Post-Merger Product Repositioning: An Empirical Analysis

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Abstract

This paper investigates firms' post-merger product repositioning. We compile information on conglomerate firms' additions and removals of products for a sample of 61 mergers and acquisitions 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, and the products that are dropped tend to be particularly dissimilar to the firms' existing products. These results are consistent with theories of the firm that emphasize core competencies linked to particular segments of the product market.

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1 Introduction

Analyses of horizontal mergers have focused primarily on price effects, because 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); Blonigen and Pierce (2016) to name a few examples), and concerns about price effects 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. This paper's aim is to quantify and describe patterns in these changes to merging firms' product portfolios.

We focus on measuring whether merging firms increase or decrease the number of products they offer, and whether the added or dropped products tend to be similar vs. dissimilar to the products in the firms' existing portfolios. 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 previously-competing business lines or to discontinue previously-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, 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 implies lower consumer surplus, beyond the higher prices that the previous literature has generally focused on.

Our main analysis combines two datasets, one containing detailed information on firms' product offerings and a second comprising a comprehensive list of mergers and acquisitions. The latter are recorded in the Securities Data Company (SDC) database of mergers and acquisitions. The former, the Nielsen Retail Scanner dataset, contains information about each universal product code (UPC) sold by each brand in each quarter between 2006 and 2017. Critically for our analysis, this dataset contains a short product description and information on the size of the product sold. Based on the text within the product description and on the product's size, we calculate the similarity between any two products within a given market: Products with a high fraction of overlapping text, or which are of similar size, are defined to be "close" to one another. Though coarser than comparisons one might make when looking carefully at a small set of products involved in one specific merger, this approach enables us to compare tens of thousands of products across many different product categories. We can then compute the distance among the UPCs within firms' product portfolios in periods surrounding a merger or acquisition, and employ an event-study framework to assess mergers' impact on the number and variety of products sold by firms participating in the merger.

Looking across a sample of 61 conglomerate mergers – across a wide variety of consumer packaged goods markets – we find that mergers lead to significant net reductions in the number of offered products, but only with a lag. Beginning one year after the merger, we observe a statistically significant 6 percent decrease in the number of UPCs, and this reduction persists for several years beyond 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 and less likely to be added. In other words, the merged firm's products increasingly become close to one another.

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. Gandhi et al. (2008) theoretically show that product repositioning can mitigate the anticompetitve effects of a merger. Using a Hotelling-type model to analyze firms' pre-and post-merger product location decisions, they find that mergers lead to greater product differentiation, 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.[1] Their analysis holds fixed the number of products in the market and ignores fixed costs. Berry and Waldfogel (2001) illustrates that, when one considers the fixed cost of product introductions, the effect of 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.[2] 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 which ignores repositioning can be misleading. As the aim of this literature is to measure

[1] See also Mazzeo and Varela (2018).

[2] Variety may further be impacted if the merger results in coordinated effects. Sullivan (2020*a*,*b*) document 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 (2019) and Chilet, Chen and Li (2019) 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.

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. We extend this body of work by demonstrating the effect of mergers on endogenous product repositioning for a large set of mergers across many consumer packaged goods markets. While our approach does not allow us to document merger effects on prices or welfare, we are able to be agnostic as to the underlying model generating the pre- and post-merger equilibria. 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' 10-K filings 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 that a sizable fraction of target firms' plants is either spun off or shut down in the first three years after being acquired; see also Li (2013). Those target firm plants that are kept tend to be in the acquiring firms' main industries of production. 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 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 declines 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 characterizes a primary channel through which this reallocation of inputs occurs—namely in the reshuffling of product lines during and after mergers and acquisitions.

In the remainder of the paper, we describe our data sources and our measurement of product similarity (Section 2), present our main empirical results (Section 3) and briefly conclude (Section 4).

2 Data Sources and Definitions

Our data set has two main components: (1) the Nielsen Retail Scanner database– data on individual products and their weekly sales from 2006 to 2017, and (2) the SDC Platinum Mergers and Acquisitions database– a list of mergers and acquisitions between 1979 to 2018. We supplement these datasets with a mapping we have compiled between brands and their parent firms, drawing on the GS1 Database. These three pieces of information, in combination, allow us to measure how firms' product portfolios evolve following each merger and acquisition. We close this section by describing how we measure product dissimilarity.[3]

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 2006-2017. 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 US grocery and drug stores, and more than 30 percent of all U.S. mass merchandiser sales volume.

For each UPC (Universal Product Code), 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 2006-2017.[4] 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 was dropped.

In addition, Nielsen categorizes products into a set of modules, groups, and departments. Each of these are groups 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 each product module as a distinct product market. In the four departments of our sample, there are 612 product modules. 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,

[3]Additional details on our data cleaning procedures are given in Appendix A.

[4]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, out main measurements, but from a separate Nielsen file of product attributes.

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 in at least some product markets—we focus on cases where there was at least some overlap in the merging firms' products' module codes prior to the merger. [5]

2.2 The 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 all corporate transactions, both public and private, for which the transaction (i) represents at least 5 percent of the value of the companies involved, and (ii) is valued at $1 million or more, or has an undisclosed value. For each merger, we observe the announced and effective date of the transaction, as well as the name and industry (defined by the Standard Industrial Classification (SIC) code) of the companies involved. Throughout the paper, we apply SDC's labeling of the firms which acquire or sell assets as, respectively the "acquirer" and the "target". To be consistent with the product data, we limit our attention to transactions whose acquirer and target both operate in the aforementioned four Nielsen departments.[6]

2.3 The Company Prefix Data

While Nielsen reports the brand of the product (e.g. Sprite), it does not indicate the parent company that 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.[7] We use the GS1 Company Database to get the name of manu-

[5] Of the 61 mergers that will form our baseline sample, there were 286 merger-product module pairs. In addition, outside of our sample, are 251 merger-product module pairs associated with the target firm but not the acquiring firm, and 2,779 merger-product module pairs associated with the acquiring firm but not the target firm.

[6] The SDC Platinum database includes not only mergers and full takeovers but also acquisitions of certain lines of business. As an example of the latter case, 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 the relevant product modules.

[7] 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 the manufacturer's products.

facturer 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. To address this issue, we manually collected listings of subsidiaries of the largest 100 conglomerates in the United States, and then associated company prefixes to those conglomerates. Our M&A sample focuses only on transactions in which the acquirer was one of these 100 conglomerates.

2.4 Calculation of Distance Measures

A key component of our analysis requires measures of the dissimilarity ("distance") between any two products in our dataset. In computing these distances, the first step is to represent each product, p, within our database as a vector $\mathbf{v}_p$ summarizing its characteristics. To construct these vector representations, we draw on two components of the Nielsen Retail Scanner Data: the UPC description and the size of the product that is being sold.

First, Nielsen's UPC descriptions comprise 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 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.)

Second, Nielsen 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. Continuing with our nonfat vanilla greet yogurt example, each packet of Dannon's nonfat vanilla Greek yogurt is 5.3 ounces, which is within the first (smallest) quartile of the size distribution for the refrigerated yogurt module.

For each product, p, we construct a vector $\mathbf{v}_p$ 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$\in$ 1st Quartile" will be nonzero. For all other possible word abbreviations, and for the "Size$\in$2nd Quartile", "Size$\in$3rd Quartile", and "Size$\in$4th Quartile" categories, the elements of $\mathbf{v}_p$ will be equal to 0. Like in other applications of text data, we apply a *term frequency-inverse document frequency* weighting scheme to fill in the nonzero elements of

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.

$\mathbf{v}_p$. This scheme assigns greater weight to strings that appear more frequently (this is what "term frequency" refers to) in product p'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, $\mathbf{d}_{p,p'}$ between any two products p and p' 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, to $\sqrt{2}$ for products with no overlapping characteristics.

For each transaction in our sample, we aggregate over the products that the acquiring firm and target firm sell in each product module. 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 $\mathcal{P}_{i,m,t}$ to refer to the union of these two sets. 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:

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

In other words, for each quarter we take the products sold by the parties to the transaction, then compute the average Euclidean 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 will also, below, compute distances that focus only on the set of products associated with either the acquiring or target firm:

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

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

Finally, 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. The distribution of $\mathbf{d}_{p,p'}$ has significant mass near the maximum value of $\sqrt{2}$. For this reason, it will be useful to consider quantiles that accentuate whatever variation exists among similar products, in the left tail of the $\mathbf{d}_{p,p'}$ 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. Finally, in Section 3.4 we relate individual products' likelihood of being dropped to their similarity to other products in their parent firms' portfolios.

3.1 Summary Statistics

Our sample consists of 61 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 286 merger-module pairs. Table 1 presents summary statistics for the 61 mergers. The first panel of this table indicates that the size distribution of the merging firms – whether measured in terms of modules, products, or sales — is skewed. The median number of UPCs (combining the products of the acquiring and target firms within our sample of modules) in the quarter preceding the M&A is 116; the mean is 180. Second, the firm which SDC labels to be the acquirer tends to sell, on average, 4 to 5 times as many products as the target firm.

Table 1: Summary Statistics

	Percentile						
	10	25	50	75	90	Mean	SD
Panel A: Before the Merger							
# Modules involved	1	1	3	6	10	4.69	4.61
# Products involved	5	16	116	234	420	180.93	234.61
Revenues	0.09	0.45	9.83	42.57	58.09	26.77	40.49
Products of the Acquirer	2	10	84	193	323	147.69	210.73
Products of the Target	0	3	11	37	78	33.25	56.98
Panel B: Change in the Number of UPCs							
Unweighted	-0.10	-0.01	0.00	0.04	0.07	0.03	0.31
Weighted by Products	-0.37	-0.01	-0.00	0.03	0.06	-0.04	0.15
Weighted by Revenue	-0.17	-0.05	0.00	0.02	0.06	-0.04	0.12

Notes: The first panel presents summary statistics for the sizes of acquisitions for the 61 transactions in our sample. The second panel presents growth rates in the number of UPCs, comparing the quarter of the transaction to the quarter before the transaction. 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 revenues of the two firms in the period before the acquisition in the modules in our sample.

The second panel of Table 1 describes the distribution of the change in the number of UPCs, for the merging firms, during the quarter of the merger relative to the quarter before. Here, we weight mergers equally, according to the number of products involved in the quarter before the acquisition, or according to the total sales of the products in the period before the acquisition. The table indicates an average 3 percent increase in the number of UPCs after a merger if no weighting is applied, or a 4 percent decrease if mergers are weighted by total sales. However, there is wide dispersion, around the mean, in the number of products added and dropped.

Table 2 provides summary statistics for the 286 merger-module pairs in our sample. In the quarter before the merger, the two firms produced 39 products within the average product module in our sample, with 32 products associated with the acquiring firm and 7 with the target firm. As in Table 1, the distribution of acquisition sizes is skewed. Also like in Table 1, acquisitions involve a net reduction in the number of products when merger-module pairs are weighted according to their size.

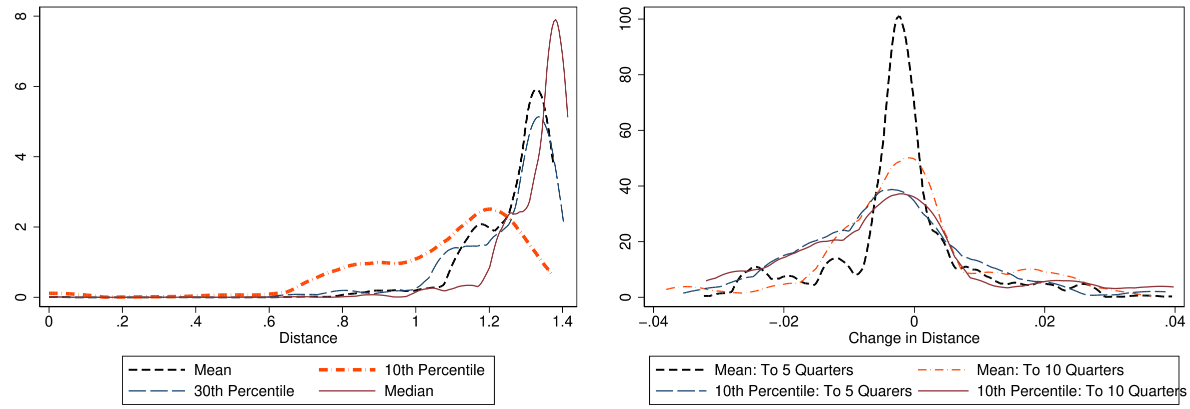
Table 2: Summary Statistics for Merger-Module Pairs

	Percentile						
	10	25	50	75	90	Mean	SD
Panel A: Before the Merger							
Products	1	3	12	44	105	38.59	73.88
Revenues	0.00	0.06	0.61	3.57	13.28	5.71	18.84
Products of the Acquirer	0	2	8	39	84	31.50	67.15
Products of the Target	0	0	1	6	18	7.09	18.88
Panel B: Change in the Number of UPCs							
Unweighted	-0.11	0.00	0.00	0.04	0.17	0.01	0.46
Weighted by Products	-0.13	-0.03	0.00	0.04	0.07	-0.06	0.29
Weighted by Revenue	-0.13	-0.06	-0.01	0.02	0.06	-0.05	0.20

Notes: The first panel presents summary statistics for the sizes of acquisition-product module pairs, for the 268 pairs in our sample. The second panel presents growth rates in the number of UPCs for each transaction-product module pair, comparing the quarter of the transaction to the quarter before the transaction. 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 total revenues of the two firms in the period before the acquisition.

Figure 1 presents distributions of within-firm distances in the quarter before the merger (left panel) and changes in within-firm distances in the periods surrounding the merger (right panel). In more detail, over all pairs of products corresponding to an individual acquisition - product module pair, we compute various distributional statistics: the mean, 10th percentile, 30th percentile, and 50th percentile distances. The left panel of Figure 1 plots the distribution of these statistics, looking across all pairs of acquisitions and product modules. 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. Looking at quantiles which emphasize the left tail of the distribution generates more variation across acquisition-product module pairs. In our event study regressions, below, our analysis will focus on $\mathbf{D}^{0.1}_{i,m,t}$, the 10th percentile distance among products sold by merging firm i product module m and quarter t.

Figure 1: Product Dissimilarity Distributions



Notes: The left panel presents distributions, across firm-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 right panel, we present differences in the within-firm distances, comparing the quarter before the acquisition with 5 or 10 quarters after the acquisition.

The right panel of Figure 1 presents the change in our distance measures, comparing the quarter before the M&A to 5 or 10 quarters after. 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. Product portfolios condense subsequent to a merger or acquisition. While these results are suggestive, they may be explained by confounding factors for which this simple analysis does not control. With that in mind, in the subsequent subsections, 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.

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 firm i in product module m in quarter t, and letting τ denote the quarter in which firm i was involved in a merger (either as acquirer or target), we estimate the following regression:

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

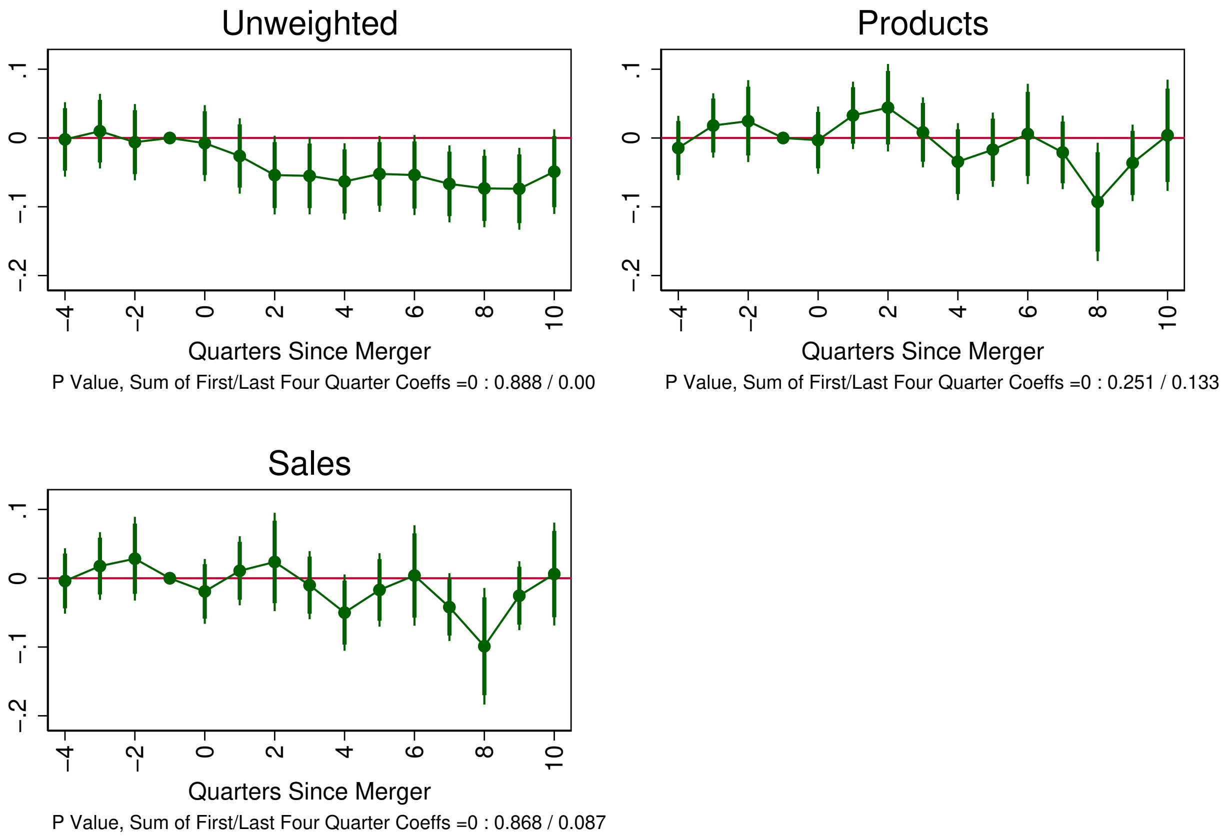
The β_t are quarter fixed effects and the $\beta_{i,m}$ are firm×module fixed effects. Our coefficients of interest, the $\lambda_{t-\tau_i}$, represent the effect of the merger on the number of products sold by the merging firm.

For each merger, we compare the total number of products offered by the merged firm up to 10 quarters after the M&A to the combined number of UPCs offered by the merging firms directly before. As the top left panel of Figure 2 indicates, when observations (M&A-product module pairs) are weighted equally, the number of products offered declines by 6 percent four quarters after the merger, then is relatively constant for at least the subsequent year. In the other two panels, we weight observations by the number of products of the combined firms directly before the merger (top right panel), or the total sales of the products of the combined firm (bottom left panel). In these specifications, the number of products offered also declines, but with substantially larger standard errors.

Within each panel, we first test whether the average of the $\lambda_{t-\tau_i}$ coefficients in the four quarters preceding the merger are different from zero. We then test whether the average of the $\lambda_{t-\tau_i}$ coefficients in quarters 7 through 10 after the merger are different from zero. In all three specifications we find no evidence that $\lambda_{t-\tau_i}$ were different from zero in the periods before the merger. Depending on the weighting scheme, we either strongly reject (unweighted), marginally reject (weighted by sales), or do not reject (weighted by the number of UPCs) the hypothesis that $\lambda_{t-\tau_i}$ are on average different from zero seven to ten quarters after the merger.[8]

[8] In Appendix B, 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 similar for these two groups of products.

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 top left panel, no weights are applied. In the top right panel, observations are weighted according to the number of products involved in the acquisition (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. Within each panel, we test the hypothesis that the sum of the coefficients, either in the four quarters before the acquisition or in quarters seventh through tenth after the merger, are equal to 0.

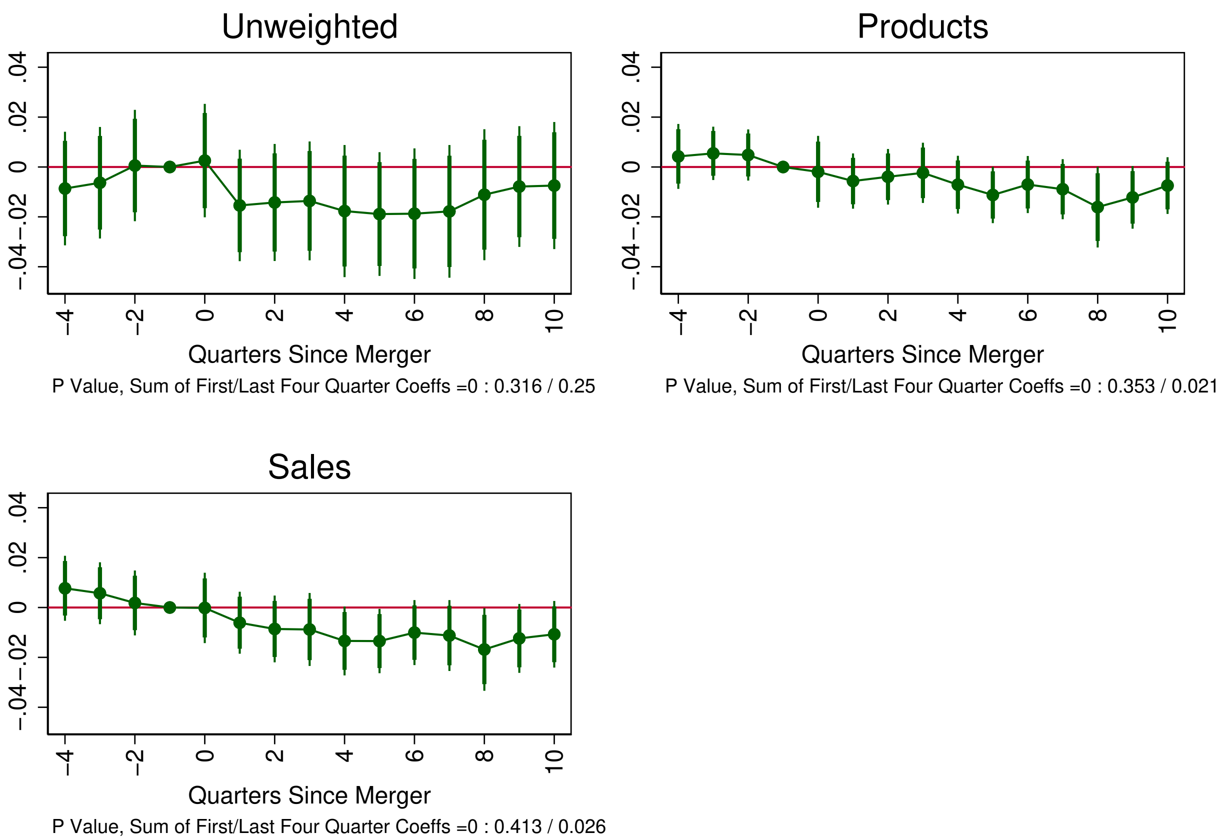
3.3 Distance within Firms

Having identified a net drop in the number of products offered by the merging firm, 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:

$$\mathbf{D}^{0.1}_{i,m,t} = \lambda_{(t-\tau_i)} + \beta_t + \beta_{i,m} + \epsilon_{i,m,t} \ , \tag{5}$$

Here, our dependent variable equals the 10th percentile of the distances among the 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.[9]

Figure 3: Event Study Regression Results–10th Percentile Distance



Notes: This figure presents changes in the distance among products involved in the merger, using estimates of Equation 5 and $\mathbf{D}^{0.1}_{i,m,t}$ as the distance measure. In the top left panel, no weights are applied. In the top right panel, 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. Within each panel, we test the hypothesis that the sum of the coefficients, either in the four quarters before the acquisition or in quarters seventh through tenth after the merger, are equal to 0.

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. When merger-module pairs are weighted equally there is a small but not statistically significant decline in within-firm product distances as a result of the merger. Furthermore, we estimate a negative long-term impact on distance when observations are weighted according to the number of products

[9]In Appendix B, we reestimate 5 with $\bar{\mathbf{D}}_{i,m,t}$ as the dependent variable. Here, the $\lambda_{(t-\tau_i)}$ coefficients are similar, but with somewhat smaller magnitude and with wider standard errors.

(top right panel) or the sales of the products associated with the merger (bottom left panel). In other words, firms tend to drop products that are far from the merging firms' product portfolio (and tend to add relatively more products towards the center of the firms' product portfolio). The effects that we identify are relatively modest: The coefficient estimates in the top right and bottom left panel, when looking 7 to 10 quarters after the M&A, respectively, represent a 0.05 and 0.08 standard deviation decrease in $\mathbf{D}^{0.1}_{i,m,t}$.[10]

3.4 Product-Level Analysis

Building on the firm-product module-level analysis in the previous sections, in Table 3 we compare individual products' likelihood of being dropped to various product characteristics. According to column (1) 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 a 1.3 percentage point percent increase in the probability that the product is dropped within 10 quarters of the merger.[11] In column (2), 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 effect as having sales that are 76 percent smaller.[12] Furthermore, whether the product was initially produced by the target or the acquiring firm has little relationship with its likelihood of being sold in the future. The acquiring firm's products are roughly 10 percent less likely to be dropped. In column (3), we investigate the relative importance of distance to the acquiring and target firms for whether a product is dropped. As this column indicates, Columns (4) though (6) apply a more stringent set of fixed effects, controlling for not only the module in which the product is located but also identity of the merging firms. Within these specifications, the importance of distance to the firms' other products is somewhat muted, but still at least half as large as in columns (1) through (3).

[10] To provide a second point of reference, we compare the estimated $\lambda_{(t-\tau_i)}$ to the dispersion in $\mathbf{D}^{0.1}_{i,m,t}$ that is unexplained by the $\beta_{i,m}$ fixed effects. Here, the $\lambda_{(t-\tau_i)}$ coefficients, 7 to 10 quarters after the merger, are 0.16 times (weighting by products) or 0.24 times (weighting by sales) the unexplained variation in $\mathbf{D}^{0.1}_{i,m,t}$.

[11] The marginal effect associated with column (1) equals 0.117; the standard deviation of the distance to the combined firm's products equals 0.116. So, $0.013 = 0.117 \cdot 0.116$.

[12] To arrive at this figure, note that $0.24 \approx \exp\left(\frac{1.689 \cdot 0.116}{-0.137}\right)$.

Table 3: Logit Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)		-0.137	-0.165		-0.143	-0.173
		(0.004)	(0.006)		(0.004)	(0.006)
1(Acquiring Firm's Product)		-0.0172	-0.119		-0.0317	-0.106
		(0.072)	(0.083)		(0.075)	(0.085)
Distance to Target Firm's Products			0.981			0.604
			(0.326)			(0.340)
Distance to Acquiring Firm's Products			-0.115			0.0531
			(0.430)			(0.461)
Distance to Combined Firm's Products	2.243	1.689		1.866	1.280	
	(0.256)	(0.268)		(0.279)	(0.292)	
Observations	16,858	16,858	7,645	16,818	16,818	7,636
Module-Merger FE	No	No	No	Yes	Yes	Yes
Module FE	Yes	Yes	Yes	No	No	No
Number of Groups	86	86	58	131	131	78

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

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 two main patterns, First, mergers tend to result in net reductions in the number of offered products, with approximately half of the reduction occurring immediately following the merger and the remainder materializing over the subsequent three years. Second, the dropped products tend to be relatively dissimilar to others in the merged firms' product portfolios.

The first of these findings is unsurprising, as the standard economic logic is that merging firms will have incentives to eliminate previously competing products that now cannibalize each others' sales. In other words, assuming that 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. When firms that operate in the same product markets merge, 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 withing the newly-formed firm are relatively less profitable to operate, and thus more likely to be dropped.

While some of the effects that we have identified — in particular on the declines of within-firm distances — are modest, we still think it will be valuable to undertake careful studies of product repositioning for individual mergers. Antitrust policy is concerned with the effect of mergers on welfare, and small changes in product similarity may still have substantial ramifications for consumer welfare. Furthermore, our current analysis does not consider the product adjustments by non-merging firms or the effect 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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A Data Cleaning Details

We clean the product data in five steps. First, we drop all private-label products, those manufactured and sold under a retailer's brand name. 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 special promoted product size and then reverts to its 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. Third, some products have different UPC codes but are not different products. 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% of each other and collapse them to a single product. Fourth, we drop products whose maximum quarterly sales in all time or maximum number of selling stores in all time is too small.[13] This prevents our results from being affected by the noise of niche products. Finally, sometimes a product is no longer produced but still has a positive and small sales in a quarter due to retailers' inventory issues. We set the sales of a product in a quarter to be zero if it is smaller than 1% of the product's maximum quarterly sales and if the number of selling stores in that quarter is smaller than 1% of the maximum number of selling stores in all time. After cleaning, the product data is merged with the company prefix data on UPC prefix.

Since company names in the GS1 and SDC datasets may be written differently, the two data sources are not a priori directly compatible. For instance, the Alpine Valley Bakery Company is called "alpine valley bread co" in the SDC merger data but "alpine lace brands, inc." in the company prefix data. To fix this problem, we standardize all company names via a fuzzy matching exercise. For every company name in the SDC merger data, we search across the company prefix data to find 5 closest names. Among these, we consolidate to the most appropriate firm name (which we determine by hand). We only include mergers and acquisitions for which we can match both the acquirer and target firm in our company prefix dataset.

[13] In the final sample selection criterion, we require that all products in our sample have at least one quarter with 900 units sold and at least one quarter with sales in at least 10 stores.

B Additional Figures and Tables

In this appendix, we compile additional figures and tables, ancillary to our Section 3 analysis. First, Table 4 lists the mergers within our sample.[14]

[14]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 4). 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.

Table 4: List of Transactions

		Products		Sales			Effective
Acquirer	Target	Acquirer	Target	Acquirer	Target	Modules	Date
Campbell	Pacific Foods of Oregon	323	40	203.2	0.8	10	2017Q4
Coca Cola	Monster Energy	222	4	190.3	1.3	1	2015Q2
Mondelez	Enjoy Life	213	21	98.5	0.5	5	2015Q1
Lindt & Sprungli	Russell Stover	387	287	46.5	41.5	5	2014Q3
McCormick	Unilever	1148	61	75.2	9.1	19	2008Q3
Flowers Foods	Bimbo Bakeries	459	60	64.3	6.4	9	2013Q1
Anheuser-Busch	Latrobe Brewing	226	11	57.1	0.9	2	2006Q2
Unilever	Talenti	297	36	52.7	5.2	3	2014Q4
Dr Pepper Snapple	Bai Brands	310	19	49.1	4.5	4	2017Q1
Flowers Foods	Aryzta LLC	332	88	48.1	4.2	7	2013Q3
Dean	Wells Enterprises	1020	45	49.1	1.3	10	2007Q4
Heinz	Kraft	108	170	15.3	33.6	22	2015Q3
Nestle	Kraft	60	108	18.3	30.2	2	2010Q1
Flowers Foods	Lepage Bakeries	193	78	40.2	4.1	7	2012Q3
Flowers Foods	General Mills	297	31	41.7	2.4	9	2009Q4
Flowers Foods	Hostess Brands	181	11	41.2	1.4	2	2013Q3
Conagra Brands	Unilever	142	48	33.5	8.0	8	2012Q3
Flowers Foods	Alpine Valley Bread	193	16	39.8	0.3	3	2015Q4
Flowers Foods	H&S Bakery	186	24	31.7	0.3	6	2008Q3
Tyson	Hillshire Brands	195	13	26.8	0.5	9	2014Q3
McCormick	Reckitt Benckiser LLC	153	30	17.3	3.4	15	2017Q3
Campbell	Ecce Panis	86	18	19.9	0.3	4	2009Q2
Ferrero	Ferrara Candy Company	162	278	3.6	16.3	9	2017Q4

Notes: Continued on the next page.

Table 4: List of Transactions (continued)

		Products		Sales			Effective
Acquirer	Target	Acquirer	Target	Acquirer	Target	Modules	Date
Anheuser-Busch InBev	Four Peaks LLC	184	10	19.3	0.1	3	2016Q1
Tyson	Advancepierre Foods	166	57	17.5	1.3	11	2017Q2
Anheuser-Busch InBev	10 Barrel Brewing Co	196	11	17.4	0.1	2	2014Q4
Dean	Friendly Ice Cream Corp	385	110	7.5	9.8	5	2016Q2
General Mills	Epic Provisions LLC	100	3	16.7	0.0	1	2016Q1
Land O Lakes	Vermont Creamery Inc	27	15	13.7	0.1	4	2017Q1
Anheuser-Busch InBev	Karbach Brewing Co	174	10	11.7	0.1	2	2016Q4
Snyder's Lance Inc	Diamond Food Holdings	74	74	5.5	4.3	6	2016Q1
Hormel Foods	Justins LLC	33	4	9.3	0.4	1	2016Q2
Hormel Foods	Unilever	4	27	2.0	7.5	1	2013Q1
Dairy Farmers of America	Oakhurst Dairy	192	66	5.3	2.2	15	2014Q1
Constellation Brands	Funky Buddha Brewery	38	2	7.4	0.0	1	2017Q3
Ferrero	Fanny May Confections	84	32	5.6	0.4	5	2017Q2
Smucker's	Eagle Family Foods	36	7	4.0	1.4	3	2007Q2
Hormel Foods	Valley Fresh Inc	19	10	2.4	2.4	3	2006Q2
Dairy Farmers of America	Dairy Maid Dairy	133	0	4.4	0.0	4	2013Q3
Saputo	Alto Dairy Cooperative	51	6	3.2	0.0	3	2008Q2
Conagra Brands	Angie's Artisan Treats	73	0	3.1	0.0	3	2017Q4
Hormel Foods	Unilever	0	4	0.0	1.6	1	2010Q1
Campbell	WM Bolthouse Farms	34	9	1.2	0.3	3	2012Q3
Dean	Uncle Matt's Organic	27	6	1.1	0.0	5	2017Q2
Flowers Foods	Leo's Foods	10	2	0.5	0.0	1	2009Q4

Notes: Continued on the next page.

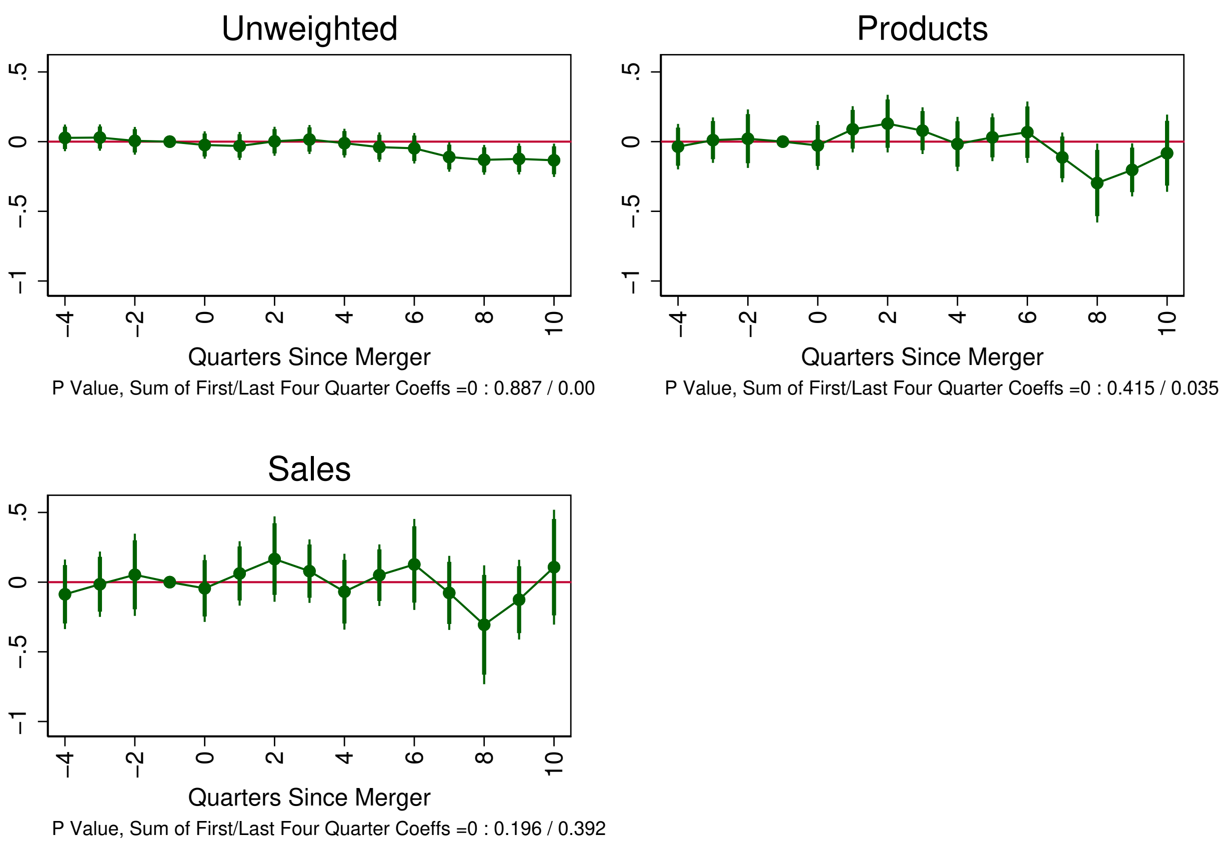
Table 4: List of Transactions (continued)

		Products		Sales			Effective
Acquirer	Target	Acquirer	Target	Acquirer	Target	Modules	Date
Schreiber Foods	Dean	4	37	0.0	0.4	1	2011Q2
Mars	Preferred Brands Intl.	6	0	0.4	0.0	1	2017Q4
CHS	Legacy Foods	4	12	0.0	0.3	1	2008Q2
Nestle	Vitaly Foodservice Inc	6	0	0.3	0.0	1	2009Q4
Tyson	Circle Foods LLC	11	0	0.3	0.0	2	2013Q2
Tyson	Don Julio Foods	1	4	0.0	0.2	1	2013Q1
Conagra Brands	Ralcorp Holdings	4	2	0.1	0.0	1	2013Q1
Bunge	The CF Sauer Co	4	3	0.1	0.0	2	2011Q3
Cargill	FPL Food LLC	2	0	0.1	0.0	2	2016Q1
Hormel Foods	Columbus Manufacturing	10	0	0.1	0.0	11	2017Q4
Campbell	Garden-Fresh Foods	21	0	0.1	0.0	3	2015Q2
Cargill	AFA Foods Inc	2	1	0.0	0.0	1	2013Q3
Smucker's	CF Guenther & Son	1	5	0.0	0.0	2	2006Q4
Hormel Foods	Cytosport Inc	0	2	0.0	0.0	1	2014Q3
Nestle	Chameleon Cold Brew	0	0	0.0	0.0	1	2017Q4
Kerry Group	Island Oasis Frozen Cocktail	0	0	0.0	0.0	1	2015Q4

Notes: For the 61 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.

In Section 3.2, we documented that mergers led to a decline in the number of products offered overall. Are these declines larger for products that were initially sold by the target firm or the acquiring firm? In Figures 4 and 5, we re-estimate Equation 4 using only the sample of products initially offered by the target firm or initially offered by the acquiring firm. Overall, we find somewhat more pronounced changes for products that were initially produced by the acquiring firm. However, these differences depend somewhat on the weighting scheme applied.

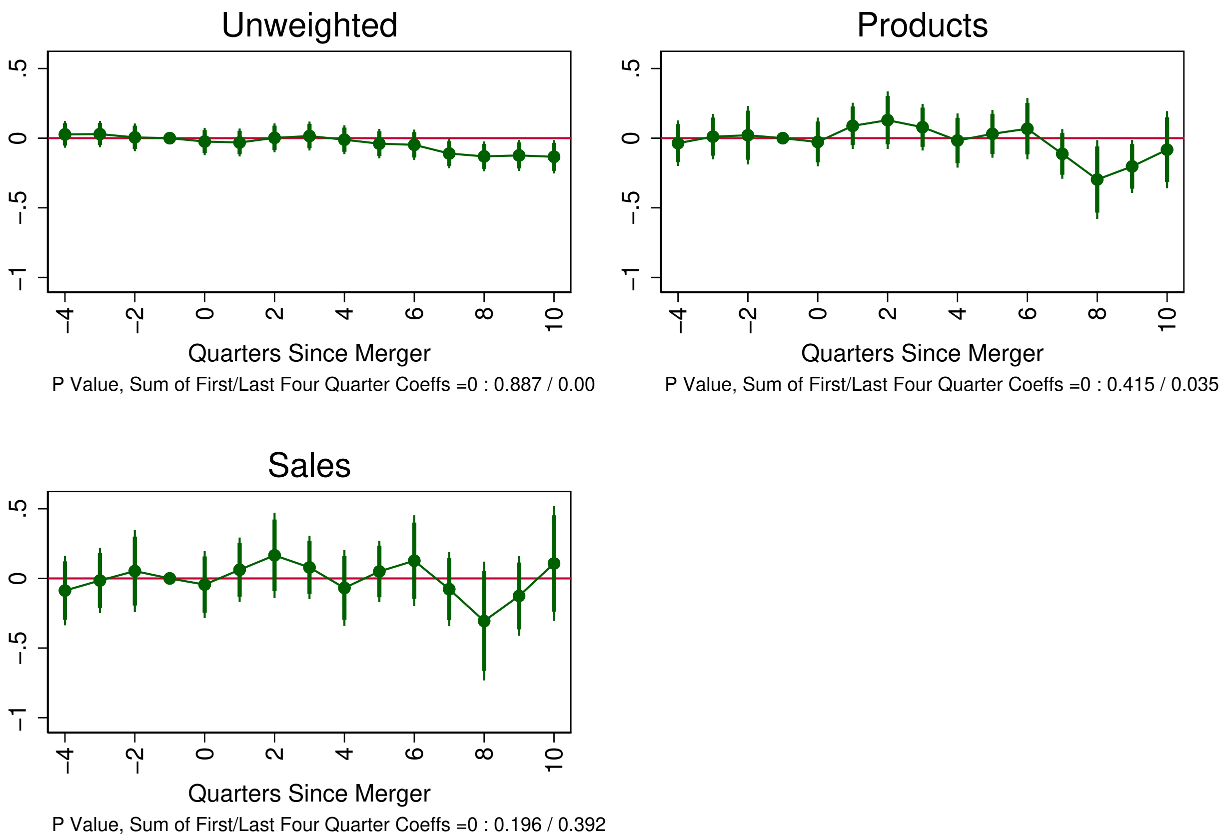
Figure 4: Event Study Regression Results–Target Firm Distance



Notes: See notes for Figure 3. In contrast to that figure, the sample includes only products belonging to the target firm.

Figure 5: Event Study Regression Results—Acquiring Firm Distance

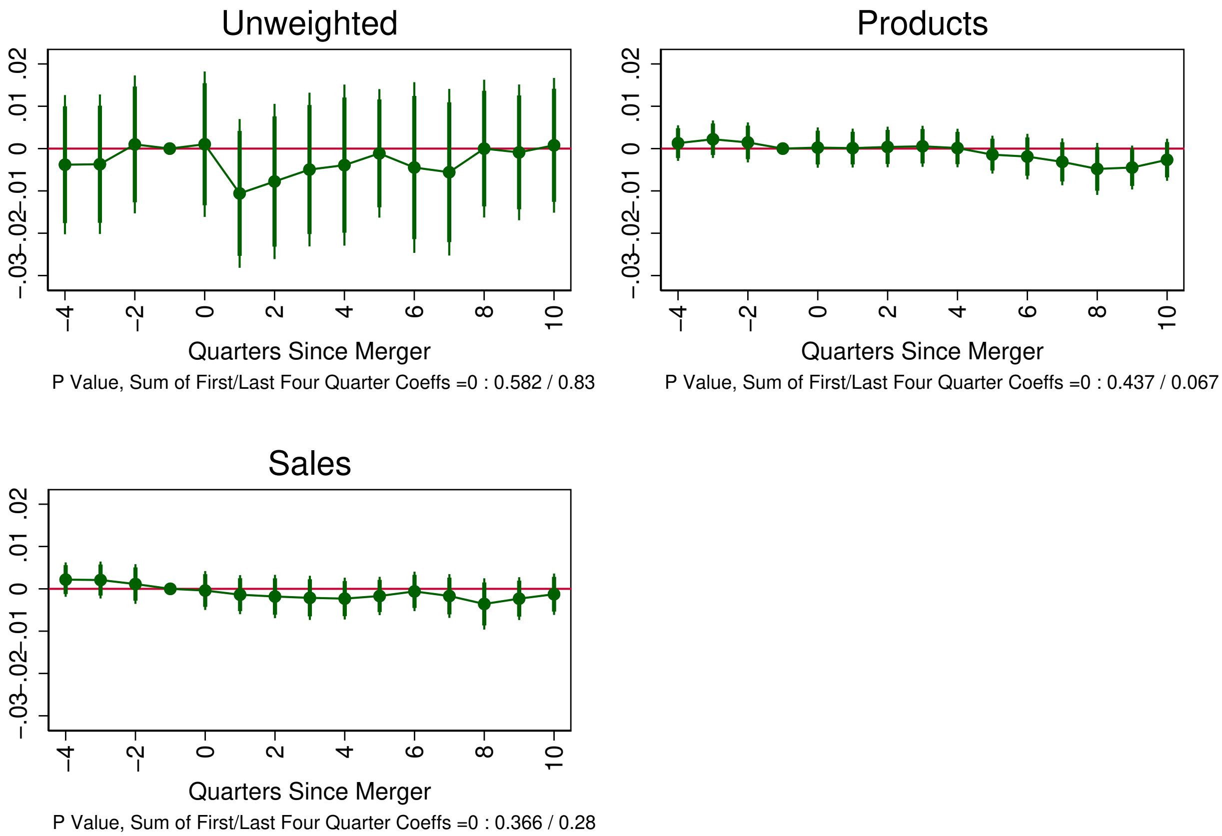
w



See notes for Figure 3. In contrast to that figure, the sample includes only products belonging to the acquiring firm.

In Figure 6, we re-estimate Figure 3 using $\bar{\mathbf{D}}_{i,m,t}$ instead of $\mathbf{D}^{0.1}_{i,m,t}$ as our explanatory variable. Since the distribution of distances is skewed — whereby a substantial fraction of distances among pairs of products is close to the maximum value of $2^{1/2}$ — $\bar{\mathbf{D}}_{i,m,t}$ is less dispersed, also close to $2^{1/2}$ for most acquisition, product module, quarter triples. We find, as before, acquisitions are associated with a decline in the diversity of the products that firms bring to the market. However, this relationship is statistically significant, and only marginally so, only in the specification in which transactions are weighted by the number of products involved.

Figure 6: Event Study Regression Results —Mean Distance



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

Finally, Tables 5 and 6 present the logit regression results, relating product characteristics to the probability that the product disappears from the market. Analogous to Table 3, our samples now comprise products initially corresponding to the target firm (Table 5) or the acquiring firm (Table 6). In each subsample, we find that distance to the acquiring firm's products is strongly associated with product disappearance.

Table 5: Logit Regression Results—Target

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)		-0.176	-0.173		-0.182	-0.180
		(0.012)	(0.012)		(0.012)	(0.012)
Distance to Target			0.859			0.928
Firm's Products			(0.938)			(1.079)
Distance to Acquiring			2.657			2.454
Firm's Products			(1.213)			(1.274)
Distance to Combined	3.669	3.484		3.886	3.191	
Firm's Products	(1.034)	(1.117)		(1.135)	(1.233)	
Observations	2,034	2,034	1,972	1,976	1,976	1,940
Module-Merger FE	No	No	No	Yes	Yes	Yes
Module FE	Yes	Yes	Yes	No	No	No
Number of Groups	39	39	35	42	42	41

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

Table 6: Logit Regression Results—Acquirer

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)		-0.134	-0.167		-0.140	-0.174
		(0.004)	(0.007)		(0.004)	(0.007)
Distance to Target			0.702*			0.202
Firm's Products			(0.392)			(0.409)
Distance to Acquiring			-0.241			0.103
Firm's Products			(0.534)			(0.594)
Distance to Combined	2.365	1.818		1.932	1.362	
Firm's Products	(0.270)	(0.281)		(0.296)	(0.309)	
Observations	14,699	14,699	5,557	14,673	14,673	5,554
Module-Merger FE	No	No	No	Yes	Yes	Yes
Module FE	Yes	Yes	Yes	No	No	No
Number of Groups	76	76	50	118	118	69

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