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Oligopolistic "Agreement" and/or "Superiority"?:
New Findings from New Methodologies and Data

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Preface

The influential Scherer and Ross text (1990, p. 411) states that the “main question” in empirical industrial organization in the latter part of the twentieth century is Bain’s (1951) “collusion” or “agreement” hypothesis versus Demsetz’s (1973) “superior firm” hypothesis. Prior to the Federal Trade Commission Line-of-Business (LOB) studies the “contending schools were deadlocked,” but these studies led to a win being declared for the superiority hypothesis by Scherer writing with seven other LOB researchers (1987). These studies found that the effect of concentration on profits disappeared when controlling for firm shares. As many economists agreed, merger policy shifted away from a focus on agreement to applying a “unilateral effects” (non-cooperative Nash) approach.

We develop a nine year panel LOB data set for Korea. We perform three types of tests, all of which support both hypotheses, but which show that the agreement effect overwhelmingly dominates the superiority effect in pricing. First we examine a secondary implication of the superiority model: profit aggregation should imply that if share is negatively related to firm profits, so should concentration be negatively related to industry profits. Instead, we find that for those industries with a negative share relationship, the concentration profits relationship is positive and virtually identical to the relationship for the full sample in both within and between panel tests.

Next we introduce a commonly cited model in the empirical literature. This model is cited to motivate the proposition that both share and concentration should have an effect on firm profits. However, authors who cite this model then typically use an ad hoc specification rather than estimating this as a structural model. We develop our structural model and define latent variables to distinguish between domestic and export price cost margins (PCMs) and to identify firm “conjectures” as they impact the domestic PCM. Demand elasticities are captured in non-linear industry fixed effects. We show that concentration plays an overwhelming role in determining firm PCMs, with firm share playing a far smaller role. We additionally exploit the structural characteristics of the model to deal with the possibility that deviations between marginal costs and average costs might be driving the results.

For supporting evidence we construct a new latent variable identifying the domestic/export price ratio. We find a strong “within” relationship between concentration and the domestic/export price ratio, again firm shares play a weaker role.

Finally, we discuss why our results differ from the FTC-LOB studies and provide evidence that would suggest that the FTC studies’ conclusions are biased due to the 1973 removal of price controls and energy crisis, the “stagflation” of the 1970s, and the use of national firm shares along with geographically weighted averages of concentration ratios.

1. Introduction

Scherer and Ross (1990, p. 411) state that the "main question" in empirical industrial organization in the latter part of the twentieth century is Bain's (*e.g.*, 1951) "collusion" or "agreement" hypothesis versus Demsetz's (1973) "superior firm" hypothesis.[1] Bain showed a correlation between industry concentration (the share of industry shipments by the largest 8 firms) and industry profits and attributed this to some form of agreement or collusion between firms. Harold Demsetz in 1973 pointed out that if an industry has some superior firms, these firms will increase their shares and their profits, hence industry concentration will rise and industry profits will rise. The Demsetz argument then is that the aggregation of firm shares and profits to the industry level will lead to a concentration-profit rate correlation due not to collusion, but to dynamic competition. To address the extent to which each of these non-mutually exclusive views has validity and how much each one affects industry outcomes, one needs data not only on industry concentration and profits, but also on firm shares and profits: Line-of-Business (LOB) data. For the United States, such data were collected by the Federal Trade Commission (FTC) for a few years in the mid 1970s.

"The contending schools were deadlocked," declared Scherer *et* al. (1987) writing collectively with seven other LOB authors (Long, Martin, Mueller, Pascoe, Ravenscraft, Scott, and Weiss). But, they continued, the LOB data *broke the deadlock*.[2] The LOB data integrated firm shares and concentration in explaining firm level **price-cost margins** ((P-AC)/P hereinafter PCM). (The implicit assumption is that AC and MC are similar, so this will capture the price-marginal cost margin.) These found that share (superiority), not concentration (agreement), explained PCMs. The superiority hypothesis was declared the winner![3]

Following this, the influential Scherer text (1980 p. 294-95; with Ross in 1990 p. 446) changed its tune to "power appears to be wielded *not collectively* . . ." (emphasis added to the new 1990 wording). The consequent revolution in thought had profound influences on public policy. Antitrust merger analysis in the 1992 DOJ-FTC "Merger Guidelines" switched from:

> the major emphasis . . . [being] merger-induced 'coordination effects', or 'implicit collusion' . . . [to] a focus on 'unilateral effects' . . . [T]his unilateral effects theory has often been the major theme of merger investigations. (White 2003)[4]

"Unilateral Effects" are essentially the question of whether a merger induced change in industry structure raises prices in a non-cooperative Nash Equilibrium (conditional upon any efficiency gains likely to also be induced by the merger).

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[1] It is worth noting Brozen's (1971) "Disequilibrium hypothesis." He showed mean reversion: high concentration industries with high profits tended to have profits decline over time. Jeong and Masson (2003) argue that mean reversion is natural in a simultaneous equations profit and structure market power model which they estimate using Korean data. Brozen mentions the possibility of superior firms and notes that in Bain's (mid depression) data, the low concentration industries were more likely to have the leading firm's profits lower than industry profits, suggesting that where small firms are superior, concentration would be lower. In our data set, however, the industries with negative share profit relationships have somewhat greater concentration than the other industries and the frequency is the same across categories.

[2] Scherer and Ross (1990, p. 429) attribute the "Definitive evidence" to Ravenscraft (1983), and go on to say that the earlier results "... appear to be spurious, a construct of aggregating..." shares to concentration (p. 430).

[3] It is noteworthy that since then Machin and Van Reenen (1993) published a line of business study for the UK (*e.g.*, they used firm data with judgement about whether each firm is really mostly in one line of business) in which they find strong concentration effects after adjusting for share effects. This paper, however, has done little to turn the tide.

[4] White does continue, "The pendulum now seems to be swinging back, with a rekindled interest in coordinated effects." Papers following his special volume introduction make this point as well.

Still, despite the revolution in thought about agreement in the 1980s and 90s, Scherer's texts (1980 p. 295; 1990 with Ross p. 447) discussing "agreement" versus "superiority" conclude with almost identical wording:

> The research agenda for the future must stress obtaining data of high quality and assaulting them imaginatively with high-powered econometric tools to discriminate among the still-contending behavioral hypotheses (1990).

It is our contention that the conclusions from the FTC-LOB studies are seriously flawed, in part because the data were collected for only a few highly atypical (energy crisis, stagflation) years. We will provide evidence for this after our main results are presented. We also note that virtually all previous work uses econometric tools which are not up to the task of addressing the issues raised by the authors in this literature. This is in part because these studies have used a model to "justify" ad hoc specifications, whereas we estimate the structure implied by the model.[5] To estimate the structural model, as we do, requires more sophisticated econometric tools, such as sparse matrix inversion algorithms, which may be part of the reason why the earlier literature is mostly using the model for motivation but not for actual structural estimation.

We have constructed a new LOB data set for Korea: a panel from 1987 through 1995. We analyze the superiority and "agreement" hypotheses using both reduced form and structural modeling. Our structural model derives firm price cost margins as a function of industry concentration, industry demand elasticity, and firm share. We find that most of the industry cross section PCM effect, at least in Korea, is explained by the "agreement" hypothesis. The "superiority" effect is present as well, but it plays little role in biasing the "agreement" results.

Our results start with reduced form results demonstrating that aggregation bias is not explaining the Korean data. We show that industries which have *negative* share-PCM relationships have concentration-PCM relationships very close to those for the entire sample, whereas the Demsetz aggregation argument would predict the opposite sign for such industries. That is, only the "agreement" hypothesis explains this sign result. We then use panel data techniques to show that the signs and significance of the cross-section reduced forms results are robust to inter-industry excluded variables (such as demand elasticity, accounting rules, scale economies and capacity utilization, four factors which have been mentioned by others as potentially leading to biases[6]). It should be noted, however, that we show there is also evidence supporting the "superiority" hypothesis.

Next we present a structural model. This model has been derived by several FTC-LOB authors (Kwoka and Ravenscraft (1986), Rosenbaum and Manns (1994)) and others (Machin and Van Reenen (1993)), but they have not proceeded with structural estimation (they use the model and then add "control variables"). The model is also derived by Clarke, Davies, and Waterson (1984) (hereinafter CDW), who employ a novel structural approach, but one which is not as efficient as the Generalized Least Squares (GLS) approach we employ.[7] It also cannot be used to model unobservables in the error term, as we do herein.

Our structural model has, of course, the same simplifying assumptions used by others, including (at least initially) homogeneous products. However, we can derive other implications of the model because it is structural. One key ingredient is that we can distinguish between domestic and export PCMs and also between the different competitive conditions domestically and in exports. Furthermore, the model can be modified to check for sensitivity to alternative assumptions. For example, we explore a structural model

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[5] As we shall note later, the only way one could meaningfully estimate the structural model using U.S. data is with the subset of truly national industries.

[6] *Cf.* Fisher and McGowen 1983; Benston 1987 (Scherer *et al*. reply); and Rotemberg and Saloner (1986); not to mention reviewers of this paper. Note, in the U.S., if depreciation rates are inaccurate and capital intensity is related to concentration, then accounting data could lead to biased results. In Korea, where firms were doubling in size in matters of only a few years, biases due to depreciation formulae are less likely to bias results.

[7] In the computing environment of the early 1980s, using our techniques would have been a major undertaking and the techniques were not well known or entirely derived as of that time.

in which MC≠AC (leading to a non-zero expected value of the error term) and explore different assumptions on product differentiation as well as examining sub samples of homogeneous industries.

After presenting the core structural model relating firm PCMs to concentration and firm shares, under the assumption of industry specific demand elasticities, we move on to a supporting test. We derive a variable which is equal to a firm's domestic price divided by its export price. From this we can allow for a highly flexible form of the agreement hypothesis (agreement is an industry specific parameter) and ask if concentration affects this price ratio after controlling for the superiority/share effects, which it does.

From all of our tests we find that there is strong support for the "superiority" hypothesis but that its magnitude is such that the "agreement" hypothesis dominates the results.

Since our results are revisionist relative to the FTC-LOB results, we finally address possible reasons for the sharp contrast between our Korean LOB results and the FTC-LOB results.

2. "Agreement" versus "Superiority" ⇔ Concentration versus Share?

Before turning to the literature we address why we use quotation marks around "agreement" instead of employing the more commonly used term "collusive." By "agreement" we do not mean to restrict ourselves to concepts like price-fixing or trigger strategy equilibria. Mutual forbearance can spring from behavioral explanations or enlightened self interest. By "agreement" we simply mean some relationship which suggests that when leading firms jointly have larger shares (*i.e.*, the industry exhibits high concentration, or a high "CR") they are less aggressive price competitors.[8] In fact, this hypothesis has many names in the literature. It is variously called the "market power," the "collusive," or the "Structure-Conduct-Performance" hypothesis. Demsetz's "superior efficiency hypothesis" is sometimes called the "efficiency hypothesis." We prefer to refer to it as the "superiority hypothesis" because, as Demsetz and others note, it applies to more than technical efficiency, *e.g.*, consumer preferences for what they feel is a "superior" product.

Following Demsetz (1973), which used questionable 3-digit industry data,[9] the next series of papers on firm shares versus concentration effects used the PIMS data which produced the general result that once one controls for market share, the concentration-profit relationship disappears. But again, the data can be questioned.[10] Following these studies, the key papers leading to a decline in the Structure-Conduct-Performance methodology were those based on the Federal Trade Commission Line-of-Business data for 1973-77. The published studies generally found that once the market shares of individual firms were used as some form of control, concentration had no independent effect on firm profits (indeed its influence was typically negative). Scherer, with seven other LOB scholars (1987):

[8] The collusion or agreement hypothesis has support in the trigger strategy literature (*cf.* Tirole 1990). "Agreement" can be a Nash equilibrium in a supergame. These models depend upon common knowledge. "Agreement" may require "pregame communication" to agree on the relevant parameters: rival's costs, discount factors, what form of behavior may be triggered, and so on. To effectuate such "tacit collusion" in trigger price games with explicit communication would be found to be "explicit collusion" in antitrust cases (see *e.g.*, Hay and Kelley 1974 for the "tasks" for agreement). We have a wider concept in mind: "agreement" in a behavioral world need not be "collusion" but forbearance from harsher forms of competition.

[9] He tested the share-profitability relationship with three digit data and found a positive relationship. He used weighted averages of four digit concentration levels to find three digit concentration levels. This approach has already been criticized, *cf.* Vernon 1972 and Telser 1964.

[10] A representative study is Gale and Branch (1982) which finds a negative concentration effect adjusting for share. Regarding the data, Scherer and Ross (1990) state, "First, there is an element of self-selection for both the cooperating companies and the businesses on which they choose to report, and in some quantifiable respects the sample is clearly not representative. Second, the data sets are subjected to stringent confidentiality restrictions so that an analyst cannot ascertain what companies and industries are being studied or what the absolute size of any given business is."

> recognize the impact *LB* data analyses have had in modifying views on such structure-performance relationships . . . *The contending schools were deadlocked* . . . [LOB research] has shown that individual *market share effects are indeed much more powerful* than the traditionally emphasized concentration effects in explaining profitability . . . concentration coefficients turn out to be negative. (Emphasis added)

From this and other influences, there have been changes in U.S. antitrust policies that were formerly predicated on the market power theory. Merger analysis used to be based upon market power "agreement" arguments. But following the FTC-LOB studies, much of the merger policy in the U.S. today is based on what is called "unilateral effects" analysis (White 2003). Rather than examining concentration as a matter of concern due to an enhanced propensity for "agreement," the question brought to merger data today is typically whether the change in shares or concentration suggest that the non-cooperative Nash equilibrium is likely to be altered in such a fashion that prices will rise given a merger.[11] Privatization analyses also generally ignore the "agreement hypothesis."

To properly interpret our results and conclusions, it is useful to understand the empirical context: the Korean economy.

3. The Korean Economy: Relevant Contrasts to the United States

It is not our intent to provide a detailed analysis of the Korean economy; we merely seek to highlight the differences that affect our methodology and may affect one's interpretation of our tests and results.

The Korean economy has had little effective (or actual) antitrust policy so we are able to examine the market power-agreement hypothesis in the absence of effective antitrust policies. Over our sample period, 1987-95, the Korean economy had an annual average growth rate of 8.21%. The U.S. grew at 2.78% and Japan grew at 3.18% over this period. This means the Korean economy **doubled** over this period and manufacturing grew even faster. With this growth comes a greater potential for volatility in firm shares and in concentration ratios over time. A greater variance in the independent variables potentially leads to greater explanatory power in panel estimation.

Another salient feature of the Korean economy is that it is geographically compact. There are only two major which are located within a half a day's drive of each other. This has a significant advantage over using U.S. data, as in the FTC-LOB studies. For example, consider the Borden or Carnation companies in fresh fluid milk sales in the U.S. over the last thirty years.[12] Processed fluid milk is typically sold within a one day route delivery distance from a plant. Thus, there are many geographically defined competitive zones or markets. Suppose, as seems likely, Carnation and Borden were "superior firms." They would then have a large incentive to operate in many geographic markets, and indeed both had fluid milk plants in multiple geographic markets. Taking superiority literally for each market, the firms might have somewhat higher local shares leading to somewhat higher local concentration, but these firms' incentives to be in many markets will lead to proportionally larger national shares than one would associate with the superiority effect in any given market. The relevant concentration effects, though, will remain the average of local effects, with proportionally much smaller local "share" effects. Although the geographic aggregation problems have been discussed in great detail in the context of market power

[11] As shares and concentration rise, is price likely to rise given reasonable estimates of synergies from the merger? See, *e.g.*, Baker (1997) and the U.S. Department of Justice and the Federal Trade Commission, 1997, *Horizontal Merger Guidelines*.

[12] An unknown reviewer claimed that a flaw in our example was that Borden and Carnation produced only condensed milk. In fact, they had dominant national shares in fresh fluid milk consumption which is exactly the point. The fact that a reviewer did not know this fact demonstrates how geographically fragmented the market for fluid milk is.

studies, their import for the superiority hypothesis, especially in contrast to the agreement hypothesis in nested testing, has been largely ignored.[13] The potential bias created by using an average of local concentrations but national shares, rather than local shares, is great.[14]

More strikingly, Borden and Carnation are also excellent examples of "agreement." They both have been involved in several fluid milk price-fixing cases over the last thirty years, each case covering a limited geographic area.

Other geographic factors are, however, more problematic. Korea has significant imports and exports leading to adjustments which we discuss in the data section.

Another unique aspect of the Korean economy is an industrial structure which enables us to construct an LOB data set. Our data covers 365 firms from 54 industries in nine years giving 2,698 observations across firms, years, and industries. Our data was not collected specifically by LOB's, but rather by noting that in Korea many firms are essentially selling in only one LOB. In Korea there is a "Chaebol" or "Group" structure. Samsung, during our data period, was not one firm but roughly forty firms. The Samsung firm that produced picture tubes was not the same firm that produced TV's. Later there was a separate Samsung auto firm as well. One could own stock in one firm and not another and so the firms are stand alone entities except in a few respects such as internal capital market credit allocations, cosigning agreements, and, relatedly, strategic planning.

The vast majority of Chaebol firms have coverage ratios of over 90% in a single four digit industry (Korean Standard Industry Codes *(KSIC*s*)* and U.S. *SIC* four digit industry definitions are similar in level of differentiation), and those few which do not have high coverage are readily identifiable in our data.

4. Methodological Discussion

As noted earlier, several studies have motivated PCM-concentration-share modeling on a homogeneous goods oligopoly model but then they have not applied a structural approach to the model. CDW (1984) did apply a structural approach but in an econometrically less efficient method than the one we use. They, as others, show the theory of an oligopoly allowing for "consistent conjectures" (conjectural variations[15]) in a quantity setting model. They show the theory leads to a *structure* which can be estimated *if* they carry out four steps: first, regress PCM on shares by industry; second, select the subset of industries for which there is a positive market share - profit relationship (capturing the efficiency effect) and from this derive the non-linear estimate of "conjectures"; third, limit the sample to the subset of industries for which this parameter is less competitive than the Cournot conjecture; fourth, regress the estimated "conjectures" parameter on market concentration. CDW apply this methodology to U.K. manufacturing data for the mid 1970s and find support for both the market power and the efficiency effects hypotheses.[16]

We pursue a similar model using more powerful techniques. We then examine sensitivity of our results to the homogeneous products specification. We provide two sets of tests assuming heterogeneous products and analyze a sub-sample of definitely homogeneous products industries. For the simple model, firms maximize profits:

$$\pi_i = p(X)\, x_i - c_i\, x_i\,, \qquad X \equiv \sum_{j=1} x_j \tag{1}$$

[13] We demonstrate this more formally using an equilibrium market entry game in footnote .

[14] Note, these arguments have normally been posed as if they applied to a single market. Recognizing national share does not always refer to a single market is important in understanding applications to the United States in which researchers have used national shares but used estimated averages of local market concentration levels.

[15] This is a static concept pertaining to a firm's perception of how its rivals would set their outputs if they correctly anticipated the original firm's output decision; generally one refers to this using more dynamic sounding language, *e.g.*, what would my rivals do "in response" to a change in my output?

[16] They find significant concentration effects. Why does this not offset the conclusions from the FTC-LOB studies? There is probably some feeling that the British data are not as well defined as the FTC-LOB data.

where the i subscript refers to firm i.

Defining X_{-i} as the total quantity of i's rivals' output and the conjectural variation as the elasticity , the FOC gives $\alpha \equiv (\partial X_{-i}/\partial x_i)(x_i/X_{-i})$, the FOC gives

$$PCM_i = \left(\frac{x_i}{X} + \frac{\partial X_{-i}}{\partial x_i}\frac{x_i}{X}\right) \Big/ \eta = [s_i + \alpha(1-s_i)]/\eta = [\alpha + (1-\alpha)s_i]/\eta \tag{2}$$

where η is the industry demand elasticity.

For Cournot, $\alpha = 0$ and for a monopoly α is said to be equal to 1.[17, 18]

CDW run share regressions of the form $PCM_{ik} = \beta_{0k} + \beta_{1k} s_{ik}$ for each industry k, to arrive at industry k "conjectural variations" defined as $\hat{\alpha}_k \equiv \hat{\beta}_{0k} \big/ (\hat{\beta}_{0k} + \hat{\beta}_{1k})$, canceling out the industry specific demand elasticities. They take "agreement" as meaning "less competitive than Cournot," so they exclude industries for which $\hat{\alpha}_k < 0$ [19]

They then regress:

$$\hat{\alpha}_k = \gamma_0 + \gamma_1 CR_k + \varepsilon_k \tag{3}$$

to test whether the conjectures are a positive function of concentration, finding that they are.[20]

Our structural tests use the same mathematics but apply more powerful econometric techniques. Our tests are related to the CDW conjectural specification, but construct latent variables in an entirely new fashion. We model the *domestic PCM* using a non-linear constrained regression, creating a latent variable for α_k as a function of CR, and estimating the elasticity, η_k, as an industry fixed effect:

$$PCM_{ik} = [s_{ik} + (\gamma_0 + \gamma_1 CR_k)(1 - s_{ik})]/\eta_k \tag{4}$$

As we demonstrate, this is a more powerful econometric formulation. The CDW methodology weighs each estimated α_k equally, regardless of "goodness of fit," but this should not be the case. Should a positive $\alpha_1 = 0.30$ with a standard deviation of $\sigma_1 = 0.01$ be outweighed by an $\alpha_2 = -0.35$ if it has a $\sigma_2 =$

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17 The fact that neither statement can be literally true of an asymmetric cost constant returns to scale industry is seldom acknowledged.

18 If this model is literally true and Cournot is the actual state of affairs, a regression of PCM_i on $[s_i + \alpha(1-s_i)]/\eta$ would lead to an $\alpha = 0$. *Industry level* CR affects *industry* PCM when $\alpha = 0$ because industry PCM is $\sum s_i PCM_i = \sum s_i^2 / h = \text{Herfendahl}/h$, but, in both CDW and our model, defining $\alpha \equiv \gamma_0 + \gamma_1 CR$ must lead to $\gamma_0 = \gamma_1 = 0$ with *firm level PCM data* if the world is Cournot.

19 For symmetric oligopoly: $\alpha = 1 \Rightarrow$ "monopoly": $\alpha = 0 \Rightarrow$ Cournot; and $\alpha = -1/(n-1) \Rightarrow$ "competition." With linear conjectures, $\lambda = \partial X_{-i} / \partial x_i$, rather than our elasticity conjectures, $\lambda = (n-1)$ "monopoly"; $\lambda = 0 \Rightarrow$ Cournot; and $\lambda = -1 \Rightarrow$ "competition." One can make a case for using α for conjectures greater than 0 and λ for conjectures less than zero, but with only seven industries with α slightly less than zero for some years, we do not pursue this here.

20 The data do not permit firm level α's to be based upon considerations such as whether they are the largest firm in the industry.

1.0 (when α_1 is significantly greater than zero, but α_2 is not significantly different from α_1)? Obviously not.

The intuition can be explained in the context of OLS. Suppose the model were of the form $Y_{ki} = \alpha_k + \beta X_{ki}$ (k is industry, i is firm within industry) and we only cared about the parameter β which we feel is positive and *common across industries*. One has the option of first running individual industry regressions to obtain an estimated industry parameter $\hat{\beta}_k$ for each industry. Treating each estimated value as an estimate of a single common β, then one can test the simple average of the estimated $\hat{\beta}_k$'s to see if it is positive. What this does is equally weight each observed $\hat{\beta}_k$ regardless of its goodness of fit in the first stage. A more efficient estimator of the common β would be to use GLS *at the second stage*. The GLS estimator would use *inverse variance weighting* of the first stage parameters so that more precisely estimated $\hat{\beta}_k$'s would receive a greater weight in the second stage regression.

If these OLS regressions are combined into a single OLS regression, analogous to what we do here, the individual $\hat{\beta}_k$'s would not be estimated, rather one would obtain the common parameter β directly. The estimated β, in effect, would be the inverse variance *weighted* mean of the $\hat{\beta}_k$'s. The implementation in our case is much more complicated than this example suggests, as we will estimate a common latent variable (not a single parameter) across industries and our model is non-linear in its fixed effects.

Since our model is non-linear in fixed effects we cannot use the standard differences from means method of panel fixed effect estimation. We use dummy variables for the fixed effects, ηk's., Returning to our OLS example, suppose there were N industries. If we used dummies for the fixed effects there would be N+2 parameters to estimate. For an individual industry, its assigned dummy will be a one, and the other N-1 industry dummies will have zeros. With numerous firms, industries, and years, zeroes will dominate. So the X`X matrix is said to be "sparse." Two computational problems are discussed in the literature. First, the size of the matrix can exceed the storage capacity of the computer used (not a problem in our application, but this would have been for CDW in the early 1980s). Secondly, zeroes in floating point computations are not exact zeroes: using standard computational techniques will exacerbate "round-off" errors in the computations, potentially making the computations unreliable (Thisted 1988). This is particularly important in nonlinear fixed effect estimation, as we have here.

The theoretical structure applies to the domestic market, but the Korean economy has many industries with substantial exports. Although concentration may affect domestic pricing, Korean firms are unlikely to have much market power in international markets. Efficiency effects, however, should be important for exports. This too can be handled by the construction of latent variables. Consider the following accounting identity for any given firm and industry:

$$\begin{aligned} PCM &\equiv \frac{p^D x^D + p^f E x^X - c^D x^D - c^X x^X}{p^D x^D + p^f E x^X} \\ &= PCM^D \Gamma^D + PCM^X \Gamma^X \end{aligned} \tag{5}$$

where $\Gamma^D = (1 - \Gamma^X) \equiv$ domestic sales share. The PCM is defined as total net revenue divided by total revenue. Total revenue is calculated as the domestic price times domestic quantity ($p^D x^D$) plus the foreign

price deflated by the exchange rate times export quantity (p^fEx^x). Net revenue is calculated as total revenue minus domestic and foreign product costs per unit,
$\{c^D, c^X\}$, multiplied by their respective quantities. Firm PCM is simply a weighted average of the domestic and export PCMs (in domestic currency).

By applying the same substitutions as above for equations and to obtain the domestic PCM latent variable and α we can embed the concentration terms in the domestic PCM, substituting out for the β_0 and β_1 in the CDW model. For the export PCM, we assume a common conjecture and a common export demand elasticity, $(\beta_2 + \beta_3 s_{ik}^X)$ (*e.g.*, if exports were competitive there would be a common demand elasticity). This leads to

$$PCM_{ik} = [s_{ik}^D + (\gamma_0 + \gamma_1 CR_k)(1 - s_{ik}^D)]\Gamma_{ik}^D/\eta_k + (\beta_2 + \beta_3 s_{ik}^X) E\, \Gamma_{ik}^X + \varepsilon_{ik} \qquad (6)$$

where the latent variable for domestic PCM is the first expression on the right hand side. The latent variable for α is given by $\alpha_k \equiv \gamma_0 + \gamma_1 CR_k$ and η_k is the domestic demand elasticity, an industry fixed effect. For domestic PCMs we have 54 industry specific parameters (the η_k's) and two "common" parameters $\{\gamma_0, \gamma_1\}$. For the export PCM, these assumptions lead to two common parameters. There are four common parameters and 54 fixed effects. The two common parameters in the domestic PCM are part of the maintained hypothesis in CDW. Many other models also posit a common function relating CR to profits (and other variables) across industries. (Allowing for industry specific demand elasticities is uncommon in this literature, with the exception of CDW and work following their methodology.[21])

Before turning to model variants, we discuss implementation. As noted above, one must use dummy variables for our industry fixed effects. This leads to a sparse matrix problem which we handle by extending an approach pioneered by Mundlak (1961). He noted that the design matrix for a linear regression with dummies had a special structure so that one could analytically do the partitioned inversion of the $X'X$ matrix to obtain an analytic expression for the common coefficients (as well as the individual effects). Chamberlain (1980) noted that one could use a similar technique in a maximum likelihood setting.[22] If one were using Newton-Raphson (or something similar) to maximize the (log) likelihood, each iteration of the procedure will have a structure similar to the linear case. One can analytically simplify the Newton-Raphson procedure to update the common parameters by inverting a matrix of only size (k×k), where k is the number of common parameters. One then updates the estimates of the individual effects one at a time as a function of the update to the common parameters. Iterating this process until it converges maximizes the log likelihood. Chamberlain did this in a logit setting. Jakubson (1988) applies similar calculations to a Tobit model. Jakubson (2001) notes that a similar updating technique could be used for nonlinear least squares, which is what we introduce here; the details of which are in the Appendix.

Einstein said "Make your theory as simple as possible, but no simpler." Our basic model, as in (6), is highly simplified. We do test more complex models including firm specific demand elasticities, a form of symmetric product differentiation and apply the simple model to a subsample of homogeneous goods industries. We also model the error term $\varepsilon_{ikt} = \mu_{ikt} + \varepsilon_{ikt}'$ where ε' has a zero mean and the μ reflects factors that could lead to a measurement error due to MC≠AC. As the results from these additional, more

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[21] See Masson and Shaanan (1984) for another variant of industry specific demand elasticities.
[22] The computational problems which may occur without sparse matrix inversion techniques are covered in Thisted 1988.

complex, specifications deviate only slightly from those in the basic model in (6), we analyze this basic and simplest model in most detail.

5. Data

Our data come from various sources. For the firm level panel data we obtained balance sheets, income statements, and manufacturing cost statements from the Korean Investors Service, Inc. data base (KIS) for 1987 to 1995. We selected all manufacturing firms listed on the Korean stock market which we then matched to their respective industries according to their 4-digit *KSIC*s (Korean Standard Industry Codes) in order to measure market share and concentration. We excluded firms matched to the Census "catch all" industries (with names like, *etc, misc, nec, and nsk*, each denoting non-homogeneous sub definitions). We screened to make certain that firms in our sample had high coverage ratios in individual Census industries; only a couple firms needed to be dropped by this criterion. Finally we required at least two firms with full information to include an industry/year in the sample; the remaining sample includes 363 firms in 54 industries.[23]

The KIS data contain a firm's domestic and export sales. A firm's sales are divided into manufacturing sales and merchandise sales; we analyze only manufacturing sales and manufacturing costs. *KSIC* industry sales are obtained from the "Report on Mining and Manufacturing Survey" from the National Statistical Office. We merge industry export and import data with the Input-Output Table from the Bank of Korea, adjusting for minor differences in industry code definitions between the *KSIC* and the I-O classifications.

We turn next to defining the variables in the data.

5.1. PCM

Our dependent variable is the price-cost margin.[24] The theoretical definition is PCM ≡ (P - MC)/P. Since marginal cost is not observable, given U.S. data availability, most researchers have used short-run average variable costs in place of MC.[25] In cost minimization, where

MC = AC > AVC, it is common to control for the industry capital output ratio (K/O) on the right side and interpret the coefficient on K/O as the opportunity cost of capital – as if it had been deducted from the left side and hence the remainder of the right side is interpreted as explaining the price to marginal cost ratio. We instead calculate (P - AC) / P, with estimates of capital costs deducted from the dependent variable (our results are robust to using AVC and including K/O as a regressor). In non-strategic equilibria (ignoring excess capacity strategies), once a firm is past its *mes* (minimum efficient scale) it should attempt to minimize costs where SRMC = SRAC = LRMC = LRAC. Most detailed cost studies imply that when there is an AC elevation below *mes*, it is typically moderate (*cf*. Scherer and Ross 1990). Hence, AC should, in equilibrium, be close to MC (*e.g.*, with substantial price cost margins, only a small fraction may be explained by an AC - MC differences). This argument is *a priori*. However,

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[23] 206 firms have data for all 9 nine years, the mean number of years is 7.4.

[24] As noted elsewhere (*e.g.*, Jeong and Masson (2003), Schmalensee (1985)) for an entry study one would wish to use some form of return on investment. Our use of PCM is justified by the use of the conjectural model which assumes firms interact only with *existing* rivals. In Jeong and Masson (1990) the argument is presented that in high growth industries (e.g., most of Korean manufacturing) limit pricing should not be observed, and they present results consistent with this interpretation. (If entry considerations affect current pricing in this model, it would be captured in the industry fixed effect like a "long run demand elasticity" effect).

[25] If a firm is at or above its minimum efficient scale (mes), where long run costs reach their minimum, any cost minimizing equilibrium will have MC = AC. Given cost function studies, MC should generally be very close to AC for cost minimizing firms, even firms which are smaller than mes.

because our model is a structural model, we can test for biases due to differences between AC and MC in a fashion which will be demonstrated after the results from the first structural model are presented.

LOB data have an advantage over many other data sets in that we have firm specific measures of K/O, K_i/O_i. Many earlier studies have been constrained to industry averages. The definition we want is the opportunity cost of capital, $r(K_i/O_i)$, where we need a measure of the cost of capital. For the opportunity cost of capital, we use each year's financial expense as a proportion of total borrowing in the manufacturing sector (11.2% to 13.6% over our sample period) published in the Financial Statement Analysis by the Bank of Korea.[26] For capital we use tangible fixed assets.[27] The "Cost of Goods Manufactured" in the KIS data includes raw material costs, labor costs, electricity, utilities, taxes, and the like. PCM is defined as sales net of the cost of goods manufactured and capital costs divided by sales.

5.2. Market Shares Concentration

The numerator for the share data comes from KIS. Industry shipments data come from the National Statistical Office (NSO). An almost unique element in our panel is CR being measured as the **annual** three firm concentration ratio calculated from raw Census data provided by the NSO. Domowitz, Hubbard, and Petersen (1986a, 1986b), for example, had to extrapolate between Census years. They noted stable concentration trends justify extrapolation. In Korea, with high manufacturing growth rates, there is a sufficient enough amount of volatility that having annual data provides power for our tests (*e.g.*, for establishing "within" results). Machin and Van Reenen (1993) also had annual data and only had to extrapolate one year.

There is no unique method for adjusting concentration for exports and imports. For example, consider a trigger strategy. If a firm has excess capacity it can use this to drive down domestic prices at will. Are exports like excess capacity? If a trigger is "pulled," can one simply reduce exports and flood the domestic market? This depends upon many imponderables, such as what contracts one has with importers elsewhere. How exports should be treated then depends upon unobservables. We base the numerator of domestic concentration on a measure of domestic sales: total sales net of exports. So, suppressing the annual subscripts, we use:

$$CR_k = \frac{\sum_{i=1}^{3}(x_{ik} - \hat{e}_{ik})}{X_k - EX_k + IM_k} \quad \text{and} \quad s_{ik} = \frac{x_{ik} - e_{ik}}{X_k - EX_k + IM_k} \tag{7}$$

where $\hat{e}_{ik}$ is an estimate of firm exports under the assumption that the top three firms are exporting at the industry average intensity (the denominators are from industry level data and the share numerator is from our firm sample data). Note, e_{ik} in the share is a firm's actual exports.

5.3. Advertising Intensity

Although we have not discussed advertising above, we use industry advertising for some model specifications, since this is a traditional market power model proxy for product differentiation. For the Advertising-Sales Ratio we use 4-digit industry level data.[28] The advertising expenditure data is obtained

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[26] Note that at this time Korean debt financing was highly dependent on short term (one year) bank loans.

[27] This measure of capital stock does not include assets unrelated to manufacturing costs (*e.g.*, financial assets and land unused in manufacturing).

[28] We have firm level data, but since this is being used as a proxy for differentiation, we feel the industry data are better suited. *E.g.*, advertising differences between auto firms or for one auto firm across time, are not likely to represent real differences in the degree of auto differentiation.

from the advertising expenditures in the Financial Statement Analysis by the Bank of Korea. Advertising is divided by industry total sales that are also available from the same source.

5.4 Data Values

The data have the following characteristics:

Variable	Mean	Std. Dev.	Max	Min
CR (3 firm concentration)	0.394	0.179	0.997	0.065
PCM (price cost margin)	0.142	0.156	0.715	-0.264
ASR (advertising-sales ratio)	0.013	0.019	0.088	0.0008
s^D (domestic share of firm in industry)	0.046	0.083	0.785	0.000
s^X (export share of firm in industry)	0.098	0.175	0.976	0.000
Γ^D (ratio: domestic to total firm sales)	0.663	0.319	1.000	0.000
Γ^X (ratio: export to total firm sales)	0.337	0.319	1.000	0.000

6. Empirical Model Results

6.1. Test 1: Superiority-Aggregation Bias? Accounting Bias?

Here we introduce a new methodology to examine whether superiority is driving the concentration-PCM correlation: we examine a secondary implication of the superiority hypothesis. The superiority hypothesis suggests that firms with a technical advantage which lowers their costs will have both larger shares and higher profits than the norm. When we aggregate to the industry level, the implication is highly concentrated industries will have higher profit rates.

Now consider the subsample of industries for which the correlation between shares and profits is negative. Here the largest firms have the lowest profits and the lower share firms have profits above the norm.[29] Higher concentration (larger leading firms) would imply that industry profits would be lower. The key, however, is that only a small fraction of the industry experiences profits above the norm in such industries. Hence, according to the superior firm hypothesis, aggregating to the industry level, concentration should no longer be associated with higher profits. Rather the aggregation effect would lead higher concentration to imply lower profits in industries with a negative share-PCM relationship.[30] Does this subset of industries have greater profits associated with greater concentrations? More specifically, do they have the same positive relationship between concentration and profits as the entire sample? If so, this is what would be predicted by an agreement hypothesis, but this would be inconsistent with the aggregation of profits from superior firms.

To address these issues we construct standard market power industry cross-sections (later we present panel results) for our full sample of 54 industries and run two regressions on this data. The first is simply

[29] The simplest way to conceptualize this is to assume that the lowest profit firms are earning normal profits (not exiting). Then if there is a positive share-profit relationship, the high share firms would be earning higher profits than the norm and, conversely, if there is a negative share-profit relationship the small share firms earn profits above the norm.

[30] One has to be careful to avoid a fallacy at this point. Industries with each firm having equal shares and equal profits might have all firms earning normal profits, so the negative relationship may be local, but not global. In practice, however, industries have wide size distributions, suggesting that the expected relationship is negative in observed data.

the standard regression of PCM (price-cost margin) on CR (concentration), the second adds ASR (the advertising-sales ratio) to this regression. These follow the traditional methodology of regressing the average industry PCMs over the sample period on the average industry concentrations for the sample period.[31,32] Hence there are only 54 industry observations. The results are (*t*-statistics in parentheses):

$$\begin{array}{llll} PCM_k = \underset{(2.98)}{0.0814} + \underset{(2.06)}{0.124\,CR_k} & & R^2 = 0.076 & F = 4.25 \\ PCM_k = \underset{(3.00)}{0.0735} + \underset{(1.53)}{0.084\,CR_k} + \underset{(3.78)}{1.94\,ASR_k} & & R^2 = 0.278 & F = 9.81 \end{array} \tag{8}$$

The CR term in the regression with ASR only meets the 90% significance level whereas alone it meets the 95% level.

We next look at the subsample of the 16 industries out of the original 54 for which there is a negative relationship between firm domestic market share and PCM. The industry PCM is calculated as the sales weighted average of the PCMs of the firms in our sample. For this subsample the same simple regressions yield:

$$\begin{array}{llll} PCM_k = \underset{(1.24)}{0.052} + \underset{(1.90)}{0.162\,CR_k} & & R^2 = 0.204 & F = 3.60 \\ PCM_k = \underset{(0.59)}{0.024} + \underset{(2.35)}{0.185\,CR_k} + \underset{(1.96)}{1.50\,ASR_k} & & R^2 = 0.385 & F = 4.07 \end{array} \tag{9}$$

CR is significant at the 95% level for both tests using this subsample; in fact the coefficients are also somewhat greater than those of the full sample.[33] Despite a negative relationship between share and the PCM for the subsample firms in each industry, there is a positive relationship between the weighted average PCMs *of these firms* and industry concentration.

This new methodology addresses a secondary implication of the superiority hypothesis nested with a primary implication of the agreement hypothesis. Finding a positive and significant CR effect for the subsample with a negative share PCM relationship supports the agreement hypothesis and rejects the

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[31] Sometimes advertising is treated as endogenous; Hausman tests sometimes suggest that this need not be the case. For our purposes, however, the additional tests we provide demonstrate that the results from our key models are insensitive to the inclusion of advertising.

[32] Jeong and Masson (1990) find that other standard variables were not important in Korean data for an earlier time period and argue this is because of the high growth rates which lead to the conclusion that firms would not pursue limit pricing strategies.

[33] As noted in the previous note, the aggregation argument is not necessarily monotone in concentration for the subsample, but certainly the aggregation argument is inconsistent with having parameter estimates at the level of, or higher than, those from the full sample.

implication that the superior firm aggregation bias is the sole factor which leads to the CR correlation with PCM.

This test was meant to be as close to the traditional empirical work as possible. We can gain additional insights by exploiting the panel nature of our data. The panel uses firm level data and includes firm fixed effects. We no longer control for ASR since industry product differentiation is in the firm fixed effects. Obviously other systematic factors, *e.g.*, scale economies, growth, demand elasticity, exports, and *industry (and firm) accounting conventions*, will also be captured in the firm fixed effects. We also include three growth rates, the growth in GDP, the growth in Industry Sales and Firm Growth. The results for the full sample are:

$$PCM_{kt} = \underset{(2.86)}{0.066}\, CR_{kt} + \underset{(2.37)}{0.117}\, GDPGrowth + \underset{(2.65)}{0.049}\, Industgrowth + \underset{(1.14)}{0.004}\, FirmGrowth + Fixed\ Effects \qquad (10)$$
$$F = 89.25$$

and the results for the firms in the 16 industries with a negative share-PCM relationship are:

$$PCM_{kt} = \underset{(2.05)}{0.059}\, CR_{kt} + \underset{(1.97)}{0.125}\, GDPGrowth + \underset{(2.18)}{0.042}\, Industgrowth + \underset{(0.72)}{0.003}\, FirmGrowth + Fixed\ Effects \qquad (11)$$
$$F = 45.64$$

CR is significant at the 99% level for the full sample as well as the subsample and the coefficients are virtually identical. By examining the secondary implication of the superiority hypothesis nested with the primary implication of the agreement hypothesis, one can certainly reject the proposition that a positive share-PCM relationship is "causing" a correlation between CR and PCM. At a minimum one can reject it for the subsample of 16 industries.

The parameter estimates for the two panels are nearly identical, and somewhat lower than those for the industry cross section. This fact implies that unobserved firm/industry effects are somewhat correlated with observable regressors in the market power cross section model. Putting in fixed effects implies that coefficients of interest are identified by *within firm/industry variation over time*: "within" estimates. The between industry variation, *i.e.*, regressing the mean of industry PCM's on the mean of the CR's, as we do in our market power cross section model above, identifies a "between" estimate of the parameter. If the individual effects are not correlated with the observed regressors, both the "within" and "between" models estimate the true parameter. If not, the "between" estimator is biased. The fact that the within estimator is somewhat lower than the between estimator implies there is some omitted variable bias problem when omitting the firm/industry effects as is done in most studies.

Note what this means regarding the use of traditional modeling with accounting data, at least in our Korean sample. Accounting biases have been hypothesized to be related to industry characteristics in such a fashion that they create a positive correlation between industry concentration and accounting PCMs.[34] A secondary implication is the "between" model would be biased, but the "within" model would not be biased. The argument that the inter-industry accounting bias fully explains the positive CR-PCM relationship would also imply the within results would have zero correlation. The fact that the within and between estimates have roughly the same magnitude of their positive relationship indicates industry accounting biases are not totally responsible for causing this relationship. The positive relationship in the within estimates are not predicted by this hypothesis but are predicted by the agreement hypothesis.[35]

[34] E.g., high capital output ratio firms would have depreciation being more important in profit calculations and high capital output ratio industries might be prone to have greater concentration. If depreciation is mismeasured, this could cause an apparent correlation between concentration and profits.

[35] Earlier work (for the U.S. Masson and Shaanan 1982, Geroski, Masson and Shaanan 1987, and for Korea Jeong and Masson 1990, Jeong and Masson 2003) finds that entry and structural change are explained by accounting profits data in ways one would expect given the hypotheses. This provides indirect evidence pertaining to both

Another criticism of accounting PCM data is that the numerator is price minus average costs, not the theoretical marginal costs. In cost minimization with constant returns to scale in the long run, LMC=LAC=SMC=SAC. But reviewers expressed concern that under rapid growth, firms would possibly face capacity constraints. In our structural model we address the issue of MC≠AC. In our within estimator above, however, we see that firm growth has virtually no effect on PCM (as would be implied by capacity constraints), whereas both industry growth and GDP growth have strong effects (and virtually the same effects in both samples).

Finally, reviewers have suggested accounting biases within industries may be correlated with firm shares, we test for this when we model MC ≠ AC in a structural model.

Note, we have implicitly shown evidence for the **Superiority Hypothesis** as well as the agreement hypothesis. We found that for 38 of the 54 industries the share-PCM relationship was positive. If there were no superiority effect, we should find that approximately half of our industries would have a positive share-PCM relationship. We can reject the null hypothesis that one half of our industries will have a positive PCM slope on share at the 99.5% level (p-value 0.0014) when applying a "zero test"; the equivalent to testing how likely it is that one would get 38 heads out of 54 trials with a fair coin. We go further and estimate the magnitude of the superiority effect, that is, how much of our PCM variation is attributable to the share effect.

We now add structure to the model permitting us to test the "agreement" hypothesis controlling for efficiency effects and separating domestic and export PCMs by use of latent variables. The nonlinear regression models we develop next are presented using "within group"[36] estimation (*i.e.*, industry fixed effects) which are consistent.[37] (In this non-linear specification it is not feasible to identify purely the "between group" effects.)

6.2. Test 2: Conjectures and Concentration

Now we turn to the implications of the primary model. There are multiple papers which consider how share and concentration (including interactions) affect PCMs. Even if the model is not explicitly stated, their models contain the same maintained hypothesis that treats demand elasticities as being constant across industries.[38] The CDW contribution is to use a structural model by estimating an equation derived from oligopoly first order conditions and permitting demand elasticities to be industry specific. This inherently is a non-linear model. They solve this computationally by their multistage procedure. We

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whether accounting profits reflect true profitability and whether incumbents or market leaders have superiority advantages that others cannot hope to replicate.

[36] The "within group" estimator uses only intertemporal variation in concentration and shares to estimate the common parameters. We say "within group" because the linear within group estimator, *using differences from means,* is typically called the "within" estimator. Achieving *the identical* estimates using dummies in a linear model is not usually called a "within" estimator. In a non-linear (or linear) model one can use dummies to achieve the within group estimates.

[37] Technically, consistency of the dummy variable estimator in the nonlinear setting requires the number of time periods T to grow large. Intuitively, we have T = 9 observations to estimate each industry's effect. Since the model is nonlinear, any inconsistency in the industry intercepts is transmitted to the common slopes. However, Monte Carlo evidence (*e.g.*, Heckman 1981) suggests that this inconsistency empirically grows small quickly for models without a lagged dependent variable as one of the regressors.

[38] See, for example, the papers reviewed in Scherer *et al*. (1987). They assume a structure such as PCM = f(CR,s) + βX, where βX are "control variables" or fixed effects. But, the function f(CR,s) is assumed to be common, hence the demand elasticity is assumed to be common *even if* the control variables are supposed to be controlling for demand. See Machin and Van Reenen (1993) for discussion of a model such as

$$PCM_{ikt} = [s_{ikt} + (\gamma_0 + \gamma_1 CR_{kt})(1 - s_{ikt})]/\eta + f_{ik} + \varepsilon_{ikt}$$

where the implicitly maintained hypothesis is a common η and the firm level fixed effect is said to be for unobservables such as management style. E.g., it is like our later model in which we model the error term as $\varepsilon_{ikt} = \mu_{ikt} + \varepsilon_{ikt}'$,except for the fact that their η is common for all i,k,t.

solve this directly with computational methodologies designed for non-linear models dominated by sparse matrices.

Recalling equation (6) we estimate

$$PCM_{ik} = [s_{ik}^{D} + (\gamma_0 + \gamma_1 CR_k)(1 - s_{ik}^{D})]\Gamma_{ik}^{D}/\eta_k + (\beta_2 + \beta_3 s_{ik}^{X})\, E\, \Gamma_{ik}^{X} + \varepsilon_{ik} \qquad (12)$$

There are three new methodologies used here: (1) latent variables to identify the domestic and export PCMs; (2) imbedding the latent variable for conjectures in a single step model with industry specific demand elasticities; (3) a sparse matrix estimation methodology modified to handle the non-linear model fixed effects.

As noted above, there are 16 industries with a negative slope on the share variable. There are also 7 industries with positive slopes but negative vertical intercepts in this first stage, *i.e.*, these industries appear to be "more competitive" than Cournot competition. Accordingly we look at three samples: (1) all 54 industries; (2) the 38 industries with the expected positive efficiency relationship between shares and PCMs; (3) the 31 industries which have both the expected positive slope and positive intercept ("less competitive" than Cournot industries).

The third sample is what CDW advocate using. Our reason for using the full sample is based on the following logic. Suppose all industries are less competitive than Cournot and reflect efficiency effects (higher shares associated with higher PCMs). Sampling is likely to lead to the occurrence of some industries for which the *ex post* samples do not exhibit these *a priori* properties. Alternatively, use of the subsamples leads to the potential criticism that we are eliminating data which are counter to our *ex ante* hypothesis, biasing our results towards acceptance of our hypothesis.

Use of the full sample is equally justified by noting that the conjectures are simply a metric, not to be confused with actual behavior (*cf.* Bresnahan 1989). The result that the elasticity form of the conjectures when $\alpha < 0$ is not defined as simply as when $\alpha > 0$ (see note) might induce one to model the seven industries with $\alpha < 0$ differently. When α is negative it is close to zero, so we present one model for the entire sample.[39] On the other hand, we provide subsample results as well. Our second and third samples which eliminate industries can be compared to the multistage CDW methodology. We can also examine whether the results are robust to the various samples (which they are).

The results from this basic model are:

The Basic Non-Linear Model

	Domestic Conjecture $\alpha \equiv \gamma_0 + \gamma_1 CR_k$		Exports $\hat{PCM}^X = (\hat{\beta}_2 + \hat{\beta}_3 s^X)\, E$		
Sample	γ_0	γ_1	β_2	β_3	# industries (observations)
Full	-0.055 (3.26)	0.649 (8.77)	-0.038 (4.75)	0.172 (5.38)	54 (2698)
Efficiency hypothesis, all industries	-0.024 (1.42)	0.581 (7.74)	0.023 (2.76)	0.129 (3.83)	38 (1756)
Efficiency hypothesis, $\alpha > 0$ (supra Cournot)	-0.038 (1.54)	0.596 (9.49)	0.045 (5.49)	0.146 (4.46)	31 (1557)

t-values are in parentheses. The relevant critical values are 95% = 1.64; 99% = 2.33; 99.5% = 2.58; and 99.95% = 3.29.

[39] The estimated α's for the entire sample has a min = -0.01, max = 0.58, mean = 0.22, and a standard deviation = 0.12.

As was noted for the aggregation tests in the previous section, there was some sensitivity when the advertising sales ratio, ASR was added to the traditional model. Accordingly, we also estimate the model with the addition of the ASR *in the conjecture term* (the product differentiation effects on demand elasticity should be captured in the industry specific demand elasticity fixed effects).

The Basic Non-Linear Model with ASR

	Domestic Conjectures $\alpha \equiv \gamma_0 + \gamma_1 CR_k + \gamma_2 ASR$			Exports $\widehat{PCM}^X$		
Sample	γ_0	γ_1	γ_2	β_2	β_3	# industries (observations)
Full	-0.149 (3.98)	0.623 (6.22)	0.103 (3.32)	-0.030 (2.82)	0.223 (5.19)	54 (2698)
Efficiency hypothesis, all industries	-0.048 (1.26)	0.588 (3.03)	0.043 (2.83)	0.074 (7.72)	0.141 (3.58)	38 (1756)
Efficiency hypothesis, $\alpha > 0$ (supra Cournot)	-0.103 (7.52)	0.540 (7.76)	0.031 (3.80)	0.060 (7.13)	0.219 (6.04)	31 (1557)

( ) *t*-values: 95% = 1.64; 99% = 2.33; 99.5% = 2.58; and 99.95% = 3.29.

The crucial coefficient for the hypothesis is γ_1, the influence of concentration on the conjectural variation parameter. In a one-tailed *t*-test for each model specification the γ_1 is strongly significantly greater than zero. Unlike the tests in the earlier section which were based on firm PCM rather than on a latent variable for firm domestic PCM, the addition of the ASR does not alter the point estimates of γ_1 by very much.[40]

To understand the importance of letting demand elasticities vary across industries, as do CDW and as we do here, we briefly examine the elasticity results. Using the full sample model, without ASR, our mean demand elasticity is 1.70 with a standard deviation of 0.88 with a minimum and maximum value of 0.25 and 3.87, respectively. Now consider two firms within an industry with shares $s''$and s', with $s'' = \beta s'$, $\beta>1$. Evaluating the predicted PCMs for this industry at an elasticity of the mean plus one standard deviation and at an elasticity of the mean level minus one standard deviation, we can inquire how these estimates differ. Clearly the PCM estimates for s' are lower for the higher elasticity. And for $\beta > 1$ (or $s'' > s'$) the PCM is greater for s''. What is useful to know is the difference between the PCM values for the two industries. If conjectures are Cournot, the PCM of the higher elasticity industry is only 31% of that for the lower elasticity industry. For min and max elasticities the PCM in the more elastic demand industry is only 7% of that of the high demand elasticity industry.[41] If we had assumed an additive fixed effect (or additive control variables) as in the studies cited in Scherer *et al*. (1987) or as in Machin and Van Reenen (1993), the PCM differences caused by differences between $s''$and s' would be assumed to be identical across all industries, only the levels would change.

Another way to see the importance of modeling elasticities is to constrain the elasticities to be the same across industries. When one does so with additive *industry* fixed effects the full sample *t*-value on

[40] The earlier tests used firm PCM (total sales including exports), whereas the ASR is defined by the domestic market. Furthermore, the η_k fixed effects should capture demand elasticity aspects of ASR.

[41] For conjectures differing from the Cournot level, the difference is more non-linear and cannot be expressed as a percentage without specifying the $s''$and s' values.

γ_1 drops from 8.77 to 3.38 (its magnitude drops only slightly to 0.505), and if one uses *firm* fixed effects, as in Machin and Van Reenen (1993), the *t*-value drops to 2.10. Additionally, using firm fixed effects, the estimated common elasticity is 4.10 which is greater than the maximum industry specific elasticity, 3.87, measured as an industry fixed effect.

One remaining methodological question is how do our more powerful econometric tools' results differ from using the CDW multistage estimation technique? Using their multistage testing approach we reran the model. First, it is interesting to note that we found the results to be robust in terms of the magnitude of the parameter estimates, although the point estimates on γ_1 are slightly higher with their methodology. For the full sample (which CDW would not use) the coefficient on CR is 0.806 with a *t*-value of 1.78 (which is significant at the 95% level on the appropriate one-tailed test). For the industries matching the efficiency hypothesis that were less competitive than Cournot (their sampling methodology) we applied their estimation methodology and found a coefficient of 0.85 and a *t*-value of 3.49. Our nonlinear one step model provides slightly lower point estimates and far greater precision around the point estimates than their multistage methodology. Finally, it is worthy of note that the superiority effect (β_3) is statistically significant in the export PCM latent variable (we return to this below).

Before we analyze the robustness of this test to issues such as product differentiation and the potential for MC $\neq$ AC, we examine the empirical magnitudes. This is important as we, unlike many authors, do not treat the two hypotheses as if they were mutually exclusive "contending" hypotheses, instead we find support for both hypotheses in our structural model. Accordingly, we need to assess how important each hypothesis is in terms of actual empirical effects.

6.3. Test 2's: Empirical Magnitudes

Consider an industry with a concentration ratio of 21.5%, which is equal to the sample mean concentration ratio of 39.4% minus one standard deviation of 17.9%. Suppose all three leading firms have equal shares of 7.2%. Consider what would happen if these three firms developed a new technology leading concentration to expand to the mean plus a standard deviation, 57.3%.

For this hypothetical, evaluating all other values at their means, price would increase by 16.6% and the leading firms would have a cost reduction of 7.8%. Conventional welfare effects are hard to assess with the known information even when supposing that producer and consumer surplus are equally weighted. For example, it is unknown how much R&D would have been spent to accomplish this cost effect, and furthermore, one would need to make strong assumptions about the costs of the firms which lost share. What we can say, *given the mean level of demand elasticity in our estimates*, is that the leading firms do not come close to tripling their total output when they triple their share: they roughly double their output at these lower costs.

Given that this is a quantity model, evaluating mergers may be suspect (*cf*. Salant, Switzer, and Reynolds 1983), but suppose that we solely examined the conjectural effect on prices as if the shares were predetermined with no cost savings (*i.e.*, raise the concentration ratio without raising shares). The effects would be that price would increase by 17.8%. That is the agreement effect suggests a 17.8% price increase which would be ameliorated by 1.2 percentage points to 16.6% due to the superiority effects.[42]

The conclusion is that the superiority effect on prices is very small relative to the agreement effect!

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[42] Following the Williamson (1968) argument, the cost reductions could be substantial relative to the welfare triangle effect. Alternatively, following Posner (1975), the welfare gains from the cost reductions may be eroded by the rent seeking expenditures to obtain them (*e.g.*, high R&D costs).

6.4. Test 3: Robustness to Product Differentiation and Possible MC ≠ AC Biases

6.4.1. Is Use of the Accounting PCM Leading to a MC ≠ AC Bias Problem?

It has been hypothesized[43] that AC may be unequal to MC in a systematic fashion which is correlated with concentration.[44] Since we posit a structural model, this can be tested directly by altering the structure to nest this hypothesis.[45] Equation 12 is now

$$PCM_{ik} = [s_{ik}^{D} + (\gamma_0 + \gamma_1 CR_k)(1 - s_{ik}^{D})]\Gamma_{ik}^{D}/\eta_k + (\beta_2 + \beta_3 s_{ik}^{X})\, E\, \Gamma_{ik}^{X} + \mu_{ikt} + \varepsilon_{ik}' \qquad (12')$$

The change is that the error term is now $(\mu_{ikt} + \varepsilon_{ik}')$. The first term is assumed to have a non-zero mean and is firm, industry and time varying. By modeling μ_{ikt} we can incorporate various ways in which MC≠AC might create biased estimates of the basic model.

Suppose the measurement of MC is not equal to the measurement of AC. We have the accounting identity $PCM^{O} = PCM^{D}\Gamma^{D} + PCM^{X}\Gamma^{X}$ where PCM^{O}s are the "Observed" accounting PCMs based on AC, not on MC. So,

$$PCM^{O} = \left[\frac{P^{D}X^{D} - MC*X^{D} + MC*X^{D} - AC*X^{D}}{P^{D}X^{D}}\right]\Gamma^{D} + \left[\frac{P^{X}X^{X} - MC*X^{X} + MC*X^{X} - AC*X^{X}}{P^{X}X^{X}}\right]\Gamma^{X} \qquad (13)$$

$$PCM^{O} = PCM^{D^{T}}\Gamma^{D} + PCM^{X^{T}}\Gamma^{X} + \left[\frac{(MC - AC)X^{D}}{P^{D}X^{D}}\right]\Gamma^{D} + \left[\frac{(MC - AC)X^{X}}{P^{X}X^{X}}\right]\Gamma^{X} \qquad (14)$$

Using the superscript T for the "Theoretical" PCM based on MC we have

The bias argument comes from a variety of reviewers. One argument is that the measurement of MC-AC is non-zero and positively correlated with domestic concentration (leading to the possibility of a positive observed PCM-CR relationship without this being "caused" by behavior). This argument is based in part on economies of scale, which would be related to the share of industry shipments, s_i^{I} (the superscript indicates the Industry share of production for both export and domestic markets). Reviewers have also hypothesized that accounting biases may also be related to firm shares in industries, so including s_i can cover both potentials for MC ≠ AC bias. To capture this suppose $(MC - AC)/P^{X} = \delta_0 + \delta_1 * CR + \delta_2 * s_i^{I}$, indexing P^{X} to equal 1, also supposing that

[43] *E.g.*, by journal reviewers.

[44] *E.g.*, greater economies of scale may lead to a higher concentration. The effects of economies of scale on the costs of firms in observed equilibria are, in our opinion, not likely to be great, but the argument has *a priori* validity.

[45] A model which is motivated by theory, but does not have the non-linear structure implied by the theory, cannot address this issue.

$P^{D}/P^{X} = \xi,\ \xi \geq 1$. Then

$$PCM^{O} = PCM^{D\,T}\Gamma^{D} + PCM^{X\,T}\Gamma^{X} + (\delta_0 + \delta_1 * CR + \delta_2 * s^{I})[\Gamma^{D}/\xi + \Gamma^{X}] \tag{15}$$

As we demonstrate later, estimating $P^{D}/P^{X} = \varphi_0 + \varphi_1 * CR$ leads to $\varphi_0 > 1$ and $\varphi_1 > 0$. (This cancels out the cost terms in the PCMs, serving as another test which should be robust to MC ≠ AC regardless of the reasons for this difference.)

This model led to γ_1 rising from 0.649 to 0.658 and its *t*-value dropping slightly from 8.77 to 7.59.

Following this another reviewer discussed measures of economies of scale. [S]he posited that measures such as firm share and concentration might be correlated with economies of scale differences between MC and AC in such fashion as to drive our results. Recall that Korean manufacturing doubled over the period of the data, so we construct an alternative to share which is "size." This is firm sales at time t divided by industry sales at time zero (sales deflated by the industry price index). We add this to the model as size^{-1}, as would be the case if there were a fixed cost and a constant marginal cost. This reviewer also argued that the capital output ratio would be a proxy for an industry with economies of scale, so this is added to the specification of the error term. Note that our size^{-1} variable is a measure of size which, if taken alone would be like assuming economies of scale to be the same across industries. If economies of scale indeed vary across industries in a fashion related to K/O, then one can think of an economies of scale coefficient which varies by capital intensity. So, to capture economies of scale we add a measure of economies of scale given by $(\delta_4 + \delta_5 * K/O) * size^{-1}$.

At the same time yet another reviewer was concerned with adjustment costs and sunk costs. We added firm sales growth (deflated by the industry price index), "Gro," and following the argument of the reviewer that these would be more prevalent in higher capital cost industries we again use K/O and estimate $(\delta_6 + \delta_7 * K/O) * Gro$. Note that to get sales growth we need to truncate the first year of data for each firm. Further, it is possible that "unexpected" growth could create a deviation between MC and AC. Given that we have a fairly short time series, if we used lagged sales growth to proxy for expected growth, we would lose much of our data. We instead constructed each firm's mean growth and then constructed its deviations from its mean for each time period, DGro, and treated it like Gro as having a K/O varying parameter. Incorporating these three reviewers' hypotheses into the structural model we have:

$$\begin{aligned} PCM_{ikt} = {} & [s^{D}_{ikt} + (\gamma_0 + \gamma_1 CR_{kt})(1 - s^{D}_{ikt})]\Gamma^{D}_{ikt}/\eta_{kt} + (\beta_2 + \beta_3 s^{X}_{ikt}) E_t \Gamma^{X}_{ikt} \\ & + [\delta_0 + \delta_1 * CR_{kt} + \delta_2 * s^{I}_{ikt} + \delta_4 * K/O_{kt} + (\delta_3 + \delta_5 * K/O_{kt}) * size^{-1}_{ikt} \\ & + (\delta_6 + \delta_7 * K/O_{kt}) * Gro_{ikt} + (\delta_8 + \delta_9 * K/O_{kt}) * DGro_{ikt}] * \left[\frac{\Gamma^{D}_{ikt}}{\varphi_0 + \varphi_1 * CR_{kt}} + \Gamma^{X}_{ikt} \right] + \varepsilon_{ikt}' \end{aligned} \tag{16}$$

Estimating this model for the full sample leads to

The Basic Model with MC≠AC Bias adjustments

Domestic Conjecture		Export PCM	
$\alpha \equiv \gamma_0 + \gamma_1 \, CR$		$\widehat{PCM}^X = (\hat{\beta}_2 + \hat{\beta}_3 s^X)\, E$	
γ_0	γ_1	β_2	β_3
-0.033 (3.41)	0.716 (5.98)	0.021 (2.15)	0.123 (2.76)

Domestic over export price ratio
$P^D/P^X = \varphi_0 + \varphi_1 * CR$

ϕ_0	ϕ_1
1.183 (1.20)	0.257 (0.57)

(MC-AC), the MC≠AC Bias term

$$[\delta_0 + \delta_1 * CR + \delta_2 * s^I + \delta_3 * K/O + (\delta_4 + \delta_5 * K/O) * size^{-1}$$
$$(\delta_6 + \delta_7 * K/O) * Gro + (\delta_8 + \delta_9 * K/O) * DGro]$$

δ_0	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	δ_7	δ_8	δ_9
0.256 (1.75)	-.053 (0.08)	-.271 (0.91)	-.058 (1.19)	.0001 (1.25)	-.0002 (1.32)	-.012 (0.11)	.039 (0.19)	.034 (0.29)	-0.055 (0.24)

The parameter values for the conjectural term are virtually unchanged by the adjustments. In particular, the crucial parameter γ_1 rises slightly from 0.649 to 0.716 and its *t*-value drops slightly from 8.77 to 5.98, but still remains very highly significant. The export PCM estimates change somewhat more, but not by a considerable amount. This brings us to the bias adjustment parameters. None of these are significant at even the 90% level except for the constant term and the addition of these terms is only jointly significant at the 85% level. The point estimates suggest that as CR rises, MC falls relative to AC (the opposite sign than the first reviewer conjectured[46]), and that as firm share rises, MC falls relative to AC as well, but neither effect is significant and the terms do not lead to lower significance in the estimates of the key parameters. Furthermore, these suggest, as in the within estimator results in the linear model, that firm growth is not causing a substantial deviation between MC and AC due to capacity constraints.

Finally, the domestic to export price ratio is very poorly fitted in terms of its *t*-values. When we directly estimate this price ratio in a later section the parameter ϕ_0 is virtually the same as above (1.12 rather than 1.18 above) but the *t*-value is very high. The point estimate later for ϕ_1 is 0.12 with a *t*-value of 7.14, whereas here it is 0.26. But using the standard deviation here, 0.12 is about half a standard deviation from the 0.26 here. The similarity of the point estimates (which *apriori* could have been wildly different from the entirely different methodologies used to estimate them) is additional support for the legitimacy of our model results. The resulting conclusion is that these adjustments do show some

[46] The conjecture was that if (P - MC)/P were to remain unchanged by a greater CR then a greater CR could be associated with a greater (P - AC)/P if AC were to fall relative to MC.

potential validity to the proposition that there might be some deviation between MC and AC, but that the magnitude of the bias as it pertains to the estimates of the basic model is small.

One point should be made in closing. Parameters are being identified by functional form, as is usual in structural models. Were exports zero, the bias part of the model and the basic part of the model would be highly colinear; what is primarily identifying this model is that the bias of MC relative to AC must inherently be affecting production for both domestic and export markets whereas the market power results apply to the domestic market alone. Whether the same test could be usefully applied to data without exports and variance in exports, appears to be doubtful to us.

6.4.2. Testing for Product Differentiation Bias

There are numerous papers following Cowling and Waterson (1976) which have used the homogeneous goods model to motivate traditional IO empirical models with data sets which are not entirely composed of homogeneous product industries. They point out that in a conjectural model, $PCM = \alpha H/\eta$, or for an industry this is the conjecture times the Herfendahl divided by the demand elasticity. This logic has been applied at the line-of-business level as well. But these models (*cf.* Machin and Van Reenen 1993; Kwoka and Ravenscraft 1986; Rosenbaum and Manns 1994) are not structural in that they have universally treated demand elasticity as if it were uniform across industries and they have incorporated "control variables" in an additive fashion.

A critique of this entire path of research is that it is based on the homogeneous products model. Suppose the true situation is that product differentiation is both substantial and ubiquitous. As Dixit (1986) points out, although the comparative statics of homogeneous goods oligopolies in conjectural models are simple, for heterogeneous goods, once one moves past monopoly and duopoly, there is little that can be said about the comparative statics without a precise form of the demand structure. We perform three tests to analyze product differentiation. First, we move from the assumption of an industry specific demand elasticity in the estimation of equation (6) to assuming firm specific demand elasticities. This permits virtually any demand structure and allows for the data to directly pick up any firm specific PCM relationship, such as one leading to a negative share-PCM relationship. This specification does still imply that the conjectures are similar to those in the homogeneous products case. Little changes in this highly general demand structure model. The homogeneous product model results are $\alpha = -0.055 + 0.649 * CR$ with a *t*-value of 8.77 and the firm specific demand elasticity model results are $\alpha = -0.126 + 0.729 * CR$ with a *t*-value of 4.60. Although this permits virtually any demand system, this is no longer a structural model in the sense that the conjectures and share equations are based on the homogeneous goods conjectures (*e.g.*, all rivals are equally close as in symmetric differentiation).

Second we follow Clarke, Davies, and Waterson (1984) and introduce a specific demand structure capable of making the heterogeneous products case into a true structural model. They assume that $\partial p_i/\partial x_j = \kappa(\partial p_i/\partial x_i)$, where κ is a measure of product differentiation (κ = 1 implies homogeneous products and κ=0 implies completely unrelated products).[47] Assuming that κ is an industry wide constant, then the implied estimation equation for domestic PCM is

$$PCM_{ikt} = \{\alpha_{kt}\kappa_k + (1-\alpha_{kt}\kappa_k)s_{ikt}\}/\eta_{ik}s_{ikt} \tag{17}$$

This implies not only firm specific demand elasticities but another share effect and the product differentiation effect. To implement this as a structural model we continue to assume that

[47] Although this demand structure permits firm asymmetries in total demand, it assumes that an increase in the quantity of any one rival has the same effect on firm demand as the increase in quantity of any other rival.

$\alpha \equiv \gamma_0 + \gamma_1 * CR$. We model industry product differentiation as $\kappa \equiv \omega_1 + \omega_2 * ASR$. The resulting estimation is now $\alpha = -0.013 + 0.395 * CR$ with the *t*-value on CR equal to 2.83 and $\kappa = 0.823 - 0.257 * ASR$ with the *t*-value for $\omega_1 < 1$ (where ω_1=1 and ω_2=0 implies homogeneous goods) being only 0.741. The ω_2, however, is negative (as predicted) and significant with a *t*-value of 2.49.

Third, we divide the sample in half and examine the results for the 27 industries which have the lowest advertising sales ratios. This takes us from Steel Rolling and Extruding, with A/S=0.08% [Advertising=0.0008*Sales], to Products from Metal Forging, Pressing, Metallurgy, A/S=0.46%. These are with little doubt about as close to homogeneous product markets as one can get. With this subsample we ran the full model, including the MC-AC bias terms. The results were $\alpha = -0.036 + 0.832 * CR$, with a *t*-value of 6.95 on the concentration term. The results are similar to, but the point estimates are slightly stronger than, the full sample results.

One might argue that our results are biased due to the inclusion of differentiated products in a test using a structural model of homogeneous product markets. Our interpretation is that we have a good model of the central tendencies of concentration/agreement, holding share/superiority constant.

Following the tests of both MC$\neq$AC bias and product differentiation bias it is our view that most of the evidence on the measurement of the conjectures is consistent with the homogeneous goods model providing reasonably reliable structural results. This is not to say that, for example, product differentiation is irrelevant, it is to assert that it does not appear to have a major effect on the results. In terms of point estimates, the concentration effect, $\hat{\gamma}_1$, is slightly lower in the basic model than in the other models, so the estimated concentration price effects are more conservative in the basic model. Accordingly, we used our basic model and the full data set for our empirical magnitudes presented above and for the set of tests which we present next.

6.5. Test 3: Domestic/Export Price Discrimination

Again we turn to a secondary implication of the models for our methodology. This has more than one important feature. First, we can test if domestic prices are greater than export prices, as would be expected in an agreement model. Secondly, we can examine whether our latent variables for domestic and export PCMs are "reasonable" in what should be expected from a model with domestic and foreign sales. (*E.g.*, one would question the latent variables in the above section if they predicted that export prices vastly exceeded domestic prices.) This model has not only the ability to test for the determinants of the price ratio but can help substantiate that the latent variables used in the primary causality model in the second set of tests match *a priori* expectations. Finally, since this price ratio cancels out the AC part of the PCM measures, if AC$\neq$MC, this is not as problematic as it would be in the above tests.

The following tests continue to use the sparse matrix methodology. There will now be two fixed effects, doubling the numbers of zeros in the $X'X$ matrix. In this section we no longer constrain the conjectures to be the same function of CR across industries. We also allow conjectures to be industry specific fixed effects. Our new methodology here is employing a new latent variable which can be derived from the same basic model: we identify the domestic to export price ratio of each firm as a latent variable which is treated as a common function of CR.

In the traditional model it is surmised that export markets are close to competitive and domestic markets may or may not be close to competitive. If this hypothesis has validity for the Korean manufacturing sector, it would be expected that high concentration Korean exporters act as price discriminating oligopolists, exploiting market power in domestic markets, while being close to price takers in export markets. Yang and Hwang (1994) look into the behavior of Korean domestic and export prices for six broad manufacturing sectors. They find export prices moving with international markets, yet domestic prices move with domestic factors. From this they conclude that there is domestic price discrimination and hence domestic market power. They do not, however, provide a direct link between market structure and evidence of domestic market power.

If export and domestic products are identical with common marginal (or average) costs, then:

$$\frac{P_{ik}^{D}}{P_{ik}^{X}} = \frac{1 - PCM_{ik}^{X}}{1 - PCM_{ik}^{D}} \tag{18}$$

That is, we can directly find the ratio of domestic to export prices if we have the relevant PCMs. To the extent that export and domestic products (or product mixes) are not identical, we are finding the ratio of domestic price over export price where units are indexed to a common marginal cost of production.

Let us return to our basic model but with the conjecture, α_k, being an industry fixed effect. That is, we do not constrain α_k to be a common function of CR, but leave it "free." Now we have That is, we can directly find the ratio of domestic to export prices if we have the relevant PCMs. To the extent that export and domestic products (or product mixes) are not identical, we are finding the ratio of domestic price over export price where units are indexed to a common marginal cost of production.

Let us return to our basic model but with the conjecture, α_k, being an industry fixed effect. That is, we do not constrain α_k to be a common function of CR, but leave it "free." Now we have

$$PCM_{ik} = \{[s_{ik}^{D} + \alpha_k (1 - s_{ik}^{D})]/\boldsymbol{\eta_k}\}\,\Gamma_{ik}^{D} + \{(\beta_2 + \beta_3 s_{ik}^{X})\,E\}\,\Gamma_{ik}^{X} + \boldsymbol{\varepsilon}_{ik} \tag{19}$$

Suppose that the domestic price to export price ratio is a function of concentration. We test the hypothesis that $P_{ik}^{D}/P_{ik}^{X} = \varphi_0 + \varphi_1 CR_k$. By estimating the PCM above using the parameter constraints

$$\frac{1 - (\beta_2 + \beta_3 s_{ik}^{X})\,E}{1 - [s_{ik}^{D} + \alpha_k (1 - s_{ik}^{D})]/\boldsymbol{\eta_k}} = \varphi_0 + \varphi_1 CR_k \tag{20}$$

we can test whether domestic prices are above export prices and whether the degree to which they exceed export prices is related to market structure. *A priori*, $\phi_0 \geq 1$ and $\phi_1 \geq 0$ suggest that on average all industries have domestic prices at least at or above export prices. Furthermore, if $\phi_1 > 0$ and is significant, this would support the domestic market power hypothesis.

In this environment with industry effects, constrained estimation is not straightforward.[48] Our alternative is to estimate the conjectural model, as above, but with a new set of assumptions. We no longer restrict α_k to be a common function of the concentration ratio; we let α_k be an industry specific fixed effect along with the η_k fixed effect. (The conjecture term as a fixed effect basically means that we let the industries' best fit on firms share drive the PCM estimation.) Given the parameter estimates from this model, one can construct predicted values for the price ratio for each firm and year combination in the data. We can then regress the price ratios on industry concentration to examine the hypotheses.

In principle, one would like this regression to take account of the variance of the predicted price ratio. That is, we would like a "one step model," as in our second set of tests, to place higher weight on firm-year observations for which the predicted price ratio is more precise, the equivalent of having a two

[48] If the constraints were exact functions of the parameters, one could substitute the constraints through and reparameterize the model. That is not the case here.

step model using a GLS approach to factor in the variances in the second stage regression. The one step approach is no longer feasible, and in our setting the computation of the variance of the price ratio is rather involved, so given that our method is consistent and the results are strong, we choose to only use an OLS regression instead.[49] This regression will account for some of the variance differences. Industries with more firms/observations, which are those for which we expect tighter estimates of the industry effects, will enter the second stage OLS regression more times and will therefore carry more weight in the regressions.

The results follow:

Domestic to Export Price Ratio Nonlinear Model

Sample	$P_{ik}^{D}/P_{ik}^{X} \equiv \varphi_0 + \varphi_1 \, CR_k$ φ_0	φ_1	# of Industries (observations)
Full	1.12 (157.94) [16.93]	0.117 (7.14)	54 (2698)
Efficiency hypothesis, all industries	1.10 (147.19) [13.38]	0.146 (8.02)	38 (1756)
Efficiency hypothesis, supra Cournot	1.11 (146.04) [14.47]	0.167 (8.98)	31 (1557)

( ) *t*-values; [ ] *t*-values for the hypothesis $\phi_0 > 1$; and each *t*-value exceeds 3.29 = 99.95%.

Keeping in mind that the model includes share effects, *i.e.*, controls for the superiority effect, the CR effect is in addition to any superiority effect and should be interpreted as an agreement effect. There is a strong relationship between domestic concentration and the degree of domestic price discrimination which is evidenced by a $\phi_1 > 0$ and a *t*-value greater than 7.14 for all samples. Furthermore, there is strong support for the hypotheses of *even low concentration industries* have higher domestic prices than export prices, $\phi_0 > 1$ (*t*-values in [ ]'s, all of which exceed 13). The former result, $\phi_1 > 0$, is a secondary implication of the market power agreement hypothesis. $\phi_0 > 1$ (but not greater by a significant amount) demonstrates that the latent variables developed in this study have empirical validity.[50]

Recalling that the superiority effect is demonstrated for export PCMs in the second set of tests, this only reenforces the interpretation that market power is generating this result. For example, higher export shares, to the extent that they are related to higher concentration, lead to higher export prices conditioned on costs. The denominator is inflated by the higher concentration, yet the ratio is still positive in CR and is highly significant.

The results from **tests 1, 2,** and **3** on Korean Line-of-Business data are consistent with the agreement hypothesis, even after controlling for the superior firm or efficiency hypothesis. These results are statistically strong and survive three levels of scrutiny: (1) for those industries for which the superior

[49] In a sense, we are using a sequential approach similar to the less powerful CDW approach we reference above. A GLS estimator should be more efficient (have a lower variance) but should have the same expected values for parameters. Since none of our relevant *t*-values are less than 7.00, this appears to be the rational way to continue.

[50] Exports may be even more competitive than low concentration domestic markets for a variety of reasons. For example, product differentiation. Domestic consumers may look at "brand names," whereas importers may solicit bids to ascertain which firm will offer the lowest price to produce a product after which they have a foreign brand added for the sale elsewhere. Even without branding, the individual firm demand elasticity in exports may be lower than domestically. Furthermore, importers may have more buying power than domestic purchasers.

efficiency hypothesis is not supported, the agreement hypothesis is still supported using a traditional test; (2) controlling for firm shares to capture the superior efficiency hypothesis, the effect of concentration on a hypothetical conjectural variations parameter is statistically strong; (3) the hypothesis that domestic/export price discrimination would be positively related to concentration is also supported with strong statistical significance. Finally, even with statistical support for the superiority effect, the estimated empirical magnitude of the "agreement" effect on prices is far stronger than the superiority effect.

7. Our Results Contrasted with U.S. LOB Studies

The published FTC-LOB studies generally looked at primary model implications and found that after controlling for the market shares of individual firms, concentration had no independent effect on firm profit levels (indeed, its influence was typically negative). Why are our results diametrically opposite to these?

One obvious answer is that the U.S. and Korean economies are entirely different. The U.S. economy is, for example, mature. Results from an earlier period, 1978-82, suggest that the Korean markets deviated further from a structural equilibria than do markets in mature economies (Jeong and Masson 2003). For the U.S., the 1970s FTC-LOB data come from a period that included price controls (and their removal), an energy crisis (major energy price inflation), a unique period of "stagflation" (high inflation and high unemployment), and the end of the Vietnam War.[51] Other contrasts include greater reliance on information technologies in the U.S., which could allow for more rapid competitive adjustments when pockets of power emerge.[52]

Another major difference may be attributed to the disparity of antitrust enforcement in the two countries. In Korea, if major mergers are permitted, sufficient unilateral firm power not matched by the cost decreases associated with our equilibrium model may lead to estimates that suggest a high α. Also, agreements may be simpler to achieve in Korea when antitrust laws and enforcement are weak.

Additionally, there is some related evidence which suggests that the FTC-LOB studies may be misleading for the U.S. First there are some temporal effects which we shall document with secondhand statistical evidence. Second, there have been two studies with the FTC data which suggest that when using different methodologies the agreement hypothesis may still be relevant. Third, these studies use a combination of national firm shares, yet they use average geographic market concentration levels. This favors the superior firm hypothesis, as we shall see. Despite the vast number of papers with similar conclusions, they are not independent tests: they are all using the same data set which contains only a limited number of time period. Idiosyncratic aspects of the data will have similar effects across the tests.

We look first at some temporal factors, noting that this potentially valuable source of U.S. LOB data was only collected for a short number of atypical years before the program was destroyed in Reagan era politics (for the demise of the program see Scherer 1990). There are numerous hypotheses about the behavior of PCMs over business cycles, which are reviewed in Domowitz, Hubbard, and Petersen (DHP)

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[51] For the years of 1974-77 unemployment was 5.5%, 8.3%, 7.6%, and 6.9%, respectively; inflation was 12.2%, 7.0%, 4.8%, and 6.8%, respectively; energy inflation was 21.6%, 11.6%, 6.9%, and 7.2%, respectively. For 1973-77 energy prices rose by over 80 percent, whereas general inflation (including energy) rose by less than 50%. High energy use industries had far different cost structure changes than low energy use industries. If energy use is correlated with minimum optimal scale, then it should be correlated with concentration. Also, if energy sellers (*e.g.*, gasoline) are correlated with concentration and if energy has quasi-rents (*i.e.*, upward sloping short run supply) this may lead to biased results.

[52] Another possibility is that the Chaebol structure leads to multimarket contacts (MMC) and mutual forbearance. Feinberg (1985) finds some evidence of this in the FTC-LOB data, while he still has the standard FTC negative result on C4 and profits. Given the looser structure of Chaebols relative to U.S. conglomerates, we would expect a lower MMC effect in Korea, but we have not tested for this.

(1986a, 1986b) where they analyze a panel of 284 industries. DHP (1986b) shows traditional cross-sectional regressions of PCM on (extrapolated) CR4 for each year from 1958 through 1981. The concentration effect in 1972 is lower than in any of the 14 previous years, it falls again in 1973 and 1974 where it remains at half its historic levels thereafter. Using a panel model, they attribute this to the high level of unemployment in these years (see note).

Using a different methodology, Mueller and Sial (1993) also present annual regressions for the U.S. over the period of 1958-1990, extending past the period of the DHP results. Despite a different methodology (more aggregate industry definitions), their concentration coefficients for 1958-1981 have a correlation of 0.72 with those estimated by DHP (*t*-value = 4.90). In their paper only two years out of the thirty-three have negative CR effects on profits, 1974 is one of these. For ten of their years the coefficients are not positive and significant at the 95% level. The first time the coefficient drops below the 95% level is 1973, becoming significant again in 1977 (at the 99% level). Their weak results are associated with the FTC-LOB time period. Mueller and Sial associate the periods of insignificance with inflation as opposed to the unemployment focus of DHP (of course, the period of the 1970s was one of stagflation, see note).[53,54]

Ghosal (2000), rather than looking at unemployment or inflation, looks at the influence of monetary policy and the influence of the relative price of energy on PCMs. He analyzes a panel for 1958-1991. He finds that both monetary policy and relative energy price changes influence low CR industries differently than high CR industries. For high CR industries a rise in energy prices relative to the producer price index leads to lower PCMs in the following year. For low CR industries it leads to (a statistically insignificant) rise. Given the substantial energy price increases in the mid 1970s, this should lower the cross-section CR effect on PCMs, as he notes.

These results all suggest that the only period for which the FTC-LOB data were collected was highly unusual with respect to the CR relationship with PCM. There are also two papers using the FTC-LOB data which find positive CR effects. One paper is Scott and Pascoe (1986). They hypothesize that during these turbulent years the high capital cost industries would have a breakdown in coordination. Testing, they find that CR has a positive effect in lower capital-output ratio industries (significance of the CR effect for these industries is not clear).

Ross (1987) applies the CDW methodology by first applying a screen that only permits an industry to be included in the test if its share effect on PCM was significant at the 10% level. Starting with a one year FTC sample of over 250 industries used by others (some authors used subsamples, but typically these were also large), this criterion left him with only 28 industries. In this paper he finds the four firm concentration is weakly related to PCMs and the Herfendahl index is negatively related to PCMs. But, of his 28 sample industries, half (14) are *misc.,n.e.c.,n.s.k.* or *etc.* industries, "industries" which are definitionally mixtures of products.[55]

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[53] Salinger (1990) also finds a decreased effect in the 1970s, but finds it is restored in the early 1980s. His interpretation of this differs from ours. He looks at price and margin changes over a decade starting in 1972 as they relate to changing concentration. Again, we would argue that the atypical time period of that decade makes drawing inferences difficult.

[54] These also correspond with the energy crisis periods of 1973-74 and 1979-80.

[55] We provide only one of many possible examples from his sample. The 4 digit "hardware *n.e.c.*" includes five digit sub industries such as "vacuum . . . bottles . . . and chests" with CR = 93%; furniture hardware, CR = 38% (*e.g.*, drawer slides and casters); builders' hardware, CR = 29% (*e.g.*, padlocks, safes, closet shelving, screen door closers, and hinges); motor vehicle hardware, CR = 83% (*e.g.*, door handles and license plate brackets); other hardware *n.e.c.* CR=23% (*e.g.*, saddlery hardware, casket hardware and fireplace fixtures). Weiss and Pascoe used judgment and other means to try to calculate the average concentration ratio for many industries. For example, they adjusted denominators for imports, tried to find geographic concentration ratios for geographically dispersed industries, and for industries like "hardware" they tried to find the average across the various sub industries. These data were the primary concentration source of the FTC-LOB papers. The Weiss-Pascoe "hardware" weighted average CR = 35%. Clearly these sub industries have different firms.

Recognizing the industry definition problem, in 1988 Ross completely redid his estimation using a balanced panel covering the period 1975-77. Not wishing to use subjective industry inclusion methods he applied the Bradburd and Ross (1988) criteria, eliminating not only the catchall industries, *but also eliminating industries for which the five digit sub industries in the Census have widely diverging concentration ratios*. The logic behind this sample selection criterion is that if the four digit industry is "an industry of competitors" then it should in fact be that the five digit sub industries should appear to be structured like an aggregated four digit industry in terms of competitors. He includes all industries with positive slopes and intercepts in the profits-share regressions. Applying these criteria he only had 43 remaining industries, but now he uses three years of data. Regressing
func{α horz -50 vert 30 \^} on concentration leads to a positive effect for the Herfendahl, with a *t*-value = 1.72, and the CR4 has a *t*-value = 1.81 (both are significant at the 95% level).

Industry definition problems may be playing a role in the other FTC-LOB studies. The importance of industry definitions ***especially when comparing share effects with concentration effects*** deserves some deeper discussion. Although others have discussed the industry definition problem in detail in the context of market power testing, we are not aware of much discussion with regards to the implications to superiority – efficiency hypothesis testing. Accordingly we replicate some known results, along with stating their implications for tests which involve *both* superiority and agreement testing. Suppose that some U.S. LOB data are based on industries which have sub industries which are not really in the same market. Suppose one *SIC* industry has two equal sized sub industries, one with higher concentration than the other due to differences in economies of scale or simply historical accident. Suppose further that the Weiss-Pascoe data used by the LOB researchers in fact has the correct average concentration (they use the weighted average of geographically and otherwise adjusted 5-digit concentrations). Also suppose that the superiority effect is zero whereas the agreement hypothesis is correct. Finally, for simplicity, suppose that the top four firms in each sub industry are equally sized. The result is that the concentration number will be the correct *average*, the higher concentration sub industry will have higher PCMs, and furthermore *the top four market share firms for the "full industry" will all be in the concentrated market and have higher PCMs than the "lower share" firms located in the less concentrated industry*. That is, by constructing a hypothetical industry based on the traditional "agreement" effect, but with no superiority effect, we find that there will be an artificial share-profits relationship and that concentration is at best only measured with error.[56]

There are even stronger conclusions about aggregation bias. Under Census definitions, an industry may be defined by a "like product or process." Suppose that there is no market rivalry between the two sub industries, but that there is a shared technology. One obvious example is a regional industry for the same product, it could also be a technological commonality across different nationally sold products. Suppose that one firm develops a better technology. The logical consequence would be that this firm, if located in one sub industry, would acquire (or otherwise enter) the other sub industry (which would be permitted under U.S. antitrust laws). It would also have higher PCMs in each sub industry. Of course firm share and concentration in each sub industry should go up as well. But note, the equilibrium market by market share and concentration increase will be far smaller than the firm increase in national share.[57]

[56] Using the above assumptions, suppose one "industry" has sub industries with CR of 40 and 60 and another "industry" has CR of 30 and 70. Both will have the same "industry" average CR. Thus, the CR effect on leading firm PCM will be zero even though the latter "industry" would have higher PCMs under the agreement hypothesis. Yet, the share effect will be positive (leading firms in the latter "industry" will have greater shares and PCMs).

[57] Consider the following entry-acquisition game. Suppose there are three firms and two markets and the first stage is an entry stage. L draws low costs and H1 and H2 draw high costs. Each market can support two firms, but only two firms. The set of pure strategy equilibria for each market are {L,H1}, {L,H2}, {H1,H2}. Before the market game, the second stage permits Pareto improving ownership transactions, but does not permit mergers within a market. Then for any market with {H1,H2} L will purchase one of the players, without loss of generality call it player H1, at a price offering H1 its profits were the outcome to be {L,H1} (the alternative to purchasing player H2). The resulting pure strategies for the two markets are {{L,H1},{L,H1}}, {{L,H1},{L,H2}}, {{L,H2},{L,H1}}, {{L,H2},{L,H2}}. Then obtain the market outcome (which in our context need not be Nash in quantities) and

If the only data available does not include "local market share," the structural model cannot be well defined whereas the Demsetz argument clearly leads to L being in every served market (e.g., having a large "national" share). If the market equilibrium is as per our model, the α conjecture would be based on the local "concentration" were this an N firm market, which is what the LOB researchers state is "on average" what they have in their Weiss-Pascoe data. So, to apply our testing framework to U.S. data, we would need a richer model or a data set comprised of only national industries. This is a superiority effect, but one which is artificially inflated relative to the *individual market* superiority hypothesis. This bias results towards finding a (national) firm share to profit relationship at the same time that geographic differences in concentration, by being averaged, create errors in the variables that measure market concentration.

For example, before McDonald's came into existence hamburgers were mostly sold by local or regional firms. McDonald's clearly developed a superior product (regardless of our personal preferences) and rapidly changed the market (followed by Burger King, Wendy's, *etc*.). City by city, concentration in hamburgers may have been altered little but the national shares of these chains have exploded. These new firms presumably out earned their predecessor rivals. What is not clear is what would have been the pricing effects in small towns with only a few rivals versus more densely populated areas. In any case, the Weiss-Pascoe technique, if used for hamburger local markets, would simply give an average level of concentration/rivalry.[58]

The tests on the FTC-LOB data are not independent. The time period of these appears to be one for which standard models of market power have anomalous results. There are reasons to believe that for U.S. data the firm share effect on PCM would be enhanced by cross market expansions of superior firms, whereas the concentration effects would be weakened by averaging across markets.

In short, the FTC-LOB studies have flaws, not of their authors' making, which compromise their conclusions. The data come from a highly atypical time period, a time period for which traditional agreement tests fail, when they do not fail before or after this period. And, given the U.S. data has geographically dispersed markets, the methods used are inherently biased towards accepting the superiority hypothesis (as they certainly should do), but are stacked against the agreement hypothesis by use of averaging across market concentration levels.

8. Conclusions

The seminal work on oligopolistic "agreement" by Bain in the early 1950s was questioned by the seminal paper by Demsetz in 1973 positing that the "superior efficiency" of firms in dynamic competition could explain Bain's evidence. The influential Scherer and Ross text (1990, p. 411) states that the "main question" in empirical industrial organization in the late twentieth century was research trying to sort out these two "contending" hypotheses. Eight LOB researchers (Scherer *et al*. 1987) stated that the "deadlock" between these two hypotheses was broken with the FTC-LOB studies and declared the "superiority hypothesis" the "winner"!

Since this time there has been a general presumption on many economists' parts that the role of industrial concentration on "agreement" was vastly overstated in earlier years. There is no doubt that pure cross sectional analyses *could* be biased due to superior firm effects, but without LOB data there is no way to address how much these results are biased. The FTC-LOB studies suggested that this bias was a major cause, or more likely the sole cause, of the observed profits-concentration correlation in the

implied profits. Permitting mixed strategies in the first stage leads to a positive probability of some markets with L alone following the second stage (assuming that if an H is the sole entrant the purchase price negotiations lead to a cooperative game equilibrium). There is also a positive probability of an unserved market and a positive probability of "over entry," with negative profits (at least for the H types).

[58] A related observation is hence that the structural model cannot be estimated on U.S. data unless one knew market by market share and concentration (e.g., if one were to use only national industries).

literature. This perception has had profound impacts not only on academic thought but on how U.S. merger policy and privatization policy has evolved in recent decades.

We construct a new LOB data set for Korea, a panel from 1987 through 1995. We analyze the "superiority" and "agreement" hypotheses using four new methodologies incorporated into three different types of tests. We first examine the "superiority" hypothesis contention that reduced form tests simply aggregate superior high share firms' high profits in such a fashion that it creates a correlation between concentration and profits. We show that even when firm shares are negatively related to profits, concentration and profits are still positively correlated; the opposite result from the aggregation bias supposed by the "superiority" hypothesis.

Next we develop a structural model. Its theoretical structure is often cited in the literature examining the agreement hypothesis, but these studies then jump from this "justification" to *ad hoc* specifications rather than estimating the non-linear system implied by the theory. We directly estimate the non-linear structural model and show that this test is far more powerful. In order to do so we need to introduce sparse matrix techniques which have not been used in this literature. In this section we also examine structural models in which product differentiation is explicitly introduced and a subsample of firms for which we know that product differentiation is low. The results remain similar to the basic model. We also identify the potential gap between MC and AC (if they differ) as a systematic factor in the error term. Empirical magnitudes from this estimation suggest that the model has a very strong fit (*e.g.*, crucial *t*-values far greater than the 99% level) and that both the "superiority" and "agreement" hypotheses are valid. This being said, the results demonstrate that the "agreement" hypothesis vastly outweighs the superiority hypothesis in terms of price effects.

We then move to an entirely new indirect method to identify firms' domestic prices relative to their export prices. This is embedded in our structural model and the result is that domestic prices exceed export prices and the amount by which they exceed export prices increases with increases in concentration.

All of our tests support both the "superiority" and "agreement" hypotheses; the "agreement" effects, however, empirically dominate the "superiority" effects in price formation. Finally we examine the FTC-LOB studies for the U.S. and demonstrate why these appear to not be robust to the time period for which the data was collected and why they may be inherently biased due to geographic considerations which we do not have to deal with in our Korean data.

We have established the *primae facie* case that agreement effects are substantial, at least when antitrust policy is weak. Our evidence establishes the importance of having effective antitrust policies, including merger policy, based on more than "unilateral effects," including the actuality that, at least without active antitrust, oligopolistic agreement is likely to elevate prices when industry concentration is high.

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Appendix: One Stage Estimation with Sparse Matrices

The panel data problem is simply a "cluster sampling" where we are concerned about a "cluster specific" effect. In our problem the "cluster" is an industry (a cluster of firms observed over time).

Our fixed effects estimation treats the cluster/industry specific effects as another set of parameters to be estimated. Since our problem is non-linear in its parameters, use of standard panel "differences from means" cannot be used. The differences from means in linear models can be replicated via the use of dummy variables for fixed effects. In principle, one could think about adding dummy variables to our model for each cluster/industry to the right hand side of the model. In practice, this may fail to be efficient because, as we will see below, the matrix to be inverted is "sparse," dominated by zeroes. Since an exact zero does not exist in floating point arithmetic, there is the danger of accumulating nontrivial roundoff errors by simply putting in the dummies. **This is especially problematic in non-linear models**, as is ours.

What we will do, then, is use the special structure of the problem to find expressions which are analytically the same as what we would have gotten by simply putting in the dummies. These expressions, however, will not require us to invert large sparse matrices. Chamberlain (1980) showed the comparable expressions for the maximum likelihood case. We will do the nonlinear least squares case here.

Notation: $i = 1, \ldots, N$ clusters (large)
$t = 1, \ldots, T$ time periods (small)

Partitioning: Partition the parameter vector θ into $\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}$ where θ_1 ($k\times1$) contains those parameters common to all clusters and θ_2 ($N\times1$) contains the cluster-specific parameters (one per cluster, as in our first model, assumed for notational convenience).

Non-Linear Least Squares:

The Model: $y_{it} = g(x_{it}, \beta, \alpha_i) + \varepsilon_{it}$

The minimization problem:
Define $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_N)'$ and $\theta = (\beta', \alpha')' = (\theta_1', \theta_2')'$.

$$\min_{<\theta>} \sum_{i,t} (y_{it} - g(x_{it}, \theta))^2$$

The Gauss-Newton update:
Given a current "guess" θ^*, the Gauss-Newton update is $\Delta\theta = (G'G)^{-1}G'e$,

where $$\underset{((k+N)\times(k+N))}{G'G} = \sum_{i,t} \frac{\partial g(x_{it},\theta^*)}{\partial\theta} \frac{\partial g(x_{it},\theta^*)}{\partial\theta'} \equiv H,$$ where the H simplifies the notation.

$e_{it} \equiv y_{it} - g(x_{it}, \theta^*)$

$$\underset{((k+N)\times 1)}{G'e} = \sum_{i,t} \frac{\partial g(x_{it},\theta^*)}{\partial \theta} e_{it} = S,$$

again simplifying notation to S.

Then the above step looks like $\Delta\theta = H^{-1}S$ or

$$\Delta\theta = \begin{pmatrix} \Delta\theta_1 \\ \Delta\theta_2 \end{pmatrix} = H^{-1}S = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}^{-1} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix} = \begin{bmatrix} H^{11} & H^{12} \\ H^{21} & H^{22} \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix} = \begin{pmatrix} H^{11}S_1 + H^{12}S_2 \\ H^{21}S_1 + H^{22}S_2 \end{pmatrix}$$

Using the partitioned inverse formulae (for a symmetric matrix) we have:

$$\begin{aligned} H^{11} &= (H_{11} - H_{12}H_{22}^{-1}H_{21})^{-1} \\ H^{12} &= -H^{11}H_{12}H_{22}^{-1} \\ H^{22} &= H_{22}^{-1} + H_{22}^{-1}H_{21}H^{11}H_{12}H_{22}^{-1} \end{aligned}$$

Now substituting and simplifying:

$$\Delta\theta_1 = H^{11}S_1 + H^{12}S_2 = (H^{11})[S_1 - H_{12}H_{22}^{-1}S_2]$$

$$\begin{aligned} \Delta\theta_2 &= H^{21}S_1 + H^{22}S_2 \\ &= (-H_{22}^{-1}H_{21}H^{11}S_1) + H_{22}^{-1}S_2 + H_{22}^{-1}H_{21}H^{11}H_{12}H_{22}^{-1}S_2 \\ &= H_{22}^{-1}S_2 + (H_{22}^{-1}H_{21})[(H^{11})(S_1 - H_{12}H_{22}^{-1}S_2)] \\ &= (H_{22}^{-1})[S_2 + H_{21}\Delta\theta_1] \end{aligned}$$

Now evaluate, simplify, and factor the terms:

H_{22}^{-1} :H_{22} is an (N×N) matrix with zeroes off the diagonal. The j[th] diagonal term, which corresponds to the cluster effect for cluster/industry j, is

$$H_{22_{jj}} = \sum_t \left(\frac{\partial g(x_{jt},\theta^*)}{\partial \theta_{2_j}^2} \right)^2 \equiv h_j,$$

for notational convenience. Hence H_{22}^{-1} is an (N × N) matrix with zeroes off the diagonal and diagonal elements $(1/h_i)$, i = 1, ... , N:

$$H_{22}^{-1} = \begin{bmatrix} 1/h_1 & 0 & 0 & \dots & 0 \\ 0 & 1/h_2 & 0 & \dots & 0 \\ 0 & 0 & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \dots & 0 & 1/h_N \end{bmatrix}$$

H_{12}: H_{12} is a (k × N) matrix. Each column corresponds to a different cluster. The j^{th} column, corresponding to the j^{th} cluster, is

$$\sum_t \frac{\partial g(x_{jt}, \theta^*)}{\partial \theta_1} \frac{\partial g(x_{jt}, \theta^*)}{\partial \theta_{2_j}} \equiv m_j,$$

the m_j being a compact notation for this (k × 1) vector. Hence, H_{12} looks like

$$\underset{(k\times N)}{H_{12}} = \begin{bmatrix} \underset{(k\times 1)}{m_1} & \underset{(k\times 1)}{m_2} & \dots & \dots \underset{(k\times 1)}{m_N} \end{bmatrix}$$

$$H_{12}H_{22}^{-1}: \quad H_{12}H_{22}^{-1} = \begin{bmatrix} \underset{(k\times 1)}{m_1} & \underset{(k\times 1)}{m_2} & \dots & \dots & \underset{(k\times 1)}{m_N} \end{bmatrix} \begin{bmatrix} 1/h_1 & 0 & 0 & \dots & 0 \\ 0 & 1/h_2 & 0 & \dots & 0 \\ 0 & 0 & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \dots & 0 & 1/h_N \end{bmatrix}$$

and is a (k × N) matrix with one column for each observation. The j^{th} column $m_j / h_j \equiv \bar{m}_j$, provides a compact notation where m_j is a (k × 1) vector and h_j is the scalar defined above. So,

$$H_{12}H_{22}^{-1} = \begin{bmatrix} \bar{m}_1 & \bar{m}_2 & \dots & \dots & \bar{m}_N \end{bmatrix}$$

$H_{12}H_{22}^{-1}S_2$: This is a (k × 1) vector equal to $\sum_{i=1}^{N} \underset{(1\times 1)}{S_{2_i}} \underset{(k\times 1)}{\bar{m}_i}$ where $S_{2_i} = \sum_t \frac{\partial g(x_{it}, \theta^*)}{\partial \theta_{2_i}}$.

$$H_{12}H_{22}^{-1}H_{21}: \quad H_{12}H_{22}^{-1}H_{21} = \begin{bmatrix} \underset{(k\times 1)}{m_1} & \underset{(k\times 1)}{m_2} & \ldots & \ldots & \underset{(k\times 1)}{m_N} \end{bmatrix} \begin{bmatrix} 1/h_1 & 0 & 0 & \ldots & 0 \\ 0 & 1/h_2 & 0 & \ldots & 0 \\ 0 & 0 & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \ldots & 0 & 1/h_N \end{bmatrix} \begin{bmatrix} m_1' \\ m_2' \\ \vdots \\ \vdots \\ m_N' \end{bmatrix}$$

which is a (k × k) matrix equal to $\sum_{i=1}^{N}\left(\frac{1}{h_i}\right) m_i m_i' = \sum_{i=1}^{N} \underset{(1\times 1)}{h_i} \; \underset{(k\times 1)}{\bar{m}_i} \; \underset{(1\times k)}{\bar{m}_i'}$.

$$H^{11}: \quad H^{11} = \left[\sum_{i,t} \frac{\partial g(x_{it},\theta^*)}{\partial \theta_1} \frac{\partial g(x_{it},\theta^*)}{\partial \theta_1'} - \left(\sum_{i=1}^{N} h_i \bar{m}_i \bar{m}_i \right) \right]^{-1}$$

NB: *The form of this expression is similar to the standard panel deviation from means.*

$$[S_1 - H_{12}H_{22}^{-1}S_2]: \quad [S_1 - H_{12}H_{22}^{-1}S_2] = \left[\left(\sum_{i,t} \frac{\partial g(x_{it},\theta^*)}{\partial \theta_1} \right) - \left(\sum_{i=1}^{N} h_i \bar{m}_i \bar{m}_i' \right) \right]$$

The final updating formulae are thus:

$$\Delta\theta_1 = \left[\sum_{i,t} \frac{\partial g(x_{it},\theta^*)}{\partial \theta_1} \frac{\partial g(x_{it},\theta^*)}{\partial \theta_1'} - \left(\sum_{i=1}^{N} h_i \bar{m}_i \bar{m}_i' \right) \right]^{-1} \left[\left(\sum_{i,t} \frac{\partial g(x_{it},\theta^*)}{\partial \theta_1} \right) - \left(\sum_{i=1}^{N} h_i \bar{m}_i \bar{m}_i' \right) \right]$$

$$\Delta\theta_{2_i} = \left(\frac{1}{h_i} \right) \left[S_{2_i} + m_i' \Delta\theta_1 \right], \; i = 1, \ldots, N$$

We see that the updating can proceed to two stages. First, compute the update of the common parameters ($\Delta\theta_1$). Then use that result to successively update the cluster or industry-specific parameters ($\Delta\theta_2$).

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