Post-Merger Product Repositioning: An Empirical Analysis

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Abstract

We examine merging firms' additions and removals of products for a sample of 66 mergers across a wide variety of consumer packaged goods markets. We find that mergers lead to a net reduction in the number of products offered by the merging firms. Merging firms tend to both drop and add products at the periphery of their joint product portfolios, with the net effect of increasing within-firm product similarity. These results are consistent with theories of the firm that emphasize cost synergies among similar types products or managerial core competencies linked to particular segments of the product market.

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1 Introduction

A central tenet of industrial organization theory and antitrust policy is that mergers lead firms — both merging firms and their rivals — to charge higher prices. Such price effects have been affirmed in a wide variety of contexts (Kim and Singal, 1993; Prager and Hannan, 1998; Nevo, 2000; Town, 2001; Vita and Sacher, 2001; and Blonigen and Pierce, 2016 to name a few examples), and concerns about prices form the basis for the antitrust authorities' horizontal merger guidelines. However, prices are but one channel through which mergers affect consumer welfare; mergers also typically result in a substantial reshuffling of the products offered in the market. How this reshuffling occurs is a vital open question in assessing the welfare consequences of mergers and in the development and enforcement of antitrust policy. This paper's aim is to describe patterns in these changes to merging firms' product portfolios.

We focus on measuring the extent to which merging firms reduce the number of products they offer, and whether the added and dropped products tend to be similar or dissimilar to the products in their existing portfolios.[1] These are both open empirical questions, since firms face competing incentives when making these decisions. On the one hand, merging firms may decide to close competing business lines or to discontinue competing products so as to reduce costly duplication and product market cannibalization. On the other hand, to the extent that the target and acquiring firms have "core competencies" over the sets of products they are able to produce and distribute, or there are cost synergies among products that are similar to one another, post-merger restructuring may involve the merged firms discontinuing products that are far from the center of their product portfolios, thus leading to a narrower range of products to which consumers have access. Whether consumers have access to a narrower or wider range of products has potentially important implications for consumer welfare and antitrust policy. Reduction in the diversity of products may reduce consumer surplus, beyond the higher prices and fewer products offered that the previous literature has generally focused on.

Our main analysis combines the Securities Data Company (SDC) database of mergers and acquisitions with two datasets provided by Nielsen: the Retail Scanner dataset and the Consumer Panel dataset. The Nielsen Retail Scanner dataset contains information about each universal product code (UPC) sold by each brand in each quarter between 2006 and 2019. A key component of our analysis is the dissimilarity ("distance") between any two products in our dataset. We develop a procedure for measuring dissimilarity that scales to tens of thousands of products. We consider two alternative approaches: one that relies on

[1] Throughout, with an abuse of terminology, we use "mergers" to refer to both mergers and acquisitions.

abbreviated product descriptions contained in the Retail Scanner dataset, and another that relies on purchase patterns in the Consumer Panel dataset. In the first approach, products are defined to be close to one another if they have a high fraction of overlapping text in their product descriptions. In the second approach, the proximity between two products is measured by how commonly they are purchased by the same household — i.e., if households that sometimes purchase product A are also likely to sometimes purchase product B, then A and B will be considered close to one another.

Our sample contains 66 conglomerate mergers, across a wide variety of consumer packaged goods markets. From this sample of mergers, using an event study empirical methodology, we consider how the number of products and within-firm product distances change in the quarters preceding and subsequent to each merger. We find that mergers are associated with significant net reductions in the number of offered products, but only with a lag. The number of products offered begins to decline two quarters after the merger and these declines accelerate, so that by four years after the merger the number of products offered by the merging firm is 40 percent lower. After this, the number of products is constant for at least the subsequent two years. We further demonstrate that net changes are negative for both for products originally sold by the target firm and those sold by the acquiring firm, but with larger effects for products related to the target. We do not find any change in the number of products offered by the merging firms in the quarters preceding the merger.

We then turn to the question of *which* products tend to be added and dropped subsequent to a merger. We find that products that are far away from the merged firm's product portfolio are substantially more likely to be dropped as well as added. In assessing whether, on net, within-firm product distances increase following M&As, the addition of faraway products countervails the removal of faraway products. On balance, we find that merged firm's products increasingly become close to one another, when using product descriptions: After an M&A, within-firm product dissimilarity declines by 0.13 standard deviations when merger-product market pairs are weighted equally and 0.08 standard deviations when merger-product market pairs are weighted according to the number of products involved. When using household purchasing patterns to compute distances across pairs of products, we find similar patterns, but our coefficient estimates are not statistically different from zero. As with our analysis on the number of products offered, we do not find any changes in within-firm distances before mergers take place. Moreover, changes in product variety only begin to manifest eight to ten quarters after the merger has taken place, with accelerating effects thereafter.

Our analysis builds on three literatures. While the IO literature has long sought to quantify the unilateral price effects of mergers, a more recent strand has considered how mergers affect the products offered by firms. Without distinguishing between products at the "center" or "periphery" of firms' product portfolios, Götz and Gugler (2006) and Ashenfelter, Hosken and Weinberg (2013) argue – in the context of gasoline and home appliance markets, respectively – that mergers lead to fewer distinct products offered in the market. Holding fixed the number of products offered, Gandhi et al. (2008) theoretically consider post-merger product repositioning. They show that such repositioning can mitigate the anti-competitve effects of a merger, implying that analyses of mergers that focus only on the effect of price or the number of products in the market may be overstating mergers' harm to consumers.[2] Berry and Waldfogel (2001) illustrates that, when one considers the fixed cost of product introductions, the effect of a merger on product variety becomes theoretically ambiguous, necessitating empirical analysis.

A growing body of empirical work has considered the effect of endogenous product positioning on the unilateral effects of mergers.[3] Examples include Draganska, Mazzeo and Seim (2009), Fan (2013), and Mao (2018), which demonstrate empirically — in the respective contexts of premium ice cream, newspapers, and shampoo — that prospective merger analysis can be misleading if it ignores product repositioning. As the aim of this literature is to measure the effect of a specific merger on welfare, these papers restrict attention to a single product market and necessarily make assumptions concerning the models of demand and supply. Our descriptive approach complements this body of work by describing patterns of firms' post-merger product repositioning, using data from a large set of mergers across many consumer packaged goods markets. Thus, it is similar in spirit to Sweeting (2010) and Berry and Waldfogel (2001), which find that across mergers in the radio industry, merging stations modify their formats and playlists to reduce within-firm audience cannibalization.

Second, a parallel literature, largely within management and finance, emphasizes that asset synergies, both during and subsequent to mergers, shape firms' decisions about when and with whom to merge, and about which lines of business to add and drop following the merger. Hoberg and Phillips (2010) parse the text from firms' annual filings to the Securities and Exchange Commission to characterize the lines of business in which firms operate. They document that pairs of firms with overlapping business lines are more likely to merge and, conditional on merging, experience faster sales and profitability growth. Maksimovic, Phillips and Prabhala (2011) use data from the Census Longitudinal Business Database, documenting

[2]See also Mazzeo, Seim and Varela (2018), who additionally consider cost synergies in their analysis of post-merger product repositioning for hypothetical mergers among ice cream manufacturers.

[3]Variety may further be impacted if the merger results in coordinated effects. Sullivan (2020*a*,*b*) documents that firms may coordinate their product choices in a horizontally differentiated product market, resulting in reduced cannibalization and greater product variety. Bourreau, Sun and Verboven (2021) find that firms may collude to restrict the availability of vertically differentiated offerings. See Porter (2020) for a discussion of the literature on coordinated effects.

that a sizable fraction of target firms' plants are either spun off or shut down in the first three years after being acquired; see also Li (2013). Target firm plants that are kept tend to be in the acquiring firms' main industries of production. Chan, Irlacher and Koch (2022) explore mergers of multiproduct firms using Danish registrar data, finding that merged firms reduce the overall number of products offered in order to reallocate assets to their core varieties. These analyses focus on the broad product lines that target and acquired firms produce before and after merging. Our contribution, relative to this literature, is to establish that firms' product portfolios condense as a result of merger and acquisition (M&A) activity, even within product lines.

Finally, this paper contributes to a long macroeconomic literature emphasizing the reallocation of inputs across firms (see Van Reenen, 2018 for a review). Even within industries, firms differ markedly in their productivity (Syverson, 2004, 2011), labor shares (Autor et al., 2020; Kehrig and Vincent, 2020), and organizational practices (Bloom et al., 2012, 2019). The re-allocation of inputs across firms is of central importance in explaining the decline in the aggregate labor share, increases in price-marginal cost markups, and expanding wage inequality (Song et al., 2019; De Loecker, Eeckhout and Unger, 2020). Our paper suggests a primary channel through which this reallocation of inputs occurs — namely in the reshuffling of product lines during and after mergers and acquisitions.

2 Data Sources and Definitions

Our dataset has two main components: (1) the Nielsen Retail Scanner database, consisting of data on individual products and their weekly sales from 2006 to 2019, and (2) the SDC Platinum Mergers and Acquisitions database, a list of mergers and acquisitions between 1979 and 2018. We supplement these datasets with a mapping we have compiled between brands and their parent firms, drawing both on the GS1 Database and on manual searches of changes in brands' ownership. These three pieces of information, in combination, allow us to measure how firms' product portfolios evolve following each merger. In what follows we explain these datasets in more detail, and then explain how we use the Nielsen data to measure product similarity.

2.1 The Product Data

The Nielsen Retail Scanner Dataset, obtained from the Kilts Center for Marketing at the University of Chicago Booth School of Business, contains detailed information on products sold in a wide variety of retail chains from 2006-2019. This database draws on more than

35,000 participating grocery, drug, mass merchandiser, and other stores. It covers more than half of the total sales volume of U.S. grocery and drug stores, and more than 30 percent of all U.S. mass merchandiser sales volume.[4]

For each UPC, we obtain a description of the product along with information on the product's brand, size, and weekly sales from the Nielsen database for the years 2006-2019.[5] We use the sales data primarily to determine when new products are added or existing products are dropped. If an existing UPC disappears from the data or stops having positive sales, we infer that the product has been dropped.[6]

In addition to information on sales of individual UPCs, Nielsen categorizes products into a set of product modules, groups, and departments. Each of these are sets of products, at increasing levels of aggregation, that are relatively similar to one another. We focus on products from four Nielsen departments: dry grocery, frozen foods, dairy, and alcoholic beverages. In our analysis, we define a product market as a distinct product module. In the four departments of our sample, there are 604 product modules with data in the Retail Scanner dataset. Among these product modules, we omit six which contain too few branded UPCs to meaningfully analyze within-firm product distances.[7] To provide a sense of the scope of the typical product module, broader examples include "Ready-to-Eat Cereal" and "Diet Soda", while more narrow examples include "Capers", "Matzo Meal / Mixes", "Breading Products", and "Croutons". We use Nielsen's module codes to determine when a merger involves firms in overlapping product markets. In many mergers, the merging firms' product portfolios are at least partially in separate markets. Since we are interested in the product portfolio decisions made after a horizontal merger — i.e., a union of firms that previously competed against each other in at least one product market—we consider mergers in which there was at least some overlap in the merging firms' product module codes prior to the merger. Our main analysis will be on the merger-module pairs for which the merging firms both sold products in the quarter prior to the M&A.[8]

[4]These figures on the scope of the Nielsen Retail Scanner Dataset are from https://www.chicagobooth.edu/research/kilts/datasets/nielsenIQ-nielsen. Accessed August 25, 2022.

[5]Similar to our paper, Argente et al. (2020) apply information from the Nielsen Retail Scanner dataset to measure the evolution of firms' product portfolios. Their aim is to link firm patenting activity, from the U.S. Patent and Trademark Office, to the introduction of "novel" products. Product novelty is computed not from the text UPC product description and size measures, as in our main measurements, but from a separate Nielsen file of product attributes.

[6]For additional details on our sample of Nielsen products and how we clean and process these data, see Appendix A.1.

[7]The six product modules we drop are "Salad-Jellied", "Retort-Pouch Bags", "Prepared Sandwich-Shelf Stable", "Frozen Vegetables-In Pastry", "Fountain Beverage", and "Meal Kit". In these six modules, nearly all products correspond to private label brands. For these products we cannot observe the actual brand or the ultimate manufacturer.

[8]Of the 66 mergers that will form our baseline sample, there were 361 merger-product module pairs where

2.2 The SDC Merger Data

We use the Securities Data Company (SDC) Platinum Mergers and Acquisitions database for merger-and-acquisition (M&A)-level information. The database covers corporate transactions, both public and private. For each merger, the dataset describes the announced and effective date of the transaction as well as the names of the companies involved and the SIC industries in which the firms operate. Throughout the paper, we apply SDC's labeling of the firms which acquire and sell assets as the "acquirer" and the "target," respectively. We include only mergers or acquisitions announced between January 1, 2000 and March 29, 2019 and executed between January 1, 2006 and March 29, 2019. From this list of SDC mergers, we restrict attentions to mergers and acquisitions in which both the target and acquirer operate in a food-and-beverage related industry.[9] We further include only M&As in which the acquiring firm acquires a 100 percent stake of the target firm (or a subset of the target firm's lines of business.)[10,11]

2.3 The Company Prefix Data

While Nielsen reports the brand of the product (e.g., Sprite), it does not indicate which parent company manufactures that brand (e.g., Coca-Cola). In order to merge the Nielsen product data with the SDC transaction data, we need to know the parent company that produces each product at each point in time in our sample. Each product is uniquely identified by a UPC code; the first six digits of each UPC (the "company prefix") is associated with an individual manufacturer.[12] We use the GS1 database to get the name of manufacturer

both firms were selling products prior to the merger. In addition, among the same 66 mergers but outside of our baseline sample, are 363 merger-product module pairs associated with the target firm but not the acquiring firm and 3,340 merger-product module pairs associated with the acquiring firm but not the target firm.

[9] In terms of 4-digit SIC industries, we require each firm to have its primary SIC within the following list: 0100-0999, 2000-2099, 2830-2849, 5000-5799, or 5900-5999.

[10] An example of the types of acquisitions we would exclude based on this last criterion includes Heineken's purchase of a 50 percent stake of Lagunitas Brewing Company, an acquisition which was announced in September 2015 and executed the following month.

[11] The SDC Platinum database includes not only mergers and full takeovers but also acquisitions of certain lines of business. So long as the acquiring firm purchases a 100 percent stake in these lines of business, we include these acquisitions in our sample. As an example, Flowers Foods acquired Wonder Bread and other bread brands from Hostess in 2013 (Hals and Stempel, 2013). Other Hostess Brands — including Twinkies, Sno Balls, and Hostess CupCakes — were retained. Below, when we analyze the impact of the transaction between Flowers Foods and Hostess, we will restrict our sample to Nielsen modules that correspond to bread products. More generally, for each transaction in our dataset, we focus only on switches in product ownership among products in the dry grocery, frozen foods, dairy, and alcoholic beverages departments.

[12] UPC codes and UPC prefixes are managed by GS1, a not-for-profit organization that develops and maintains global standards for business communication. In principle, manufacturers do not need to purchase their UPC prefixes from GS1. However, purchasing a UPC prefix from GS1 lowers retailers' cost of stocking

for every company prefix in the product data. One complication with the GS1 data is that the owners of company prefixes are sometimes subsidiaries of larger conglomerates, so the prefixes are not always perfect indicators of products' owners.

In Appendix A.2, we discuss our algorithm to consistently identify the name of the target and acquiring firm within each transaction in the SDC data, and changes in the ownership of each product in the Nielsen data. In brief, given the complications of finding the ultimate parent company of each subsidiary and of name matching across the GS1 and SDC datasets, we focus our attention on mergers and acquisitions for which the acquiring firm is a large conglomerate firm.[13] For these transactions, we apply a mix of fuzzy name-matching procedures and manual verification to link each mergers' acquiring and target firm to their associated prefixes. For each of these transactions, we manually search for partial acquisitions (i.e., where only certain lines of business switch ownership).

2.4 Calculation of Distance Measures

A key component of our analysis is the dissimilarity ("distance") between any two products in our dataset. While a human can readily see the similarity of any two products, we cannot rely on direct human judgment — we need a procedure that scales to tens of thousands of products. We consider two alternative approaches: one that relies on abbreviated product descriptions contained in the Nielsen Retail Scanner data, and another that relies on purchase patterns in the Nielsen Consumer Panel.

2.4.1 Distances Based on Product Descriptions

To compute distances based on product descriptions, we begin by representing each product, j, as a vector $\mathbf{v}_j$ summarizing its characteristics. To construct these vector representations, we draw on two components of the Nielsen Retail Scanner data: the UPC description and the product's size.

Nielsen's UPC description is typically a list of abbreviations, describing the brand of the product, certain product characteristics, and (if applicable) the number of units within the package. For instance, the UPC description for a 4-pack of Dannon's nonfat vanilla Greek

the manufacturer's products.

The terms UPC and GTIN (Global Trade Item Number) are sometimes used interchangeably. UPC codes may be 8, 12, 13 or 14 digits long, and each of these four numbering structures are constructed in a similar fashion, combining company prefix, item reference, and a calculated check digit. To make different numbering structures compatible, leading zeros are added to shorter codes.

[13] We search for food-and-beverage-related conglomerate firms from *Food Engineering*'s list of the "Top 100" firms in the industry. See See https://www.foodengineeringmag.com/2018-top-100-food-beverage-companies. Accessed August 25, 2022.

yogurt would be “DN-A NF GK Y V 4P”. Since we want our measures to describe the characteristics of the product, and not mechanically capture information on the manufacturer of each UPC, we excise information about the brand (e.g., removing the DN-A).

Nielsen also records the size of the product sold — a continuous variable, in different units for different product modules (ounces for carbonated soft drinks, counts within packets of gum, and so forth). For each product module, we compute the quartiles of the size distribution and record the quartile to which each product belongs. Continuing with our nonfat vanilla Greek yogurt example, each container of Dannon’s nonfat vanilla Greek yogurt is 5.3 ounces, which falls in the first (smallest) quartile of the size distribution for the refrigerated yogurt module.

For each product, we construct a vector $\mathbf{v}_j$ based on the occurrence (or lack thereof) of the elements within that product’s UPC description and on the product’s size. For our 4-pack of nonfat vanilla Greek yogurt, the elements associated with “NF”, “GK”, “Y”, “V”, “Size∈1st Quartile” will be nonzero. For all other possible word abbreviations, and for the “Size∈2nd Quartile”, “Size∈3rd Quartile”, and “Size∈4th Quartile” categories, the elements of $\mathbf{v}_j$ will be equal to 0. As in other applications of text data, we apply a *term frequency-inverse document frequency* weighting scheme to fill in the nonzero elements of $\mathbf{v}_j$. This scheme assigns greater weight to strings that appear more frequently (this is what “term frequency” refers to) in product j’s UPC description or size categorization, and less weight to strings that appear commonly across all products (this is what “inverse document frequency” refers to). We set these weights separately for each product module, since inverse document frequency varies across modules. Finally, we normalize each product’s vector so that it has magnitude equal to 1.

Given a vector representation for each product, we measure the dissimilarity, $\mathbf{d}_{j,j'}$ between any two products j and j' as the Euclidean distance between their corresponding vectors. Intuitively, two products’ vectors will have a small distance if they share similar characteristics. The distance measure ranges between 0, for two products with complete overlap, and $\sqrt{2}$, for products with no overlapping characteristics.[14]

As an illustrative example, consider Nestlé’s 2010 acquisition of Kraft’s frozen pizza brands. One of the acquirer’s (Nestlé’s) products was Stouffer’s Deluxe French Bread Pizzas, described in the Nielsen data as “STFR CFB DX SAU/PEP/MSH/ON 2’S” with a size of 12.375 ounces. Among the closest products of the target firm (Kraft) is the Tombstone Original Deluxe 13.15-ounce pizza, for which the UPC description is “TMB ORIG DX SAU/PR/ON/MSH”. In comparing these two product descriptions, our algorithm first ex-

[14]The maximum value equals $\sqrt{2}$ as this is the maximum distance between two unit-length vectors whose entries all have positive values.

cises the brand abbreviations (STFR and TMB) and separates terms based on white space and/or punctuation marks of any kind (e.g., the forward slashes in this example). The similarity of these two products is based on the overlapping terms SAU, MSH, and ON (abbreviations for sausage, mushrooms, and onions). The Euclidean distance between the two products' vectors equals 0.977, exceptionally low compared to other pairs of products.[15] By contrast, several of the target firm's products had no overlapping terms. For instance, our measure would say that Stouffer's Deluxe French Bread Pizzas are maximally dissimilar — with a distance equal to $\sqrt{2}$ — to the 23-ounce DiGiorno Thin Crust 4-Cheese Pizza ("DG TN CC 4CH").

2.4.2 Distances Based on Purchase Correlations

As an alternative approach to measuring products' distances we borrow an idea from Atalay et al. (2022), gauging the substitutability of a given pair of products by how commonly the two products are purchased by the same household in the Nielsen Consumer Panel. The underlying premise is that if individuals within each household have stable preferences, then temporary changes in relative prices (e.g., due to periodic sales or stockouts) will induce consumers to purchase substitutes for their preferred product. For instance, if a household sometimes purchases Coke and sometimes purchases Pepsi, but never purchases Sprite, the implication is that Pepsi is a closer substitute to Coke than Sprite for that household. The idea is formalized by computing pairwise product distances as $\mathbf{d}_{j,j'} = 1 - \rho_{j,j'}$, where $\rho_{j,j'}$ is the pairwise purchase correlation between products j and j' — i.e., a measure of how likely a household is to have ever purchased product j' conditional on having ever purchased product j.

Distances based on purchase correlations are generally similar to those based on product descriptions, but there are significant differences between the two approaches. The most important advantage of the measure based on purchase correlations is that it can give meaningful measures even when product descriptions in the Nielsen scanner data are quite sparse. When the product descriptions in the Nielsen data are fairly informative, the two approaches deliver similar distances. For instance, in the frozen pizza example mentioned above, among the products supplied by Kraft before the merger, the closest product to Stouffer's Deluxe based on purchase correlations is DiGiorno's 10 oz. Traditional Crust Supreme (sausage/pepperoni/green pepper/red pepper/onion). Consistent with the high purchase correlation, the two products' descriptions also have exceptionally high levels of

[15] Compare this value to the distances displayed in the top left panel of Figure 1. There, we plot the distribution of distances, aggregating observations to the merger-module pair. Approximately 3 percent of merger-module pairs have average product distances less than 0.977.

overlap with one another.[16] However, in some product modules the Nielsen descriptions contain little information beyond the brand names of the products. For example, in the breakfast cereal category, the description for Cheerios is simply "GM CHR RTE", which when stripped of brand information becomes only "RTE" (for ready-to-eat). Obviously the distance measure based on product descriptions will have little content in such cases, since only the product's size remains as a basis of comparison.

The main drawback of using the measure based on purchase correlations is that not every product appears in the Consumer Panel, since it only contains products that were ever purchased by households in the panel. As a result, our sample sizes shrink considerably if we use this measure. Whereas our benchmark analysis — based on product descriptions on products in modules where both the target and acquiring firm operate — contains information on 66 mergers, 361 merger-module pairs, and 39,466 products, the sample in our analysis of distances based on household purchasing correlations contains 50 mergers, 134 merger-module pairs, and 7,071 products.

2.4.3 Distances at the Firm by Product Module Level

For some of our analyses we need measures that summarize the distances between all of the acquiring and target firms' products. For each M&A, let $\mathcal{P}_{A,m,t}$ refer to the set of products sold by the acquiring firm A in product module m and quarter t, $\mathcal{P}_{T,m,t}$ refer to the analogous set of products for the target firm, and $\mathcal{P}_{i,m,t}$ refer to the union of these two sets. We use $n_{A,m,t}$ and $n_{T,m,t}$ to refer to the cardinality of these sets, and define $n_{i,m,t} \equiv n_{A,m,t} + n_{T,m,t}$. We first define the mean distance among the products associated with an acquisition i as:

$$\bar{\mathbf{D}}_{i,m,t} = \frac{1}{n_{i,m,t}} \cdot \sum_{j,j' \in \mathcal{P}_{i,m,t}} \mathbf{d}_{j,j'} \ . \tag{1}$$

In other words, for each quarter we take the products sold by the parties to the transaction, then compute the average distance among all of the pairs of products sold by either firm (or by the combined firm, when looking in quarters after the acquisition). We apply this equation both when using product descriptions or when using household purchase correlations to compute $\mathbf{d}_{j,j'}$. Thus, we have two separate measures of $\bar{\mathbf{D}}_{i,m,t}$.

We will also, below, compute distances that focus only on the set of products associated

[16] The product description-based Euclidean distance between Stouffer's Deluxe French Bread Pizza and DiGiorno's 10 oz. Traditional Crust Supreme equals 1.291. While considerably greater than the product-description-based distance between Stouffer's Deluxe French Bread and Tombstone Original Deluxe, this distance is still considerably below the average distance in our dataset.

with either the acquiring or target firm:

$$\bar{\mathbf{D}}_{A,m,t} = \frac{1}{n_{A,m,t}} \cdot \sum_{j,j' \in \mathcal{P}_{A,m,t}} \mathbf{d}_{j,j'} \text{ and} \tag{2}$$

$$\bar{\mathbf{D}}_{T,m,t} = \frac{1}{n_{T,m,t}} \cdot \sum_{j,j' \in \mathcal{P}_{T,m,t}} \mathbf{d}_{j,j'} \ . \tag{3}$$

Finally, we define $\mathbf{D}^{q}_{i,m,t}$ as the q^{th} quantile of distances among the products in $\mathcal{P}_{i,m,t}$. As we will see below, most pairs of products have little overlap in their characteristics and low purchase correlations in the Nielsen Consumer Panel. Consequently, the distribution of $\mathbf{d}_{j,j'}$ has significant mass near its maximum value ($\sqrt{2}$ for the measure based on product descriptions, 1 for the measure based on purchase correlations). For this reason, it will be useful to consider quantiles that accentuate whatever variation exists among similar products, in the left tail of the $\mathbf{d}_{j,j'}$ distribution.

3 Results

This section contains the main empirical results of our paper. We first provide descriptive statistics on our sample of mergers and acquisitions (Section 3.1). Next, we apply an event study regression to analyze the impact of M&As on the number (Section 3.2) and similarity (Section 3.3) of the merging firms' products. In Section 3.4 we relate individual products' likelihood of being dropped or added to their similarity to other products in their parent firms' portfolios. Finally, in Section 3.5 we discuss the potential theoretical mechanisms consistent with the empirical patterns uncovered in Sections 3.1 to 3.4.

3.1 Summary Statistics

Our sample consists of 66 mergers for which the target and acquirer had products in at least one overlapping product module prior to the merger. In many cases the merging firms had products in multiple overlapping product modules, so our sample includes 361 merger-module pairs.

Table 1 presents summary statistics for the 66 mergers in our sample. The first panel describes the number of product modules of the merging firms. In the quarter before the M&A, the merging firms operated in 62 product modules on average, though with considerable dispersion and some skewness within this distribution. The firm that SDC labels as the acquiring firm operated in five to six times as many product modules as the target firm.

The second panel zooms in on the set of product modules in which both the acquiring and target firm operated in the quarter before the M&A. The average merger involved 5.5 overlapping product modules, with 229 products and $40 million sold by either the target or the acquiring firm. Among the 229 products involved, on average 188 were sold by the acquiring firm and 49 were sold by the target firm.

Table 1: Summary Statistics

	Percentile						
	10	25	50	75	90	Mean	SD
Panel A: Before the Merger							
Modules	8	19	46	100	131	61.57	53.12
Modules of the Acquirer	7	17	40	95	131	56.08	50.14
Modules of the Target	2	3	6	10	23	10.97	19.39
Panel B: Before the Merger, Overlapping Modules							
Modules	1	2	4	7	13	5.47	5.46
Units Sold (millions)	0.22	1.63	19.14	48.48	90.86	39.86	77.16
Products	6	31	175	301	536	229.05	261.40
Products of the Acquirer	2	15	146	241	400	188.20	232.23
Products of the Target	0	6	18	44	91	40.85	67.32
Panel C: Change in the Log Number of UPCs, Overlapping Modules							
Unweighted	-3.87	-0.29	-0.08	0.01	0.14	-0.87	1.90
Weighted by Products	-7.10	-0.39	-0.03	0.01	0.13	-1.63	2.90
Weighted by Sales	-5.51	-0.07	-0.01	0.01	0.13	-0.79	2.12

Notes: The first and second panels present summary statistics for the merger sizes for the 66 transactions in our sample. The first panel presents information for all product modules, while the second panel focuses on the product modules for which both the target and acquiring firm have a presence within the sample period. These summary statistics pertain to the quarter directly before the merger. The final panel presents growth rates in the number of UPCs, comparing 10 quarters after the transaction to the quarter before the transaction. The sample includes the 53 mergers for which this 10-quarter-ahead growth can be computed. Here, we apply three different weighting schemes: applying the same weight across transactions, weighting by the number of products sold by the two firms in the period before the acquisition in the product modules in our sample, or weighting by the total number of units sold by the two firms in the period before the acquisition in the modules in our sample.

The third panel of Table 1 describes the distribution of the growth in the number of UPCs, comparing 10 quarters after the merger relative to the quarter before.[17] Here, we apply three

[17] In this panel, using $n_{i,t}$ to refer to the number of UPCs sold in quarter t by the firms involved in M&A i, we use $\frac{\log(1+n_{i,t+10})}{\log(1+n_{i,t-1})}$ to refer to the change in the log number of UPCs. The "1+" term is necessary, as $n_{i,t+10} = 0$ for certain merger-module pairs.

separate weighting schemes. We weight mergers equally, according to the number of products involved in the quarter before the acquisition, or according to the total units sold among in the period before the acquisition. The table indicates, for the median merger, an 8 log point decline in the number of UPCs after a merger if no weighting is applied, a 3 log point decline if mergers are weighted by units sold, or a 1 log point decline if mergers are weighted by the number of products sold. However, the distribution in the change in the number of products is both skewed heavily to the left and highly dispersed.[18]

Table 2: Summary Statistics for Merger-Module Pairs

	Percentile						
	10	25	50	75	90	Mean	SD
Panel A: Before the Merger							
Products	1	3	13	46	113	41.87	80.65
Units Sold (millions)	0.00	0.07	0.65	3.86	18.38	7.29	21.18
Products of the Acquirer	0	2	8	39	98	34.41	72.22
Products of the Target	0	0	1	6	17	7.47	21.80
Panel B: Change in the Log Number of UPCs							
Unweighted	-3.00	-0.58	0.00	0.11	0.41	-0.54	1.42
Weighted by Products	-6.20	-1.50	-0.08	0.01	0.20	-1.30	2.31
Weighted by Sales	-3.40	-0.12	-0.04	0.03	0.15	-0.60	1.61

Notes: The first panel presents summary statistics for the sizes of acquisition-product module pairs, for the 361 pairs in our sample, using data in the quarter before the merger. The second panel presents growth rates in the number of UPCs for each merger-product module pair, comparing 10 quarters after the transaction to the quarter before the transaction. The sample includes the 278 merger-product module pairs for which this 10-quarter-ahead growth can be computed. Here, we apply three different weighting schemes: applying the same weight across transaction-product module pairs, weighting by the number of products sold by the two firms in the period before the acquisition in the relevant product module, or weighting by the number of units sold by of the two firms in the period before the acquisition.

Table 2 provides summary statistics for the 361 merger-module pairs in our sample. In the quarter before the merger, the two firms produced 42 products within the average product module in our sample, with 34 products associated with the acquiring firm and 7 with the

[18] Although the data indicate a net reduction in the number of products offered by the merged firm, there is slightly less churn in the overlapping modules than the non-overlapping ones. Acquirer products that existed prior to the merger in overlapping modules had a 71 percent survival rate after 10 quarters, compared to 67 percent for products in non-overlapping modules. The analogous numbers for target products are 75 percent and 63 percent. Among the products present 10 quarters after the merger, the fraction that is new — i.e., added between the quarter before and 10 quarters after the merger — is similar in overlapping and non-overlapping modules: 31 percent versus 33 percent.

target firm. As in Table 1, the distribution of acquisition sizes is skewed. Also as in Table 1, acquisitions involve a net reduction in the number of products when merger-module pairs are weighted according to their size.

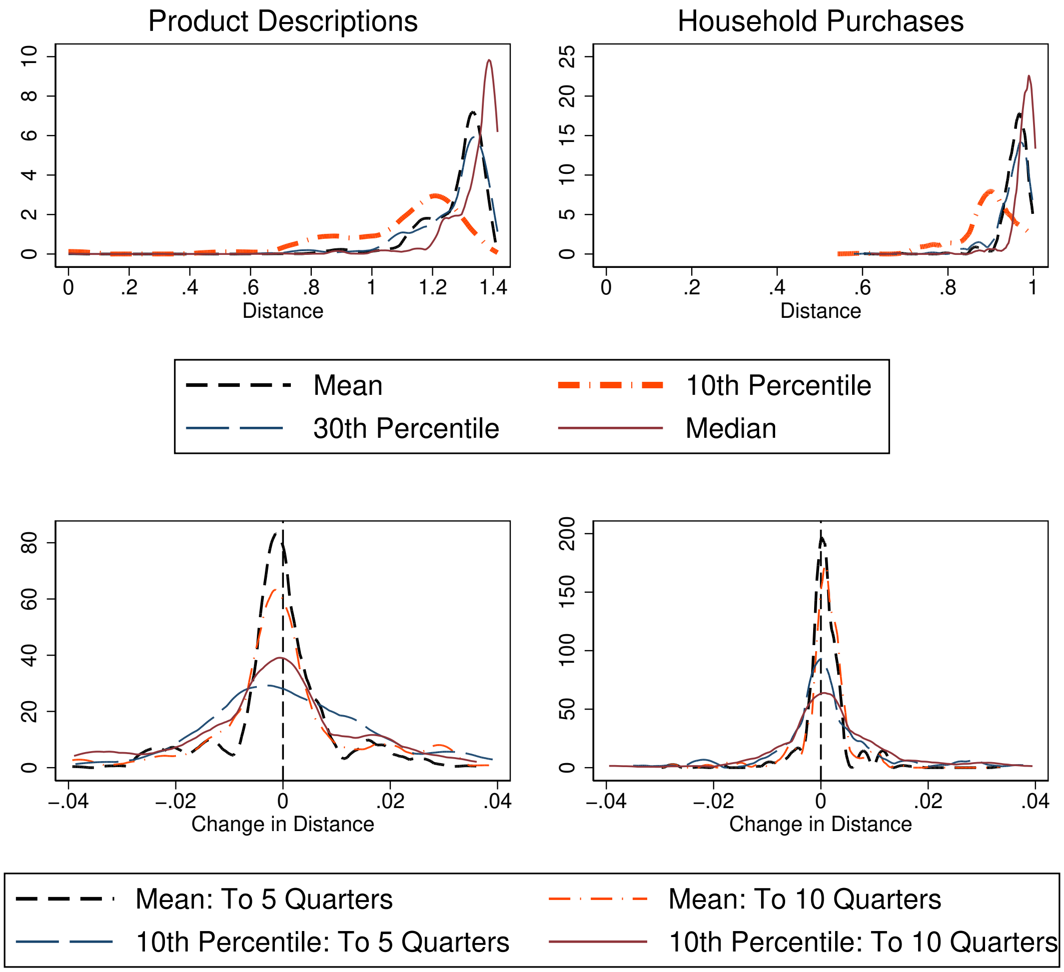
Figure 1 shows distributions of within-firm distances in the quarter before the merger (top panels) and changes in within-firm distances after the merger (bottom panels). To create this figure, we compute various distributional statistics for all product pairs associated with an acquisition:[19] the mean, 10th percentile, 30th percentile, and 50th percentile distances. The top panel of Figure 1 plots the distribution of these statistics, looking across all pairs of acquisitions and product modules. In the top left panel, we use the text of product descriptions to compute distances across pairs of products. For most pairs of products, there is little to no overlap in their product characteristics, yielding a distance equal to $\sqrt{2}$. Given this, the mean or median distance, among the set of products for each acquisition-product module pair, is also close to $\sqrt{2}$ in most cases. Because of this, it may be more instructive to look at lower quantiles, which exhibit more variation across acquisition-product module pairs. The top right panel shows analogous distributions using the distance measure based on purchase correlations. For most pairs of products, correlations are close to zero (and, as a result, our distance measure is close to one): whether a household tends to purchase product i has little predictive power in determining whether that household purchases product i'. As a result, when computing quantiles or averages among pairs of products produced by two firms involved in a merger, most of the distribution is centered at one.

The bottom panels of Figure 1 show distributions of changes in our distance measures, comparing the quarter before the M&A to 5 or 10 quarters after. In the bottom left panel, we consider distance measures based on product descriptions. While there is substantial variation across acquisitions and product modules, in each of the four plotted distributions the mean and median are both to the left of zero. In other words, most acquisitions are associated with a net decline in our dissimilarity measure, meaning that product portfolios condense subsequent to a merger or acquisition. In the bottom right panel, we repeat this exercise, now applying correlations based on household purchasing behavior to define distances. Here, whether product portfolios are condensing or expanding is more ambiguous.

The bottom panels of Figure 1 suggest the possibility that merging firms tend to reduce the variety in the types products they offer, at least when using product descriptions to compute distances among UPCs. In what follows we apply an event study methodology to more rigorously assess the impact of acquisitions on the number and diversity of products supplied to the market.

[19] That is, taking the union of the target's and acquirer's products within the product module, we compute pairwise product distances for all possible pairs in that set.

Figure 1: Product Dissimilarity Distributions



Notes: The top panels present distributions, across merger-product module pairs, of the distances among products. These are given by $\bar{\mathbf{D}}_{i,m,t}$, $\mathbf{D}^{0.1}_{i,m,t}$, $\mathbf{D}^{0.3}_{i,m,t}$, and $\mathbf{D}^{0.5}_{i,m,t}$. In the bottom panels, we present differences in the within-firm distances, comparing the quarter before the acquisition with 5 or 10 quarters after the acquisition. The left panels apply product descriptions to form distances across pairs of products; the right panels apply correlations in household purchase patterns to form distances.

3.2 Changes in the Number of Products

To examine the effect of mergers on the number of offered products, we employ a standard event study framework. Letting $n_{i,m,t}$ denote the number of products offered by merging firm i in product module m in quarter t, and letting τ denote the quarter in which firm i was involved in a merger, we estimate the following regression:

$$\log\left(n_{i,m,t}+1\right) = \lambda_{(t-\tau_i)} + \beta_t + \beta_{i,m} + \epsilon_{i,m,t}\ . \tag{4}$$

The β_t are quarter fixed effects and the $\beta_{i,m}$ are merger×module fixed effects. Our coefficients of interest, the $\lambda_{t-\tau_i}$, represent the effect of the merger on the number of products sold by the merging firm. Throughout, we apply the estimator developed by Callaway and Sant'Anna (2021).[20]

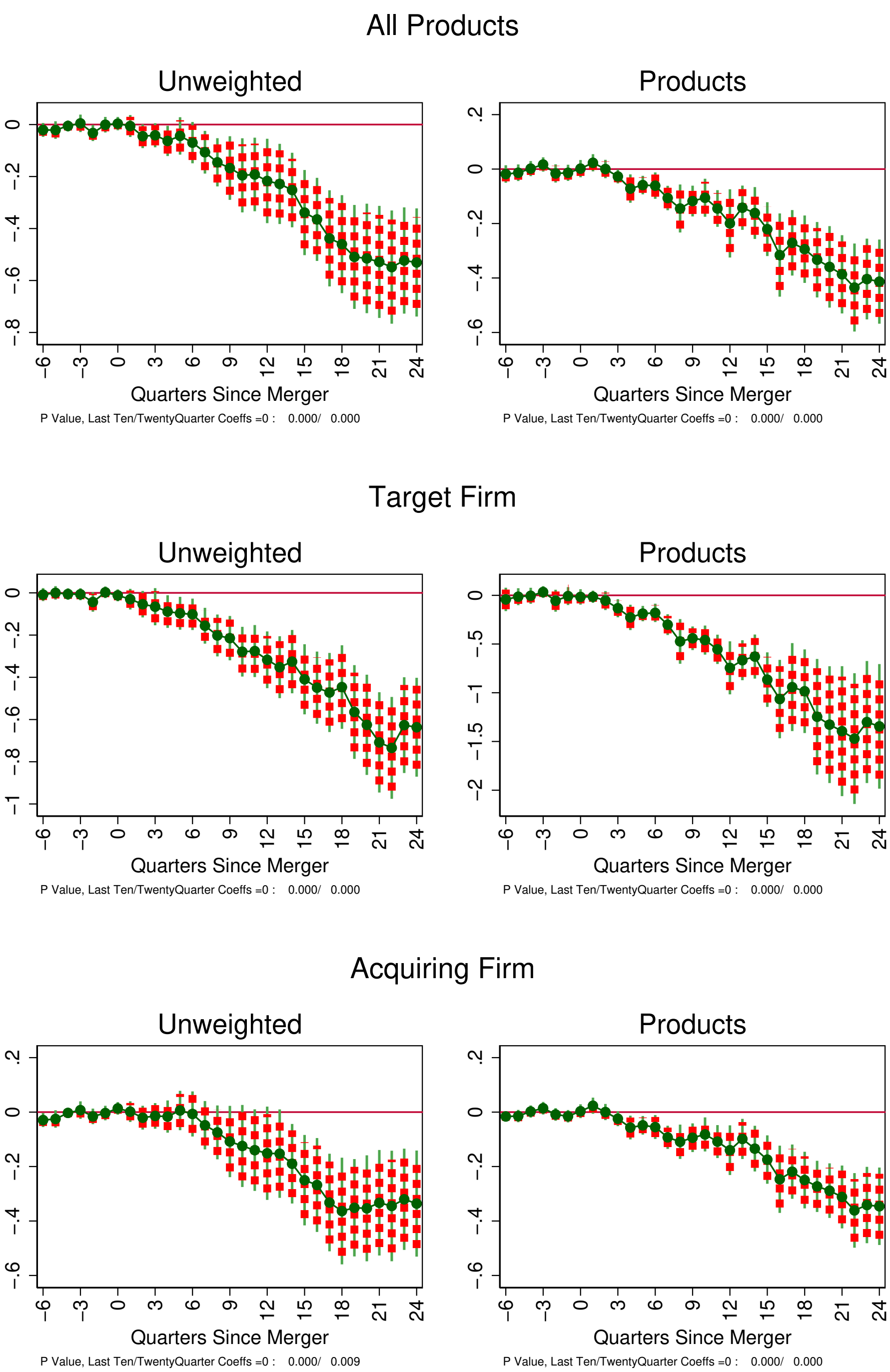
For each merger-product module pair, we compare the total number of products offered by the merged firm up to six years after the M&A to the combined number of UPCs offered by the merging firms directly before. As the top panels of Figure 2 indicate, the number of products offered begins to decline roughly eight quarters after the merger. These declines accelerate, so that by four years after the merger the number of products offered by the merging firm is 40 percent lower. After this, the number of products is constant for at least the subsequent two years. We observe these relationships in specifications where merger-module pairs are weighted equally, or are weighted by the number of products sold (in the period directly before the merger). In the remaining panels of Figure 2, we report the results of regressions using the sample of products initially offered by the target firm or the acquiring firm, separately. There, we demonstrate that net changes are negative for both sets of products, but with larger effects for products originally sold by the target firm.

3.3 Distances within Firms

As noted above, a net reduction in the number of products offered by merging firms is consistent with at least two hyotheses. One is that merging firms eliminate competing products to avoid cannibalization; another is that products are dropped if they are peripheral to the merged firm's core competencies. To distinguish between these two hypotheses, we next examine which types of products tend to be added or dropped. To do so, we again conduct an event-study analysis, estimating the following regression:

[20]Our estimates of λ in Equation 4 are similar when using a two-way fixed effects estimator. However, with regards to the impact of mergers on within-firm distances (Section 3.3) two-way fixed effects estimators yield estimates that are slightly greater in magnitude and with narrower coefficient intervals, compared to the ones presented in Figure 3

Figure 2: Event Study Regression Results –Number of Products



Notes: This figure presents changes in the number of products surrounding an acquisition, using estimates of Equation 4. In the left panels of this figure, no weights are applied. In the right panels, observations are weighted according to the number of products involved in the acquisition (as of the quarter preceding the merger). The top two panels report changes in the number of products produced either by the acquiring or target firm; the middle two panels report changes in the number of products produced by the target firm; and the bottom two panels report changes in the number of products produced by the acquiring firm. Within each panel, we test the hypothesis that the sum of the coefficients, either in the final 10 quarters included in the plot or in the final 20 quarters included in the plot, is equal to 0.

$$\bar{\mathbf{D}}_{i,m,t} = \lambda_{(t-\tau_i)} + \beta_t + \beta_{i,m} + \epsilon_{i,m,t} \ . \tag{5}$$

Here, our dependent variable is the average of the pairwise distances among products sold by merging firm i in module m and quarter t. In the periods before the merger, our distance measure is computed for the union of products sold by the acquirer and target.[21]

The results of our estimation are depicted in Figure 3. Similar to what we found in our analysis of the number of products offered, we find no evidence of increases or decreases in product similarity in the quarters preceding the M&A. Both when merger-module pairs are weighted equally and or they are weighted according to the number of products involved in the merger (in the quarter directly before the merger took place), the average distance in product portfolios decreases slightly in the first three years after the merger, then continues to decrease. The effects we identify are modest yet economically meaningful: the coefficient estimates in the top left panel, when looking 18 to 24 quarters after the M&A, represent a 0.13 standard deviation reduction in $\bar{\mathbf{D}}_{\mathbf{i,m,t}}$.[22] The effects depicted in the top right panel correspond to a 0.08 standard deviation reduction in the $\bar{\mathbf{D}}_{\mathbf{i,m,t}}$.[23] The bottom panels of Figure 3 show a qualitatively similar relationship between M&A activity and within-firm distances. However, when the distance measures are based on purchase correlations the effects are not statistically significant. This lack of a statistically significant correlation largely reflects the smaller sample of products for which we can compute these distances.

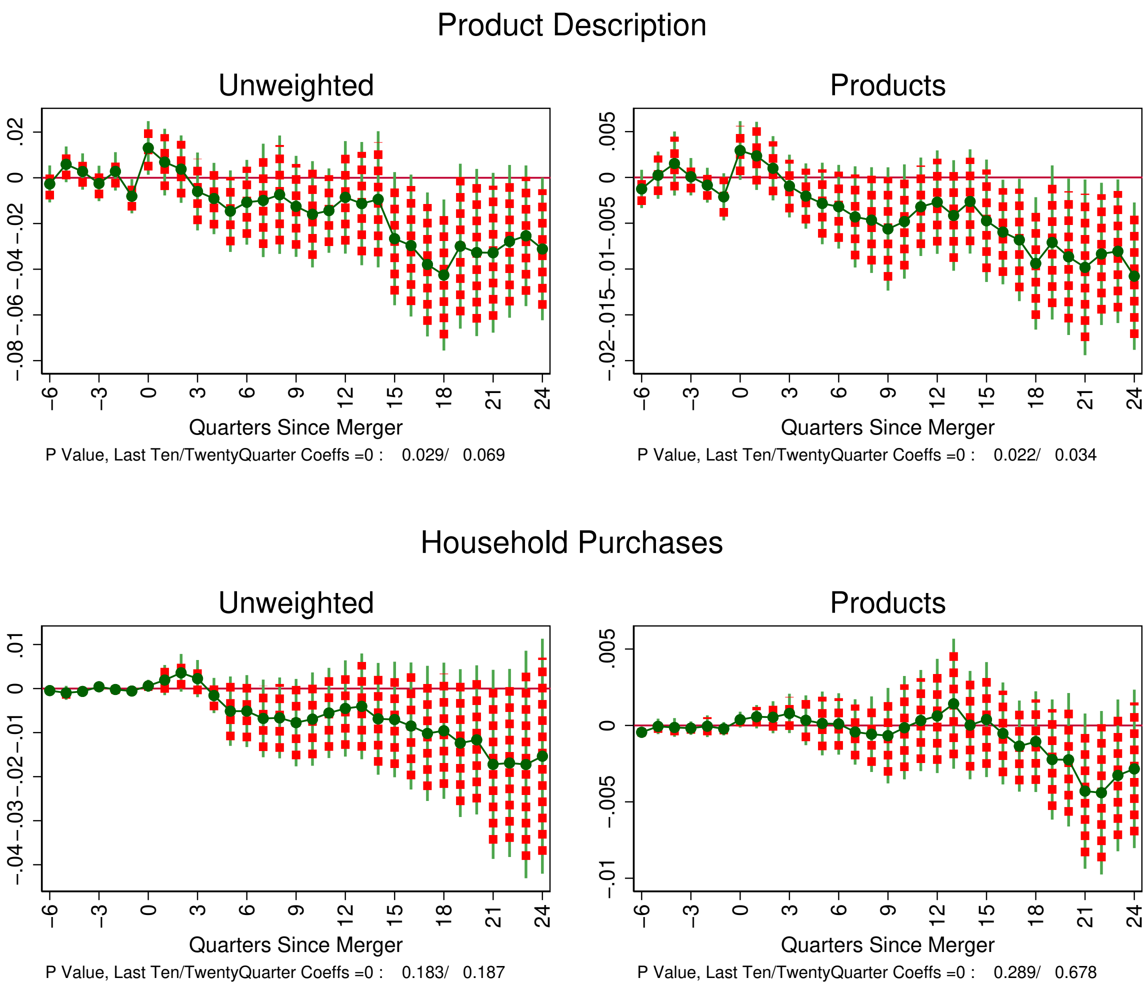
These results are consistent with fixed cost synergies", whereby product-specific costs of offering a good to the market is higher when the similarity to other products in its portfolio is lower when there are other increasing in the number of goods sold but is lower. They are also consistent with theories of the firm emphasizing "core competencies", whereby the merging firm's managers have specialty the produce, sell, and market goods only in certain regions of the product space. By contrast, the results in this section are not consistent with a cannibalization hypothesis. If the net reduction in products were driven by cannibalization — i.e., the removal of overlapping products to avoid self-competition — then average product distances should increase following a merger, not decrease.

[21] In Appendix B, we re-estimate Equation 5 with $\mathbf{D}^{\mathbf{q}}_{\mathbf{i,m,t}}$, for $q = 0.1$, 0.3, or 0.5, as the dependent variable. Here, our estimates of $\lambda_{(t-\tau_i)}$ are similar to those depicted in Figure 3.

[22] Looking 18 to 24 quarters after the M&A, the coefficient estimates average -0.032. The standard deviation of $\bar{\mathbf{D}}_{\mathbf{i,m,t}}$ in the regression sample equals 0.248. Finally, $0.13 \approx \frac{0.032}{0.248}$.

[23] Here, $0.08 \approx \frac{-0.009}{0.113}$, where 0.113 is the product-weighted sample standard deviation of $\bar{\mathbf{D}}_{\mathbf{i,m,t}}$.

Figure 3: Event Study Regression Results –Mean Distance



Notes: This figure presents changes in the distance among products involved in the merger, using estimates of Equation 5 and $\mathbf{\bar{D}_{i,m,t}}$ as the distance measure. In the left panels, no weights are applied; and in the right panels, observations are weighted according to the number of products involved in the merger (as of the quarter preceding the merger). In the bottom left panel, observations are weighted according to the sum of sales of the products involved in the merger. In the top two panels, we use product descriptions to compute distances across pairs of products; in the bottom two panels we use household purchasing patterns to compute distances. Thick red dashed lines present 90 percent uniform confidence intervals; thinner green solid lines present 95 percent uniform confidence intervals. Within each panel, we test the hypothesis that the sum of the coefficients, either in the final 10 quarters included in the plot or in the final 20 quarters included in the plot, is equal to 0.

3.4 Product-Level Analysis

The relationships that we have identified in the previous section — with declines in distances among products within firms' product portfolios subsequent to an M&A — may reflect either (a) the removal of products at the edge of merging firms' product portfolios, (b) the addition of products near the center of firms' portfolios, or (c) some combination of the two. In this section, we explore the relative importance of newly appearing or disappearing products in explaining the patterns discussed in Figure 5.

To begin, in Table 3 we relate individual products' likelihood of being dropped to various product characteristics. In the first four columns, we apply information on product descriptions to compute distances; in the final four columns, we use information on household purchases. Most specifications indicate that products further from the center of the merging firms' portfolios are more likely to be dropped. According to column (3) of this table, a one standard deviation increase in the distance between the product's location and the other products of the merging firm is associated with an 10.9 percentage point percent increase in the probability that the product is dropped within 10 quarters of the merger.[24] In column (4), we include the product's sales in addition to an indicator describing whether the product was initially produced by the acquiring (as opposed to the target) firm. A one standard deviation increase in our distance variable has roughly the same association as having sales that are 33 percent smaller.[25]

In Table 4, we examine the characteristics of products newly added after a merger. In particular, we relate the probability that a product that we observe in period $t + 10$ was added some time between periods $t - 1$ and $t + 10$ to (a) the products' sales and (b) the distance to the firms' other products (both as of 10 periods *after* the merger). We find that newly added products tend to have lower sales (ten periods after the merger) compared to those that had been sold either by the acquiring or the target firm before the merger. Moreover, whether distance is computed using product descriptions or using household purchase behavior, products at the periphery of their firms' product portfolios are more likely to have been newly added in the quarters succeeding the merger.

So, the moderate within-firm product differences that we document in Section 3.3 reflect two countervailing forces. On the one hand, merging firms tend to drop products that are far from the center of their joint product portfolio, leading to a reduction in distances among the merging firms' products. On the other hand, merging firms tend to also add products that are far from the center of their joint product portfolio, leading to an increase in within-firm

[24] The marginal effect associated with column (3) equals 0.952; the standard deviation of the distance to the combined firm's products equals 0.115. So, $0.109 = 0.952 \cdot 0.115$.

[25] To arrive at this figure, note that $0.67 \approx \exp\left(\frac{1.316 \cdot 0.109}{-0.364}\right)$.

distances. Since mergers tend to involve so many more old products exiting the market than new products entering the market (Section 3.2), the former effect dominates the latter. On net, mergers lead to a reduction in within-firm product distances.

Table 3: Logit Regression Results: Products Dropped

	(1)	(2)	(3)	(4)
Log(Sales)		-0.347***		-0.364***
		(0.012)		(0.013)
1(Acquiring Firm's Product)		0.077***		0.084***
		(0.069)		(0.079)
Distance to Merged Firm's Products	0.571*	0.256	2.358***	1.316***
	(0.325)	(0.337)	(0.393)	(0.412)
Distance Measure	——— Product Description ———			
Observations	11,348	11,348	10,616	10,616
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	104	104	170	170
	(5)	(6)	(7)	(8)
Log(Sales)		-0.712***		-0.804***
		(0.044)		(0.052)
1(Acquiring Firm's Product)		0.378**		0.487**
		(0.180)		(0.231)
Distance to Merged Firm's Products	7.611***	-1.272	27.731***	3.987
	(2.276)	(2.265)	(3.748)	(4.108)
Distance Measure	——— Household Purchases ———			
Observations	3,007	3,007	2,696	2,696
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	35	35	62	62

Notes: The dependent variable equals 1 if the product is dropped within ten quarters of the merger.

Table 4: Logit Regression Results: Products Added

	(1)	(2)	(3)	(4)
Log(Sales)		-0.881***		-0.884***
		(0.052)		(0.052)
Distance to Merged	1.892***	0.680	2.553***	1.716**
Firm's Products	(0.346)	(0.530)	(0.418)	(0.689)
Distance Measure	——— Product Description ———			
Observations	11,512	9,927	11,111	9,829
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	96	86	167	151
	(5)	(6)	(7)	(8)
Log(Sales)		-0.785***		-0.812***
		(0.136)		(0.138)
Distance to Merged	17.166***	1.596	23.952***	15.978***
Firm's Products	(2.460)	(2.622)	(2.913)	(4.622)
Distance Measure	——— Household Purchases ———			
Observations	3,077	2,721	2,929	2,612
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	34	32	64	60

Notes: For products that were sold by a firm experiencing an M&A in period t, the dependent variable equals 1 if it was added between period t and $t + 10$.

3.5 Discussion

In this section, we have documented that, after an M&A, merging firms sell fewer products in the market. The products they add and drop tend to be at the periphery of their product portfolios. On net, within-firm product dissimilarity falls subsequent to M&As.

Our finding of a reduction in the number of distinct products sold is unsurprising, as the standard economic logic is that merging firms will have incentives to eliminate previously competing products that now cannibalize each other's sales. In other words, if offering a product involves fixed costs, merged firms will tend to drop products that merely steal sales from another of the firm's own products. However, this logic suggests the products most likely to be dropped are ones that are similar to others in the firm's portfolio, and we find the opposite to be true. Instead, firms tend to drop products at the periphery of their portfolios.

This finding does not mean conglomerate mergers never diversify the firms' product portfolios: In constructing our sample we intentionally excluded many mergers in which the acquired firm sells products in modules where the acquirer was not previously active. However, it does suggest the main thrust of these mergers is *not* typically to eliminate the closely competing products of a rival, a motive highlighted by Cunningham, Ederer and Ma (2021), among others. When firms that operate in the same product markets merge with one another, they drop products in a way that makes their combined portfolio more dense rather than more sparse.

Our findings can be rationalized by theories of the firm emphasizing core competencies. Firms have heterogeneous capabilities in the markets that they serve. While mergers and acquisitions allow firms to rapidly expand into new product markets (Levine, 2017), some lines of business acquired during the transaction may not align with the merging firms' core competencies (Maksimovic and Phillips, 2002; Maksimovic, Phillips and Prabhala, 2011). These "far away" lines of business from others within the newly-formed firm are relatively less profitable to operate, and thus more likely to be dropped. Our empirical results are also consistent with fixed cost synergies, as explored in other contexts by Jeziorski (2014) and Mazzeo, Seim and Varela (2018): To the extent that the fixed cost of supplying a particular product decreases if there are other nearby products that the firm is selling, all else equal merging firms will tend to drop those that are farther away from others in their joint product portfolio.

4 Conclusion

Our goal in this paper has been to describe post-merger changes to firms' product portfolios. Using data from a large sample of mergers across a variety of product markets, we document three main patterns, First, mergers tend to result in net reductions in the number of offered products, and the reductions appear to occur gradually over several years following the merger. Second, there is a modest and gradual increase in the similarity among the products that firms offer following a merger or acquisition. Both the products that firms add and those they drop tend to be relatively dissimilar to others in the merged firms' product portfolios, but more products are dropped than added so that the net effect is an increase in product similarity.

Although some of the effects we have identified through our descriptive analysis — in particular the declines of within-firm distances — are modest, taken together our results highlight the importance of examining post-merger product repositioning in individual merger cases. Antitrust policy is concerned with the effect of mergers on welfare, and even small changes in product assortments may have substantial ramifications for consumer welfare. Furthermore, our current analysis does not consider the possible adjustments made by non-merging firms in response to a merger, nor the effects of mergers in markets where the merging firms do not compete before the merger. These effects may also be important for welfare. We leave an exploration of these important issues to future research.

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Appendixes

A Data Processing Details

A.1 Cleaning and Processing the Product Data

We clean the product data in five steps.

First, we drop all private-label ("Control Brand") products. These are manufactured and sold under a retailer's brand name, with the identity of the retailer unobservable to us.

Second, some products have the same UPC but different UPC versions. This happens when a firm changes the size, multipack or other attributes of a product. For example, a firm might temporarily change a product's size to reflect a special promoted product size and then revert to the original size. These products are in fact the same product. We ignore different UPC versions and combine the sales of products with the same UPC.[26]

Third, in some instances multiple UPC codes may refer to the same product. Firms might slightly change the attributes of a product and give it a new UPC. To deal with this problem, we combine the sales of products with the same descriptive information (description, brand, multipack and size) and treat them as a single product. Furthermore, any time there are multiple products with the same description, brand, and multipack, we search for a set of products whose sizes are within 10 percent of each other and collapse them to a single product.

Fourth, we drop niche products, those with exceedingly small sales and are sold in only a few stores. We require each product in our sample to have been sold in at least 10 stores in one quarter during our sample and to have at least 900 units sold in one quarter in our sample.

Finally, in certain occasions, a product is no longer produced but still registers a small number of sales in a quarter. This can occur, for example, if retailers sell off existing inventory without purchasing any units from the product's manufacturer. To accurately capture manufacturers' supply decisions, we set the sales of a product in a quarter to be zero if both (a) the units sold in the quarter is less than 1 percent of the product's maximum quarterly sales and if (b) the number of stores in which the product is sold in the quarter is less than 1 percent of the maximum number of stores in which the product was sold in any quarter.

After performing these five steps, we retrieve each product's owner — for each quarter

[26] Different UPC versions typically reflect small changes in product size which are not likely to reflect the quartile of the size distribution that the product is in.

in the sample — based on that product's UPC prefix and (in certain scenarios) on its brand description.[27] We describe our procedure to assign products' owners in the following section.

A.2 Details on Linking SDC and Nielsen Data: Assigning Firm Names

We follow a multi-step procedure to ascertain the products associated with the acquiring and target firm within each merger in the SDC mergers and acquisitions dataset and in the Nielsen dataset. Our primary data source is GS1, a correspondence between firm names and UPC prefixes. Since the number of firms in the SDC dataset and the GS1 dataset are each in the thousands, and since each dataset may record the same firm in multiple, slightly distinct ways, ascertaining changes in firm ownership for each of the products in our sample would be prohibitively time-consuming.[28] Given these constraints, we restrict our sample to mergers in which the acquiring firm is a large food-and-beverage related conglomerate.

Specifically, we begin with a sample of firms mentioned in *Food Engineering*'s "Top 100" list of food and beverage conglomerates. For each of these firms, we search for through the prefixes associated with their subsidiaries within the GS1 data, ensuring that firms with names recorded differently are assigned a common name. This yields a correspondence of 73 (among the "Top 100") large firms, mapping to 594 prefixes.

For each of the acquiring firms in the SDC M&A dataset, we apply a fuzzy name matching algorithm to our list of 73 conglomerates. We manually inspect the closest name matches to determine which (if any) is the appropriate match. For each of the target firms in the SDC M&A dataset, we apply a fuzzy name matching algorithm to all of the firm names listed in the GS1 dataset. Again, we manually inspect the closest name matches to determine which (if any) is the appropriate match.

Next, we manually drop — from our list of M&A's — a small number of spuriously included mergers and add a somewhat larger number of mergers that our fuzzy name matching algorithm mistakenly missed. The mergers we add include: Pepsico's purchases of Stacy's Pita Chip Company, Pepsi-cola Batavia Bottling, and Better Beverages Inc; General Mills' purchases of Humm Foods and Annies Inc; Coca-Cola's purchase of Coca-Cola Enterprises; Dean's purchase of Foremost Farms' milk-processing plants; Nestle's acquisition of Kraft Foods' frozen pizza division; Campbell's acquisition of Plum Inc.; Unilever's acquisition of

[27] In certain scenarios, we must measure firms' ownership of products at the brand level (as opposed to the more aggregated prefix level) since, within certain partial acquisitions, the acquiring firm purchases only a subset of the brands within a prefix from the target firms.

[28] To give one example, the Alpine Valley Bakery Company is called "alpine valley bread co" in the SDC merger data but "alpine lace brands, inc." in the GS1 company prefix data.

Talenti; the Kraft-Heinz merger; Flower Foods acquisition of Alpine Lace Brands; Snyder's Lance purchase of Diamond Food Holdings; and NH Foods purchase of Clougherty Packing LLC.

The GS1 data provide a snapshot of the prefix-company mapping at the time we downloaded these data, in 2019. In order to measure changes in prefixes before and after the date of each M&A, in a final step, we conduct a manual internet search of the brands and prefixes in each product module in the Nielsen data and the 137 mergers listed above. In particular, we attempt to record exactly which lines of business — which brands and prefixes — changed ownership around each acquisition date. At this point, we have a list of prefixes associated with acquiring and target firms before and after the date at which the M&A was executed.

At this stage, we have 137 mergers and acquisitions. Of these, the final sample includes the 66 mergers and acquisitions for which both firms were operating — in the quarter before the merger — at least one product module in common. We discard the remaining 71 mergers and acquisitions from our dataset.

B Additional Figures and Tables

In this appendix, we compile additional figures and tables, ancillary to our Section 3 analysis.

List of Mergers in the Sample

Table 5 lists the mergers within our sample.[29] Overall, there is wide heterogeneity in the the size of mergers and acquisitions. Our sample's largest mergers — in terms of the unit sales of the merging firms in their overlapping modules — include Coca-Cola's purchase of Monster Energy, Campbell Soup Company's purchase of Pacific Foods of Oregon (a broth and soup producer), and Pepsico's purchase of Health Warrior (a maker of nutrition bars, among other products). Each of these mergers involve multiple overlapping product modules, dozens of products which switch ownership. At the other end of our sample's merger size distribution, many of the mergers within our sample relate to one or two overlapping product modules, with a handful of products changing ownership.

[29] For certain transactions, either the acquiring or target firm may sell zero products in the quarter preceding the merger (e.g., the transaction between Mars and Preferred Brands International, as listed in the second row of the final page of Table 5). We retain these acquisitions in our sample so long as both firms share a product module with positive sales in at least one quarter at some point before the M&A, subject to the restrictions described in Appendix A.1.

Table 5: List of Transactions

		Products		Sales		Effective	
Acquirer	Target	Acquirer	Target	Acquirer	Target	Date	Modules
Coca-Cola	Monster Energy	733	71	568.3	3.5	2015Q1	14
Campbell	Pacific Foods Of Oregon, Inc.	379	90	178.8	8.7	2017Q4	13
Pepsico	Health Warrior Inc	335	31	140.7	0.4	2018Q4	3
Heinz	Kraft	177	285	36.3	85.7	2015Q3	29
Mondelez	Tate'S Bake Shop Inc	216	18	115.7	3.4	2018Q1	2
Mondelez	Enjoy Life Natural Brands Llc	218	23	98.4	0.8	2015Q2	7
Lindt & Sprungli	Russell Stover	399	291	47.6	43.3	2014Q3	6
Dr Pepper Snapple	Bai Brands Llc	400	43	72.8	12.3	2017Q2	4
Mccormick	Unilever	1155	58	75	9	2008Q3	18
Flowers Foods	Bimbo Bakeries Usa, Inc.	465	60	65.8	6.4	2013Q2	9
Mccormick	Reckitt Benckiser Llc	769	43	62.6	6.4	2017Q3	21
Ferrero	Ferrara Candy Company	328	349	38	27.5	2017Q4	8
Unilever	Talenti	316	38	56.6	5.3	2014Q4	3
Anheuser-Busch	Latrobe Brewing Co	234	12	56.6	1	2006Q1	2
Dean	Wells Enterprises	1035	46	52	1.3	2007Q4	10
Flowers Foods	Aryzta, Llc	335	91	48.2	4.6	2013Q3	7
Nestle	Kraft	61	108	18.3	30.2	2010Q2	2
Flowers Foods	Canyon Bakehouse Llc	219	21	46.3	1.4	2018Q4	5
Flowers Foods	Lepage Bakeries, Inc.	197	78	40.9	4.1	2012Q3	7
Flowers Foods	General Mills	297	37	42.2	2.6	2009Q4	9
Flowers Foods	Hostess Brands Inc.	182	12	41.2	1.5	2013Q3	2
Flowers Foods	Alpine Valley Bread Co.	208	18	40.5	0.3	2015Q4	4
Tyson	Advancepierre Foods Inc.	233	68	33.1	2	2017Q1	12
Snyder'S-Lance, Inc.	Diamond Foods Holdings, Llc	243	164	20.3	14.7	2016Q2	11

Notes: Continued on the next page.

Table 5: List of Transactions (continued)

		Products		Sales		Effective	
Acquirer	Target	Acquirer	Target	Acquirer	Target	Date	Modules
Flowers Foods	H & S Bakery Inc.	190	24	32.1	0.2	2008Q3	6
Tyson	The Hillshire Brands Company	204	14	27.4	0.5	2014Q3	12
General Mills	Epic Provisions Llc	137	27	23.7	0.1	2016Q2	5
Land O Lakes	Vermont Creamery Inc.	32	23	23	0.3	2017Q2	5
Constellation Brands	Four Corners Brewing Co	60	6	21.1	0	2018Q3	2
Nestle	Zuke Llc	131	0	21.1	0	2014Q2	1
Conagra Brands	Angie'S Artisan Treats Llc	137	44	14.2	6.4	2017Q4	7
Campbell	Ecce Panis, Inc.	90	19	20	0.5	2009Q1	4
Anheuser-Busch Inbev	Four Peaks Llc	241	13	20.2	0.1	2016Q2	3
Dean	Friendly Ice Cream Corp.	425	111	8	9.9	2016Q1	5
Anheuser-Busch Inbev	10 Barrel Brewing Co	234	15	17.5	0.1	2014Q4	2
Anheuser-Busch Inbev	Karbach Brewing Co	241	17	15.8	0.1	2016Q4	3
Ferrero	Fannie May Confections, Inc.	161	46	14.6	0.4	2017Q1	5
Constellation Brands	Funky Buddha Brewery Llc	60	13	12.1	0	2017Q3	3
Hormel Foods	Justins Llc	33	10	9.3	1	2016Q1	2
Hormel Foods	Unilever	11	20	1.7	7.8	2013Q2	1
Dairy Farmers Of America	Oakhurst Dairy	208	66	5.5	2.2	2014Q2	17
Dean	Uncle Matt'S Organic, Inc.	208	7	6.5	0	2017Q1	8
Smucker'S	Eagle Family Foods Hldgs Inc	39	8	4	1.6	2007Q1	4
Hormel Foods	Valley Fresh Inc.	21	10	2.7	2.4	2006Q1	3
Dairy Farmers Of America	Dairy Maid Dairy	155	0	5.1	0	2013Q3	6
Hormel Foods	Columbus Manufacturing, Inc.	58	14	3.5	0.3	2017Q4	14

Notes: Continued on the next page.

Table 5: List of Transactions (continued)

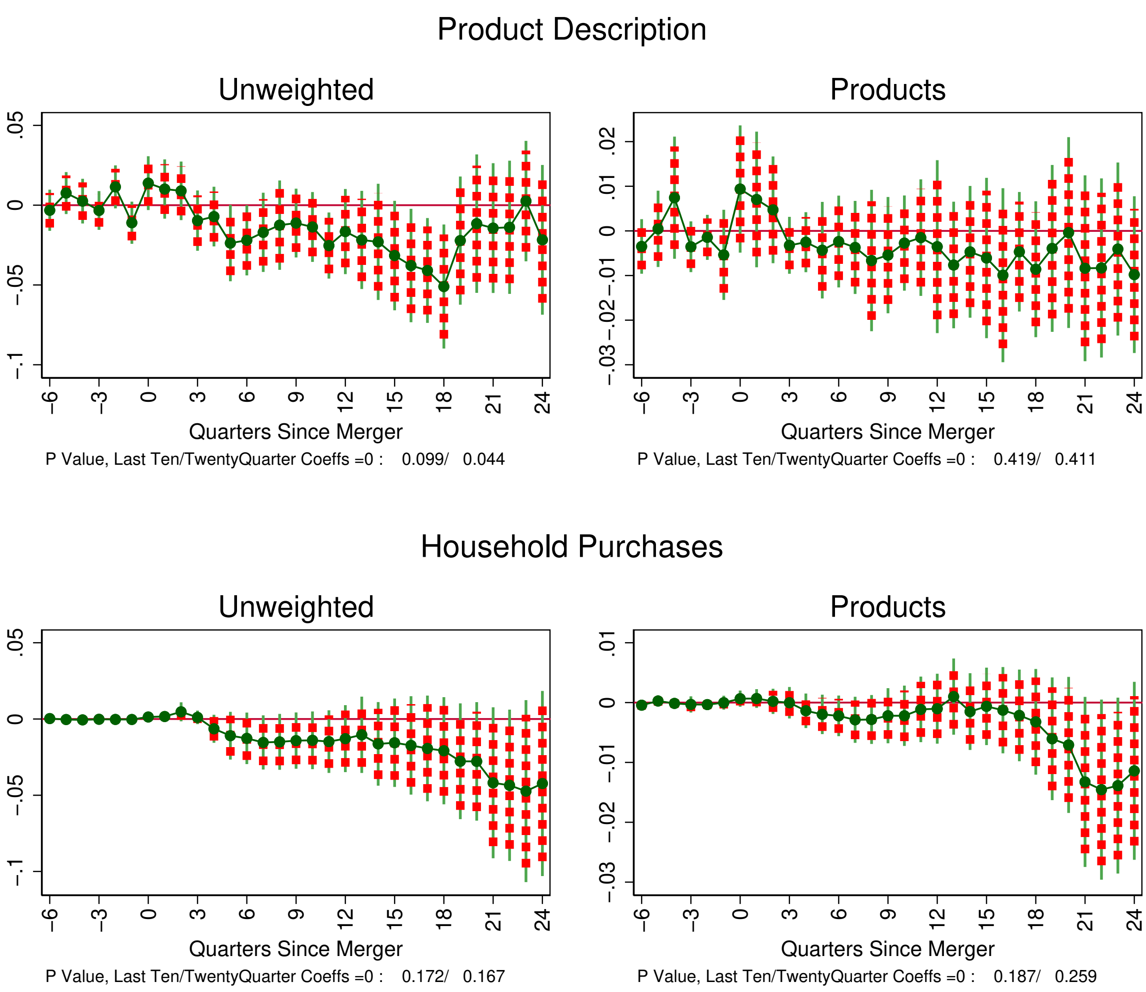
		Products		Sales		Effective	
Acquirer	Target	Acquirer	Target	Acquirer	Target	Date	Modules
Nestle	Chameleon Cold Brew Llc	18	13	2.6	0.5	2017Q4	2
Saputo	Alto Dairy Cooperative	52	6	2.6	0	2008Q1	3
Campbell	Wm. Bolthouse Farms Inc.	44	7	1.7	0.1	2012Q3	4
Mars	Preferred Brands International	8	0	1.6	0	2017Q4	1
Hormel Foods	Unilever	0	4	0	1.6	2010Q2	1
Hershey	B &G Foods, Inc.	15	0	1.1	0	2018Q4	2
Mars	S & M Nutec, Llc	0	29	0	0.6	2006Q1	1
Schreiber Foods	Dean	4	40	0	0.5	2011Q1	1
Flowers Foods	Leo'S Foods Inc	10	2	0.5	0	2009Q4	1
Chs	Legacy Foods, Llc	4	13	0	0.3	2008Q1	2
Nestle	Vitality Foodservice Inc	6	0	0.3	0	2009Q4	1
Tyson	Circle Foods, Llc	11	0	0.3	0	2013Q1	2
Tyson	Don Julio Foods Inc.	1	4	0	0.2	2013Q2	1
Campbell	Garden-Fresh Foods, Inc.	26	2	0.2	0	2015Q1	4
Bunge	The C. F. Sauer Co.	3	4	0	0.1	2011Q3	2
Conagra Brands	Ralcorp Holdings Inc	4	1	0.1	0	2013Q2	1
Cargill	Fpl Food Llc-	2	0	0.1	0	2016Q2	2
Cargill	Afa Foods Inc-Beef Plant	2	1	0	0	2012Q3	1
Smucker'S	C.H. Guenther & Son, Inc.	1	5	0	0	2006Q4	2
Hormel Foods	Cytosport, Inc.	0	3	0	0	2014Q3	1

Notes: For the 66 mergers and acquisitions in our sample, we list the number of products and the sales of the associated products in the modules for which the target and acquiring firms overlap in the period directly before the merger. The "Modules" column lists the number of modules for which the two firms overlap.

Figures Supplementing Section 3.3

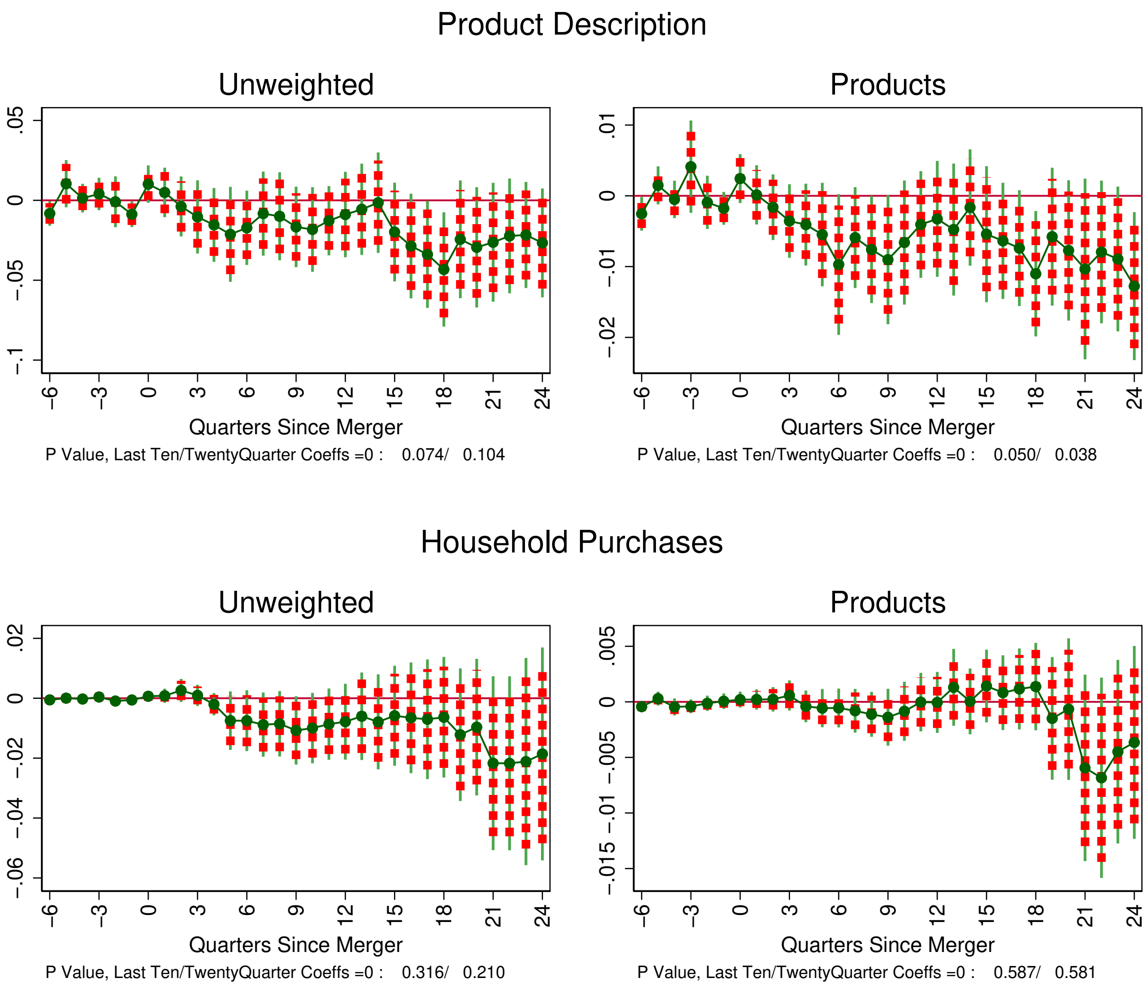
In Figures 4, 5, and 6, respectively, we re-estimate Figure 3 using $\mathbf{D}^{0.1}_{i,m,t}$, $\mathbf{D}^{0.3}_{i,m,t}$, or $\mathbf{D}^{0.5}_{i,m,t}$ instead of $\bar{\mathbf{D}}_{i,m,t}$ as our explanatory variable. Our results in this section mirror those in Section 3.3. When using descriptions to compute products' locations, within-firm distances tend to decline following an M&A; when using household purchasing behavior, we find no statistically significant change.

Figure 4: Event Study Regression Results –10th Percentile Distance



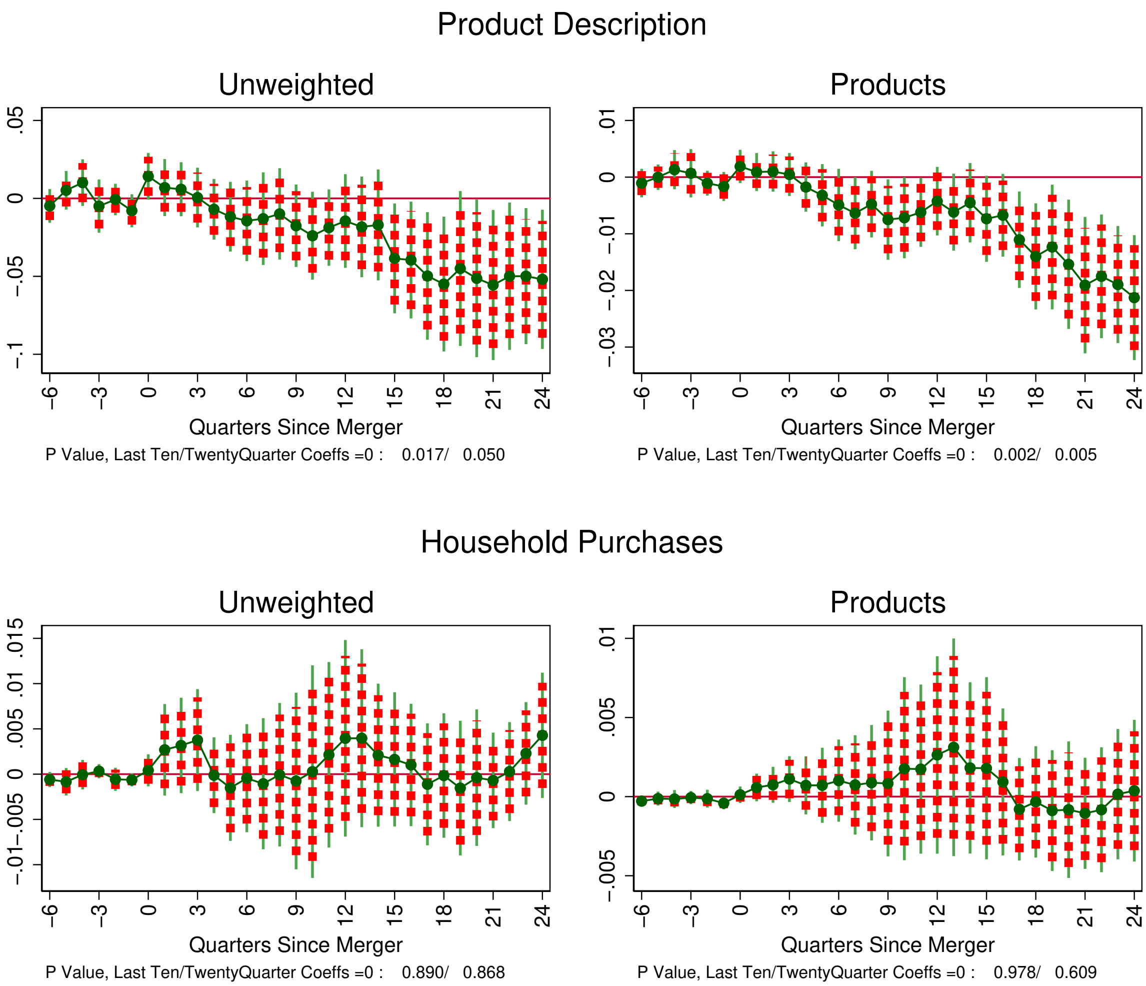
Notes: See notes for Figure 3. In contrast to that figure, we compute the 10th percentile distance, instead of the mean, of the distance for each firm-year-product module as our dependent variable.

Figure 5: Event Study Regression Results –30th Percentile Distance



Notes: See notes for Figure 3. In contrast to that figure, we compute the 30th percentile distance, instead of the mean, of the distance for each firm-year-product module as our dependent variable.

Figure 6: Event Study Regression Results –Median Distance



Notes: See notes for Figure 3. In contrast to that figure, we compute the median distance, instead of the mean, of the distance for each firm-year-product module as our dependent variable.

Tables Supplementing Section 3.4

In this section, we present tables supplementing the analysis in Section 3.4. First, Tables 6 and 7, as in Table 3, relate product characteristics to the probability that the product disappears from the market within 10 quarters following the M&A. Our samples now comprise products initially corresponding to the target firm (Table 6) or the acquiring firm (Table 7). We find that distance to the merging firm's products predict product removal for products originally sold by the target firm (Table 6), while the results for acquiring firm products are sensitive to the method by which product distances are computed and the types of controls included in the regression specification.

Table 6: Logit Regression Results: Products Dropped (Originally Sold by Target)

	(1)	(2)	(3)	(4)
Log(Sales)		-0.461***		-0.490**
		(0.032)		(0.036)
Distance to Merged	3.041***	2.513***	8.119***	6.757***
Firm's Products	(0.925)	(0.931)	(1.464)	(1.570)
Distance Measure	——— Product Description ———			
Observations	1,837	1,837	1,611	1,611
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	62	62	69	69
	(5)	(6)	(7)	(8)
Log(Sales)		-0.931***		-0.976***
		(0.158)		(0.164)
Distance to Merged	52.961***	13.737	54.807***	3.744
Firm's Products	(12.249)	(13.346)	(13.908)	(15.139)
Distance Measure	——— Household Purchases ———			
Observations	375	375	344	344
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	15	15	15	15

Notes: See notes for Table 3. In contrast to that table, the sample involves only products originally supplied by from the target firm.

Finally, in Table 8 we assess the robustness of the results presented in Table 4 to the way in which we compute distances to the merged firm's products. Instead of computing each product's distance to those produced by the merged firm ten quarters after to the merger, we consider the distance to the products sold by either the acquiring or the target firm in the quarter directly before the merger. As in Table 4, we find that products far from the center of the merging firm's product portfolios are likely to have been added in the first ten quarters after the merger.

Table 7: Logit Regression Results: Products Dropped (Originally Sold by Acquiring Firm)

	(1)	(2)	(3)	(4)
Log(Sales)		-0.339***		-0.372***
		(0.013)		(0.014)
Distance to Merged	0.433	0.0490	2.122***	1.023**
Firm's Products	(0.374)	(0.384)	(0.449)	(0.470)
Distance Measure	——— Product Description ———			
Observations	2,516	2,516	2,266	2,266
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	93	93	149	149
	(5)	(6)	(7)	(8)
Log(Sales)		-0.697***		-0.792***
		(0.047)		(0.056)
Distance to Merged	4.383*	-4.254*	26.208***	3.821
Firm's Products	(2.375)	(2.433)	(3.992)	(4.401)
Distance Measure	——— Household Purchases ———			
Observations	2,516	2,516	2,266	2,266
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	31	31	57	57

Notes: See notes for Table 3. In contrast to that table, the sample involves only products originally supplied by the acquiring firm.

Table 8: Logit Regression Results: Products Added (Alternate Measure of Distance)

	(1)	(2)	(3)	(4)
Log(Sales)		-0.880***		-0.887***
		(0.052)		(0.053)
Distance to Combined	4.722***	2.937***	6.096***	4.436***
Firm's Products	(0.371)	(0.504)	(0.429)	(0.632)
Distance Measure	——— Product Description ———			
Observations	11,519	9,935	11,106	9,824
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	96	86	165	149
	(5)	(6)	(7)	(8)
Log(Sales)		-0.799***		-0.860***
		(0.141)		(0.152)
Distance to Combined	61.202***	48.321***	69.851***	64.931***
Firm's Products	(3.866)	(5.496)	(4.282)	(6.867)
Distance Measure	——— Household Purchases ———			
Observations	3,080	2,724	2,929	2,612
Module-Merger FE	No	No	Yes	Yes
Module FE	Yes	Yes	No	No
Number of Groups	34	32	64	60

Notes: See the notes for Table 4. In contrast to that figure, for each product we compute the average distance to the products of the merged firms' products that were present in the quarter immediately before the merger.