# Growth Policy, Agglomeration and (the Lack of) Competition *

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*Industrial clusters are promoted by policy and generally viewed as good for growth and development, but both clusters and policies may also enable non-competitive behavior. This paper studies the presence of non-competitive pricing in geographic industrial clusters. We develop, validate, and apply a novel screen for collusive behavior. We derive the screen from the solution to a partial cartel of perfectly colluding firms in an industry. Outside of a cartel, a firm's markup depends on its market share, but in the cartel, markups across firms converge and depend instead on the total market share of the cartel. Empirically, we validate the screen using plants with common owners, and then screen for collusion using data from Chinese manufacturing firms (1999-2009). We find strong evidence for non-competitive pricing within a subset of industrial clusters, and we find the level of non-competitive pricing is about four times higher in Chinese special economic zones than outside those zones.*

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Both rich and poor countries generally regard industrial clusters as good for productivity, growth, and development. The conventional economic wisdom dates back to Marshall (1890)'s causes of agglomeration. Marshall's first two causes, resource and demand concentration, cause agglomeration to occur naturally without any need for policy intervention, but or local externalities. His third cause, positive external spillovers on nearby firms, could lead to too little agglomeration, and this is used to justify cluster-fostering industrial policies. Many studies find support for Marshall's hypotheses.[1] Influential work, including Marshall, has also viewed industrial clusters as productivity-enhancing through pro-competitive pressures they may foster (e.g., Porter (1990)). Therefore, perhaps we should not be surprised that both advanced and developing economies adopt policies that promote clusters.[2]

Industrial clusters may indeed be cost reducing and productivity enhancing, but there is an even older concern – dating back to at least Adam Smith – that gathering competitors in the same locale could instead lead to non-competitive behavior.[3] It may seem paradoxical that multiple producers in the same area would lead to noncompetitive behavior rather than increased competition, but close proximity facilitates easy communication and observation, which are theoretically (e.g., Green and Porter (1984), in the case of tacit collusion) and empirically (see Marshall and Marx (2012) and Genesove and Mullin (1998), for example, which document the behavior of actual cartels) associated with collusive behavior. They may also foster the close relationships needed to support cooperative agreements.

We know of specific examples of collusion in industrial clusters. Historically,

[1]See, for example, Greenstone, Hornbeck and Moretti (2010), Ellison, Glaeser and Kerr (2010), and Guiso and Schivardi (2007), for recent evidence. In contrast, Cabral, Wang and Xu (2015) finds little evidence of agglomeration economies in Detroit's Motor City, however.

[2]There are currently an estimated 1400 global initiatives fostering industrial clusters.

[3]Smith (1776)'s famous quote: "People of the same trade seldom meet together, even for merriment and diversion, but the conversation ends in a conspiracy against the public, or in some contrivance to raise prices. It is impossible indeed to prevent such meetings, by any law which either could be executed, or would be consistent with liberty and justice. But though the law cannot hinder people of the same trade from sometimes assembling together, it ought to do nothing to facilitate such assemblies; much less to render them necessary. (Book I, Chapter X)."

the most famous industrial clusters in the United States have all been accused of explicitly collusive behavior.[4] Our own interviews with firm owners and administrators of industrial clusters in China uncovered explicit cooperation on pricing. For example, the leader of an industry association acknowledged, “We do not allow internal competition on pricing. If a firm tried price cutting, we would kick them out.” [5] Such “smoking guns” for particular cases exist. What we lack is a sense of the overall prevalence of such non-competitive behavior in an economy, and the extent to which it may be linked to development policy.

This paper examines the hypothesis that non-competitive behavior is associated with geographic concentration and cluster policies from a much broader perspective. We define non-competitive behavior as behavior in either firm sales, hiring, or input purchasing that internalizes pecuniary externalities on other firms. We make three major contributions toward this end. First, we derive a novel, intuitive screen for measuring the extent of non-independent behavior among firms competing in the same industry. Firms that are pricing independently consider their own market share but not the market shares of other firms when setting markups. In contrast, firms in a cartel internalize the impact of their pricing on the other cartel firms, so their markups depend on the aggregate market share of the cartel. Second, using panel data on Chinese manufacturing firms, we validate that our screen can identify non-competitive behavior in sales by applying our screen to firms that are affiliates of the same parent company. The screen verifies that these firms are colluding, which we would expect from firms with the same owner. Third, we show evidence of non-competitive behavior at the level of organized industrial clusters in the Chinese economy. Although we find limited levels of non-competitive behavior in the economy overall, it is four times

[4]See Bresnahan (1987) for evidence of Detroit’s Big 3 automakers in the 1950s, and Christie, Harris and Schultz (1994) for Wall Street in the 1990s. The major Hollywood production studios were convicted of anti-competitive agreements in the theaters that they owned in the Paramount anti-trust case of the 1940s. Ongoing litigation alleges non-compete agreements for workers among Silicon Valley firms.

[5]One role of this industry association was to accept and manage large orders that were “too large or difficult for one firm to fill.” The industry association leader allocated orders among its member firms while also maintaining quality.

higher in China's "special economic zones" (SEZs) than outside of them. Furthermore, we find that the levels of non-competitive behavior are also high in a set of industry-geography pairs that pre-identified using the theory.

Our screen is derived from a standard nested constant-elasticity-of-substitution (CES) demand system with a finite number of competing firms and with a higher elasticity of substitution within an industry than across industries. As is well known in this setup and empirically confirmed (e.g., Atkeson and Burstein (2008),Edmond, Midrigan and Xu (2015)), the gross markup that a firm charges is increasing in its own market share. We show that a subset of firms acting as a perfect cartel, and therefore maximizing joint profits, leads to convergence in markups across cartel members, as each member's markup is set based on the total market share of the cartel firms rather than its own firm-specific market share.

Our screen follows directly from the firm's first-order condition in the model. We regress the reciprocal of the firm's markup on the firm's own market share and the total market share of its potential set of fellow cartel members.[6] If firms are acting independently, only the coefficient on own market share should be significant, while under perfect collusion, only the coefficient on the cartel's market share should be significant. The screen is similar in spirit to the standard risk-sharing regression of Townsend (1994), focusing on a cartel of local (colluding) firms rather than a syndicate of local (risk-sharing) households.[7] It has similar strengths, in that it allows for the two extreme cases of independent decision-making and perfect joint maximization. However, it also allows intermediate cases. As in Townsend, we can be somewhat agnostic about the actual details

[6]Throughout the paper we consider several different possibilities for sets of firms that are colluding, such as firms with a common owner, firms in the same geographic region, and firms in the same special economic zone.

[7]An important difference between our context and that of Townsend (1994) is the potential confounding effect of measurement error. Ravallion and Chaudhuri (1997) argue that idiosyncratic measurement error potentially biases the measure of risk-sharing upward when measurement error in the dependent variable is unrelated to that in the independent variable. In our context, measurement error in revenue affects both our measure of market shares and of markups. As discussed in Section II.B, that implies that idiosyncratic measurement error actually biases our measure of collusion *downward*. Hence, idiosyncratic measurement error cannot explain our results.

of how non-competitive behavior occurs. In principle, collusion could be either explicit or tacit, for example, and firm behavior could be Cournot or Bertrand. The screen is also robust along other avenues. Importantly, our theoretical results, and so the validity of the screen, depend only on the constant elasticity demand system. They are therefore robust to arbitrary assumptions on the (differentiable) cost functions and geographical locations of the individual firms. Moreover, we use simulations to show that our screen performs well for plausible levels of firm uncertainty, including correlated demand or cost shocks, and when we relax our strong assumptions on the demand system. Indeed, simulations calibrated to our empirical exercise show only small biases when departures from our assumptions are in the empirically plausible range.

Empirically, we use the screen to assess the possibility of collusion in Chinese industrial clusters and SEZs. SEZs are generally considered to have played a key role in its growth miracle, and we have a high quality panel of firms with a great deal of spatial and industrial variation. The panel structure of the Annual Survey of Chinese Industrial Enterprises (CIE) allows us to estimate markups using the cost-minimization methods of De Loecker and Warzynski (2012) and implement our screen using within-firm variation.

Our screen both identifies non-competitive pricing in simple validation exercises and rejects it in simple placebo tests. Specifically, we test for joint profit maximization among groups of affiliates with the same parent company and in the same industry. Similarly, we test for joint profit maximization among state-owned firms in the same industry. Consistent with the theory, in our validation tests we estimate a highly significant relationship between markups and cartel market share, but an insignificant relationship with own market share. This is exactly what the theory predicts for firms that maximize their joint profits. In our placebo tests, we find no response in markups to industrial cluster market shares and no influence of SEZs on markup behavior among these sets of firms.

In the broader sample of Chinese firms, competitive behavior appears much more prevalent than collusive behavior, but behavior becomes somewhat more collusive as we move to smaller geographic definitions of a cluster. Moreover, we find stronger evidence in subsets of clusters: SEZs and clusters pre-screened as having low initial cross-sectional variation in markups. SEZs have policies targeting firms in specific industries and locations, and give them benefits such as special tax treatment or favorable regulation. [8] They also attempt to foster co-operation through industry associations, trade fairs, and coordinated marketing, but such venues can be used to reduce competition. We find that the intensity of collusion is four times higher for clusters in SEZs than for those not in SEZs. Our results therefore have normative importance for evaluating the desirability of cluster policies in China and elsewhere. Moreover, we apply our pre-screening criteria, focusing on clusters in the lowest three deciles of cross-sectional markup variation, and find that only the cluster market share is a significant predictor of the panel variation in markups. That is, this subsample appears to be dominated by effectively collusive behavior. These clusters are characterized by disproportionately higher concentration industries, have lower export intensities, and contain a greater proportion of private domestic enterprises (as opposed to foreign or state-owned ventures).

Our paper contributes and complements the literatures on both industrial clusters and collusion. We are not the first paper to examine collusion in cooperative industry associations, industrial clusters or agglomerations. The 19th century railroad associations in the U.S., originally formed to cooperate on technical (e.g., track width) and safety standards to link the various rails, soon turned to an explicit cartel designed to manage competition (see, e.g., Chandler (1977)). Colluding clusters in the 20th century have also been studied. Bresnahan (1987) studied collusion of the Big 3 automakers in Detroit, and Christie, Harris and Schultz (1994) examine NASDAQ collusion on Wall Street. More recently, Gan

[8]We use SEZ in the broad sense of the term. See Alder, Shao and Zilibotti (2013) for a summary of SEZs, their history, and their policies.

and Hernandez (2013) shows that hotels near one another effectively collude.

Methodologically, the recent industrial organization literature on collusion has tended toward "smoking gun" analysis: detailed case studies of particular industries, making less stringent assumptions on demand or basing them on deep institutional knowledge of the industry.[9] We complement these papers by developing a screen that can be applied to a wide range of industries. We apply the screen to the entire economy of a developing country that has actively promoted industrial clusters. Thus, our screen can be used to guide broad industrial policy *ex ante*, rather than focusing on a case study that could be useful for prosecuting a specific cartel *ex post* .

The local growth impact of Chinese SEZs has been studied in Alder, Shao and Zilibotti (2013), Wang (2013), and Cheng (2014), and they have been found to have sizable positive effects using panel level data at the local administrative units. Our firm-level evidence of non-competitive behavior suggests that this growth may have important, unintended consequences.[10] Measured value added may be higher among firms in SEZs in part because collusion allowed them to achieve higher markups, which is an important caveat when interpreting the previous results. Finally, we contribute to an emerging literature examining the role of firm competition – markups in particular – on macro development, including Asturias, Garcia-Santana and Ramos (2015), Edmond, Midrigan and Xu (2015), Galle (2016), and Peters (2015).

The rest of this paper is organized as follows. Section I presents the model and derives the key theoretical results. Section II lays out are empirical screen and reviews our empirical application. Section III discusses our data and methods for identifying markups. Section IV discusses the empirical results, while Section V

[9] Einav and Levin (2010) give an excellent review of the rationale for moving away from cross-industry identification. Our screen also relies on within-industry (indeed, within-firm) identification.

[10] While collusion is likely an unintended consequence of agglomeration it is not obvious that the effect is negative. In a second best world, collusion itself may be welfare improving over high levels of competition. See, for example, Galle (2016) or Itskhoki and Moll (2015) for the case where financial frictions are present. In this paper we do not need to take any stand on whether the welfare consequences of collusion are negative or positive.

concludes.

## I. Model

We develop a simple static model of a finite number of differentiated firms that yields relationships between firm markups and market shares under competition and cartel behavior, and we show the robustness of these results to various assumptions. We assume a nested CES demand system of industries and varieties within the industry, which we assume is independent of location. Whereas the structure of demand is critical, we make minimal assumptions on the production side, allowing for a wide variety of determinants of firms costs, such as location choice, arbitrary productivity spillovers, and productivity growth for firms.[11]

### *A. Firm Demand*

A finite number of firms operate in an industry $i$. The demand function of firm $n$ in industry $i$ is:

$$y_{ni} = D_i \left(\frac{p_{ni}}{P_i}\right)^{-\sigma} \left(\frac{P_i}{P}\right)^{-\gamma}, \tag{1}$$

where $p_{ni}$ is the firm's price, and $P_i$ and $P$ are the price indexes for industry $i$ and the economy overall, respectively. Thus, $\sigma > 1$ is the own price elasticity of any variety within industry $i$, while $\gamma > 1$ is the elasticity of industry demand to changes in the relative price index of the industry.[12] Typically, $\sigma > \gamma$, so that products are more substitutable within industries than industries are with one another. The parameters $D_i$ captures the overall demand at the industry level. For exposition, we define units so that demand is symmetric across firms in the same industry, but this is without loss of generality. As each firm in the industry

[11]Our assumption that demand is independent of location implicitly assumes negligible trade costs in output, which is important in allowing for agglomeration based on externalities rather than local demand. Empirically, we will focus on manufactured goods.

[12]We analyze highly disaggregated industries, so the assumption $\gamma > 1$ is natural.

faces symmetric demand, the industry price index within industry $i$ is:

$$P_i = \left( \sum_{m \in \Omega_i} p_{mi}^{1-\sigma} \right)^{1/(1-\sigma)}, \tag{2}$$

where $\Omega_i$ is the set of all firms operating in industry $i$.

As we show in the online appendix, this demand system can be derived as the solution to a household's problem that has nested CES utility.

One can invert the demand function to get the following inverse demand:

$$p_{ni} = P \left( \frac{y_{ni}}{Y_i} \right)^{-1/\sigma} \left( \frac{Y_i}{D_i} \right)^{-1/\gamma}, \tag{3}$$

where:

$$Y_i = \left( \sum_{m \in \Omega_i} y_{mi}^{1-1/\sigma} \right)^{\frac{\sigma}{\sigma-1}}. \tag{4}$$

To establish notation that will be used throughout this paper, we define market shares as:

$$s_{ni} = \frac{p_{ni} y_{ni}}{\sum\limits_{m \in \Omega_i} p_{mi} y_{mi}} = \frac{y_{ni}^{1-1/\sigma}}{\sum\limits_{m \in \Omega_i} y_{mi}^{1-1/\sigma}}, \tag{5}$$

where the second equality follows from substituting in (1) for prices and simplifying.

This demand system implies that the cross-price elasticity is given by a simple expression:

$$\forall m \neq n, \frac{\partial \log(y_{in})}{\partial \log(p_{im})} = (\sigma - \gamma)\, s_{im}. \tag{6}$$

which allows for simple aggregation in the results that follow. Our structure of demand, which implies a this cross-price elasticity restriction and a constant elasticity of demand, allows us to be very general in our specification of firm costs. The cost to firm $n$ of producing $y_{ni}$ units of output is $C(y_{ni}; X_{ni})$, where $X_{ni}$ represents a general vector of characteristics such as capital, technology, firm productivity, location, externalities operating through the production levels of other firms, and any other characteristics that are taken as given by the producer when making production choices. For example, a special case of our model would be one in which an initial stage involves a firm placement game in which each firms' productivity is determined by the placement of each other firm through external spillovers, local input prices, or other channels. Then the results from that first stage determine $X_{ni}$ that firms take as given when production choices are made, which is a special case of our framework.[13]

We now separately consider two extreme cases: firms operating totally independently and firms acting as a perfect cartel. We then consider intermediate cases.

### *B. Firms Operating Independently*

First, we consider the case of all firms operate independently of one another. The static profit maximization problem of a firm $n$ in industry $i$ is:

$$\pi_{ni} = \max_{y_{ni}} p_{ni} y_{ni} - C(y_{ni}; X_{ni}). \tag{7}$$

Using (3), the firm's optimal pricing condition equates marginal revenue with marginal cost:

$$p_{ni} \left( \frac{\sigma - 1}{\sigma} + \left[ \frac{1}{\sigma} - \frac{1}{\gamma} \right] \frac{y_{ni}^{1-1/\sigma}}{\sum_{m \in \Omega_i} y_{mi}^{1-1/\sigma}} \right) = C'(y_{ni}; X_{ni}). \tag{8}$$

[13]However, note that the fact that firms maximize static profits below implicitly limits the way the vector $X_{ni}$ can relate to past production decisions, such as dynamic learning-by-doing, sticky market shares, or dynamic contracts.

Using the definition of market shares, $s_{ni}$, given above, rearranging (8), and defining the firm's gross markup, $\mu_n$, as the ratio of price to marginal cost yields the well-known result:[14]

$$\frac{1}{\mu_{ni}} = \frac{\sigma - 1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma}\right) s_{ni}. \tag{9}$$

When a firm is operating independently, and given values of the elasticity parameters, this equation implies that the only information that is needed to predict a firm's markup is that firm's market share. In particular, while factor prices, productivity, and local externalities captured by $X_{ni}$ would certainly affect quantities, prices, costs, and profits, markups are only affected by $X_{ni}$ through their impact on market shares. For $\sigma > \gamma$, the empirically relevant case, additional sales that accompany lower markups come more from substitution within the industry than from growing the relative size of the industry itself. Firms with larger market shares have more to lose by lowering their prices, so they charge higher markups.

### *C. Cartel*

We contrast the case of independent firms with the opposite extreme: a subset of firms within an industry forms a cartel to maximize the sum of their profits. Within an industry $i$, consider a set $S \subseteq \Omega_i$ of firms that solve the following joint maximization problem:

$$\sum_{m \in S} \pi_{mi} = \max_{\{y_{mi}\}_{m \in S}} \sum_{m \in S} p_{mi} y_{mi} - C(y_{mi}; X_{mi}). \tag{10}$$

[14] See, for example, Edmond, Midrigan and Xu (2015) or Atkeson and Burstein (2008).

Using our definition of market shares again, we can express the first order condition as:

$$\forall n \in S, \quad C'(y_{ni}; X_{ni}) = p_{ni}\frac{\sigma - 1}{\sigma} + p_{ni}\sum_{m\in S}\left(\frac{1}{\sigma} - \frac{1}{\gamma}\right)s_{mi}. \tag{11}$$

Then rearranging (11) gives the relationship between markups and market shares:

$$\frac{1}{\mu_{ni}} = \frac{\sigma - 1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma}\right)\sum_{m\in S} s_{mi}. \tag{12}$$

The markup of a firm within the set $S$ depends only on the total market share of all firms within the group. While the independent firm considered only its own market share, the cartel internalizes the costs to its own members of any one firm selling more goods, and these cost depends on the total market shares of the member firms. In this extreme case of a perfect cartel, the firm's own market share influences its markup only to the extent that it affects the cartel's share.

A number of corollary results follow from equations (9) and (12). First, clearly $\sigma > \gamma > 1$ implies that an independent firm's markup is increasing in its own market share. Second, for a firm in a cartel, the firm's markup is increasing in the total market share of the cartel. That is, the firm's own market share plays no role except to the extent that it affects the cartel market share. Third, cartel members all charge the same markup, since their markup is based on the sum of their market shares. In our empirical work later we interpret this to mean that there is less variation in markups when firms collude than they would have if they operated independently. Fourth, if any member of a cartel were instead operating independently, that firm's markup would be lower and its market share would be higher. Finally, the market shares of any set of colluding firms exhibit more variation than if the same set of firms was operating independently.

We summarize the above characterization in the following proposition.

PROPOSITION 1: *Given $\sigma > \gamma > 1$:*

*1) When operating independently, firm markups are increasing in the firm's own market share.*

*2) When maximizing joint profits, firm markups are increasing in total cartel market share, with the firm's own market share playing no additional role.*

*3) Cartel firm markups are more similar under perfect cartel than independent decisions.*

*4) Firm markups are higher under perfect cartel decisions than independent decisions.*

*5) Firm market shares are less similar under perfect cartel decisions than independent decisions.*

Each of these claims will be addressed in our empirical work that follows. We will use the first two claims to derive our screen in Section II, while the third and fourth claims will be used to pre-identify potential collusive clusters. Finally, we will use the fifth claim as additional testable implication. We have intentionally written Proposition 1 in general language. In the subsection below, we will show that, while the precise formulas vary, these more general claims are robust to several alternative specifications.

### *D. Alternative Models*

We present related results below for the cases of firm-specific price elasticities, Bertrand competition rather than Cournot, an imperfect cartel, and monopsonistic collusion.

#### Firm-specific price elasticities

To allow for markups to vary among competitive firms with the same market share, we allow for a firm-specific elasticity of demand. In particular, suppose that inverse demand takes the form:

$$p_{in} = D_i^{1/\gamma} P y_{in}^{-1/\sigma+\delta_{in}} Y_i^{1/\gamma-1/\sigma}. \tag{13}$$

Here $\delta_{in}$ captures the firm-specific component of demand, and we think of these as deviations from the average elasticity $\sigma$: $\sum_{n\in\Omega_i} \delta_{in} = 0$. Proceeding as before to derive markup equations, the first order conditions for an independent firm imply:

$$\frac{1}{\mu_{ni}} = \delta_{ni} + \frac{\sigma-1}{\sigma} + \left(\frac{1}{\gamma} - \frac{1}{\sigma}\right) s_{ni}, \tag{14}$$

and for a cartel, the analogous equation is:

$$\frac{1}{\mu_{ni}} = \delta_{ni} + \frac{\sigma-1}{\sigma} + \left(\frac{1}{\gamma} - \frac{1}{\sigma}\right) \cdot \sum_{m\in S} s_{mi} \tag{15}$$

Firm markups are again increasing in either the firm or cartel's market share and the magnitude of this relationship is governed by the difference between the within- and across-industry elasticities. In addition, however, the presence of $\delta_{ni}$ in both equations shows the level of markups may be firm-specific, even when market share is arbitrarily small or firms are members of the same cartel. This could explain why firms in the same cartel have differing markups.

### Bertrand competition

Now we consider the case where firms take competitors' prices as given instead of quantities when making production choices. From the demand function (1), we can write the problem of a firm operating independently as:

$$\max_{\{p_{ni}, y_{ni}\}} p_{ni} y_{ni} - C(y_{ni}; X_{ni})$$

$$\text{subject to:} \quad y_{ni} = D_i \left(\frac{p_{ni}}{P_i}\right)^{-\sigma} \left(\frac{P_i}{P}\right)^{-\gamma}.$$

Taking first-order conditions with respect to both choice variables and dividing them yields the following equations, which are analogous to (9) and (12), respectively:

$$\frac{\mu_{in}}{\mu_{in}-1} = \sigma - (\sigma - \gamma) s_{in} \tag{16}$$

and

$$\frac{\mu_{in}}{\mu_{in}-1} = \sigma - (\sigma - \gamma) \sum_{m \in S} s_{im}. \tag{17}$$

Equation (16) corresponds to the case where firms operate independently, and equation (17) to the case where firms are in a perfect cartel. Again, given elasticity parameters we see that firms' market shares (in the case of independent firms) or cartels' market shares (in the case of perfect cartels) are sufficient to solve for the firms' markups. As before, higher markups coincide with higher market shares, and the magnitude of this increasing relationship depends on the gap between the two elasticity parameters.

### Imperfect Cartel

Purely independent pricing and pure cartel represent two extreme cases. Here we consider an imperfect cartel, in which firms place a positive weight $\kappa \in (0,1)$ on other firms' profits relative to its own, so that each firm maximizes:

$$\pi_{in} + \kappa \sum_{m \in S/\{n\}} \pi_{im}.$$

It is easy to show that the markup now depends on both the firm and cartel market shares. For the Cournot case, we have:

$$\frac{1}{\mu_{ni}} = \frac{\sigma - 1}{\sigma} + (1-\kappa)\left(\frac{1}{\sigma} - \frac{1}{\gamma}\right)s_{ni} + \kappa\left(\frac{1}{\sigma} - \frac{1}{\gamma}\right)\sum_{m\in S} s_{mi}. \tag{18}$$

General Demand

Our result is not true for all demand systems, but it is useful to consider the extent to which it may hold for other demand systems, and what are the chief characteristics of demand driving this relationship. To examine this, we start with a very general demand system $p_{in}(y_{in}; y_{im}$. Denoting the inverse price elasticity $\frac{y_{im}\partial p_{in}}{p_{in}\partial y_{im}}$ as $\varepsilon_{nm}$, we can solve the Cournot problem to derive the following general relationship for the perfect cartel:

$$\frac{1}{\mu_{ni}} = 1 - \varepsilon_{nn} - \sum_{m\in S} \varepsilon_{nm}\frac{s_{mi}}{s_{ni}}. \tag{19}$$

In order for this approximate equation (12) above, we need to assume $\varepsilon_{nn} = \varepsilon^*_{1,nn} + \varepsilon^*_{2,nn}s_{ni}$ and $\varepsilon_{nm} = \varepsilon^*_{nm}s_{ni}$, where the starred elasticities are (approximately) constant. That leads to

$$\frac{1}{\mu_{ni}} = \frac{\varepsilon^*_{1,nn} - 1}{\varepsilon^*_{1,nn}} - \varepsilon^*_{2,nn}\left(s_{ni} + \sum_{m\in S}\frac{\varepsilon^*_{nm}}{\varepsilon^*_{2,nn}}s_{mi}\right). \tag{20}$$

In this expression, inverse markups involve a constant and an elasticity weighted sum of own and colluding firm market shares.

Interpreting the above assumption, the inverse own price elasticity has both a component that is independent of market share and a component that increases in market share, while the inverse cross price elasticity is inversely related to market share. The components of these elasticities that are increasing in market share capture the idea that the impact on a price of a percentage output increase of a firm depends positively on the relative size of that firm in the market overall.

The precise summation result depends on the inverse cross-price elasticities being equal to the second component of the inverse own price elasticity.

### Monopsony behavior

Instead of colluding to increase output prices, firms may instead collude to reduce input costs. As a simple case to evaluate this possibility, suppose each firm $n$ in location $j$ uses a single factor to produce its output by a production function $y_{nj} = F(l_{nj}; X_{nj})$. To fix ideas, we refer to this as labor. The aggregate supply of labor $L_j$ depends on the market wage $w_j$, which is common across firms in a given location. For simplicity, we assume the function for the market wage takes the following form:

$$w_j(L_j) = A_j L_j^{\phi}. \tag{21}$$

Firms take the labor demand decisions of other firms (or those outside their own cartel) as given. To isolate the effect of monopsony power, suppose that firms take the price of their output as given. Then the problem of an independent firm $n$ in location $j$ is:

$$\max_{y_{nj}, l_{nj}} p_{nj} y_{nj} - w_j(L_j) l_{nj}$$

$$\text{subject to:} \quad y_{nj} \leq F(l_{nj}; X_{nj})$$

$$L_j = \sum_m l_{mj}.$$

Since there are a finite number of firms purchasing labor, firm optimality implies a markup because firms restrict their purchases of labor to keep wages low. A firm $n$ in location $j$ has labor market share:

$$s_{nj}^L = \frac{l_{nj}}{L_j}. \tag{22}$$

Optimality for the independent firm implies that the markup is given by:

$$\mu_{nj} = 1 + \phi s_{nj}^L \tag{23}$$

and the analog for the cartel imply a result similar to (12):

$$\mu_{nj} = 1 + \phi \sum_{m \in S} s_{mj}^L \tag{24}$$

Three things are important to note. First, the expressions above define marginal cost as the cost of producing an additional unit at market prices. Therefore the markup is:

$$\mu_{nj} = \frac{p_{nj}}{w_j(L_j)/F'(l_{nj}; X_{nj})} \tag{25}$$

Second, the shares in the expressions depend critically on the view of labor markets and the definition of relevant labor supply, $L_j$. If labor is mobile across industries but not across locations, it would be the total local labor force. If labor is specialized by industry but mobile across locations, it would be the total industry labor force. If immobile along both dimensions, it would be the total local industry-specific labor, while if mobile in both dimensions, it would be the economy-wide total labor force. Finally, note that it would be trivial to replace labor with any other input in the analysis.

## II. Empirical Approach

In this section, we present our empirical screen for non-competitive pricing; assess the robustness of the screen on Monte Carlo simulations; and discuss our application to China, including the data and methods of acquiring markups.

### A. Screen for Non-Competitive Pricing

The model of the previous section yielded the result that the markups of competitive firms depend on the within-industry elasticity of demand and their own market share, while the markups of perfectly colluding firms depend on the total market share of the firms in the cartel. This motivates the following single empirical regression equation for inverse markups:

$$\frac{1}{\mu_{nit}} = \theta_t + \alpha_{ni} + \beta_1 s_{nit} + \beta_2 \sum_{m \in S} s_{mit} + \varepsilon_{nit} \tag{26}$$

for firm $n$, a member of (potential) cartel $S$, in industry $i$ at time $t$.

In the case of purely independent pricing, the hypothesis is $\beta_2 = 0$ and $\beta_1 < 0$. The case of a pure cartel, we have the inverted hypothesis of $\beta_2 < 0$ and $\beta_1 = 0$. The relationships in equations (9) and (12) hold deterministically. The error term $\varepsilon_{nit}$ could stem from (classical) measurement error in the estimation of markups, which we discuss in Section III.B, or from uncertainty or other model specification error as discussed in Section II.B.

Moreover, for the case of intermediate collusion, $\kappa$ in (18) can be easily estimated from equation (26) as:

$$\hat{\kappa} = \frac{\hat{\beta}_2}{\hat{\beta}_1 + \hat{\beta}_2} \tag{27}$$

Furthermore, equation (18) implies that we can use the regression in equation (26) to estimate the elasticity parameters. These equations imply that:

$$\frac{1}{\hat{\sigma}} - \frac{1}{\hat{\gamma}} = \hat{\beta}_1 + \hat{\beta}_2 \tag{28}$$

$$\frac{\hat{\sigma} - 1}{\hat{\sigma}} = \frac{1}{N} \sum_i \sum_{n \in \Omega_i} \left( \frac{1}{\mu_{ni}} - \hat{\beta}_1 s_{ni} - \hat{\beta}_2 \sum_{m \in S_{ni}} s_{mi} \right)$$

where $N$ is the number of firms. It is then immediate to solve these equations simultaneously to generate estimates of the elasticity parameters.

An alternative interpretation of $\hat{\kappa}$ as a measure of the intensity of collusion can be derived from considering the case of a subset of $\tilde{S} \subset S$ firms who perfectly collude, while the others compete independently. This also leads to intermediate estimates in both coefficients, with $\beta_1$ larger and $\beta_2$ smaller for $\tilde{S}$ than for $S$. Under somewhat stronger assumptions that the distribution of market shares is the same for colluding and non-colluding firms, we can show that $\kappa$ equals the fraction of firms perfectly colluding.[15]

Equation (26) has strong parallels with the risk-sharing test developed by Townsend (1994). In that family of risk-sharing regressions, household consumption is regressed on household income and total (village) consumption in the risk-sharing syndicate. Townsend solves the problem of a syndicate of households jointly maximizing utility and perfectly risk-sharing, and contrasts that with households in financial autarky; We solve the problem of a syndicate of firms jointly maximizing profits in perfect collusion and contrast with those independently maximizing profits. Townsend posited that households in proximity are likely to be able to more easily cooperate, defining villages as the appropriate risk-sharing network. We posit the same is true for firms and examine local cooperation of firms. Our screen also shares another key strength of risk-sharing tests: we do not need to be explicit about the details of collusion because we only look at its effects on pricing.[16] Finally, as discussed in Section I.D, firms could compete as in Cournot or Bertrand, and the essential elements of the screen hold in each.

We also note the presence of time and firm dummies in our screening equation. The time dummies, $\theta_t$, capture time-specific variation, which is important since markups have increased over time, as we show in the next section. In principle, firm-specific fixed effects are not explicitly required in the case of symmetric

[15]Details of this claim are provided in the appendix.
[16]For example, we do not need to distinguish between implicit or explicit price collusion.

demand elasticities.[17] Nevertheless, we add $\alpha_{ni}$ to capture fixed firm-specific variation in the markup, stemming perhaps from firm-specific variation in demand elasticities, as discussed in Section I.D. Together, these time and firm controls assure that the identification in the regression stems from within-cluster and within-firm variation over time in markups and market shares.

### *B. Simulation Results*

We derived our screen from the model in Section I, which assumed that (i) all relevant information is known to the firm before it makes its production or pricing decisions, (ii) demand is nested-CES, and (iii) there is no measurement error. In reality firms face unanticipated shocks to production costs and demand, and they take this uncertainty into account when making decisions. Indeed we require such unanticipated shocks in order to identify our production functions used in our empirical implementation. Moreover, demand may not be CES, and there may be measurement error with specific levels of correlation. Here we examine the robustness of our screen to relaxing these assumptions by running our regression on simulated data from an augmented model.

We augment demand and technologies for firm $n$ in industry $i$ located in region $k$ in year $t$ according to the following equations:

$$y_{nikt} = \varepsilon_{nikt} D_{nikt} \left(\frac{p_{nikt} + \bar{p}}{P_i}\right)^{-\sigma} \left(\frac{P_i}{P}\right)^{-\gamma}, \tag{29}$$

$$y_{nikt} = \rho_{nikt} z_{nikt} l_{nikt}^{\eta}$$

The parameter $\eta$ allows for curvature in the cost function, while the parameter $\bar{p}$ allows for decreasing ($\bar{p} < 0$) and increasing ($\bar{p} > 0$) demand elasticities. Here $D_{nikt}$ and $z_{nikt}$ are the known component of (firm-specific) demand and produc-

[17] Here the parallel with Townsend breaks, since risk-sharing regression require household fixed effects, or differencing, in order to account for household-specific Pareto weights. In contrast, cartels maximize profits rather than Pareto-weighted utility, and as long as profits can be freely transferred – an assumption needed for a perfect cartel – all profits are weighted equally.

tivity, respectively, while $\varepsilon_{nikt}$ and $\rho_{nikt}$ are the unanticipated shocks to demand and productivity, respectively. Note that demand and productivity shocks are not equivalent in this model, since productivity shocks affect marginal cost, while demand shocks do not.

We then augment the firm's problem to allow for partial collusion captured by $\kappa$ and take into account firm uncertainty:

$$\max_{l_{nikt}} \int_{\varepsilon}\int_{\rho} \left[(1-\kappa)\pi_{nikt}(l,\varepsilon,\rho) + \kappa \sum_{m\in S_{ikt}} \pi_{mikt}(l,\varepsilon,\rho)\right] dF(\varepsilon)dG(\rho) \tag{30}$$

where the unsubscripted $\varepsilon$, $\rho$, $l$ are *vectors* of demand shocks, cost shocks, and labor input choices. We assume that each firm belows to a cluster $S_{ikt}$ that jointly solve (30). In later sections we consider different cases for the sets of firms that may be colluding, but in this section we refer to them generally as clusters. Notice that $F$ and $G$ are probability distributions over vectors. We will consider covariation of these shocks across firms at the firm, cluster, region-industry, industry, and year levels.

We simulate this model for various parameter values, run our screening regression on the simulated data, and evaluate the bias in $\kappa$ as measured by equation (27). We overview the results here, and full details are given in the online appendix.

Our first exercise is to measure the bias to our estimates from unanticipated shocks. When shocks are at the level of the individual firm or are correlated at the level of the cluster, we find that they can bias our results, but these work in opposite directions. Unanticipated shocks at the individual level push our estimate of $\kappa$ toward zero, while those at the cluster level push $\kappa$ toward one. This is because individual shocks cause comovement in markups and individual shares independent of the cluster shares, which causes the coefficient on the individual share to increase in magnitude. The opposite is true for the cluster shock, which causes the coefficient on cluster share to increase in magnitude relative to that on the individual share. These effects can bias our $\hat{\beta}_1$ and $\hat{\beta}_2$ estimates. These estimates can lead to bias in $\hat{\kappa}$ for two reasons. First, biases in $\hat{\beta}_1$ and $\hat{\beta}_2$ feed directly into $\hat{\kappa}$. Second, since $\hat{\kappa}$ is a nonlinear function of $\hat{\beta}_1$ and $\hat{\beta}_2$, then variance in the estimates of those coefficients leads to bias in $\hat{\kappa}$.

In all of these results, we stress that this bias only results from unanticipated shocks, and any shocks to cost or demand that are anticipated will not bias our results no matter how those shocks are correlated across firms as discussed in Section I. In particular, if changes in the price of inputs are spatially or industrially correlated it only biases our results to the extent to which they are unanticipated.

In our second exercise, we study how large these unanticipated shocks would have to be to generate economically significant bias in our results. We parameterize the simulation to match the regression output from our baseline exercise, which is discussed in Section IV.B. We select the variance of individual shocks, the variance of cluster shocks as well as values of $\sigma$, $\kappa$ and $\gamma$ in order to match the point estimates and standard errors on the coefficients on own and cluster shares, the average markup, the estimated value of $\kappa$ and the adjusted $R^2$ (when averaged across all simulations) to their counterparts in the Chinese analysis. We find that magnitudes of these shocks are not large enough to substantially bias our estimates of $\kappa$. In our parameterized simulation, the true value of $\kappa$ is 0.32 while the estimated value is 0.26. In general, the quantitative importance of these depend on the magnitude of shocks relative to predictable variation in the data. Hence, large bias in estimates of $\kappa$ would require a substantially lower adjusted $R^2$ than we observe in the data.

In our third exercise, we simulate a non-CES demand system. Applying the form of non-CES demand given in equation (29), we find that, as the CES-deviating parameter, $\bar{p}$, moves away from zero, our estimated coefficient on firms' own shares can be biased. In the case of $\bar{p} > 0$ (implying a decreasing elasticity, as in linear demand, for example), the estimate would be upward biased, since a firm's markups would increase with its output (and firm's market share) simply from the decreasing elasticity. The converse is true for $\bar{p} < 0$. Nevertheless, the coefficient estimate on the cluster shares are unbiased. This is important because, if we wished to screen for the presence of collusion, our model implies that we should test if the coefficient on the cluster share is positive. Thus, the fact that our coefficient on cluster share is unbiased with non-CES demand implies that our screen for the presence of collusion is unaffected by non-CES demand. However, the fact that the coefficient on firms' own shares is biased implies that our estimate of the *magnitude* of collusion, $\hat{\kappa}$, is biased when demand is non-CES, and the direction of bias depends on the direction of the deviation from CES demand.

Our final exercise is to consider measurement error in revenues and costs in the model to see how that affects our estimate of $\kappa$.[18] One might suspect that idiosyncratic measurement error would lead to overestimation of collusion in a way that it can lead to overestimates of risk-sharing.[19] However, we find that idiosyncratic measurement error actually leads to a *downward* bias in our estimate of $\kappa$.

This bias may seem surprising, but it has a simple explanation. Measurement error in regressors typically biases their coefficient estimates toward zero, so measurement error in a firm's own market shares alone should shrink that regressor's coefficient and push the estimate of $\kappa$ toward one. However, this intuition relies on market share measurement error being independent of markups, but measurement error in revenue affects both measured market shares and measured markups. If the measured value of revenue is higher than its true value, both measured markups *and* measured market shares are by construction higher than their true values, and therefore idiosyncratic measurement error causes them to positively comove. We therefore*overestimate* the strength of the relationship be-

[18]Measurement error is distinguished from the case of model misspecification described above in that unanticipated shocks are taken into account when firms make choices, while measurement error has no effect on firm choices.

[19]See, for example, Ravallion and Chaudhuri (1997)'s critique of Townsend (1994).

tween the two, increasing our estimate of $\hat{\beta}_1$ and causing a downward bias in $\hat{\kappa}$. Hence, if measurement error is idiosyncratic, we would tend to *underestimate* the extent of collusion. [20]

Our conclusion from these simulations is that the most serious threat to the interpretation of our results as evidence of collusion is any shock correlated at the level of the cluster. We address this concern in multiple ways, as discussed in detail in the following sections. We examine variation across different sets of firms, where we have stronger or weaker *a priori* reasons to suspect collusion. First, we examine affiliated of the same parent company as a validation. Second, using similar reasoning, we evaluate firms that are state-owned enterprises within an industry, and we also run a placebo test for local collusion in the sample of state-owned firms. Third, we utilize the result in Proposition 1 that collusion makes markups more similar (Result 3) to motivate separately examining clusters with low coefficients of variation in markups over the cross-section of firms in the cluster. To limit potential endogeneity, we identify these clusters using the cross-sectional variation of firms in the initial year of our data (1999). Within the model, these clusters could have low markup variation because (i) they are colluding or (ii) they have lower variation in market shares (because of similarity in firm-specific demand or technology, for example). We assume the former in our *ex ante* identification strategy, but then we evaluate the latter *ex post.* Finally, as a robustness check, we add region-time specific fixed effects to control for any region-time specific cost shocks, such as unanticipated shocks to factor prices.

## III. Application to Chinese Data

For our empirical analysis, we examine manufacturing firms in China. Manufacturing firms have the advantage of being highly tradable, as is consistent with the assumption in our model that demand does not depend on location or local

[20]By the same argument, however, measurement error that is perfectly correlated at the level of the cluster biases the estimate of $\kappa$ upward, and the overall bias for a mix of idiosyncratic and cluster-specific measurement error depends on the relative strength of each.

markets. Our measurement methods are standard and closely follow the existing literature.

### A. *Why China?*

China has several advantages. First, it has the world's largest population and second largest economy. The size of the Chinese country and economy give us wide industrial and geographic heterogeneity. Second, China is a well-known development miracle, and its success is often attributed, at least in part, to its policies fostering special economic zones and industrial clusters.[21] Third, both agglomeration and markups have increased over time as shown in Figure 1, which plots the average level of industrial agglomeration (as defined below) and average markups.

Finally, we have a high quality panel of firms for China: the Annual Survey of Chinese Industrial Enterprises (CIE), which was conducted by the National Bureau of Statistics of China (NBSC). The database covers all state-owned enterprises (SOEs), and non-state-owned enterprises with annual sales of at least 5 million RMB (about $750,000 in 2008).[22] It contains the most comprehensive information on firms in China. These data have been previously used in many influential development studies (e.g., Hsieh and Klenow (2009), Song, Storesletten and Zilibotti (2011)).

### B. *Measurement*

Between 1999 and 2009, the approximate number of firms covered in the NBSC database varied from 162,000 to 411,000. The number of firms increased over time, mainly because manufacturing firms in China have been growing rapidly, and over the sample period, more firms reached the threshold for inclusion in

[21] For example, a World Bank volume (Zeng, 2011) cites industrial clusters as an "undoubtedly important engine [in China's] meteoric economic rise."

[22] We drop firms with less than ten employees, and firms with incomplete data or unusual patterns/discrepancies (e.g., negative input usage). The omission of smaller firms precludes us from speaking to their behavior, but the impact on our proposed screen would only operate through our estimates of market share and should therefore be minimal.

the survey. Since there is a great variation in the number of firms contained in the database, we used an unbalanced panel to conduct our empirical analysis.[23] This NBSC database contains 29 2-digit manufacturing industries and 425 4-digit industries.[24]

The data also contain detailed data on revenue, fixed assets, labor, and, importantly, firm location at the province, city, and county location. Of the three designations, provinces are largest, and counties are smallest. We construct real capital stocks by deflating fixed assets using investment deflators from China's National Bureau of Statistics and a 1998 base year. Finally, the "parent id code", which we use to identify affiliated firms, is only available for the year 2004, but we assume that ownership is time invariant. We construct market shares using sales data and following the definition in Equation (5). We also use firms' registered designation to distinguish state-owned enterprises (SOEs) from domestic private enterprises (DPEs), multinational firms (MNFs), and joint ventures (JVs).

We do not have direct measures of prices and marginal cost, so we cannot directly measure markups. Instead, we must estimate firm markups using structural assumptions and structural methods, the method of De Loecker and Warzynski (2012), referred to as DW hereafter, in particular. DW extend Hall (1987) to show that one can use the first-order condition for any input that is flexibly chosen to derive the firm-specific markup as the ratio of the factor's output elasticities to its firm-specific factor payment shares:

$$\mu_{i,t} = \frac{\theta^{v}_{i,t}}{\alpha^{x}_{i,t}}. \tag{31}$$

This structural approach has the advantage of yielding a plant-specific, rather than a product-specific, markup. The result follows from cost-minimization and holds for any flexibly chosen input where factor price equals the value of marginal

[23]The Chinese growth experience necessitates that we use the unbalanced panel. Using a balanced panel would require dropping the bulk of our firms (from 1,470,892 to 60,291 observations), or shortening the panel length substantially.

[24]We use the adjusted 4-digit industrial classification from Brandt, Van Biesebroeck and Zhang (2012).

product. Importantly, we use materials as the relevant flexibly chosen factor. The denominator $\alpha^x_{i,t}$ is therefore easily measured.

The more difficult aspect is calculating the firm-specific output elasticity with respect to materials, $\theta^v_{i,t}$, which requires estimating firm-specific production functions. The issue is that inputs are generally chosen endogenously to productivity (or profitability). We address this by applying Ackerberg, Caves and Frazer (2006)'s methodology, presuming a 3rd-order translog gross output production function in capital, labor, and materials that is:

$$
\begin{aligned}
(32) \quad q_{nit} = {} & \beta_{k,i}k_{nit} + \beta_{l,i}l_{nit} + \beta_{m,i}m_{nit} + \\
& \beta_{k2,i}k^2_{nit} + \beta_{l2,i}l^2_{nit} + \beta_{m2,i}m^2_{nit} + \beta_{kl,i}k_{nit}l_{nit} + \beta_{km,i}k_{nit}m_{nit} + \\
& \beta_{lm,i}l_{nit}m_{nit} + \beta_{k3,i}k^3_{nit} + ... + \omega_{nit} + \epsilon_{nit}.
\end{aligned}
$$

Note that the coefficients vary across industry $i$, but only the level of productivity is firm-specific. This firm-specific productivity has two stochastic components. $\epsilon_{nit}$ is a shock that was unobserved/anticipated by the firm (and could reflect measurement error, as mentioned above) and is therefore exogenous to the firm's input choices. However, $\omega_{nit}$ is a component of TFP that is observed/anticipated, and so it is potentially correlated with $k_{i,t}$ , $l_{nit}$, and $m_{nit}$ because the inputs are chosen endogenously based on knowledge of the former. They assume that $\omega_{nit}$ is Markovian and linear in $\omega_{ni(t-1)}$. Identification comes from orthogonality moment conditions that stem from the timing of decisions, namely lagged labor and materials and current capital (and their lags) are all decided before observing the innovation to the TFP shock, and a two-step procedure is used to first estimate $\epsilon_{nit}$ and then the production function.

Production functions are estimated at the industry-level (although the estimation allows for firm-specific factor-neutral levels of productivity). The precision of the production function estimates – and hence the measurement error in markups – therefore depends on the number of firms in an industry. For this reason, we follow DW and weight the data in our regressions using the total number of firms in the industry. Moreover, estimation of markups is noisy in practice, and within each industry we Windsorize the 3 percent of observations in the tails.

Finally, we use information on the geographic industries and clusters that we study. Namely, we merge our geographic and industry data together with detailed data from the China SEZs Approval Catalog (2006) on whether or not a firm's address falls within the geographic boundaries of targeted SEZ policies, and, if so, when the SEZ started. We use the broad understanding of SEZs, including both the traditional SEZs but also the more local zones such as High-tech Industry Development Zones (HIDZ), Economic and Technological Development Zones (ETDZ), Bonded Zones (BZ), Export Processing Zones (EPZ), and Border Economic Cooperation Zones (BECZ). Since no SEZs were added after 2006, these data are complete. Since our data start in 1999, the broad, well-known SEZs that were established earlier offer us no time variation. We also measure agglomeration at the industry level using using the Ellison and Glaeser (1997) measure, where 0 indicates no geographic agglomeration (beyond that expected by industrial concentration), 1 is complete agglomeration, and negative would indicate "excess diffusion" relative to a random balls-and-bins approach.[25]

Table 1 presents the relevant summary statistics for our sample of firms.

[25]Specifically, start by defining a measure of geographic concentration, G:

$$G \equiv \sum_i (s_i - x_i)^2$$

, where $s_i$ is the share of industry employment in area $i$ and $x_i$ is the share of total manufacturing employment in area $i$. This therefore captures disproportionate concentration in industry $i$ relative to total manufacturing. Using the Herfindahl index $H = \sum_{j=1}^{N} z_j^2$, where $z_j$ is plant $j$'s share in total industry employment, we have the following formula for the agglomeration index $g$:

$$g \equiv \frac{G - \left(1 - \sum_i x_i^2\right) H}{\left(1 - \sum_i x_i^2\right)(1 - H)}.$$

## IV. Results

We start by presenting the results validating our screen using affiliated firms. We then present the results for the overall sample (which are mixed), the results for those pre-identified clusters with low variation in markups across firms (which strongly indicate collusion), and some important characteristics of these collusive clusters. Throughout our regression analysis, we report robust standard errors, clustered at the firm level.[26]

### *A. Validation and Placebo Exercises*

We start by running our screen on the sample of affiliated firms. That is, we define our potential cartels in equation (26) as groups of affiliated firms in the same industry who all have the same parent, and we construct the relevant market shares of these cartels. We know from existing empirical work (e.g., Edmond, Midrigan and Xu (2015)) that markups tend to be positively correlated with market share. Our hypothesis is $\beta_1 = 0$ and $\beta_2 < 0$, however, so that own market share will not impact markups after controlling for total market share. We estimate (26) for various definition of industries: 2-digit, 3-digit, and 4-digit industries. Note that the definition of industry affects not only the market share of the firm and cartel, but the set of affiliates in the cartel. The broader industry classification incorporates potential vertical collusion, but it also makes market shares themselves likely less informative.

Table 2 present the estimates, $\hat{\beta}_1$ and $\hat{\beta}_2$. (We omit the firm and time fixed effects from the tables.) The first column shows the estimates, where we assume perfectly independent behavior and constrain the coefficient on collusion share to be zero. In the next three columns, we assume perfect collusion at the cluster level (constraining the coefficient on firm share to be zero), and define clusters

[26]We cluster at the firm level, since the identification involves within-firm variation, and we can maintain the same clustering for all our analysis. The significance of our main results are robust to clustering at the "cluster" level as well, but such clustering varies from analysis to analysis, while clustering at the firm level allows us to remain consistent throughout.

at the 2-digit, 3-digit, and 4-digit levels, respectively. The last three columns are analogous in their cluster definitions, but we do not constrain either coefficient. The sample of observations is a very small subset (less than two percent) of our full sample both because we only include affiliates, and because we only have parent/affiliate information for firms present in the 2004 subsample.

Focusing on the last three columns, we see that our hypothesis is confirmed for the finer industry classifications, especially the 4-digit industry classification. In particular, the coefficient on own share is small and statistically insignificant, while the the cartel share is negative and marginally significant at a ten percent level. Returning the results that constrain $\hat{\beta}_1$ to zero (i.e., column (iv)), and applying (28), yields estimates of $\sigma = 4.5$ and $\gamma = 2.9$. (The corresponding values implied by column 7 are very similar at 4.5 and 3.1. The implied demand elasticities in all of our results are consistent with those found using other methods, e.g., elasticities based on international trade patterns in Simonovska and Waugh (2014), which is encouraging given the potential biases discussed in Section **??**.) For the 3-digit industry classification, the impact of cartel market share is larger and even more significant, but the coefficient on own share actually exceeds the coefficient on cartel share (though statistically insignificant). The broad 2-digit industry classification gives insignificant results, however, likely reflecting the fact that our screening approach is based on horizontal competition where industrial markets are narrowly defined.

Our second validation exercise is analogous. Instead of examining private affiliates owned by the same parent, however, we examine state-owned enterprises (SOEs), which are all owned by the government. The variation in the data naturally reflect the privatization process occurring in China over the period (declining market share of SOEs), and the corresponding decrease in markups, but we hypothesize that competition amongst SOEs is weaker than competition between SOEs and private firms.

Indeed, the results in Table 3 verify this hypothesis. Columns 2-4 examine collusion at different industry aggregations, and, once again, our screen is consistent with perfect collusion at the disaggregate industry level. In column 4, we find the coefficient on own share to be insignificant at the 4-digit level, while the coefficient on cluster's share is negative and significant. While our screen uncovers negative and statistically significant coefficients on cluster's share at the broader industry levels too, own share is also significant and the implied $\kappa$ values are tiny. Again, our model is one of horizontal competition, so it is natural that the results are most consistent when using the most disaggregate industries. For this reason, we focus on the 4-digit industry classification, our narrowest, for the remainder of our analyses.

Columns 5-7 consider variants where SOEs only collude with other SOEs (in their 4-digit industry) that are in geographic proximity, i.e., at more local levels of province, city, or county, respectively. We view this in some sense as a placebo test, and indeed the evidence for collusion disappears at these more local levels. We take this as evidence that the presence of any correlated local shocks are not enough to erroneously lead to an assumption of only *local* collusion in the case of SOEs.

We also run placebo tests that replicate our screens for industrial cluster-based collusion, but use these subsets of firms. We use the identical measure of industrial cluster market share that we use below, but consider only the markup response for these sets of firms. The results are quite strong: we find no significant responses of markups to the total market share of industrial clusters in either the SOE or affiliated firm samples, and no effect of being in an SEZ. See the online appendix for full results. These negative results are an important counter-example to the idea that something about the construction of our screen (e.g., biases due to spurious local correlations) or our data automatically lead to false positives in detecting collusion at cluster levels.

In sum, both validation exercises are consistent with firms colluding within ownership structures at the disaggregate industry level, and our screen is able to reject cluster-based collusion in placebo tests.

### *B. Non-Competitive Behavior in Industrial Clusters*

We now turn to industrial clusters more generally by defining our potential cartels as sets of firms in the same industry and geographic location. Table 4 presents the results. The first column shows the estimates, where we assume perfectly independent behavior and constrain the coefficient on collusion share to be zero. In the next three columns, we assume perfect collusion at the cluster level (constraining the coefficient on firm share to be zero), and define clusters at the province, city, and county level respectively. The next three columns allow for both shares to influence inverse markups, while the final three interact firm market share and cluster market share with an indicator variable for whether the firm is in a SEZ.

Focusing on columns 1 through 7, we note several strong results. First, all of the estimates are highly significant indicating that both firm share and market share are strongly related to markups. Because all estimates are statistically different from zero, we can rule out either perfectly independent behavior or perfect collusion at the cluster level. Second, all the coefficients on market shares are negative, as we would predict if output within an industry are more substitutable than output between industries. Third, the magnitudes are substantially larger for own firm share. Fourth, as we define clusters at a more local level, the coefficient on cluster share increases in magnitude, while the the coefficient on own share decreases. This suggests that collusion is indeed more prevalent among firms that are in proximity to one another.

The $\beta_2 < 0$ estimates indicate some level of cluster-level collusion in the overall sample.[27] Again, applying equation (28), we can interpret the magnitude of the implied elasticities and the extent of collusion. At the county level, we estimate

[27]We verify that this is not driven by the affiliated firms in two ways: (i) dropping the affiliated firms from the sample, and (ii) assigning the parent group share within the cluster to firm share. Neither changes affect our results substantially.

$\hat{\kappa} = 0.26$, while we estimate just $\hat{\kappa} = 0.07$ at the province level. This indicates a relatively low level of non-competitive behavior overall, especially when examining firms only located within the same province. The implied elasticity estimates are $\sigma = 4.8$ and $\gamma = 3.1$. These implied elasticities are quite similar to those implied in the smaller sample of affiliated firms, even though the level of collusion is greater.

Finally, we examine the role of SEZs examined in columns 8-10 of Table 4. The coefficients on the interaction of the SEZ dummy with firm market share are positive and significant but smaller in absolute value than the coefficient on firm market share itself. Adding the two coefficients, own market share is therefore a less important a predictor of (inverse markups) in SEZs. Similarly, the coefficients on cluster market share are negative, so that overall cluster market share is a more important predictor in SEZs. Indeed, using the county-level estimates in the last column, we estimate a collusion index $\hat{\kappa} = 0.45$ for firms within SEZs, four times higher than that of firms not in SEZs, where $\hat{\kappa} = 0.11$. Again, the results for SEZs are strongest, the more local the definition of clusters. Recall, that SEZs are essentially pro-business zones, combining tax breaks, infrastructure investment, and government cooperation in order to attract investment. A common goal with industry-specific zones or clusters is to foster technical coordination in order to internalize productive externalities. The evidence suggests that such zones may also facilitate marketing coordination and internalizing pecuniary externalities.

We have estimated similar regressions where we differentiate across industries using the Rauch (1999) classification. Rauch classifies industries depending on whether they sell homogeneous goods (e.g., goods sold on exchanges), referenced priced goods, and differentiated goods. Without agriculture and raw materials, our sample of homogeneous goods is limited, but we can distinguish between industries that produce differentiated goods, and those that produce homogenous/reference priced goods. Our estimates of $\kappa$ are 0.14 for the former and 0.30 for the latter, indicating somewhat stronger collusion for more homogeneous goods, consistent with existing arguments and evidence that collusion is less beneficial and common in industries with differentiated products Dick (1996). Equally interesting, the coefficients themselves are much larger for these goods, consistent with a larger $\rho$, which would be expected, since goods should be highly substitutable within these industries.[28] Again, we view this latter consistency as further evidence that our results are driven by the pricing-market share mechanism we highlight rather than some other statistical phenomenon.

We have also examined robustness of the (county-level, unrestricted) results in Table 4 to various alternative specifications. Although the theory motivates weighting our regressions, neither the significance nor magnitudes of our results are dependent on the weighting in our regressions. We can also use the Bertrand specification rather than Cournot, by replacing the dependent variable with $\mu_{nit}/(\mu_{nit} - 1)$. This Bertrand formulation require us to Windsorize the data, however, because for very low markups the dependent variable explodes. These observations take on huge weight, and very low markups are inconsistent with the model for reasonable values of $\gamma$. If we drop all observations below 1.06, a lower bound on markups for a conservative estimate of $\gamma = 10$ (much larger than implied by the Cournot estimates, for example), we get very similar results, with implied elasticities $\sigma = 5.5$ and $\gamma = 3.1$ and the fraction colluding $\kappa = 0.40$. Finally, we can use log markup, rather than inverse markup, as our dependent variable. The log function may make these regressions more robust to very large outlier markups. Naturally, the predicted signs are reversed, but they are both statistically significant, indicating partial collusion, and the implied semi-elasticities with respect to own and cluster share are 9.7 and 3.6 percent, respectively. The details of these robustness studies are in our online appendix.

We next turn to clusters which appear a priori likely to be potentially collusive because they have low cross-sectional variation in markups. We do this by sorting clusters into deciles according to their coefficient of variation of the markup. Table

[28] See the online appendix for details.

5 presents the coefficient of variation of these deciles, along with other cluster decile characteristics, when clusters are defined at the county level. Note that the average markup increases with coefficient of variation of markups over the top seven deciles, but that this pattern inverts for the lowest three deciles, where the average markup is actually higher as the coefficient of variation decreases. Higher markups and lower coefficients of variation may be more likely to be collusive, given claims 3 and 4 in Proposition 1. We therefore focus on firms in the these bottom three clusters, and the lowest thirty percent is not inconsistent with the estimate that 26 percent of firms collude.[29]

The other key characteristics of these lowest deciles of clusters are also of interest. First, although they have lower variation in markups, this does not appear to be connected to lower variation in market shares, as the coefficients of variations in market shares are similar, showing no clear patterns across the deciles. They have fewer firms per cluster, and are in industries with higher geographic concentration (measured by the Ellison-Glaeser agglomeration index) and higher industry concentration (as measured by the Hirschman-Herfindahl index). The firms themselves are somewhat smaller in terms of fewer employees per firm. Fewer firms in these clusters export, and overall exports are a lower fraction of sales. Finally, although there are not sharp differences in the ownership distribution, they are disproportionately domestic private enterprises and somewhat less likely to be multi-national enterprises or joint ventures. [30]

Table 6 presents the results for this restricted sample of the lower three deciles. The columns follow a parallel structure as in Table 4, but there are three columns even for the regressions that only include firm market share because the set of firms here varies depending on whether we define our clusters at the province, city, or county level. In the results that assume perfectly independent behavior

[29] These low markup variation deciles contain fewer firms on average, however, and so they constitute only 16 percent of firms.

[30] Moreover, the single most disproportionately overrepresented industry in these clusters is petroleum refining, a classic cartel in U.S. history.

we again find negative and significant estimates at the province and county level.[31] In the results, that assume perfectly collusive behavior, we again find negative significant estimates on cluster market share, and the results are again stronger, the more locally the cluster is defined. The most interesting results in the table, however, are those where we do constrain either coefficient. In this restricted sample, we again find evidence of partially collusive behavior at the province level.

What is striking, however, is that the collusive behavior appears complete at local levels within these restricted samples: only the $\hat{\beta}_2$ estimates are negative and significant. The *positive* $\hat{\beta}_1$ at the city and county level are admittedly at odds with the theory, but the coefficient are not statistically significant. Moreover, the magnitude of the $\hat{\beta}_1$ (0.037) is less than half that of $\hat{\beta}_2$ (0.077) at the county level. The county-level estimate in column (vi) implies a within-industry elasticity $\sigma$ that compares well with that in the full sample (5.0 vs. 4.8), but the between-industry elasticity is somewhat higher than in the full sample (3.9 vs. 3.1).

Once again, we find significant impacts of SEZs when interacted with market share. For counties, the region's share is nearly twice as large for firms in SEZs.

### *C. Robustness*

We now examine the robustness of our results to various alternatives. In particular, we attempt to address the issue that the correlation between markups and cluster share may simply be driven by spatially correlated shocks to costs or demand across firms, as our Monte Carlo simulations indicated could be problematic. We address this concern in two ways.

First, we add region-time specific fixed effects as controls into our regressions. Our Monte Carlo simulations showed that these effectively control for any general shocks or trends to production or costs at the region level, e.g., rising costs of land or (non-industry-specific) labor from agglomeration economies. Controlling for

[31] The city estimates have fewer observations, since there are fewer firms in the low markup variation deciles of city clusters.

these, our regressions will only be identified by cross-industry variation in market shares within a geographic location. Table 7 shows these results for the sample of clusters with low initial variation in markups. The patterns are quite similar to those in Table 6, although the magnitudes of the coefficients on cluster share are somewhat smaller (e.g., -0.054 vs. -0.077) in column 9. The results are significant at a five percent level. We find very similar results for the overall sample, but since our SEZs show very little variation with counties, we cannot separately run our SEZ regression using these fixed effects. Nonetheless, we view the robustness of our results as evidence that spatially correlated shocks (or trends) do not drive our inference, although in principle, industry-specific spatially correlated shocks could still play a role.

Second, we attempt an instrumental variable approach, since shares themselves are endogenous. Identifying general instruments may be difficult, but in the context of the model and our Ackerberg, Caves and Frazer (2006) estimation, exogenous productivity shocks affect costs and therefore exogenously drive both market share and markups. We motivate our instrument using an approximation, the case of known productivity $z_{in}$ and monopolistic competition. This set up yields the following relationship between shares and the distribution of productivity:

$$s_{in} = \frac{p_{in} y_{in}}{\sum\limits_{m \in \Omega_i} p_{im} y_{im}} \approx \frac{z_{in}^{1-1/\sigma}}{\sum\limits_{m \in \Omega_i} z_{im}^{1-1/\sigma}} \tag{33}$$

We construct instruments for own market share ($I_1$) and cluster market share ($I_2$) using variants of the above formula that exclude the firm's own productivity and the productivities of all firms in the firm's cluster ($S_n$), respectively:

$$I_1 = \frac{1}{\sum\limits_{m \in \Omega_i / n} z_{im}^{1-1/\sigma}}, \qquad I_2 = \frac{1}{\sum\limits_{m \in \Omega_i / S_n} z_{im}^{1-1/\sigma}} \tag{34}$$

This two-stage estimation yields very similar results (see Table A.3). For example, the coefficient on cluster share in the analog to column (ix) is -0.050 and is significant at the five percent level. Again, the patterns we develop are broadly robust.

In sum, we have shown that: the screen detects collusion among firms owned by the same parents in the affiliated and SOE samples; the markups of local SOEs in a placebo test do not respond to their cluster market share; the estimates are consistent with the model's mechanism based on the Rauch classification; our collusion patterns are stronger in SEZs; the collusion patterns are very strong in clusters that the model pre-identifies as likely colluders; these collusion patterns are robust to inclusion of time-region specific fixed effects and instrumenting for market share.

## V. Conclusion

We have developed a simple, intuitive and robust screen for identifying non-competitive behavior for subsets of firms competing in the same industry. Using this screen we have found evidence of collusion in Chinese industrial clusters. These results are strongest within narrowly-defined clusters in terms of narrow industries and narrow geographic units. A small but non-negligible share of firms and clusters appear to exhibit from non-competitive behavior. This behavior is disproportionately strong – four times greater – in special economic zones.

The results open several avenues for future research. In this paper we have focused exclusively on China. However, the fact that it satisfied our validation exercises means it could easily applied more generally to other countries and contexts where firm panel data are available. Furthermore, the potential normative importance of our results are compelling with respect to evaluating industrial policies that promote clustering, such as local tax breaks, subsidized credit, or targeted infrastructure investments. They motivate more rigorous evaluation of various normative considerations, including weighing the extent to which cartels hurt (or perhaps even help) consumers, productivity gains from external economies of scale vs. monopoly pricing losses from cartels, and local vs. global welfare implications and incentives. Precisely these issues are the subjects of our continuing research.

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Figure 1: Increasing Agglomeration and Markups over Time in China

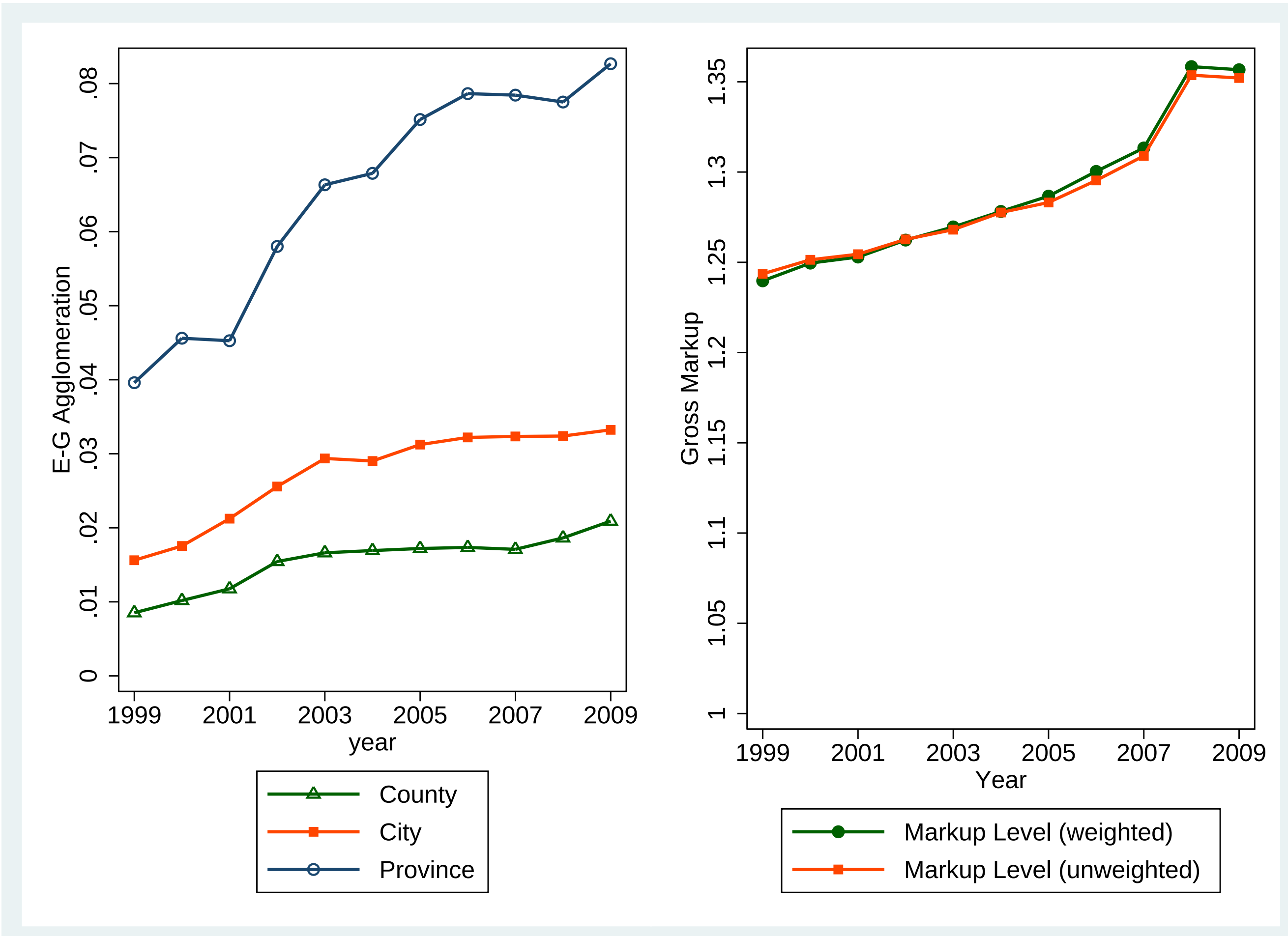

Table 1: Key Summary Statistics of Data

| Variable | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|
| Markup | 1.29 | 1.26 | 0.21 | 0.61 | 4.76 |
| Firm Share | 0.00 | 0.00 | 0.01 | 0 | 1 |
| Cluster Share (Province) | 0.14 | 0.10 | 0.14 | 0 | 1 |
| Cluster Share (City) | 0.04 | 0.02 | 0.06 | 0 | 1 |
| Cluster Share (County) | 0.02 | 0.00 | 0.04 | 0 | 1 |
| Capital per Firm | 320 | 50 | 3720 | 0.01 | 1,035,380 |
| Materials per Firm | 720 | 170 | 5940 | 0.05 | 860,550 |
| Real Output per Firm | 1000 | 240 | 7970 | 0.08 | 1,434,840 |
| Workers per Firm | 290 | 120 | 1010 | 10 | 166,860 |
| No. of Firms | | | 408,848 | | |

Notes: Market shares are computed using 4-digit industries. Capital, output and materials are in thousand RMB (in real value).

Table 2: Baseline Results Using Affiliated Firms

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) 4-digit | (2) 2-digit | (3) 3-digit | (4) 4-digit | (5) 2-digit | (6) 3-digit | (7) 4-digit |
| Firm's share | -0.036 | | | | -0.223 | 0.283 | 0.073 |
| | (0.057) | | | | (0.666) | (0.268) | (0.086) |
| Cluster's share | | -0.206 | -0.196** | -0.077 | -0.190 | -0.258*** | -0.119* |
| | | (0.171) | (0.090) | (0.049) | (0.182) | (0.100) | (0.072) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES |
| Observations | 26779 | 26779 | 26779 | 26779 | 26779 | 26779 | 26779 |
| Adjusted $R^2$ | .518 | .518 | .519 | .518 | .518 | .519 | .518 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Various industry aggregation levels are employed, including 4-digit industry (in specifications 1, 4 and 7), 3-digit industry (in specifications 3 and 6), and 2-digit industry (in specifications 2 and 5). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table 3: Baseline Results Using SOEs as Cluster

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | all SOEs in the industry | | | province | city | county |
| | 4-digit | 2-digit | 3-digit | 4-digit | 4-digit | 4-digit | 4-digit |
| Firm's Share | -0.047 | -1.801** | -0.331* | -0.028 | 0.012 | 0.004 | -0.018 |
| | (0.056) | (0.810) | (0.201) | (0.056) | (0.064) | (0.072) | (0.120) |
| Cluster's Share | | -0.047** | -0.020** | -0.026*** | -0.062** | -0.053 | -0.030 |
| | | (0.019) | (0.010) | (0.007) | (0.031) | (0.049) | (0.112) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES |
| Observations | 111520 | 111520 | 111520 | 111520 | 111520 | 111520 | 111520 |
| Adjusted $R^2$ | .572 | .572 | .572 | .572 | .572 | .572 | .572 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Various industry aggregation levels are employed, including 4-digit industry (in specifications 1 and 4-7), 3-digit industry in specifications, and 2-digit industry in specifications 2. All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table 4: Baseline Results Using Overall Sample

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) Province | (3) City | (4) County | (5) Province | (6) City | (7) County | (8) Province | (9) City | (10) County |
| Firm's Share | -0.112*** | | | | -0.104*** | -0.086*** | -0.081*** | -0.157*** | -0.142*** | -0.142*** |
| | (0.021) | | | | (0.021) | (0.021) | (0.022) | (0.027) | (0.028) | (0.028) |
| Region's Share | | -0.011*** | -0.031*** | -0.041*** | -0.009*** | -0.024*** | -0.029*** | -0.003 | -0.017*** | -0.017** |
| | | (0.002) | (0.004) | (0.006) | (0.002) | (0.005) | (0.007) | (0.003) | (0.005) | (0.008) |
| SEZ*Firm's Share | | | | | | | | 0.073* | 0.086** | 0.090** |
| | | | | | | | | (0.040) | (0.041) | (0.042) |
| SEZ*Region's Share | | | | | | | | -0.012*** | -0.022*** | -0.026** |
| | | | | | | | | (0.004) | (0.007) | (0.011) |
| SEZ Dummy | | | | | | | | 0.001 | 0.001 | -0.000 |
| | | | | | | | | (0.001) | (0.001) | (0.001) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 1470892 | 1470892 | 1470892 | 1470892 | 1470892 | 1470892 | 1470892 | 1205337 | 1205337 | 1205337 |
| Adjusted $R^2$ | 0.541 | 0.541 | 0.541 | 0.541 | 0.541 | 0.541 | 0.541 | 0.538 | 0.538 | 0.538 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at various aggregation levels, including province (in specifications 2, 5, and 8), city (in specifications 3, 6, and 9), and county (in specifications 4, 7, and 10). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table 5: Cluster Characteristics by Cluster Decile of Coefficient of Variation of Markup

| Cluster Decile of Coefficient of Variation of Markup | Avg. Coefficient of Variation of Markup | Local Competition Indicator | | | Industry Concentration Characteristics | | Firm Exporting | Firm Ownership Distribution | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg. Mean Markup | Avg. Coefficient of Variation of Market Share | Avg. Firms Per Cluster | Avg. EG Agglomeration Index | Hirschman-Herfindahl Index | Avg. Mean Export Share | Avg. Percent DPE | Avg. Percent FIE | Avg. Percent SOE |
| 1 | 0.01 | 1.224 | 4.3 | 1.69 | 0.0102 | 0.023 | 0.16 | 79 | 14 | 7 |
| 2 | 0.03 | 1.223 | 4.3 | 2.22 | 0.0100 | 0.020 | 0.14 | 81 | 14 | 5 |
| 3 | 0.04 | 1.223 | 4.5 | 2.92 | 0.0099 | 0.018 | 0.16 | 81 | 14 | 4 |
| 4 | 0.06 | 1.219 | 4.4 | 3.72 | 0.0100 | 0.017 | 0.19 | 79 | 17 | 4 |
| 5 | 0.08 | 1.225 | 4.4 | 4.35 | 0.0098 | 0.017 | 0.22 | 79 | 18 | 4 |
| 6 | 0.09 | 1.232 | 4.9 | 4.70 | 0.0099 | 0.017 | 0.24 | 75 | 21 | 4 |
| 7 | 0.11 | 1.234 | 4.4 | 4.99 | 0.0100 | 0.016 | 0.23 | 70 | 25 | 4 |
| 8 | 0.14 | 1.252 | 5.5 | 5.03 | 0.0096 | 0.018 | 0.28 | 62 | 33 | 5 |
| 9 | 0.17 | 1.280 | 5.0 | 4.57 | 0.0095 | 0.018 | 0.29 | 57 | 37 | 6 |
| 10 | 0.26 | 1.345 | 4.5 | 3.27 | 0.0095 | 0.022 | 0.20 | 54 | 34 | 12 |

Table 6: Baseline Results Using Low CV Deciles

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Province | (2) City | (3) County | (4) Province | (5) City | (6) County | (7) Province | (8) City | (9) County |
| Firm's share | -0.072* | -0.002 | -0.040 | | | | -0.060 | 0.027 | 0.037 |
| | (0.044) | (0.064) | (0.035) | | | | (0.044) | (0.064) | (0.043) |
| Region's share | | | | -0.014** | -0.024 | -0.059*** | -0.012** | -0.028* | -0.077*** |
| | | | | (0.006) | (0.016) | (0.022) | (0.006) | (0.014) | (0.025) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 271403 | 159353 | 192068 | 271403 | 159353 | 192068 | 271403 | 159353 | 192068 |
| Adjusted $R^2$ | 0.57 | 0.713 | 0.841 | 0.57 | 0.713 | 0.841 | 0.57 | 0.713 | 0.841 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at various aggregation levels, including province (in specifications 1, 4, and 7), city (in specifications 2, 5, and 8), and county (in specifications 3, 6 and 9). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table 7: Low CV Deciles with Region-Year Fixed Effects

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Province | City | County | Province | City | County | Province | City | County |
| Firm's Share | -0.076** | -0.009 | -0.020 | | | | -0.066* | 0.025 | 0.034 |
| | (0.037) | (0.048) | (0.031) | | | | (0.037) | (0.049) | (0.039) |
| Region's Share | | | | -0.012** | -0.030** | -0.037* | -0.011** | -0.034** | -0.054** |
| | | | | (0.005) | (0.014) | (0.021) | (0.005) | (0.013) | (0.024) |
| Region-Year FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 271403 | 159353 | 192068 | 271403 | 159353 | 192068 | 271403 | 159353 | 192068 |
| Adjusted $R^2$ | .574 | .724 | .861 | .574 | .724 | .861 | .574 | .724 | .861 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at various aggregation levels, including province (in specifications 1, 4, and 7), city (in specifications 2, 5, and 8), and county (in specifications 3, 6 and 9). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table A.1: Appendix Table–Placebo Test Using Affiliate Sample

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) Province | (3) City | (4) County | (5) Province | (6) City | (7) County | (8) Province | (9) City | (10) County |
| Firm's share | -0.036 | | | | -0.051 | -0.041 | -0.054 | -0.087 | -0.073 | -0.091 |
| | (0.057) | | | | (0.060) | (0.066) | (0.076) | (0.069) | (0.074) | (0.085) |
| Region's share | | 0.012 | -0.004 | -0.006 | 0.016 | 0.005 | 0.018 | 0.023 | 0.008 | 0.026 |
| | | (0.020) | (0.029) | (0.037) | (0.021) | (0.033) | (0.051) | (0.023) | (0.035) | (0.054) |
| SEZ*Firm's share | | | | | | | | 0.060 | 0.063 | 0.063 |
| | | | | | | | | (0.114) | (0.114) | (0.114) |
| SEZ*Region's share | | | | | | | | 0.014 | 0.018 | 0.017 |
| | | | | | | | | (0.041) | (0.041) | (0.041) |
| SEZ Dummy | | | | | | | | 0.003 | 0.003 | 0.003 |
| | | | | | | | | (0.006) | (0.006) | (0.006) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 26779 | 26779 | 26779 | 26779 | 26779 | 26779 | 26779 | 22331 | 22331 | 22331 |
| Adjusted $R^2$ | .518 | .518 | .518 | .518 | .518 | .518 | .518 | .514 | .514 | .514 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at various aggregation levels, including province (in specifications 2, 5, and 8), city (in specifications 3, 6, and 9), and county (in specifications 4, 7, and 10). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table A.2: Appendix Table–Placebo Test Using SOE Sample

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) Province | (3) City | (4) County | (5) Province | (6) City | (7) County | (8) Province | (9) City | (10) County |
| Firm's share | -0.055 | | | | -0.039 | -0.071 | -0.066 | -0.086 | -0.102 | -0.138 |
| | (0.059) | | | | (0.061) | (0.064) | (0.080) | (0.061) | (0.067) | (0.089) |
| Region's share | | -0.021 | 0.000 | -0.027 | -0.018 | 0.017 | 0.011 | -0.007 | 0.010 | 0.045 |
| | | (0.015) | (0.026) | (0.042) | (0.016) | (0.028) | (0.058) | (0.018) | (0.032) | (0.067) |
| SEZ*Firm's share | | | | | | | | 0.050 | 0.049 | 0.049 |
| | | | | | | | | (0.138) | (0.139) | (0.138) |
| SEZ*Region's share | | | | | | | | -0.003 | -0.005 | -0.005 |
| | | | | | | | | (0.048) | (0.048) | (0.048) |
| SEZ Dummy | | | | | | | | -0.000 | -0.000 | -0.000 |
| | | | | | | | | (0.005) | (0.005) | (0.005) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 111520 | 111520 | 111520 | 111520 | 111520 | 111520 | 111520 | 72657 | 72657 | 72657 |
| Adjusted $R^2$ | .572 | .572 | .572 | .572 | .572 | .572 | .572 | .564 | .564 | .564 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at various aggregation levels, including province (in specifications 2, 5, and 8), city (in specifications 3, 6, and 9), and county (in specifications 4, 7, and 10). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table A.3: Appendix Table–Rauch Product Classification Results

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) homo/ref | (2) diff. | (3) overall | (4) homo/ref | (5) diff. | (6) overall |
| Firm's Share | -0.170** | -0.050** | -0.150*** | -0.075 | -0.031 | -0.185*** |
| | (0.084) | (0.024) | (0.058) | (0.224) | (0.026) | (0.044) |
| Region's Share | -0.071*** | -0.013 | -0.064*** | -0.293*** | -0.006 | -0.066*** |
| | (0.013) | (0.009) | (0.012) | (0.100) | (0.010) | (0.010) |
| Differentiated X firm share | | | 0.087 | | | 0.147*** |
| | | | (0.062) | | | (0.049) |
| Differentiated X region share | | | 0.054*** | | | 0.065*** |
| | | | (0.014) | | | (0.014) |
| Differentiated Dummy | | | -0.003** | | | -0.001 |
| | | | (0.001) | | | (0.001) |
| Year FEs | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES |
| Observations | 283277 | 1037618 | 1398020 | 78326 | 715552 | 1398020 |
| Adjusted $R^2$ | .568 | .532 | .537 | .434 | .538 | .537 |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Specifications 1-3 refer to product classification using "most frequent" principle; specifications 4-6 refer to product classification using "pure" principle. All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table A.4: Appendix Table–Instrumental Variable Estimation Results Using Low CV Deciles

| | Dependent Variable: $\frac{1}{\mu_{nit}}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Province | (2) City | (3) County | (4) Province | (5) City | (6) County | (7) Province | (8) City | (9) County |
| Firm's share | 0.107 | -0.284* | -0.196*** | | | | 0.172 | -0.087 | -0.085 |
| | (0.158) | (0.158) | (0.050) | | | | (0.213) | (0.187) | (0.069) |
| Region's share | | | | -0.001 | -0.045*** | -0.057*** | 0.013 | -0.041*** | -0.050** |
| | | | | (0.019) | (0.013) | (0.020) | (0.026) | (0.015) | (0.022) |
| Year FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 266924 | 159245 | 191987 | 266924 | 159245 | 191987 | 266924 | 159245 | 191987 |
| Adjusted $R^2$ | 0.57 | 0.713 | 0.841 | 0.57 | 0.713 | 0.841 | 0.57 | 0.713 | 0.841 |
| First-Stage Instruments: | (Sum of other firms' productivity; Sum of outside-cluster firms' productivity) | | | | | | | | |
| Weak Instrument ( Prob > F ) | 0.0000 | | | | | | | | |

Notes: Robust standard errors clustered at firm level in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at various aggregation levels, including province (in specifications 1, 4, and 7), city (in specifications 2, 5, and 8), and county (in specifications 3, 6 and 9). All specifications are regressions weighted by the number of observations for each two-digit CIC sector production function estimation reported (following De Loecker et al. 2014). All regressions include a constant term.

Table A.5: Appendix Table–Robustness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Dependent Variable* $= 1/\mu_{nit}$ | | | | | | | | |
| Firm's Share | -0.112*** | | -0.081*** | -0.142*** | -0.049*** | | -0.031*** | -0.073*** |
| | (0.011) | | (0.012) | (0.015) | (0.009) | | (0.010) | (0.013) |
| Region's Share | | -0.041*** | -0.029*** | -0.017*** | | -0.023*** | -0.017*** | -0.002 |
| | | (0.004) | (0.004) | (0.005) | | (0.004) | (0.005) | (0.005) |
| SEZ*Firm's Share | | | | 0.090*** | | | | 0.076*** |
| | | | | (0.023) | | | | (0.021) |
| SEZ*Region's Share | | | | -0.026*** | | | | -0.032*** |
| | | | | (0.007) | | | | (0.007) |
| Observations | 1470892 | 1470892 | 1470892 | 1205337 | 1470892 | 1470892 | 1470892 | 1205337 |
| Adjusted $R^2$ | 0.541 | 0.541 | 0.541 | 0.538 | 0.539 | 0.539 | 0.539 | 0.536 |
| *Panel B: Dependent Variable* $= \mu_{nit}/(\mu_{nit}-1)$ *(full sample)* | | | | | | | | |
| Firm's Share | 169.961 | | 143.820 | 295.045 | 352.320 | | 329.188 | 605.930 |
| | (256.601) | | (280.289) | (364.181) | (346.765) | | (390.900) | (530.172) |
| Region's Share | | 45.849 | 24.251 | 16.686 | | 89.076 | 22.092 | 11.689 |
| | | (95.777) | (104.618) | (123.835) | | (152.865) | (172.321) | (217.461) |
| SEZ*Firm's Share | | | | -300.513 | | | | -547.209 |
| | | | | (562.327) | | | | (842.053) |
| SEZ*Region's Share | | | | 24.188 | | | | 29.639 |
| | | | | (164.433) | | | | (305.981) |
| Observations | 1470892 | 1470892 | 1470892 | 1205337 | 1470892 | 1470892 | 1470892 | 1205337 |
| Adjusted $R^2$ | -0.021 | -0.021 | -0.021 | -0.068 | -0.068 | -0.068 | -0.068 | -0.098 |
| *Panel C: Dependent Variable* $= \mu_{nit}/(\mu_{nit}-1)$ *(drop* $\mu_{nit} < 1.06$*)* | | | | | | | | |
| Firm's Share | -2.482*** | | -1.429*** | -3.048*** | -1.724*** | | -0.958*** | -2.077*** |
| | (0.322) | | (0.352) | (0.462) | (0.284) | | (0.318) | (0.406) |
| Region's Share | | -1.185*** | -0.971*** | -0.842*** | | -0.913*** | -0.726*** | -0.473*** |
| | | (0.120) | (0.131) | (0.156) | | (0.122) | (0.137) | (0.163) |
| SEZ*Firm's Share | | | | 2.937*** | | | | 2.693*** |
| | | | | (0.716) | | | | (0.649) |
| SEZ*Region's Share | | | | -0.445** | | | | -0.677*** |
| | | | | (0.204) | | | | (0.226) |
| Observations | 1335576 | 1335576 | 1335576 | 1093555 | 1335576 | 1335576 | 1335576 | 1093555 |
| Adjusted $R^2$ | 0.438 | 0.438 | 0.438 | 0.439 | 0.432 | 0.432 | 0.433 | 0.434 |
| *Panel D: Dependent Variable* $= log(mu)_{nit}$ | | | | | | | | |
| Firm's Share | 0.136*** | | 0.097*** | 0.171*** | 0.057*** | | 0.035** | 0.087*** |
| | (0.014) | | (0.016) | (0.020) | (0.012) | | (0.014) | (0.017) |
| Region's Share | | 0.051*** | 0.036*** | 0.016** | | 0.028*** | 0.021*** | -0.001 |
| | | (0.005) | (0.006) | (0.007) | | (0.005) | (0.006) | (0.007) |
| SEZ*Firm's Share | | | | -0.097*** | | | | -0.089*** |
| | | | | (0.031) | | | | (0.027) |
| SEZ*Region's Share | | | | 0.042*** | | | | 0.047*** |
| | | | | (0.009) | | | | (0.010) |
| Observations | 1470892 | 1470892 | 1470892 | 1205337 | 1470892 | 1470892 | 1470892 | 1205337 |
| Adjusted $R^2$ | 0.53 | 0.53 | 0.53 | 0.529 | 0.529 | 0.529 | 0.529 | 0.528 |
| *All Panels* | | | | | | | | |
| Year FEs | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm FEs | YES | YES | YES | YES | YES | YES | YES | YES |

Notes: Robust standard errors in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at county level. Specifications 1-4 are weighted regressions; specifications 5-8 are unweighted regressions. All regressions include a constant term.