunication subindustries (yellow nodes). We also find some evidence of 'regional branching' (Neffke et al., 2011), whereby some industries appear to grow quite rapidly when they share close technological proximity to leading industries. Some transportation equipment subindustries (light green nodes), for instance, that share close technological proximity with leading electronics and telecommunication subindustries witnessed rapid sales growth during the ten year time period. By 2007, a second grouping of related industries, agro-food, food and drink industries (red nodes), metals and minerals (light blue nodes) and chemicals (black nodes) also appear to have benefited in terms of higher sales growth from their co-agglomeration to one another.

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

$$w_{it}^{k} = \frac{\sum_j x_{jt}^{k} \phi_{ij}}{\sum_j \phi_{ij}} \tag{3}$$

where $w_{it}^{k}$ is the density around industry $i$ for region $k$ in year $t$, $x_{jt}^{k} = 1$ 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 $w_{it}^{k}$ indicates that sector $i$ is closer to the productive advantage of city $k$ in time $t$. Note that our regional unit of k is at the province level. The effects of agglomeration are known to critically depend on scale, however. As a robustness check we also calculate density, along with RCA, at the city level.

**Indicator for Marketization:** 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

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

includes 23 sub-indices divided into 5 major dimensions related to the marketization progress in each of the 31 provinces (see the Appendix for more information). 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.

## 4. Model Specification

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

$$y_{it}(\tau_k|X = x) = x'_{it}\beta(\tau_k) \tag{4}$$

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 $10^{th}$,$25^{th}$,$50^{th}$,$75^{th}$, and $90^{th}$ quantiles, $\tau_k$. Equation (4) is estimated by solving for the $\tau$th regression quantile,

$$\hat{\beta}(\tau) = \min_{\beta \in \mathbf{R^P}} \sum_{i=1}^{n} \rho_\tau(y_{it} - x'_{it}\beta) \tag{5}$$

for all quantiles $\tau \in (0,1)$. $\beta(\theta)$ solves the following minimization problem:

$$\min_{\beta} \left[ \left( \sum_{i=1}^{n} \rho_\theta y_{it} - X_{it} i \beta(\theta) ) \right) \right] \tag{6}$$

$$where \begin{cases} \rho_\theta(u) = \theta u & if u > 0 \\ \rho_\theta(u) = (\theta - 1) & if u < 0. \end{cases} \tag{7}$$

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. A penalty term is added to the minimization algorithm to account for the computational problem arising from estimating a large number of individual fixed effects for the $q$ quantiles. This technique is discussed and implemented in various contexts (Koenker, 2004).

Endogeneity issues may still produce biased estimates not accounted for by the fixed effects due, in part, to firm sorting. To alleviate these concerns, we include a lagged variable of the firm's TFP to take into account possible dynamics. We estimate the model using first differences and use the two-year lagged levels as instruments. This is analogous to the procedure by Anderson and Hsiao (1982) applied to conventional dynamic panel models. The technical discussion of the procedure is relegated to the Appendix.

## 5. Results: Agglomeration on Firm Productivity

We begin by first estimating the effect of agglomeration 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 agglomeration and China's market reforms. 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 of agglomeration 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 two-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 coefficients are all highly statistically significant and are similar across each model specification, therefore we focus our discussion on the results from the dynamic models. The results show that firm characteristics influence the firm's productivity. Older firms and smaller firms respectively have higher TFP levels, although both effects are found to be non-linear.

The positive coefficients on our regional variables reveal that both density and RCA stimulate firm productivity. In terms of economic impact, density exhibits a marginally larger positive impact on the firm's TFP relative to RCA, in support of our Hypothesis (1). In other words, co-agglomerating nearby to firms belonging to industries that share close technological relatedness benefit slightly more from greater performance-enhancing spillovers than those generated purely by localization economies.

**Please Place Table 2 Approximately Here**

We next attempt to investigate whether all firms equally benefit from agglomeration economies. We rely on dynamic quantile regression models using the same instrumentation procedure as above to test whether the size of the agglomeration effects is conditioned by the firm's own production capabilities. If there is a pure location shift effect as is implicitly assumed in the mean regression models, then the coefficients at each of the estimated quantiles will be the same as the mean effect.

Table 3 reports the results for the agglomeration variables, which are our central interest. All coefficients are highly statistically significant. The signs on the coefficients for both RCA and Density are negative for firms at the $10^{th}$ percentile, but become positive and monotonically increase moving along the TFP distribution. In support of our Hypothesis (2), the results show that the size of the agglomeration indeed hinges critically upon the internal production capabilities of the firm. These findings are consistent across both the province and city level units of aggregation.

**Please Place Table 3 Approximately Here**

### 5.1. *Results: Moderating Effects of Market Reforms on the Agglomeration-Firm Productivity Relationship*

Lastly, we exploit the quasi-experimental nature of China's reform process in an attempt to examine how changes in the local industrial mix brought about by economic reforms influences the ability of different firms to benefit from agglomeration economies. We first dichotomize each measure of agglomeration to indicate lower versus higher levels of agglomeration: firms with a density value greater than the median value across all local industries or with a RCA value greater than 1.0 are respectively assigned a value of 1, and 0 otherwise.

Next, we create interaction terms by respectively splitting the dichotomous agglomeration variables into mutually exclusive groups according to whether the firm is located within a region that has a larger versus smaller share of SOE employment. A larger [smaller] share of SOE employment is defined as a region that has more [less] than the median value of SOE employment across all regions for each year. These new set of variables enable us to examine the effects of agglomeration on firm productivity at the comparatively earlier- and later-stages of market reforms.

A summary of the findings is provided in Table 4 (For the complete set of results, please refer to the Appendix). To ease interpretation we explain how to read the results. 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 respective place-based economies. Based on a t-test, the statistical significance stars, in this case, indicate that the coefficient on the agglomeration proxy observed in the later stages of market reforms is statistically different from the one observed in the earlier stages.

**Please Place Table 4 Approximately Here**

In support of Hypothesis (3), the results indicate that deepening economic reforms does influence the ability of the firm to benefit from agglomeration economies, conditioned on both the internal production capabilities of the firm, and the dimension of agglomeration. The negative sign in the first row in column (1) shows that deepening market reforms, i.e. the change in the share of SOE employment from higher to lower, 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). The effects of RCA on the other hand have the opposite effects. Deepening economic reforms enable the bottom performing firms to benefit from localization economies, yet have a mitigating effect for the top performing firms.

One potential explanation for these results 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 knowledge spillovers within their own industry due to the greater overlap in their core competences. In contrast, the top performing firms are at the forefront of their fields, and therefore are unable to learn anything new from spillovers within their own industry. Instead, they exploit existing knowledge created outside of their industry by other related industries.

## 6. Summary of Findings and Concluding Remarks

The role of local economies has important implications for firm performance and by extension regional competitiveness and development. This paper investigates the effects of technological relatedness on firm productivity and whether such effects 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 main findings are as follows. First, the productivity of the 'average' firm in denser areas is higher due to local economies that arise as a result of sharing close technological proximity to the productive advantage of the region. Second, the density effect spurs productivity for better performing firms, but reduces it for the least performing firms. Third, deepening market reforms intensify the negative (positive) density effect for the least (better) performing firms.

The findings therefore indicate a delicate balance that exists between the costs and benefits of agglomeration that depends, in part, on the production capabilities of the firm. The least performing firms ultimately lack the necessary internal resources to sufficiently exploit the local supplier/buyer networks, attract labour from related industries since they cannot provide competitive wages, or capture knowledge spillovers between related industries. Such underperforming firms are simultaneously exposed to increasing negative externalities, such as unfair competition and increasing rents, that coincide with market-oriented reforms.

An economic rationale may therefore exist for local state interventions to protect under-performing firms in dense areas during transition. Protectionist-based policies would help ensure underperforming firms remain in the market long enough to hopefully build up their pool of internal resources to the point where they can take advantage of emerging place-based economies. We acknowledge, however, that China's economic reforms have not been randomly implemented, thereby raising the concern of possible site-selection bias. As a result, our findings are not necessarily indicative of the expected relationship between agglomeration and firm productivity in other regions, or countries for that fact, as they pursue deeper economic reforms.

Nevertheless, our findings are relevant for China's regional policy. Much of the existing literature on China target various dimension of the country's rampant inter-regional inequalities, i.e. coastal versus inland, rural versus urban, and agglomerated versus non-agglomerated. One of the subtle and unexpected findings from our research draws attention to another potential source of inequality – widening disparities in productivity gains between firms within agglomerated regions. Our research therefore suggests a need for additional work on China, and perhaps elsewhere, to examine the main factors influencing uneven productivity gains within agglomerations and to identify potential mitigating solutions.

Building on the evolutionary economic geography literature, our findings also help contribute to the ongoing debate regarding whether cities should become more specialized or diverse. Our findings support a strategy of regional branching – i.e using policy incentives to attract new firms that are related to the productivity advantage of the region – as opposed to supporting and attracting new firms that belong to local industry leaders that are already doing well. At the same time, our results also offer a cautionary tale for lower performing firms who may be disproportionately harmed by pursuing a regional policy emphasizing regional branching.

## Appendix A. Variable Summaries and Definitions

**Please Place Table A1 Approximately Here**

## Appendix B. TFP Estimation Procedure

TFP is the difference between the growth rate of output and the weighted average of the input factors' growth rate. It assumes the contribution from technological progress and is often estimated using the Cobb-Douglas production function with constant return to scales. This traditional approach suffers from endogeneity bias related to simultaneity and selection. Olley and Pakes (1996) develop a three-step approach to correct for the endogeneity issues. In order to obtain TFP estimates, the firm's value added, capital stock and investment must first be developed. The process is briefly described next.

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 per cent 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. Firm $i$ chooses whether it will continue production at the beginning of the period. If the firm decides to continue, it will select a combination of variable inputs (i.e. labour, raw materials and energy) and investments to generate a certain profit with the initial TFP shock $(\Omega_{it})$ and capital stock $(k_{it})$. To begin, consider a simple Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + u_{it} \tag{B.1}$$

where $y_{it}$ is logged value added for firm $i$ in period $t$. The coefficients $l_{it}, k_{it}$ and $a_{it}$ represent the log of labour, capital and age of firm $i$ in year $t$. $u_{it} = \Omega_{it} + \eta_{it}$, where $\Omega_{it}$ is the productivity shock observed by the firm's decision makers and $\eta_{it}$ is the unobserved errors.

In the second step, the investment equation is inverted non-parametrically to proxy for unobserved productivity that controls for the non-random sample selection that results from differing exit probabilities of small and large lowproductivity firms. In many cases this step is problematic due to a high number of zero investments, but in the high growth Chinese context only 1 per cent of firms suffer from negative real investment. To control for the simultaneity issue, we rewrite $\Omega_{it}$ as,

$$\Omega_{it} = I^{-1}(I_{it}, K_{it}, a_{it} + \beta_0 + \beta_l l_{it}) + \eta_{it} \tag{B.2}$$

where $\Omega_{it}$ is a strictly monotone function of $I_{it}$. We re-write our productivity equation as

$$y_{it} = \beta_l l_{it} + \phi(i_{it}, k_{it}, a_{it}) + \eta_{it}, \tag{B.3}$$

where $\phi(i_{it}, k_{it}, a_{it}) = \beta_0 = \beta_k k_{it} + \beta_a a_{it} + h(i_{it}, k_{it}, a_{it})$. We estimate $\phi(\bullet)$ as a function of firm age, log of capital and log of investment. Because $\phi(\bullet)$ controls for unobserved productivity shocks and errors not correlate with variable inputs we can use OLS to recover the parameters on variables inputs that will be consistent.

We can control for the selection bias issue by separating the impacts of capital and age on output and carrying out the second step estimation to generate the survival probability of firm $i$. In the exit equation, if the productivity of firm $i$ is greater than the threshold productivity determined by $K_{it}$ and $a_{it}$, then it will remain in the market. We use the probit model to estimate the survival probability by regressing $\chi_{it}$ on $I_{i,t-1}, K_{i,t-1}, a_{i,t-1}$ and their respective squares and integrations. The survival probability of firm $i$ further depends on $\Omega_{it}$ and $\underline{\Omega}_{it}$, which is in turn, determined by age, capital and investment in the period $t-1$.

In the third step, we estimate the following non-linear equations using the OLS method

$$y - \beta_l l_{it} = \beta_k k_{it} + \beta_a a_{it} + g(\widehat{\phi}_{t-1} - \beta_k k_{it-1} - \beta_a a_{it-1}) + \eta_{it}, \tag{B.4}$$

where g is a function of $\hat{\phi}_{t-1} - \beta_k k_{it-1} - \beta_a a_{it-1}$. Using the estimates for $\beta_l$ and $\beta_k$, using the OP method we generate TFP as follows,

$$TFP_{it}^{op} = lnVA_{it} - \beta_l l_{it} - \beta_a a_{it} \tag{B.5}$$

As indicated by the subscripts, the production function is estimated separately for each industry to control for differences in production technology. Note that the TFP estimates obtained with by the Olley and Pakes (1996) method produce highly correlated estimates when compared to other approaches, thereby offering some confidence that the findings are not dependent on the TFP estimation approach.

## Appendix C. NERI Marketization Index

The total composite index is the equal weight of the following 23 sub-indices:

1. The relation between the government and the market
   a. The degree to which resources are allocated by the market
   b. The reduction in tax and fee burdens on farmers
   c. The reduction in interventions on enterprises by government
   d. The reduction in fee burdens on enterprises beyond tax
   e. The reduction in government size
2. The development of the non-state sector
   a. The proportion of non-state sectors in GDP
   b. The proportion of non-state sectors in total fixed investments
   c. The proportion of non-state sectors in urban employment
3. The development of the product market
   a. The reduction in price control
      i. The reduction in price control on retail goods
      ii. The reduction in price control on production goods
      iii. The reduction in price control on agricultural goods
   b. The reduction in regional protection
4. The development of the factor market
   a. The development of the financial market
      i. Financial market competition
      ii. The degree to which bank loans and credits are allocated by the market
   b. The degree of foreign direct investment
   c. Labor mobility
   d. The development of the market for technologies
5. The development of market intermediaries and the legal environment
   a. The development of intermediary institutions
      i. The ratio of lawyers in local population
      ii. The ratio of accountants in local population
   b. Legal protection of enterprise rights
   c. Legal protection of intellectual property rights
      i. The ratio of patent applications to the number of science and technology personnel
      ii. The ratio of patent approvals to the number of science and technology personnel
   d. Legal protection of consumer rights

## Appendix D. Dynamic Quantile Regression Procedure

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

$$y_{it}(\tau|x_{it}) = \alpha_i + x'_{it}\beta(\tau) \qquad i = 1, ..., N, \quad t = 1, ..., T. \tag{D.1}$$

where the $\alpha$'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, $\tau$, of interest, but the $\alpha$'s do not.

To estimate equation (5) for several quantiles simultaneously, we perform the following estimation procedure,

$$\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T} \xi_k \rho_{\tau_k}(y_{it} - \alpha_i - x'_{it}\beta(\tau_k)) \tag{D.2}$$

The piecemeal linear quantile loss function developed by Koenker et al. (1978) is denoted as $\rho_\tau(u) = u(\tau - I(u < 0))$. The weights, $\xi_k$, set to equal in our case, control for the relative influence of the $q$ quantiles on the estimation of $\alpha_i$'s parameters.

We assume the $\alpha$'s are constant across quantiles, which works to reduce the number of parameters to be estimated, and permits each chosen quantile, $\rho_k$ to be estimated simultaneously. In the fixed-effect quantile regression a penalty term is added to the minimization algorithm to account for the computational problem arising from estimating a large number of individual fixed effects for the $q$ quantiles. The penalty term involves shrinking the $\alpha$'s to a common value, which is useful when $n$ is large relative to the $m_i$'s, such as our case. This parameter penalization approach is beneficial because it significantly reduces the variability – introduced by the large number of $\alpha$ parameters that require estimating – of the estimate of the slope of $\beta$, all without sacrificing bias.

There are several penalty terms that can be selected. As found in the literature, we opt for $\ell_1$ to serve as our penalty term since $P(\alpha) = \sum_i = 1^n|\alpha_i|$ offers advantages over other penalty terms. The revised minimization algorithm that includes the $\ell_1$ penalty term is expressed as follows:

$$\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T} \xi_k \rho_{\tau_k}(y_{it} - \alpha_i - x'_i\beta) + \lambda \sum_{i=1}^{n} |\alpha_i| \tag{D.3}$$

where the last term represents the $\ell_1$ penalty term, and $\lambda$ describes the importance of the penalty term in the minimization formula.

Dynamic quantile regression (DQR) rely on estimating a structural quantile function with the following relationship:

$$y_{it} = d'_{it}\delta + x'_{it}\beta + \alpha_i + u_{it}, \qquad i = 1, ...N; \quad t = 1, ...T, \tag{D.4}$$

$$where\ u|x, d \sim Uniform(0, 1); \tag{D.5}$$

$$d_{it} = h(x_{it}, \omega_{it}, v_{it}), \qquad \textit{where } v \textit{ is stochastically dependent on } u \tag{D.6}$$

$$\alpha_i = g(x_{i1}, ..., x_{iT}, d_{i1}, ..., d_{iT}, \epsilon_i). \tag{D.7}$$

$$\tau \mapsto D'\alpha(\tau) + X'\beta(\tau) + \alpha(\tau) \tag{D.8}$$

where $y$, $X$ and $\alpha$ have the same interpretation as before. $d$ is the endogenous regressor, and $u$ is a scalar random variable that aggregates all unobserved factors affecting the structural outcome equation. In equation (10), $d$ is related to a vector of instruments $w$, which are assumed to be stochastically independent of $u$. $v$ is a vector of unobserved disturbances determining $D$ and correlated with $U$. Equation (11) corresponds to the typical case of the correlation between the individual effects and the covariates and in equation (12) $\tau$ is strictly increasing.

Following Chernozhukov and Hansen (2008), we proceed with the following two-step estimation procedure expressed as:

$$\{\hat{\beta}(\tau,\delta), \hat{\gamma}(\tau,\delta), \hat{\alpha}(\tau,\delta)\} = arg \min_{\beta,\gamma,\alpha} R(\tau,\delta,\beta,\lambda,\alpha) \tag{D.9}$$

$$\hat{\delta}(\tau) = arg \min_{\delta} \hat{\gamma}(\tau,\delta) A \hat{\gamma}(\tau,\delta) \tag{D.10}$$

for a given positive definite matrix **A**. We minimize $\beta$, $\gamma$, and $\alpha$ from equation (15) in the first step and then estimate the coefficient on the endogenous variable in the second step finding the value of $\delta$ that minimizes a weighted distance function defined on $\gamma$.

By estimating $\delta$ at different quantiles of the conditional distribution, we can investigate how the treatment $d$ impacts the location, scale and shape of the distribution. The objective function for the conditional DQR relationship can be written as follows:

$$\min_{\alpha,\beta,\delta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T} \xi_k \rho_{\tau_k}(y_{it} - d'_{it}\delta - x'_{it}\beta - \alpha_i - \hat{w}'_{it}\gamma) + \lambda \sum_{i=1}^{n} |\alpha_i| \tag{D.11}$$

where $\rho_{\tau_k} = u(\tau - I(u <= 0))$ is the quantile regression loss function. $\hat{w}$ is the least squares projection of the endogenous variable $d$ on the instrument $w$, the exogenous variables $x$, and the vector of individual effects $z$. As in the FEQR model, the last term represents the $\ell_1$ penalty term, and $\lambda$ describes the importance of the penalty term in the minimization formula.

## Appendix E. Quantile Regression Results

**Please Place Table A2 Approximately Here**

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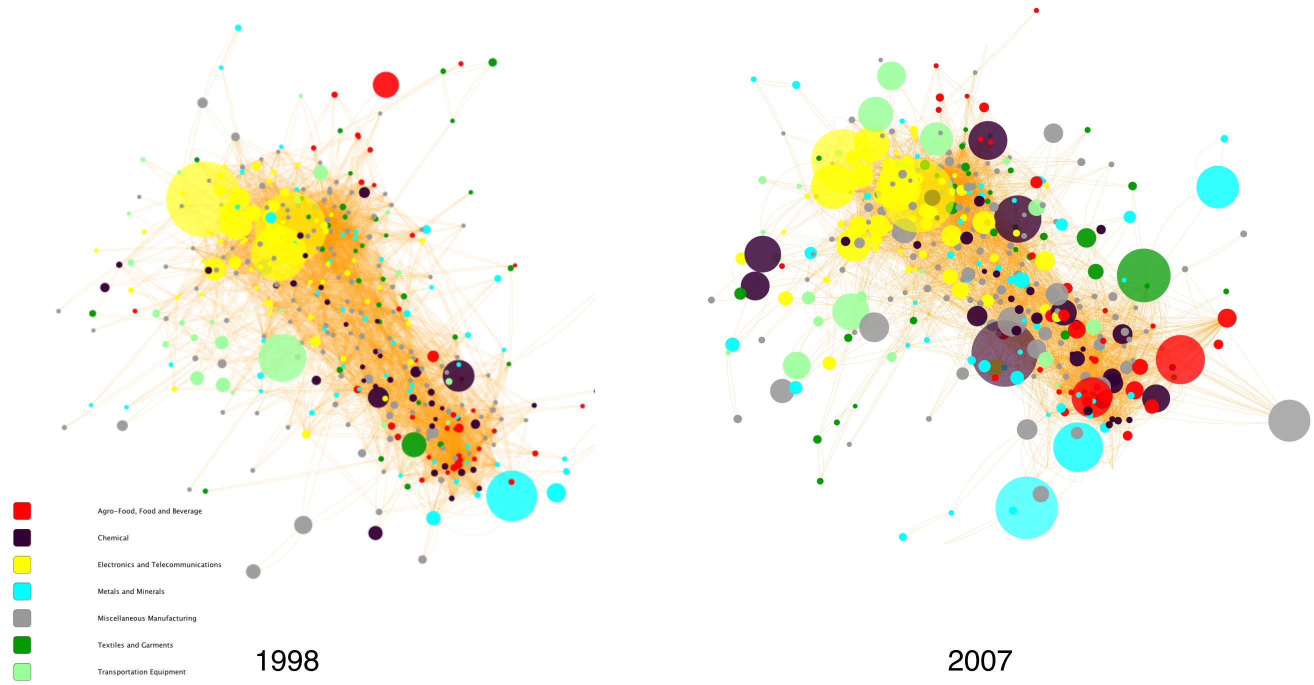


**Figure 1:** *China's Product Space, 1998 and 2007*

**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 2-Digit Industry | 0.194 | 0.194 | 0.054 | 0.091 | 0.321 |
| Among Different 2-Digit Industry | 0.131 | 0.131 | 0.038 | 0.045 | 0.243 |
| Within the Same 3-Digit Industry | 0.198 | 0.200 | 0.097 | 0.000 | 0.449 |
| Among Different 3-Digit Industry | 0.141 | 0.135 | 0.061 | 0.005 | 0.545 |

**Table 2:** *Results: Estimating the Impacts of Agglomeration on Firm Productivity*

| *Regional Unit* | | *Province* | | *City* | |
|---|---|---|---|---|---|
| | *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) | | |
| Share of SOE Emp. | | 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) |
| Share of SOE Emp. | | | | 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. | 404796 | 404796 | 69339 | 404796 | 69339 |
| Anderson Canon. Corr. LM statistic P-Value (Underidentification Test) | | | 0.000 | | 0.000 |
| Cragg-Donald Wald F-statistic (Weak identification test) | | | 478 | | 606 |

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The dynamic estimations in Columns (3) and (5), the Anderson-Hsiao specifications are valid as indicated by the Anderson canon. corr. LM statistic for underidentification and the Cragg-Donald Wald F statistic test for weak identification test.

**Table 3:** *Dynamic Quantile Regression Results: Distributional Impacts of Agglomeration on Firm Productivity*

| | *Quantile* | | | | | |
|---|---|---|---|---|---|---|
| **Province Level** | 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) |

Notes: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Models are estimated using dynamic quantile regression models in first differences 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.

**Table 4:** *Summary of the geographical welfare changes within agglomerations during Economic Transition*

| | Bottom 10% Firms | | Top 10% Firms | | Average (Mean) Firm | |
|---|---|---|---|---|---|---|
| *Proxy for Economic Transition* | *Province* | *City* | *Province* | *City* | *Province* | *City* |
| *($\Delta$SOE Share of Emp.)* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
| Density | $-^{***}$ | $-^{***}$ | $+^{***}$ | $+^{***}$ | $+^{***}$ | $+^{***}$ |
| RCA | $+^{***}$ | $+^{***}$ | $-^{***}$ | $-^{***}$ | $+^{***}$ | $+^{***}$ |

Notes: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The summary of findings are based on dynamic quantile regressions estimated in first differences. Complete model results are reported in the Appendix. The signs (+/-) correspond to the direction of the moderating effect of deepening economic reforms on the ability of the firm to benefit from agglomeration economies. A positive sign indicates that the shift from earlier to later stages of economic reforms intensifies the moderating effect, whereas a negative sign indicates a mitigating effect. Statistical significance stars are based on t-tests used to test for whether the change in the size of the agglomeration effect in later stages of market reforms is statistically different from the size of the effect at comparatively earlier stages of market reforms.

**Table A1:** *Variable Definitions and Summary Statistics*

| | Definition | Mean | St. Dev. |
|---|---|---|---|
| Firm Productivity | Total factor productivity (TFP) of firm *i* in year *t*, constructed using the Olley and Pakes (1996) method. See Appendix 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] Share of SOE Emp. | 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 sub-index (2c) constructed by the National Economic Research Institute (NERI) in each year for each of the 31 provinces. | 0.345 [0.384] | 0.382 [0.322] |
| **Interactions Terms** | | | |
| Higher Density *x* higher [lower] Share of SOE Emp. | Variable equals 1 if Density is above the median values across all local industries for each city and Share of SOE Emp. is above [below] the median value across all regions, and 0 otherwise | 0.114 [0.023] | 0.261 [0.052] |
| Higher RCA *x* higher [lower] Share of SOE Emp. | Variable equals 1 RCA is above one and where the proportion of state-owned enterprises' market share is above [below] the median value across all cities, and 0 otherwise | 0.011 [0.004] | 0.062 [0.043] |

**Table A2:** *Dynamic Quantile Regression Results: Estimating the Agglomeration-Firm Productivity Relationship During Economic Transition*

| | *Quantile* | | | | | |
|---|---|---|---|---|---|---|
| | 0.1 | 0.25 | 0.5 | 0.75 | 0.90 | Mean |
| **Panel A: Province Level** | | | | | | |
| Higher Density | | | | | | |
| x Larger Share of SOE Emp | $0.070^{***}$ | $0.042^{***}$ | $0.028^{***}$ | $0.016^{***}$ | $0.012^{***}$ | $0.031^{***}$ |
| | (0.014) | (0.010) | (0.007) | (0.005) | (0.003) | (0.008) |
| x Smaller Share of SOE Emp | $-0.151^{***}$ | $-0.091^{***}$ | $0.077^{***}$ | $0.081^{***}$ | $0.096^{***}$ | $0.070^{***}$ |
| | (0.008) | (0.006) | (0.006) | (0.006) | (0.009) | (0.005) |
| *Difference* (ΔSOE Share of Emp) | $-^{***}$ | $-^{***}$ | $+^{***}$ | $+^{***}$ | $+^{***}$ | $+^{***}$ |
| Higher RCA | | | | | | |
| x Larger Share of SOE Emp | $0.133^{***}$ | $0.127^{***}$ | $0.120^{***}$ | $0.083^{***}$ | $0.031^{***}$ | $0.101^{***}$ |
| | (0.009) | (0.007) | (0.006) | (0.007) | (0.009) | (0.005) |
| x Smaller Share of SOE Emp | $0.160^{***}$ | $0.134^{***}$ | $0.115^{***}$ | $0.022^{***}$ | $-0.037^{***}$ | $0.112^{***}$ |
| | (0.007) | (0.005) | (0.005) | (0.005) | (0.007) | (0.004) |
| *Difference* (ΔSOE Share of Emp) | $+^{***}$ | $+^{***}$ | $-^{***}$ | $-^{***}$ | $-^{***}$ | $+^{***}$ |
| **Panel B: City Level** | | | | | | |
| Higher Density | | | | | | |
| x Larger Share of SOE Emp | $0.107^{***}$ | $0.082^{***}$ | $0.060^{***}$ | $0.050^{***}$ | $0.023^{*}$ | $0.061^{***}$ |
| | (0.013) | (0.009) | (0.008) | (0.009) | (0.012) | (0.007) |
| x Smaller Share of SOE Emp | $-0.163^{***}$ | $0.045^{***}$ | $0.114^{***}$ | $0.148^{***}$ | $0.178^{***}$ | $0.111^{***}$ |
| | (0.018) | (0.011) | (0.010) | (0.012) | (0.016) | (0.009) |
| *Difference* (ΔSOE Share of Emp) | $-^{***}$ | $-^{***}$ | $+^{***}$ | $+^{***}$ | $+^{***}$ | $+^{***}$ |
| Higher RCA | | | | | | |
| x Larger Share of SOE Emp | $0.068^{***}$ | $0.055^{***}$ | $0.044^{***}$ | $0.032^{***}$ | $0.018^{**}$ | $0.043^{***}$ |
| | (0.012) | (0.008) | (0.007) | (0.008) | (0.010) | (0.006) |
| x Smaller Share of SOE Emp | $0.282^{***}$ | $0.132^{**}$ | $0.116^{***}$ | $-0.072^{***}$ | $-0.119^{***}$ | $0.101^{***}$ |
| | (0.018) | (0.012) | (0.009) | (0.012) | (0.016) | (0.009) |
| *Difference* (ΔSOE Share of Emp) | $+^{***}$ | $+^{***}$ | $+^{***}$ | $-^{***}$ | $-^{***}$ | $+^{***}$ |

Notes: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Models are estimated using dynamic quantile regression models in first differences 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. Note that a larger share of SOE employment is the proxy for regions in the earlier stages of market reform, whereas a smaller share of SOE employment is the proxy for regions in the comparatively later stages of market reforms.