Equilibrium Price Dispersion, Mergers and Synergies: An Experimental Investigation of Differentiated Product Competition[*]

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Abstract

This paper reports an experiment conducted to examine market performance and mergers in an asymmetric differentiated product oligopoly. We find that static Nash predictions organize mean market outcomes reasonably well. Markets on average respond to horizontal mergers with price increases as predicted and marginal cost synergies exert the predicted the power-mitigating price effects. Nash predictions, however, organize outcomes for specific markets and for the different firm-types less precisely. The variability of individual markets and firm-level decisions undermine the predictive capacity of merger simulations conducted with the Antitrust Logit Model, a merger device used by U.S. antitrust authorities to help identify problematic mergers.

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1. Introduction

Product differentiation stands out as an important dimension of competition. As a stroll through any supermarket or shopping mall readily attests, product differentiation is an empirically important component of competition in developed economies. In addition to prices, firms very publicly distinguish their products by flavors, convenience, qualities (perceived and actual), warranties and other attributes. The behavioral foundations of differentiated product competition, however, are under-investigated. The overwhelming majority of experimental markets involve contexts where buyers and sellers trade a single homogenous commodity. The limited experimental studies of differentiated product markets include: Huck, Normann and Oechssler (2000), García-Gallego and Georgantzís (2001), Davis (2002), and Davis and Wilson (2004). From an aggregate (across-market) perspective, convergence to Nash predictions stands as a common feature of these studies, at least in price-setting contexts.[1] However, these studies all share the feature that the products offered by the different sellers are symmetrically differentiated from each other. More generally, we may expect to observe some asymmetries in substitutability across products in naturally occurring markets. Volvos, for example, probably substitute much more closely with Saabs, than, for example Cadillacs. Further, asymmetric differentiation may be interesting behaviorally because asymmetries induce price heterogeneity. To the extent sellers use rivals prices as part of the price discovery process, asymmetric product differentiation may weaken or even undermine convergence to Nash predictions. Understanding the effects of these differences on market outcomes is an important research question. A primary objective of this paper is to conduct an experiment that allows some insight into the dynamics of the competitive process of markets with asymmetrically differentiated products.

We also consider in this paper two related policy questions possibly impacted by asymmetric differentiation. Both questions involve horizontal consolidations. A first question regards the capacity of static Nash equilibrium predictions to organize behavioral responses to mergers and to merger-related asymmetries. In standard differentiated product oligopoly models, equilibrium responses to mergers require rather subtle seller responses. For example, a multi-product (consolidated) firm behaves differently than two separate single-product firms in

[1] In quantity-setting (Cournot) environments Huck, Norman and Oechssler (2000) find that the provision of "EXTRA" information regarding the earning's consequences of others' actions tends to reduce prices and increase quantities. Davis (2002) reports a similar result. However, in price-setting (Bertrand) environments, information conditions do not affect outcomes importantly. García-Gallego and Georgantzís (2001) find that parallel pricing rules help symmetric multi-product firms achieve Nash equilibrium outcomes.

that the multi-product firm attends to cross price effects when making optimal price determinations. With symmetric differentiation, "parallel pricing" rules for jointly-managed products may facilitate the process of exercising market power, as studied by García-Gallego and Georgantzís (2001). But with asymmetric differentiation, parallel pricing rules are not helpful, because optimal prices differ across products pre-merger, and because firms respond optimally to consolidations by increasing prices for different products by different percentage amounts. Similarly, consolidating firms enjoying marginal cost synergies optimally respond differently to synergies that offset market power. For this reason, we examine market responses to horizontal mergers, and to market-power mitigating cost synergies in asymmetrically differentiated product markets.

As a third research objective we explore the predictive capacity of the Antitrust Logit Model (ALM), a merger simulation tool that the United States Department of Justice (DOJ) staff currently use to help identify potentially problematic consolidations (for a description, see Werden and Froeb, 1996). The ALM generates predictions in a robust variety of contexts, including markets with asymmetric prices and market shares, and mergers where the consolidating parties enjoy merger-associated synergies. The ALM is potentially a very useful policy tool because it makes precise predictions from readily observable variables. Importantly, however, these predictions rest on a number of rather strong assumptions. In addition to exogenously specifying the structure of demand (logit), costs (constant for each seller) and strategic interactions (Bertrand), the ALM presumes strictly equilibrium behavior pre-merger, and that sellers recognize and respond to the relatively subtle incentive changes associated with the consolidation post-merger. Our focus on asymmetric environments addresses issues critical to the policy relevance of the ALM, because the tool was created largely to screen mergers in such contexts.

A brief review of related experimental research provides some context for this paper. In addition to the experimental papers that investigate differentiated product competition mentioned above, two themes are pertinent. A first literature regards experiments conducted to assess sellers' capacities to recognize and exercise market power. In stark homogeneous-product price-setting environments where sellers produce discrete units and face binding capacity constraints, seller responses both to the market power created by a horizontal consolidation and to cost-reducing synergies, in the predicted directions. Davis and Holt (1994) and Wilson (1998) report that sellers respond to market power by increasing prices. Also, Davis and Wilson (2000) and Davis and Wilson (2003) find that cost synergies can mitigate market power created by a merger when the synergy undermines the unilateral price-increasing incentives created by the consolidation.[2] Similar group effects are observed in environments that implement versions of the relevant theoretical models with continuous units. For example, in a symmetric Cournot environment Huck, Konrad, Müller and Normann (2001) observe a tendency for sellers to decrease quantities post-merger in a symmetric Cournot environment. Similarly, in symmetric Bertrand environments, Davis (2002) and Davis and Wilson (2004) find that on average prices tend to increase post-merger, as predicted.

A second strand of research includes experimental studies that examine the predictive power of merger simulations. Davis (2002) and Davis and Wilson (2004) examine the predictive capacity of merger simulations for symmetrically differentiated product markets. A common result to both studies is that while static Nash predictions organize group outcomes reasonably well, individual markets are characterized by considerable variability, a factor that tends to undermine the predictive power of merger simulations. Nevertheless, in these symmetric environments the ALM performs quite well as a *screening device,* in the sense that large price increases tend to occur in the markets where fairly large (5% or greater) increases are predicted pre-merger. However, a deeper examination of the data reveals that post-merger pricing behavior is explained more by adjustments to pre-merger deviations from the underlying Nash equilibrium than by the exercise of market power.

As a brief overview, we find in this paper that asymmetric differentiation does not cripple the organizing power of static Nash predictions. Mean market outcomes conform perhaps surprisingly well to static Nash predictions, and in general, individual firms respond as predicted, to asymmetries with price heterogeneity. Furthermore, on average our asymmetric markets react both to horizontal consolidations and to merger-specific cost synergies largely as predicted. Despite these affirmative results, the ALM fails to serve even a screening role here. Most of the ALM's failure to screen out problematic consolidations is explained by an unanticipated interaction effect between the elasticities that generate large predicted price effects from mergers and the cost synergies that mitigate market power.

[2] Davis and Wilson (2003) also find that strategic withholding by powerful buyers undermines predicted seller market power.

We organize the remainder of this paper as follows. The next section develops the static Bertrand-Nash predictions for a differentiated product oligopoly, and then explains how the ALM simulation makes predictions of post-merger performance from pre-merger behavior. The three remaining sections respectively explain the design and procedures, present the experimental results, and offer some parting comments.

2. Differentiated Product Competition, Logit Demand and Predicting Post-Merger Performance with the ALM

This section consists of three parts. First, we develop general expressions for equilibrium pre- and post-merger pricing, in terms of own and cross price demand elasticities. A second subsection derives more specific predictions for the case of logit demand. A third subsection reviews the ALM simulation methodology.

2.1 Bertrand-Nash Predictions. Consider a market with n price-setting sellers, each of whom produces a single product that substitutes imperfectly for any rival offering. Firms produce without fixed costs, and with a constant marginal cost, c_i. Defining $q_i(\mathbf{p})$ as seller i's demand function given the vector $\mathbf{p}$ of own and other price choices, each seller i optimizes $\pi_i = (p_i - c_i)q_i(\mathbf{p})$.

Taking first order conditions and rearranging terms generates the standard condition

$$p_i - c_i = p_i / \eta_i , \tag{1}$$

where own price elasticity η_i is defined as a positive number. If two firms j and k merge, the corresponding first order condition for firm j is $p_j - c_j = p_j / \eta_j + (p_k - c_k)\dfrac{\eta_{kj}}{\eta_j}\dfrac{q_k}{q_j}$.

We evaluate performance in terms of two alternative reference outcomes. The competitive outcome, where price equals marginal cost, is one natural alternative, since this outcome represents a limit to non-strategic, non-cooperative behavior. The joint profit maximizing (JPM) condition, a limit to gains from cooperation, is another. Acting in concert, firms maximize $\pi_{JPM} = \sum_j (p_j - c_j) q_j(\mathbf{p})$, the first order conditions for which yield

$$p_j - c_j = p_j / \eta_j + \sum_{k \neq j} (p_k - c_k) \frac{\eta_{kj}}{\eta_j} \frac{q_k}{q_j}, \tag{2}$$

for any firm j. The second term on the right side of (2) indicates how a firm accounts for the interaction effects on all other firms as part of a JPM pricing decision.

2.2 Logit Demand. More particular predictions require specifying a demand function. We use a logit demand specification for two reasons. First, logit demand parsimoniously accommodates asymmetries among sellers. Second, the ALM, which we wish to evaluate, presumes logit demand. The logit demand specification, developed by McFadden (1974), is based on a random utility model of consumer choice. For consumer l, the utility of a choice i = 1, …, n, is $u_{il} = \alpha_i - \beta\ p_i + v_{il}$, where α_i is a quality parameter, β is a common slope parameter reflecting sensitivity of consumers to a price change, v_{il} is a consumer-specific preference for the product. If v_{il} follows an extreme value distribution, the probability P_i that consumers purchase from a particular seller i is

$$P_i = \frac{e^{\alpha_i - \beta p_i}}{\sum_{m=1}^{n} e^{\alpha_m - \beta p_m}} \tag{3}$$

Own and cross-price elasticities follow immediately from (3) as the middle terms in (4) and (5):

$$\eta_j \quad = \quad \beta\ p_j(1-P_j) \quad = \quad [\beta\ \overline{p}(1-s_j) + \eta\ s_j] p_j / (\overline{p}) \tag{4}$$

$$\eta_{kj} \quad = \quad \beta\ p_j P_j \quad = \quad (\beta\ \overline{p} - \eta) s_j p_j / (\overline{p}), \tag{5}$$

where s_i is firm i's market share conditional on the choice of an inside good (e.g., $s_i = P_i/[1 - P_n]$) and $\overline{p}$ is the share-weighted market price. The implied (positive) aggregate elasticity for all inside goods is

$$\eta \quad \equiv \quad -\frac{\partial P_I(\lambda\,\mathbf{p})}{\partial \lambda} \frac{\lambda}{P_I(\mathbf{p})} \quad = \quad \beta\ \overline{p} P_n, \tag{6}$$

where λ is a scalar evaluated at λ = 1, and $P_I = (1 - P_n)$. The expressions for η_j and η_{kj}, in terms of market shares and prices is particularly useful, since these variables are more readily observable than choice probabilities.

The own and cross price elasticities in (4) and (5) provide information sufficient to generate pre- and post-merger predictions. Inserting (4) into (1) yields

$$p_i - c_i = \overline{p}/[\beta\overline{p}(1-s_i)+\eta\, s_{\ i}]\,. \tag{7}$$

Similarly, inserting (4) and (5) into the post-merger expression (2) yields

$$p_j - c_j = p_k - c_k = \overline{p}/[\beta\ \overline{p}(1-s_m)+\eta\, s_m], \tag{8}$$

where $s_m = s_j + s_k$.

Anderson, de Palma and Thisse (1992) establish that a unique equilibrium exists for the differentiated product pricing game with logit demand. The solutions, however, must be computed numerically, since price appears on both sides of equations (7) and (8). Werden and Froeb (1994) analyze this model in some detail. Two prominent properties of their results merit comment. First, all sellers increase prices and earnings post-merger. Changes in prices and profits, however, are asymmetric when the merging parties are asymmetric pre-merger. Small merging sellers increase prices more than large sellers. Further, larger non-merging sellers increase prices more than smaller non-merging sellers. Second, since larger sellers are, by assumption, more efficient, profits and total welfare often increase post-merger.

The JPM condition is similarly expressed, via (4) and (5), as

$$p_i - c_i = 1/((1-\sum_k P_k)\beta) = \overline{p}/\eta\,. \tag{9}$$

2.3. Simulating Merger Predictions with the ALM. Notice that for the most part equations (7) and (8) are expressed in terms relatively easily observed or (roughly) estimated variables: price and share vectors **p** and **s** are standard inputs in merger investigations. The equations also include two parameters: β, a measure of substitutability across products, and η, the aggregate elasticity of inside goods. Given price and share data, β is the slope term in a linear estimate of the log of the ratio of shares for any two arbitrarily selected goods:

$$\ln(s_i / s_k) = \alpha_i - \alpha_k - \beta\ (p_i - p_k)\,. \tag{10}$$

The aggregate inside elasticity η, on the other hand, is not so easily estimated from transactions data. In practice, antitrust authorities estimate η (or P_I) from external data.[3] Only the vector of marginal costs **c** is difficult to measure in practice. Importantly, however, the simulation process requires no marginal cost information. Instead, costs are used as a degree of freedom to equilibrate the first order conditions.

[3] The accuracy of η estimates is a degree of freedom that we do not evaluate within the laboratory. In our analysis that follows, we give the ALM a "best shot" by assuming the true underlying η.

The simulation process proceeds in a two-step fashion. First, analysts calculate an implied cost vector **c** to balance both sides of the pre-merger equilibrium condition (7) for a series of single-product competitors. Given implied costs, analysts simulate post-merger prices by inserting **s**, β and η and **c** into a system of equations consisting of (8) for the consolidating firm and (7) for the remaining firms, and adjusting the post-merger price vector until both sides of each equation balances for each firm. Finally, analysts may incorporate marginal cost synergies into the analysis, by adjusting the appropriate elements of the implied cost vector **c** prior to simulating post-merger prices.

3. Experimental Design and Procedures

3.1 Experimental Design. To initiate a study of competition with asymmetric differentiation we induce a particularly simple asymmetry: we vary in direct relation firm-specific marginal costs and market shares.[4] Thus, our markets consist of a variety of sellers ranging from low-cost/low-quality producers, who enjoy only a small share in equilibrium, to high cost/high-quality producers, who enjoy a large predicted equilibrium share. Table 1 reports the pre-merger parameters in columns (1a) and (1b). In what follows we refer to firms by an "*F*" followed an index number 1 to 4. For example, we denote firm 1 as *F1*. Prices increase in approximate \$6.50 increments starting from \$42.37 for *F4* to \$63.93 for *F3*. Shares also increase in roughly 5% increments.

Increasing the absolute values of β and η tends to generate outcomes more nearly consistent with static Nash predictions.[5] At the same time, (absolutely) smaller own and inside elasticities increase the predicted effects of horizontal consolidations. Thus, we combine a pair of β and η parameters with the cost vectors shown in column (1c) to generate identical predictions. In both the *Small Effects* treatment (η = -1.566 and β =.0614) and in the *Large Effects* treatment (η = -.2295 and β =.0367), the pre-merger share weighted price prediction, P_{swa} is \$54.98.

[4] There is nothing unique about this design choice. However, creating asymmetries by varying costs and shares inversely across firms would largely cancel out price differences, and would allow some participants to stumble on an equilibrium by copying the choices of others, as may happen in a symmetric context. Importantly, much more complicated asymmetries are possible. For example, the substitutability parameter β may vary across firms.

[5] Intuitively, this is easily understood in a symmetric context. With symmetric firms, absolutely larger β's and η's flatten each firm's best response to a vector of identical price choices by rivals.

To evaluate market responses to horizontal consolidations, we combine *F1* and *F2.* The middle columns (2a) and (2b) of Table 1 summarize static Nash predictions following a consolidation. Notice in the *Small Effects* treatment, the post-merger P_{swa} increases by 2.4% to \$56.29, whereas in the *Large Effects* treatment, the post-merger P_{swa} increases by 8.3% to \$59.58. These predictions clearly separate about a 5% price increase, a natural benchmark specified in the United States Department of Justice and Federal Trade Commission *Horizontal Merger Guidelines*.[6]

The cost synergy treatments, summarized columns (3a) and (3b) of Table 1, provide insight into the capacity of merger-associated synergies to mitigate the price-increasing effects of a consolidation. In each case, we reduce marginal costs for *F1* and *F2* by \$10 and \$8, respectively. In the *Small Effects* design these cost savings more than offset the market power created by the consolidation. The predicted post-merger P_{swa} falls by 4.89% to \$52.26. This same synergy exerts more modest effects in the *Large Effects* treatment. Scanning across columns of the *Large Effects* treatment rows, notice that the synergy virtually restores the predicted pre-merger price vector. Post-merger the overall P_{swa} of \$55.75 only exceeds the pre-merger P_{swa} =\$54.98 by 1.44%.[7]

Our experimental design consists of two parts. Pre-merger, we examine whether parameters generating *Small Effects* and *Large Effects* affect convergence, as summarized in the leftmost column of Table 2. We examine a total of 10 markets in each condition. Post-merger, we divide the *Small Effects* and *Large Effects Sessions* into *No Synergy* and *Synergy* treatments, to generate a standard 2 × 2 experimental design summarized under the "Post-Merger" heading in Table 2. We conduct five markets in each of the four post-merger treatment cells, for a total of 20 markets.

Summarizing the anticipated results in terms of a series of explicit conjectures facilitates our presentation of the experimental results. Evaluating convergence to static Nash predictions

[6] Our design has the added desirable feature that we calibrate predictions to allow comparison with Davis and Wilson (2004). The pre-merger and post-merger P_{swa}'s, as well as the predicted percentage price increases induced by the consolidations, match predictions in the *Small Effects* and *Large Effects* treatments in our symmetric designs.

[7] As an alternative design choice we could have induced synergies in each treatment that exactly cancelled the predicted price effects of the consolidation in both the *Small Effects* and the *Large Effects* designs. We elected to maintain the size of the synergy across treatments, in order to get some insight as to whether predicted post-merger prices reductions actually materialize in these environments. In any event, the synergies necessary to maintain constant prices post-merger in the *Small Effects* treatment are perhaps too small to find any treatment effect.

represents a natural first issue of inquiry. We focus on three comparative statements regarding the organizing power of static Nash predictions on group outcomes.

Conjecture 1: *Static Nash predictions organize mean outcomes by treatment better than rival competitive (marginal cost) and joint profit maximizing predictions.*

Conjecture 2: *Mean prices increase significantly post-merger in the treatments where the own and cross effects parameters* η *and* β *predict large effects, and where no offsetting synergies undermine market power effects.*

Conjecture 3: *Marginal cost synergies either offset the predicted price effects of mergers, or actually result in post-merger price reductions. Own and cross effects parameters* η *and* β *affect the magnitude of the observed mean price reductions.*

Two additional conjectures regard predicted performance as the data are disaggregated across markets within treatments, and across individuals.

Conjecture 4: *Convergence to Nash predictions is more complete in the* Small Effects *Treatments than in the* Large Effects *Treatments,*

Conjecture 5: *Mean prices for the asymmetrically differentiated firms tend to separate as predicted.*

Finally, a sixth and last conjecture pertains to the capacity to simulate the effects of mergers.

Conjecture 6: *ALM simulations identify problematic consolidations.*

As indicated in the introduction, there is support for conjecture 6 with symmetrically differentiated products.

3.2 Experimental Procedures. At the beginning of each session, four subjects are randomly seated at visually-isolated personal computers. A monitor then reads the instructions aloud as participants follow along on copies of their own. The instructions explain that the market proceeds as a series of two-stage trading periods. At the beginning of each period, participants simultaneously choose prices, which the monitor collects and records. The monitor then announces the entire set of price decisions, which the participants record. To facilitate record keeping and the calculation of results, participants record decisions on a spreadsheet with programmed macros. After entering their own and the other price decisions, the press of a macro key calculates sales quantities, per-period earnings and cumulative earnings. The macro also prompts participants to make a decision for the subsequent period. To assist with the decision-making, sellers have a "profit calculator" that computes earnings based on hypothetical own and others' price choices. Participants' screens also display own and others' price histories as well as own earnings in both tabular and graphical forms.

This two-step trading sequence repeats each period throughout the session, with one exception. Without prior warning, trading stops after period 30, and a "buyout" occurs. An "acquired" firm (*F2*) is identified, paid a $6 supplement in addition to his or her appearance fee and salient earnings, and dismissed. For the remainder of the market, the participant making decisions for *F1* is given "dual-firm" status, making price decisions at the *F1* and *F2* terminals each period and earning the profits from both terminals. The market continues in this manner for an additional 30 periods. Following period 60, the market ends, again without prior warning, and participants are privately paid and dismissed.

Two features of the experiment design merit emphasis. First, we did not randomly select the acquiring decision-maker, *F1*. Rather, results of a 10-period monopoly-pricing exercise conducted prior to the start of the market determine who is *F1*. The initial instructions explain that at some point in the market, one participant will be placed in an advantageous position relative to the others. We wanted someone to win the right to be in the advantaged position. The person who posted the highest period 10 profits took the "to be privileged" *F1* position.[8,9] The acquired firm (*F2*) was the participant who had randomly been seated in the *F2* position at the beginning of the session.

Second, despite the relative sophistication of the underlying model, the decision environment faced by the participants is both simple, and at least by current laboratory standards,

[8] The monopoly pricing exercise also served the purpose of familiarizing participants with incentives, record keeping procedures, and screen displays for the market that followed. With only a few exceptions, screen displays and macro-key presses for the monopoly pricing exercise are the same as those in the subsequent market experiment.

[9] In one instance there was a tie, and the *F1* position decided via a coin toss. Other than identifying *F1*, we did not rank participants by monopoly earnings. This procedure for identifying the acquiring firm differs somewhat from related research. In Davis and Wilson (2003) and in many of the sessions in Davis and Wilson (2004) we assign dual-firm status randomly. Also Davis and Wilson (2004) includes a treatment where the acquiring party was identified as the participant with the highest pre-merger earnings, and this participant "bought out" the firm with the lowest earnings pre-merger. (The assignment rule was not explained to participants). The evidence suggests that the choice of assignment rule does not importantly affect results.

extensively repeated. Sellers need only enter a single price, and observe the profit consequences of their decisions, as they do in any standard oligopoly model. Further, including the 10-period monopoly problem used to identify the acquiring seller, participants made a total of 70 decisions. This compares 35 period markets in García-Gallego and Georgantzís (2001), and 40 period markets in Huck, Normann and Oechssler (2000).[10]

The participants were volunteers from undergraduate economics and business classes at the University of Mississippi in the spring semester of 2001. No one had previously participated in a laboratory market experiment, and no one participated in this experiment more than once. The laboratory to U.S. currency conversion rate was LAB$10,000 to US$1 rate in the *Large Effects* sessions, and LAB$6,000 = US$1 in the *Small Effects* sessions. Earnings for the sessions, which lasted between 80 and 110 minutes, ranged from $14 to $43 and averaged $23.25, inclusive of a $6 appearance fee and earnings in the monopoly pricing exercise.

4. Experimental Results

We discuss the results in three parts. The first subsection evaluates market performance relative to static Nash predictions. The second subsection evaluates convergence tendencies across markets and individuals, while a third subsection evaluates the predictive power of the ALM.

4.1 Market Performance and Nash Predictions. The mean share-weighted-average price (P_{swa}) paths for the five markets in each treatment cell, shown in the two panels of Figure 1, provide an overview of group results. The panels of the figure illustrate clearly the drawing power of static Nash predictions. In both the *Small Effects* and *Large Effects* treatments, the *No-Synergy* series (the solid dots) and the *Synergy* series (the hollow dots) hover about the (bolded horizontal) reference predictions, far removed from the joint profit maximizing P^{JPM} and marginal cost c predictions.

Notice further that the mean price paths in Figure 1 also suggest some of the comparative static effects predicted to arise from the merger-specific cost synergies and the increased market power concomitant with the merger. Toward the end of the post-merger sequence the P_{swa} series

[10] Although we do note that neither García-Gallego and Georgantzís (2001) nor Huck, Normann and Oechssler (2000) induce an environmental shift halfway through their sessions.

for the *Large Effects* and the *Large Effects/Synergy* treatments drift apart, reflecting both the predicted tendency for prices to increase post-merger and the tendency for the synergy to largely offset the price effects of merger-induced market power increases. The rather more subtle price adjustments predicted in the *Small Effects* treatment are less obvious in a chart drawn on the scale of Figure 1. Nevertheless, notice that while the P_{swa} path for the *Small Effects* treatment (the dark dots) remains largely unaffected by the consolidation, the P_{swa} path for the *Small Effects/Synergy* treatment (the hollow dots) falls from slightly above the no-synergy P_{swa} path pre-merger, to slightly below it post merger, reflecting the predicted price-depressing effects of the synergy in *Small Effects* treatment.

For quantitative support we employ a linear mixed-effects model to exploit the repeated measures in our data set. As a control for learning, we focus on the data from the last ten pre- and post-merger periods. (Notice in Figure 1, that considerable movement toward Nash predictions occurs toward the end of the *Large Effects* Treatments, particularly post-merger.[11]) Consider first share weighted average prices, P_{swa}. We model the treatment effects, *Large Effects* vs. *Small Effects* and *Synergies* vs. *No Synergies*, as (zero-one) fixed effects, and the sessions as random effects, e_i. Indexing sessions by i = 1,…,20 and pre-merger periods by t = 21, …, 30 and post-merger periods by t = 51,…,60, we estimate

$$P_{SWA_{it}} = \beta_0 + \beta_{LE} LargeEffects_i + \beta_{SYN} Synergy_i + \beta_{LE-SYN} LargeEffects_i \times Synergy_i + e_i + \varepsilon_{it}, \qquad (11)$$

where $\varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it}, e_i \sim N(0,\sigma_1^2)$, and $u_{it} \sim N(0,\sigma_{i,2}^2)$.[12]

The intercept β_o estimates the P_{swa} for the *Small Effects* treatment. Adding to the intercept the marginal impacts of the *Synergy* (β_{SYN}) and *Large Effects* (β_{LE}) generates share weighted average price estimates for the *Small Effects/Synergy* and *Large Effects* treatments. Finally, the estimate of the share weighted average price for the *Large Effects/Synergy* treatment is the sum of the intercept and the two treatment parameters, plus an interaction term, or $\beta_o + \beta_{SYN} + \beta_{LE} + \beta_{LE-SYN}$.

The predicted coefficients, listed in column (4) of Table 3, follow by appropriately differencing the predicted treatment means. Pre-merger, for example, the static Nash P_{swa} for all

[11] Our primary results, however, are unaffected if the analysis is based upon the last 5 or the last 15 periods. Results of these analyses appear in an (unpublished) data appendix available at http://www.people.vcu.edu/~dddavis.

[12] The linear mixed effects model treats each session as one degree of freedom with respect to the treatments. Hence, with 20 sessions and 4 parameters, each treatment effect has 16 degrees of freedom. The intercept has 200 – 20 = 180 degrees of freedom. The model is fit by maximum likelihood. For purposes of brevity the random effects are not included in the table. See Longford (1993) for a description of this technique commonly employed in experimental sciences.

treatments equals 54.98. Thus, the predicted value for the intercept, β_o which estimates P_{swa} for the *Small Effects* treatment, is 54.98, while predicted marginal effects all equal zero. Post-merger, the predicted P_{swa} for the *Small Effects* treatment is 56.29. The marginal effect of the *Large Effects* treatment is β_{LE} = 3.29, the difference between the predicted P_{swa} for the *Large Effects* treatment and the *Small Effects* treatment. Reasoning similarly, the post-merger predicted values for the remaining terms are β_{SYN} = – 4.03 and $\beta_{LE\text{-}SYN}$ = 0.20.

The point estimates of the coefficients in Table 3 indicate that the Nash predictions organize outcomes reasonably well. The estimated intercept terms lie respectably close to the predicted level both pre-merger (52.55 vs. 54.98) and post-merger (53.71 vs. 56.29). Further, except for the largely offsetting post-merger estimates of β_{LE} and $\beta_{LE\text{-}SYN}$, the marginal effects are relatively small in magnitude, and, as seen in column (5) only the post-merger $\beta_{LE\text{-}SYN}$ coefficient deviates from its predicted value with a *p*-value of .10 or less.

Conformance of the data with Nash predictions is perhaps more clearly evaluated when considered relative to rival outcomes, as reported in Table 4. Column (2) lists the mean pre-merger share weighted price for each treatment implied by the estimates in Table 3. Columns (3) to (5) list deviations of these pre-merger estimates from reference predictions, expressed as a percentage of the difference between marginal costs, *c*, and the joint profit maximizing price, P^{JPM}. Notice in column (3) that treatments do not collapse completely on Nash predictions. Estimated deviations range from 3.6% to 8.7% of the *c* to P^{JPM} range. However, Nash predictions clearly organize the data better than marginal cost, or joint profit maximizing reference predictions. As shown in columns (4) and (5), estimated treatment means deviate from the competitive outcome, *c*, by at least 39.3% of the *c* to P^{JPM} range, and deviate from P^{JPM} by at least 28.0% of that same range. Post-merger results, listed in columns (6) to (9) reflect similarly the superior relative organizing power of static Nash predictions. Post-merger estimated treatment means deviate from Nash predictions by 0.4% to 9.3% of the *c* to P^{JPM} range. This compares with deviations from marginal costs of at least 44.9% of the *c* to P^{JPM} range, and deviations from P^{JPM} of at least 24.5% of the *c* to P^{JPM} range. We summarize these observations regarding organizing power of Nash predictions relative to rival predictions represents as our first finding.

Finding 1. *Although absolute convergence to Nash predictions remains incomplete, Nash predictions organize outcomes far better than alternative reference predictions.*

Regression results on share weighted average prices, summarized in Table 3 similarly suggest some of the comparative static effects predicted to arise from horizontal mergers and merger-associated synergies. For example comparing pre- and post-merger estimates, notice that the post-merger intercept, 53.71 slightly exceeds its pre-merger counterpart, 52.55, suggesting the small predicted increase prices post-merger in the *Small Effects* treatment. Again, the β_{LE} estimate shifts from -3.39 pre-merger to 6.42 post-merger, reflecting the predicted tendency for prices to increase in the *Large Effects* treatment.

These differences from the pre-merger static Nash P_{swa} prediction across treatments make these results less than ideal for evaluating the comparative static effects of mergers and synergies. To evaluate more directly these comparative static effects we estimate percentage increases in the P_{swa} over the comparable pre-merger average as a function of the *Large Effects* and *Synergy* indicator variables in (11). Specifically, we estimate

$$\frac{P_{SWA\,it} - \overline{P_{SWA\,i,21-30}}}{\overline{P_{SWA\,i,21-30}}} \times 100 = \beta_0 + \beta_{LE} LargeEffects_i + \beta_{SYN} Synergy_i + \beta_{LE-SYN} LargeEffects_i \times Synergy_i + e_i + \varepsilon_{it} \qquad (12)$$

where $\varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it}, e_i \sim N(0,\sigma_1^2)$, and $u_{it} \sim N(0,\sigma_{i,2}^2)$. Again, we use the last 10 post-merger periods for the analysis (t = 51, …, 60). The predicted values for the coefficients in (12) are listed in column (4) of Table 5.[13]

The results in Table 5 support the predicted comparative static effects. Most prominently, the *Large Effects* coefficient of 10.91 reflects a nearly 11% increase in post-merger prices over pre-merger prices, and easily exceeds zero (p-value =.04). Similarly, the *Synergy* coefficient of -7.10 almost matches identically the predicted 7.3% price decrease associated with a synergy post-merger in the *Small Effects* treatment, and again is significantly less than zero (p-

[13] Specifically, the intercept of 2.4% is the predicted $\%\Delta P_{swa}$ in the *Small Effects* Treatment. For the *Large Effects* treatment $\%\Delta P_{swa} = \beta o + \beta_{LE} = 8.4\%$. Hence, $\beta_{LE} = 6.0$. Similarly, for the *Small Effects/Synergy* treatment $\%\Delta P_{swa} = \beta o + \beta_{SYN} = -4.89$ so that $\beta_{SYN} = -7.1$. Finally, for the *Large Effects/Synergy* Treatment, $\%\Delta P_{swa} = \beta o + \beta_{LE} + \beta_{SYN} + \beta_{LE\text{-}SYN} = 1.44$. Lastly, $\beta_{LE\text{-}SYN} = 1.93$.

value = .06). Notice further that point estimates for the intercept term of 2.28 and for the *Large Effects* × *Synergy* interaction effect of 1.93 are close to respective predicted values of 2.4 and 0.3 values, and neither differ significantly from zero. These results form our second finding.

Finding 2. *On average, merger-induced market power increases prices and cost synergies decrease prices, as predicted.*

4.2 Variability across Markets and across Firm-Types. Although static Nash predictions tend to organize the data at an aggregate level quite well, specific markets (sessions) may or may not vary substantially about the treatment means. Similarly, the different types of sellers may or may not converge to the Nash predictions. Consider first the variability in outcomes across markets. Figure 2 displays the average individual market prices (the hollow dots) relative to static Nash predictions (the thin horizontal lines) and the treatment means (the thick horizontal lines). We observe much more session variability in the *Large Effects* treatments than in the *Small Effects* treatments, both pre-merger and post-merger. The standard deviation for the ten *Large Effects* sessions (8.30), more than doubles the standard deviation for the comparable *Small Effects* sessions (3.48). Similarly, pooling across *Synergy* treatments post-merger, the standard deviation for the post-merger *Large Effects* sessions (7.54) more than doubles the comparable standard deviation for the *Small Effects* session (3.42). These differences are easily significant using an *F*-test.[14] We state this result as a third finding.

Finding 3: *Static Nash predictions organize individual session outcomes more completely in the* Small Effects *treatments than in the* Large Effects *treatments in the sense that individual market outcomes are significantly less variable in the* Small Effects *treatments.*

Consider next equilibrium price dispersion in these asymmetric markets. As with individual market outcomes, static Nash predictions for individual firms tend to organize decisions for the firms much more completely in the *Small Effects* treatments than in the *Large Effects* treatments. The upper and lower panels of Figure 3 display the mean prices for firms *F1* to *F4* in the last 10 pre-merger periods. In the *Small Effects* treatment, observed mean prices for *F1* to *F4* (progressively smaller dots) separate in the predicted direction (dashed lines: P_o^1 to P_o^4 pre-merger and P_m^1 to P_m^4 post-merger). This price separation, however, is generally less than

[14] Pre-merger, we reject the null hypothesis of equal variances in the *Large Effects* and *Small Effects* treatments ($F_{9,9}$ = 5.66, *p*-value = .01). Similarly, we reject the null hypothesis post-merger ($F_{9,9}$ = 5.42, *p*-value = .01).

predicted. Furthermore and contrary to predictions, we observe post-merger that *F1* charges higher prices than *F4* in *Small Effects/Synergy* treatment. Nevertheless, the predicted price separation occurs fairly impressively in the other *Small Effects* sessions.

There is considerably less complete price separation in the *Large Effects s*essions. Pre-merger, prices are much lower than the predicted levels for *F1* and *F3*. Post-merger, prices largely separate without a cost synergy; however the combination of *Large Effects* and a *Synergy* appears to undermine the predicted price separation.

For quantitative support, we again employ a linear mixed-effects model. This time, we model the seller types *F1*, *F3* and *F4* as (zero-one) fixed effects, and treat the sessions and subjects within each session as random effects, e_i and u_j, respectively. Again we focus on decisions in the final 10 periods pre- and post-merger. We index sessions by i = 1,…,10 pre-merger (i = 1,…,5, post-merger), subjects by j =1,…,4, and periods by t = 21…,30 (t = 51,…,60, post-merger). The dependent variable is the difference between seller j's price and the P_{swa} in period t for session i. Specifically, we estimate

$$P_{ijt} - P_{SWA_{it}} = \beta_o + \beta_{F1}F1_i + \beta_{F3}F3_i + \beta_{F4}F4_i + e_i + u_j + \varepsilon_{ijt}, \tag{13}$$

where $\varepsilon_{ijt} = \rho\varepsilon_{it-1} + \xi_{ijt}, e_i \sim N(0,\sigma_1^2), u_j \sim N(0,\sigma_2^2), \text{and}\, \xi_{ijt} \sim N(0,\sigma_{i,3}^2)$. We use *F2* as the baseline since its predicted value generally lies closest to the predicted P_{swa}. Tables 6 and 7 report, respectively, the pre-merger and post-merger estimates. In each table Column (4) lists the predicted values for the coefficients. The intercept is the difference between the Nash prediction for *F2* (in Table 1) and the predicted P_{SWA}, or $\beta_o = P_{F2} - P_{SWA}$. Pre-merger, for example, β_o = 56.62 – 54.98 = 1.64. As before, the remaining coefficients are marginal deviations from *F2*. We pool the pre-merger data across all *Large Effects* and *Small Effects* sessions, but estimate post-merger models for each treatment separately.

For the pre-merger estimates in Table 6, we notice that the estimated and predicted values deviate considerably, with the estimated values generally being smaller than the predicted ones (in the 7 instances highlighted with bolding in column 4). We can reject the null hypothesis that the estimated value equals the predicted level at a minimum 90% minimum confidence level in 7 instances (the entries highlighted with bolding in column (5)). Nevertheless, firm prices clearly tend to separate, and in the predicted direction. Notice first that estimates deviate in the predicted direction (in 7 of the 8 cases, those highlighted with bolding in column 6). Further, the estimates tend to differ from zero in the predicted direction at a minimum 90% level (the 6 sessions highlighted with bolding in column 7).

Post-merger, prices for different firm types again separate in the *Small Effects* and *Small Effects/Synergy* treatments, as reported in the top-half of Table 7. The estimates, while generally smaller than predicted values, tend to deviate from zero in the predicted direction (in the 6 of 8 instances highlighted with bolding in column 6) and significantly (the 5 instances highlighted in column 7 denote *p*-values of .10 or less.) Price separation, weakens somewhat post-merger in the *Large Effects* treatment, summarized as the third block of rows in the Table 7. Coefficients deviate from zero in the predicted direction in each of the 4 instances (highlighted in column 6), however only one of the coefficients differs from zero at a minimum 90% confidence level.

Price separation largely fails in the *Large Effects/Synergy* treatment, summarized at the bottom of Table 7. The estimates shown in column (4) are quantitatively very small, and, as seen in column (7) none of them are even close to significantly differing from zero. We summarize these results regarding price separation as our fourth finding.

Finding 4. *Pre-merger, prices for the different firm types separate incompletely, but largely as predicted. Post-merger, price separate clearly in the* Small Effects *and* Small Effects/Synergy *treatments, and to a marginally lesser extent the* Large Effects *treatment. However, in the* Large Effects/Synergy *treatment prices fail to separate post-merger.*

Prior to proceeding, we comment on the failure of prices to separate post-merger in the *Large Effects/Synergy* treatment. Although our explanation cannot be taken as definitive we offer two factors that plausibly explain the absence of price separation in this treatment. First, as the magnitude of "inside" elasticity and substitutability parameters, η and β increase, each seller's own earnings become increasingly sensitive to rivals' decisions.[15] This increased sensitivity likely complicates the problem of learning optimal individual prices. The extra learning difficultly is at least partially reflected by the higher standard errors for coefficients in the *Large Effects* treatments in Tables 6 and 7 than for the comparable *Small Effects* treatments. Nevertheless, absent a synergy, the increased sensitivity of individuals to others choices does not appear to have undermined price separation in the *Large Effects* treatment. Comparing price

[15] As Davis and Wilson (2004) observe in a symmetric environment, increases in the magnitude of inside elasticity η and substitutability β parameters increases the slope of "pseudo reaction" functions, which express a seller's optimal response to a vector of identical prices by all rivals. The same logic applies to the asymmetric case, with the added complication that sellers do not optimally post homogenous prices.

predictions across the *Large Effects* and *Large Effects/Synergy* charts shown in the bottom panel of Figure 3 suggests a second possible explanation for the failure of prices to separate post-merger in the *Large Effects/Synergy* treatment. Notice that post-merger in the *Large Effects* treatment, *F1*, *F2* and *F3* are all predicted to post high prices. For reasonably complete separation, only *F4* need undercut his rivals. In contrast, with a synergy, sellers *F1*, *F2* and *F4* post relatively low prices, leaving seller *F3* to price lead, largely alone. We suspect that sellers may find themselves feeling less "exposed" with unilateral price reductions than with unilateral price increases.

4.3 Predicting Mergers with Simulations. We now turn to the predictive capabilities of the ALM. Note at the outset that the merger simulations turn on much stronger assumptions about individual firm behavior than do our conclusions regarding group effects discussed above in section 4.1. This is because the ALM requires that simulation predictions be robust to the variability of individual markets and firm-types observed in section 4.2. The ALM presumes strict conformance of individual markets, and individuals within those markets, with equilibrium predictions, both pre-merger and post-merger. The variability across individual markets shown in Figures 2, and the sometimes incomplete price separation across firm types shown in Figure 3 indicates that these assumptions are clearly not met in our experimental markets.

To generate post-merger predictions, we follow the simulation methodology discussed above in section 2.4. For a summary price measure, we use average price choices for each firm, for the final ten pre-merger periods (periods 21-30). Shares are measured as those implied by inserting mean prices for each firm into the underlying demand function. Both for simplicity, and to give the ALM a "best shot" we use actual substitutability and inside elasticity parameters, β and η. Recall that the simulation procedure requires inserting pre-merger prices, shares, β and η into equation (7), and then generating a pre-merger cost vector $\mathbf{c}$ that balances both sides of the equation. To generate post-merger predictions insert the implied costs, into (8) and then adjust the post-merger price vector until both sides of (8) balance.

The scattergram in Figure 4 illustrates the relationship between predicted and observed P_{swa} increases.[16] The extremely poor organizing power of the ALM is obvious from the wide scattering of dots in the figure. One simple way to quantify this result is to regress observed percentage price increases on the predicted percentage price increases. Column (2) of Table 8 reports this regression. If the ALM predicts perfectly, the intercept should be 0 and the slope 1. Although neither the intercept nor the slope deviates sufficiently from these predicted values, as the adjusted R^2 of .117 indicates, the regression explains less than 12% of the movement in the data. The poor performance of the ALM as a *predictor* of post-merger performance is also found in symmetric environments by Davis (2002) and Davis and Wilson (2004). These results therefore were hardly surprising. (We do note, however that the ALM appears to perform at least marginally better in a symmetric context. For example, a comparable regression using data from Davis and Wilson (2004) generates an adjusted R^2 values of 0.36.)

More troublesome is that the ALM here fails to serve even as a *screening* device. For example, in Davis and Wilson (2004), predicted P_{swa} increases of 5% or more identified 10 of the 12 instances where prices did actually increase by 5% or more post-merger. Further only 2 predictions were "false negatives", with prices increasing more than a predicted 5% or more. This screening function, however, clearly fails here. To see this, consider again Figure 4. The dotted vertical and horizontal lines in Figure 4 demark, respectively, predicted and observed 5% price increases. The ALM functions well as a screening device to the extent that dots fall below and to the left of the dotted lines, or above and to the right of them. Observations in the upper left corner indicate particularly critical errors. These "false negatives" represent markets where, contrary to predictions P_{swa} increased more than 5% subsequently post-merger. As seen in the figure, of the eight instances where prices increased by more the 5% post-merger, only three were predicted. Thus, the ALM here generates more false negatives (5) than correct positives (3). This is our last finding.

Finding 5. *In contrast to markets with symmetric differentiation and absent synergies, the ALM fails to even serve as a screening device.*

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[16] We summarize simulation results with the scattergram in Figure 4 for purposes of brevity. Tables A1 and A2 in the Appendix provide more detailed results. Table A1 lists observed pre-merger share weighted average price for each firm, along with implied costs. Table A2 lists predicted and observed post-merger prices.

Further inspection of Figure 4 provides insight as to the failure of the ALM to serve a screening role in this context. Consider the five instances where prices increased by more than 5% post-merger, contrary to predictions (highlighted with a circle). Notice that four of these markets were *Large Effects/Synergy* sessions. The ALM particularly fails when a synergy is predicted to offset particularly large anticipated price effect.

Removing the 5 *Large Effects/Synergy* sessions from the analysis yields results that closely parallel those observed in previous work. Of the 15 remaining markets, the ALM predicts correctly in 12 instances. Further, only one of the remaining 3 instances is a "false negative." As shown in column (3) of Table 8, excluding the *Large Effects/Synergy* sessions raises the adjusted R^2 to 0.304, a level much closer to that generated in a comparable regression for the data from a symmetric environment in Davis and Wilson (2004).

However, even for these markets where the screening power of the ALM is relatively good, it is important to emphasize that the ALM works, but for the wrong reasons. That is, the ALM here is predicting not the exercising of market power, but predicted price increases based on observed deviations from the underlying equilibrium. Recall from equation (8) that the predicted post-merger price is an inverse function of the inside elasticity η. Pre-merger prices that are below the equilibrium generate small η's, which, in turn, lead to large predicted price increases. Similarly, high pre-merger prices generate larger η's, which, in turn lead to smaller predicted price increases. Hence, independent of incentives to exercise market power, there is an additional positive correlation between the model's price predictions and the tendency of sellers to make (profitable) adjustments in the direction of equilibrium predictions, rather than to (unprofitably) deviate further from equilibrium predictions. The regression results in columns (4) and (5) of Table 8 explicate this. These regressions explain observe percentage price increases as a function of deviations from the pre-merger static Nash equilibrium prediction. Comparing entries columns (2) and (4), and with entries in columns (3) and (5), observe that deviations from the Nash prediction explain a much larger portion of the movement in the data than the model's predicted price increases.

5. Parting Comments

This paper uses experimental methods to address three inter-related issues. First, we examine the organizing capacity of equilibrium predictions in a differentiated product model with asymmetric sellers. We find considerable support for the proposition that static Nash predictions organize *average* outcomes across treatments reasonably well. More specifically, market prices tend to respond to horizontal mergers and to cost synergies, in the predicted directions.

Second, we disaggregate treatment means first by markets, and then by firm types. Here we find a treatment effect. In *Small Effects* markets with large own and cross price elasticities, static Nash predictions organize individual outcomes relatively well. Further, prices for individual firms separate largely as predicted. On the other hand, *Large Effects* markets exhibit substantial variability from market to market and across firm types.

Third, we assess the predictive power of the ALM. As in symmetric environments, the ALM fails to predict post-merger price increases for specific markets with any reasonable accuracy. But the increased variability in the *Large Effects* treatments undermines the ability of the ALM to even serve as a screening device. In asymmetrically differentiated markets, the ALM fails to identify more problematic mergers than it correctly identifies.

We close this paper with three observations regarding the policy relevance of our results. First, many other experimental studies have found strong support, at an aggregate level, for the theoretical predictions of various oligopoly models. This paper is no different in that our affirmative results are at the highest level of aggregation—treatment means. Given the range of outcomes possible in our experiment, our comparative statics results are nontrivial. Nevertheless, that our positive results pertain to *average* outcomes across replicated markets, rather than results for specific *individual* markets, merits emphasis. Even strongly supported mean results provide relatively little insight into the performance of individual markets, if the variability within treatments is sufficiently large. Caution must thus be taken in attempting to draw inferences about any particular market outcome from (even highly significant) treatment results.

Second, we comment on the potential policy relevance of our results to the ALM. There are many dimensions on which our simple laboratory markets do not parallel natural contexts, the chief of which being the rich, complexity of the natural economy. That complexity, however, is also excluded from the ALM, and it is the simplicity of the laboratory environment which gives the model a much better shot of empirical validation. As is always the case, any number of factors from the naturally occurring economy, not specified by the model nor implemented in our experiment, could interact to serve as a corrective lens for the predictive power of the ALM. As Smith (2002) articulates, when an experiment rejects a model's hypothesis, conditional on the auxiliary assumptions necessarily made to implement a test of the theory, then we should assume that either the model or the auxiliary assumptions may be false. Thus, we do not unequivocally claim from our results that the ALM "doesn't work" in the naturally occurring economy. We can, however, say the following. The tendency for markets to equilibrate reasonably well towards competitive predictions "behaviorally precedes" the observation of effective merger predictions via simulations. Thus, when a policy-maker uses the ALM as a screening or predictive tool, it is important to emphasize that the policy maker assumes not only that markets in general tend to static Nash predictions, but further that the specific market being investigated is itself very powerfully drawn to the precise predictions of the model.

Finally, to the extent that our results do cast any doubts about policy relevance of merger simulation tools, we observe that our evidence does not leave antitrust authorities with the nihilistic recommendation of replacing the ALM with "nothing" as a screening device. In both the experiment reported here, and in our previous related research (Davis, 2002; and Davis and Wilson, 2004) markets become much less predictable as the magnitude of inside elasticity, and substitutability parameters become absolutely small. (The ameliorative effects of synergies appear to be particularly weak in our *Large Effects* designs.) As a practical alternative to the ALM, we recommend concentrating efforts in the screening phase of a merger investigation on developing good estimates of η and β. Sufficiently small values of these parameters would suggest that a proposed consolidation merits further investigation. In addition to being consistent with our experimental results, this alternative approach confers the important advantages of transparency and understandability in the merger-screening process.

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Table 1. Individual Parameters

Small Effects (η=-1.5660, β=.0614)

Firm	**Pre-Merger**			**Post-Merger**			
				No Synergy		***Synergy*** $c_{1S}= c_1 -10, c_{2S}= c_2 -8$	
	(1a)	(1b)	(1c)	(2a)	(2b)	(3a)	(3b)
	p_i	s_i	c_i	p_i	s_i	p_i	s_i
F1	49.05	22.03	30.58	51.96	19.9	41.96	19.91
F2	56.62	27.75	37.48	58.86	26.1	50.14	26.15
F3	63.93	33.33	44.11	64.08	35.6	64.08	35.69
F4	42.37	16.90	24.45	42.25	18.4	42.43	18.25
P_{swa}	**54.98**			**56.29**		**52.26**	

Large Effects (η=-.2295, β=.0367)

Firm	**Pre-Merger**			**Post-Merger**			
				No Synergy		***Synergy*** $c_{1S}= c_1 -10, c_{2S}= c_2 -8$	
	(1a)	(1b)	(1c)	(2a)	(2b)	(3a)	(3b)
	p_i	s_i	c_i	p_i	s_i	p_i	s_i
F1	49.05	22.03	15.22	58.81	18.26	48.81	18.26
F2	56.62	27.75	20.52	64.11	24.99	56.11	25.00
F3	63.93	33.33	25.32	65.54	37.24	65.54	37.24
F4	42.37	16.90	10.35	43.12	19.50	43.12	19.50
P_{swa}	**54.98**			**59.58**		**55.75**	

Table 2. Experimental Treatments and Design

	Pre-Merger (Periods 1-30)	Post-Merger (Periods 31-60)	
		No Synergy	*Synergy* ($c_{o1} = c_{p1}$-8, $c_{o2} = c_{p2}$-10)
Small Effects η =-1.5660 β = .0614	(10 Sessions)	(5 sessions) Predicted Price Increase $\%\Delta P_{swa}$ = **2.42%**	(5 sessions) Predicted Price Increase: $\%\Delta P_{swa}$ = **-4.89%**
Large Effects η = -.2295 β = .0367	(10 Sessions)	(5 sessions) Predicted Price Increase $\%\Delta P_{swa}$ = **8.4%**	(5 sessions) Predicted Price Increase: $\%\Delta P_{swa}$ = **1.44%**

Table 3. Share Weighted Average Price Estimates

$$P_{SWA_{it}} = \beta_0 + \beta_{LE} LargeEffects_i + \beta_{SYN} Synergy_i + \beta_{LE-SYN} LargeEffects_i \times Synergy_i + e_i + \varepsilon_{it},$$

$$\text{where } \varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it}, e_i \sim N(0,\sigma_1^2), \text{and } u_{it} \sim N(0,\sigma_{i,2}^2)$$

(1) Variable	(2) Estimate	(3) Std. Error	(4) H_a	(5) *p*-value
	Pre-Merger (Periods 21-30)			
Intercept	52.55	2.34	$\beta_o \neq 54.98$	0.40
LargeEffects	-3.39	3.47	$\beta_{LE} \neq 0.00$	0.34
Synergy	3.43	3.41	$\beta_{SYN} \neq 0.00$	0.33
LargeEffects×Synergy	-2.38	5.15	$\beta_{LE\text{-}SYN} \neq 0.00$	0.65
	$\rho = 0.93$			
	Post Merger (Periods 51-60)			
Intercept	53.71	1.64	$\beta_o \neq 56.29$	0.12
LargeEffects	6.42	3.14	$\beta_{LE} \neq 3.29$	0.33
Synergy	-1.14	2.55	$\beta_{SYN} \neq -4.03$	0.27
LargeEffects×Synergy	-9.78	4.73	$\beta_{LE\text{-}SYN} \neq 0.20$	**0.05**
N = 200	$\rho = 0.97$			

Table 4. Group Share Weighted Average Prices Implied by Estimates.

	Pre-Merger (Periods 21-30)				*Post Merger (Periods 51-60)*			
Treatment	$\hat{P}_{SWA}$	$\frac{\hat{P}_{SWA} - Prediction}{P^{JPM} - c}$			$\hat{P}_{SWA}$	$\frac{\hat{P}_{SWA} - Prediction}{P^{JPM} - c}$		
		Nash	*c*	P^{JPM}		*Nash*	*c*	P^{JPM}
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Small Effects	52.55	-8.7%	59.7%	-40.3%	53.71	-9.3%	63.8%	-36.2%
Small Effects/ Synergy	55.98	3.6%	72.0%	-28.0%	52.57	0.4%	75.5%	-24.5%
Large Effects	49.16	-7.7%	39.3%	-60.7%	60.13	0.7%	53.7%	-46.3%
Large Effects/ Synergy	50.21	-6.3%	40.7%	-59.3%	49.21	-8.5%	44.9%	-55.1%

Table 5. Estimates of the Linear Mixed-Effects Model of Comparative Static Effects

$$\frac{P_{SWA_{it}} - \overline{P_{SWA\,i,21-30}}}{\overline{P_{SWA\,i,21-30}}} \times 100 = \beta_0 + \beta_{1LE} LargeEffects_i + \beta_{SYN} Synergy_i + \beta_{LE-SYN} LargeEffects_i \times Synergy_i$$

$$e_i + \varepsilon_{it}, \text{ where } \varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it}, e_i \sim N(0,\sigma_1^2), \text{and } u_{it} \sim N(0,\sigma_{i,2}^2)$$

(1) Variable	(2) Estimate	(3) Std Error	*Nash Predictions* (4) H_a	*Nash Predictions* (5) p-value	*Predicted Directional Deviation* (6) H_a	*Predicted Directional Deviation* (7) p-value
Intercept	2.28	2.88	$\beta_0 \neq 2.4$	0.97	$\beta_o > 0$	0.42
Large Effects	10.91	5.79	$\beta_1 \neq 6.0$	0.41	$\boldsymbol{\beta_1 > 0}$	**0.04**
Synergy	-7.10	4.44	$\beta_2 \neq -7.3$	0.96	$\boldsymbol{\beta_2 < 0}$	**0.06**
Large Effects×Synergy	1.93	8.91	$\beta_3 \neq 0.3$	0.86	$\beta_3 > 0$	0.83
N = 200	$\rho = 0.97$					

Table 6. Price Spread Estimates Pre-Merger (Periods 21-30)

$$P_{ijt} - P_{SWAit} = \beta_o + \beta_{F1}F1_i + \beta_{F3}F3_i + \beta_{F4}F4_i + e_i + u_j + \varepsilon_{ijt},$$

where $\varepsilon_{ijt} = \rho\varepsilon_{it-1} + \xi_{ijt}, e_i \sim N(0,\sigma_1^2), u_j \sim N(0,\sigma_2^2)$, and $\xi_{ijt} \sim N(0,\sigma_{i,3}^2)$.

			Absolute Convergence		Predicted Deviation Direction	
(1) Variable	(2) Estimate	(3) Std. Error	(4) H_a	(5) *p*-value	(6) H_a	(7) *p*-value
			Small Effects			
Intercept	-0.47	1.06	β	**0.00**	β	0.67
F1	-3.37	1.50	β	**0.08**	β	**0.02**
F3	6.76	1.50	β	0.90	β	**0.00**
F4	-5.74	1.50	β	**0.04**	β	**0.00**
N = 400	ρ					
			Large Effects			
Intercept	2.37	1.41	β	0.66	β	**0.05**
F1	-5.27	1.99	β	0.41	β	**0.01**
F3	1.12	1.99	β	**0.00**	β	0.29
F4	-6.69	1.99	β	**0.03**	β	**0.00**
N = 400	ρ					

Table 7. Price Spread Estimates Post-Merger (Periods 51-60)

$$P_{ijt} - P_{SWAit} = \beta_o + \beta_{F1}F1_i + \beta_{F3}F3_i + \beta_{F4}F4_i + e_i + u_j + \varepsilon_{ijt},$$

where $\varepsilon_{ijt} = \rho\varepsilon_{it-1} + \xi_{ijt}, e_i \sim N(0,\sigma_1^2), u_j \sim N(0,\sigma_2^2)$, and $\xi_{ijt} \sim N(0,\sigma_{i,3}^2)$.

			Absolute Convergence		Predicted Deviation Direction	
(1) Parameter	(2) Estimate	(3) Std. Error	(4) H_a	(5) *p*-value	(6) H_a	(7) *p*-value
	Small Effects					
Intercept	-0.91	1.49	β	**0.02**	β	0.73
F1	-2.78	2.10	β	**0.07**	β	0.11
F3	9.16	2.10	β	**0.08**	β	**0.00**
F4	-7.62	2.10	β	**0.00**	β	**0.00**
N=200	ρ					
	Small Effects/Synergy					
Intercept	0.31	0.31	$\beta_o \neq$ **- 2.12**	**0.03**	$\beta_o < 0$	0.60
F1	-6.81	1.65	$\boldsymbol{\beta_{F1} \neq -8.18}$	0.45	$\boldsymbol{\beta_{F1} < 0}$	**0.00**
F3	8.82	1.65	$\boldsymbol{\beta_{F3} \neq 13.94}$	**0.00**	$\boldsymbol{\beta_{F3} > 0}$	**0.00**
F4	-8.08	1.65	$\beta_{F4} \neq -7.71$	0.82	$\boldsymbol{\beta_{F4} < 0}$	**0.00**
N=200	ρ=0.51					
	Large Effects					
Intercept	3.37	2.74	β	0.67	β	0.11
F1	-3.99	3.87	β	0.74	β	0.16
F3	3.34	3.87	β	0.63	β	0.20
F4	-14.73	3.87	β	0.13	β	**0.00**
N=200	ρ					
	Large Effects/Synergy					
Intercept	0.69	2.57	$\beta_o \neq 0.36$	0.90	$\beta_o >$ **0**	0.39
F1	-1.14	3.63	$\beta_{F1} \neq -7.30$	0.11	$\boldsymbol{\beta_{F1} < 0}$	0.38
F3	2.28	3.63	$\boldsymbol{\beta_{F3} \neq 9.5}$	**0.07**	$\boldsymbol{\beta_{F3} > 0}$	0.27
F4	-0.20	3.63	$\boldsymbol{\beta_{F4} \neq -12.99}$	**0.00**	$\boldsymbol{\beta_{F4} < 0}$	0.48
N=200	ρ=0.34					

Table 8. Predicting Post-Merger Performance

(1) Coefficient	(2) All Sessions	(3) Excluding *Large Effects-Synergy* sessions	(4) All Sessions	(5) Excluding *Large Effects-Synergy* sessions
Intercept	2.23 (2.97)	0.92 (2.66)	0.41 (2.92)	0.17 (2.33)
Predicted % ΔP	1.07 (0.56)	1.18 (0.44)		
%ΔDeviation from Pre-Merger Price			-0.60 (0.22)	-0.70 (0.19)
N	20	15	20	15
Adj. R^2	.117	.304	.248	.461

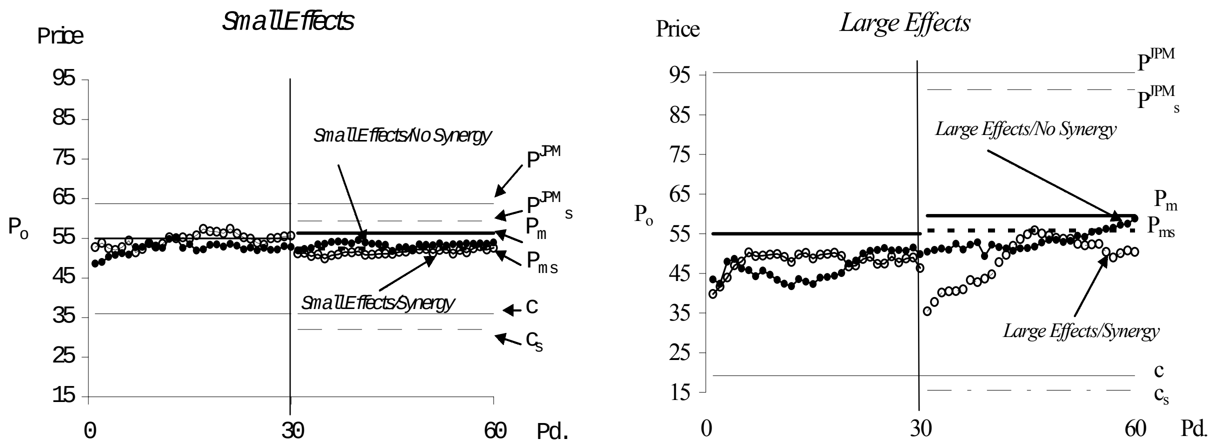

Figure 1. Mean Share Weighted Average Price Paths by Treatment.

Key: The solid and dashed horizontal lines indicate the predictions for the share-weighted average price.

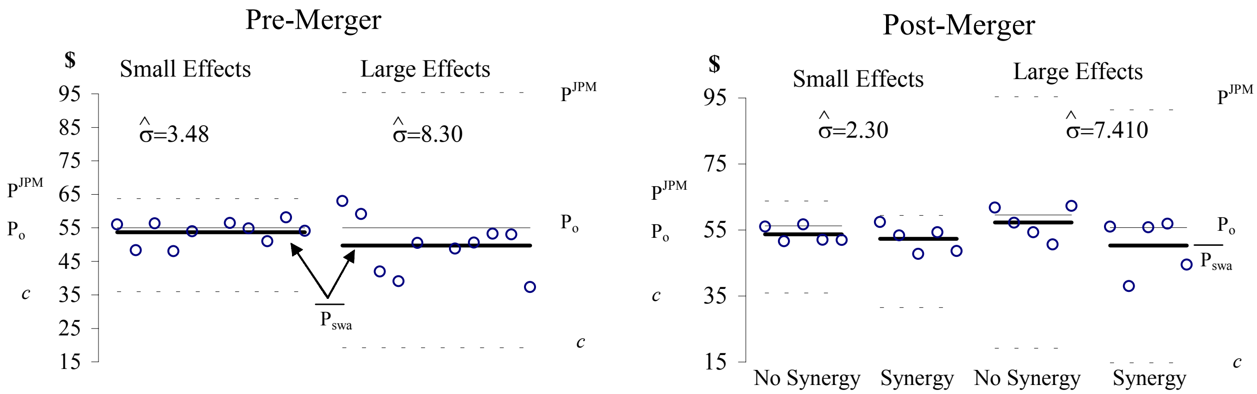

Figure 2. Variability of Average Session Prices.

Key: Average sessions are prices are displayed as dots, the deviation of markets from the (solid thick line) treatment average, and from the Nash prediction (solid thin line).

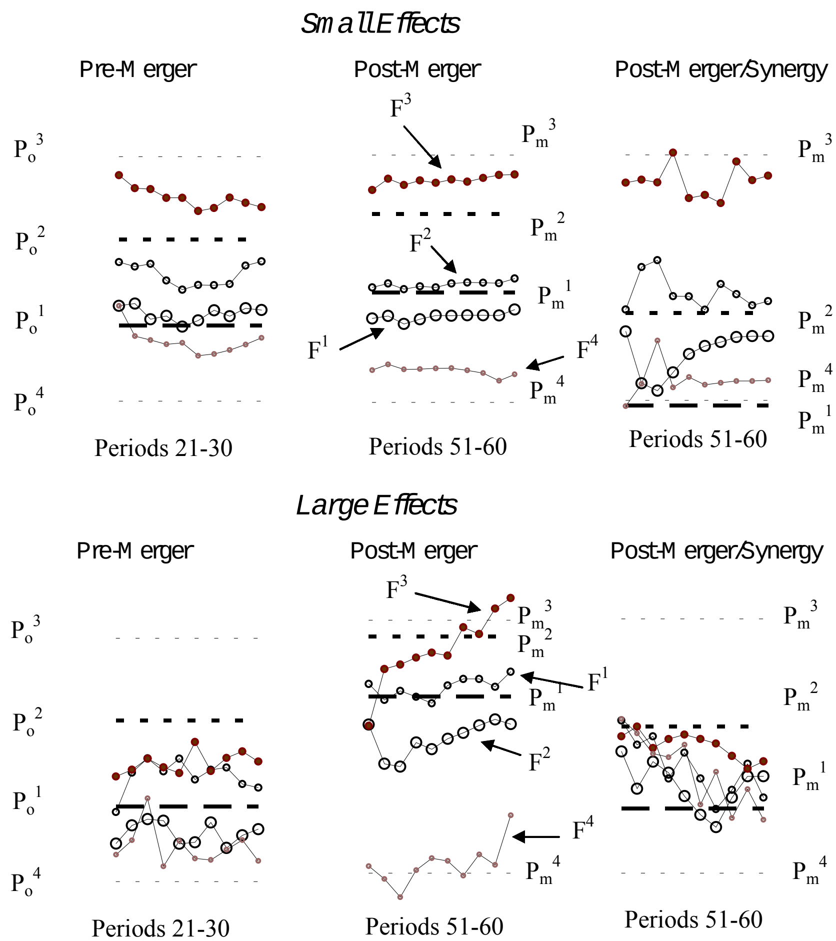

Figure 3. Mean Prices for Firms 1 to 4 by Treatment for the Last 10 Periods Pre-Merger and Post-Merger.

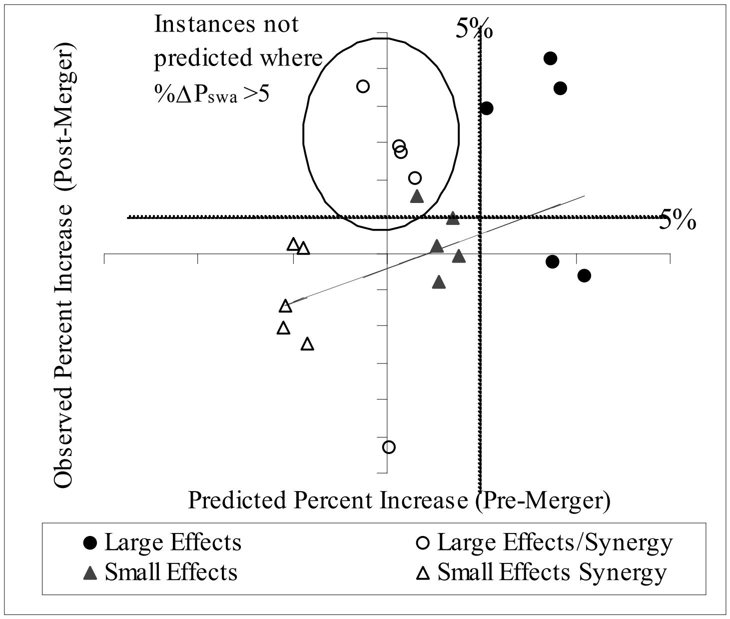

Figure 4. Predicted and Observed Percentage Price Increases. The Scattergram Plots Observed Price Increases Against Price Increases Predicted Pre-Merger by the ALM.

Table A1a Pre-Merger Share-Weighted Average Prices, and Implied Costs (Periods 16-30)

Market	*Pre-Merger Share-Weighted Price (P_{swa})*		*Implied Share Weighted Costs (c_{ALM})*	
(1)	(1)	(2)	(3)	(4)
	P_{ALM}	$\frac{P_{ALM}-P_{post}}{P_{post}}$	c_{ALM}	$\frac{c_{ALM}-c_{swa}}{c_{swa}}$
S1	56.31	2.42%	36.79	-0.74%
S2	48.83	-11.19%	29.73	-19.05%
S3	55.98	1.82%	37.03	2.10%
S4	48.52	-11.75%	28.79	-25.76%
S5	53.78	-2.18%	34.63	-5.05%
SSyn1	56.77	3.25%	32.33	-13.50%
SSyn1	56.36	2.51%	32.18	-11.78%
SSyn1	52.14	-5.17%	28.85	-23.17%
SSyn1	58.87	7.08%	34.88	-7.64%
SSyn1	54.08	-1.64%	30.52	-18.42%
L1	61.72	12.26%	25.52	31.14%
L2	59.62	8.45%	23.99	28.01%
L3	44.29	-19.44%	4.54	-78.03%
L4	38.23	-30.47%	0.63	-96.93%
L5	49.61	-9.76%	13.07	-33.32%
LSyn1	49.74	-9.53%	6.36	-69.50%
LSyn2	49.37	-10.20%	8.27	-58.80%
LSyn3	51.94	-5.53%	9.54	-53.87%
LSyn4	52.22	-5.02%	10.27	-49.71%
LSyn5	39.13	-28.83%	-2.42	-111.82%

Table A2. Predicted and Observed Changes in Share Weighted Prices (Periods 21-30 vs. Periods 51-60)

Market	Share Weighted Average Prices		Percentage Increases	
(1)	(2) Predicted P_{ALM}	(2) Observed P_{swa}	(3) Predicted $\frac{P_{ALM} - P_{pre}}{P_{pre}}$	(4) Observed $\frac{P_{ALM} - P_{pre}}{P_{pre}}$
S1	58.48	56.14	3.9%	-0.3%
S2	50.53	51.17	3.5%	4.8%
S3	57.43	56.56	2.6%	1.0%
S4	49.29	52.28	1.6%	7.7%
S5	55.23	51.73	2.7%	-3.8%
SSyn1	53.96	57.42	-4.9%	1.2%
SSyn2	53.85	56.77	-4.4%	0.7%
SSyn3	49.32	48.34	-5.4%	-7.3%
SSyn4	56.37	51.58	-4.2%	-12.4%
SSyn5	51.09	48.60	-5.5%	-10.1%
L1	67.12	61.05	8.7%	-1.1%
L2	65.84	57.69	10.4%	-3.2%
L3	46.64	53.04	5.3%	19.7%
L4	41.74	46.79	9.2%	22.4%
L5	53.93	62.73	8.7%	26.4%
LSyn1	49.09	61.07	-1.3%	22.8%
LSyn2	49.43	36.35	0.1%	-26.4%
LSyn3	52.31	59.19	0.7%	14.0%
LSyn4	53.01	57.51	1.5%	10.1%
LSyn5	39.37	44.74	0.6%	14.3%