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Cycles in Economic Activity, Industrial Structure and Price-Cost Margins:

A New Methodology using a Structural Model

by

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Abstract

We illustrate a new structural estimation methodology which nests the "agreement" hypothesis and the "superior firm" hypothesis for a Line-of-Business data set. We examine demand growth at the country level (business cycle) and at the industry level. Firms' "conjectures" concerning rivals' competitiveness (or degree of market power extracted) are allowed to be a function of growth. Demand elasticity is modeled as industry specific and is also permitted to vary with growth. We identify domestic sales PCMs and export sales PCMs by use of latent variables. The domestic PCM is modeled as a function of firm share, industry concentration and the growth. We examine the model error structure to see if the use of the price average cost margins, rather than margins over marginal costs biases our results, modeling (MC-AC) as a function of firm size, industry concentration and various measures of firm growth. We examine sensitivity to using only homogeneous products industries.

We examine a nine year panel of Korean firms. Both the agreement hypothesis and the superior firm hypothesis are supported by the data, but most of the effect on prices is due to the "agreement" effect, rather than the "superior firm" effect. Our results indicate that PCMs are procyclical. Because we use a structural model, we can attribute about two-thirds of this to the effect of behavior (the conjecture term), whereas cyclical demand elasticities contribute the other third. There is little evidence of much deviation between MC and AC across firms or across time. We find that industries with concentration one standard deviation above the mean have three times the procyclical variability in margins of those which are one standard deviation below the mean.

1 Introduction

In this paper we integrate issues from three literatures into a set of tests using Korean data in a structural model.

The first literature in terms of historical importance is on the effects of concentration (dominance of an industry by a few firms) on pricing and employment over the business cycle. The Administered Pricing Hypothesis (Means introduced this in 1935, see Means 1972) suggested that firms in concentrated industries lowered prices less during downturns. That is, that margins were counter cyclical for concentrated industries in which firms used "administered pricing" and that one can then infer that this behavior exacerbated the business cycle because it caused "... a fall in sales, production, and employment" in more concentrated industries. This hypothesis had/has many supporters and detractors, to be discussed later.

Next was the literature on estimation of "market power," and its detractors. The key starting point is a seminal paper by Bain (1951) in which he found that profits in concentrated industries exceeded those in unconcentrated industries (his results were statistically significant and were derived using 1930s data and hence might be consistent with the Means' hypothesis above). Bain felt that he had shown that concentrated industries had collusive "agreements" (not defined necessarily as explicit agreements) which raised prices. But this was followed two decades later by a seminal paper by Demsetz (1973). He posited the "superior efficiency hypothesis," what we call the "superiority hypothesis."[1] He noted that if an industry had an innovator, that this firm would be expected to increase its market share and its profits. This would increase industry concentration (shares of the top firms) and industry (sales weighted) profits. So, competition to become more efficient - dynamic competition - might lead to a static

[1] His superiority could be in either efficient production or a superior product reputation, so we prefer to call this "superiority," rather than "superior efficiency."

observation of a correlation between industry concentration and industry profitability *even without any agreement between firms.*

Scherer and Ross (1990, p. 411) state that studies of the tension between these two hypotheses was the "main question" in empirical industrial organization of the latter part of the 20th century. Additionally, Scherer *et als.* (1987) declared that the "superiority hypothesis" won over the "agreement hypothesis." In a companion paper to this paper (Jakubson, Jeong, Kim and Masson 2004) we use the same data set that we use herein to critique this conclusion and provide evidence for both of the hypotheses, agreement *and* superiority, but provide simulations which suggest that the agreement hypothesis has a substantially greater effect on prices than does the superior firm hypothesis.

The third branch of literature deals with how *individual industries* would react to cycles in demand for their industries' products. Key papers in this literature are Green and Porter (1984, coupled with Porter 1983) and Rotemberg and Saloner (1986). All three papers assume that there is an "agreement" between firms in a concentrated industry. In the Green and Porter paper, when industry demand falls (which is not necessarily the same thing as a fall in GDP in a business cycle), firms may not know this and instead fear that they are losing business to rivals. In this case they respond with "trigger prices," or low prices during demand "downturns." That is, they try to punish cheating rivals.[2]

Rotemberg and Saloner has an opposite result in terms of the reactions to industry demand, in part because the observables in their model are different. Consider the following problem. Firms can observe whether lower prices are due to cheating, rather than lower demand (unlike Green and Porter), but, this can only be observed with a lag. Firms with an agreement would not necessarily be able to reach a joint profit maximizing price, as the incentive for rivals

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[2] Which in equilibrium are not cheating, but were the triggering not expected, in equilibrium they would cheat.

to cheat for a finite period before being observed would rise with higher prices. Stable agreed upon prices are determined by incentive compatibility constraints. They have a model in which the incentive compatibility constraints lead the firms with an agreement to have a lower markup in upturns and a higher one in downturns. They present data consistent with this proposition and the Porter paper presents data consistent with the Green and Porter proposition.

We weave these three literature's hypotheses together in a structural panel model of Korean manufacturing. We nest "agreement" and "superiority" into a structural model. We look at both business cycle effects (growth in GDP) and industry specific growth. We additionally look at some other issues. One issue (Waterson 1984) is whether changes in demand elasticities are driving prices. Another important issue is raised by Rotemberg and Saloner (1986), that MC may differ from AC in a systematic fashion over demand cycles. To examine this we look at firm growth. Further, we examine whether there are significant effects of product differentiation which lead to potential biases in our structural model.

After reviewing the literature we move to some aspects relevant to understanding the Korean data. Then we move to our model followed by a description of the data. Results and conclusions follow.

2 Some Relevant Literature

2.1 Pricing over the business cycle

In the Great Depression, Gardner C. Means popularized the concept of "Administered Pricing" (see Means 1972). According to this view, concentrated oligopolies could "administer" their own prices, rather than having them driven by competitive forces.

> It specifically held that in business recessions administered prices showed a tendency not to fall as much as market prices while the recession fall in demand worked itself out primarily through a fall in sales, production and employment. Similarly ... they tended not to rise as much in recovery... (Means 1972)

In the context of the literature, this is called counter cyclical margins or pricing.

Stigler and Kindahl (1970) challenged the Means data, producing a data set that they felt better represented actual transactions prices (rather than "list" prices). They asserted that prices in concentrated industries were not set counter cyclically but were driven by the market. Means (1972) disagreed.

In the more recent literature there have been various authors from Industrial Organization, or allied to Industrial Organization, who have regressed firm price - cost margins (PCMs) on business cycle factors and on concentration. These studies have typically found that rather than margins being counter cyclical in concentrated industries, they are more procyclical in these industries than are the margins in low concentration industries. (As we note later, since price - cost margins are margins over average costs, the marginal cost margin may be behaving differently.) Some of these studies are Domowitz, Hubbard and Petersen (1986a, 1986b, 1987), Mueller and Sial (1993), Machin and van Reenan (1993),[3] and Ghosal (2000).

2.2 Market power or Superiority?

Bain (1951) advanced an "agreement hypothesis"[4] under which he expected that firms in highly concentrated markets would be more likely to achieve some form of agreement and hence elevate prices above "workably competitive" levels. He then showed that high concentration industries had higher profit rates than low concentration industries. Two decades later, Demsetz (1973) advanced the "superior firm hypothesis." Following this hypothesis, if some firms are more effective dynamic competitors, they will gain market share *and* reap higher profits (e.g.,

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[3] The Machin van Reenan paper appears to use a structural model similar to ours on a panel of firms in England. Their model differs in some significant ways from our model. First, they implicitly assume all industries have the same demand elasticities. Second their error term is modeled as firm fixed effects plus noise. We use industry and time varying demand elasticities and model firm level time varying characteristics in our error term.

[4] This is often referred to as the *collusion hypothesis*, as Bain refers to explicit or tacit collusion. This terminology can lead to ambiguity, especially now that tacit collusion in game theoretic models means something much different from what Bain had in mind.

winners of a patent race). He posited that this could lead to higher concentration and higher profit rates without any "agreement" between firms. In other words, Bain's empirical findings need not support "agreement" at all, they could be the outcome of dynamic competition. The importance of these two competing explanations for concentration-profits correlations were at odds for decades.

Scherer and Ross (1990, p. 411) refer to this as the "main question" in empirical Industrial Organization (implicitly between 1973 and the late 1980s). They also conclude, from Federal Trade Commission data Line-of-Business [LOB] studies that "most, if not all" of the ubiquitous relationship between profitability and concentration "was almost surely spurious - the result of aggregating a positive relationship between sellers' market shares and profitability to the industry level."[5] Scherer *et als.* (1987) in fact declare that Federal Trade Commission LOB studies demonstrate that the effect of concentration on profits disappears when controlling for firm shares, thereby "breaking the deadlock" between the "competing hypotheses."

In a companion paper to this paper Jakubson, Jeong, Kim, and Masson (2004) [hereinafter JJKM] use the same Korean Line-of-Business (LOB) data set we use here to re-examine the "contest." They demonstrate that, at least in Korea, aggregation is not what is driving the results. They find support for both hypotheses, but find that the price effects from the agreement effect are stronger than those of the superiority effect. And in that paper they analyze factors relevant to the FTC LOB data which could confound estimation of the relevant hypotheses.[6]

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[5] 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).

[6] E.g., the time period included the end of price controls and the 1973 energy crisis. Traditional profits concentration studies became insignificant during this period and reestablished significance shortly thereafter. Furthermore, the firm shares being used were

2.3 Industry responses to demand shifts

The administered pricing hypothesis asks an interesting question. Are concentrated industries likely to have prices over the business cycle which would exacerbate unemployment problems (e.g., not lowering prices as much implies a lower labor demand).

John Blair (1959) refers to "Administered Prices: A Phenomenon in Search of a Theory." More recently we have had theories in search for phenomena. Unlike the literature directly above, which is trying to ask if market power in fact is an empirically important phenomenon, there is a literature on the theory of "tacit collusion."[7] This literature starts from the presumption of agreement/collusion, rather than questioning it.

There are a variety of important papers, we shall only look at three. Green and Porter (1984) coupled with Porter (1983) look at a trigger pricing equilibrium in which demand shocks are unobservable. Again, it is crucial to keep in mind that a trigger pricing equilibrium is a collusive equilibrium. Because firms cannot differentiate between an adverse demand shock and the loss of business due to "cheating" on the part of some rival, an adverse demand shock may lead to a "punishment period" of "trigger pricing." This suggests strong margins when demand is increasing, but the potential for a collapse in margins when demand is decreasing. That is, in the context of demand cycles, procyclical margins. Porter (1983) takes this to the data, looking at 19th century railroad data, and finds price wars during low demand periods.

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national, whereas the concentration was not national, but the average of regional concentration figures.

[7] We dislike this characterization of the literature which is why "tacit collusion" is within quotation marks. The theories have strong common knowledge assumptions. One must know one's rivals' marginal costs (all rivals' marginal costs), perceived demand elasticities from deviations in prices, and rivals' perceptions of the consequences of a period of trigger pricing occurring (e.g., a price-war). To achieve common knowledge may well require pre-game communication. This is what the antitrust literature essentially calls explicit (illegal) collusion.

Rotemberg and Saloner (1986) approach things differently by changing the information environment. To simplify, suppose that a decrease in demand from cheating can be differentiated from a decline in general demand conditions, but this will occur with a lag. A potential cheater knows that if it is found to be cheating a period of low prices will be triggered. It must consider whether it can make enough additional profits from cheating so as to make the present discounted value of cheating positive despite future low prices. Over the demand cycle, the profits from cheating vary, as do the costs of punishment. There is an incentive compatibility constraint, the maximal collusive price such that no-one would have an incentive to cheat. In their model the incentive compatibility constraint falls in high demand times because of the high profits that a cheater could make during a high demand period.

In their work they consider, for example, Domowitz, Hubbard and Petersen's (1986 a&b) work. They note that the price - cost margins they look at are (P-AC)/P, not (P-MC)/P. During a downturn, firms with sunk fixed costs (in capital and in human capital) will have MC fall relative to AC. During an upturn, adjustment costs may lead to MC rising above AC. Their theory applies to (P-MC)/P, so it is possible to find that (P-AC)/P is procyclical, yet that the Rotemberg and Saloner theory of counter cyclical margins is correct.

They then cite evidence about two actual price wars studied in the literature. Both, they find, occurred during periods of high demand. They examine Bresnahan (1987) for the automobile price war in the 1950s. Importantly, they reexamine and reinterpret the Porter data and argue that his price wars occurred during periods of high demand.

They conclude with

> The data we study show moderate support for the theories developed in this paper. This suggests that both the theories and their empirical validation deserve to be extended.

2.4 Synthesis

The administered pricing hypothesis and the effects of pricing over the business cycle assumes that there is market power in concentrated oligopolies and then looks to see the effects of market power over the cycle. An important point is that *if* firms in concentrated industries lower prices less in downturns, they contribute to more unemployment in downturns (but less inflation in upturns).

The industry demand shift literature is testing theories of "agreement." That is, "agreement" is a maintained hypothesis. Further, because the focus is on industry demand, which may, or may not, reflect the business cycle, it does not focus on macro unemployment effects.

The literature on Agreement versus Superiority presents two hypotheses, one of which implies that the concentration-profits relationship in the data doesn't imply agreement (but is not inconsistent with agreement).

We address a model in which we nest the agreement and superiority hypotheses. We test whether the agreement effect for domestic pricing varies with the business cycle and also test whether it varies with the industry demand cycle. We further assume industry specific and time varying demand elasticities, the variation again is over the business cycle or the industry demand cycle. We separately identify the firm's export margins and relate these to the Korean economy's export cycle or the industry's export growth.

We note that marginal costs may also be varying over time as well. We model this in the error term. Marginal cost variation is of course going to affect both the firm's domestic and export margins and will be firm specific. We model this in the error term as a measurement error related to the difference (MC-AC) where this is related to firm level growth in total sales and other factors.

Hence we leave open the proposition whether there is agreement and estimate a model of variation in margins over the business cycle and separately over the industry demand growth cycle. We model variation in margins controlling for demand elasticity varying systematically over the cycle and for the gap between MC and AC varying systematically over the cycle.

3 Model

The structural model we use is based on homogeneous goods oligopoly. This has been a standard way of motivating PCM as a function of concentration in the empirical literature. One reason for this is that comparative statics for this model are simple, comparative statics for heterogeneous product oligopoly are dependent upon the assumed demand structure. Despite the model "motivation" in the literature, the standard analysis then ignores structural issues.[8] That is, the theory leads to something of the form $PCM_k = f(CR_k,\bullet)/\eta_k$ where PCM is the k^{th} industry's price-cost margin, CR_k is the industry's concentration and η_k is the industry's demand elasticity. This is then estimated as $PCM_k = h(CR_k,\bullet) + \beta X_k$. Implicitly, $h(\bullet) \equiv f(\bullet)/\eta$, or that all industries have a common demand elasticity and the βX is a decomposition of the error term around the structural prediction, something which we pursue in more detail later.

Clarke, Davies, and Waterson (1984) suggest a heterogeneous product demand structure which leads to a similar model structure with heterogeneous products and firm specific, rather than industry specific, demand elasticities. We follow much of this literature and use the

[8] Numerous studies following Cowling and Waterson (1976) have noted that this model implies that PCM for an industry is the Herfendahl divided by the industry demand elasticity. The typical pattern is to then ***add*** "control variables" to this relationship. Much of this literature is cross sectional. Machin and van Reenen (1993) similarly use an additive fixed effect in a panel estimation. JJKM show how this significantly reduces the power of the tests relative to assuming that the demand elasticity varies across industries (dividing by industry fixed effects or control variables, rather than adding them).

homogeneous product case to motivate our empirical implementation. Note, however, we test whether this is an important restriction in our results section.[9]

3.1 The Basic Model

Consider a standard homogeneous product model where each firm chooses output to maximize profits given conjectures concerning competitors' output responses. Note we will check for sensitivity to the homogeneous products assumption when presenting results. The model is

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

Define X_{-i} as total quantity of i's rivals' output and the conjectural variation as the elasticity $\alpha \equiv (\partial X_{-i}/\partial x_i)(x_i/X_{-i})$, which is assumed to be constant and identical for all firms within a given industry.[10] The FOC of firm i's profit maximization problem gives

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

where s_i is the share of the i[th] firm in the industry and η is the industry demand elasticity. For Cournot quantity competition $\alpha \equiv 0$, and for monopoly α is said to be equal to 1.[11]

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[9] We use a variety of heterogeneous product tests in JJKM 2004. Herein we examine sensitivity to estimation of the model using only homogeneous goods industries.

[10] Ideally one might model conjectures to be a function of one's rank within the industry or in some other firm specific fashion. This is not possible with our data because we do not know the shares of firms excluded from our sample.

[11] The fact that this cannot be true of an asymmetric cost constant returns to scale industry is seldom acknowledged. There is a similar failure to be exactly correct for asymmetric competition as well.

The unique contribution of Clarke, Davies and Waterson (1987) is to recognize the importance of not assuming that all industries have the same demand elasticities. What they develop is a method for modeling demand elasticity as an industry fixed effect, but they do so without using panel estimation techniques. At the time that they wrote (published in 1984), however, the techniques we use herein were not well known or even available. The model arrives at an estimate of the conjecture term for each industry allowing industry demand elasticity to be industry specific (what would be called a "fixed effect" were this panel estimation). They consider a regression of the form $PCM_{ik} = \beta_{0k} + \beta_{1k} s_{ik}$ run for each industry, k, separately. This allows them to arrive at industry specific "conjectural variations" defined as $\hat{\alpha}_k \equiv \hat{\beta}_{0k} / (\hat{\beta}_{0k} + \hat{\beta}_{1k})$ (e.g., from the last expression in (2), $(\alpha/\eta) / [(\alpha + (1 - \alpha))/\eta] = \alpha$).

They take "agreement" as meaning "less competitive than Cournot," so they exclude industries for which $\hat{\alpha}_k < 0$.[12] They then regress:

$$\hat{\alpha}_k = \gamma_0 + \gamma_1 CR_k + \epsilon_k \qquad \textbf{(3)}$$

to test whether the conjectures are a positive function of concentration.

This approach was novel for the time, but ignored the Generalized Least Squares [GLS] intuition which would weight precisely estimated $\hat{\alpha}$'s more highly than poorly estimated ones in estimation of (3). We take the GLS intuition into account and generalize (e.g., not only is the GLS "inverse variance weighting" taken into account, the potential for non-zero covariances is also permitted). We also note that one can model the error term using a structural model. The

[12] For symmetric oligopoly the following relationships hold: α=1 ⇒ "monopoly": α=0 ⇒ Cournot; α=-1/(n-1) ⇒ "competition." With linear conjectures, λ, rather than elasticity conjectures, λ=(n-1) ⇒ "monopoly"; 0 is Cournot; λ=-1 ⇒ "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 in only a few years, we do not pursue this herein.

empirical PCM is based on AC whereas the theoretical PCM in the structural model is based on MC. This potentially non-zero mean error term can be modeled explicitly using our model, whereas it cannot be modeled using the CDW multi stage estimation.

In this paper the *domestic* PCM is estimated using non-linear constrained regression. The conjectural variation term in (2) is estimated directly as a concentration varying latent variable using the third expression in equation (2). That is, the right side of (3) is imbedded directly in the estimation. And, as in Clarke, Davies and Waterson (1987), we let the demand elasticity, η_k, be industry specific. Before taking into account demand fluctuations our model is of the form

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

where the conjecture is a latent variable of the form $\alpha_k \equiv \gamma_0 + \gamma_1 CR_k$.

We will modify this basic model to allow both the conjectures, α_k, and the demand elasticity, η_k, to be functions of economic growth or industry demand growth.

Before turning to this, however, we need to discuss the fact that the Korean PCM data is at the firm level, whereas the conjectures should be examined at the level of the firm's domestic sales, e.g., (4) should apply to the firm's domestic sales. The Korean economy has many industries with substantial exports. Although concentration within Korea may affect domestic pricing, it is unlikely to have any significant effect on Korean firms' market power in international markets. Efficiency effects, however, should be important for exports. This too can be handled by construction of latent variables. Consider the following ***accounting identity***:

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

where $\Gamma^D = (1 - \Gamma^X) \equiv \text{domestic sales share}$. We identify the expressions in braces, { }'s, as latent variables. The PCM is total net revenue divided by total revenue. Total revenue is calculated as the domestic price times domestic quantity ($p^D x^D$) plus foreign price deflated by the exchange rate times export quantity ($p^f E x^X$). Net revenue is calculated as total revenue less domestic and foreign product costs per unit $(c^D x^D + c^X x^X)$. Firm PCM is simply a sales weighted average of the domestic and export PCMs (in domestic currency).

Substituting (4) for the domestic PCM embeds the concentration term in the domestic PCM. 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 and a common conjecture). This leads to

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

where the latent variable for domestic PCM times the domestic sales share 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 domestic demand elasticity, an industry fixed effect. For domestic PCMs there are 54 industry specific parameters (the η_k's) and two "common" parameters $\{\gamma_0,\gamma_1\}$ (the existence of common parameters is implicity the maintained hypothesis in Clarke, Davies and Waterson (1987) and other Traditional Empirical Industrial Organization models positing a common function relating CR to profits across industries). For the export PCM these assumptions lead to two more common parameters. Hence there are four common parameters and 54 fixed effects.

Before modeling the effects of demand growth and the error term, we review some econometric challenges that even this relatively simple model poses.

3.2 Some Estimation Issues

The resulting model is deceptively simple in this form. However, unlike the case in which fixed effects are linear and additive, one cannot use “differences from means” to eliminate the fixed effects and thereby reduce the dimensionality of the $X'X$ matrix.[13] Instead one must use dummy variables for each of the η_k's. Were we using only one firm per industry, then for any individual industry this dummy would be set equal to 1 for nine observations and 0 for 477 (=9*53) observations. This would lead to an X matrix dominated by zeros (85% of the matrix in our case). Thisted (1988) covers why this creates inaccuracy in matrix inversion (the $X'X$ matrix inversion). The reason is, essentially, that computers use a floating point approximation for zero rather than a true zero.[14] We handle this by extending an approach pioneered by Mundlak (1961). He noted that the design matrix for the linear regression with the dummies had a special structure, so that one could analytically do the partitioned inversion of the $X'X$ matrix to get an analytic expression for the common coefficients (as well as the individual effects).

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[13] Machin and van Reenan (1993) posit a model that looks like our model, suppressing subscripts. When it comes to empirical implementation, however, their model is different. They estimate $PCM_{ikt} = [s_{ikt} + \alpha_k(1 - s_{ikt})]/\eta + f_i + \epsilon_{ikt}$. By assuming the fixed effects are additive, they estimate this using first differences to cancel the fixed effect terms. Note that implicitly they assume a common η. And, importantly, consider a Cournot world with α=0. When ϵ=0 their model does not imply that $PCM_i = s_i/\eta$, as there is a non-zero fixed effect. That is, they do not estimate the structural model. (Note, by using additive fixed effects and first differences they avoid the sparse matrix problem.)

Machin and van Reenan are in fact following a standard methodology of positing the model then appending control variables in additive form and suppressing industry specific demand elasticities. See Kwoka and Ravenscraft (1986) and Rosenbaum and Manns (1994) for examples of this using FTC-LOB data.

[14] The importance of using sparse matrix methods is tested in da Graça and Masson (2004). Using an X matrix with 98% zeros and a linear hypothesis they demonstrate that SAS’s PROC MIXED does not converge to the correct parameter values, which can be calculated using sparse matrix techniques. We only have 85% of the X matrix with zeros but our highly non-linear specification is likely to be more sensitive to estimation errors due to approximations of zero in the matrix inversion.

Chamberlain (1980) noted that one could use a similar technique in a maximum likelihood setting. If one uses the Newton-Raphson procedure (or something similar) to maximize the (log) likelihood, each iteration of the procedure has 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 parameters which are common across industries. 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 to convergence 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 use here.[15]

3.3 Adding Business Cycle Effects

In this section, we augment the basic model in order to allow for business cycle effects on the conjecture and demand elasticity terms.

Note that for the domestic part of the price-cost margin we modify the conjectures latent variable to allow for business cycle effects by adding growth in demand. We also modify the industry fixed effect demand elasticity and make it a time varying industry specific latent variable by adding growth in demand. For the export price-cost margin we do not introduce conjectures or industry specific demand elasticities, but we again allow for growth (in this case export growth) to have an effect on the export PCMs.

Define the growth rate of demand as G_{kt}. (In some specifications we use GDP growth and G is not industry specific.) We multiply the base model conjectural term times one (reproducing the original term) plus a concentration varying parameter (e.g., we allow the slope

[15] The econometric details for the implementation of the matrix inversion are in JJKM (2004).

effect of growth to be different in more concentrated industries) times growth. If G_{kt}=0, we have our base model conjectures. Then equation (3) becomes:

$$\hat{\alpha}_{kt} = (\gamma_0 + \gamma_1 CR_{kt})(1 + (\gamma_2 + \gamma_3 CR_{kt}) G_{kt}) \qquad \textbf{(7)}$$

Note the concentration varying coefficient on growth is $(\gamma_2 + \gamma_3 CR)$. This allows us to test whether the effect of growth is more, or less pronounced in concentrated industries.

Industry price elasticity also can change with the business cycle. As before we assume industry specific demand elasticities but allow growth to increase or decrease this industry specific elasticity over time. We do so by modeling the k^{th} industry demand elasticity as

$$\eta_{kt} = \eta_k (1 + \gamma_4 G_t) \qquad \textbf{(8)}$$

Again, for an industry with no growth (or $\gamma_4 = 0$), this is identical to the original specification. If γ_4<0, then as growth increases the PCM increases and margins, based on demand elasticity alone, would be procyclical.

So we have three parameters which can influence the pro or counter cyclicality of the domestic PCMs, $\{\gamma_2, \gamma_3, \gamma_4\}$. For export PCMs we similarly control for export growth, G^X_{kt}

Hence our model can be represented as follows:

$$PCM_{ikt} = \{[s^D_{ikt} + (\gamma_0 + \gamma_1 CR_{kt})(1 + \gamma_2 G_t + \gamma_3 G_t CR_{kt})(1 - s^D_{ikt})] / [\eta_k (1 + \gamma_4 G_t)]\} \bullet \Gamma^D_{ikt}$$
$$+ \{(\beta_2 + \beta_3 s^X_{ikt})(1 + \beta_4 G_t^X) E\} \bullet \Gamma^X_{ikt} + \varepsilon_{ikt} \qquad \textbf{(9)}$$

This latent variable decomposition allows us to examine the domestic PCM over the business cycle (or industry specific demand cycle by using G_{kt} in place of G_t) and decompose this further into demand elasticity effects and effects due to changes in competitiveness (the conjectures in this model). It also allows us to separately examine the export PCM as it is influenced by export growth. Note, in Korea exports are a major influence in the manufacturing sector (about a third of the sales of our sample firms) and the export cycle is very pronounced and not following the same pattern as the domestic GDP cycle (as we shall see in the data discussion).

3.4 Modeling the Error Term: MC differs from AC and this varies over the cycle

It has been hypothesized that AC may be unequal to MC in a systematic fashion which is correlated with concentration or other of our exogenous variables.[16] Since we posit a structural model, this can be tested directly by altering the structure to nest this hypothesis.[17] Equation (9) is now

$$PCM_{ikt} = \{[s^D_{ikt} + (\gamma_0 + \gamma_1 CR_{kt})(1 + \gamma_2 G_t + \gamma_3 G_t CR_{kt})(1 - s^D_{ikt})] / [\eta_k (1 + \gamma_4 G_t)]\} \bullet \Gamma^D_{ikt} + \{(\beta_2 + \beta_3 s^X_{ikt})(1 + \beta_4 G_t^X) E\} \bullet \Gamma^X_{ikt} + \mu_{ikt} + \varepsilon_{ikt}' \quad \textbf{(9')}$$

The change is that the error term is now $(\mu_{ikt} + \varepsilon_{ik}')$. The first term, μ, is permitted to have a non-zero mean and is firm, industry and time varying. By modeling μ_{ikt} we can incorporate various reasons why it may be that $MC \neq AC$.

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

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[16] *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.

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

numerators we have

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

Using the superscipt T for the theoretical PCM, this can be written

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

There are a variety of reasons why MC may be unequal to AC.[18] Many of the potential reasons for deviations have been provided by helpful reviewers. Clearly in our cycles context MC may rise relative to AC during expansions and fall during contractions. There may also be an economies of scale issue. And finally, one reviewer felt that it was possible that our core explanatory variables of share and concentration may be correlated with deviations between these two measures.

A key element for identification is that the posited biases are biases which affect the **firm** PCM, not the firm's **domestic** PCM or its **export** PCM, but the entire PCM. (E.g., if costs are elevated by some influence, these affect both the export and domestic PCM). The fact that we can decompose the domestic and export PCM enables us to identify whether domestic and export exogenous variables are orthogonal to total firm PCM errors in measurement.

We deal first with the potential that (MC - AC) is non-zero and positively correlated with domestic concentration (leading to the possibility of a positive observed PCM-CR relationship

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[18] In cost minimization with constant returns to scale SMC=SAC=LAC=LMC. There are, however, deviations from cost minimization and from constant returns to scale.

without this being "caused" by behavior).[19] 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^I can cover both potentials for MC $\neq$ 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

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

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

Following this another reviewer discussed measures of economies of scale such as firm size. 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

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[19] We initially used constant returns to scale and the assumption that AC=MC. In Korea with its high growth rates we believe that plants are constructed to be "flexible" and "adaptable" in the sense of Stigler (1939). A flexible plant, in his sense, would be one which could readily be expanded, or contracted, using mostly variable inputs. For example, his firms do not statically cost minimize. They may use less efficient machines which can be added to, or subtracted from, incrementally rather than potentially larger machines which may be dedicated to one use only. An adaptable plant is one which can be added on to easily. For example, by building in a rural area one may be able to add more and more assembly lines, whereas an urban plant might be limited by neighbors in expansion.

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 $(\delta_4 + \delta_5 * K/O) * size^{-1}$.

Finally, we examine the parameter $\xi \equiv P^D/P^X$. We would hypothesis that if our model finds α positively related to CR, we would expect that ξ would be an increasing function of concentration (e.g., domestic prices would rise relative to competitive export prices with greater concentration). We model this as $\xi = \phi_o + \phi_1 CR$.

Now we turn to our primary topic, demand growth. The reviewer concerned with this 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 $(\delta_6 + \delta_7 * K/O) * Gro$. It is also 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 all of the above into the error term we have[20]

[20] JJKM estimate the domestic to export price ratio directly and demonstrate that estimating $P^D/P^X = \phi_0 + \phi_1 * CR$ leads to $\phi_0 > 1$ and $\phi_1 > 0$ and both are significant.

$$\varepsilon_{ikt} = \mu_{ikt} + \varepsilon_{ikt}' =$$

$$[\delta_0 + \delta_1 * CR_{kt} + \delta_2 * s_{ikt}^{I} + \delta_4 * K/O_{kt} + (\delta_3 + \delta_5 * K/O_{kt}) * size_{ikt}^{-1}$$
$$+ (\delta_6 + \delta_7 * K/O_{kt}) * Gro_{ikt} + (\delta_8 + \delta_9 * K/O_{kt}) * DGro_{ikt}] * \left[\frac{\Gamma_{ikt}^{D}}{\phi_0 + \phi_1 * CR_{kt}} + \Gamma_{ikt}^{X}\right] + \varepsilon_{ikt}' \quad \textbf{(16)}$$

4 Data

Before explaining the specifics of the data set, we need to explain why it is a Line-of-Business data set (e.g., why each firm is interpreted as being associated with only one industry). This is because of the "business group" structure of Korean Chaebol firms. Samsung, for example, is not a "firm," it is a Chaebol composed of roughly forty affiliated firms during our sample time period. One could own stock in the Samsung firm which makes picture tubes, but not in the Samsung firm which makes television sets. Because of this, the firms must be at arms' length in transactions.[21] With our data we can examine "coverage ratios," the percent of firm sales in its primary four digit census industry. To be selected for our data set, the coverage ratio needed to be very high, and indeed almost all Korean firms (e.g., sub parts of Chaebols) have coverage ratios over 80% and a very high fraction have coverage ratios exceeding 90%. Accordingly we construct what is, in effect, Line-of-Business data by using firm level data.

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 data] for 1987 to 1995. We selected manufacturing firms which we matched to industries according to 4-digit KSICs (Korean Standard Industry Codes) to measure market share and concentration.

[21] In practice only a very small fraction of the Samsung picture tubes are sold to Samsung firms.

We exclude the census "catch all" industries (with names like, *etc, misc, nec, nsk*; each denoting non-homogeneous sub definitions). Finally, to include an industry in the sample for any individual year we required having data for at least two firms for that industry and year. The remaining sample includes 363 firms in 54 industries.[22]

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

4.1 PCM

The dependent variable in equation (9) is price-cost margin.[23] The theoretical definition of PCM is (P-MC)/P. However, marginal cost is not observable. Given data availability, most previous researchers have used short-run average variable costs in place of MC. Since in static cost minimization, MC=AC>AVC, it is common to control for the capital output ratio, including K/O as an independent variable and interpreting the coefficient on K/O as the opportunity cost of capital (as if it had been deducted from the PCM side and hence the remainder of the right side of the regression equation is interpreted as explaining the price to marginal cost ratio).[24] We

[22] 206 firms have data for all 9 nine years, the mean number of years is 7.4.

[23] As noted elsewhere, e.g., Jeong and Masson (1990), 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 has firms assumed to interact with only *existing* rivals (although entry considerations would be captured in the industry fixed effect).

[24] In a neoclassical model with constant returns to scale and only labor and capital, PCM=(pY-wL-rK)/pY. If PCM=βX, one could regress $PCM = (pY - wL - \hat{r}K)/pY$ on βX, where we have data on {pY, wL, K}, but no data on r and need to use an estimate of r. This is what we do. Alternatively, most of the literature regresses $PCM' = (pY - wL)/pY$ on βX + ρ(K/pY),

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). LOB data have an advantage over many other data sets in that we have firm specific measures of K/O, many earlier studies have been constrained to industry averages.[25]

The definition that we want is the cost of capital, $\hat{r}K/O$, where $\hat{r}$ is a measure of the opportunity cost of capital.[26] For the opportunity cost of capital, we use each year's manufacturing sector financial expenses as a proportion of total borrowing in the sector (11.2% to 13.6% over our sample period) published in the Financial Statement Analysis by the Bank of Korea. For capital we use tangible fixed assets.[27]

There is an important historical issue about the cost of capital. Debt in Korea through most of the 1980s and 1990s was almost entirely comprised of short term (one year) loans from banks. So, the sample period variation in interest paid is actually reflecting current capital costs times current capital.[28] It is also noteworthy that our firms doubled in size over the period of analysis, which means that our measure of the value of capital stock is mostly based on fairly recently acquired capital (e.g., depreciation adjustments are less likely to have much influence in the potential for the measurement of capital).

The "Cost of Goods Manufactured" in the KIS data includes all flow costs, raw material

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where ρ is then interpreted as $\hat{r}$.

[25] Masson and Shaanan (1984) similarly deduct estimated opportunity cost of capital in forming PCM rather than controlling for K/O as an independent variable.

[26] Ideally, we would like to know the marginal opportunity cost of capital, at either the equity or borrowing levels (e.g., which ever source would be used for the next investments).

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

[28] The reasons why this was the pattern are covered in Masson, Tookes and Um (2004).

costs, labor costs, electricity, utilities, taxes and the like, but excludes costs such as marketing costs which are not "manufacturing costs" (and not part of MC). Given all of this, our PCM measure is constructed as:

$$\text{PCM} \equiv \frac{\text{Manufacturing Sales} - \text{Costs of Goods Manufactured} - \text{Capital Costs}}{\text{Manufacturing Sales}}$$

4.2 Market Shares and Concentration

The numerator for the share data comes from KIS. For the denominator, industry shipments data come from the National Statistical Office [NSO].

A unique element in our panel is that CR is the **annual** three firm concentration ratio calculated from raw census data provided by the NSO.[29] Many other studies (e.g., Domowitz, Hubbard and Petersen 1986a, 1986b) have had to extrapolate concentration between census years (five year intervals). They noted, however, that concentration trends were stable in the U.S., so extrapolation was a reasonable strategy. In Korea, with rapid manufacturing growth rates, there is sufficient intertemporal variation in concentration that having annual data provides power for our tests (e.g., for establishing "within" results).

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 unobservable factors. We follow the convention that for domestic sales, the numerator in

[29] We are not very much different than Machin and van Reenen (1993) in that they only needed to extrapolate one year of concentration data.

each case should be, in fact, domestic sales. We use domestic sales net of exports (we do not include imports). So, suppressing the annual subscripts, we use:

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

where $\hat{ex}_{ik}$ for calculating domestic concentration is estimated under the assumption that the top three firms export at the industry average intensity.[30]

4.3 Domestic and Export Market Growth Rates

The growth term (G) in the domestic market cycle part of equation (9) is the growth rate in real GDP or alternatively the industry domestic sales growth. Export Growth (G^X) is the growth in country wide exports of goods and services from Korean National Accounts in real terms or the industry growth in real terms. The data source for both GDP and total exports is The Bank of Korea's Statistics database. We estimate industry specific domestic and export shipments merging industry sales from the National Statistical office with import and export data from Input-Output tables from the Bank of Korea.

4.3.1 Data Values

Table 1 below provides summary statistics on the variables used in the estimation of equation (9):

[30] To the extent that superiority dictates that leading firms are more efficient and hence export at greater rates than the industry average, the underestimation of the concentration ratio is greatest for high concentration industries. We feel that this assumption is, thus, conservative.

Table 1: Data Statistics

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
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
K/O (capital output ratio)	0.475	0.185	0.876	0.214
$size^{-1}$ (firm sales at t/industry sales, t=0)	135.99	168.96	821.91	1.212
G_t (domestic GDP growth rate)	0.082	0.021	0.110	0.054
G_t^X (Korean export growth rate)	0.139	0.138	0.334	-0.037
G_{kt} (domestic industry growth)	0.127	0.125	0.473	-0.149
G_{kt}^X (industry export growth)	0.154	0.204	0.729	-0.296
Gro_{ikt} (firm growth)	0.106	0.127	0.458	-0.149

Given our focus on cyclicality, it is instructive to look in more detail at two of the growth variables.

Table 2 gives the time series for GDP and total Korean export growth rates.

Table 2: GDP and Export Growth Rates

	1987	1988	1989	1990	1991	1992	1993	1994	1995
G_t	11.0%	10.5%	6.1%	9.0%	9.2%	5.4%	5.5%	8.3%	8.9%
G_t^X	33.4%	30.0%	-3.7%	-1.3%	4.7%	7.4%	8.6%	18.9%	26.8%

The cyclical effects on exports are *far* more volatile than those for domestic GDP, indicating the importance of separating these two growth rates in terms of explaining PCMs.

GDP shows two peak years, followed by a trough, two more peaks, two troughs and two peaks again. These are "relative" peaks and troughs, however, since all growth is positive. The export growth rates basically are at a peak for two years, then collapse to a negative growth trough which slowly starts to recover, only to go back to peak levels in the last two years. The patterns of domestic and export growth are not very similar.

5 Estimation Results

5.1 Some data forensics

Before moving to the structural model, we will see what the data tells us about some underlying factors.

Consider the Superior Firm hypothesis. This suggests that firms with greater market shares due to superior technologies or products will have greater than normal profits. So, consider an industry with a relatively equal size distribution and close to normal profits. Then suppose a small number of firms develop superior technologies or products. Industry concentration will rise as will industry profits due to this effect. So, the superiority hypothesis suggests that the positive relationship between concentration and profits is due to an aggregation of the high profits of large firms. Also consider the accounting biases hypothesis, suggesting that exactly the same factors which make for economies of scale (e.g., capital intensity) will lead to systematic accounting biases (e.g., depreciation rates on capital being influential) and cause a concentration-profits correlation.

We first examine both of these contentions along with yet another contention. That is, firm PCMs should vary with firm growth due to firm behavior and/or capacity constraints and excess capacity causing MC to deviate from AC. The argument suggests that this could create procyclical measured PCMs even if true PCMs are not procyclical. Then, when aggregating firms up to the industry level (as is most common in this literature), procyclical industry demand would lead to apparent procyclical industry PCMs.

Before turning to the structural modeling, we look at these three issues using a simple panel model. Of our 54 industries, 16 had a *negative*, relationship between firm PCMs and firm shares. If the superiority "aggregation bias" model explains the positive relationship between concentration and PCMs in general, then for these 16 industries the bias should be opposite, e.g., they should demonstrate a negative concentration-PCM relationship.

If *inter* industry accounting differences explain the positive concentration-PCM relationship, a "within" panel estimation which uses no inter industry data, only within industry changes across time, should not have a positive correlation between concentration and PCM. If *intra* industry accounting definitions explain the positive concentration-PCM relationship, then there should be no observed relationship in a panel model with firm fixed effects.

If the procyclical PCM is caused by firm level changes in growth rates aggregated up to the level of the industry, then firm growth in a "within" estimator regression with both firm growth and industry growth should have the firm growth explaining PCM, eroding the significance of industry growth. So we regressed firm PCM on industry concentration, GDP growth, industry domestic market growth and firm growth using firm fixed effects.

For the full sample with firm fixed effects our results are

$$\begin{array}{l} PCM_{ikt} = \underset{(2.86)}{0.066}\, CR_{kt} + \underset{(2.37)}{0.117}\, G_t + \underset{(2.65)}{0.049}\, G_{kt} + \underset{(1.14)}{0.004}\, G_{ikt} + \text{fixed effects} \\ F = 89.25 \end{array} \qquad \textbf{(10)}$$

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

$$\begin{array}{l} PCM_{ikt} = \underset{(2.05)}{0.059}\, CR_{kt} + \underset{(1.97)}{0.125}\, G_t + \underset{(2.18)}{0.042}\, G_{kt} + \underset{(0.72)}{0.003}\, G_{ikt} + \text{fixed effects} \\ F = 45.64 \end{array} \qquad \textbf{(11)}$$

CR is significant at the 99% level for the full sample as well as the subsample and the coefficients are virtually identical to those for the full sample. 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. Furthermore, *inter* industry accounting differences cannot be explaining the results, all results are strictly driven by the within industry concentration changes and within firm PCM changes. Even *intra* industry accounting changes cannot be driving results, as these are in the firm fixed effects. Finally, GDP Growth and Industry Sales Growth are influencing PCM, but Firm Growth, as in firm bottlenecks, has little influence on PCMs. This *suggests* that changes in behavior, rather than gaps in the measurement of (MC-AC) are leading to the results. Of course the next question is "Whose behavior is changing?" That is, in high growth periods demand may become less elastic, so consumer behavior changes could lead to procyclical PCM behavior. It could be that firm behavior changes with industry or country growth. And of course these are not mutually exclusive, both consumers' and firms' behaviors may change over the cycle, which is one reason for us to turn to structural modeling.

5.2 The Business Cycle Regression

We start with the business cycle regression based on Growth of GDP, as this was the strongest (in point estimate) influence in the simple panel we presented above. Equation (9) is estimated using a non-linear least squares technique with sparse matrix inversion routines. We present four sets of estimates. First, we present business cycle estimates under the assumption that MC=AC. Second we present business cycle results with the MC$\neq$AC modeled in the error term. Third we replace business cycle GDP growth with individual industry growth in the MC$\neq$AC specification. Finally we examine sensitivity to the homogeneous product assumption in a model allowing for MC$\neq$AC.

5.2.1 Business Cycle Results assuming MC=AC

For all tests we are presenting *t*-values in parentheses because the important hypotheses have to do with differences from zero.

$$PCM_{ikt} = \{s^{D}_{ikt} + (\underset{(0.34)}{-0.015} + \underset{(6.16)}{0.623}\,CR_{kt})[1 + (\underset{(3.45)}{1.355} + \underset{(6.36)}{0.506}\,CR_{kt})\,G_t](1 - s^{D}_{ikt})\} \bullet \frac{\Gamma^{D}_{ikt}}{\{\eta_k(1 - \underset{(3.57)}{0.582}\,G_t)\}}$$

$$+ \{(\underset{(1.31)}{0.006} + \underset{(11.92)}{0.389}\,s^{X}_{ikt})\,E\,(1 + \underset{(2.54)}{2.169}\,G_t{}^{X})\} \bullet \Gamma^{X}_{ikt} + \varepsilon_{ikt} \qquad \textbf{(13)}$$

We delay discussion of results until all four models have been reported.

5.2.2 Business Cycle Results assuming MC≠AC

$$PCM_{ikt} = \{s^{D}_{ikt} + (\underset{(0.48)}{-0.016} + \underset{(5.12)}{0.653}\,CR_{kt})[1 + (\underset{(2.97)}{1.293} + \underset{(5.54)}{0.589}\,CR_{kt})\,G_t](1 - s^{D}_{ikt})\} \bullet \frac{\Gamma^{D}_{ikt}}{\{\eta_k(1 - \underset{(3.18)}{0.487}\,G_t)\}}$$

$$+ \{(\underset{(1.54)}{0.005} + \underset{(5.94)}{0.287}\,s^{X}_{ikt})\,E\,(1 + \underset{(2.26)}{2.175}\,G_t{}^{X})\} \bullet \Gamma^{X}_{ikt}$$

$$+ [\underset{(1.44)}{0.651} - \underset{(0.08)}{0.039}\,CR_{kt} - \underset{(1.13)}{0.274}\,s^{I}_{ikt} - \underset{(1.08)}{0.061}\,K/O_{kt} + (\underset{(1.29)}{0.0001} - \underset{(0.84)\ 0}{0.0003}\,K/O_{kt})\,size^{-1}_{ikt} \qquad \textbf{(13)}$$

$$+ (\underset{(0.25)}{-0.030} + \underset{(0.26)}{0.059}\,K/O_{kt})\,Gro_{ikt} + (\underset{(0.39)}{0.049} - \underset{(0.30)}{0.073}\,K/O_{kt})\,DGro_{ikt}]\left[\frac{\Gamma^{D}_{ikt}}{\underset{(1.24)}{1.198} + \underset{(0.48)}{0.216}\,CR_{kt}} + \Gamma^{X}_{ikt}\right] + \varepsilon_{ik}$$

5.2.3 Industry Growth Results assuming MC≠AC

$$
\begin{aligned}
PCM_{ikt} = {} & \Big\{s_{ikt}^{D} + (\underset{(0.52)}{-0.056} + \underset{(5.34)}{0.689}\,CR_{kt})[1 + (\underset{(3.25)}{1.187} + \underset{(5.79)}{0.579}CR_{kt})G_{kt}](1 - s_{ikt}^{D})\Big\} \bullet \frac{\Gamma_{ikt}^{D}}{\{\eta_k(1 - \underset{(4.17)}{0.612}G_{kt})\}} \\
& + \{(\underset{(1.69)}{0.002} + \underset{(4.84)}{0.253}s_{ikt}^{X})\,E\,(1 + \underset{(3.21)}{3.113}G_{kt}^{X})\} \bullet \Gamma_{ikt}^{X} \\
& + [\underset{(1.57)}{0.516} - \underset{(0.04)}{0.048}\,CR_{kt} - \underset{(1.02)}{0.363}\,s_{ikt}^{I} - \underset{(0.96)}{0.064}K/O_{kt} + (\underset{(1.34)}{0.0002} - \underset{(1.25)\ 0}{0.0004}K/O_{kt})\,size_{ikt}^{-1} \\
& + (\underset{(0.14)}{-0.035} + \underset{(0.16)}{0.046}\,K/O_{kt})\,Gro_{ikt} + (\underset{(0.20)}{0.051} - \underset{(0.16)}{0.059}K/O_{kt})\,DGro_{ikt}]\left[\frac{\Gamma_{ikt}^{D}}{\underset{(1.17)}{1.199} + \underset{(0.36)}{0.176}\,CR_{kt}} + \Gamma_{ikt}^{X}\right] + \varepsilon_{ik}
\end{aligned}
\quad \textbf{(13)}
$$

5.2.4 Checking Homogeneous product industries assuming MC≠AC

The structural model we presented is based on homogeneous product industries, and some of our industries are clearly not homogeneous products (e.g., autos). To test for sensitivity to this assumption 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

$$
\begin{aligned}
PCM_{ikt} = {} & \Big\{ s^{D}_{ikt} + (\underset{(0.76)}{-0.024} + \underset{(6.23)}{0.801}\,CR_{kt})\,[1 + (\underset{(2.72)}{1.339} + \underset{(5.16)}{0.557}\,CR_{kt})\,G_{kt}]\,(1 - s^{D}_{ikt}) \Big\} \bullet \frac{\Gamma^{D}_{ikt}}{\{\eta_k (1 - \underset{(3.09)}{0.572}\,G_{kt})\}} \\
& + \{(\underset{(1.47)}{0.041} + \underset{(3.98)}{0.178}\,s^{X}_{ikt})\,E\,(1 + \underset{(2.13)}{2.276}\,G^{X}_{kt})\} \bullet \Gamma^{X}_{ikt} \\
& + [\underset{(0.62)}{0.032} - \underset{(0.09)}{0.067}\,CR_{kt} - \underset{(1.12)}{0.379}\,s^{I}_{ikt} - \underset{(0.93)}{0.056}\,K/O_{kt} + (\underset{(1.22)}{0.0004} - \underset{(0.49)\ 0}{0.0004}\,K/O_{kt})\,size^{-1}_{ikt} \\
& + (\underset{(0.30)}{-0.047} + \underset{(0.07)}{0.016}\,K/O_{kt})\,Gro_{ikt} + (\underset{(0.19)}{0.025} - \underset{(0.43)}{0.099}\,K/O_{kt})\,DGro_{ikt}] \left[\frac{\Gamma^{D}_{ikt}}{\underset{(1.13)}{1.177} + \underset{(0.51)}{0.192}\,CR_{kt}} + \Gamma^{X}_{ikt} \right] + \varepsilon_{ik}
\end{aligned}
\qquad \textbf{(14)}
$$

The results are very close to the models above. The point estimate on CR is a bit higher, but not by very much, and its *t*-value is a bit higher as well. But basically the results from the clearly homogeneous industry sub sample are very similar to the results above.

5.3 Parameter Estimates

The first thing which is apparent across the four models is that the important coefficients in the structural model are stable across the three specifications. For example, the coefficients on concentration are respectively 0.623, 0.653, 0.689, and 0.801. The coefficients on how the concentration effect varies over the business cycle are 0.506, 0.589, 0.579 and 0.557, respectively. It is interesting to note that results for subsamples of more heterogeneous industries also lead to similar, albeit slightly less strong, results.[31]

The effects of concentration with no growth and the additional affect of concentration as growth increases are both greater after adjusting for MC≠AC biases. Note as well that the

[31] For the other half of the industries, from industry “Paper Containers” with A/S of 0.61% through industry Pharmaceuticals with A/S of 8.75% the concentration parameter is 0.532 (*t*=4.31) and the concentration growth interaction parameter is 0.519 (*t*=4.87). Truncating to the 13 most heterogeneous industry subsample, starting with industry Footwear with A/S of 1.29%, these parameters are 0.475 (*t*=3.87) and 0.489 (*t*=3.84).

t-values drop marginally in the specifications with the MC≠AC bias adjustments and that the *t*-value rises in the model tested on only homogeneous goods industries.

Accordingly, it is difficult say which model is "best," but the one for the full sample and without the MC≠AC adjustments is the most conservative in terms of the magnitudes of concentration effects on margins in the estimates of the "behavior" implied by the model (as opposed to the sum of behavioral and MC fluctuations results). But there is another important set of criteria. The MC≠AC part of the estimation has few coefficients with *t*-values even arguably "high." This doesn't mean that the joint significance of these coefficients is unimportant. They are "important" to the extent that the joint significance of the entire set of terms meets an 80% level of confidence, for the business cycle, and 85% for the demand cycle estimates. This implies significant evidence of some effect, definitely not a strong effect, and certainly not an effect which leads to biases in the estimation of the primary model.[32]

Without strong evidence supporting these estimates, and given the fact that the parameters from the estimation without MC≠AC adjustments are conservative relative to the agreement hypothesis and the procyclical margins hypothesis, we resort to Occam's Razor and Einstein's entreaty ("Make your theory as simple as possible, but no simpler"). We shall analyze the implications of model parameters for the case without MC≠AC adjustments over the business cycle (e.g., we also ignore the industry specific demand cycle results for our analysis of results).

5.4 Interpreting the Results

5.4.1 Concentration and Domestic PCMs over the Business Cycle

We are interested in both the effects of concentration on PCMs and in how business cycle effects on domestic PCMs vary across concentration levels.

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[32] Looking at "controls" suggests examining much lower level of significance than looking at hypotheses given Type I - Type II error analysis.

In Table 3 we address the effects of the business cycle on the PCMs. We break this into four parts: the total effect; the indirect effect through the conjectures term; the indirect effect through demand elasticities; the direct effect on the conjecture term alone. The estimates of these effects are shown for three levels of industry concentration, its mean and plus or minus one standard deviation around this mean. Estimates assume all other variables are at their mean levels of $\bar{G}$ = 0.082, $\bar{\eta}$ = 1.721, $\bar{s}_D$ = 0.046, $\bar{s}_X$ = 0.098, and $\bar{E}$ = 0.998.

Table 3: Concentration and Business Cycle Effects

Concentration Level	$\bar{C} - \sigma_C$ 0.215	$\bar{C}$ 0.394	$\bar{C} + \sigma_C$ 0.573
Total: $\frac{\partial PCM^D_{It}}{\partial G_t} = \frac{\partial PCM^D_{It}}{\partial \alpha_{It}} \bullet \frac{\partial \alpha_{It}}{\partial G_t} + \frac{\partial PCM^D_{It}}{\partial \eta_{It}} \bullet \frac{\partial \eta_{It}}{\partial G_t}$	0.166 (2.182)**	0.318 (2.229)**	0.483 (2.424)**
Conjecture Effect: $\frac{\partial PCM^D_{It}}{\partial \alpha_{It}} \bullet \frac{\partial \alpha_{It}}{\partial G_t}$	0.101 61% (2.153)**	0.209 66% (2.189)**	0.327 68% (2.191)**
Elasticity Effect: $\frac{\partial PCM^D_{It}}{\partial \eta_{It}} \bullet \frac{\partial \eta_{It}}{\partial G_t}$	0.065 39% (2.027)**	0.110 34% (2.154)**	0.156 32% (2.243)**
$\frac{\partial \alpha}{\partial G_t}$	0.174 (1.783)***	0.358 (3.513)*	0.563 (5.422)*
$\frac{\partial \eta}{\partial G}$	Same as at mean	-1.002 (2.174)**	Same as at mean

Note: ( ) asymptotic *t*-values estimated by the delta-method. * = significant at 1%; ** = significant at 5 %; *** = significant at 10 % with ***two tails***, respectively.

The PCM business cycle hypotheses have suggested that PCMs can be either procyclical or counter cyclical, accordingly *two tailed tests* are appropriate for the effects of growth on PCMs. The literature has suggested that the pro or counter cyclical effects may be more likely to occur in more highly concentrated industries where "agreement" may be a factor in the determination of PCMs.

The first row in Table 3 shows the gross effect of Growth on PCMs for low, medium and high concentration levels. At each concentration level the effect of growth on PCMs is procyclical and significant at the 95% level (two tails). The point estimates for the high concentration industries are three times those for the low concentration industries, suggesting that, as the theories predict, the effects are likely to be more pronounced when "agreement" is more likely to be playing a role in PCM formation. We return to this relationship below after discussing the effect of Growth on the estimated conjecture.

The second and third rows partition the total effect into the effects created by procyclical conjectures and those from procyclical demand elasticity effects (i.e., counter cyclical movement in the absolute value of the demand elasticity). The percentages reported in a smaller font in the columns to the right of the estimates indicate what percent of the total effect is from the conjectures effect and the elasticity effect, respectively. Roughly two thirds of the cyclical effect of Growth on PCMs is accounted for by the conjecture effect, and one third by the demand elasticity effect. Both the elasticity effect and the conjecture effect are roughly three times greater at higher concentration than at lower concentration, although the conjecture effect more than triples and the elasticity effect falls short of tripling.[33] Again, all results are significant at the 95% level.

Next we look at the effects of growth on the conjecture alone. The pattern is similar to the effects on PCM through the action of Growth on the conjecture. Interestingly, the significance pattern is somewhat different in this case. If low concentration industries were

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[33] The greater elasticity effect at higher concentration levels should be independent of the "agreement" hypotheses. It is possible, however, that industries with greater demand elasticity variability might have a tendency to become more concentrated.

perfectly competitive, one wouldn't expect to find cyclical PCMs (with MC=AC and rapid price and output adjustments). In the table we find that at low concentration, the effect of growth in determining the level of the conjecture is only significant at the 90% percent level.[34] In contrast, for medium and high concentration industries the statistical significance is much greater, rising to 99% for the mean level of concentration and far higher for the high level of concentration. This is what the various agreement hypotheses suggest would be observed (e.g., whether concentration leads to procyclical or counter cyclical PCMs, they should be more volatile at high concentration levels than at low ones for which there should be little or no agreement effect).

Finally we look at the effect of growth on the demand elasticity. This is negative and significant at the 95% level, implying a procyclical PCM effect (as the absolute value of η falls, the joint profit maximizing price rises). Note, this is not modeled as a function of concentration, so the same value is implied for each of the three concentration levels; also note there is still an industry specific effect in these estimates. That is, demand elasticity is $[\eta_k(1 + \gamma_4 G_t)]$, which is an industry fixed effect plus a proportional cyclical effect of growth.

We return to the fact that the effects of Growth on PCMs and on α essentially triple as one moves from $\bar{C} - \sigma_C$ to $\bar{C} + \sigma_C$. There is no direct test for the significance of this effect. One can look at suggestive statistics, however. For $\partial PCM^D/\partial G$, the higher point estimate is more than four standard deviations above the lower point estimate, using the lower point estimate's standard deviation. Using the upper point estimate's standard deviation, the lower point estimate is only about one and a half standard deviations away. Looking at the results of the effect on

[34] The Table 3 definition of low concentration is defined by the mean minus one standard deviation. At the sample min of C=6.5% $\partial\alpha/\partial G = 0.035$ and the *t*-value is only 0.36. Extrapolation to sample endpoints is dependent upon the model specification. In our case we have terms with CR, G, CR*G and CR^2*G.

$\partial\alpha/\partial G$, using either the upper or the lower point estimate's standard deviation, the two point estimates are about four standard deviations apart. This suggests that there are strong differences in the cyclical effects for low concentration and high concentration industries.

5.4.2 Concentration and the Agreement versus Superior Firm Hypotheses

Next we can examine the standard agreement hypothesis results. We can look at both $\partial PCM^{D}/\partial CR = (\partial PCM^{D}/\partial\alpha)(\partial\alpha/\partial CR)$ and $\partial\alpha/\partial CR$. In Table 4 we present these over the business cycle, at low, mean and high values of the growth rate.

Table 4: Concentration and both PCMs and Conjectures

Growth Level	$\bar{G} - \sigma_G$ 0.061	$\bar{G}$ 0.082	$\bar{G} + \sigma_G$ 0.103
$\frac{\partial PCM^{D}_{Iit}}{\partial CR_t} = \frac{\partial PCM^{D}_{Iit}}{\partial\alpha_{It}} \bullet \frac{\partial\alpha_{It}}{\partial CR_t}$	0.396* (4.599)	0.414* (4.610)	0.433* (4.619)
$\frac{\partial\alpha}{\partial CR_t}$	0.689* (5.680)	0.712* (6.287)	0.735* (6.588)

Note: ( ) asymptotic *t*-values estimated by the delta-method. * = significant at 1%.

The concentration effect on PCMs and α are positive and significant in both high growth and low growth years. We know from the above that PCMs and α are higher in high growth years, but here the derivative with respect to concentration is similar for both low and high growth years. What this means is that over the cycle, as growth increases, the PCM at each level of concentration increases (e.g., the conjecture increases) and that these increases are uniform. The "slope" of PCM (and of α) with respect to concentration remains stable across the cycle (e.g., the effect of the cycle on the concentration-PCM relationship is essentially an intercept shift with a close to constant slope).[35]

[35] This suggests that JJKM do not lose a great deal by estimating a constant slope across this time period. Their slope estimate for α of 0.645 (t=8.77), for example, is only slightly lower

The discussion of PCMs and oligopoly has been based on the agreement effect. Undoubtedly the superior firm hypothesis has validity as well. At a fundamental level, suppose that there were no superiority effect biasing the concentration-PCM relationships. Then one would expect that there would be no systematic pattern between firm shares and PCMs; in expected value terms, half of all industries would exhibit a positive share-PCM relationship, half a negative one. What we observe, however, is that only 16 of our 54 industries have negative share-PCM relationships. The hypothesis that 16 our of 54 industries have this relationship due to random factors, rather than superiority, can be rejected at the 99% level (p-value 0.0014).

This being said, there must be some superiority biases in attributing ***all*** of the concentration-PCM effects to agreement alone. But our model nests the agreement and superior firm effects and finds the derivative of PCM with respect to concentration allowing for this effect.

5.4.3 Returning to the Question of Biases due to MC≠AC

The model in (13) nests the assumption that MC-AC is related to firm size (economies of scale) and firm Growth (both absolute growth and growth relative to the firms mean growth over this time period). The effects of firm growth on MC-AC are very weak in our tests. Growth itself has a counter intuitive negative effect on MC-AC (evaluated at mean K/O) and firm growth relative to mean firm growth has the expected positive sign. None of the coefficients, however, have a *t*-value in excess of 0.20!

One might question why this should be the case. Shouldn't there be a strong procyclical MC-AC effect due to sunk fixed capital and other potential sunk costs? The answer comes in several dimensions. For example, the Korean "downturns" were slowing rates of growth, rather than negative growth rates. But first, we turn to how firms adapt to their environments.

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than ours.

Stigler (1939) posited that firms would select technologies reflecting their environments. For example, a firm in a low growth industry with highly fluctuating demand would select to build a plant which would have its minimal average cost above the envelope curve, but would have a much wider U-shape, e.g., a wide range of SMC close to SAC relative to a plant designed to minimize costs at some specific level of output (one on the envelope curve). E.g., they would build “flexible” plants.

Stigler also posited that firms which are in strongly growing industries would build plants which could easily be expanded in incremental units. E.g., parallel assembly lines which would possibly be below the optimal scale per assembly line, but which could be easily added to with growth. These were what he called “adaptable” plants. With an industry which experiences high growth, but fluctuating levels of high growth, firms should pick technologies which should have short lead times and be modular in nature (e.g., not build cost minimizing plants, but ones which can more easily adapt to short swings in the environment).

Put in other terms, Korean firms, with knowledge of high growth, but unpredictable growth, should select different technologies than firms in the United States. If growth is greater in Korea, they should build more adaptable plants which can be added to easily. If growth is less predictable in Korea they should build more flexible plants which have less cost penalty if there are deviations from expected demand. In this Stiglerian context, it might not be surprising to find that SMC is close to SAC in Korea, in a way which might not be apparent in the United States.[36]

There is yet another factor which suggests that SMC should be close to SAC in Korea. Substantial exports provide this rationale. Suppose, for now, that the export market is perfectly

[36] Although one could argue that the US plants again would build production facilities which would not deviate widely from SMC=SAC given the observed growth and uncertainty in the US. Indeed this was Stigler’s perspective, writing in a time of uncertainty - the Great Depression.

competitive (and has no long term contracts). Then the opportunity cost of a unit of domestic sales is the value of the export price. E.g., in equilibrium, over the business cycle, the exogenous export price is the relevant marginal cost for sales in the domestic market. A firm would simply adjust exports to set its production SMC equal to the export price and take up domestic growth fluctuations by changing export levels. Of course firms may have export contracts and exports which are not perfectly competitive, but large exports are likely to have the effect of making the marginal opportunity cost for domestic sales fluctuate by less than would be the case in low export industries.

We can also address a question of magnitudes. Suppose that one feels that we haven't adequately controlled for MC$\neq$AC bias. We have sufficient evidence to ask whether the potential for this bias could reverse our basic results as stated above. We believe not. We examine this for the case of dynamic bias, e.g., over demand cycles.

The argument is that in high concentration industries, fixed costs may raise AC relative to MC in downturns and hence bias PCM results sufficiently that an observed procyclical PCM effect might occur even if the price cost margin above marginal costs is counter cyclical. We examined the factors above which makes this *a priori* unlikely (e.g., most costs are variable materials costs[37] and even in the Korean business cycle troughs, the growth rate is positive so firms are generally not "cutting back"). But now we can look at our empirical results and see if they can provide additional insights into this issue.

We examine high concentration industries where the definition of high concentration will be $\bar{C} + \sigma_C$ (one standard deviation above the mean of concentration in our sample). The predicted value of domestic PCM at this level of concentration is $\widehat{PCM} = 0.185873$. Indexing

[37] It is generally accepted that there is less vertical integration in Korea than in the United States, making variable materials a greater fraction of costs.

price to be P=1, this implies AC=0.814127 (AC is based on manufacturing costs and does not factor in marketing costs, front office and the like).

Now suppose there were a small increase in output for an industry with this level of concentration. Let us use as a benchmark the cyclical result of ΔP=0 (e.g., not procyclical, but not counter cyclical either). By assuming ΔP=0 we are essentially assuming that the price to marginal cost margin is [virtually] invariant to the business cycle. (The caveat of "virtually" reflects the assumption that the slope of MC has very little influence on the price to marginal cost margin for small changes in output.) Noting that our PCM is based on AC and holding price constant then $\frac{\partial PCM}{\partial G} = \frac{\partial[(P-AC)/P]}{\partial G} = \frac{\partial[1-AC/P]}{\partial G}$ and if AC is a function of G and P=1 is invariant to G then we have $\partial PCM/\partial G = -(\partial AC/\partial G)/P = 0.483$. Knowing the change in AC means we can calculate the change in TC, which means we can derive the implied level of MC. This is MC=0.32630 which is only 40% of the level of AC and a third of price. So, to eliminate the positive association between growth and the price marginal cost margin would require MC to be far lower than AC and P by amounts that to us would seem implausible (recall, we have been assuming that AC and MC are close and our control variables seem to suggest that this is the case).

This doesn't negate the Rotemberg and Saloner (1986) critique of the U.S. PCM literature, where the business cycles include downturns and layoffs and firms are more vertically integrated, raising the ratio of fixed costs to variable costs. It does suggest, however, that they may be wrong (they present only two "case studies" in support, one of which was a case study also cited for the opposite proposition). Our analysis does suggest directions one might pursue with U.S. PCM data.

5.4.4 Export Margins and Export Demand Cycles

Turning from the procyclical domestic price-cost margins let us look at export price-cost margins. In this case we related these price-cost margins to cyclicality in exports. We look at the effect of country wide export growth on export PCMs. The positive effect of export growth on export PCM also indicates procyclical tendencies. We arrive at

$$\frac{\partial PCM_{Iit}^{x}}{\partial G_t^{x}} = (0.0006 + 0.389\, s_{Iit}^{x})(\bar{E})(2.169) = 0.096 \tag{14}$$

The *t*-statistic for rejecting the null hypothesis of no business cycle effect is 2.818, implying that the null is rejected at the 99% level in a two-tailed test.

For Korea this is particularly important to understand. As noted in the data section, for our firms the mean level of firm exports is one third of total value of sales. Decomposing the export margins is hence important for properly measuring the domestic margins. But the observation of procyclical export margins following the export cycle is important in its own right.

5.4.5 Export and Domestic PCM Cyclicality Contrasts

The finding that both the domestic and export PCMs are procyclical could be in part related to unanticipated growth and upwards sloping short-run marginal cost curves. In evaluating this possibility, it is useful to consider some magnitudes of growth rate changes and the patterns of PCMs.

As shown in Table 2, GDP growth over the years 1987 to 1995 varied from a low of 5.4% to a high of 11.0%. The biggest one year growth rate change is the drop of 4.4% from 10.5% in 1988 to 6.1% in 1989. Especially given that this is a slowdown in growth, not a contraction, this is not likely to have a major impact on our results even if this were unanticipated. E.g., these changes do not suggest that firms are likely to deviate considerably from the minimum points on their short-run average cost curves (where SAC=SMC and PCM based on SAC can be interpreted as a proxy for the price *marginal cost* margin). Export growth, however, has a much different pattern. It varies from a low of -3.7% to a high of 33.4% over this period. The largest one year change is -33.7%, a drop from 30.0% to -3.7% between 1988 and 1989. Given these differences, changes in export growth are likely to have been somewhat, if not mostly, unanticipated. Furthermore the magnitudes are large enough that unanticipated changes could have significant consequences for capital utilization for high export firms. In other words, there are may be some firms in some industries in our sample which experienced the type of dynamic AC/MC cost curve bias suggested by Rotemberg and Saloner (1986) for this year.

This export cycle -- domestic demand cycle difference suggests that firm level demand cycles may not have MC fluctuate with the domestic demand cycle, even if they are highly inflexible or not very adaptable in the sense which Stigler (1939) referred to. For example, with a domestic growth rate of 10.5% in 1988, exports grew at 30%. But with a slightly lower domestic growth rate of 9.0 % in 1990, the export growth that year was -1.3%! Firm average growth, with an average of one third exports, would be far higher in 1998 than in 1990, and if MC varies from this growth, the two years would look quite different. Yet, the domestic PCM behavior implied by the administered pricing or alternative business cycle hypotheses should be similar across these two years.

All of the above factors lead us to believe that cyclicality is not affecting marginal cost fluctuations in a fashion which could potentially mean that firm behavior is not procyclical in price cost margins.

6 Conclusions

In this paper we integrate issues from three literatures into a set of tests using Korean data in a structural model.

The first literature is on the effects of concentration on pricing and employment over the business cycle. The Administered Pricing Hypothesis (Means introduced this in 1935, see Means 1972) suggested that firms in concentrated industries lowered prices less during downturns causing "... a fall in sales, production, and employment." The focus was on the effects of pricing behavior on exacerbating the business cycle. This hypothesis has had its detractors and indeed our results are opposite of those in Administered Pricing.

The second is the literature on estimation of "market power," and its detractors. The key starting point is a seminal paper by Bain (1951) in which he found that profits in concentrated industries exceeded those in unconcentrated industries. Bain felt that he had shown that concentrated industries had collusive "agreements" (not defined necessarily as explicit agreements) which raised prices. But this was followed two decades later by a seminal paper by Demsetz (1973). He posited the "superiority hypothesis." He noted that if an industry had an innovator, that this firm would be expected to increase its share and its profits. This would increase industry concentration (shares of the top firms) and industry profits. So, competition to become more efficient, dynamic competition, might lead to a static observation of a correlation between industry competition industry profitability *even without any agreement between firms.*

The tension between these two hypotheses became the "main question" in empirical industrial organization of the latter part of the 20th century according to Scherer and Ross (1990, p. 411). Scherer *et als.* (1987) declared that the "superiority hypothesis" won over the "agreement hypothesis." In this paper, and elsewhere (JJKM 2004), we find that there is support for both hypotheses, but that the primary price effects stem from the agreement hypothesis, with far smaller effects from superiority.

Green and Porter (1984) have a model of procyclical pricing over the (industry specific) demand cycle supported empirically by Porter (1983). Firms do not know whether a drop in their own demand is caused by cheating, and hence must enter into a period of punishment prices, in case there was cheating. Rotemberg and Saloner (1994) has an opposite counter cyclical pricing result. Their information structure is different, cheaters can be detected (with lags). They find that the incentive compatibility constraint to maintain agreement implies counter cyclical margins. They cite to empirical results consistent with their theory (including a reinterpretation of the Porter 1983 results). Our results are all procyclical, but do not disprove either theory.[38]

We weave these three literature's four hypotheses together in a structural panel model of Korean manufacturing. We nest "agreement" and "superiority" in the structural model. We look at both business cycle effects (growth in GDP) and industry specific demand growth. We let both the demand elasticity and a conjectural measure of agreement vary over the cycle. We also examine an important issue raised by Rotemberg and Saloner (1986), that MC may differ from AC in a systematic fashion over demand cycles. To examine this we look at how firm growth affects firm price cost margins. Furthermore we examine how sensitive our results might be to the assumption of product homogeneity.

Our results reject the counter cyclical pricing of Rotemberg and Saloner (using industry demand growth) and administered pricing (using GDP growth). Our results support the "agreement hypothesis" in two ways. First we find that concentration raises price cost margins at all phases of the business cycle. Second, even after adjusting for firm growth and industry demand elasticities varying over the cycle, we find that more concentrated industries have far more volatile margins over the cycle, something which is not predicted by the "superiority hypothesis."

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[38] Our results may indicate that the information structures do not closely approximate those in Rotemberg and Saloner, at least for the majority of industries in Korea.

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