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Abstract

Agglomeration brings costs (e.g., intensified local competition) as well as benefits (e.g., knowledge spillover). It is important to examine the net impact of agglomeration to understand the geographic distribution of economic activities. In this study, we use firm markup (defined as the ratio of price over marginal cost) to capture the net impact of agglomeration. Using data from Chinese manufacturing firms in the 1998-2005 period, we first recover the markup ratio for each firm following De Locker and Warzynski (2012), and then use changes in industrial affiliation as a quasi-experiment to identify the impact of agglomeration on firm markup. Our difference-in-differences (DID) estimation shows that agglomeration has a negative impact on firm markup, suggesting that the devastating competition effect dominates the beneficial spillover effect in Chinese context. Moreover, we find that the impact of agglomeration on firm markup varies across different industries and types of firms.

Keywords: Agglomeration; Firm Markup; Difference-in-Differences Estimation; Spillover effect; Competition effect
JEL Codes: R11; L25; D22

1 Introduction

The geographic concentration of economic activities has been widely documented across countries and industries, for example, the manufacturing belt in the United States, the blue banana belt in the European Union, and the Pacific coast industrial belt in Japan.[1] Although agglomeration brings about substantial positive spillover,[2] it also leads to greater competition[3] and, consequently, lower prices (e.g., Ottaviano, Tabuchi, and Thisse, 2002; Melitz and Ottaviano, 2008).[4] An important yet overlooked question concerns the net effect of agglomeration on firm performance.

In this study, we use firm markup (defined as the ratio of price over marginal cost) to investigate these two offsetting effects of agglomeration (namely, the beneficial spillover effect and the devastating competition effect). The spillover effect, on the one hand, is found to increase firm productivity,[5] which results in lower marginal production costs and higher firm markup. On the other hand, the competition effect leads to lower market prices and lower firm markup. Thus, firm markup allows us to capture the net effect of agglomeration on firm performance. Furthermore, by looking at various scenarios in which the spillover effect and the competition effect may have different relative importance, we can further disentangle these two competing effects of agglomeration on firm performance.

There are, however, two empirical challenges to this research goal: how to calculate firm markup; and how to identify the causal effect of agglomeration on firm markup. Firm-level data rarely contain information on product prices, let alone information on marginal costs. Additionally, more agglomerated industries may differ from less agglomerated industries in many other dimensions, compounding the effect of agglomeration. Our study is the first

[1]See Holmes and Stevens (2004) for a detailed description of the spatial distribution of economic activities in the United States and Canada; Combes and Overman (2004) for the case of the European Union; and Fujita, Mori, Henderson, and Kanemoto (2004) for the case of Japan and China.

[2]The spillover may come from, for example, labor pooling, input sharing or knowledge spillover. For a literature review, see Rosenthal and Strange (2004).

[3]Comparably speaking, much less attention has been paid to the costs associated with agglomeration. The available studies have highlighted higher wages, higher rents and more congestion as costs of agglomeration. These costs are mostly indirect, compared with the impact of agglomeration on market prices.

[4]Recently, there are two studies showing that market competition may increase prices under some conditions, i.e., Chen and Riordan (2008); Zhelobodko, Kokovin, Parenti, and Thisse (2011).

[5]For a review, see Melo, Graham, and Noland (2009). We also find evidence for the positive impact of agglomeration on firm productivity in the case of China's manufacturing industries in the 1998-2005 period (see Table A1 for details).

to use firm markup to capture the net effect of agglomeration. We also contribute to the literature by carefully addressing the two empirical issues mentioned above.

Specifically, following the recent work by De Loecker and Warzynski (2012), we first recover the markup ratio for each firm using standard firm-level financial information such as output, capital, labor and materials. Next, as a quasi-experiment to identify the causal effect of agglomeration on firm markup, we explore a scenario in which some firms change their industrial affiliations. Our identification strategy relies on the comparison of the markup values of firms that changed their industrial affiliations (the treatment group) with the markup values of firms that did not change their industrial affiliations (the control group) before and after the year of change, i.e., the difference-in-differences (DID) estimation.

The data for our study come from annual surveys of manufacturing firms conducted by the National Bureau of Statistics of China for the 1998-2005 period. Our DID estimation finds that agglomeration has a negative and statistically significant effect on firm markup, implying that overall in China the direct costs of agglomeration caused by enhanced competition outweigh the benefits of agglomeration. To ensure the validity of our DID estimation, we conduct the following series of robustness checks on the identification assumption of the DID estimation and other estimation concerns:

- Check whether the treatment and control groups have differential time trends in the pre-treatment period

- Allow firms in the treatment and control groups to follow different time trends

- Include more firm-level controls to check whether the treatment and control groups are balanced

- Use an outcome variable that is not supposed to be affected by the change in industrial affiliation as a placebo test

- Measure Ellison-Glaeser's industrial agglomeration index at three different geographic scopes (i.e., province, city, or county), as a check on the sensitivity of the index to geographic scopes (the so-called modifiable area unit problem, see Arbia, 2001)

- Exclude firms with extreme markup ratios, to address the concern that our results could be driven by a few outlying observations

- Examine the one-shot effect of the change in industrial affiliation to rule out the concern that our DID estimator may capture the effect of other events happening later in the post-treatment period
- Define the change of industrial affiliation at the two-digit industry level to address the concerns about the misreporting of industrial affiliation
- Control for the omitted price bias in the estimation of the production function by following Klette and Griliches (1996)'s method
- Incorporate the role of agglomeration into the estimation of the production function

In the second part of the empirical analysis, we investigate the differential effects of agglomeration on firm markup across different industries and types of firms, which allows us to disentangle the two offsetting effects of agglomeration.

First, despite three decades of economic reform in China, the state still plays an important and dominant role in the economy. State-owned enterprises, protected by the central and local governments, enjoy various favorable policies and are shielded from local competition. As a result, agglomeration is expected to have a less damaging impact on markup for state-owned enterprises than on markup for non-state-owned enterprises. Indeed, we find that the impact of agglomeration on markup is statistically insignificant for state-owned enterprises, whereas it is negative and significant for non-state-owned enterprises.

Second, given the established production technologies and stagnant market demand in mature industries, as compared to fast-growing industries, the devastating competition effect vis-à-vis the beneficial spillover effect is expected to be more prominent and, consequently, the negative net impact of agglomeration more pronounced in the former industries than in the latter. Following the classification method of Henderson et al. (1995), we divide industries into mature industries and fast-growing industries. As expected, the impact of agglomeration on markup is negative and significant for mature industries, but is insignificant for fast-growing industries.

Third, for industries producing goods for nationally integrated markets, the negative competition effect of agglomeration is muted, although the positive spillover effect remains intact, implying a less negative or even a positive impact of agglomeration on firm markup. Following the definition of Rauch (1999), we divide industries into those with goods traded at exchanges, those with reference-prices, and other industries. It is found that the impact of agglomeration on markup is positive and significant for industries with goods traded at exchanges, but remains negative and significant for the other two types of industries.

Our study is related to an emerging literature on firm markup. Studies along this line include those on markup estimation methodologies (Roeger, 1995; Klette, 1999; De Loecker and Warzynski, 2012), and various factors affecting markup ratios such as anti-trust policy (Warzynski, 2001), trade policy (Konings and Vandenbussche, 2005), privatization and competition (Konings, Cayseele, and Warzynski, 2005), and exporting behavior (De Loecker and Warzynski, 2012).

The remainder of this paper is organized as follows. Section 2 discusses the estimation method of firm markup, and our strategy for identifying the effect of agglomeration. Section 3 describes the data and variables. Empirical results regarding the effect of agglomeration on firm markup are reported in Section 4. The paper concludes with Section 5.

2 A Brief Discussion of Theories of Agglomeration and Firm Markup

Current theories of trade and urban economics offer very limited analysis of how agglomeration affects firm markup. Previous researchers have examined the effect of agglomeration on product prices, but they generally assume that firm productivity (and hence marginal production costs) is constant. As a result, the effect of agglomeration on firm markup mostly comes from the price channel. In this section, we briefly discuss two leading models of this literature, and investigate how agglomeration affects firm markup when firm productivity is positively affected by agglomeration.

Krugman (1979, 1980) uses the monopolistic competition model developed by Dixit and Stiglitz (1977) to examine the pattern of agglomeration. This has been the most influential model in the trade and urban literature. This model was later modified by Melitz (2003) to incorporate firm heterogeneity, that is, firms with different productivity levels. The core element of Krugman's model is that the preference of the representative consumer is characterized by the CES utility function, and market competition is modeled as monopolistic competition. As a result, each firm produces a unique variety and charges a constant markup, a natural consequence of which is that agglomeration does not have any effect on each individual firm's markup. Though neither Krugman (1979) nor Melitz (2003) considers the possibility that agglomeration increases firm productivity, incorporating this fact does not change the result; agglomeration still does not affect firm markup.

Specifically, agglomeration lowers both firm productivity and price, but these two effects cancel each other out so that on balance firm markup does not change.

Ottaviano, Tabuchi and Thisse's (2002) alternative model addresses the unsatisfactory feature of constant markup. In their model, the preference of the representative consumer is modeled as a quasi-linear utility with a quadratic subutility. Given the assumption of constant firm productivity, the model generates the result that agglomeration lowers firm price and further lowers firm markup. Melitz and Ottaviano (2008) revise the model of Ottaviano, Tabuchi and Thisse (2002) by allowing firms to have different productivity levels. However, as productivity is assumed to be exogenous to agglomeration, Melitz and Ottaviano (2008) also find that firm markup is unambiguously lower in more agglomerated regions. Recently, Zhao (2011) builds upon Melitz and Ottaviano's (2008) framework by assuming firm productivity to be a monotonic and positive function of agglomeration. Hence, it is not clear whether agglomeration has a positive or negative effect on firm markup, as agglomeration increases firm productivity (and then lowers marginal cost) but also lowers firm price. The numerical results in Zhao (2011) suggest agglomeration is more likely to have a negative effect on firm markup.

3 Estimation Methodologies

In this section, we discuss the method for estimating firm markup, and the estimation strategy for identifying the effect of agglomeration on firm markup.

3.1 Estimation of Firm Markup

To recover firm-level markup, we follow the recent work of De Loecker and Warzynski (2012). Specifically, we assume that firm i at time t has the following production technology[6]

$$Q_{it} = F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right), \tag{1}$$

where L_{it}, K_{it}, and M_{it} are the inputs of labor, capital, and intermediate materials, respectively; ω_{it} denotes firm-specific productivity. The production function $F(.)$ is assumed to be continuous and twice-differentiable with respect to all of its arguments.

[6]Note that the framework is robust to any arbitrary number of inputs. As we only observe three inputs (i.e., labor, capital, and intermediate materials) in our data, here we focus on a production technology involving only these three inputs.

Consider the following cost minimization problem faced by firm i at time t[7]

$$\min_{\{L_{it},K_{it},M_{it}\}} w_{it}L_{it} + r_{it}K_{it} + p_{it}^{m}M_{it} \tag{2}$$
$$s.t.\ F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right) \geq Q_{it},$$

where w_{it}, r_{it}, and p_{it}^{m} denote the wage rate, rental price of capital, and the price of intermediate inputs, respectively; and Q_{it} is a given number of output.

The estimation of firm-level markup hinges upon the choice of an input that is free of any adjustment costs, and the estimation of its output elasticity. As labor is largely not freely chosen in China (particularly for state-owned enterprises) and capital is often considered a dynamic input (as a result of which its output elasticity is difficult to interpret), we choose intermediate materials as the input to estimate firm markup (see also De Loecker and Warzynski, 2012). Specifically, the Lagrangian function associated with the optimization problem (2) can be written as

$$\begin{aligned} \mathcal{L}\left(L_{it}, K_{it}, M_{it}, \lambda_{it}, \eta_{it}\right) &= w_{it}L_{it} + r_{it}K_{it} + p_{it}^{m}M_{it} \\ &\quad + \lambda_{it}\left[Q_{it} - F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right)\right]. \end{aligned} \tag{3}$$

Hence, the first-order-condition for intermediate materials is

$$\frac{\partial \mathcal{L}}{\partial M_{it}} = p_{it}^{m} - \lambda_{it}\frac{\partial F_{it}}{\partial M_{it}} = 0. \tag{4}$$

Re-arranging equation (4) and multiplying both sides by $\frac{M_{it}}{Q_{it}}$ yield

$$\begin{aligned} \frac{\partial F_{it}}{\partial M_{it}}\frac{M_{it}}{Q_{it}} &= \frac{1}{\lambda_{it}}\frac{p_{it}^{m}M_{it}}{Q_{it}} \\ &= \frac{P_{it}}{\lambda_{it}}\frac{p_{it}^{m}M_{it}}{P_{it}Q_{it}}, \end{aligned} \tag{5}$$

where P_{it} is the price of the final good.

Note that $\lambda_{it} = \frac{\partial \mathcal{L}}{\partial Q_{it}} = mc_{it}$ represents the marginal cost of production at a given level of output, and define firm markup μ_{it} as the ratio of price over marginal cost, i.e., $\mu_{it} \equiv \frac{P_{it}}{mc_{it}} = \frac{P_{it}}{\lambda_{it}}$. Hence, equation (5) leads to the following estimation expression of firm markup

$$\mu_{it} = \theta_{it}^{m}\left(\alpha_{it}^{m}\right)^{-1}, \tag{6}$$

[7] De Locker and Frederic (2012) discuss some alternative settings of market competition, which lead to a similar estimation expression for firm markup. These alternative settings include Cournot competition, Bertrand competition, and monopolistic competition.

where $\theta_{it}^{m} \equiv \frac{\partial F_{it}}{\partial M_{it}}\frac{M_{it}}{Q_{it}}$ is the output elasticity of intermediate materials and $\alpha_{it}^{m} \equiv \frac{p_{it}^{m}M_{it}}{P_{it}Q_{it}}$ is the share of the expenditure of intermediate materials in total revenue.

As the information about the expenditure on intermediate materials and total revenue is available in the data, α_{it}^{m} can be readily calculated. However, the output elasticity of intermediate materials, θ_{it}^{m}, needs to be obtained through the estimation of the production function (1). There is a large literature on the estimation of the production function focusing on how to control for unobserved productivity shocks (see Ackerberg, Benkard, Berry, and Pakes, 2007, for a review). The solutions range from the instrumental variable estimation, to the GMM estimation, and to the control function approach proposed by Olley and Pakes (1996). We adopt the control function approach developed by Ackerberg, Caves, and Frazier (2006), which comprises a two-steps estimation.[8]

The production function to be estimated is expressed as

$$q_{it} = \theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it} + \omega_{it} + \varepsilon_{it}, \tag{7}$$

where the lower case letters represent the logarithm of the upper case letters; $\boldsymbol{\theta}= (\theta_l, \theta_k, \theta_m)$ is the vector of the production function coefficients, or the output elasticities; ω_{it} is the total factor productivity (TFP); and ε_{it} is an i.i.d. error term. In Appendix A, we lay out the details of the procedure for estimating the production function.

We estimate the translog production function (7) separately for each two-digit industry. After we recover the coefficient of the intermediate materials in the production function $\hat{\theta}_m$, firm markup can be calculated based on equation (6), i.e.,

$$\hat{\mu}_{it} = \hat{\theta}_m \left(\hat{\alpha}_{it}^{m}\right)^{-1}, \tag{8}$$

where $\hat{\alpha}_{it}^{m} = p_{it}^{m}M_{it}/\left(P_{it}Q_{it}/exp\left(\hat{\varepsilon}_{it}\right)\right)$.

Several caveats are worth noting. First, the above framework implicitly assumes a single-product firm. In reality, however, firms may produce a range of products. In the absence of detailed information on the amounts of inputs used for each product, the markup calculated in equation (8) should be interpreted as the average markup across all products for a firm. The existence of multi-product firms should not, in any case, affect our identification strategy for the effect of agglomeration on markup because our identification utilizes the variations in markup over time for the same firm.

[8]Our results obtained using the Olley and Pakes (2006)'s method are qualitatively the same.

Second, the estimation of the production function requires an observation of the quantity of firm-level output. Unfortunately, such information is not available in most of the firm-level data sets, including ours. As a compromise, the quantity-based output is recovered by deflating the observed revenue with the industry-level price index, which is subject to the omitted price bias as pointed out by Klette and Griliches (1996). However, this may not be a concern in the context of our study. The omitted price bias affects the level of the estimated markup, whereas our identification relies on the differences in the estimated markup across time and across firms (see De Loecker and Warzynski, 2012, for more discussion on this point). Nonetheless, in a robustness check, we follow Klette and Griliches (1996) to control for this potential omitted price bias in the estimation of the production function.

Third, it is widely documented that agglomeration positively affects firm productivity, and consequently the estimation of the production function. To address this concern, in a robustness check we revise the estimation procedure of the production function by explicitly incorporating the role of agglomeration. See Appendix B for details of the revised estimation procedure.

3.2 Identification of the Effect of Agglomeration on Firm Markup

To illustrate our identification strategy for the effect of agglomeration on firm markup, we adopt the Rubin causal model. Assume that for firm i of industry j at time t, we can observe two potential outcomes, $Y_{i,t}^{j}(EG_t^j = A)$ and $Y_{i,t}^{j}(EG_t^j = B)$, where $Y_{i,t}^{j}$ represents the outcome variables such as the logarithm of price, the logarithm of marginal cost, and the logarithm of markup; EG_t^j is a measure of the degree of agglomeration (namely EG index, following Ellison and Glaeser (1997); see the next section for details); and without loss of generality, it is assumed that $A > B$.

The effect of agglomeration can be then calculated as

$$\gamma_{i,t}^{\chi} = E\left[Y_{i,t}^{j}(EG_t^j = A) - Y_{i,t}^{j}(EG_t^j = B)\right], \tag{9}$$

where $\chi = c$ when the outcome variable is the logarithm of marginal cost; $\chi = P$ when the outcome variable is the logarithm of price; and $\chi = \mu$ when the outcome variable is the logarithm of markup. In the baseline analysis, we estimate the average treatment effect, that is, $\gamma_{i,t}^{\chi} = \gamma^{\chi}$. While in the second part of the empirical analysis, we allow the treatment effect to vary across different industries and different types of firms.

It is expected that $\gamma^c < 0$, implying that firms have lower marginal costs in more agglomerated areas (that is, the positive spillover effect). It is also generally expected that $\gamma^P < 0$, implying that agglomeration generally reduces firm prices (that is, the negative competition effect). And $\gamma^\mu \equiv \gamma^P - \gamma^c$ captures the net of these two effects of agglomeration (spillover versus competition effects). Specifically, if $\gamma^\mu > 0$, we have $0 > \gamma^P > \gamma^c$, which implies that the spillover effect dominates the competition effect. And if $\gamma^\mu < 0$, we have the opposite finding, that is, the competition effect is larger than the spillover effect.

However, in observational data like ours, we are only able to observe one of the two potential outcome values, that is, either $Y^j_{i,t}(EG^j_t = A)$ or $Y^j_{i,t}(EG^j_t = B)$. This makes the calculation described in equation (9) unfeasible. To retrieve the effect of agglomeration on firm markup (i.e., γ^μ), we exploit a quasi-natural experiment, that is, we use a sample of firms that changed their industrial affiliation during the sample period, to conduct a DID analysis.

Specifically, assume that a treatment firm i changed its industrial affiliation from industry j' to industry j at time t_{i0}. The control firm is a firm from the same prior industry j' (and with several similar firm characteristics) that did not change industrial affiliation. The indicator of the treatment status $Treatment_i$ is denoted as

$$Treatment_i = \begin{cases} 1 & \text{if firm } i \text{ is in the treatment group} \\ 0 & \text{if firm } i \text{ is in the control group} \end{cases} . \tag{10}$$

Our DID estimator is

$$\begin{aligned}
\gamma^\mu_{\mathbf{DID}} &= E\left[Y^j_{i,t_{i0}}(EG^j_{t_{i0}} = A) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 1\right] \\
&\quad -E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 0\right] \\
&= E\left[Y^j_{i,t_{i0}}(EG^j_{t_{i0}} = A) - Y^j_{i,t_{i0}}(EG^j_{t_{i0}} = B)\middle| Treatment_i = 1\right] \\
&\quad +E\left[Y^j_{i,t_{i0}}(EG^j_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B)\middle| Treatment_i = 1\right] \\
&\quad + \left(\begin{array}{c} E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 1\right] \\ -E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 0\right] \end{array}\right) \\
&= \gamma^\mu + IA1 + IA2,
\end{aligned} \tag{11}$$

where

$$IA1 = E\left[Y^j_{i,t_{i0}}(EG^j_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B)\middle| Treatment_i = 1\right] \tag{12}$$

$$\begin{aligned} IA2 &= E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 1\right] \\ &\quad -E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 0\right] \end{aligned} \tag{13}$$

There are two identification assumptions in our DID estimation. The first identification assumption, (12), reflects the potential effect due to the change of industrial affiliation but without the change in the degree of agglomeration. The second identification assumption, (13), requires the treatment group to have followed the trend of the control group in markup changes, if they had not changed industrial affiliation. As long as our identification assumptions are satisfied (i.e., $IA1 = 0$ and $IA2 = 0$), our DID estimator recovers the true effect of agglomeration on firm markup, i.e., $\gamma^{\mu}_{\mathbf{DID}} = \gamma^{\mu}$.[9]

In regression form, the DID estimation has the following specification

$$\begin{aligned} \ln \mu^j_{it} &= \beta \cdot Treatment_i \times Post_{it} + \gamma \cdot EG^j_t \times Post_{it} \\ &\quad +\eta_i + \lambda_t + \varepsilon^j_{it}, \end{aligned} \tag{14}$$

where λ_t is the time dummy, capturing those factors common to all firms at time t; η_i is the firm dummy, capturing firm i's all time-invariant characteristics; $Post_{it}$ indicates the post-treatment period for firm i and is defined as follows

$$Post_{it} = \begin{cases} 1 & \forall t \geq t_{i0} \\ 0 & \text{otherwise} \end{cases}; \tag{15}$$

and ε^j_{it} is the error term. γ is our key interest, representing the effect of agglomeration on firm markup. To deal with the potential heteroskedasticity and serial correlation, we cluster the standard errors at the firm level following Bertrand, Duflo, and Mullainathan (2004).

Note that the inclusion of $Treatment_i \times Post_{it}$ controls for the identification assumption (12), that is, any effects due to the change in the industrial affiliation, beyond the change in the degree of agglomeration. In other words, whether the estimated coefficient $\tilde{\gamma}$ from equation (14) captures the true effect γ^{μ} only hinges upon the satisfaction of the identification assumption (13), i.e., $\tilde{\gamma} = \gamma^{\mu} + IA2$ and $IA2 = 0 \Rightarrow \tilde{\gamma} = \gamma^{\mu}$.

Below, we discuss a few estimation issues, especially the checks on the identification assumption (13).

[9] In the matching stage, we find that firm markup is not correlated with the probability of changing industrial affiliation, i.e., there is no selection on the outcome variable.

First, to improve the comparability between the treatment and control groups, we construct a matched control group, that is, unaffected firms (i.e., those without changes in their industrial affiliation) in the same prior treatment industry and with similar firm characteristics. Specifically, we first estimate the probability of changing industrial affiliation based on firm markup, size, age, productivity, ownership structure, and industry and year dummies. The matched control firm is the firm with the closest predicted probability as that of the focus treatment firm.

Second, the change in industrial affiliation is defined at the three-digit industry level. To relieve the concern of misreporting industrial affiliation, we restrict the selection to permanent changers, that is, we exclude those firms that changed industrial affiliation many times in the sample period. As a further check on the potential misreporting issue, we repeat the analysis for changes defined at the two-digit industry level.

Third, one way to check whether the identification assumption (13) holds is to examine whether the assumption is satisfied for several years before the treatment happened, i.e.,

$$\begin{aligned} IA2_s &= E\left[Y^{j'}_{i,t_{i0}-s}(EG^{j'}_{t_{i0}-s}=B) - Y^{j'}_{i,t_{i0}-1-s}(EG^{j'}_{t_{i0}-s-1}=C)\middle| Treatment_i = 1\right] \\ &\quad -E\left[Y^{j'}_{i,t_{i0}-s}(EG^{j'}_{t_{i0}}=B) - Y^{j'}_{i,t_{i0}-1-s}(EG^{j'}_{t_{i0}-s-1}=C)\middle| Treatment_i = 0\right] \\ &= 0 \ \forall s \geq 1. \end{aligned} \tag{16}$$

A finding of $IA2_s = 0 \forall s$ may imply that our identification assumption (13) also holds. The corresponding regression specification of this robustness check is

$$\begin{aligned} \ln \mu^j_{it} &= \beta \cdot Treatment_i \times Post_{it} + \gamma \cdot EG^j_t \times Post_{it} \\ &\quad + \sum\nolimits_{s=1} \delta_s \cdot Treatment_i \times \lambda_{t-s} + \eta_i + \lambda_t + \varepsilon^j_{it}, \end{aligned} \tag{17}$$

and the joint test of $\delta_s = 0$ implies $IA2_s = 0 \forall s$, lending support to our identification assumption (13).

Fourth, firms in the treatment and control groups may follow different time trends, which may compound our DID estimator. To address this concern, we allow firm-specific time trends in our DID estimation. The new regression specification becomes

$$\begin{aligned} \ln \mu^j_{it} &= \beta \cdot Treatment_i \times Post_{it} + \gamma \cdot EG^j_t \times Post_{it} \\ &\quad + \eta_i + \lambda_t + \eta_i \times t + \varepsilon^j_{it}, \end{aligned} \tag{18}$$

and our identification assumption (13) is relaxed as

$$\begin{aligned} IA2 &= E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}}=B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1}=C) \middle| Treatment_i = 1, \eta_i \right] \\ &\quad - E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}}=B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1}=C) \middle| Treatment_i = 0, \eta_i \right]. \end{aligned} \tag{19}$$

Fifth, if the treatment and control groups are balanced (and hence the identification assumption (13) holds), the inclusion of additional firm-level controls should not significantly change the DID estimator. As a check, we include a number of firm characteristics ($\mathbf{X}_{it}$) in the DID estimation. The new regression specification becomes

$$\begin{aligned} \ln \mu^j_{it} &= \beta \cdot Treatment_i \times Post_{it} + \gamma \cdot EG^j_t \times Post_{it} \\ &\quad + \eta_i + \lambda_t + \mathbf{X}'_{it} \cdot \boldsymbol{\rho} + \varepsilon^j_{it}, \end{aligned} \tag{20}$$

and our identification assumption (13) is relaxed as

$$\begin{aligned} IA2 &= E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}}=B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1}=C) \middle| Treatment_i = 1, \Delta\mathbf{X}_{i,t_{i0}} \right] \\ &\quad - E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}}=B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1}=C) \middle| Treatment_i = 0, \Delta\mathbf{X}_{i,t_{i0}} \right]. \end{aligned} \tag{21}$$

Sixth, as a placebo test, instead of looking at firm markup as the outcome variable, we examine an alternative outcome variable z^j_{it} that is not supposed to be affected by the change in industrial affiliation. Hence, the DID estimator of z^j_{it} is similar to equation (11), i.e., $\gamma^z_{\mathbf{DID}} = \gamma^z + IA1^z + IA2^z$. As $\gamma^z = 0$ and $IA1^z$ is controlled in the regression, the estimator $\gamma^z_{\mathbf{DID}}$ is reduced to as $\gamma^z_{\mathbf{DID}} = IA2^z$. A finding of $\gamma^z_{\mathbf{DID}} = 0$ means $IA2^z = 0$, which implies the satisfaction of our identification assumption (13). For the choice of outcome variable z^j_{it}, we use an indicator of whether a firm changed its ownership structure, e.g., from state-owned enterprise to private enterprise. The premise is that a change in industrial affiliation should not systematically lead to a change in ownership structure.

4 Data and Variables

The data for this study comes from the Annual Survey of Manufacturing Firms conducted by the National Bureau of Statistics of China for the period of 1998 to 2005. It is the most comprehensive firm-level data set in China.

The survey covers all state-owned enterprises and those non-state-owned enterprises with annual sales of five million Renminbi (Chinese currency) or more. The number of enterprises in the sample ranges from 149,556 in 1998 to 244,315 in 2005. These firms are distributed among 29 two-digit or 171 three-digit manufacturing industries, and across 31 provinces, 344 cities, and 2,829 counties.

During the sample period, there were several changes in China's administrative boundaries and consequently in the county or city codes in our data set. For example, new counties were established, while existing counties were combined into larger ones or even elevated to cities. Using the 1999 National Standard (promulgated at the end of 1998 and called GB/T 2260-1999) as the benchmark codes, we convert the regional codes of all the firms to these benchmark codes to achieve consistency in the regional codes throughout the sample period. Meanwhile, a new classification system for industry codes (GB/T 4754-2002) was adopted in 2003 to replace the old classification system (GB/T 4754-1994) that had been used from 1995 to 2002. To achieve consistency in the industry codes for the whole sample period (1998-2005), we convert the industry codes in the 2003-2005 data to the old classification system.

Our DID analysis uses the change of industrial affiliation of firms over the sample period. A total of 29,399 firms changed their three-digit industrial affiliations during the sample period; they comprise our treatment group.[10] There are a total of 27,050 firms in the matched control group.[11] Deleting observations missing valid information for key variables (such as output and inputs), we end up with a final regression sample of 214,138.

To measure the degree of agglomeration, we follow the method developed by Ellison and Glaeser (1997), which tackles the large plant issue suffered by other measures of agglomeration. Ellison and Glaeser's index (henceforth referred to as the EG index) is constructed as follows:

$$EG_t^j \equiv \frac{G_t^j - (1 - \sum_r s_{rt}^2) H_t^j}{(1 - \sum_r s_{rt}^2)(1 - H_t^j)},$$

where $G_t^j \equiv \sum_r (s_{rt}^j - s_{rt})^2$ is the spatial Gini coefficient, with s_{rt}^j being the share of region's r employment in industry j in the total country's employ-

[10] Note that in constructing the treatment group, we exclude firms that changed their industrial affiliations more than once over the sample period, to alleviate the concern of misreporting.

[11] The number of firms in the control group is slightly below that in the treatment group because replacement is allowed in the matching process.

ment of this industry at year t, and s_{rt} being the share of region r's total manufacturing employment in the country's total at year t; and $H_t^j = \sum_j h_{ejt}^2$ is the Herfindahl index of industry j at year t, with h_{ejt} standing for the output share of a particular firm e in industry j. The EG index, which is essentially the difference between the Gini coefficient and the Herfindahl index, measures the degree of industrial agglomeration beyond the level implied by the industrial structures. In the main analysis, we measure the EG index by using the city as the geographic unit. For robustness checks, we also measure the EG index using the county and the province as the geographic unit.

Control variables used in the analysis include: firm size (measured as the logarithm of total employment), firm age (measured as the logarithm of years of establishment), exporter status (a dummy variable indicating whether a firm is an exporter or not), and foreign firm status (a dummy variable indicating whether a firm is registered as a foreign firm).

5 Empirical Findings

5.1 Descriptive Analysis

Table 1 lists the average markup for the 29 two-digit manufacturing industries. Generally, monopolized industries have the highest average markup values, for example, tobacco processing (1.54), medical and pharmaceutical products (1.47), and petroleum processing, coking products, and gas production and supply (1.37). Industries with the lowest average markup are garments and other fiber products (1.16), leather, furs, down and related products (1.17), and the textile industry (1.21), which have low entry barriers and numerous small firms.

[Insert Table 1]

Figure 1 presents the unconditional correlation between the EG index and average markup at the two-digit industry level. There is a clear, negative correlation between the EG index and markup, implying that overall agglomeration has a negative impact on markup in China.

[Insert Figure 1]

5.2 Baseline Results

Our baseline DID estimation results, corresponding to equation (14), are reported in Column 1 of Table 2. It is found that the estimated coefficient of

$Treatment_i \times Post_{it}$ is statistically insignificant and close to 0 in magnitude. This implies that when the degree of agglomeration does not change, the change in industrial affiliation does not have an effect on firm markup.

[Insert Table 2]

With respect to our central issue, the estimated coefficient ($\gamma^{\mu}_{\mathbf{DID}}$) of $EG^j_t \times Post_{it}$ is negative and highly significant. This result implies that the increase in the degree of agglomeration reduces firm markup, which is consistent with Figure 1. In terms of magnitude, a one-standard-deviation increase (i.e., 0.469) in the degree of agglomeration causes firm markup to drop by 4.3%.

Note that in the aforementioned estimation, we include firms from all 171 three-digit manufacturing industries in the same regression and estimate only one coefficient $\gamma^{\mu}_{\mathbf{DID}}$. Hence, the estimated coefficient $\gamma^{\mu}_{\mathbf{DID}}$ represents the average effect of agglomeration on firm markup in China across all industries. This implies that overall in China agglomeration has a negative effect on firm markup. In other words, in China, the devastating competition effect dominates the beneficial spillover effect, i.e., $|\gamma^c| > |\gamma^P|$. There are two possible explanations for this. First, China's market has been highly fragmented due to its low economic development on the one hand and local protectionism on the other, which limits the degree of inter-regional competition. In other words, market competition comes mostly from local competitors. As a result, the competition effect brought by industrial agglomeration is fiercer in China, compared with countries that have nationally integrated markets and nationwide market competition. Second, there is limited opportunity for firms in China to learn from competitors located nearby, because China has specialized in low value added manufacturing industries and low value added segments of manufacturing industries. Taken together, these factors have led to the domination of the competition effect of agglomeration over the spillover effect of agglomeration in China.

5.3 Checks on the Identification Assumption of the DID Estimation

In this sub-section, we report a series of sensitivity checks, as discussed in Section 2.2, on the identification assumption (13).

Pre-treatment differential time trends. The first robustness check on the validity of our DID estimation examines whether the identification assumption (13) holds in the pre-treatment period. Regression results according to equation (17) are presented in Column 2 of Table 2. The insignificant joint test (F-test) of δ_1 and δ_2 gives no evidence for any differential time trends between the treatment and control groups in the two years before the treatment, lending support to our identification assumption (13). Therefore, our main finding on the effect of agglomeration on firm markup remains robust.

Firm-specific time trend. One further concern is that firms in the treatment and control group may follow different time trends over the whole sample period, which may then compound our findings. To address this concern, we allow firm-specific time trends in the DID estimation. Regression results according to equation (18) are reported in Column 3 of Table 2. Clearly, our main finding on the effect of agglomeration on firm markup remains robust to the inclusion of firm-specific time trends, despite the fall in the magnitude of the estimated coefficient.

Additional controls. A corollary of the satisfaction of our identification assumption (13) is that the inclusion of additional controls in the DID estimation should not significantly change the DID estimate as the treatment and control groups are balanced. Hence, we repeat our DID analysis with the addition of several firm characteristics such as firm size, firm age, productivity, foreign firm status, and exporter status. Regression results according to equation (20) are reported in Column 4 of Table 2. It is found that our regressor of interest, $EG_t^j \times Post_{it}$, remains negative and statistically significant. Although the estimated coefficient increases a little bit, it is not statistically different from the corresponding number in our baseline estimation.

Placebo test. The use of an outcome variable (z) that is not supposed to be affected by our treatment allows us to check whether our identification assumption (13) holds or not. Regression results using the indicator of changing firm ownership structure as the dependent variable are reported in Column 5 of Table 2. Clearly, the regressor of interest, $EG_t^j \times Post_{it}$, becomes highly insignificant and close to 0 in magnitude. This result means that our identification assumption (13) holds, implying our baseline DID estimation is not biased due to some underlying compounding factors.

5.4 Other Robustness Checks

In this sub-section, we report some further robustness checks on our aforementioned findings.

EG indices at alternative geographic scopes. Thus far our analysis uses city as the geographic unit to measure the degree of agglomeration. One concern is whether our findings are sensitive to the choice of geographic scope, or the so-called modifiable area unit problem (Arbia, 2001). To address this concern, we repeat our analysis using both province and county as the geographic scopes to measure the degree of agglomeration. Regression results are reported in Columns 1-2 of Table 3. It is found that agglomeration continues to cast a negative and statistically significant impact on firm markup, implying that our findings are not driven by the choice of geographic scope.

[Insert Table 3]

One-shot effect. The use of multiple periods in our DID analysis raises the concern that the DID estimator captures the variations of agglomeration due to events that happened in the post-treatment period. To alleviate this concern, we restrict the post-treatment period to one year after the change in industrial affiliation. Regression results are reported in Column 3 of Table 3. It is found that agglomeration still has a negative and statistically significant effect and the magnitude is even stronger. This result implies that DID estimate identified in Table 2 is not caused by events occurring after the change in industrial affiliation.

Exclusion of outliers. Another concern is whether our findings are driven by some outlying observations. To address this concern, we exclude firms whose markup values are at the top or bottom 1% of the entire sample. Regression results are reported in Column 4 of Table 3. Clearly, our main findings on the negative effect of agglomeration on firm markup remain robust, implying that the concern about outliers is not relevant in this context.

Change at the two-digit industry. One possible concern is that firms may misreport their industrial affiliations, which would invalidate our DID setting. In the above analysis, we restrict our analysis to a sample of firms that during the whole sample period either did not change their industrial affiliations (the control group), or changed only once (the treatment group), which may reduce the problem of misreporting. As a further check, we define the treatment group as firms that changed their industrial affiliations once at the two-digit industry level; misreporting is less likely at this level than at the three-digit industry level. Regression results are reported in Column 5 of Table 3. We still find a negative and statistically significant effect of agglomeration on firm markup, implying the validity of our DID setting.

Control for omitted price bias in the estimation of production function. As our data does not have price information, we recover output in quantity by deflating output in value with the industry price index. This may bias the estimated coefficients of production function (Klette and Griliches, 1996). However, the omitted price bias should not affect our DID estimation as our identification uses the double-differenced instead of the level of estimated coefficients of production function. Nonetheless, we conduct a further robustness check by using the method proposed by Klette and Griliches (1996) to control for the omitted price issue in the estimation of production function. Regression results are reported in Column 6 of Table 3. Consistent with our previous findings, agglomeration still has a negative and statistically significant effect on firm markup, implying that the omitted price bias in the estimation of production function does not drive our findings.

Incorporating the role of agglomeration into the estimation of production function. As agglomeration is found to affect firm productivity, it is possible that it could also affect our estimation of production function. As a robustness check, we explicitly incorporate the role of agglomeration into our estimation of production function. The DID estimation results are reported in Column 7 of Table 3. Again, our main findings remain robust to the control for the role of agglomeration in the estimation of production function.

5.5 Heterogeneous Responses

Our results thus far demonstrate a negative impact of agglomeration on firm markup, implying that, on the whole, the devastating competition effect dominates the beneficial spillover effect in China. In this sub-section, we look at several scenarios in which these two offsetting effects have different relative importance, so that we can disentangle them.

SOEs versus non-SOEs. A unique feature of China's economic reform is its gradualism, that is, the state retains dominant control of the economy (Cao, Qian, and Weingast, 1999). Indeed, China still retains a significant amount of state ownership, despite thirty years of economic reform (CAI JING Magazine, 2007). As the privileged children of the state, state-owned enterprises enjoy numerous favorable policies. For example, state-owned enterprises have easy access to bank loans, while non-state-owned enterprises are typically denied access to bank loans (Li, 2001). And, as sources of fiscal revenue and employment, state-owned enterprises are strongly protected by local governments and, hence, shielded from local competition. As a result, it is expected that the devastating competition effect brought by industrial agglomeration will be smaller for state-owned enterprises than for non-state owned enterprises. In addition, state-owned enterprises are found to benefit more from spillover than non-state-owned enterprises, presumably due to heavy government investment and the resulting technical capabilities (e.g., Hale and Long, 2011). Taken together, it is expected that the net impact of agglomeration on firm markup will be less negative or even positive for state-owned enterprises. These hypotheses are supported by our analysis. Columns 1-2 of Table 4 show that for the sub-sample of state-owned enterprises, the impact of agglomeration on firm markup is statistically insignificant, whereas for the sub-sample of non-state-owned enterprises, the impact of agglomeration on firm markup is negative and significant.

[Insert Table 4]

Mature versus fast-growing industries. In industries with fast growth rates, firms enjoy the expansion of markets. As a result, the negative, local competition brought by industrial agglomeration is less fierce. However, in mature industries with barely any growth, firms compete for limited numbers of clients, as a result of which industrial agglomeration brings stronger local competition. Furthermore, in mature industries with established technologies, industrial agglomeration does not have a strong beneficial spillover effect. Indeed, Henderson (2003) finds no significant impact of agglomeration on firm productivity in mature industries. In summary, it is expected that the relative importance of the competition effect over the spillover effect will be more prominent in mature industries than in fast-growing industries. In other words, the net impact of agglomeration on firm markup should be more negative in mature industries, but less negative or even insignificant in fast-growing industries.

To divide industries into mature industries and fast-growing industries, we follow the classification of Henderson et al. (1995). Specifically, mature industries are defined as those that experience no growth at all during our sample period, and fast-growing industries are defined as those that experience 100% employment growth during the sample period.[12] We also experiment with an alternative classification of mature industries (i.e., those with growth rates $< -20\%$) and fast-growing industries (i.e., those with growth rates $> 150\%$). Regression results for the subsamples of fast-growing and mature industries are shown in Columns 3-6 of Table 4. Consistent with the above argument, the impact of agglomeration on firm markup turns out to be insignificant for fast-growing industries, whereas the negative impact of agglomeration on firm markup is negative and statistically significant for the mature industries.

Homogenous versus differentiated industries. The devastating competition effect brought by industrial agglomeration largely stems from the enhanced opportunity for consumers to search for the lowest prices. If the prices of the relevant goods are publicly available, industrial agglomeration

[12] See Table A2 for a list of the fast-growing and mature industries.

does not bring any extra localized competition. As long as there is some beneficial spillover effect from agglomeration, the net impact of agglomeration on markup should be less negative or even positive for industries/goods for which the price information is publicly available. Following the classification of Rauch (1999), we divide industries into three categories in declining order of the degree of public informativeness of prices: those with goods traded at exchanges (denoted as *Homogenous*), those with goods for which there are some reference prices (denoted as *Reference*), and the remaining industries (denoted as *Differentiated*). Regression results are reported in Columns 7-9 of Table 4. Consistent with the above argument, we find a positive and significant effect of agglomeration on firm markup in industries with goods traded at exchanges, but significant and negative effects in industries with reference prices and the remaining industries.

6 Conclusion

The study of the geographic distribution of economic activities across countries and regions dates back at least to the days of Alfred Marshall (see Book 4, Chapter 10 of *Principles of Economics* (1890)). An intriguing phenomenon uncovered by research in this area is the geographic clustering of firms concentrating on the provision of certain goods or services. Subsequent research has focused on the benefits of agglomeration, which are related to decreases in the costs of production due to the positive spillover effect. However, comparably much less attention has been paid to the costs of agglomeration. While acknowledging the importance of some of the indirect costs of agglomeration (such as congestion) discussed in the literature, we believe a much neglected, direct cost of agglomeration is enhanced competition brought out by agglomeration. To fully understand the geographic distribution of economic activities, it is imperative to examine the costs as well as benefits of agglomeration.

Given that the negative competition effect of agglomeration lowers prices, whereas the positive spillover effect lowers the marginal production costs, in this paper, we use firm markup (defined as the ratio of price over marginal cost) as a simple and comprehensive measure to capture the net impact of agglomeration. Following a methodology recently developed by De Loecker and Warzynski (2012), we first estimate the markup ratio for each firm from the data set of Chinese manufacturing firms in the 1998-2005 period. To identify the causal impact of agglomeration on firm markup, we use a scenario in which some firms change their industrial affiliations as a quasi-experiment. Our DID estimation shows that the overall impact of agglomeration on firm markup is negative, suggesting the dominance of the negative competition effect over the positive spillover effect in the Chinese context. Our results are robust to various sensitivity checks on the satisfaction of our DID identification assumption and other estimation issues. Furthermore, we find that the impacts of agglomeration on firm markup vary across different industries and types of firms, as the relative strength of the negative competitive effect versus the positive spillover effect varies under different circumstances.

Our research highlights the importance of examining the costs as well as the benefits of agglomeration. It contributes to the economic geography literature by demonstrating the use of markup ratio as a measure of the net impact of agglomeration. Our findings on the negative impact of agglomeration on markup, based on data from China's manufacturing firms, suggest there are limits to agglomeration, as firms need to balance the lower production costs afforded by agglomeration against the lower prices caused by enhanced competition. Furthermore, our findings call for more studies on the net impact of agglomeration using data from other countries and regions.

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Appendix A: Estimation of the Production Function

We re-write the production function (1) in the translog form

$$q_{it} = \theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it} + \omega_{it} + \varepsilon_{it}, \tag{22}$$

where the lower case letters represent the logarithm of the upper case letters; $\boldsymbol{\theta}= (\theta_l, \theta_k, \theta_m)$ is the vector of the production function coefficients; and ε_{it} is an i.i.d. error term. To proxy ω_{it}, Levinsohn and Petrin (2003) assume that

$$m_{it} = m_t \left(l_{it}, k_{it}, \omega_{it}\right). \tag{23}$$

Given the monotonicity of $m_t\,(.)$, we can have

$$\omega_{it} = h_t \left(l_{it}, k_{it}, m_{it}\right). \tag{24}$$

In the first stage, we estimate the following equation

$$q_{it} = \phi_t \left(l_{it}, k_{it}, \omega_{it}\right) + \varepsilon_{it}, \tag{25}$$

where

$$\phi_{it} = \theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it} + h_t \left(l_{it}, k_{it}, m_{it}\right), \tag{26}$$

and obtain the estimates of the expected output $(\hat{\phi}_{it})$ and the error term $(\hat{\varepsilon}_{it})$.

Meanwhile, to recover all the production function coefficients $\boldsymbol{\theta}$ in the second stage, we model that firm productivity follows a first-order Markov movement, i.e.,

$$\omega_{it} = g_t \left(\omega_{it-1}\right) + \xi_{it}, \tag{27}$$

where ξ_{it} is an idiosyncratic shock.

From the first stage, the productivity for any given value of $\boldsymbol{\theta}$ can be computed as

$$\omega_{it} \left(\boldsymbol{\theta}\right) = \hat{\phi}_{it} - \left(\theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it}\right). \tag{28}$$

Then the idiosyncratic shock to productivity given $\boldsymbol{\theta}$, $\xi_{it}\left(\boldsymbol{\theta}\right)$, can be obtained through a nonparametric regression of $\omega_{it}\left(\boldsymbol{\theta}\right)$ on $\omega_{it-1}\left(\boldsymbol{\theta}\right)$.

To identify the coefficients of the production function, Ackerberg, Caves, and Frazier (2006) assume that capital is determined one period beforehand

and hence is not correlated with $\xi_{it}(\boldsymbol{\theta})$. In addition, wage rates and prices of intermediate materials are assumed to vary across firms and be serially correlated. Therefore, the moment conditions used to estimate the coefficients of the production function are

$$E\left(\xi_{it}(\boldsymbol{\theta})\begin{pmatrix} l_{it-1} \\ k_{it} \\ m_{it-1} \end{pmatrix}\right) = 0. \tag{29}$$

Appendix B: Incorporating the Role of Agglomeration into the Estimation of the Production Function

Agglomeration has been found to positively affect firm productivity, which may raise the concern that it could then potentially affect the production function. To address this concern, we explicitly incorporate the role of agglomeration into the estimation procedure of the production function. Specifically, firm productivity is assumed to follow the following Markov movement

$$\omega_{it} = g_t\left(\omega_{it-1}, agglomeration_{jt-1}\right) + \xi_{it}, \tag{30}$$

where $agglomeration_{jt-1}$ is the degree of agglomeration in industry j (for which firm i belongs to) at time $t-1$. Other procedures are similar to those in Appendix A.

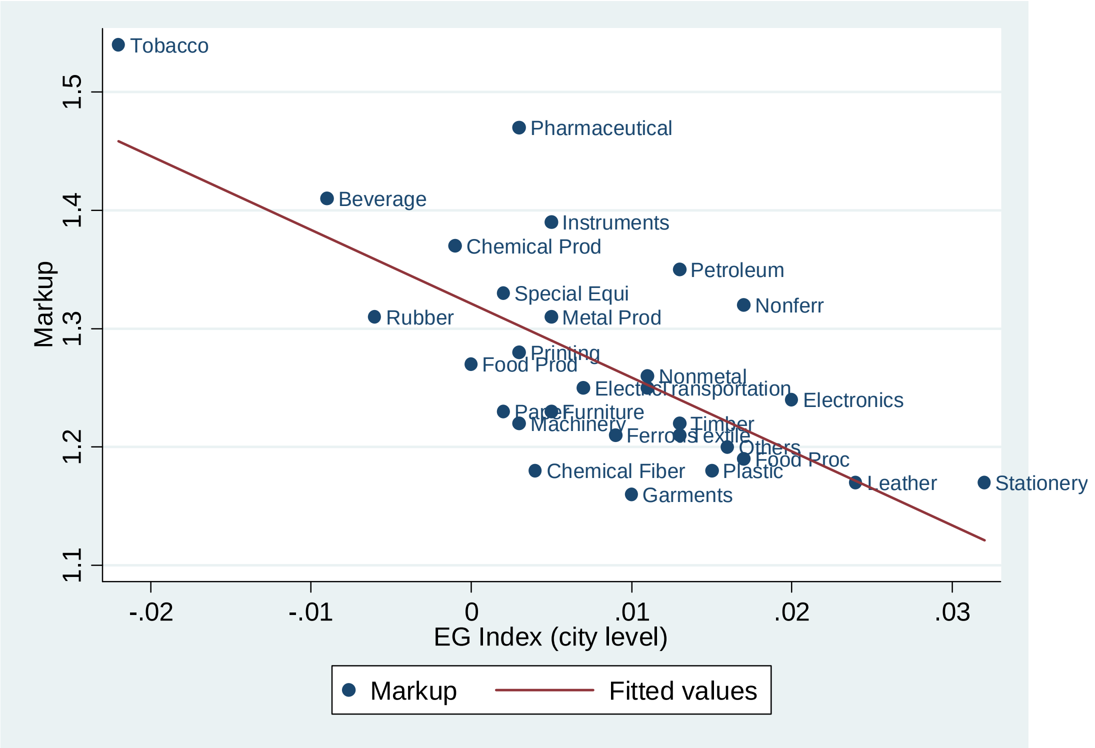

Figure 1: Industry agglomeration and firm markup (EG index measured at two-digit SIC industry and city level)

Table1: Markup ratios and EG indices for two-digit manufacturing industries

Industry	Markup	EG index Province	City	County
Food Processing	1.19	0.061	0.017	0.006
Food Production	1.27	0.016	0.000	-0.004
Beverage Production	1.41	0.013	-0.009	-0.013
Tobacco Processing	1.54	0.032	-0.022	-0.025
Textiles	1.21	0.048	0.013	0.005
Garments & Other Fiber Products	1.16	0.035	0.010	0.005
Leather, Furs, Down & Related Products	1.17	0.081	0.024	0.008
Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products	1.22	0.030	0.013	0.004
Furniture Manufacturing	1.23	0.036	0.005	0.003
Papermaking & Paper Products	1.23	0.018	0.002	-0.001
Printing & Reproduction of Recording Media	1.28	0.010	0.003	0.000
Stationery, Educational & Sports Goods	1.17	0.139	0.032	0.017
Petroleum Processing, Coking Products, Gas Production & Supply	1.35	0.127	0.013	0.001
Chemical Raw Materials & Chemical Products	1.37	0.015	-0.001	-0.004
Medical & Pharmaceutical Products	1.47	0.016	0.003	-0.002
Chemical Fibers Manufacturing	1.18	0.028	0.004	-0.003
Rubber Products	1.31	0.004	-0.006	-0.011
Plastic Products	1.18	0.054	0.015	0.007
Non-metal Mineral Products	1.26	0.027	0.011	0.003
Ferrous Metal Smelting & Rolling Processing	1.21	0.059	0.009	0.002
Non-ferrous Metal Smelting & Rolling Processing	1.32	0.043	0.017	0.009
Metal Products	1.31	0.028	0.005	0.001
General Machinery Manufacturing	1.22	0.022	0.003	0.000
Special Equipment Manufacturing	1.33	0.021	0.002	-0.002
Transportation Equipment Manufacturing	1.25	0.029	0.011	-0.004
Electric Equipment & Machinery	1.25	0.029	0.007	0.004
Electronics & Telecommunications	1.24	0.083	0.020	0.003
Instruments, Meters, Cultural & Official Machinery	1.39	0.039	0.005	-0.005
Other Manufacturing	1.20	0.043	0.016	0.005

Note: Firm-level markup ratios are estimated using De Loecker and Warzynski (2011)'s method. Weighted (output) average markup is calculated for each two-digit industry in 1998-2005. Agglomeration is calculated using EG index (Ellison and Glaeser, 1997) at three geographic scopes (province, city, and county).

Table 2: Main results

	Whole period effect	Pre-treatment terms included	Firm-time trends	More controls	Placebo test
	1	2	3	4	5
Treatment*Post	0.000	-0.002	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EG*Post	-0.092***	-0.093***	-0.049**	-0.115***	0.000
	(0.017)	(0.017)	(0.020)	(0.019)	(0.001)
F test (treatment*Pre(-1), treatment*Pre(-2))		[1.51]			
Firm size (output)				-0.080***	
				(0.001)	
Firm age				0.000	
				(0.000)	
Firm productivity				0.046***	
				(0.002)	
Foreign ownership				0.002	
				(0.002)	
Export status				0.000	
				(0.001)	
Firm dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Firm time trend	No	No	Yes	No	No
Obs. #	214138	214138	214138	214138	214138

Note: Standard errors, clustered at firm level, are in parenthesis. *, **, *** denote significance at 10%, 5%, and 1% level, respectively.

Table 3: Robustness checks

	EG at province level	EG at county level	One-shot effect	Excl. markup outliers	Change across two-digit industry	Allow for omitted prices bias	Role of agglomeration
	1	2	3	4	5	6	7
Treatment*Post	0.000	0.000	0.001	0.000	0.000	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EG*Post	-0.030***	-0.057***	-0.194***	-0.072***	-0.140***	-0.151***	-0.042**
	(0.009)	(0.019)	(0.023)	(0.016)	(0.026)	(0.023)	(0.019)
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. #	214138	214138	142900	210103	132284	214138	214138

Note: Standard errors, clustered at firm level, are in parenthesis. *, **, *** denote significance at 10%, 5%, and 1% level, respectively.

Table 4: Heterogeneous responses

	Ownership		Industry growth rate				Product price informativeness		
	SOEs	Non-SOEs	>100%	>150%	<0%	<-20%	Homogeneous	Reference	Differentiated
	1	2	3	4	5	6	7	8	9
Treatment*post	-0.005	0.001	-0.025***	0.014***	-0.006***	0.009***	-0.010***	0.004**	0.000
	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)
EG*post	0.018	-0.101***	-0.043	-0.081	-0.086***	-0.073***	0.233***	-0.097**	-0.100***
	(0.077)	(0.018)	(0.072)	(0.095)	(0.021)	(0.021)	(0.077)	(0.038)	(0.020)
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. #	21701	192437	26643	11810	71991	36323	11777	52761	149600

Note: Standard errors, clustered at firm level, are in parenthesis. *, **, *** denote significance at 10%, 5%, and 1% level, respectively.

Table A1: Impact of agglomeration on firm productivity

	Whole period effect	Pre-treatment terms included	One-shot effect	Firm-time trends included	Additional controls	Allow for omitted price bias	Role of agglomeration
	1	2	3	4	5	6	7
Treatment*Post	0.006	0.019***	0.007*	0.006	0.004	-0.018***	-0.022***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
EG*Post	0.360***	0.364***	0.596***	0.218**	0.373***	0.605***	0.283***
	(0.085)	(0.085)	(0.112)	(0.099)	(0.082)	(0.094)	(0.103)
F test (treatment*Pre(-1), treatment*Pre(-2))		[0.09]					
Firm size (output)					0.180***		
					(0.005)		
Firm age					-0.001***		
					(0.000)		
Foreign ownership					-0.004		
					(0.012)		
Export status					-0.001		
					(0.004)		
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm time trend	No	No	No	Yes	No	No	No
Obs. #	236630	236630	157079	236630	236630	236630	236630

Note: Standard errors, clustered at firm level, are in parenthesis. *, **, *** denote significance at 10%, 5%, and 1% level, respectively.

Table A2: Typical fast-growing and mature industries in China

Fast-growing industries (three-digit SIC code)	**Mature industries (two-digit SIC code)**
Apparel Manufacturing (181)	Food Processing (13)
Leather Shoes, Apparel, Luggage & Handbags, and Bags Manufacturing (192)	Food Production (14)
Plywood, Fiberboard, Chipboard, and Other Artificial Boards Manufacturing (202)	Beverage Production (15)
Wood Furniture Manufacturing (211)	Tobacco Processing (16)
Metal Furniture Manufacturing (213)	Textiles (17)
Sporting and Athletic Goods Manufacturing (242)	Papermaking and Paper Products (22)
Toys manufacturing (244)	Printing and Reproduction of Recording Media (23)
Coking (257)	Chemical Raw Materials and Chemical Products (26)
Biological Products (275)	Chemical Fibers Manufacturing (28)
Household Plastic Goods Manufacturing (307)	Rubber products (29)
Plastic Parts Manufacturing (308)	Non-metal Mineral Products (31)
Metal Fabric Manufacturing (341)	Ferrous Metal Smelting & Rolling Processing (32)
Electricity Transmission, Distribution and Control Equipment Manufacturing (404)	Non-ferrous Metal Smelting & Rolling Processing (33)
Computers Manufacturing (414)	General Machinery Manufacturing (35)
Vacuum Tubes, Semi-conductor Devices, and Integrated Circuits Manufacturing (415)	Special Equipment Manufacturing (36)
Electronic Components Manufacturing (416)	Transportation Equipment Manufacturing (37)
Mirrors, Eye Glasses, Umbrellas, Bristle Processing and Brush Manufacturing (435)	

Note: We define fast-growing industries as those whose total employment growth rate in the 1998-2005 period is above 100%, mature industries as those whose total employment growth rate in the 1998-2005 period is below 0%.