GROWTH POLICY, AGGLOMERATION, AND (THE LACK OF) COMPETITION[1]

Wyatt J. Brooks[a], Joseph P. Kaboski[b] and Yao Amber Li[c]

Industrial clusters are generally viewed as good for growth and development and promoted by cluster policies, but these 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 test for collusive behavior. We derive the test from the solution to a partial cartel of perfectly colluding firms in an industry. Outside of a cartel, markups depend on a firm's market share, but in the cartel, markups across firms converge and depend instead on the overall market share of the cartel. Empirically, we validate the test using plants with a common owner, and then test 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.

Keywords: Growth, Industrial Policy, Collusion, China, Special Economic Zones.

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: resource concentration, demand concentration, or local but external economies of scale. The first two often lead to efficient agglomeration, but external economies of scale can lead to less than efficient agglomeration and act as a justification for 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)). 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

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[a]University of Notre Dame, 434 Flanner Hall, Notre Dame, IN, USA 46617, wbrooks@nd.edu.

[b]University of Notre Dame and the National Bureau of Economic Research, 434 Flanner Hall, Notre Dame, IN, USA 46617, jkaboski@nd.edu.

[c]Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong SAR, yaoli@ust.hk.

[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 Motor City, however.

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

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. Indeed, the most famous industrial clusters in the United States have all been accused of explicitly collusive behavior.[4] Moreover, programs designed to enable firm cooperation in other areas can also have the unintended side effect of encouraging collusion. Nevertheless, this possibility has been overlooked in development policy.

This paper examines whether non-competitive behavior is associated with geographic concentration and cluster policies. Specifically, we define non-competitive behavior as behavior in either firm sales, hiring, or purchases that internalizes pecuniary externalities on other firms. We make three major contributions toward this end. First, we derive a novel, intuitive test for identifying non-independent behavior for firms competing in the same industry. Essentially, firms who 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 test can identify non-competitive behavior in sales using firms that are affiliates of the same parent company as assumed "cartels." 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 higher in China's "special economic zones" (SEZs) than outside of them. Also, the theory pre-identifies some industry-location pairs as more likely to exhibit non-competitive behavior (i.e., those with little cross-sectional variation in markups), and we find that the levels of such behavior are also high in those.

Our test is derived from a standard nested 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

[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)."

[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 Paramount anti-trust case in the 1940s was against Hollywood movie studios, while ongoing litigation alleges non-compete agreements for workers in Silicon Valley.

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 the individual firms.

Following this, our tests regresses a firm's (inverse) markups on its own market share and the total market share of its suspected or potential set of fellow cartel members. Under perfectly independent pricing, only the coefficient on own market share should be significant, while under perfect collusion, only the coefficient on cartel market share should be significant. The test 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. 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 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 test is also robust along other avenues. Importantly, our theoretical results, and so the validity of the test, 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, using Monte Carlo simulations we show that our tests are fairly robust to firm uncertainty, including correlated demand or cost shocks, and relaxing the strong assumption of constant elasticity demand. 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 test to assess industrial clusters in China, a natural country to consider:"Special economic zones" (SEZs) are reputed 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) allow us to estimate markups using the cost-minimization methods of De Loecker and Warzynski (2012) and implement our test using within-firm variation.

Our test 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, we estimate a highly significant relationship between markups and cartel market share but an insignificant relationship with own market share in our validation exercises. In our placebo tests, we find no response in markups to industrial cluster market shares among these sets of firms and no influence of SEZs on markup behavior.

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 for special treatment, foreign partnerships, etc. [5] They also attempt to foster cooperation through industry associations, trade fairs, and coordinated marketing, but such venues can be used to "manage competition".[6] We find that the intensity of collusion is four times higher for clusters in SEZs than for those not in SEZs. Our results are therefore of potentially normative importance to evaluating the desirability of such policies in China and elsewhere. Moreover, when 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, and these clusters are characterized by disproportionately higher concentration industries, lower export intensities, and more private domestic enterprises as opposed to foreign ventures or state-owned.

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)). In the 20th century, 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 and Hernandez (2013) shows that hotels near one another effectively collude.

Methodologically, the recent industrial organization literature on collusion has tended toward detailed case studies of particular industries, making less stringent assumptions on demand or basing them on deep institutional knowledge the industry.[7] We complement these papers by developing a test that can be applied to a wide range of industries and, rather than focusing on a case study, applying the test to an entire economy, in particular, a developing country that has actively promoted industrial clusters.

[5] 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.

[6] Our own interviews with firm owners and administrators of industrial clusters in China uncovered explicit cooperation on pricing. For example, 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." 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.

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

The local growth impact of Chinese SEZs has been studied in Alder, Shao and Zilibotti (2013), Wang (2013), and Cheng (2014), and they have found 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 a potential beggar-thy-neighbor element.[8] This is consistent with the interpretation that local governments fostered these SEZs, and that local growth success was important to the careers of local politicians. 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 1 presents the model and derives the key theoretical results. Section 2 lays out are empirical test and reviews our empirical application. Section 3 discusses our data and methods for identifying markups. Section 4 discusses the empirical results, while Section 5 concludes.

1. 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.[9]

1.1. *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

[8]Nonetheless, 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.

[9]Our assumption that demand is independent of location impliciltly 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.

to changes in the relative price index of the industry.[10] 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 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 Ω_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:

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

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 that implies a constant elasticity of demand and this cross-price elasticity restriction 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

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

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.[11]

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

1.2. *Firms Operating Independently*

First, we consider the case of all firms operate independently of one another. The 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:

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

Using the definition of market shares, s_{ni}, given above, rearranging (8), and defining the firm's gross markup, μ_n, as the ratio of price to marginal cost yields the well-known result:[12]

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

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 and therefore less to gain, so they charge higher markups.

[11]However, it is important to note that the fact that we maximize static profits 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.

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

1.3. *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 there is a set $S \subseteq \Omega_i$ of firms that solve the following joint maximization problem:

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

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

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

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

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

Note that 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.

Note a number of corollary results follow from equation (12). First, it is immediately clear that firms within the cartel equalize their markups. Second, market shares across cartel firms are more dissimilar than they are with independent pricing, since under independent pricing, it is the larger share firms that charge higher markups. Third, one can show that firms within a cartel charge higher markups then they would under independent pricing. Fourth, given that $\sigma > 1$, each individual firm in the cartel has lower market share under the cartel than it would under independent pricing. Finally, the presence of a cartel in a given industry increases the markups of non-cartel firms in the same industry. This is because firms in a cartel restrict their own output more than they would if they were operating independently, since they take into account their effect on the prices of the other members of the cartel. Non-cartel members of the same industry also benefit because the cartel's lower level of output results in non-cartel firms having higher market shares and markups than if all firms operated independently.

We summarize the above characterization in the following proposition.

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

1. *Under independent decisions, firm markups are increasing in the firm's own market share.*
2. *Under perfect cartel decisions, cartel 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 more dissimilar 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 test in Section 2, 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.

1.4. *Alternative Models*

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

1.4.1. *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 δ_{in} captures the firm-specific component of demand, and we think of these as deviations from the average elasticity σ: $\sum_{n\in\Omega_i} \delta_{in} = 0$. 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 markup 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 δ_{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.

1.4.2. *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.

1.4.3. *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:

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

1.4.4. *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:

$$w_j(L_j) = A_j L_j^{\phi}. \tag{19}$$

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:

$$\begin{aligned} &\max_{y_{nj}, l_{nj}} \; p_{nj} y_{nj} - w_j(L_j) l_{nj} \\ &\text{subject to:} \quad y_{nj} \leq F(l_{nj}; X_{nj}) \\ &\qquad\qquad\qquad L_j = \sum_m l_{mj}. \end{aligned}$$

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:

$$s_{nj}^L = \frac{l_{nj}}{L_j}. \tag{20}$$

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

$$\mu_{nj} = 1 + \phi s_{nj}^L \tag{21}$$

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

$$\mu_{nj} = 1 + \phi \sum_{m \in S} s_{mj}^L \tag{22}$$

Two 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:

$$\mu_{nj} = \frac{p_{nj}}{w_j(L_j)/F'(l_{nj}; X_{nj})} \tag{23}$$

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.

2. EMPIRICAL APPROACH

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

2.1. *Test for Non-Competitive Pricing*

The model of the previous section yielded the result that the markups of competitive firms depend on on the within-industry elasticity of demand and their 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:

$$\frac{1}{\mu_{nit}} = \theta_t + \alpha_{ni} + \beta_1 s_{nit} + \beta_2 \sum_{m \in S} s_{mit} + \varepsilon_{nit} \tag{24}$$

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 ε_{nit} could stem from (classical) measurement error in the estimation of markups, which we discuss in Section 3.2, or from uncertainty or other model specification error as discussed in Section 2.2.

Moreover, for the case of intermediate collusion, κ in 18 can be easily estimated from equation (24) as:

$$\hat{\kappa} = \frac{\hat{\beta}_2}{\hat{\beta}_1 + \hat{\beta}_2} \tag{25}$$

Furthermore, equation (18) implies that we can use the regression in equation (24) to estimate the elasticity parameters. These equations imply that:

$$\hat{\beta}_1 + \hat{\beta}_2 = \frac{1}{\hat{\sigma}} - \frac{1}{\hat{\gamma}} \tag{26}$$

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

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 β_1 larger and β_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 κ equals the fraction of firms perfectly colluding.[13]

Equation (24) 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 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 test 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.[14] Finally, as discussed in Section 1.4, firms could compete as in Cournot or Bertrand, and the essential elements of the test hold in each.

We also note the presence of time and firm dummies in our test. The time dummies, θ_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 demand elasticities.[15] Nevertheless, we add α_{ni} to capture fixed firm-specific variation in the markup, stemming perhaps from firm-specific variation in demand elasticities, as discussed in Section 1.4. Together, these time and firm controls assure that the identification in the regression stems from within-firm, within-cluster and within-firm variation over time in markups and market shares.

2.2. *Simulation Results*

We derived our test from the model in Section 1., 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.

[13]Details of this claim are provided in the appendix.

[14]For example, we do not need to distinguish between implicit or explicit price collusion.

[15]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.

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 tests to relaxing these assumptions by running our test 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:

$$y_{nikt} = \varepsilon_{nikt} D_{nikt} \left(\frac{p_{nikt} + \bar{p}}{P_i} \right)^{-\sigma} \left(\frac{P_i}{P} \right)^{-\gamma}, \tag{27}$$

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

The parameter η 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 productivity, respectively, while ε_{nikt} and ρ_{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 κ and take into account firm uncertainty:

$$\max_{l_{nikt}} \int_{\varepsilon} \int_{\rho} \left[(1-\kappa) \pi_{nikt}(l, \varepsilon, \rho) + \kappa \sum_{m \in S_{ikt}} \pi_{mikt}(l, \varepsilon, \rho) \right] dF(\varepsilon) dG(\rho) \tag{28}$$

where the unsubscripted ε, ρ, 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 (28). 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 covariance 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 test regression on the simulated data, and evaluate the bias in κ as measured by equation (25). 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 κ toward zero, while those at the cluster level push κ 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. In additional to these effects, which bias our coefficient estimates, the fact that unanticipated shocks generate positive standard errors for our coefficient estimates generates further bias in our estimate of κ, as defined in equation (25). In particular, because κ is convex in the coefficient on the firm's own share, then by Jensen's Inequality we know that variance in our estimates of that coefficient bias κ downward. Likewise, since κ is concave in the coefficient on the cluster's share, variance in that estimate bias κ upward.

In all of these results, we stress that this bias only results from unanticipated shocks, and any shocks to cost or demand that is anticipated will not bias our results no matter how those shocks are correlated across firms as discussed in Section 1. 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 4.2. We select the variance of individual shocks, the variance of cluster shocks as well as values of σ, κ and γ 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 κ 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 κ. In our parameterized simulation, the true value of κ 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 κ 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-homotheticity given in equation (27), we find that, as $\bar{p}$ 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), 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 test 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 test 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 κ of the *magnitude* of collusion 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 κ.[16] When measurement error is idiosyncratic, our estimate of κ is biased downward, and when it is correlated at the cluster level, it is biased upward.

This pattern may seem counterintuitive. Measurement error in regressors biases their coefficient estimates toward zero, so measurement error in a firm's own market shares that is independent of markups should shrink that regressor's coefficient and push the estimate of κ toward one. However, measurement error in revenue affects both measured market shares and measured markups. Therefore, if the measured value of revenue is higher than its true value, measured markups and measured market shares are both higher than their true values. Therefore, we *overestimate* the strength of the relationship between the two causing the opposite of the bias found when the measurement error is independent of markups. Hence, if measurement error is idiosyncratic, we would tend to *underestimate* the extent of collusion. By the same argument, measurement error that is correlated at the level of the cluster biases the estimate of κ upward.

The fact that idiosyncratic measurement error causes us to *underestimate* the extent of collusion allows us to avoid the critique of Ravallion and Chaudhuri (1997). If income is measured with a high level of idiosyncratic measurement error and income has strong enough spatial correlation, then average village income has explanatory power for individual consumption merely because it may be a better measure of individual income than is reported individual income. In that case, joint maximization may be inferred incorrectly or attributed too much weight. However, this argument depends crucially on the independence of the measurement error in the independent variable with the measured value of the dependent variable. In our context, by construction the measurement error in the dependent and independent variable are positively correlated, which reverses the bias. Therefore, where we find evidence of collusion the results cannot be due to idiosyncratic measurement error.

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

[16] 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.

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.

3. APPLICATION TO CHINESE DATA

For our empirical test, 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 markets. Our measurement methods are standard and closely follow the existing literature.

3.1. *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.[17] 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).[18] 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)).

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

[18] 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 of from speaking to their behavior, but the impact on our proposed test would only operate through our estimates of market share and should therefore be minimal.

3.2. *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 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. This NBSC database contains 29 2-digit manufacturing industries and 425 4-digit industries.[19]

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:

$$\mu_{i,t} = \frac{\theta^v_{i,t}}{\alpha^x_{i,t}}. \tag{29}$$

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 product. Importantly, we use materials as the relevant flexibly chosen factor. The denominator $\alpha^x_{i,t}$ is therefore easily measured, though we follow DW in adjusting measured output $\widetilde{Q}_{i,t} = Q_{i,t} exp(\epsilon_{i,t})$, by dividing by an estimate of the proportionate error term $exp(\widehat{\epsilon}_{it})$ defined below.

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

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

(2006)'s methodology, presuming a 3rd-order translog gross output production function in capital, labor, and materials that is:

$$(30) \quad q_{nit} = \beta_{k,i}k_{nit} + \beta_{l,i}l_{nit} + \beta_{m,i}m_{nit} + \beta_{k2,i}k_{nit}^2 + \beta_{l2,i}l_{nit}^2 + \beta_{m2,i}m_{nit}^2 + \beta_{kl,i}k_{nit}l_{nit} + \beta_{km,i}k_{nit}m_{nit} + \beta_{lm,i}l_{nit}m_{nit} + \beta_{k3,i}k_{nit}^3 + ... + \omega_{nit} + \epsilon_{nit}.$$

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. ϵ_{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, ω_{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 ω_{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 ϵ_{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.

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.[20].

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

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

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

4. RESULTS

We start by presenting the results validating our test 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.

4.1. *Validation and Placebo Exercises*

We start by running our test on our sample of affiliated firms. That is, we define our potential cartels in equation (24) 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 (24) 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 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 at the 2-, 3-, and 4-digit levels, respectively. The last three columns are analogous in terms cluster definitions, but we do not constrain either coefficient. The standard errors are robust standard errors, clustered at the firm level. The sample of observations is a very small subset (less than two percent) of our full sample because we only include affiliates, and we also only have parent/affiliate information for firms present in a subsample of firms in the year (2004).

, 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:

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

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 (26), 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).) 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 test 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 test 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 test uncovers negative and statistically significant coefficients on cluster's share at the broader industry levels too, own share is also significant and the implied κ 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.

Indeed, we run placebo tests that replicate are tests 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 we only look at the markup response for these sets of firms. The results are quit 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 test (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 tests are consistent with firms colluding within ownership structures at the disaggregate industry level, and our test is able to reject cluster-based collusion in placebo tests.

4.2. *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. Again, we report robust standard errors clustered at the firm level.

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.[21] Again, applying equations (26), we can interpret the magnitude of the implied elasticities and the extent of collusion. At the county level, we estimate $\hat{\kappa} = 0.26$, 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

[21]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.

those implied in the smaller sample of affiliated firms, even though the level of collusion is greater.

We turn to 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 κ 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 ρ, which would be expected, since goods should be highly substitutable within these industries. (See appendix for details.) 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 may be 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 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.[22]

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. In the appendix, we include lists of the top 10 4-digit industries and top 10 cities that are most overrepresented in the bottom three deciles.

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. Examining the results, in the results that assume perfectly independent behavior we again find negative significant estimates at the province and county level. (The city estimates have fewer observations, since there are

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

fewer firms in the low markup variation deciles of city clusters.) 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 estimates on $beta_2$ are negative and significant. The emphpositive $\hat{\beta}_1$ 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 σ 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.

4.3. *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 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 test 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:

$$s_{in} = \frac{p_{in}y_{in}}{\sum_{m \in \Omega_i} p_{im}y_{im}} \approx \frac{z_{in}^{1-1/\sigma}}{\sum_{m \in \Omega_i} z_{im}^{1-1/\sigma}} \tag{31}$$

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:

$$I_1 = \frac{1}{\sum_{m \in \Omega_i / n} z_{im}^{1-1/\sigma}}, \qquad I_2 = \frac{1}{\sum_{m \in \Omega_i / S_n} z_{im}^{1-1/\sigma}} \tag{32}$$

This two-stage estimation yields very similar results (see the Online Appendix for details). 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 test 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.

5. CONCLUSION

We have developed a simple and intuitive yet fairly robust test for identifying non-competitive behavior for subsets of firms competing in the same industry. Using this test 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 minority but non-negligible share of firms and clusters appear to suffer from from non-competitive behavior, and these are disproportionately so – four times as strong – in special economic zones.

The results open several avenues for future research. We have focused 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. Finally, the potential normative importance of our results are compelling with respect to evaluating cluster promoting industrial policies, such as local tax breaks, subsidized credit, or targeted infrastructure investments. They motivate more rigorous evaluation of various normative considerations including: weighing 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

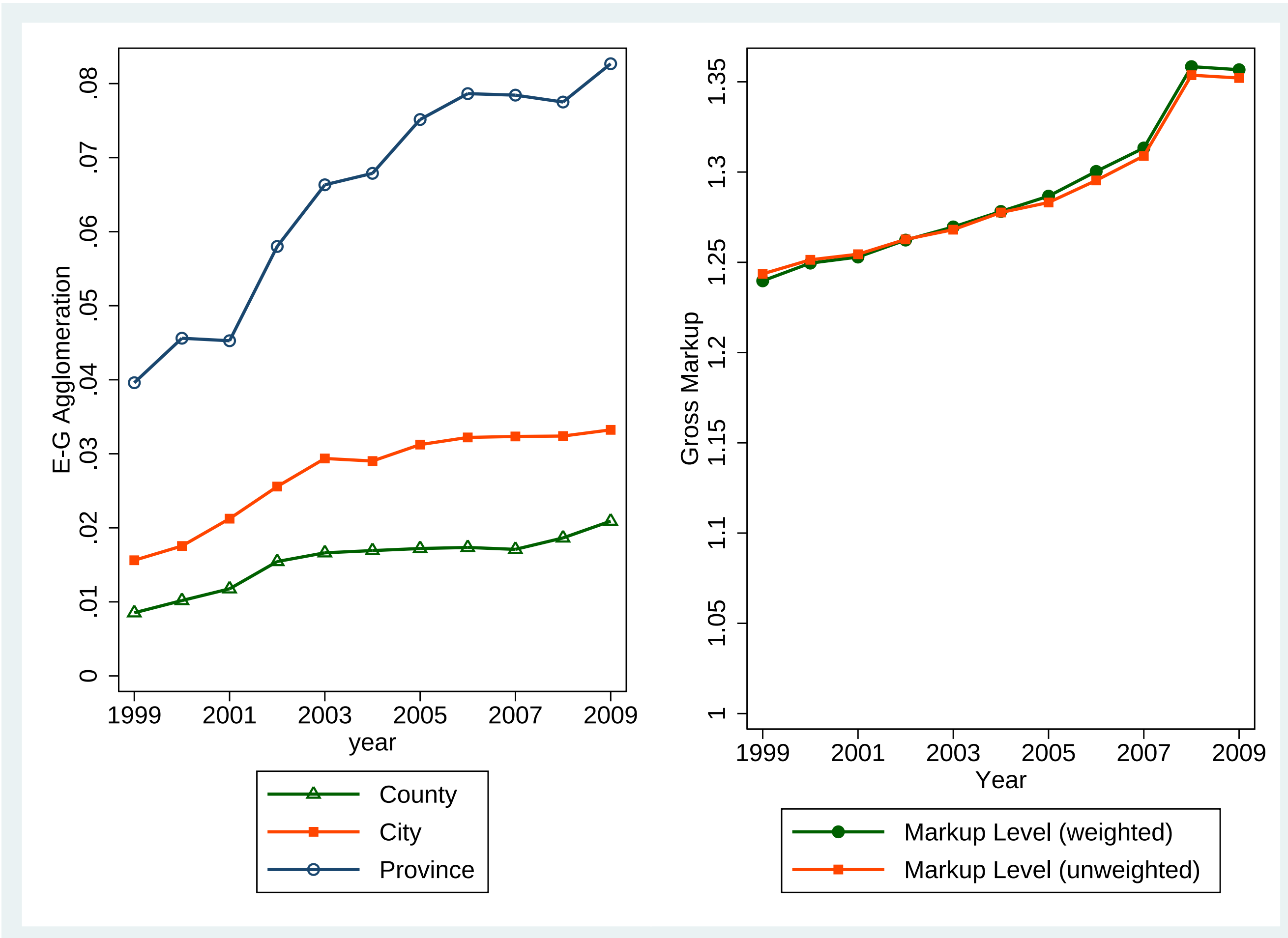


Table 1: Key Summary Statistics of Data

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	322.85	48.17	3719.52	0.01	1035383.00
Materials per Firm	719.09	167.95	5944.99	0.05	860549.30
Real Output per Firm	998.76	243.45	7967.81	0.08	1434835.00
Workers per Firm	287.82	120	1005.62	10	166857
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–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.

Table A.2: 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.3: Appendix Table–Instrument 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.4: 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.5: 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.

A. Derivation of the Demand Function

Suppose the household solves the following problem:

$$\max_{\{Y_i\}} \left(\sum_i D_i^{1/\gamma} Y_i^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}} \tag{1}$$

subject to:

$$\sum_i P_i Y_i \leq P$$

We take the budget of the household P to be exogenous. Cost minimization on the part of the representative household implies the demand function:

$$Y_i = D_i \left(\frac{P_i}{P} \right)^{-\gamma} \tag{2}$$

The final product in each industry is assembled by competitive firms in each industry that solves:

$$P_i Y_i = \min_{\{y_{ni}\}} \sum_{n \in \Omega_i} p_{ni} y_{ni} \tag{3}$$

subject to:

$$Y_i = \left(\sum_i y_{ni}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

Cost minimization on the part of these competitive firms implies:

$$y_{ni} = Y_i \left(\frac{p_{ni}}{P_i} \right)^{-\sigma} \tag{4}$$

Combining equations (2) and (4) implies:

$$y_{ni} = D_i \left(\frac{P_i}{P} \right)^{-\gamma} \left(\frac{p_{ni}}{P_i} \right)^{-\sigma} \tag{5}$$

B. Proof of Proposition 1

Suppose marginal costs of all firms are bounded and non-decreasing. Proposition 1 has the following five parts:

1) If operating independently, firm markups are increasing in a firm's own market share,
2) If operating as a cartel, cartel markups are increasing in total cartel market share with each firm's own market share playing no additional role,

3) Firm markups are higher under cartel decisions than when operating independently,

4) Firm markups are more similar when operating as a cartel than when operating independently,

5) Firm market shares are more similar when operating independently than when operating as a cartel

PROOF:

Suppose any firm n in industry i weights the profits of the set of firms $S \subset \Omega_i$ with constant $\kappa \in [0,1]$. Then their objective is:

$$\max_{y_{ni}} p(y_{ni})y_{ni} - C(y_{ni}; X_{ni}) + \kappa \sum_{m \in S} [p(y_{mi})y_{mi} - C(y_{mi}; X_{mi})] \tag{6}$$

Then for μ_{ni} defined as price divided by marginal cost and share defined as the firm's revenue divided by the sum of firm revenues in the industry, the firm's first order condition can be rewritten as:

$$\frac{1}{\mu_{ni}} = 1 + (1-\kappa)\frac{\partial \log(p_{ni})}{\partial \log(y_{ni})} + \kappa \sum_{m \in S} \frac{s_{mi}}{s_{ni}} \frac{\partial \log(p_{mi})}{\partial \log(y_{ni})} \tag{7}$$

If inverse demand is given by:

$$p_{ni} = D_i y_{ni}^{-1/\sigma} \left(\sum_{m \in \Omega_i} y_{mi}^{1-1/\sigma} \right)^{\frac{\sigma}{\gamma}\frac{\gamma-1}{\sigma-1}-1} \tag{8}$$

Then the cross-price elasticities are:

$$\frac{\partial \log(p_{mi})}{\partial \log(y_{ni})} = \left(\frac{1}{\sigma} - \frac{1}{\gamma} \right) s_{ni} \tag{9}$$

The own-price elasticity is:

$$\frac{\partial \log(p_{ni})}{\partial \log(y_{ni})} = -\frac{1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma} \right) s_{ni} \tag{10}$$

Together these imply that:

$$\frac{1}{\mu_{ni}} = 1 - \frac{1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma} \right) \left((1-\kappa)s_{ni} + \kappa \sum_{m \in S} s_{mi} \right) \tag{11}$$

Firms operating independently is the case where $\kappa = 0$, so then:

$$\frac{1}{\mu_{ni}} = 1 - \frac{1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma}\right) s_{ni} \tag{12}$$

This implies result 1, when $\sigma > \gamma$. Likewise, if firms are operating as a perfect cartel, then $\kappa = 1$:

$$\frac{1}{\mu_{ni}} = 1 - \frac{1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma}\right) \sum_{m \in S} s_{mi} \tag{13}$$

This immediately implies the second result. Moreover, equations (12) and (13) together imply the fourth result, as cartels have no variation in markups (even if they have variation in market shares) while independent firms have markups that vary with their shares.

To compare firms in a cartel to those operating independently, we construct an artificial single firm that is equivalent to the cartel. That is, suppose $\kappa = 1$ so that the cartel solves:

$$\max_{\{y_{mi}\}} \sum_{m \in S} \left(p_{mi} y_{mi} - C(y_{mi}; X_{mi})\right) \tag{14}$$

where p_{mi} is given by (8). Now define a cartel aggregate of production:

$$Y = \left(\sum_{m \in S} y_{mi}^{1-1/\sigma}\right)^{\frac{\sigma}{\sigma-1}} \tag{15}$$

Let $\tilde{C}(Y)$ be the cost function of the cartel defined as:

$$\tilde{C}(Y) = \min_{\{y_{mi}\}} \sum_{m \in S} C(y_{mi}; X_{mi}) \tag{16}$$

$$\text{subject to:} \quad Y = \left(\sum_{m \in S} y_{mi}^{1-1/\sigma}\right)^{\frac{\sigma}{\sigma-1}}$$

Then the following problem is equivalent to (14):

$$\max_{Y} D_i Y^{1-1/\sigma} \left(Y^{1-1/\sigma} + \sum_{n \notin S} y_{ni}^{1-1/\sigma}\right)^{\frac{\sigma}{\gamma}\frac{\gamma-1}{\sigma-1}-1} - \tilde{C}(Y) \tag{17}$$

First notice that the Envelope Theorem applied to the problem in (16):

$$\forall m \in S, \qquad \tilde{C}'(Y) = \lambda = \frac{C'(y_{mi}; X_{mi})}{y_{mi}^{-1/\sigma} Y^{1/\sigma}} \tag{18}$$

Then we can relate the size of the cartel to the cost of the cartel's production.

LEMMA 1: *Consider a cartel made up of in $T \subset S$. Then for every level of production Y, the marginal cost in the cartel composed of T is strictly higher than in the cartel composed of S.*

To prove this lemma, suppose y_{mi}^T is how much firm m produces when part of the cartel composed of T and y_{mi}^S is how much the same firm produces when part of the cartel composed of S. Then for any given Y it must be the case that:

$$y_{mi}^S < y_{mi}^T \implies \frac{C'(y_{mi}^S; X_{mi})}{{y_{mi}^S}^{-1/\sigma} Y^{1/\sigma}} < \frac{C'(y_{mi}^T; X_{mi})}{{y_{mi}^T}^{-1/\sigma} Y^{1/\sigma}} \implies \tilde{C^S}'(Y) < \tilde{C^T}'(Y)$$

where the second implication follows from the fact that all firms have non-decreasing marginal costs. The first inequality follows from bounded marginal costs and Inada conditions in the aggregation of individual firm production to cartel-level production. Therefore, if more firms are added to a cartel, marginal costs for the cartel are reduced for every level of output.

Given this lemma, notice that as a cartel grows, the markup that the cartel charges strictly increases. This follows immediately from that fact that, given the lemma, marginal costs decline so cartel production increases, and as another firm from within the same industry is brought into the cartel, that firm's production is no longer counted in the denominator when computing the cartel's market share. Therefore, the cartel's market share strictly increases as more firms are added. Hence, by (13), the markup charged by the cartel increases.

A special case of this result is part 3 of Proposition 1. If a firm is operating outside of an existing cartel then is brought into it, the new cartel would have strictly higher markups than either the original cartel or the formerly independent firm.

To demonstrate the last result, consider any two firms n and m within the same cartel. Manipulating (18) gives:

$$\frac{C'(y_{mi}; X_{mi})}{C'(y_{ni}; X_{ni})} = \left(\frac{y_{mi}}{y_{ni}}\right)^{-\frac{1}{\sigma}} = \left(\frac{s_{mi}}{s_{ni}}\right)^{\frac{1}{1-\sigma}} \tag{19}$$

Then consider two other firms v and w that are operating independently. Then the relationship between marginal cost and market share is:

$$\frac{C'(y_{vi}; X_{vi})}{C'(y_{wi}; X_{wi})} = \left(\frac{s_{vi}}{s_{wi}}\right)^{\frac{1}{1-\sigma}} \frac{1 - 1/\sigma + (1/\sigma - 1/\gamma)s_{vi}}{1 - 1/\sigma + (1/\sigma - 1/\gamma)s_{wi}} \tag{20}$$

Suppose these two pairs of firms have the same relative marginal costs. Then:

$$\text{(21)} \qquad \frac{C'(y_{mi};X_{mi})}{C'(y_{ni};X_{ni})} = \frac{C'(y_{vi};X_{vi})}{C'(y_{wi};X_{wi})} \implies$$

$$\left(\frac{s_{mi}}{s_{ni}}\right)^{\frac{1}{1-\sigma}} = \left(\frac{s_{vi}}{s_{wi}}\right)^{\frac{1}{1-\sigma}} \frac{1-1/\sigma+(1/\sigma-1/\gamma)s_{vi}}{1-1/\sigma+(1/\sigma-1/\gamma)s_{wi}}$$

Without loss, if firms v and m have relatively high costs, then:

$$\text{(22)} \qquad \frac{C'(y_{mi};X_{mi})}{C'(y_{ni};X_{ni})} = \frac{C'(y_{vi};X_{vi})}{C'(y_{wi};X_{wi})} > 1 \implies$$

$$\frac{1-1/\sigma+(1/\sigma-1/\gamma)s_{vi}}{1-1/\sigma+(1/\sigma-1/\gamma)s_{wi}} > 1 \implies \frac{s_{ni}}{s_{mi}} > \frac{s_{wi}}{s_{vi}}$$

Therefore, independently operating firms have wider variation in market shares conditional on marginal cost than do firms operating as a cartel. This completes the proof.

C. Simulation of Model with Shocks to Demand and Costs

We now consider a version of the model where some uncertainty in costs or demand is realized after production choices are made. Firm i in industry j located in region k in year t solves the following problem:

$$\max_{l_{ijkt}} \int_{S_\varepsilon}\int_{S_\rho} \left[(1-\kappa)\pi_{ijkt}(l,\varepsilon,\rho) + \kappa \sum_{m\in\omega_{jkt}} \pi_{mjkt}(l,\varepsilon,\rho)\right] dF(\varepsilon)dG(\rho)$$

where:

$$\pi_{ijkt}(l,\varepsilon,\rho) = D_j(\varepsilon_{ijkt} l_{ijkt}^{1/\eta})^{1-1/\sigma}\left(\sum_{m\in\Omega_{jt}} (\varepsilon_{mjkt} l_{mjkt}^{1/\eta})^{1-1/\sigma}\right)^{\frac{\sigma}{\gamma}\frac{\gamma-1}{\sigma-1}-1} - \rho_{ijkt}\frac{l_{ijkt}}{z_{ijkt}}$$

Here ε is the vector of demand shocks, ρ is the vector of cost shocks, and l is the vector of production choices. The set of firms operating in industry j at time t is Ω_{jt}, and its subset of firms operating within region k is ω_{jkt}. For any given firm, z_{ijkt} is the component of their costs that is known before production decisions are made. Without heterogeneity in this, there would be no heterogeneity in l_{ijkt}. The parameter η allows for curvature in the cost function.

Notice that F and G are probability distributions over vectors, and we will consider covariance at the cluster, industry and year levels.

The first order condition implies:

$$\int_{S_\rho} \frac{\eta \rho_{ijkt} l_{ijkt}^{1-1/\eta}}{z_{ijkt}} dG(\rho) =$$

$$= \int_{S_\varepsilon} p_{ijkt}(l,\varepsilon) \left[\frac{\sigma-1}{\sigma} + \left(\frac{1}{\sigma} - \frac{1}{\gamma}\right) \frac{\kappa(\varepsilon_{ijkt} l_{ijkt}^{1/\eta})^{1-1/\sigma} + (1-\kappa) \sum_{n\in\omega_{jkt}} (\varepsilon_{njkt} l_{njkt}^{1/\eta})^{1-1/\sigma}}{\sum_{m\in\Omega_{jt}} (\varepsilon_{mjkt} l_{mjkt}^{1/\eta})^{1-1/\sigma}} \right] dF(\varepsilon)$$

where:

$$p_{ijkt}(l,\varepsilon) = D_j \varepsilon_{ijkt}^{1-1/\sigma} l_{ijkt}^{-1/\eta\sigma} \left(\sum_{m\in\Omega_{jt}} (\varepsilon_{mjkt} l_{mjkt})^{1/\eta(1-1/\sigma)} \right)^{\frac{\sigma}{\gamma}\frac{\gamma-1}{\sigma-1}-1}$$

Firms face a variety of shocks at different levels:

$$\varepsilon_{ijkt} = \nu_1 \varepsilon_t^1 + \nu_2 \varepsilon_{jt}^2 + \nu_3 \varepsilon_{ijkt}^3 + \nu_4 \varepsilon_{jkt}^4 + \nu_5 \varepsilon_{kt}^5$$

$$\rho_{ijkt} = \mu_1 \rho_t^1 + \mu_2 \rho_{jt}^2 + \mu_3 \rho_{ijkt}^3 + \mu_4 \rho_{jkt}^4 + \mu_5 \rho_{kt}^5$$

Therefore, we can separately analyze shocks at different levels.

Computational Implementation

The simulated dataset has T years, J industries and K regions. Every industry-region-year has I firms within it. The vectors ε and ρ are therefore of length $I \times J \times K \times T$. First, both ε and ρ are simulated M times. Then a vector L is drawn. Then L is input as the vector of production choices of firms. Using the first order condition, we then solve for the vector Z of anticipated costs that rationalizes the vector L. Together, Z, L, and the realization of shocks implies markups (using the method of De Loecker and Warzynski) and market shares for each firm. Then, for each realization, the regression described in the paper is run on the simulated data. This is done M times.

For these results we choose $\sigma = 5$, $\gamma = 3$, and $\kappa = 0.3$. We set $T = 11$, $J = 5$, $K = 8$, $I = 10$ and $M = 1000$. We assume that the log of each shock is a standard normal random variable.

Effects of Shocks: Comparative Statics

First we look at the effects of all twelve types of shocks individually. The table below presents the results of setting $\mu_1 = ... = \mu_5 = \nu_1 = ... = \nu_5 = 0$, then individually setting each to 1.

In each iteration of the simulation we run the following regression:

$$\frac{1}{\text{markup}_{ijkt}} = \alpha + \beta_1 s_{ijkt} + \beta_2 c_{jkt} + \delta_{ijkt}$$

where:

$$s_{ijkt} = \frac{(\varepsilon_{ijkt} y_{ijkt})^{1-1/\sigma}}{\sum_{m \in \Omega_{jt}} (\varepsilon_{mjkt} y_{mjkt})^{1-1/\sigma}}$$

$$c_{jkt} = \sum_{l \in \omega_{jkt}} s_{ljkt}$$

Here we present the simulated moments of $\hat{\kappa}$ defined by:

Table 1—Simulation Results: Ex Post Shocks

	No Fixed Effects			Region-Year and Firm FEs		
Cost Shocks:	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2
Year	0.3000	0.0075	-0.0006	0.2995	0.0171	0.9999
Industry-Year	0.3000	0.0015	0.0030	0.3000	0.0024	0.1719
Firm-Year	0.0120	0.0562	0.0093	0.0044	0.0577	0.0130
Cluster-Year	0.9759	0.0059	0.0805	0.9982	0.0059	0.2628
Region-Year	0.2227	0.0332	0.0175	0.3178	0.0253	0.6229
Demand Shocks:	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2
Year	0.3000	0.0065	-0.0006	0.3000	0.0145	0.9999
Industry-Year	0.2999	0.0086	-0.0006	0.2998	0.0149	0.1650
Firm-Year	0.0652	6.7790	-0.0001	0.0199	5.3935	-0.0003
Cluster-Year	1.1084	24.2151	0.0016	0.8891	5.2687	0.1846
Region-Year	0.0179	23.5850	0.0021	0.3018	0.0215	1.0000

	Firm FEs			Region-Year FEs		
Cost Shocks:	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2
Year	0.3003	0.0124	-0.1004	0.3004	0.0098	1.000
Industry-Year	0.3000	0.0020	-0.0147	0.3000	0.0016	0.1694
Firm-Year	0.0035	0.0499	0.0125	0.0074	0.0605	0.0094
Cluster-Year	0.9986	0.0053	0.0984	0.9752	0.0066	0.2483
Region-Year	0.2253	0.0306	-0.0113	0.3101	0.0222	0.5584
Demand Shocks:	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Adj. R^2
Year	0.2995	0.0124	-0.1004	0.2999	0.0085	1.0000
Industry-Year	0.2998	0.0126	-0.0187	0.2998	0.0111	0.1711
Firm-Year	-0.2294	15.1836	0.0002	-0.1389	6.0075	-0.0002
Cluster-Year	0.7296	8.6585	-0.0002	1.1787	2.6894	0.1893
Region-Year	-1.3071	53.0598	0.0092	0.3004	0.0110	0.9999

$$\hat{\kappa} \equiv \frac{\beta_2}{\beta_1 + \beta_2}$$

The results from these experiments are given in Table .C. We provide four sets of results based on the set of fixed effects considered, and for each case we provide the average and standard deviation of κ across the 1000 simulations. We also provide the adjusted R^2 averaged across the 1000 simulations.

These results demonstrate two important things to help understand how our estimates of κ could be biased. Firm-year shocks bias estimates of κ downward, and cluster-year and region-year shocks bias estimates upward. The region-year shocks can be mitigated with region-year fixed effects: the bias is almost eliminated for cost shocks and is less severe for demand shocks. In the other cases, the adjusted R^2 of the model can fall considerably, but we see little evidence of bias in estimates of κ.

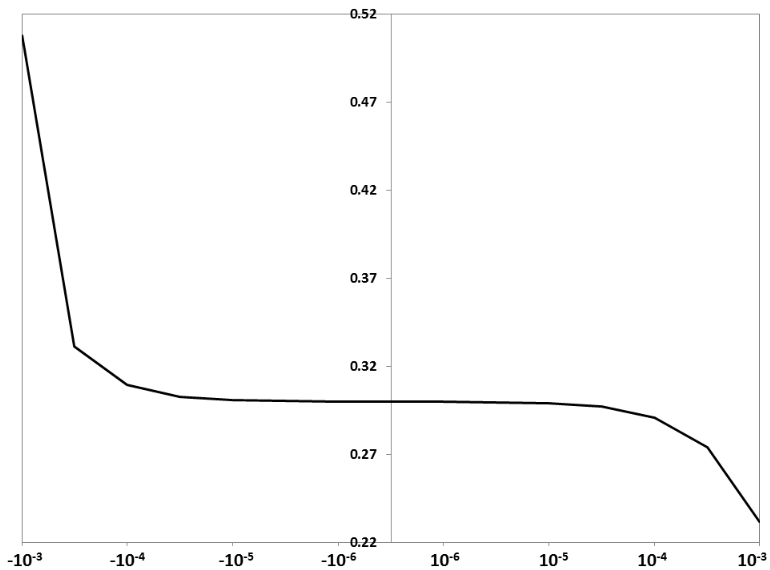
Calibrated Example

The previous subsection demonstrates that the most serious bias arises when ex post shocks are at the firm-year and cluster-year level. We now repeat the numerical exercise from the previous section but now we parameterize the model to replicate the results of our baseline results in column 7 of Table 4. As in that regression, we include firm and year fixed effects and cluster standard errors at the firm level. We first consider ex post shocks to demand at the firm-year level, the cluster-year level, and the year level. We also have idiosyncratic firm-year ex ante shocks. Each shock is assumed to be log-normal.

We calibrate seven parameters: the variance of all three ex post demand shocks, the variance of the ex ante demand shock, γ, σ, and κ. We match seven moments: the coefficient estimate on the firm's own share and on the cluster's share, the point estimate of κ from equation (17), the standard errors on the firm's own share and on the cluster share, the average markup, and the regression's adjusted R^2.

The calibrated value of κ is 0.3246, while the value in the model, as in the data, is 0.2636. This demonstrates that, in this case, we underestimate the degree of collusion with our procedure relative to its true value. This is because the calibrated standard deviation of the firm-year shock is 0.0168 while that of the cluster-year shock is 0.0015. As demonstrated in the previous subsection, the firm-year shocks tend to bias estimated values of κ downward, while cluster-year shocks bias them upward. Since the firm-year shocks are larger, our estimates in the calibrated model are biased downward. Our estimate of σ is 4.5660 and γ is 3.2746. The standard deviation of the year-level shock is 0.0244 and the standard deviation of the idiosyncratic ex ante shock is 0.4313.

Figure 1. Varying Non-Homotheticity: Estimated κ



Departure from CES Demand

Next we consider the case where the demand system is instead given by:

$$q_{ijkt} = \left(\frac{p_{ijkt} + \bar{p}}{P_{jt}}\right)^{-\sigma} \left(\frac{P_{jt}}{P_t}\right)^{-\gamma} \tag{23}$$

Proceeding with the same simulation technique as above, we consider the case where there are no ex post shocks and vary the magnitude of $\bar{p}$.

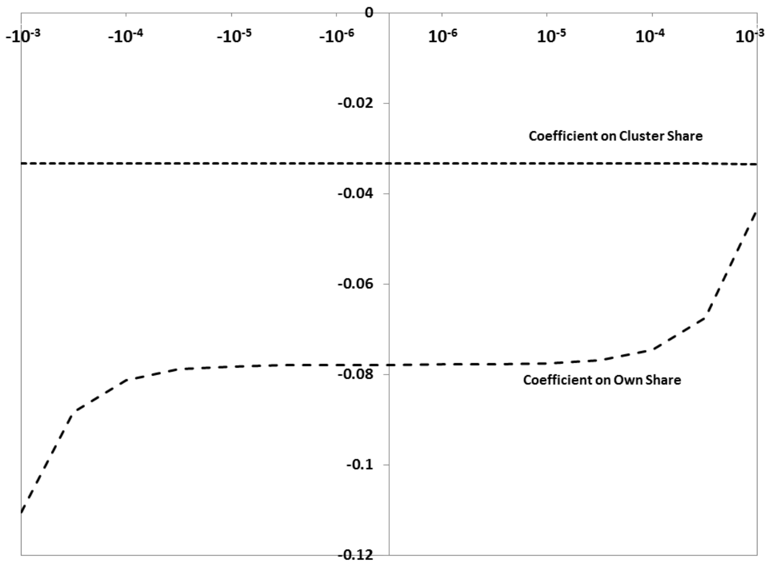
The results are summarized below in Figures 1 and 2. As the value of $\bar{p}$ varies, as shown on the horizontal axis in both figures, on average our measure of κ will be affected monotonically as shown in Figure 1. As before, the true value of κ in this simulation is equal to 0.3. Figure 2 shows that this bias is entirely due to bias in the coefficient on firms' own shares. In fact, the coefficient on cluster shares is unbiased by $\bar{p}$.

This supports our conclusion that a non-CES demand system of this type affects our estimate of the magnitude of collusion. However, if we interpret the t-test of whether or not the coefficient on the cluster share is positive to be a test of collusion, that test is unaffected by non-CES demand systems of this form.

Measurement Error

Finally, we consider the case where revenues are measured with error. We proceed as before, but now instead of unanticipated shocks, we study the effect

Figure 2. Varying Non-Homotheticity: Coefficient Estimates



of increases in the variances of the measurement error.

Following the parameterization in the first simulation exercise, .C shows the effects of measurement error. In the "Idiosyncratic" columns, we assume that measurement error has no correlation across firms. In the "Cluster" columns, we consider the extreme case of correlation within clusters where measurement errors are equal in all firms of the same cluster.

Table 2—Effects of Measurement Error

	Measurement Error, Idiosyncratic			
Var. of Error	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Avg. $\hat{\beta}_1$	$Avg.\hat{\beta}_2$
0.1	0.2763	0.0520	-0.0899	-0.0337
0.2	0.2135	0.0781	-0.1280	-0.0333
0.3	0.1563	0.0812	-0.1926	-0.0335
0.4	0.1170	0.0746	-0.2736	-0.0341
0.5	0.0840	0.0672	-0.3846	-0.0328
	Measurement Error, Cluster			
Var. of Error	Avg. $\hat{\kappa}$	St. Dev. $\hat{\kappa}$	Avg. $\hat{\beta}_1$	$Avg.\hat{\beta}_2$
0.1	0.3602	0.0855	-0.0777	-0.0457
0.2	0.4954	0.1102	-0.0775	-0.0826
0.3	0.6322	0.1116	-0.0771	-0.1469
0.4	0.7253	0.0869	-0.0769	-0.2236
0.5	0.8033	0.0599	-0.0761	-0.3391