The Markup Effect of Agglomeration

Yi LU[a], Zhigang TAO[b] and Linhui YU[c]

[a]National University of Singapore

[b]University of Hong Kong

[c]Zhejiang University

First Draft: June 2011
This Version: April 2014

Abstract

Agglomeration brings costs (e.g., intensified local competition and lower prices) as well as benefits (e.g., knowledge spillover and productivity gains). In this paper, we study the impact of agglomeration on firm markup ratio to incorporate both the spillover and competition effects in understanding the geographic distribution of economic activities. Using data from China's manufacturing firms over the 1998-2005 period, we first recover the markup ratio for each firm following De Locker and Warzynski (2012), and then use changes in industry affiliations to identify the markup effect of agglomeration. We find that agglomeration has a negative impact on firm markup ratio, suggesting that the competition effect dominates the spillover effect in the Chinese context. Moreover, we find that the markup effect of agglomeration varies across different industries and firms.

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

1 Introduction

The geographic concentration of economic activities is a widely observed phenomenon 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 industry belt in Japan.[1] In view of the prevalence and importance of agglomeration, there emerges a large body of studies showing that agglomeration brings about substantial positive spillover,[2] and enhances firm productivity,[3] which subsequently results in lower marginal costs of production (henceforth referred to as *the spillover effect*). Comparably speaking, however, much less attention has been paid to the costs associated with agglomeration. Of particular relevance to firm performance is the effect of intensified market competition and, consequently, lower prices due to the geographic concentration of producers of same industries (henceforth referred to as *the competition effect*).[4] It is thus interesting and important to consider both the spillover and competition effects at the same time. In this paper, drawing on data from China's manufacturing firms over the 1998-2005 period, we use firm markup ratio (defined as the ratio of price over marginal cost) to capture the net of these two offsetting effects, henceforth referred to as the *markup effect of agglomeration*.[5]

There are two challenges in empirically investigating the markup effect of agglomeration. The first challenge concerns with how to measure firm markup, as firm-level data rarely contain information on product prices, let alone information on marginal costs of production. In this study, using the latest method developed by De Loecker and Warzynski (2012), we are able to recover the markup ratio for each firm from the standard firm-level financial information about output, capital, labor and materials. The second challenge is how to identify the causal effect of agglomeration on firm markup, given that more agglomerated industries may differ from less agglomerated industries in many other dimensions. To deal with this problem, we explore a scenario (a quasi-experiment setting) in which some firms change their industry affiliations over the sample period, which allows us to compare the markup ratios of firms that changed their industry affiliations (the treatment group) with the those of firms that did not (the control group) before and after the year of change (i.e., the difference-in-differences or DD estimation). As the changes of firms in their industry affiliations may not be completely exogenous, we augment our DD analysis with a non-parametric propensity score matching (PSM) method, which is a highly effective method for improving the accuracy of evaluation studies (see, for example, Blundell and Costa Dias,

[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] For a review, see Melo, Graham, and Noland (2009).

[4] With a few exceptions (Salop, 1979; Ottaviano, Tabuchi, and Thisse, 2002; Syverson, 2007; Melitz and Ottaviano, 2008), the available studies have generally focused on higher wages, higher rents and more congestion as costs of agglomeration. Compared with the impact of agglomeration on market prices, however, these costs are mostly indirect.

[5] It should be pointed out that, while markup ratio allows us to examine the net of spillover and competition effects of agglomeration, it is just one possible factor affecting firm performance. Other factors include market share, product innovation, etc., which are not within the scope of research in this study.

2000).

The data for our study come from the annual surveys of manufacturing firms conducted by the National Bureau of Statistics of China over the 1998-2005 period. Our DD-PSM estimation shows that agglomeration has a negative and statistically significant effect on firm markup, implying that the negative competition effect of agglomeration outweighs the beneficial spillover effect of agglomeration. To ensure the validity of our estimation, we conduct a series of robustness checks on the identification assumption of the DD-PSM estimation and other estimation concerns, such as the check on whether treatment and control groups have differential time trends in the pre-treatment period, the control for firm-specific linear time trend, measures of industry agglomeration index at different geographic scopes, the exclusion of extreme markup ratios, alternative estimations of production function, etc.

In the second part of the empirical analysis, we investigate whether the markup effect of agglomeration may differ across industries and firms, which also allows us to disentangle the two underlying effects (i.e., the beneficial spillover effect versus the negative competition effect).

First, despite more than three decades of economic reform in China, the state still plays an important role in the economy. State-owned enterprises, protected by the relevant governments, enjoy various favorable government procurement policies and are shielded from local competition. As a result, the markup effect of agglomeration is expected to be less negative or even statistically insignificant for state-owned enterprises than for non-state-owned enterprises. Indeed, we find that the markup effect of agglomeration is statistically insignificant for state-owned enterprises, but it remains negative and statistically significant for non-state-owned enterprises.

Second, in 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 markup effect of agglomeration is positive and statistically significant for industries with goods traded at exchanges, but it remains negative and statistically 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 offers a brief discussion of the theoretical studies regarding the markup effect of agglomeration. Section 3 discusses the estimation strategy for identifying the markup effect of agglomeration. Section 4 describes the data and variables, including the estimation method of firm markup ratio and the measure of industry agglomeration. Empirical results regarding the effect of agglomeration on firm markup are reported in Section 5. The paper concludes with Section 6.

2 A Brief Discussion of Theories of Agglomeration and Firm Markup

Current economic theories on geographic location of economic activities across countries and regions (i.e., international and urban economics) offer very limited analysis of how agglomeration affects firm markup. Following the insights gained from industry organization research (see, for example, Salop, 1979; Syverson, 2007) that a dense market intensifies competition and reduces firm markups, researchers in international and urban economics have examined the effect of agglomeration on product prices, but they generally assume that firm productivity (and hence marginal costs of production) is constant. As a result, the effect of agglomeration on firm markup comes mostly from the price channel. In this section, we briefly discuss two leading models of this literature, and explore how agglomeration may affect 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 production across countries/regions and their trade, and develops it into the most influential model in international and urban economics. Melitz (2003) subsequently modifies Krugman model by incorporating firm heterogeneity in productivity. In Krugman model, the preference of the representative consumer is characterized by the constant elasticity of substitution utility function, and market competition is modeled as monopolistic competition with increasing returns to scale. As a result, each firm produces a unique variety of product and charges a constant markup. In this model, the number of producers (agglomeration) is determined by the size of the market. Nonetheless, each producer still enjoys the same markup ratio irrespective of the size of the market. Furthermore, this result remains intact, even if we incorporate into Krugman/Melize model the possibility that agglomeration increases firm productivity and lowers down the marginal costs of production. In Krugman/Melitz model with constant firm markup, any effect of agglomeration on marginal costs of production is canceled out by the corresponding effect of agglomeration on prices.

Ottaviano, Tabuchi and Thisse (2002) offer an alternative model to redress the unsatisfactory feature of constant markup in Krugman/Melize model. In their model, the preference of the representative consumer is modeled as a quadratic utility function. Given the assumption of constant firm productivity, the model generates the result that agglomeration lowers down firm price and, consequently, firm markup. Melitz and Ottaviano (2008) introduce firm heterogeneity in productivity into the model of Ottaviano, Tabuchi and Thisse (2002). However, as productivity is assumed to be exogenous to agglomeration, Melitz and Ottaviano (2008) still find that firm markup is unambiguously lower in more agglomerated regions. Most recently, Zhao (2011) builds upon Melitz and Ottaviano's (2008) framework by assuming firm productivity to be a monotonic and positive function of agglomeration. While agglomeration increases firm productivity (and then lowers down marginal costs of production) on the one hand and lowers down firm price on the other, there is no general and unambiguous prediction about the impact of agglomeration on markup.[6]

The lack of definitive theoretical predictions on the markup effect of agglomeration points

[6] The numerical results in Zhao (2011) suggest agglomeration is more likely to have a negative effect on firm markup.

to the need for conducting rigorous empirical studies on this issue, which is the main objective of this study.

3 Estimation Strategy

3.1 Specification

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, $Y^j_{i,t}(EG^j_t = A)$ and $Y^j_{i,t}(EG^j_t = B)$, where $Y^j_{i,t}$ represents the outcome variables such as the logarithm of price, the logarithm of marginal cost, and the logarithm of markup; EG^j_t 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

$$\gamma^{\chi} = E\left[Y^j_{i,t}(EG^j_t = A) - Y^j_{i,t}(EG^j_t = B)\right], \tag{1}$$

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.

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

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 (1) unfeasible. To retrieve the effect of agglomeration on firm markup (i.e., γ^{μ}), we use a sample of firms that changed their industry affiliations during our sample period to conduct a DD analysis.

Specifically, assume that a treatment firm i changed its industry 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 similar firm characteristics) that did not change its industry affiliation. The indicator of the treatment status $Treatment_i$ is denoted as

$$Treatment_i = \begin{cases} 1 & \text{if firm } i \text{ is in the treatment group} \\ 0 & \text{if firm } i \text{ is in the control group} \end{cases}. \tag{2}$$

Our DD estimator is

$$\begin{aligned} \gamma^{\mu}_{\mathbf{DD}} &= E\left[Y^j_{i,t_{i0}}(EG^j_{t_{i0}} = A) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 1\right] \\ &\quad - E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 0\right] \\ &= \gamma^{\mu} + IA1 + IA2, \end{aligned} \tag{3}$$

where

$$IA1 = E\left[Y^{j}_{i,t_{i0}}(EG^{j}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B)\middle| Treatment_i = 1\right] \tag{4}$$

$$\begin{aligned} IA2 &= E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 1\right] \\ &\quad -E\left[Y^{j'}_{i,t_{i0}}(EG^{j'}_{t_{i0}} = B) - Y^{j'}_{i,t_{i0}-1}(EG^{j'}_{t_{i0}-1} = C)\middle| Treatment_i = 0\right] \end{aligned} \tag{5}$$

There are two identification assumptions in our DD estimation. The first identification assumption, (4), reflects the potential effect due to the change of industry affiliation but without the change in the degree of agglomeration, such as industry regulations, competition degree, production technology, etc. The second identification assumption, (5), requires the treatment group to have followed the trend of the control group in markup changes, if they had not changed industry affiliation but experienced a change in the degree of agglomeration. As long as our identification assumptions are satisfied (i.e., $IA1 = 0$ and $IA2 = 0$), our DD estimator recovers the true effect of agglomeration on firm markup, i.e., $\gamma^{\mu}_{\mathbf{DD}} = \gamma^{\mu}$.

In regression form, the DD estimation takes the following specification

$$\begin{aligned} \ln \mu^{j}_{it} &= \beta \cdot Treatment_i \times Post_{it} + \gamma \cdot EG^{j}_{t} \times Post_{it} \\ &\quad +\eta_i + \lambda_t + \varepsilon^{j}_{it}, \end{aligned} \tag{6}$$

where λ_t is the time dummy, capturing 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

$$Post_{it} = \begin{cases} 1 & \forall t \geq t_{i0} \\ 0 & \text{otherwise} \end{cases}; \tag{7}$$

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 (4), that is, any effects due to the change in the industry affiliation, beyond the change in the degree of agglomeration; for example, industry technology upgrading, composition change, etc. Hence, whether the estimated coefficient $\tilde{\gamma}$ from equation (6) captures the true effect γ^{μ} hinges upon the satisfaction of the identification assumption (5), i.e., $\tilde{\gamma} = \gamma^{\mu} + IA2$ and $IA2 = 0 \Rightarrow \tilde{\gamma} = \gamma^{\mu}$.

3.2 Strategic Change of industry Affiliation

One potential challenge to our DD estimation is that firms may strategically choose whether or not to change their industry affiliations; in other words, the identification assumption (5) may not hold. Hence, it is important to understand firms' industry switching decision to isolate the effect of agglomeration on firm markups. To this end, we use a simple model to identify the potential determinants of industry switching.

Consider two firms, A and B, in industry j' at period t_0 contemplating whether or not to switch to industry j at next period $t_0 + 1$, the scenario matched to our empirical setting. Without loss of generality, assume that firm A makes the switching but firm B does not; thus, firm A is in our treatment group while firm B is in our control group.

Given this setup, by revealed preference, we have

$$\pi^{A}_{j,t_0+1} > \pi^{A}_{j',t_0+1}, \pi^{B}_{j,t_0+1} < \pi^{B}_{j',t_0+1}, \tag{8}$$

where π represents the net profit (inclusive of the switching cost). Combining these two equations, we have

$$\pi^{A}_{j,t_0+1} - \pi^{B}_{j,t_0+1} > \pi^{A}_{j',t_0+1} - \pi^{B}_{j',t_0+1}. \tag{9}$$

The differencing (of profits between firm A and firm B in the same industry at the same period) conditions out the effects of any industry-wide and national-wide factors, and hence the remaining profit difference is to be explained mostly by firm-specific characteristics.

The right-hand side of equation (9) represents the difference in future profits between firm A and firm B if they both chose to stay in industry j'. As the future profits have not yet been realized at the time of decision, firms may estimate their future profits based on the information available at the current period, particularly current financial performance. Specifically, we use two variables to capture a firm's current financial performance: net profit (both single and squared terms), and firm size (measured by the logarithm of sales).

Meanwhile, the left-hand side of equation (9) is the difference in future profits between firm A and firm B if they both switched to industry j. In estimating their future profits in the new industry, firms need to consider the assets that they could carry forward to the new industry. Specifically, we consider four variables to capture such inter-industry leverage capability: intangible assets ratio, debt-equity ratio, firm productivity (measured by labour productivity) and experience (proxied by firm age).

To investigate the importance of the aforementioned potential determinants for industry switching, we conduct Probit regressions with the outcome variable being a dummy variable indicating whether a firm changed its industry affiliation during our sample period. Aside from the above determinants, we also check whether firm ownership type (e.g., state-owned, privately-owned, and foreign-owned) is associated with the decision of industry switching. Finally, we investigate whether firms change their industry affiliations based on their current markups.

The regression results are reported in Appendix Table A1. It is found that firms with mediocre profits are more likely to switch industries. Meanwhile, firms with longer experience and higher debt-equity ratio are less likely to change industries. Moreover, relative to privately-owned firms, state-owned firms are less likely but foreign-owned firms are more likely to change industry affiliations.

Finally, there is no evidence suggesting any role of firms' current markups in their industry-switching decision, which subsequently determines the degree of agglomeration. This result is assuring, as it alleviates the concern of reverse causality in this study about the effect of agglomeration on firm markup. In Appendix Table A2, we also report the frequency of firms switching to higher agglomerated industries (47.29%), and the frequency of firms switching to lower agglomerated industries (52.71%). Clearly there is no dominant trend for firms to move into either lower or higher agglomerated industries.

In summary, these results suggest that firms do strategically choose whether or not to change their industry affiliations based on some firm-specific characteristics such as net profits, debt-equity ratio, ownership type, and firm age. In view of this potential violation of our DD identifying assumption (5), we discuss in the next sub-section our remedial strategy and other robustness checks.

3.3 Augmented Specification and Checks

To address the concern that our treatment and control groups might not be comparable due to the strategic change of industry affiliations by treatment firms, we augment our DD analysis with a non-parametric propensity score matching (PSM) method, which is a highly effective method for improving the accuracy of evaluation studies (see, for example, Blundell and Costa Dias, 2000). Specifically, based on the key variables found important for influencing firms' decision to change industry affiliation (i.e., Appendix Table A1), such as firm age, firm productivity, ownership type, net profits (single and squared terms) and debt-equity ratio, we first estimate the propensity score for each firm of the sample to change its industry affiliation. Next, based on the estimated propensity score, we use the nearest neighbor matching with no replacement to construct a control group for our treatment group.[7]

While the DD-PSM estimation allows us to control for some observed determinants of industry switching, there could remain some unobserved determinants compromising the comparability of our treatment and control groups. We further address the comparability issue by including some time-varying firm characteristics and firm-specific linear time trends, the latter of which effectively control for all potential industry switching determinants that affect firm markups in a specification of linear trends.

Finally, to further check our identifying assumption (5), we conduct one more test, a check on whether the identifying assumption (5) is satisfied for several years before the treatment happened. This test also helps us address a potential concern that actual changes in business may precede formal changes in industry affiliations, which could pose complications to our identification strategy.

4 Data and Variables

4.1 Data

The data for this study come from the Annual Survey of Manufacturing Firms conducted by the National Bureau of Statistics of China over the period 1998–2005 period. It is the most comprehensive firm-level data set about China's manufacturing industries. 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

[7]Results remain robust to other matching methods, such as the nearest neighbor matching with replacement, kernel matching, and caliper matching.

29 two-digit or 171 three-digit manufacturing industries, and across 31 provinces,[8] 344 cities, and 2,829 counties. Deleting observations with missing information for key variables (such as output and inputs that are needed for firm markup estimation), we end up with a final regression sample of 210,196.

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 DD analysis uses the change of industry affiliation at the three-digit industry level by firms over the sample period. To relieve the concern of misreporting industry affiliation, we restrict the selection to permanent changers, that is, we exclude those firms that changed industry affiliation many times in the sample period. A total of 28,450 firms changed their three-digit industry affiliations during the sample period, and they comprise our treatment group. As a further check, we repeat the analysis for changes defined at the two-digit industry level, for which misreporting is expected to be much less likely.[9]

4.2 Firm Markup

To recover firm-level markup ratio, 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[10]

$$Q_{it} = F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right), \tag{10}$$

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.

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

$$\min_{\{L_{it}, K_{it}, M_{it}\}} w_{it}L_{it} + r_{it}K_{it} + p_{it}^{m}M_{it} \tag{11}$$

$$s.t.\ F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right) \geq Q_{it},$$

[8]Province here is referred to province-level administrative unit in China. Specifically, there are 22 provinces, 4 municipalities directly under the supervision of the central government, and 5 minority autonomous regions.

[9]A total of 17,764 firms changed their two-digit industry affiliations during the sample period.

[10]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.

where w_{it}, r_{it}, and p^m_{it} 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 (11) can be written as

$$\begin{aligned}\mathcal{L}\left(L_{it}, K_{it}, M_{it}, \lambda_{it}, \eta_{it}\right) &= w_{it}L_{it} + r_{it}K_{it} + p^m_{it}M_{it} \\ &\quad +\lambda_{it}\left[Q_{it} - F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right)\right]. \end{aligned} \tag{12}$$

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

$$\frac{\partial \mathcal{L}}{\partial M_{it}} = p^m_{it} - \lambda_{it}\frac{\partial F_{it}}{\partial M_{it}} = 0. \tag{13}$$

Re-arranging equation (13) and multiplying both sides by $\frac{M_{it}}{Q_{it}}$ yield

$$\begin{aligned}\frac{\partial F_{it}}{\partial M_{it}}\frac{M_{it}}{Q_{it}} &= \frac{1}{\lambda_{it}}\frac{p^m_{it}M_{it}}{Q_{it}} \\ &= \frac{P_{it}}{\lambda_{it}}\frac{p^m_{it}M_{it}}{P_{it}Q_{it}}, \end{aligned} \tag{14}$$

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 (14) leads to the following estimation expression of firm markup[11]

$$\mu_{it} = \theta^m_{it}\left(\alpha^m_{it}\right)^{-1}, \tag{15}$$

where $\theta^m_{it} \equiv \frac{\partial F_{it}}{\partial M_{it}}\frac{M_{it}}{Q_{it}}$ is the output elasticity of intermediate materials and $\alpha^m_{it} \equiv \frac{p^m_{it}M_{it}}{P_{it}Q_{it}}$ 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^m_{it} can be readily calculated. However, the output elasticity of intermediate materials, θ^m_{it}, needs to be obtained through the estimation of the production function (10). 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.[12]

[11] Note that this expression holds under any form of market competition and demand function. Specifically, De Locker and Warzynski (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.

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

The production function to be estimated is expressed as

$$
\begin{aligned}
q_{it} &= \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\
&\quad + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} \\
&\quad + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}, \qquad (16)
\end{aligned}
$$

where the lowercase letters represent the logarithm of the uppercase letters; ω_{it} is firm-specific productivity; and ε_{it} is an i.i.d. error term. In the Appendix, we lay out the details of the procedure in estimating the production function.

We estimate the translog production function (16) separately for each two-digit industry. Once $\hat{\boldsymbol{\beta}} = \left(\hat{\beta}_l, \hat{\beta}_k, \hat{\beta}_m, \hat{\beta}_{ll}, \hat{\beta}_{kk}, \hat{\beta}_{mm}, \hat{\beta}_{lk}, \hat{\beta}_{km}, \hat{\beta}_{lm}, \hat{\beta}_{lkm}\right)$ is obtained, we can readily calculate firm markup using equation (15), i.e.,

$$\hat{\mu}_{it} = \hat{\theta}_{it}^m \left(\hat{\alpha}_{it}^m\right)^{-1}, \qquad (17)$$

$\hat{\theta}_{it}^m = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{it} + \hat{\beta}_{lm} l_{it} + \hat{\beta}_{km} k_{it} + \hat{\beta}_{lmk} l_{it} k_{it}$ and $\hat{\alpha}_{it}^m = p_{it}^m M_{it} / \left(S_{it}/exp\left(\hat{\varepsilon}_{it}\right)\right)$ where S_{it} is the total revenue.

Several caveats are worth noting up-front. 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 using equation (17) 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.

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) and De Loecker (2011) 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.

4.3 Agglomeration

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 employment 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 industry agglomeration beyond the level implied by the industry 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.

4.4 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 (1.577), non-ferrous metal smelting and rolling processing (1.419), and medical and pharmaceutical products (1.373). Industries with the lowest average markup are stationery, educational and sports goods (0.95), and electronics and telecommunications (0.99), 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 Empirical Findings

5.1 Main Results

The baseline DD-PSM estimation results are reported in Column 1 of Table 2. It is found that our regressor of interest $EG_t^j \times Post_{it}$ has a negative and highly significant estimated coefficient, i.e., $\gamma^{\mu}_{\mathbf{DD-PSM}} = -0.122$. This result implies that the increase in the degree of agglomeration reduces firm markups, which is consistent with the pattern shown in 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 5.7%. Meanwhile, the estimated coefficient of $Treatment_i \times Post_{it}$ is also statistically significant, indicating that, conditional on the degree of agglomeration, the change in industry affiliation has some additional effects on firm markups.

[Insert Table 2]

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 $\gamma^{\mu}_{\mathbf{DD-PSM}}$. Hence, the estimated coefficient $\gamma^{\mu}_{\mathbf{DD-PSM}}$ 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 markups. 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 relatively low stage of economic development on the one hand and local protectionism on the other, both of which limit the degree of inter-regional competition. In other words, market competition comes mostly from local competitors. As a result, the competition effect brought by industry 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.

5.2 Checks on the Identification Assumption of the DID Estimation

In this sub-section, we report a battery of sensitivity checks on the identification assumption (5).

Firm-specific time trend. One concern is that firms in the treatment and control group may follow different time trends over the whole sample period, which may then confound our findings. To address this concern, we include firm-specific time trends in the DD-PSM estimation. The regression results are reported in Column 2 of Table 2. Clearly, our main finding on the negative markup effect of agglomeration 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 (5) is that the inclusion of additional controls in the estimation should not significantly change either the significance or the magnitude of our estimator as treatment and control groups are balanced. Hence, we repeat our DD-PSM analysis with the addition of several firm characteristics such as firm size (measured by the logarithm of total output) and exporter status. The regression results are reported in Column 3 of Table 2. It is found that our regressor of interest, $EG^j_t \times Post_{it}$, still has a negative and statistically significant estimated coefficient, with its size of magnitude barely changing at all.

Pre-treatment differential time trends. One robustness check on the validity of our estimation is to examine whether the identification assumption (5) holds in the pre-treatment period. The regression results are presented in Column 4 of Table 2. It is clear that we cannot reject the hypothesis that up to three years before the treatment, our treatment and control groups behave similarly, lending support to our identification assumption (5) on the one hand and ruling out the concern that the actual changes in business may precede the formal changes in industry affiliations on the other hand. Meanwhile, our main finding on the negative markup effect of agglomeration remains robust.

5.3 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 post-treatment periods in our DD-PSM analysis raises the concern that the DID estimator might be contaminated by the variations of agglomeration and/or markup due to events that happened after the change in industry affiliation and later in the post-treatment periods. To alleviate this concern, we restrict the post-treatment period to one year after the change in industry affiliation. Regression results are reported in Column 3 of Table 3. It is found that agglomeration still has a negative and statistically significant effect on markup, with the magnitude of the effect growing even stronger. This result implies that our DD-PSM estimator identified in Table 2 is not caused by events occurring after the change in industry 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 level. One possible concern is that firms may misreport their industry affiliations, which would invalidate our identification. Thus far, we define treatment group as firms that changed their industry affiliations at the three-digit industry level over the sample period. As a robustness check, we define the treatment group as firms that changed their industry affiliations at the two-digit industry level, for which misreporting is less likely than at the three-digit industry level. This robustness check also helps address another concern that, if changes in industry affiliations are measured at disaggregated level (say, three-digit industry level), we might capture some ongoing firm diversification into related businesses, and that firms only report such diversification when relative magnitude of the related businesses becomes significant enough. As shown in Column

5 of Table 3, we still find a negative and statistically significant effect of agglomeration on firm markup, alleviating the concern that our results could be compromised by misreporting on industry affiliations or closely-related business diversification.

Control for omitted price bias in the estimation of production function. As our data do not contain 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 DD-PSM 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) and De Loecker (2011) 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 the degree of agglomeration affects our estimation of production function. As a robustness check, we explicitly incorporate the role of agglomeration into our estimation of production function. The DD-PSM estimation results are reported in Column 7 of Table 3. Again, our main findings on the negative markup effect of agglomeration remain robust to the control for the role of agglomeration in the estimation of production function.

5.4 Heterogeneous Responses

Our results thus far demonstrate a negative impact of agglomeration on firm markup, implying that, on the whole, the competition effect of agglomeration dominates the spillover effect of agglomeration in China. In this sub-section, we look at some 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 more than 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, whereas non-state-owned enterprises face discrimination and unfair treatment (Li, 2001). And, as a source of fiscal revenue and employment, state-owned enterprises are strongly protected by local governments, especially in bidding for government procurement contracts, and, hence, shielded from local competition. As a result, it is expected that the competition effect brought by industry 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. Indeed, 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]

Homogenous goods versus others. The competition effect brought by industry agglomeration largely stems from the enhanced opportunity for consumers to search for competitive prices. If the prices of the relevant goods are publicly available, industry agglomeration 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 3-5 of Table 4. Consistent with the above argument, we find a positive albeit statistically insignificant 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 using the data set of China's manufacturing firms over the 1998-2005 period. To identify the causal impact of agglomeration on firm markup, we use a scenario in which some firms change their industry affiliations as a quasi-experiment. Our DD-PSM 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 identification assumption and other estimation issues. Furthermore, we find that the impacts of agglomeration on firm markup vary across different industries and 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 production function (10) in the translog form (following De Loecker and Warzynski, 2012)

$$\begin{aligned} q_{it} &= \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ &\quad + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} \\ &\quad + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}, \end{aligned} \tag{18}$$

where the lower case letters represent the logarithm of the upper case letters; and ε_{it} is an i.i.d. error term. $\boldsymbol{\beta}$= $(\beta_l, \beta_k, \beta_m, \beta_{ll}, \beta_{kk}, \beta_{mm}, \beta_{lk}, \beta_{km}, \beta_{lm}, \beta_{lkm})$ is the vector of production function coefficients.

To proxy ω_{it}, Levinsohn and Petrin (2003) assume that

$$m_{it} = m_t\left(k_{it}, \omega_{it}, ex_{it}\right),$$

where ex_{it} denotes the exporter status (i.e., taking value 1 if exporters and 0 otherwise). Given the monotonicity of $m_t\left(.\right)$, we can have

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

In the first stage, we estimate the following equation

$$q_{it} = \phi_{it} + \varepsilon_{it},$$

where

$$\begin{aligned} \phi_{it} &= \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ &\quad + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + h_t\left(m_{it}, k_{it}, ex_{it}\right), \end{aligned}$$

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 $\boldsymbol{\beta}$ in the second stage, we model that firm productivity follows a first-order Markov movement, i.e.,

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

where ξ_{it} is an idiosyncratic shock.

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

$$\omega_{it}\left(\boldsymbol{\beta}\right) = \hat{\phi}_{it} - \left(\begin{array}{c} \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} \end{array} \right).$$

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

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 correlacted with $\xi_{it}\left(\boldsymbol{\beta}\right)$. Meanwhile, 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

$$E\left(\xi_{it}\left(\boldsymbol{\beta}\right)\mathbf{Y}_{it}'\right)=0,$$

where $\mathbf{Y}_{it}=\{l_{it-1},l_{it-1}^2,m_{it-1},m_{it-1}^2,k_{it},k_{it}^2,l_{it-1}m_{it-1},l_{it-1}k_{it},m_{it-1}k_{it},l_{it-1}m_{it-1}k_{it}\}$.

Under the translog output production function, the output elasticity for material is given by $\hat{\theta}_{it}^m=\hat{\beta}_m+2\hat{\beta}_{mm}m_{it}+\hat{\beta}_{lm}l_{it}+\hat{\beta}_{km}k_{it}+\hat{\beta}_{lmk}l_{it}k_{it}$. And the firm-level markup can be calculated based on Equation (15), i.e.,

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

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

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

$$\omega_{it}=g_t\left(\omega_{it-1},agglomeration_{jt-1}\right)+\xi_{it}, \tag{19}$$

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

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

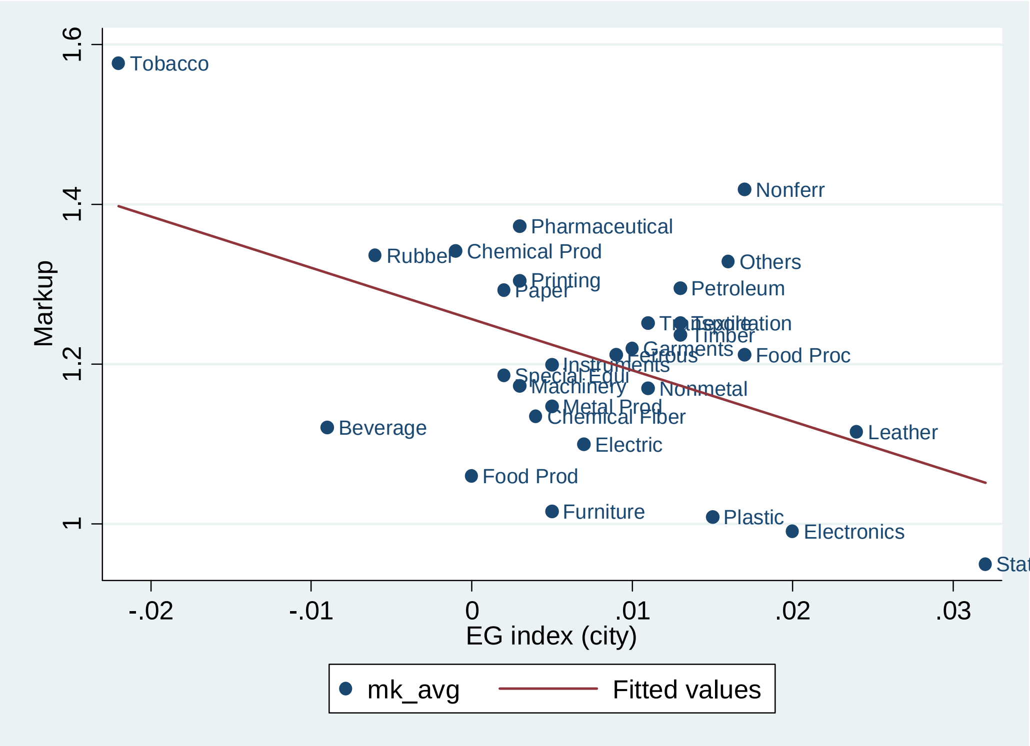

Table1: Markup ratios and EG indices for China's two-digit manufacturing industries

Industry	Markup	EG index		
		Province	City	County
Food Processing	1.212	0.061	0.017	0.006
Food Production	1.060	0.016	0.000	-0.004
Beverage Production	1.121	0.013	-0.009	-0.013
Tobacco Processing	1.577	0.032	-0.022	-0.025
Textiles	1.251	0.048	0.013	0.005
Garments & Other Fiber Products	1.220	0.035	0.010	0.005
Leather, Furs, Down & Related Products	1.115	0.081	0.024	0.008
Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products	1.237	0.030	0.013	0.004
Furniture Manufacturing	1.015	0.036	0.005	0.003
Papermaking & Paper Products	1.293	0.018	0.002	-0.001
Printing & Reproduction of Recording Media	1.305	0.010	0.003	0.000
Stationery, Educational & Sports Goods	0.950	0.139	0.032	0.017
Petroleum Processing, Coking Products, Gas Production & Supply	1.295	0.127	0.013	0.001
Chemical Raw Materials & Chemical Products	1.342	0.015	-0.001	-0.004
Medical & Pharmaceutical Products	1.373	0.016	0.003	-0.002
Chemical Fibers Manufacturing	1.135	0.028	0.004	-0.003
Rubber Products	1.336	0.004	-0.006	-0.011
Plastic Products	1.008	0.054	0.015	0.007
Non-metal Mineral Products	1.170	0.027	0.011	0.003
Ferrous Metal Smelting & Rolling Processing	1.212	0.059	0.009	0.002
Non-ferrous Metal Smelting & Rolling Processing	1.419	0.043	0.017	0.009
Metal Products	1.147	0.028	0.005	0.001
General Machinery Manufacturing	1.173	0.022	0.003	0.000
Special Equipment Manufacturing	1.186	0.021	0.002	-0.002
Transportation Equipment Manufacturing	1.251	0.029	0.011	-0.004
Electric Equipment & Machinery	1.099	0.029	0.007	0.004
Electronics & Telecommunications	0.990	0.083	0.020	0.003
Instruments, Meters, Cultural & Official Machinery	1.199	0.039	0.005	-0.005
Other Manufacturing	1.329	0.043	0.016	0.005

Note: Firm-level markup ratios are estimated using De Loecker and Warzynski (2012)'s method. Average markup is calculated for each two-digit industry over 1998-2005. Agglomeration is calculated using EG index (Ellison and Glaeser, 1997) at three geographic scopes (province, city, and county).

Table 2: Main results

	Pair time trend included	Firm time trend included	Additional controls included	Pre-treatment effects
	1	2	3	4
Treatment*Post	0.002**	0.002	0.002	0.004
	(0.001)	(0.001)	(0.001)	(0.003)
EG*Post	-0.122***	-0.083***	-0.077***	-0.077***
	(0.020)	(0.023)	(0.019)	(0.019)
Treatment*Pre(-1)				0.002
				(0.002)
Treatment*Pre(-2)				0.001
				(0.002)
Treatment*Pre(-3)				-0.001
				(0.001)
Firm size (output)			-0.071***	-0.071***
			(0.001)	(0.001)
Export status			-0.000	-0.000
			(0.001)	(0.001)
Firm dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Matching-pair time trend	Yes	No	No	Yes
Firm time trend	No	Yes	Yes	Yes
Obs. #	210,063	210,063	210,063	210,063

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	0.002*	0.001	0.005*	0.002*	0.002	0.005***	0.016***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
EG*Post	-0.025**	-0.045**	-0.161***	-0.055***	-0.076***	-0.049**	-0.059**
	(0.012)	(0.020)	(0.046)	(0.018)	(0.019)	(0.022)	(0.026)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. #	210,063	210,063	88,553	206,051	210,063	231,424	230,219

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

Table 4: Heterogeneous responses

	Ownership type		Product price informativeness		
	SOEs	Non-SOEs	Homogeneous	Reference	Differentiated
	1	2	3	4	5
Treatment*post	-0.004	0.002*	-0.007	0.006**	0.002
	(0.004)	(0.001)	(0.004)	(0.002)	(0.001)
EG*post	-0.016	-0.084***	0.142	-0.125***	-0.069***
	(0.058)	(0.020)	(0.123)	(0.048)	(0.021)
Additional controls	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes
Firm time trend	Yes	Yes	Yes	Yes	Yes
Obs. #	19,392	190,671	11,595	51,710	146,758

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

Appendix Table A1, Determinants for change of industry affiliation

D.V: (dummy=1, if a firm changed its industry; 0 otherwise)	Probit model			
	(1)	(2)	(3)	(4)
Profits	0.026***	0.018***	0.020***	0.019***
	(0.007)	(0.006)	(0.006)	(0.006)
Profits square	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (sales)	0.016**	0.003	-0.008	-0.008
	(0.007)	(0.010)	(0.010)	(0.011)
Intangibility asset ratio		0.020	0.019	0.007
		(0.025)	(0.025)	(0.029)
Labor productivity		0.024**	0.015	0.017
		(0.011)	(0.012)	(0.012)
Firm age		-0.062***	-0.038***	-0.038***
		(0.009)	(0.009)	(0.009)
Debt equity ratio		-0.121***	-0.103***	-0.099***
		(0.021)	(0.020)	(0.020)
State-owned enterprises			-0.078***	-0.075***
			(0.023)	(0.023)
Foreign-invested enterprises			0.164***	0.161***
			(0.023)	(0.023)
Markup				-0.008
				(0.062)
Constant	-1.809***	-1.599***	-1.496***	-1.566***
	(0.081)	(0.081)	(0.086)	(0.137)
Observations	103,015	99,196	99,196	97,770

Appendix Table A2: Frequency of firms switching to lower and higher agglomerated industries

Switching direction	Freq.	Percent
To lower agglomerated	14,997	52.71
To higher agglomerated	13,453	47.29
Total	28,450	100.00

Note: agglomeration is measured for each 3-digit industry at city level. Comparison of agglomeration degrees (of a firm's prior- and post-switching industries) is made using data of the year prior to the time when the switching took place.