Concentration, Product Variety and Entry-for-Merger: Evidence from New Product Introductions in the U.S. Food Industry

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Abstract

Competing theories in industrial organization predict that more concentrated industries will lead to a smaller and more efficient variety of products, or alternately, a larger and less efficient array of products. This paper presents an empirical study of these competing implications that estimates the impact of market concentration on new product introductions in a panel of nine food processing industries over 1983 to 2004. Controlling for industry-level unobservables (using fixed effects) and endogeneity of industry market structure, we find that industry concentration promotes the introduction of new products. Preliminary evidence also suggests that new product introductions spur subsequent food industry mergers. Both conclusions are consistent with the "entry for merger" theory of product variety wherein small firms introduce new products in anticipation of profitable future mergers with concentrated firms.

Key words: New Product Introductions, Market Concentration, Mergers

JEL codes: L1, L2, L66

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1. Introduction

How does an industry's market structure affect the variety of products on offer? Competing theories have opposing predictions. Traditional models, pioneered by Salop (1979), Lancaster (1979), Schmalansee (1978), Eaton and Lipsey (1979) and others, imply that large firms in a concentrated market will preempt entry of new firms, thereby reducing the array of products that entrants would otherwise provide as they compete for a place in the market (Eaton and Schmitt, 1994). Essential to this logic is that market concentration and product proliferation by incumbent firms occurs before prospective entrants can introduce their products. Recent work argues that if this premise is violated – if the process of concentration occurs by merger, *after* new products have been introduced rather than before – then the positive and normative implications of concentration for the extent of product variety and economic welfare are reversed (Innes, 2008). In such cases, new product introductions by small firms arise in anticipation of future mergers with concentrated firms. Because an industry that is more concentrated is more profitable, and new product entrants anticipate sharing in those profits when they merge, increased industry concentration promotes *more* product variety, not less. Moreover, increased concentration is generally deleterious to economic welfare because it raises the extent of excess product entry, rather than reducing it. [1]

The purpose of this paper is to examine the empirical merits of these two competing theories in the context of the U.S. food industry. First and foremost, we study the relationship between measures of market concentration and new product introductions in a panel of nine processed food industries over 22 years (1983-2004). Traditional

[1] The welfare implications of product variety hinge on a tradeoff between consumer benefits of greater variety and cost economies of constraining variety production (and reaping attendant economies of scale in production). See Lancaster (1990) for a survey of the literature.

theory predicts that a higher degree of concentration will be associated with fewer new product introductions. The anticipatory merger theory instead predicts that greater industry concentration will promote more new product introductions. Second, we attempt to trace the effects of industry product introductions on subsequent mergers using a panel of 6 food industries over 14 years (1991-2004). The anticipatory mergers theory predicts that an increased number of new products will be followed in future years by more mergers that absorb the new product entrants into bigger more profitable firms. In both cases, we find evidence consistent with predictions from anticipatory mergers logic, namely, a positive effect of concentration on new product introductions (NPI) and a positive correlation between multi-year lagged NPI and future industry mergers.

Characterized by a large numbers of product variants and increased market concentration over recent years, the U.S. processed food industry is a particularly appropriate context in which to study effects of concentration on product innovation. Between 1990 and 2004, the median number of "SKUs" (stock keeping units) held by U.S. supermarkets increased by over 50 percent, with average numbers of stocked products in each supermarket tripling from roughly 15,000 in 1980 to roughly 45,000 in 2006.[2] During this same period, large numbers of new food products were introduced; for the nine industries that we study, over 1100 new products were introduced annually in each industry. Also over this period, concentration in both food manufacturing (our interest) and food retailing has risen dramatically (Sexton, 2000; Sexton and Zhang, 2001). The process of industry concentration is fueled by merger activity. Figure 1 illustrates this process, depicting trends in both mergers and NPI for the food industry over 1991-2004. Notably, the Figure reveals that high levels of NPI are followed by an

[2] See Progressive Grocer, 2005 and www.fmi.org.

increased number of food industry mergers. Are these trends coincidental or is there a causal relationship? While the anticipatory merger theory implies that these trends are causally related – and not coincidental symptoms of correlated phenomena – traditional entry preemption logic suggests the opposite.

On one level, anecdotal evidence indicates that entry preemption is unlikely to explain new product introductions in the U.S. processed food industry. With preemption, we would expect large firms to introduce the majority of new products in order to deter entry; however, in the food industry, new products are predominantly introduced by smaller firms. The top 20 firms introduced approximately 15 percent of new food products during the period 1999 to 2002, while the top 4 firms introduced only 5 percent (based on data from the *Food Institute Report*).

Our challenge in this paper is to transcend (and supplement) such anecdotal evidence and identify causal effects of concentration on new product introductions. The "causal" qualifier is a tough one. For a number of reasons, concentration is potentially endogenous as a determinant of NPI. Unobservable phenomena can drive both of these outcomes and thereby bias any estimates of correlated effects. For example, unmeasured market circumstances might promote consumer demand for a food category that exhibits less elasticity and a greater preference for variety, simultaneously promoting both more industry concentration and higher NPI. Alternately, product innovation activity (as captured by NPI) may enhance scale economies, giving rise to reverse causation (Geroski and Pomroy, 1990). Correlated unobservables may vary at an industry level, reflecting industry attributes that favor, for example, both higher concentration and higher levels of NPI. An important step toward identification of a causal effect is therefore to control for any unobservable industry level variation using a fixed effects estimator in a panel dataset. However, correlated unobservables may also vary across time, particularly when the time series spans a period as long as ours does (22 years). Such time series correlation is potentially illustrated by the food industry trends described above. Our empirical strategy is therefore dedicated to constructing a panel instrument for concentration that is plausibly exogenous to NPI and permits the identification of a causal effect in fixed effect instrumental variable (IV) estimations.

Beyond a richer NPI dataset, our focus on causation distinguishes our study from related prior empirical work on processed food markets.[3] Key early papers by Connor (1981) and Zellner (1989) identify a positive correlation between market concentration and NPI in cross-section data from 1977-78.[4] Using panel data from 1988-1994, Roder, Herrmann and Connor (2000) estimate a negative (and non-linear) relationship between market concentration and NPI in a fixed effects model. Unlike our study, none of these key studies accounts for both industry fixed effects and the potential endogeneity of concentration. When we don't account for either of these estimation issues (in OLS regressions), we also find a negative relationship between these two phenomena in our data, similar to Roder et al. (2000); however, in our fixed effects IV models, we find a positive and significant causal effect of concentration on NPI, consistent with anticipatory merger logic.

[3] A small literature examines the link between market structure and product variety in non-food markets. Berry and Waldfogel (2001) exploit the 1996 Telecommunications Act that relaxed ownership restrictions in radio broadcasting to identify market structure impacts on numbers of radio stations and formats. They find that the increase in radio market concentration produced by the new law led to fewer stations, but a greater format variety per station. Alexander (1997) studies the music industry over 1955-1988 and finds a non-monotonic effect of market concentration on product variety, with lower variety at low and high levels of music industry concentration and higher variety at intermediate levels of concentration.

[4] While Zellner (1989) employs a simultaneous equation model, his instruments for concentration are cross section variables (capital intensity and a cost-disadvantage index) that have the potential to be driven by correlated industry unobservables.

The balance of the paper is organized as follows. Section 2 illustrates the competing theories in a simple analysis of a spatial market model. Section 3 presents our main empirical analysis of how market concentration affects NPI in the food industry. Section 4 presents a preliminary analysis of how NPI affect future mergers, identifying the positive effect predicted by the logic of anticipatory mergers. Section 5 concludes.

2. Illustrating Competing Theories

Consider a Salop (1979) circle of unit circumference. Each point on the circle represents a potential product variant. Each consumer demands one unit of one product variant and is described by a location on the circle that represents her most preferred product type. If the consumer buys a product at distance x from her location, she bears a preference cost tx. Consumers have a common (high) reservation price for the product equal to V, implying net maximum willingness to pay at distance x, V-tx. Consumers are uniformily distributed on the circle, and the consumer population is normalized to one.

Production takes place at constant marginal cost c. Producers locate product variants at different points on the circle. Product/"store" locations ae (endogenously and optimally) symmetric. The number of symmetric product variants is N>2, which we treat as continuous (for analytical convenience). The fixed cost of producing any one product variant – the entry cost – is e>0. Once a product variant is introduced at a given location, it can be moved locally at no additional cost at least once; that is, costless local "reanchoring" is possible (Normal and Thisse, 1999). To ensure that all consumers are served in an efficient configuration, we assume that

(1) $$0<c<V-(t/N^*),$$

where N* is the efficient level of product variety,

(2) $$N^* = \operatorname{argmax}\ V - 2N \int_0^{1/(2N)} tx\, dx - eN = \{t/(4e)\}^{1/2}$$

We consider two market models, the "traditional/preemption" Model 1 and the "entry for merger" Model 2. For each case, we consider two market structures, monopoly and competitive. To illustrate the competing predictions of the two models, we will show that the equilibrium number of product variants is higher under monopoly than under competition in Model 1, and vice versa in Model 2. The empirical question – to which this paper is dedicated – is which prediction describes actual food markets.

2.1. The Preemption Model 1

First consider a monopoly incumbent who introduces products, after which atomistic (single product variant) entry can take place. To avoid rent-depleting (and rent-seeking) entry, the monopolist can sign franchise contracts with each "store"/product-variant as in Hadfield (1991); here, these contracts enable (and require) a departure from monopoly pricing if and only if entry occurs at a contiguous location – that is, a location between the particular store/variant and another monopoly store (see Figure 2).[5] In this event, the franchisee is obligated to compete with a cost-plus price that exactly covers the entry cost e. The monopoly franchisee (MF) that neighbors an entrant E has two advantages over the entrant: (1) the market area over the space MF competes with his monopoly colleague M1 (area Z in Figure 1) is twice as large as the space over which E competes with MF; and (2) the monopoly competition for MF (store M1) charges a higher (monopoly) price than does E's competition (stores MF and M2). For both reasons, MF – who earns profit e by construction of the franchise contract – earns more than E. Entry by E is therefore unprofitable. Because the monopolist deters entry, he can

[5] Preemption can take many forms, including contracts (Hadfield, 1991), organizational structure (Innes, 2006), and product proliferation. We consider the simplest and lowest cost approach here.

freely choose N. Moreover, given equation (1), it is easily shown that the monopolist will price so as to maximally extract rent from consumers subject to covering the market. Hence, the monopoly choses N to mimize costs:

(3) $$N^1_M = N^* \quad \text{and} \quad P^1_M = V - [t/(2N^*)]$$

Under pure competition, every "store" is a firm and, without reanchoring opportunities, atomistic entry produces a range of possible symmetric simultaneous-move equilibria (Norman and Thisse, 1996, 1999). However, in a two-stage game with optimal post-entry reanchoring to a symmetric store configuration, the set of subgame perfect equilibria reduces to a "spatially contestable" (SC) outcome in which symmetric entry exactly eliminates producer rents:

(4) $$N^1_C = N: (P_c(N)-c)(1/N) - e = 0, \text{ where } P_c(N) = c + (t/2N) = \text{post-entry price}$$

$$\rightarrow N^1_C = N_{SC} = \{t/(2e)\}^{1/2} > N^* = N^1_M$$

In sum, by equation (4):

Observation 1. In the preemption Model 1, a monopoly establishes a lower and more efficient level of product variety than does a competitive industry, $N^1_C > N^1_M = N^*$.

2.2. The Entry-for-Merger Model 2

Now suppose instead that atomistic entry of product variants / "stores" occurs first, followed by mergers (Innes, 2008). Pure competition, under which no mergers are allowed, produces exactly the same outcome as in Model 1 by exactly the same logic:

(5) $$N^2_C = N^1_C = N_{SC}$$

Associated post-entry profit per firm is

(6) $$\pi^2_C(N) = (t/2N^2) \quad \text{for} \quad N = N_{SC}.$$

Under monopoly, there are no restrictions on mergers and, post-entry, all firms will merge to produce the most profitable firm that is possible – a single monopoly firm. The process of merging is, of course, important. As described in detail in Innes (2008), mergers occur in an ultimatum bargaining game with an ex-ante random order of play. This process yields each firm an equal expected rent,

(7) $\pi_M^2(N)$ = post-entry per-firm expected profit = $\Pi_M(N)/N$,

where

$\Pi_M(N)$ = total post-merger monopoly profit = $(P_M(N)-c)$, with $P_M(N) = V - (t/2N)$.

The monopoly firm charges the maximum price that covers the market, $P_M(N)$. Because the monopolist can charge a higher price than competing firms, i.e.,

$$P_M(N) - P_C(N) = [V-(t/2N)] - [c+(t/2N)] = V - (t/N) - c > 0,$$

rents to merging firms are higher than rents to competing firms,

(8) $$\pi_M^2(N) > \pi_C^2(N).$$

Equation (8) directly implies that entry under monopoly,

$$N_M^2 = N: \pi_M^2(N) - e = 0,$$

is greater than entry under competition, $N_C^2 = N_{SC} = N: \pi_C^2(N) - e = 0$. Because prospective product entrants enjoy an equal share of ultimate monopoly profits, their incentive to enter the market is greater than under a competitive structure that produces lower prices.

Observation 2. In the entry-for-merger Model 2, a monopoly market structure leads to a higher and less efficient level of product variety than does a competitive industry, $N_M^2 > N_C^2 > N^*$.

Observations 1 and 2 illustrate the competing hypotheses for which we test in this paper. A more concentrated industry will produce either *less* product variety with fewer new product introductions (Observation 1) or more product variety with a greater number of NPI (Observation 2). The theory presented here is meant to be illustrative. Many generalizations are possible, including intermediate levels of concentration (less than monopoly, more than competition), mixtures of incumbent firms and entrants, elastic demands that lead to welfare costs of the higher prices produced by more concentrated industries, and technical refinements such as a non-uniform distribution of consumers and returns to scale in production. Many of these generalizations are considered in prior work (see Innes, 2008) and do not alter the fundamental logic of the competing theories.

3. New Product Introductions: The Empirical Analysis

In this section we present the first (and main) part of our analysis, identifying the causal effect of industry-level market concentration on NPI. To do so, we construct annual panel data over 1983-2004 on NPI and a variety of other attributes of nine different segments of the U.S. processed food industry.

3.1. Empirical Model

Consider the following empirical model for new product introductions (NPI):

$$NPI_{it} = \alpha_i + \beta C_{it} + \gamma X_{it} + w_i(t) + \varepsilon_{it} \tag{9}$$

where NPI_{it} = new product introductions in the food industry category *i* in year *t*, C_{it} = concentration index, X_{it} = exogenous explanatory variables, α_i = industry specific fixed effect, and $w_i(t)$ represents alternate time controls (more in a moment).

Apart from market concentration, NPI is expected to be influenced by several supply and demand characteristics, represented by X in model (9). On the "supply side," X includes the following panel variables (all measured annually by industry): sales, sales growth, number of firms, research and development intensity (R&D expenditure to sales ratio),[6] and capital expenditure intensity (capital expenditure to sales ratio). Sales and sales growth rates indicate the size and growth of each market segment. Large and growing markets are expected to promote new product introductions that can capture larger market shares. Greater R&D intensity is expected to complement innovative activity in product markets, enabling the introduction of more new products.

Capital investments may either complement or substitute for investments in new products. On one hand, they may complement new product launches by enabling flexible technologies that are easily adapted to new products; alternately, they may raise barriers to new products by increasing economies of scale in existing product lines. The effect of capital investments on NPI is therefore an empirical question, but one that (for our purposes) motivates inclusion of this control. Note that, in thinking about the role of capital in driving NPI, we distinguish between capital *investment* – an annual flow that is a potentially important driver of NPI – and an industry's capital *stock*, the initial level of which is captured by an industry's fixed effect and changes to which are captured by the capital investments. We therefore include measures of capital *investment* intensity in our NPI estimations. We measure capital expenditures by the average of *gross* flows that include investments to maintain capital and *net* flows that add to the capital stock.[7]

[6] Available R&D expenditure measures (from COMPUSTAT) represent total R&D spending, including both product and process R&D.

[7] Because the" average" measures perform better in our estimations than do either the gross or net investment alternatives, we use them in our reported regressions; we have obtained similar results using the alternative (component) measures of capital expenditure.

On the demand side, X includes the following time-varying indicators of the overall demand for processed food: the share of food expenditure in disposable income and the proportion of food spending on food away from home. The food expenditure share measures potential overall demand for food, while proportionate spending on food away from home indicates preferences for processed food. Both are expected to promote new products by increasing their market potential.

We consider alternate specifications for time effects, $w_i(t)$. The simplest is a time trend t. Variations include quadratic trends (t and t^2), industry specific trends, a flexible functional form in time (adding t^3, t^4 and t^5), and time fixed effects. With a limited number of observations, the last variation has the potential to overfit our data and is considered a robustness check.

3.2. Estimation and Identification

To estimate the relationship between market concentration and NPI, as proposed in model (9), requires attention to endogeneity. Thinking first about these relationships in a cross-section of industries, unobservable industry attributes can drive both concentration and NPI, leading to spurious correlation. Resulting endogeneity bias can go in either direction. Unobservable (higher) costs of entry may deter both new competition and new products, leading to a negative correlation between concentration and NPI and a negative bias on the estimated impact of concentration. Conversely, unobservable circumstances may lead to both increased (and more inelastic) product demands and a consumer preference for more product variety. The former can increase the benefits of concentration, while the latter can increase the benefits of NPI. Together, such unobservables could produce a spurious positive correlation between concentration and NPI. Estimating with panel data, adding industry fixed effects, substantially mitigates these concerns by netting out all cross-section variation – eliminating effects of unobservables that vary only by industry and not by time. Importantly, however, accounting for cross-section variation does not eliminate the potential for endogeneity as many of the forces described here – including product preferences and technology-driven costs of entry – can be time-varying.

We address potential endogeneity by constructing a suitable instrument for concentration (HI or CI_4) and implementing a panel (fixed effects) IV estimation that adjusts standard errors appropriately for heteroscedasticity and cross-error correlation (Bertrand et al., 2004). The instrument is a Bartik type with a time series component and a cross-section component.

Recall that we are estimating a panel model with fixed effects and are therefore focused on how *changes* in industry concentration over time affect the flow of new products in an industry. One key mechanism for the change in an industry's level of concentration is merger activity. Accordingly, the instrument's time series component is the total number of mergers in the U.S. in each year. This variable captures merger waves and reflects the intuition that industry-level mergers will tend to follow aggregate merger trends to an industry-specific extent. This intuition is loosely reflected in a positive correlation between food industry mergers and total U.S. mergers equal to 0.652 over 1991-2004.

The instrument's cross--section component is each industry's capital intensity, measured by net capital stock as a percentage of sales at the start of our sample period (1983-84). We expect (and find) that the sensitivity of an industry's concentration to

U.S. mergers depends crucially on its capital intensity. There are two mechanisms at work in this effect. First is how capital intensity affects the link between overall U.S. mergers and an industry's own relevant merger activity – its sensitivity to merger waves. Second is how capital intensity affects the link between industry mergers and concentration. On the first effect, note that mergers are of different types, including (1) within industry, (2) across industry along the vertical supply chain, and (3) across industry outside of the vertical chain (conglomerate-type mergers). Although vertical control can enhance a producer's end-market power and cross-product spillovers in retail chains may also enhance within-product sales, vertical and conglomerate mergers are less likely to drive intra-industry concentration than are mergers within the industry. Within-industry mergers are a significant share of all mergers, but not predominant; for example, less than 42 percent of U.S. mergers were within industry over 1980-89 and roughly 48 percent were within industry over 1990-98 (Andrade et al., 2001). Greater industry capital intensity may potentially affect the extent to which the most relevant (within industry) mergers respond to merger waves.

Capital intensity can also mediate the second effect – of relevant industry mergers on industry concentration. When small firms merge in a large industry, the merger has little effect on concentration. When large firms merge, the effect is much greater. We expect that, in more capital intensive industries, mergers will tend to have a larger impact on concentration by combining larger firms.

The instrument we construct is the ratio of total U.S. mergers (time-varying) to an industry's capital stock intensity (industry-varying). The latter is measured by an industry's average level of net property, plant and equipment over the initial 1983-84 period, divided by average industry sales over the same period. We consider a variation of this instrument that uses the square of U.S. mergers (divided by capital intensity). The above logic suggests that the instrument (and the "square" variation) will have a *negative* effect on concentration: as capital intensity rises, the sensitivity of relevant mergers and concentration to U.S. mergers will rise.[8]

Two issues are germane in evaluated the instrument. First, is it sufficiently "strong"? We will provide statistical evidence that the instrument is a strong predictor of the endogenous (concentration) regressor, as judged by prevailing rules of thumb (Stock and Yogo, 2003).

Second, is the instrument exogenous to NPI? One might be concerned about potential links between capital asset intensity and new product innovations. Perhaps more capital intensive industries have lower costs of incremental product introductions or, conversely, higher costs of adapting production processes to new products, implying that the instrument could be relevant to the NPI generating process. However, we control for such potential effects by explicitly including industry R&D intensity, new capital investment, and the interaction between these two measures in our empirical model for NPI. Combined with industry fixed effects that capture each industry's baseline capital

[8] We also consider an alternative instrument equal to the *product* of U.S. mergers and industry capital intensity. The product instrument does not perform quite as well as the ratio counterpart, but produces similar qualitative conclusions (see Table 5 below). While differences between the two (ratio and product) alternatives are subtle, the ratio instrument produces marginal effects of its two components (U.S. mergers and capital intensity) on concentration that are opposite in sign versus the same sign with the product instrument. As a result, the negative effect of the ratio instrument on concentration implies that a rise in U.S. mergers produces a smaller change in concentration when capital intensity is higher. Note, moreover, that the time series component of U.S. mergers unexplained by quadratic time trends is positively correlated with stock price movements (with correlation of 0.43 over our sample period, using S&P 500 returns). Therefore, one interpretation of the estimated effect of our ratio instrument is that concentration in our more capital intensive food industries is less sensitive to U.S. mergers in bull markets, and more sensitive in bear markets. This conclusion, as it relates to horizontal mergers that promote industry concentration in our sample, is consistent with recent studies documenting the role of undervaluation in promoting such mergers (for example, Rhodes-Kropf et al., 2005).

stock intensity (the cross-section component of the instrument), these R&D and capital investments span potential effects of capital intensity on NPI.

Stated differently, the instrument is constructed by combining pre-determined industry attributes with nation-level trends that purge any potentially endogenous panel variation underpinning the key concentration regressor. Because each industry is small in the overall U.S. economy, the time series (U.S. mergers) component is exogenous to time series variation in industry-level circumstances. Moreover, the cross-section (capital stock) component is spanned by included industry fixed effects. As a result, the variation in the constructed instrument is plausibly exogenous to any unobservable time-varying industry-level circumstances that might drive changes in industry NPI.

3.3. Data

We construct annual data on the number of new product introductions in nine processed food categories using issues of the *Food Institute Report*. The data span the 22 year period, 1983 to 2004. Annual firm level data on publicly traded firms are obtained from COMPUSTAT and used to compute annual measures, by industry, of sales; capital expenditure; value of property, plant and equipment; and R&D expenditure. Food processing companies in COMPUSTAT are classified by 4-digit SIC and accordingly matched to the nine NPI categories listed in Table 1. For large multi-product companies that produce a wide range of processed foods (such as Unilever and Nestle), we allocate their sales, expenditures and asset values to the different food categories by using revenue shares by food segment as allocation weights.

Using annual sales data, we construct two alternative market concentration measures that have been widely used in the literature (see Roder et al, 2000; Alexander, 1997; Zellner, 1989; Connor, 1981): (1) the Herfindahl Index, $HI=\sum_{i=1}^{N}(s_i^2)$ where s_i denotes the market share of firm *i* and N is the number of firms in the industry, and (2) the four firm concentration index, $CI_4=\sum_{i=1}^{4}(s_i^2)$ with firms ranked from one to N in descending order of market share. Larger values of either index indicate greater market penetration by fewer firms.

The description of variables used in the analysis and corresponding summary statistics are presented in Tables 2 and 3 respectively.

3.4. Results

Table 4 reports our main results for the NPI model (9) using the Herfindahl index (HI) to measure market concentration. We present seven models. The first is an Ordinary Least Squares regression that does not account for either industry fixed effects or endogeneity of the key concentration regressor (HI). The second is a fixed effects estimation that, again, does not account for endogeneity. The following five regressions, Models 3-7, account for both industry fixed effects and endogeneity using a Generalized Method of Moments (GMM) instrumental variable estimator that exploits our baseline instrument (U.S. mergers divided by initial industry capital intensity in 1983-84) to identify concentration. The five models incorporate different specifications for time effects, with more time controls added as one moves from left to right. The last two models 6-7 incorporate, respectively, a flexible functional form in time and time fixed effects. In view of the potential for these last regressions to overfit the data, our most preferred specifications are Models 3- 5, with the last Model 7 presented as a robustness check on qualitative results. In all models, we construct standard errors that are clustered by industry and that thereby account for general heteroscedasticity, autocorrelation, and other within-industry error correlation (Bertrand et al., 2004).

Table 5 presents first stage regressions associated with the GMM-IV Models 3-7 in Table 4. The (baseline) instrument performs very well in our preferred Models 3-5, with F statistics above the standard (Stock and Yogo, 2003) rule of thumb for weak identification (F*=10). The instrument remains highly significant in first stages for the "robustness" Models 6-7, but falls below the "rule of thumb" in these specifications. In all cases, the instrument has a significant negative effect on concentration, consistent with the intuitive logic of Section 3.2. We also note the significant negative effect of R&D on concentration, consistent with prior work on mergers (Mitchell and Mulherin, 1996). Higher concentration is also promoted by lower numbers of firms (predictably) and higher levels of capital investment and overall consumer expenditures on food.

The first lines of Table 4 provide our main "baseline" results. While the OLS Model 1 regression reveals a negative correlation between concentration and NPI, this effect evaporates when accounting for fixed effects (in Model 2) and endogeneity (Models 3-7). In all of the latter models, concentration (HI) has a significant positive effect on NPI, consistent with anticipatory mergers logic. The magnitude of these effects is also noteworthy. In the preferred Models 3-5, a doubling of HI concentration (evaluated at the average) raises NPI by between 145 and 168 percent (as a percent of the average); stated differently, a one standard deviation increase in HI is estimated to raise NPI by between 90 and 105 percent of the NPI standard deviation.

The estimates indicate a negative bias due to endogeneity of concentration in Model 2; that is, unobservables appear to drive HI and NPI in opposite directions. By accounting for endogeneity, we therefore obtain higher estimated positive effects of HI on NPI (comparing Model 2 to Models 3-5). Possible reasons include correlated costs of new product and firm entry that deter NPI and promote concentration.

Table 4 also reveals that research intensity promotes new products, and this effect is reinforced by higher levels of capital investment. These effects are quite large. For example, a doubling of the (average) R&D expenditure intensity is estimated to raise NPI by 46 to 65 percent of its average (using estimates from Models 3-5). Conversely, capital investments appear to substitute resources away from NPI, even while they complement R&D activity in promoting NPI; however, the magnitude of these estimated effects is quite small; for example, a doubling of capital investment intensity is estimated to raise NPI by between 17 and 19 per year – less than two percent of the NPI average.

Table 6 presents alternative specifications, first using the alternative CI_4 measure of concentration (in panel A) and second using alternative instruments to identify concentration in the GMM-IV estimations (panel B). The table reveals effects of concentration on NPI across the different measures and instruments that are similar to our baseline (Table 4) results in terms of both statistical significance and magnitude.

In sum, we find that market concentration has a significant positive effect on NPI, consistent with "anticipatory mergers" logic. We study next a possible mechanism for this positive effect. In particular, do new product introductions spur subsequent mergers with concentrated firms, as implied by an "entry for merger" paradigm?

4. Mergers

If new products are introduced in anticipation of profitable future mergers, then higher levels of NPI will lead to an increased number of future mergers. In this Section, we present a preliminary empirical test of this implication – preliminary in the sense that our conclusions are limited by the data at our disposal.

Using data from "Mergerstat," we have annual industry level observations on the number of mergers over the 14 year interval 1991 to 2004, broken down by six food industries.[9] The resulting unbalanced panel has 76 observations (with six years of observations for one of the industries). Table 7 describes the industry breakdown.

Given our data limits, and associated limits on estimation, we consider parsimonious models of the merger generating process. In addition to a time trend, we include three independent variables, all averages of three and four year lags in an endeavor to mitigate potential endogeneity.[10] First is the regressor of central interest: numbers of NPI. Our main hypothesis is that lagged NPI leads to an increased number of industry mergers. Second and third are the number of firms in the industry and industry sales growth. Ceteris paribus, we expect that a larger number of firms and more rapid industry growth will both generate greater opportunities for advantageous mergers. As a robustness check, we also consider an additional regressor (as an alternative to sales growth): lagged research and development intensity.[11] Table 8 presents summary statistics for the mergers dataset.

Given the panel structure of our data, our estimations account for individual industry effects that are treated either as random or fixed. We estimate the models

[9] Our allocation of food industry mergers excludes mergers into diversified food companies. As a check, we constructed an alternative measure of mergers that allocates the latter "diversified mergers" to industry sector using the proportion of diversified company (SIC 2000) sales by food sector. Qualitatively similar results are obtained using the revised data.

[10] We considered alternative lag lengths for the NPI, and found that neither shorter nor longer lags produced significant effects. Shorter lags likely suffer from endogeneity bias, while longer lags are likely too distant to affect merger activity. Alternate (shorter) lag lengths for the other independent variables have little effect on estimation results.

[11] Random effects estimations are not possible with more independent variables, for example with both sales growth and R&D.

treating the dependent variable either as linear or as a count. Count models are appropriate in our case because the dependent variable is positive, discrete and varies in a modest range of values (from a minimum of 2 to a maximum of 35). Because the count is not always small, however, linear models also provide a good approximation to the data generating process. In the count models, we estimate with the Poisson distribution for the random effects specification and with the Negative Binomial for the fixed effects specification; both models allow for over-dispersion of the variance, which we find in our data. While Hausman tests favor the random effects specifications, fixed effects control for cross-industry variation that might drive a spurious correlation between our regressors and the dependent variable (industry mergers).

Table 9 presents the regression results for food industry mergers. The first four models are linear random effects, and the final two are count models estimated with random and fixed effects, respectively. Models 4-6 are our preferred specifications.

As expected, we find that industry mergers are favored by larger numbers of firms and higher levels of industry sales growth. A one percent increase in an industry's number of firms is estimated to produce a 0.40 to 0.50 of one percent increase in annual mergers. Similarly, a one standard deviation increase in sales growth is estimated to produce an increase in mergers equal to 45 to 60 percent of its standard deviation.

Lagged NPI has a positive estimated effect on subsequent mergers in all cases, with estimated marginal effects that are strikingly consistent across alternate model specifications. Estimated magnitudes of effect are quite small. For example, a one percent increase in NPI is estimated to produce roughly a one-quarter of one percent increase in future industry mergers. Stated differently, the introduction of roughly 400 new products yields one future merger. However, these numbers reflect (1) the large numbers of new products introduced annually, the vast majority of which fail quickly, and (2) the relative rarity of industry mergers. The sample mean number of mergers per industry per year in our data is 16.3, and corresponding NPI numbers are over one hundred times greater. The significance of effect is what is important. For those NPI that succeed, we find that mergers often follow, consistent with an "entry for merger" paradigm. Taken together, these results and those of Section 3 suggest that the anticipatory mergers paradigm is likely to be at work in the U.S. processed food industry.

5. Conclusion

Theoretical predictions about the relationship between market concentration and new product introductions (NPI) are conflicting and prior empirical evidence is both scarce and mixed. Our empirical analysis tests the relationship between market concentration and NPI using data from the U.S. processed food industry. The evidence supports the "anticipatory merger theory," which posits that fringe firms introduce new products in anticipation of subsequently merging with concentrated firms and obtaining a share of the industry profits made possible by market power. The result of this process – as borne out by our data – is that greater concentration promotes new product introductions. Empirical merits of the "entry for merger" paradigm are further strengthened by a preliminary investigation of how NPI affects mergers three and four years after products are first introduced. Consistent with this perspective, more new products are associated with more subsequent industry mergers.

Welfare implications are complicated. Product variety, other things the same, is good for consumers. High prices are not, and they are also bad for society at large whenever product demands are price-responsive. Moreover, excessive product variety – meaning that the cost of providing additional product variants exceed consumer values for those products – is deleterious to welfare. Whereas traditional theory argues that powerful firms preempt potential competitors' introduction of new products in order to support higher prices and protect market share, the "entry for merger" paradigm suggests the opposite: Entry is promoted by market power, but precisely because the concentration leads to high prices. Preemption logic thus suggests a tradeoff between costs of higher prices and welfare benefits of reduced product variety when judging effects of market concentration. "Entry for merger" logic, as borne out here, suggests instead that concentration worsens welfare on both dimensions, prices and product variety.

Beyond obvious avenues for further work – including construction and analysis of richer data on relationships between NPI, firm numbers and mergers – is investigation of another key form of food market concentration, at the retail level. While food manufacturing has experienced increased concentration in recent decades, so too has food retailing (Sexton, 2000). For example, over 50 percent of U.S. retail food markets are now served by the top four supermarket chains (Richards and Pofahl, 2010); indeed, in 2007, the top four supermarkets in each of four large U.S. cities were responsible for between 60 and 80 percent of local retail food sales (Innes and Hamilton, 2013). How does retail concentration affect NPI and intermediate the impact of concentration in food processing industries? On both theoretical and empirical levels, we believe an understanding of these relationships merits academic focus.

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Figure 1. Food Industry Trends

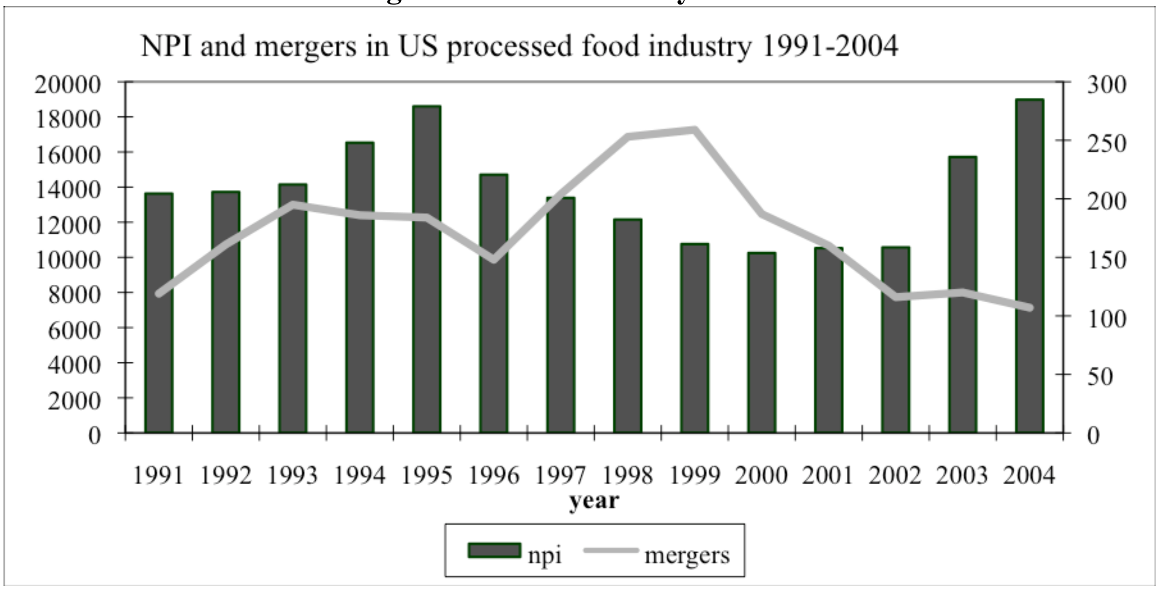
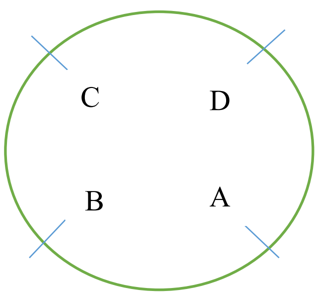


Figure 2. The Salop Circle Model



I) Salop Circle with Product Variants A, B, C, D

II) Entrant E Competition with a Monopoly Franchise MF

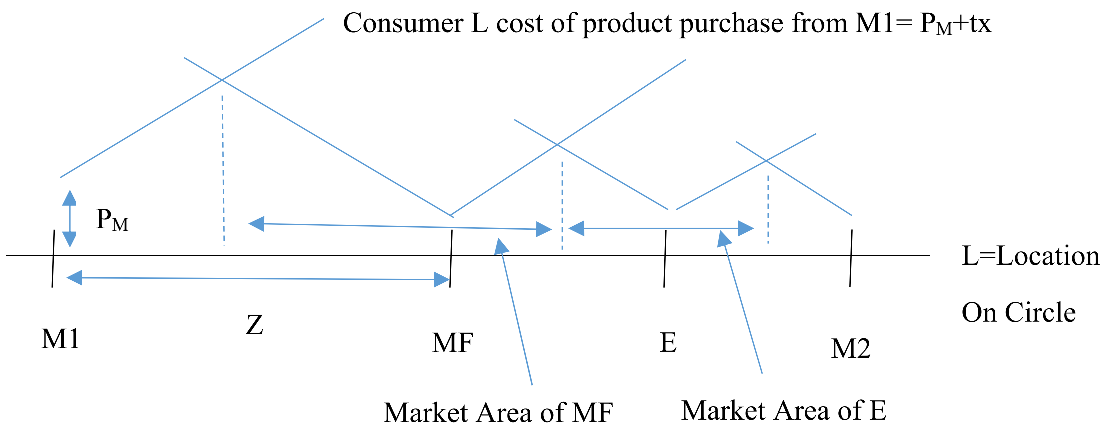


Table 1. Description of New Product Introductions (NPI) Categories

NPI Category	Description
1	Processed Meat, Fish, Egg
2	Dairy Products
3	Desserts and Ice cream
4	Fruits and Vegetable Products, Condiments
5	Breakfast Cereals, Pet food
6	Bakery Food
7	Sugar, Confectionary, Snacks
8	Beverages
9	Meals, Side dishes

Table 2. Description of Variables [+]

Variable name	Description
NPI	Number of New Product Introductions
HI	Herfindahl Index
CI4	Four Firm Herfindahl Index
N	Total number of firms
SALES	Sales ($ million)
SGR	Sales Growth Rate
R&D	R&D expenditure as percent of sales
CAPINV	Average of gross and net capital investment as % of sales
CAPSTOCK	Net Plant, Property and Equipment as percent of sales
MERGERS	Number of Mergers in the processed food industry
USMERGERS	Number of Mergers in the USA
FEXP	Food expenditure (% of disposable income)
FAFH	Food away from home (% of food expenditure)

[+] All variables are panel (by industry, by year) except the time series variables USMERGERS, FEXP and FAFH.

Table 3. Summary Statistics for the NPI Panel Data Set

Variable	Obs	Mean	Std.Dev.	Min	Max
NPI	198	1177.64	908.86	37	4596
HI	198	0.25	0.12	0.07	0.52
CI4	198	0.24	0.13	0.03	0.52
N	198	18.9	11.7	5	65
SALES	198	38281.54	32820.93	3265.57	195150.1
SGR	198	5.63	18.91	47.75	150.64
R&D	198	0.67	0.43	0	1.776
CAPINV	198	1.318	0.672	-39.56	26.99
CAPSTOCK	198	26.84	7.11	8.395	3.82
USMERGERS	198	4882.91	2877.56	1877	9783
FEXP	198	10.69	0.81	9.45	12.46
FAFH	198	38.74	2.37	34.97	43.27

Table 4. New Product Introductions (NPI) Regressions

	(1) OLS	(2) FIXED EFFECTS	(3) GMM-IV	(4) GMM-IV	(5) GMM-IV	(6) GMM-IV	(7) GMM-IV
HI	-2,837.5*	1,493.0*	7,972.7***	6,844.1***	6,894.9***	5,925.2*	3,811.9*
	(1,610.4)	(819.2)	(2,216.1)	(2,112.4)	(2,867.3)	(3,092.7)	(2,260.4)
SALES	-0.017*	0.003	0.005	0.005	0.011*	0.004	0.004
	(0.009)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.003)
SGR	-0.333	0.612	1.410	1.330	1.460	0.889	0.193
	(2.238)	(1.335)	(2.267)	(1.988)	(1.730)	(1.739)	(1.680)
N	50.509*	9.764	25.802**	18.467*	24.629	17.892*	12.296
	(26.471)	(8.298)	(10.660)	(10.582)	(17.956)	(9.430)	(7.765)
R&D	-208.435	607.2***	1,081.7***	925.4***	762.4***	772.796*	548.898*
	(245.143)	(162.032)	(252.422)	(240.834)	(187.428)	(396.094)	(293.429)
FEXP	1,181.63**	878.068**	468.813	511.497	517.819	60.804	--
	(443.798)	(398.959)	(353.216)	(329.509)	(315.348)	(273.967)	
FAFH	312.023***	186.519***	102.596	144.190	171.189**	50.145	--
	(99.113)	(58.999)	(99.991)	(96.959)	(82.012)	(83.352)	
CAPINV	11.898	-11.424	-41.192*	-38.014**	-32.772	-28.890	-21.060
	(21.782)	(10.288)	(21.346)	(19.384)	(22.170)	(17.502)	(13.212)
R&D*	4.612	15.248	39.660**	36.208**	29.432	28.446*	20.448*
CAPINV	(17.976)	(9.610)	(19.176)	(17.390)	(19.742)	(15.152)	(11.670)
Industry fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects:							
t	Yes	Yes	Yes	Yes	N/A	Yes	N/A
t^2	No	No	No	Yes	Yes	Yes	No
t^3, t^4, t^5	No	No	No	No	No	Yes	No
Industry trends	No	No	No	No	Yes	No	No
Time fixed effects	No	No	No	No	No	No	Yes
R^2	0.344	0.803					

Number of Obs = 198; Number of NPI categories = 9; robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; errors are clustered by industry.

Table 5. First Stage Results for NPI GMM-IV Regressions [+]

	(3) GMM-IV	(4) GMM-IV	(5) GMM-IV	(6) GMM-IV	(7) GMM-IV
Instrument:	-2.739***	-2.728***	-2.226***	-2.475**	-3.267**
USMERGERS/CAPSTOCK	(0.584)	(0.669)	(0.705)	(1.003)	(1.523)
1st stage F statistic	[22.00]	[16.56]	[10.24]	[6.10]	[4.58]
SALES	-3.59e-07	-3.57e-07	-1.16e-06**	-4.00e-07	-4.55e-07
	(3.28e-07)	(3.30e-07)	(5.72e-07)	(4.00e-07)	(4.26e-07)
SGR	-4.4e-04	-4.4e-04	-1.4e-04	-6.9e-05	-7.5e-05
	(2.863e-03)	(2.871e-03)	(2.45e-04)	(2.917e-04)	(3.153e-04)
N	-0.0033***	-0.0033***	-0.0030**	-0.0031**	-0.0032**
	(0.0010)	(0.0010)	(0.0013)	(0.0012)	(0.0014)
R&D	-0.1130***	-0.1131***	-0.0594***	-0.1171***	-0.1223***
	(0.0252)	(0.0247)	(0.0216)	(0.0271)	(0.0274)
FEXP	0.0675**	0.0673**	0.0630**	0.0238	--
	(0.0289)	(0.0295)	(0.0271)	(0.0250)	
FAFH	0.0045	0.0047	0.0035	-0.0030	--
	(0.0095)	(0.0095)	(0.0089)	(0.0084)	
CAPINV	0.4076	0.4070	0.3526	0.4426	0.4868**
	(0.2218)	(0.2220)	(0.2496)	(0.2328)	(0.2440)
R&D*CAPINV	-0.3570*	-0.3568*	-0.3162	-0.3936*	-0.4322**
	(0.2050)	(0.2054)	(0.2352)	(0.2102)	(0.2164)

[+] Models correspond to models (3)-(7) in Table 4. Robust standard errors in parentheses, clustered by industry. First stage dependent variable = HI.

Table 6A. NPI Regressions with Alternative Measure of Concentration +

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	FE	GMM-IV	GMM-IV	GMM-IV	GMM-IV	GMM-IV
CI4	-2,566.24	1,436.51*	7,273.2***	6,228.0***	6,731.7**	5,544.3*	3,553.4*
	(1,564.50)	(759.05)	(1,959.9)	(1,855.7)	(2,814.8)	(2,853.3)	(2,060.7)
R^2	0.337	0.804					
First Stage			-3.003***	-2.998***	-2.315***	-2.645**	-3.505**
Instrument			(0.621)	(0.710)	(0.735)	(1.068)	(1.610)
[F Stat]			[23.33]	[17.81]	[9.92]	[6.15]	[4.75]

+ Models (1)-(7) are identical to Models (1)-(7) in Table 4 except CI4 replaces HI. Robust standard errors in parentheses, clustered by industry.

Table 6B. NPI Regressions with Alternative Instruments for Concentration ++

Alternative Instrument 1: USMERGERS^2/CAPSTOCK								
	(3)	(4)	(5)	(6)	(3)	(4)	(5)	(6)
HI	7,714.0***	6,526.2***	6,123.2**	5,397.5**				
	(2,132.5)	(1,969.6)	(2,421.0)	(2,682.7)				
CI4					7,044.7***	5,946.0***	5,950.6**	5,024.9**
					(1,895.7)	(1,739.8)	(2,365.9)	(2,456.7)
1st stage Instrument F Stat	[22.34]	[17.37]	[12.08]	[6.80]	[22.35]	[18.32]	[11.61]	[6.82]
Alternative Instrument 2: USMERGERS*CAPSTOCK								
	(3)	(4)	(5)	(6)+++	(3)	(4)	(5)	(6)+++
HI	8,617.8***	7,429.4**	9,439.0**	5,612.0				
	(2,950.2)	(3,138.2)	(3,604.8)	(4,329.1)				
CI4					7,848.6***	6,744.3**	8,567.1**	5,089.3
					(2,664.9)	(2,824.7)	(3,200.1)	(3,827.3)
First Stage Instrument F Stat	[13.51]	[8.71]	[9.00]	[3.42]	[13.47]	[8.81]	[9.55]	[3.69]

++ Models (3)-(6) correspond with Models (3)-(6) in Tables 4 (for HI) and 6A (for CI4), using the indicated alternative instrument for concentration. Robust standard errors in parentheses, clustered by industry. +++ Includes industry trends.

Table 7. Description of Food Industry Categories for Mergers Analysis

NPI Category	Description
1	Processed Meat, Fish, Egg
2 & 3	Dairy Products
4	Fruits and Vegetable Products (from 1999)
6	Bakery Food
7	Sugar, Confectionary, Snacks
8	Beverages

Table 8. Summary Statistics for the Mergers Panel Data Set (1991-2004)

Variable	Obs	Mean	Std.Dev.	Min	Max
MERGERS	76	16.30	7.87	2	35
NPI	76	1643.61	737.27	453	3619
SGR	76	-0.15	19.87	-91.38	46.25
N	76	23.47	15.33	8	65
R&D	76	0.5410	0.3561	0	1.1723

Table 9. Estimation of the Food Industry Mergers Equation

	Random Effects					Fixed Effects
	Linear				Poisson +	Neg. Bin. +
	(1)	(2)	(3)	(4)	(5)	(6)
NPI-lag	0.0043	0.0031	0.0031	0.0025	0.0022	0.00254
	(2.74)***	(2.02)**	(1.78)*	(1.81)*	(2.00)**	(1.73)*
N-lag	--	0.2713	0.3046	0.2351	0.2566	0.3552
		(2.82)***	(2.79)***	(2.77)***	(3.28)***	(2.91)***
SGR-lag	--	--	--	0.1821	0.2382	0.1856
				(2.88)***	(4.65)***	(2.84)***
R&D-lag	--	--	2.5521	--	--	--
			(0.54)			
Time Trend	0.0263	-0.0840	-0.1338	0.0432	0.0873	-0.1011
	(0.14)	(-0.45)	(-0.69)	(0.23)	(0.65)	(-0.58)

Number of Observations = 76. Number of Categories = 6. z-statistics in parenthesis. *,**,*** denote significant at 10%, 5%, 1% (two sided). Lagged independent variables are an average of three and four year lags. + Marginal effects at means.