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 atomistic innovators introduce new products in anticipation of profitable future mergers with concentrated firms.

Keywords: New Product Introductions, Market Concentration, Mergers
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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, typically imply that large firms in a concentrated market will introduce a smaller range of products than would prevail in a competitive market with free entry (Eaton and Schmitt 1994). A concentrated firm has many products on offer and faces "cannibalization" costs of increasing its product assortment: new products reduce demands for the firm's other product lines. When competition increases, firms each have fewer products and cannibalization costs of introducing new products fall, ultimately evaporating entirely in the case of perfect competition by single product companies. Increasing competition thereby leads to more product variety, indeed more than is efficient.

Essential to this logic is that market concentration and product proliferation by incumbent firms occur *before* prospective entrants can put down stakes. Recent work argues that if this premise is violated - if new products are introduced first by independent entrants, followed by mergers into bigger companies - then the effects of market concentration on product variety and economic welfare are reversed (Innes 2008). In such cases, new product introductions by atomistic innovators arise in anticipation of future mergers with concentrated firms; there is "entry-for-merger." 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

[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) and Vives (1999) for surveys of the literature. More recent related literature is primarily empirical (see, for example, Draganska, Mazzeo and Seim 2009, on product assortment with fixed market structure) and includes studies on how switching costs affect product pricing with fixed product variety (Dube, Hitsch and Rossi 2009).

between measures of market concentration and new product introductions in a panel of nine processed food industries over 22 years (1983-2004). 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). In both cases, we find evidence consistent with predictions from the entry-for-merger perspective, 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] Correlated with this growth are large numbers of new food products; for the nine industries that we study, an average of over 1100 new products were introduced annually in each industry over our study period. As illustrated in Figure 1, total food industry NPI almost quadrupled from 1983 to 2004. Also over this period, concentration in both food manufacturing (our interest) and food retailing rose dramatically (Sexton 2000; Sexton and Zhang 2001). Figure 2 depicts the growth in the average Herfindahl index for U.S. food industries.

The process of industry concentration is fueled by merger activity. Figure 3 illustrates this process, depicting trends in both mergers and NPI for the food industry over 1991-2004. The Figure reveals that high levels of NPI are followed by an increased number of food industry mergers. For example, growth in NPI over 1993-95 is followed by growth in the number of food industry mergers in 1996-99. Similarly, the decline in NPI over 1995-99 is followed by a decline in mergers over 1999-2002.

Are these trends coincidental or is there a causal relationship? The entry-for-merger theory implies that these trends are causally related and not coincidental symptoms of correlated

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

phenomena. Traditional product proliferation logic suggests the opposite.

On one level, anecdotal evidence indicates that product proliferation is unlikely to explain new product introductions in the U.S. processed food industry. With proliferation, we would expect the largest firms to introduce the largest share of new products. However, in the food industry, new products are predominantly introduced by smaller players. In 2000, for example, the top 10 food companies introduced approximately 9 percent of new food products, even though these firms generated over 60 percent of industry revenue. Similarly, the top 4 firms introduced only 3 percent of new products while responsible for over 40 percent of industry revenue. [3]

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)

[3] These statistics are derived from COMPUSTAT sales data and NPI data for the top 20 NPI generators, as reported by the Food Research Institute.

estimations.

Beyond a richer NPI dataset, our focus on causation distinguishes our study from related prior empirical work on processed food markets. [4] 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. [5] 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, Herrmann and Connor (2000); however, in our fixed effects IV models, we find a positive and significant causal effect of concentration on NPI, consistent with entry-for-merger logic.

Illustrating Competing Theories

Consider a discrete Dixit-Stiglitz model of product variety (Dixit and Stiglitz 1977; Kuhn and Vives 1999; Hamilton 2009). A representative consumer has utility:

$$U(z, y) = G(z) + y \tag{1}$$

[4] 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. See also related work on variety in daily newspapers (George 2002) and retail markets for eyeglasses (Watson 2009) and automobiles (Olivares and Cachon 2007).

[5] 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.

where y is a numeraire and G measures utility of composite variety consumption,

$$z = \sum_{i=1}^{M} f(x_i) \tag{2}$$

M is the number of product variants; x_i is consumption of variant i; and the increasing concave weighting function $f(x)$ captures the preference for variety. G is also increasing concave, reflecting diminishing marginal utility of consumption. For simplicity, we assume that G and f have constant eleasticities $\eta \in (0, 1)$ and $\theta \in (0, 1)$. Maximizing (1) subject to the budget constraint gives the inverse demands:

$$p_i(z, x_i) = G'(z)f'(x_i) \tag{3}$$

In what follows, we will describe symmetric equilibria for two models: (1) entry-for-merger (Innes 2008) and (2) traditional product proliferation. In each case, the number of ultimate symmetric firms, N, is parametric. We are interested in how product variety, M, is affected by an increase in N that increases competition. Does the equilibrium level of M rise with N, so that increased market concentration (lower N) lowers product variety (M)? Or does M fall with N, so that increased concentration leads to increased product variety? To fix ideas, the thought experiment here is how a "concentration constraint" that limits each firm to $\frac{1}{N}$ share of the market affects product variety. In the entry-for-merger model, the constraint limits each merger to encompass $m = M/N$ product variants. In the "traditional" model, the constraint fixes the number of firms at N.

In the entry-for-merger model, atomistic entry of product variants occurs first, followed by merger into N symmetric firms. After the merger process is complete, each firm chooses its output x for each of its $m(= M/N)$ product variants. Mergers occur in a process that, ex-ante, produces symmetric outcomes (profits) to entrants who are in the same position. For example, the process could be a sequence of ultimatum bargaining games with random order of play, as described in Innes (2008). In each subgame, $m(= M/N)$ entrants bargain with each other to split profit of the merged firm. Because no firm has an ex-ante advantage in this process (and variants are symmetric, none generating more profit than the other), the *expected* allocation from any such process is an equal split. The result is akin to monopolistic competition in which first stage entry dissipates post-entry rents available from the exercise of market power. Here, the number of product variants is determined by the entry process.

In the "traditional" model, in contrast, each of the N firms simultaneously chooses the number of product variants to offer, followed by simultaneous choice of symmetric outputs x for its chosen variants. Here, the number of variants is determined by a process of product proliferation by concentrated firms, rather than atomistic entry. [6]

In both cases, the fixed cost of producing an added variant is $e > 0$ (the entry cost in the entry-for-merger model). We simplify mathematical exposition by assuming zero marginal costs of production and treating M and N as continuous with $N \geq 1$.

In the final stage of both models, a firm with m_i product variants chooses output x_i to maximize profit, given a total number of other firm variants M_O and per-variant output x_O, as follows:

$$\max\, m_i\{p(M_O f(x_O) + m_i f(x_i), x_i)\, x_i \,-\, e\} \tag{4}$$

Equation (4) maximizes the per-variant profit of firm i - the revenue $p\,x$ less the fixed cost e - times its number of variants m_i.

The Entry-for-Merger Model

Define $x^*(N, M)$ as the solution to (4) in a symmetric configuration, solving the first order condition:

$$H_x \,=\, p(Mf(x), x) \,+\, p_x(Mf(x), x)x \,+\, p_z(Mf(x), x)\left(\frac{M}{N}\right) f'(x)x \,=\, 0 \tag{5}$$

[6] We do not model entry deterrence in the "traditional" model. However, incumbent firms have tools at their disposal that can deter entry, including cleverly designed franchise contracts (Hadfield 1991) and choice of organizational form (Innes 2006).

Associated profit per variant is:

$$\pi(N,M) \;=\; p(Mf(x^*(N,M)), x^*(N,M))\, x^*(N,M) \;-\; e \tag{6}$$

By the merger process posited above, a prospective entrant anticipates the profit $\pi(N, M)$. Entry occurs so long as this profit is non-negative. Hence the equilibrium number of variants M is determined by

$$M^*(N):\;\; \pi(N,M) \;=\; 0 \;\text{ where }\; \frac{\partial \pi}{\partial M} \;<\; 0 \tag{7}$$

The derivative inequality is necessary for stability; if violated, M would increase without violating the non-negative profit constraint. The Appendix shows that this inequality holds under our assumptions. Differentiating (7):

$$\frac{dM^*(N)}{dN} \;=\; \frac{-\partial\pi/\partial N}{\partial\pi/\partial M} \;<\; 0 \tag{8}$$

where the inequality follows from equation (7) ($\frac{\partial \pi}{\partial M} \;<\; 0$),

$$\frac{\partial \pi}{\partial N} \;=\; \left(\frac{d\{p(Mf(x^*), x^*)x^*\}}{dx}\right)\left(\frac{\partial x^*(N,M)}{\partial N}\right) \tag{9}$$

$$\frac{d\{p(Mf(x^*), x^*)x^*\}}{dx} \;=\; x^* p_z()[(N-1)M/N]\, f'(x^*) \;<\; 0 \tag{10}$$

$$\frac{\partial x^*(N,M)}{\partial N} \;=\; \frac{\{p_z\, M\, f'(x^*)\, x^*/N^2\}}{H_{xx}} \;>\; 0 \tag{11}$$

Equation (10) substitutes from (5) and equation (11) differentiates (6). The inequalities follow from $f' > 0$, $p_z = G''(z)f'(x) < 0$, and $H_{xx} < 0$. [7] Together, equations (9)-(11) imply $\frac{\partial \pi}{\partial N} < 0$, producing the inequality in equation (8):

Observation 1. In the entry-for-merger model, the symmetric equilibrium number of product variants increases with market concentration, $\frac{dM^*(N)}{dN} < 0$.

In a more concentrated market, firms restrict output in order to raise prices. Greater market shares increase the incentive (and ability) to do so, leading to larger profits. Prospective

[7] See Appendix for derivation of $H_{xx} < 0$, also a necessary condition for equilibrium stability.

entrants, who anticipate sharing equally in the post-merger profits, therefore have a greater incentive to produce. With a contestable entry process, the result is a higher number of entrants / product variants as concentration increases.

The Product Proliferation Model

Here, instead, product variety is determined by the choices of the N existing firms, each of whom maximizes the profits in equation (4) by choice of both the number of variants m_i and output per variant x_i. Corresponding optimality conditions in a symmetric equilibrium solve (5) ($H_x = 0$) and

$$H_m \;=\; (p(Mf(x),x)x \;-\; e) \;+\; \left(\frac{M}{N}\right) p_z(Mf(x),x)\, f(x)x \;=\; 0 \tag{12}$$

Together, equations (5) and (12) define the total number of product variants, $M^*(N)$, and output per variant, $x^*(N)$, in the equilibrium. Totally differentiating (5) and (12) gives the key derivative:

$$\frac{dM^*(N)}{dN} \;=\; \frac{-H_{xx}H_{mN} + H_{mx}H_{xN}}{|H|} \tag{13}$$

where, from the Appendix (and necessary for stability of the equilibrium), $H_{xx} < 0$ and

$$|H| \;=\; H_{xx}H_{mM} \;-\; H_{mx}H_{xM} \;>\; 0 \tag{14}$$

In addition, we have:

$$H_{mx} \;=\; \left(\frac{p}{N}\right)(\eta\theta)[N + \eta - 1] \;>\; 0 \tag{15}$$

$$H_{mN} \;=\; -\left(\frac{M}{N^2}\right)\, p_z\, f(x)\, x \;>\; 0 \tag{16}$$

$$H_{xN} \;=\; -\left(\frac{M}{N^2}\right)\, p_z\, f'(x)x \;>\; 0 \tag{17}$$

where the inequalities follow from $p_z < 0$, $f' > 0$, $\eta > 0$, $\theta > 0$, and $M \geq N \geq 1$. Together, equations (13)-(17) imply:

Observation 2. In the product proliferation model, the symmetric equilibrium number of product variants falls with market concentration, $dM^*(N)/dN > 0$.

In a more concentrated market, each firm is larger and, ceteris paribus, has more product variants on offer. In choosing how many variants to offer, the larger firms consider the cannibalization effects of an added variant on its other products (the last term in equation (12)). Because these effects are larger when firms are larger, incentives for product proliferation are smaller in more concentrated markets.

Observations 1 and 2 illustrate the competing hypotheses for which we test in this paper. A more concentrated industry will produce either more product variety with a greater number of new product introductions (Observation 1) or less product variety with fewer NPI (Observation 2). [8] The theory presented here is meant to be illustrative. Many generalizations are possible, including asymmetric equilibria that encompass mixtures of incumbent firms and entrants, more complex supply and demand specifications, and dynamics. Some of these generalizations are considered in prior work (see Innes 2008) and do not alter the fundamental logic of the competing theories.

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.

Data and Empirical Model

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

$$NPI_{it} = \alpha_i + \beta C_{it} + \gamma X_{it} + \omega_i(t) + \epsilon_{it} \tag{18}$$

[8] To relate the number of product variants M, from the theory, to our empirical measure of product introductions, NPI, note that the latter represents a number of product attempts. Our implicit premise is that new product attempts are monotonically related to a target number of new product successes, which in turn are monotonically related to the target product variety measure M.

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 $\omega_i(t)$ represents alternate time controls encompassing trends that are linear (t), quadratic (t^2) and industry specific.

To estimate model (18), 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. The NPI data are obtained from issues of the Food Institute Report. Although the NPI take a count form, the industry level counts are large, averaging 1177 per sector per year in our sample, with a minimum value of 37. We therefore treat the dependent variable as continuous in our estimations.

The nine food categories / industries are matched to firm level data from COMPUSTAT using 4-digit SIC classifications. Table 1 describes both the nine food segments and the corresponding SIC code matches that define the segment to which each firm is allocated. Annual industry / food sector aggregates are obtained from the firm-level data for a variety of financial indicators, including sales, research and development expenditures, capital investments, values of property, plant and equipment, and numbers of firms. For large multi-product companies that produce a wide range of processed foods (such as Unilever and Nestle), we allocate their sales, expenditures, investments and asset values to the different food categories by using revenue shares by food segment as allocation weights. [9]

Using the annual firm-level sales data, we construct two alternative measures for market concentration C_{it} (by industry by year) that have been widely used in the literature (see Roder, Herrmann and Connor 2000; Alexander 1997; Zellner 1989; Connor 1981): (1) the

[9] Company annual reports are used to determine the diversified companies' revenue shares by category by year. A limitation of our financial data is that it is compiled from publicly traded companies and therefore excludes privately held food producers. In our defense, available statistics suggest that public companies are responsible for the preponderance of sales in processed food markets. For example, of the one hundred largest U.S. food processing companies in 2009, U.S. public companies accounted for over 86 percent of collective sales (FoodProcessing.com/top100). To the extent that private label producers are privately held, our data also excludes these producers; however, as noted by industry expert Diane Toops (2012): "New product innovation is primarily left to brand leaders... The general consensus is that private labels can play many roles in the market, but not that of innovator..."

Herfindahl Index,

$$HI = \sum_{i}^{N} (s_i^2)$$

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,

$$CI_4 = \sum_{i}^{4} (s_i^2)$$

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.

Apart from market concentration, NPI is expected to be influenced by a number of industry-level, food demand, and macroeconomic phenomena, represented by X in model (18). At the industry level, 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), 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. [10]

Capital investments may either complement or substitute for investments in new products. 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. In defining our capital measures, 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

[10] Ideally, we would like to measure product (vs. process) R&D by sector. However, available R&D expenditure measures (from COMPUSTAT) represent total RD spending, including both components.

capital and net flows that add to the capital stock. [11]

X also 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. Finally, we include two macroeconomic indicators, the real interest rate and real GDP growth. [12] We expect NPI to be favored by lower interest rates that can encourage product investments and greater GDP growth that promotes product demand.

The description of variables used in the analysis and corresponding summary statistics are presented in Tables 2 and 3 respectively. Note that there is substantial variation in both the NPI and the explanatory variables. For example, the CI_4 concentration measure ranges from a low of 0.03 to a high of 0.52, the latter representing industry dominance by the top four firms and the former indicating a diffuse market structure. The industries vary substantially in size (sales), research intensity, and capital assets. The average number of firms per industry category is almost 19, and the annual number of new products per category varies from a low of 37 to a high of almost 4600.

Estimation and Identification

To estimate the relationship between market concentration and NPI, as proposed in model (18), requires attention to endogeneity. Unobservable industry phenomena can drive both concentration and NPI, leading to spurious correlation. Resulting endogeneity bias can go in either direction. Unobservable (higher) costs of entry and product launch 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

[11]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.

[12]We thank an anonymous referee for suggesting these controls. In order to reflect a relevant cost of funds for medium-term NPI investments, the real interest rate is measured by the yield to maturity on 10-year T-bonds, adjusted for future inflation.

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. Because these forces can be time-varying, endogeneity need not be cured by our inclusion of industry fixed effects.

We address potential endogeneity by constructing a suitable instrument for the concentration regressor C_{it} and implementing a panel IV estimation that adjusts standard errors appropriately for heteroscedasticity and cross-error correlation (Bertrand, Duflo and Mullainathan 2004). The broad logic of our instrument borrows from the labor literature (e.g., Card 2001) by interacting a time series component and a cross-section component.

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 can be driven by aggregate merger trends to an industry-specific extent. The instrument's cross-section component is each industry's capital intensity, measured by its average level of net property, plant and equipment as a percentage of sales at the start of our sample period (1983-84). The instrument we construct is the ratio of total U.S. mergers (time-varying) to an industry's capital stock intensity (industry-varying): $I_{it} = USM_t/K_i$.

To understand the instrument, consider first how capital intensity intermediates the sensitivity of industry-level concentration to merger waves. There are two mechanisms at work: (1) how capital intensity affects the link between overall U.S. mergers and an industry's own relevant merger activity; and (2) how capital intensity affects the link between industry mergers and concentration. On the first mechanism, 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; 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, Mitchell and Stafford 2001). We expect greater industry capital intensity - reflecting market-specific asset investments - to affect the extent to which the most relevant (within industry) mergers respond to merger waves.

Capital intensity is also relevant to the second mechanism: the effect of relevant industry mergers on industry concentration. For the same reason that we expect greater capital intensity to favor larger firms (by erecting barriers to entry), we expect intra-industry mergers in more capital intensive industries to have a larger effect on concentration by combining larger companies. [13] Both mechanisms suggest a positive relationship between capital intensity and concentration: As capital intensity rises, the sensitivity of relevant mergers and concentration to U.S. mergers will rise, implying a negative relationship between the ratio instrument and industry-level changes in concentration.

A more subtle pattern of effect motivates the instrument's "ratio" form. If an undervaluation of assets promotes intra-industry mergers (as suggested in the work of Rhodes-Kropf, Robinson and Viswanathan 2005, and Schleifer and Vishny 2003, for example), [14] then bear markets will enhance a tendency for increases in concentration. The "time to strike," by buying up competitors, is when the competitors' stock is cheap. 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 SP 500 returns). Therefore, we expect (and find) that industry-level capital intensity and the relevant (residual) component of U.S. mergers - as an indicator for a "bull market" - will pull in opposite directions. We capture this tendency with a ratio instrument, versus a "product instrument" that requires the two to pull in the same direction. [15] In sum, we

[13] On the link between capital intensity and entry barriers, see Eaton and Lipsey (1980), Acs and Audretsch (1987, 1989).

[14] These papers have broad predictions about use of stock vs. cash in acquisitions and how firm-specific misvaluations drive the designation of takeover vs. target. Related to our argument, Schleifer and Vishny (2003) write, in explaining the conglomerate merger wave of the 1960's, that "such acquisitions might have been more attractive than those in the same industry because within industry target valuations were too high to justify acquisition" (p. 306).

[15] As a robustness check, we also consider a product instrument (U.S. mergers *times* industry capital

expect increases in concentration to be promoted most by a combination of a bear market (low value of USM_t) and a high capital intensity (K_i), both of which lower our instrument's value.

To judge the instrument's merit, two issues are relevant. 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? 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. More generally, the instrument is constructed by combining pre-determined industry attributes with nation-level trends. The cross-section (capital stock) component is spanned by included industry fixed effects. Moreover, because each industry is tiny in the overall U.S. economy - and we include a range of time controls - the time series (U.S. mergers) component is plausibly exogenous to residual variation in the NPI. The combination of the two - the constructed instrument - thereby excludes any potentially endogenous panel variation underpinning the key concentration regressor.

Results

Table 4 reports results from the NPI model (18) using the Herfindahl index (HI) to measure market concentration. We present five 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 three regressions, Models 3-5, 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 three GMM

intensity). The product instrument does not perform quite as well as the ratio counterpart (likely for the reasons we discuss above), but produces similar qualitative conclusions (see Table 6 below).

models incorporate different specifications for time effects, with more time controls added as one moves from left to right. [16] 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, Duflo and Mullainathan 2004).

Table 5 presents first stage regressions associated with the GMM-IV Models 3-5 in Table 4. [17] The (baseline) instrument performs very well in the IV models, with F statistics above the standard (Stock and Yogo 2003) rule of thumb for weak identification ($F^* = 10$). We conclude that the instrument is "strong," with a significant negative effect on concentration that is consistent with the intuitive logic described above. 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 higher capital investment, higher consumer spending on food, and lower numbers of firms.

The first lines of Table 4 provide our main 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 3-5). In the IV models, concentration (HI) has a significant positive coefficient, consistent with entry-for-merger logic. In the preferred Models 3-5, a doubling of HI concentration (measured from the mean) raises NPI by an estimated 163 to 179 percent (of mean NPI); stated differently, a one standard deviation increase in HI is estimated to raise NPI by between 102 and 112 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. [18] By accounting for endogeneity, we therefore obtain higher (positive) estimated effects of HI on NPI.[19] Possible

[16] Our expanded paper contains two additional models that include, respectively, a flexible functional form in time and year fixed effects. Qualitative results are similar, although precision is reduced due to overfitting.

[17] Our IV models in Table 4 are exactly identified with one excluded (identifying) instrument indicated at the top of Table 5 and one endogenous (concentration) regressor.

[18] Hausman statistics indicate that the concentration regressor is endogenous, rejecting the null of exogeneity at p=0.01. See Table 4.

[19] Comparing Model 2 to the GMM Models 3-5 indicates the potential negative bias from omission of unobservable *within*-industry variables. Potential bias due to unobservable *between*-industry variation also appears to be negative; comparing Models 1 and 2, fixed industry effects produce higher (positive) estimated

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 50 to 69 percent of its mean (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 the latter effects is quite small; for example, a doubling of capital investment intensity is estimated to raise NPI by between 19 and 21 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 two alternative instruments to identify concentration in the GMM-IV estimations (panel B). We consider a "product instrument" (U.S. mergers times industry capital intensity) and a non-linear ratio instrument ($I_{it} = USM_t^2/K_i$). 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 entry-for-merger 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?

Mergers

If concentrated firms proliferate new products, then NPI should have no effect on subsequent merger activity. However, if new products are introduced by atomistic innovators in anticipation of profitable future mergers, as in the entry-for-merger model, then higher levels of NPI will lead to an increased number of future mergers. In this Section, we present a

effects of concentration, versus the negative estimates from simple OLS.

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. [20] The resulting unbalanced panel has 76 observations (with six years of observations for one of the industries). Table 7 describes the industry breakdown.

In view of 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. [21] 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. [22] 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 treating the dependent variable either as linear or as a count. 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. Hausman tests favor the random effects specifications.

[20] 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.

[21] The lags do not affect the length of our time series, which is determined by the available mergers data. 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.

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

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. More important for our purposes, 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, the introduction of roughly 400 new products is estimated to yield one future merger. 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.

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. In this paper, we study the relationship between market concentration and NPI using data from the U.S. processed food industry. The evidence supports the entry-for-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. We also present a preliminary investigation of how NPI affects mergers three and four years after products are first introduced. Again consistent with the entry-for-merger perspective, we find that 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 ("product proliferation") 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. Proliferation 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 attention.

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Appendix: Derivatives for the Theory

With our constant elasticity assumptions on the Dixit-Stiglitz demands, $G(z) = \alpha z^{\eta}$ and $f(x) = \beta x^{\theta}$, the following can be derived:

$$H_{xx} = \left(\frac{p}{Nx}\right) \theta(\eta\theta - 1)[N + \eta - 1] < 0 \tag{A1}$$

$$H_{mM} = \left(\frac{px}{MN}\right) (\eta - 1)[N + \eta - 1] < 0 \tag{A2}$$

$$H_{xM} = \left(\frac{p}{MN}\right) (\eta - 1)\theta[N + \eta - 1] < 0 \tag{A3}$$

$$H_{mx} = \left(\frac{p}{N}\right) \eta\theta[N + \eta - 1] > 0 \tag{A4}$$

where the inequalities follow from $M \geq N \geq 1$, $0 < \theta < 1$, $0 < \eta < 1$, $p > 0$, and $x > 0$. The inequalities imply that $|H| > 0$ in equation (14).

In equation (7), the stated derivative is:

$$\frac{\partial \pi}{\partial M} = p_z\, f\, x + \left(\frac{d\pi}{dx}\right)\left(\frac{dx^*}{dM}\right) = \left(\frac{p_z f x}{N(1 - \eta\theta)}\right) \{N(1 - \theta) + \theta(1 - \eta)\} < 0 \tag{A5}$$

where the second equality substitutes for $dx^*/dM = -H_{xM}/H_{xx}$, and the inequality follows from $p_z = G'' f' < 0$, $0 < \theta < 1$, and $0 < \eta < 1$.

Figure 1. Trends in New Product Introductions (NPI) in Food Industries

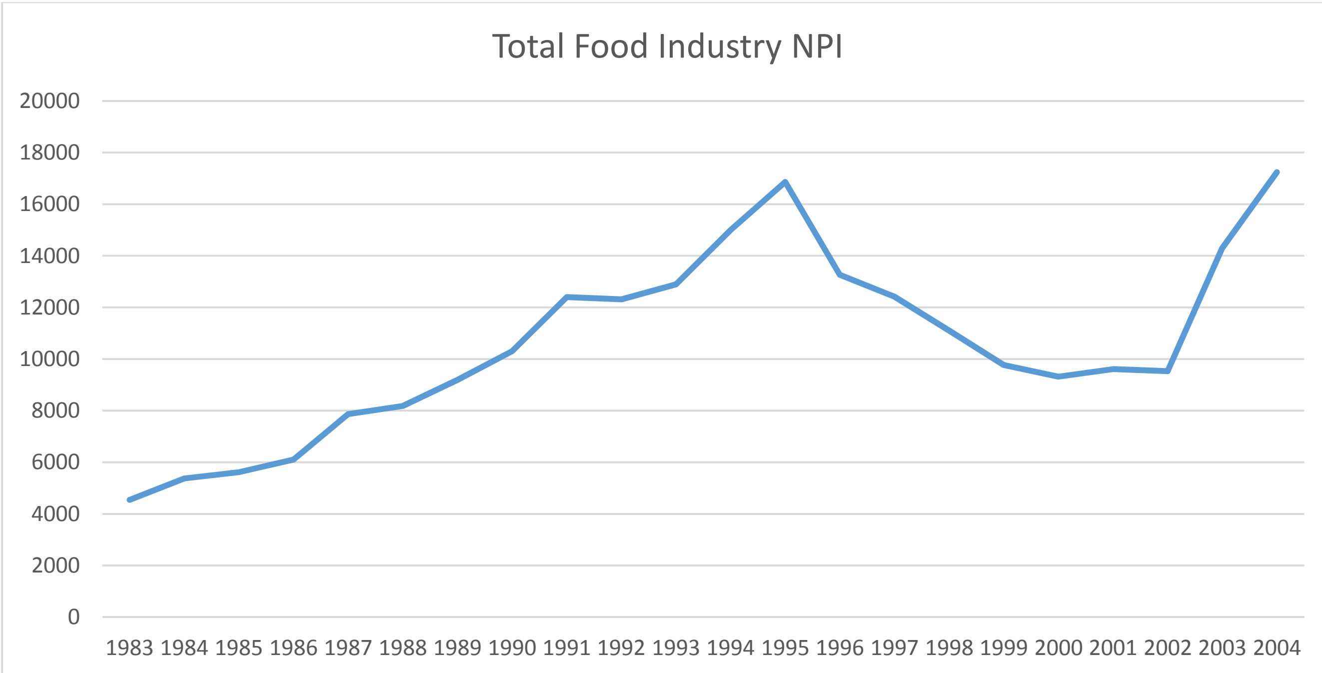

Figure 2.   Trends in Food Industry Concentration

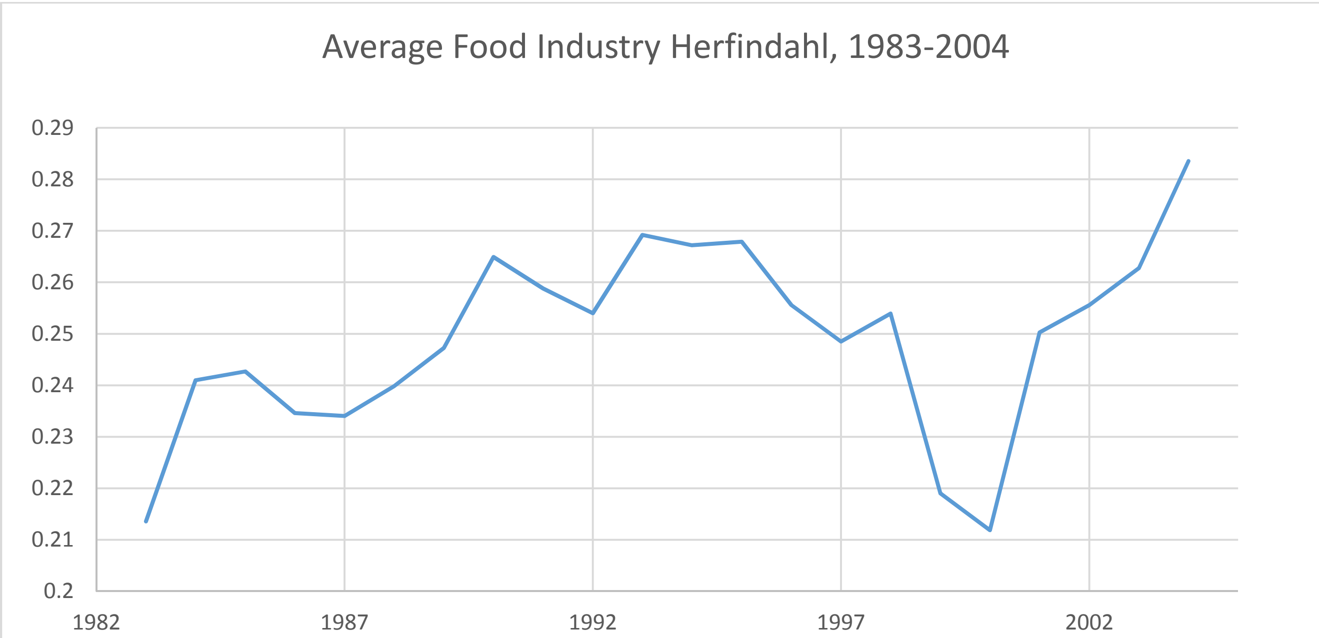

Figure 3. NPI and Food Industry Mergers, 1991-2004

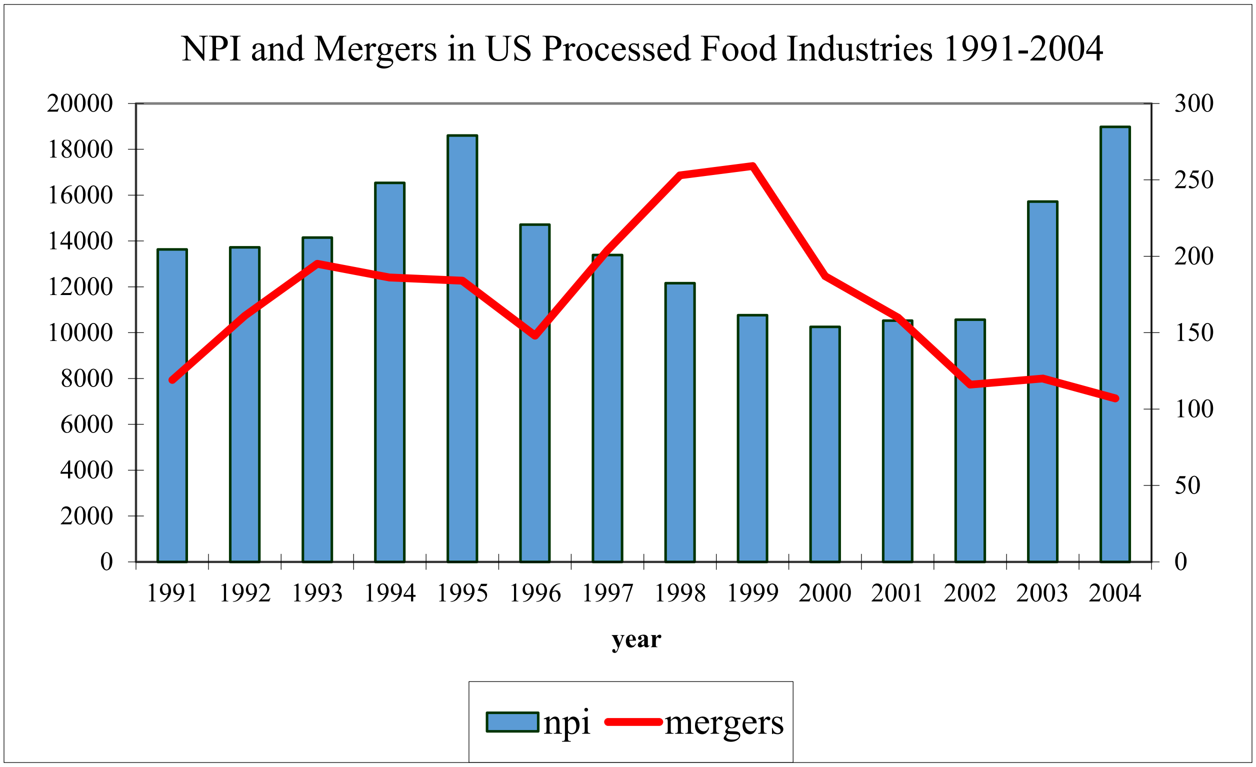

Table 1. Description of New Product Introductions (NPI) Categories

NPI Category	Description	SIC Codes
1	Processed Meat, Fish, Egg	2013[a], 2015, 2091, 2092
2	Dairy Products	2020-2023, 2026
3	Desserts and Ice cream	2024
4	Fruits and Vegetable Products, Condiments	2030, 2033-2035, 2037, 2070
5	Breakfast Cereals, Pet food	2043, 2047, 2048
6	Bakery Food	2050
7	Sugar, Confectionary, Snacks	2041[a], 2045[a], 2061-2064, 2066-2068
8	Beverages	2080
9	Meals, Side dishes	2090

[a] Included 1983-1996.

Table 2. Description of Variables

Variable name	Description	Data Source
NPI	Number of New Product Introductions	Food Institute Report
HI	Herfindahl Index (x 1000)	Compustat
CI4	Four Firm Herfindahl Index (x 1000)	Compustat
N	Total Number of Firms	Compustat
SALES	Sales ($100 million)	Compustat
SGR	Sales Growth Rate	Compustat
R&D	R&D Expenditure (percent of Sales)	Compustat
CAPINV	Average of Gross & Net Capital Investment (percent of Sales)	Compustat
CAPSTOCK	Net Plant, Property and Equipment (percent of Sales)	Compustat
MERGERS	Number of Processed Food Mergers	Mergerstat
USMERGERS	Number of Mergers in the USA	Mergerstat
FEXP	Food Expenditure (% of Disposable Income)	USDA
FAFH	Food Away From Home (% of Food Spending)	USDA
INTRT	Real 10-Year T-Bond Yield to Maturity (%)	treasury.gov & BLS
GDPGR	Real GDP Growth Rate (%)	BEA

Notes: All variables are panel (by industry, by year) except the time series variables USMERGERS, FEXP, FAFH, INTRT and GDPGR. BLS = U.S. Bureau of Labor Statistics, BEA = Bureau of Economic Analysis.

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	248.91	119.95	71.88	519.48
CI4	198	238.47	127.66	27.38	517.73
N	198	18.9	11.7	5	65
SALES	198	382.81	328.21	32.66	1951.50
SGR	198	5.63	18.91	47.75	150.64
R&D	198	0.67	0.43	0	1.776
CAPINV	189	1.32	0.67	-39.56	26.99
CAPSTOCK	198	26.84	7.11	8.39	38.82
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
INTRT	198	4.41	1.92	1.16	10.25
GDPGR	198	2.91	1.66	-0.88	6.91

Table 4. New Product Introductions (NPI) Regressions

	(1) OLS	(2) FIXED EFFECTS	(3) GMM-IV	(4) GMM-IV	(5) GMM-IV
HI	-2.87*	1.45*	8.48***	7.80***	7.73***
	(1.62)	(0.81)	(2.46)	(2.41)	(2.91)
SALES	-1.76*	0.33	0.52	0.58	1.26*
	(0.89)	(0.26)	(0.38)	(0.38)	(0.66)
SGR	0.15	0.50	1.22	1.19	1.26
	(2.23)	(1.18)	(2.40)	(2.22)	(1.88)
N	51.16*	9.39	25.49**	18.60*	25.71
	(26.73)	(8.14)	(10.84)	(11.12)	(18.21)
R&D	-234.48	570.11***	1,148.37***	1,051.90***	827.01***
	(253.26)	(157.20)	(286.27)	(278.14)	(181.74)
CAPINV	6.94	-14.02	-44.44**	-41.93**	-36.34
	(22.51)	(9.18)	(22.32)	(21.34)	(24.13)
R&D* CAPINV	6.80	17.32	42.88**	40.14**	32.74
	(19.12)	(9.58)	(20.07)	(19.30)	(21.72)
FEXP	1,256.69**	968.31**	504.34	480.62	499.56
	(475.37)	(415.13)	(367.16)	(347.48)	(317.06)
FAFH	351.25***	195.33***	80.75	107.99	147.91*
	(111.94)	(63.49)	(104.55)	(102.63)	(85.72)
INTRT	-6.58	-35.97***	-44.78	-35.59	-27.19
	(23.33)	(9.98)	(39.51)	(37.97)	(33.94)
GDPGR	-56.90***	-11.04	20.97	35.13	19.81
	(20.94)	(18.79)	(26.49)	(26.01)	(25.84)
Industry Fixed Effects	No	Yes	Yes	Yes	Yes
Time Effects:					
t	Yes	Yes	Yes	Yes	N/A
t^2	No	No	No	Yes	Yes
Industry trends	No	No	No	No	Yes
R^2	0.35	0.80	0.68	0.70	0.74
Hausman statistic			32.65***	26.67***	20.02***

Notes: Dependent Variable = NPI. Number of Obs = 189. Number of NPI Categories = 9. Robust standard errors in parentheses, clustered by industry. *** p<0.01, ** p<0.05, * p<0.1 (two sided). The Hausman statistic is distributed $\chi^2(1)$ under the null that concentration (HI) is exogenous.

Table 5. First Stage Results for HI Regressions

	(3) GMM-IV	(4) GMM-IV	(5) GMM-IV
Instrument: USMERGERS/CAPSTOCK	-0.31*** (0.07)	-0.30*** (0.08)	-0.28*** (0.08)
1st stage F statistic	[18.20]***	[15.58]***	[13.20]***
SALES	-0.33 (0.35)	-0.31 (0.35)	-1.14** (0.55)
SGR	-0.05 (0.29)	-0.05 (0.29)	0.16 (0.24)
N	-3.50*** (1.12)	-3.63*** (1.08)	-3.41** (1.41)
R&D	-110.43*** (24.74)	-111.04*** (24.66)	-55.09*** (21.13)
CAPINV	4.29* (2.22)	4.28* (2.22)	3.75 (2.54)
R&D* CAPINV	-3.71* (2.05)	-3.71* (2.05)	-3.37 (2.37)
FEXP	63.39** (28.65)	61.51** (29.42)	56.33** (27.23)
FAFH	0.67 (9.62)	1.43 (9.71)	-1.20 (8.91)
INTRT	0.08 (3.36)	0.34 (3.42)	0.02 (2.99)
GDPGR	3.76 (2.95)	4.09 (2.85)	5.34** (2.58)

Notes: Dependent Variable = HI. Number of Obs = 189; robust standard errors in parentheses, clustered by industry. Models (3)-(5) correspond to the same models in Table 4. CAPSTOCK = average net property, plant and equipment for 1983-84 (industry-level).
*** p<0.01, ** p<0.05, * p<0.1.

Table 6A. NPI Regressions with Alternative Measure of Concentration

	(1) OLS	(2) FE	(3) GMM-IV	(4) GMM-IV	(5) GMM-IV
CI4	-2.60 (1.58)	1.40 (0.76)	7.72*** (2.16)	7.10*** (2.11)	7.47*** (2.81)
First Stage Instrument			-0.34*** (0.08)	-0.33*** (0.08)	-0.29*** (0.08)
[F Stat]			[19.35]***	[16.67]***	[12.95]***

Notes: Models (1)-(5) are identical to Models (1)-(5) in Table 4 except CI4 replaces HI. Robust standard errors in parentheses, clustered by industry. *** p<0.01, ** p<0.05, * p<0.1.

Table 6B. NPI Regressions with Alternative Instruments for Concentration

Alternative Instrument 1: USMERGERS^2/CAPSTOCK

	(3)	(4)	(5)	(3)	(4)	(5)
HI	8.01***	7.24***	6.69***			
	(2.33)	(2.22)	(2.47)			
CI4				7.30***	6.59***	6.44***
				(2.06)	(1.95)	(2.39)
1st Stage Instrument F Stat	[19.07]***	[16.46]***	[14.47]***	[20.03]***	[17.37]***	[14.06]***

Alternative Instrument 2: USMERGERS*CAPSTOCK

	(3)	(4)	(5)	(3)	(4)	(5)
HI	9.73**	9.17**	10.39***			
	(3.79)	(3.86)	(3.66)			
CI4				8.84***	8.33**	9.33***
				(3.42)	(3.48)	(3.18)
1st Stage Instrument F Stat	[8.41]***	[6.82]***	[9.36]***	[8.39]***	[6.86]***	[10.21]***

Notes: Models (3)-(5) correspond with Models (3)-(5) in Tables 4 (for HI) and 6A (for CI4), using the indica
alternative instrument for concentration. Robust standard errors in parentheses, clustered by industry.
Alternative instrument 2 is constructed using the panel CAPSTOCK variable.
*** p<0.01, ** p<0.05, * p<0.1.

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 (in 100's)	76	16.44	7.37	4.53	36.19
SGR	76	-0.15	19.87	-91.38	46.25
N	76	23.47	15.33	8	65
R&D	76	0.54	0.36	0	1.17

Table 9. Estimation of the Food Industry Mergers Equation [a]

	Random Effects					Fixed Effects
	Linear				Poisson [b]	Neg. Bin. [b]
	(1)	(2)	(3)	(4)	(5)	(6)
NPI-lag	0.43***	0.31**	0.31*	0.25*	0.22**	0.25*
	(2.74)	(2.02)	(1.78)	(1.81)	(2.00)	(1.73)
N-lag	--	0.27***	0.30***	0.23***	0.26***	0.35***
		(2.82)	(2.79)	(2.77)	(3.28)	(2.91)
SGR-lag	--	--	--	0.18***	0.24***	0.19***
				(2.88)	(4.65)	(2.84)
R&D-lag	--	--	2.55	--	--	--
			(0.54)			
Time Trend	0.03	-0.08	-0.13	0.04	0.09	-0.10
	(0.14)	(-0.45)	(-0.69)	(0.23)	(0.65)	(-0.58)

[a] Dependent Variable = MERGERS. 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.

[b] Marginal effects at means.