

Barbarians at the Store?

Private Equity, Products, and Consumers*

Cesare Fracassi[†] Alessandro Previtero[‡] Albert Sheen[§]

Abstract

We investigate the effects of private equity on product markets using price and sales data for an extensive number of consumer products. Following a buyout, target firms increase sales 50% more than matched control firms. Price increases—roughly 1% on existing products—do not drive this growth. The launch of new products and geographic expansion do. Competitors lose shelf space and marginally raise prices. Results for public vs. private targets, during and after the financial crisis, and in industries that vary in structure suggest private equity tailors strategies to the environment, eases financial constraints, and provides expertise to manage growth.

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[†]University of Texas at Austin, McCombs School of Business. Address: 2110 Speedway, Stop B6600, Austin, TX 78712. Telephone: (512) 232-6843. E-mail: cesare.fracassi@mcombs.utexas.edu

[‡]Indiana University, Kelley School of Business, and NBER. Address: 1275 E. 10th St., Suite 6669, Bloomington, IN 47405. Telephone: (812) 856-3590. Email: aleprevi@indiana.edu

[§]University of Oregon, Lundquist College of Business. Address: 1208 University of Oregon, Eugene, OR 97403. Telephone: (541) 346-8057. Email: asheen@uoregon.edu

I. Introduction

Private equity firms have raised more than \$3 trillion in capital over the last five years, exercising a growing influence on the day-to-day purchases of millions of consumers.¹ Private equity (PE) firms have a simple goal: acquire businesses, and exit with gains. How they achieve gains, however, is an open question. Do PE firms simply transfer wealth from stakeholders,² or do they create value by improving firm operations? Studies show that PE firms improve total factor productivity (Davis et al., 2014a) and managerial practices (Bloom et al., 2015, Bernstein and Sheen, 2016), focus patenting activity (Lerner et al., 2011), increase employee safety (Cohn et al., 2016), and reduce agency problems (Edgerton, 2012).

Firms, however, exist to sell goods and services. Despite this, the effects of private equity on target firm products has received little academic attention. Thus in this paper, we use micro-level retail scanner data to study private equity's strategies in the consumer product market. We answer the following basic questions: When PE acquires a manufacturer of consumer goods, what happens to product prices and sales? Does the product mix change? And does product availability expand or contract? Answering these questions helps reveal whether and how PE firms attempt to create wealth. It also provides insight into how private equity impacts consumers, a topic under constant scrutiny by policy makers and the media. We find that, in the years following the buyout, target firms increase sales by 50% on average compared to matched control firms. Price increases do not drive this sales growth.

¹Bain and Company (2018) reports that private equity firms have raised \$701 billion globally in 2017, reaching a total level of over \$3 trillion in the 2012-2017 period. A series of articles published by the New York Times, titled "This is Your Life, Brought to You by Private Equity" 12/24/16, highlights the extensive influence of private equity on consumers.

²For example, by exploiting tax rules, extracting dividends, charging monopoly prices, or repackaging assets.

The launch of new products and geographic expansion do.

We compile monthly store-level prices and unit sales for nearly two million unique consumer products sold in nearly 43,000 locations in the United States between 2006 and 2016. This sample covers over 50% of grocery and drug store sales and over 30% of mass merchandiser sales in the United States. The data is remarkably detailed. For example, we can see that in the first week of August 2008, twenty-four cans of Del Monte French style green beans were sold in a particular store in Chicago at an average price of \$1.15 per can. We link each product to its parent company. Private equity firms acquired 236 of these companies over our sample period. Most of these firms (222) were privately owned at the time of the acquisition. These companies are the manufacturers of goods sold within retailers; we do not study buyouts of retail chains themselves as, for example, in Chevalier (1995a) and Chevalier (1995b).

We test for changes in product prices and sales, innovation, and availability after a PE buyout. Specifically, we first match each private equity target with a similar counterfactual at the time of the private equity event. We go beyond the firm-level match commonly used in the literature; the granularity of our data allows us to compare product lines and even products within the same store. Each of these different treatment-control pairs represents a cohort. We stack cohort-level observations and run a generalized difference-in-differences estimation.

We begin by documenting that in the five years post-buyout private equity targets increase revenues by 50% on average compared to matched control firms. Price increases do not drive this growth. The average price of the products in a firm's product line increases by about 5% relative to competitors. Further, this increase is primarily a composition effect from either the introduction of new products or expansion into richer areas, as the price of an existing

product in a particular store increases by only about 1% relative to its direct competitors sharing shelf space.

Volume growth, therefore, drives revenue growth. How do firms increase units sold? First, PE targets increase the number of products offered by 11% more than matched untreated firms by introducing more new products. Second, PE firms also innovate more into new consumer categories, such as a green bean seller branching to cauliflower. Finally, PE products expand to new stores (+25%), retail chains (+10%), and zip codes (+14%).

Firms that compete with PE targets are affected by the deals. They marginally increase prices following the buyout—less than half of one percent. This evidence is consistent with typical oligopoly models of rivals' behavior when one firm raises prices (e.g., Hotelling, 1929). Competing firms' product variety falls slightly, likely crowded out by the new offerings from PE firms given finite shelf space.

How do private equity firms enable this growth? Why weren't target firms undertaking these actions on their own? To address these questions, we further investigate our results by target firm type, time period, and industry (product category) structure. First, we study the effects of PE for public vs. private firms. PE firms achieve high growth, innovation, and geographic expansion only in private targets. In contrast, we find that public targets raise prices, reducing sales for existing products. This evidence is consistent with PE firms providing access to capital or managerial expertise for private firms (Boucly et al., 2011, Bloom et al., 2015) and taming agency costs for public firms (Jensen, 1986). Second, we examine PE deals separately during and after the late-2000s financial crisis. PE firms achieve growth in both periods and adjust prices to economic conditions more than non-PE firms. Third, we find PE buyout targets introduce more products in categories that are more fragmented, and achieve higher growth in product categories where they have a stronger market share

and in categories that are popular among high-income consumers. Last, we document that PE firms alter target company strategy by increasing corporate acquisitions and advertising expenses. Overall, this evidence suggests that PE achieves growth by pulling several operational levers: by strategically adjusting prices to economic conditions, by focusing innovation and geographic expansion in more appealing product categories, and by promoting investments.

A caveat in interpreting our results is that we cannot unambiguously conclude that private equity firms cause target firms to increase sales, product innovation, and geographic expansion, as “private equity treatment” is not randomly assigned. The standard approach used in the literature to deal with this endogeneity concern is to match treated firms with similar (in the pre-buyout period) untreated firms. A problem with this approach is that firms might differ across a multitude of characteristics, leading to poor matches. Industry codes are coarse; firms in the same broad industry are unlikely to have the same product lineup. The granularity of our data helps mitigate this concern: we match not only similar firms, but also similar product categories and products themselves, using store shelf neighbors as counterfactuals. For example, we compare a can of green beans sold by a target firm with a can of green beans sold by an untreated firm in the same store. This specificity curtails—though does not eliminate—the role that unobservables could play in explaining our results.

Our work contributes to the empirical literature on the effects of private equity on corporate performance and behavior. [Chevalier \(1995a\)](#) and [Chevalier \(1995b\)](#) study the pricing and market expansion behavior of supermarket leveraged buyouts and their competitors. These papers differ from ours along several dimensions. We do not study retail chains themselves; instead, our buyouts are of firms that manufacture products that are then sold within

supermarkets, drug stores, and mass merchandisers. Our price and sales data are thus at the individual product level, not overall store level, and we are able to investigate product innovation and geographic expansion. Moreover, we provide evidence on PE deals completed in the 2000s in contrast to the supermarket deals of the 1980s, an important comparison given the evidence that PE strategies have evolved significantly over the past few decades (see, e.g. Guo et al., 2011). Our results that PE firms spur growth complement the evidence in Boucly et al. (2011) that French target firms increase profitability, sales, debt issuance, and capital expenditures compared to control firms. Our evidence that PE deals do not seem to significantly harm consumers nicely dovetails with findings that private equity could affect firm stakeholders by, for example, reducing work-related injuries (Cohn et al., 2016), increasing employee technological human capital (Agrawal and Tambe, 2016), improving sanitation and food-safety (Bernstein and Sheen, 2016), and impacting student outcomes in for-profit higher education (Eaton et al., 2019). Last, other studies have documented that PE creates value for its investors (Robinson and Sensoy, 2013 and Harris et al., 2014). Our results on the mechanisms (section VII) shed light on how PE firms might create this value: by promoting investments and by tailoring their strategies to private vs. public target firms, to economic conditions, and to industry (product category) structures.

II. Hypotheses Development

What happens in the product market after private equity buyouts? A popular view in the media is that businesses suffer under PE ownership. To generate cash flows, "you can expand the company, but more likely you slash costs, close divisions, cut staff, curtail marketing, eliminate research and development and more. In other words, cutting to the bone."³ If PE

³ *Wall Street Journal*, 3/29/15.

firms follow such a strategy, target companies could trim product offerings and raise prices to boost short term cash flow.⁴ Scaling back investment could also be optimal for some target firms. Agency theory (e.g., Jensen, 1986) predicts that managers might engage in empire building. The added leverage and incentive alignment typical in PE buyouts might, therefore, impose discipline. If lower prices stem from an overinvestment in market share, then private equity firms could raise prices. Analogously, if firms are selling too many products in too many places, private equity could prune product offerings and distribution. Last, liquidity constraints imposed by increased leverage could also lead to higher prices (Chevalier and Scharfstein, 1996).

An alternative and more recent stance on the role of private equity would predict, instead, post-buyout product market expansion. Surveying PE firms, Gompers et al. (2016) find that in target firms revenue growth is pursued more aggressively than cost cutting. Analyzing data from 839 French PE deals, Boucly et al. (2011) indeed find that buyouts appear to infuse capital and relax credit constraints, as target firms grow faster and become more profitable than their peers, particularly when capital might be most dear ex ante. Bloom et al. (2015) find that private equity may bring better management practices to target firms. If these mechanisms are at play, we expect to see growth. Implications for pricing, however, are unclear. New or better products might be more expensive. On the contrary, leaner manufacturing or more skillful bargaining with retailers could lead to lower prices.

These contrasting predictions can co-exist in the cross-section of target firms. For example, agency theories might better describe dynamics in more mature industries and for publicly traded firms (Jensen, 1986). Capital constraints may be more relevant for private or small firms (Farre-Mensa and Ljungqvist, 2016). Bloom et al. (2015) find that private

⁴Kosman (2009) devotes an entire chapter to "Lifting Prices" in his book "The Buyout of America."

firms are more in need of managerial expertise than public firms. [Davis et al. \(2014a\)](#) document employment growth following private firm buyouts but contraction after public deals. [Boucly et al. \(2011\)](#) find stronger growth results for private-to-private buyouts. To test these different cross-sectional predictions, we repeat our main analyses separately for private and public target firms (section [VII.B](#)).

We also test if the effects of PE vary with economic conditions (section [VII.C](#)). [Bernstein et al. \(2019\)](#) study UK PE-backed companies during the financial crisis. Compared to control firms, PE targets decreased investments less and increased market share more. They attribute this findings to the ability of PE firms to raise capital or to provide strategic and operational guidance in difficult times.

How do competitors react to the entry of PE firms? [Chevalier \(1995b\)](#) finds that, following the LBO of a supermarket chain, prices in a local market rise if rival firms are also highly leveraged. Prices, instead, decline in local markets where competitors have low leverage and are concentrated. Similarly, [Goolsbee and Syverson \(2008\)](#) study the airline industry and find that incumbents cut fares when facing potential entry. [Gerardi and Shapiro \(2009\)](#) find that competition has a negative effect on price dispersion in the airline industry. We investigate competitor reaction in prices and product innovation in section [VI](#).

III. Data Description

A. Nielsen Retail Scanner Data

We combine private equity buyouts and retail store scanner data in our analyses. Product market data comes from the Nielsen Retail Scanner database from the Kilts Center for Marketing - Chicago Booth. This database tracks all purchases made in the United States

from January 2006 to December 2016 at 42,928 stores from 91 U.S. retail chains (see Table [II](#)). Almost all major chains are present in our data, but their identities are anonymized. The largest chain in the sample has 10,129 stores. The sample covers roughly 50% of total U.S. grocery and drug store sales and 30% of U.S. mass merchandiser sales. The stores are spread across the United States, covering 98% of media designated market areas (DMAs). Nielsen tracks weekly average prices and units sold at each store for close to two million unique consumer products.

The Nielsen data identifies products by name and Universal Product Code (UPC). The data are very specific. For example, Table [I](#) lists all products available under the category “Canned Green Beans” in a specific grocery store in Austin, Texas, in December 2007. Seventeen green bean products are sold in the store differing in brand (e.g. Del Monte, General Mills), type (e.g. organic, French style), and size (e.g. 8oz, 14.5oz). We exclude UPCs that do not identify unique products (e.g., private label products, products temporarily sold in different size). For each product, each week, in each store, we know the average price, units sold, and total revenue. Table [II](#) provides summary statistics. The average product is sold in 571 stores and an average store carries about 19,000 products. Nielsen groups items into mutually exclusive groups such as “Vegetables-Beans-Green-Canned,” “Fabric Softeners-Liquid,” or “Vacuum and Carpet Cleaner Appliance.” These are called “product categories” and should be thought of as highly-specific industry definitions. Panel B of Table [II](#) shows that there are 1,127 different product categories, and each one includes on average 21 items belonging to four firms.

We match each UPC to its parent firm. The GS1 organization oversees the management of UPCs. Manufacturers buy from GS1 the usage right to a UPC company prefix that corresponds to the first six to nine digits of the UPCs of its products. Firms are required

to disclose their name and address when buying a company prefix. Using the GS1 Data Hub, we exactly match 82% of the UPCs in the data to a GS1 company prefix. We map the remaining UPCs to companies by assuming that UPCs in the same firm share the first eight digits. In Panel C of Table III, we present the characteristics of the sample's over 52,000 firms. The average firm sells 10.2 products in 2.9 product categories through nine retail chains spanning 1,346 stores.

The data allows us to precisely define competitors, market structure, and plausible counterfactuals. We aggregate the data at the monthly level to make the dataset more manageable and to smooth consumption peaks (e.g. Black Friday).⁵ The monthly frequency allows us to accurately capture when firms introduce new products, discontinue products, and expand into new markets. Despite the richness of the data, we miss two important pieces of information. First, we observe the prices paid by consumers—the sum of the wholesale price and retailer markup. We cannot say with certainty which of these two price components drives our results. That said, whether PE firms are changing wholesale prices or influencing retailers to change margins, the ultimate effect on the consumer is the same. Second, we do not observe manufacturing costs and markups and, thus, we cannot draw direct conclusions about the profitability or optimality of firms' decisions before or after the private equity deal.

B. Private Equity data

We obtain data on private equity deals from Capital IQ and Preqin. From Capital IQ, we select all “closed,” North American, majority stake transactions classified as “Leveraged Buyout”, “Management Buyout”, “Secondary Buyout”, or “Going Private Transaction”. We

⁵The Nielsen data records weekly sales from Sunday morning to Saturday night. If the beginning or the end of the month is not on a Sunday, we assign a pro-rata of the weekly units sold and sales to each corresponding month.

do not include venture capital deals. From Preqin, we collect all North American private equity portfolio companies. We keep only deals closed between 2007 and 2015 as we require at least one year of product market data before and after each deal, and the Nielsen data spans 2006-2016. To link PE targets with firms in the Nielsen/GS1 database, we begin with fuzzy match algorithms based on company name and state, and then manually check each deal to make sure the firms are correctly identified. We also buttress this process with a “top-down” approach, collecting the largest PE deals from Capital IQ and manually checking if any belong in the sample. This makes sure we do not miss any large, obvious deals⁶. We end up with 236 private equity deals, of which 222 are buyouts of private firms and 14 are public.

To address the representativeness of our sample, we compare in the appendix our deals with the universe of PE deals in Capital IQ during our sample period and with the PE deals in consumer products (see Appendix Table A1). We find that our deals appear to be larger in size and involve older firms compared to the average PE deal in Capital IQ and in consumer goods. We provide more details on this comparison in the Appendix section II.

Figure I shows the number of buyouts over time. Deals are more frequent during the private equity boom of the mid-2000s to 2007 and less frequent during the financial crisis starting in 2008. Online appendix Table A3 lists the most frequent PE buyers in our sample, identified using the category *Buyers* in Capital IQ and *Investors* in Preqin. Table A4 lists the private equity targets with the highest average sales in our sample. The three largest are Del Monte, The Nature’s Bounty, and the Pabst Brewing Company. These are not necessarily the targets with the greatest deal value, just those with greatest presence in the consumer product categories we analyze.

⁶Expanded details on how the sample is formed are in the online appendix, section II.

IV. Empirical Methodology

A. Research Design

Private equity firms do not randomly select companies. As shown in Table [A5](#) in the online appendix, they are more likely to target product categories that are less concentrated and more popular among high-income consumers, firms that are larger, and products that are cheaper than competitors.⁷ While a comprehensive study of the characteristics of firms and products taken over by private equity is beyond the scope of this study, we use a matching strategy that controls for relevant observable trends. An advantage of our setting is that our detailed data allows us to match each treated unit with a very similar counterfactual.

Our matching strategy does not completely solve endogeneity problems. There are two outstanding concerns. First, while we control for pre-deal observable characteristics, there could be unobserved characteristics that explain differences in post-event outcomes. Second, even if we could match on all pre-deal characteristics, a firm could still be targeted because it is expected to change in the future. We find evidence that alleviates the first concern: after the match, treated and control groups are similar also on observable variables that we do not use in the matching procedure (see Table [A6](#)). The granularity of the data helps with the second concern. We are able to compare, for example, two cans of green beans on the same store shelf. While it is possible that one brand has a different future trajectory than another (e.g., buzz from an advertising campaign), matching with such specificity certainly reduces the scope of variation (e.g., we control for a sudden increase in green bean popularity).

An additional concern related to our empirical strategy is that both the treated firms/product categories/products and their control units could react to the treatment (the PE

⁷We provide more details on how we identify category concentration and popularity among high-income consumers in section [VII.D](#).

deal). In other words, if competitors react to the entry of PE, then our comparison of treated vs. control units does not capture the full effects of PE entry. To address this concern, in section [VI](#) we examine whether competitors change behavior when facing a PE competitor. For example, we compare the prices of the same competitor product in stores where it faces PE vs. stores in which it does not.

B. Matching Procedure

We match each private equity acquired firm, firm-product line, or product with a close competitor chosen based on observable characteristics at the time of the private equity deal. We define each resulting treated-control pair as a cohort and then stack all cohorts. Finally, we run a difference-in-differences regression specification on this stack of cohorts.

We match each of the 236 treated firms and 1,835 treated firm-categories with a similar counterfactual based on four variables measured at the time of the private equity deal: monthly sales, number of unique UPCs sold, number of stores in which they sell, and growth in monthly sales. The first three variables are measured in the most recent pre-buyout month, while growth in sales is computed from 12 months before the deal to the most recent pre-buyout month. In the firm-level analyses, 220 control firms are matched to one treated firm, six to two treated firms, and one to four treated firms.

We also perform analyses at the individual product level. For each product-store—e.g., Del Monte 14.5 oz. French Style Green Beans sold in a particular store in Austin, Texas—we select a matched product in that same store, in the same product category at the time of the private equity deal. We choose the particular green bean item (UPC) with the closest distance based on average price and units sold during the most recent month pre-buyout, and growth in price and units sold from 12 months ago to the most recent month pre-buyout.

We match with replacement each treated unit with the closest control using the [Abadie and Imbens \(2006\)](#) distance metric⁸. Both treated and control units must be in the sample for at least one year before and one year after the buyout event. In the Online Appendix, we investigate if treated or control firms are more likely to disappear post-buyout. We thus focus on deals from 2008 to 2011, so that we have the full two years before and five years after the buyout. Figure [A1](#) shows that the drop-out rate of PE targets and matched controls is very low. Furthermore, PE targets are less likely to drop compared to control firms, with this difference becoming larger especially in the years three to five post-deal.⁹

The matched control product categories and control individual products become the object of our analyses when we investigate the response of competitors in section [VI](#).

C. Econometric Specification

Our main empirical analysis employs a stacked cohort generalized difference-in-differences strategy. Essentially, we take the difference in outcome for each treated unit i (firm, product-category, or product) after the private equity deal relative to before and compare it with the difference in outcome of its matched control unit within the same cohort c .

$$y_{i,c,t} = \beta(d_{i,c} \times p_{t,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t} \quad (1)$$

All regressions are estimated from 24 months before the event to 60 months afterwards. We choose the pre-window to have enough periods to test the parallel pre-trend assumption

⁸For each of the four matching variables, we compute the difference between treated and control and then divide this difference by the variable's standard deviation in order to normalize the scale. We then compute the overall distance by summing the four scaled differences.

⁹To the extent that PE targets that are more successful than their control firms are dropped from our analyses because their match disappears, then this evidence would suggest that we are potentially understating the effects of PE, especially in the three to five years post-buyout.

and the post-window to allow enough time for any PE effects to emerge. The unit-cohort fixed effect $\alpha_{i,c}$ ensures that we compare the outcome within the same unit in the period before vs. after the deal. The time-cohort fixed effect $\delta_{t,c}$ ensures that the treatment unit is compared only with the matched control at each point in time. $d_{i,c}$ is a dummy variable identifying treated units. $p_{t,c}$ is a dummy variable equal to one if the time period is after the private equity buyout. The coefficient β represents the diff-in-diff effect of the private equity deal on the outcome variable relative to a matched counterfactual. The standard errors are double-clustered at the firm and month level to adjust for heteroskedasticity, serial correlation, and cross-sectional correlation in the error term (Bertrand et al., 2004).

To test the parallel pre-trend assumption and learn how quickly private equity firms implement change, we also estimate the impact of private equity month-by-month, using the equation below:

$$y_{i,c,t} = \sum_{k=-24}^{60} \beta_k (d_{i,c} \times \lambda_{t,k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t} \quad (2)$$

$\lambda_{t,k,c}$ is a dummy equal to one if time t is equal to k and zero otherwise. Standard errors are also double clustered at the firm and month level. Given the large number of fixed effects and observations, all regressions in the paper are estimated using the fixed point iteration procedure implemented by Correia (2014).

V. The Effect of Private Equity on Target Firms

A. Sales and Prices

What happens to the sales and pricing of goods sold by consumer products firms acquired by private equity? We start by analyzing these variables at the firm level. Each target firm is matched to an untreated firm as described in section [IV.B](#). Panel A of Table [III](#) shows estimated coefficients of regressions of each firm’s log sales, sales-weighted average log price, and log units sold on *After*, a dummy variable that equals one for firm-month observations after the private equity deal close date for target firms. We find that revenues relative to a matched firm increase dramatically. The coefficient on *After* is 0.406, translating to a 50% increase in sales in the years following the deal¹⁰. This result is consistent with papers that document growth following PE buyouts (e.g. [Boucly et al., 2011](#)). This growth is primarily driven by a 43% increase in units sold. The average price per firm increases by 5%. We compute average product prices by dividing total revenues by units sold for each firm in each month. This is a very rough price measure—it blends all categories, products, and stores into a single number for each firm and will thus be influenced heavily by composition effects. While it could capture well overall trends in pricing for single category firms, the average price per firm is not likely informative for firms that sell both cheap and expensive items.

To better understand price dynamics and what ultimately drives changes in sales and units, we begin “peeling the onion”. We break the unit of analysis down from the firm to the firm-category. In other words, now instead of treating Del Monte as a single entity, we analyze separately their green bean, canned peach, and spaghetti sauce businesses. This sharpens the analysis in two ways. First, it increases the quality of the match, as individual

¹⁰Throughout the text, we exponentiate the coefficients for regressions with logged dependent variables when reporting magnitudes.

product lines can be matched more precisely than entire firms; Del Monte and General Mills do not participate in exactly the same product categories. Second, it allows us to separate changes in existing product categories from changes in the category mix. The 236 PE treated firms in our sample range from operating in a single Nielsen-defined product category (e.g., Noosa Yoghurt, LLC only sells products in the "Yogurt-Refrigerated" category in our sample) up to 101 categories for American Roland Food Corp.

In Panel B of Table [III](#), we regress the logs of nationwide revenues, units sold, and average prices for a firm in a particular product category on the *After* variable. This breakdown at the product category level mimics the firm-level results. With the added precision of only comparing product categories, not entire firms, we find that average prices of private equity-owned firms increase by 3% relative to matched firms. Sales increase by 23% and units sold increase by 18%. All are statistically significant at 1%. These point estimates for units and revenues at the category level are a little smaller than at the firm level. This could be a sign that either PE targets' larger categories are growing the most, or that they are expanding to new categories. We explore this in the next section.

Figure [2](#) plots the trend in log sales and average log prices over time with a 90% confidence interval. The graphs show no obvious pre-trend in sales or price before the PE buyout. This provides comfort that we are comparing similar firms and firm-categories. After the event, at the firm and product-category level, there is a gradual increase in both sales and prices over the next three to five years.

After a PE buyout, we find small price increases and large unit sold increases at the category level. Multiple paths can generate these results; distinguishing between them is important for understanding PE growth strategies. The relative increase in average nationwide category-level prices could be because existing products have been marked up. Alternatively,

the composition of goods sold within a category might have shifted towards more expensive varieties (e.g., premium organic products), or the firm might be growing share in markets or retailers that simply charge more (e.g., New York City).

Similarly, there are different paths to the increase in firm-category units sold; PE targets could be gaining share within a store or expanding to new stores.

To peel the onion further, we zoom in to the individual product and store level. Instead of comparing a PE target and control firm's green bean sales nationally, we now compare a PE target's 16 ounce can of Italian-style green beans in a particular supermarket in Austin, Texas with a non-PE can of Italian-style green beans in the same store. In other words, we use literal store shelf neighbors as counterfactuals. This allows us to tease apart changes to existing products from composition and location effects.

The unit of observation is a specific UPC in a specific store in a month. A cohort is defined as a treated-untreated pair of products within the same store and category. We regress the logs of sales, average price, and units on *After*, product-cohort fixed effects, and cohort-time fixed effects.

In Panel C of Table [III](#), we find a 1% increase in the price post-PE for a given treated product relative to a competing product in the same store over the next five years. This 1% increase for existing products implies that the average category price increase of 3% shown in Panel B is mostly due to a composition effect: adding or shifting consumer tastes to products that are more expensive or expanding to locations with higher prevailing prices or cost of living. Results on revenues and units sold differ substantially from the results in Panels A and B; both *After* coefficients are essentially zero. This means that existing products are not gaining share within their current stores. Some combination of selling new products or selling in new places must, therefore, drive unit and revenue increases at the firm and

category level. We explore product innovation and geographic availability next.

B. New Product Development

Do private equity firms change the pace of new product introduction? Do they expand into new industries? [Lerner et al. \(2011\)](#) and [Amess et al. \(2015\)](#) find that after a leveraged buyout, firms increase their patenting activity and produce more influential patents, suggesting either a relaxation of financial constraints or reduced agency problems. While patents capture the early stages of innovation, our data allows us to study the end result with the release of new products.

Mimicking the price and sales analyses, we first answer these questions at the overall firm level. We match each of the 236 firms acquired by private equity with a non-private equity-owned firm with the closest sales, number of products, number of stores, and growth in sales. The unit of analysis is a firm-month. [Table IV](#) illustrates the effect of PE on product innovation. *Number of Products* is the log of the number of unique UPCs a firm sells nationwide in month t . *New products* is the number of products introduced by the firm in month t . A new product is a UPC that appears for the first time in the Nielsen database. *Discontinued Products* is the number of products dropped by the firm in month t , meaning the UPC never reappears again in the sample. To better ensure that we accurately measure introductions and discontinuations in product lines, we exclude from our analyses products that appear in the first six months of a firm's appearance in our sample. Analogously, we exclude products that disappear in the last six months of a firm's presence in our data. The reason for this is if a product (UPC) is sold in November 2016, but not December 2016 (the end of our sample), it may not have been permanently discontinued. It is possible the product simply did not sell any units in December but returned to stores later in 2017. A

six-month buffer on both ends gives us more confidence that a product is truly discontinued or new. Last, *Number of Categories* is the log of the number of categories in which a firm sells products at time t . Nielsen defines 1,127 total categories.

In Panel A of Table [IV](#) we compare the product portfolios of PE and non-PE firms. Column 1 shows that, relative to matched firms, PE-treated firms expand their number of distinct UPCs by 11% after the deal. How is this achieved? Columns 2 and 3 show greater churn—more frequent introduction and discontinuation of products. However, the coefficient on *New Products* is significant and more than double the coefficient on *Discontinued Products*, resulting in increased product variety. We also find treated firms more likely to expand into new product categories. In column 4, the coefficient on *After* is 5% and it is statistically significant. It appears that PE targets both create new varieties in existing product categories and enter into new ones.

To confirm this interpretation, in Panel B we run analyses at the firm-category level. We compare each treated firm-category with the same category of an untreated competitor. Within a category, PE controlled firms increase their product portfolio by 2.5% relative to their pre-PE ownership days. Both new product introductions and discontinuations increase at a faster rate. Given that existing products do not decline in sales (see Table [III](#)), these new products do not cannibalize existing goods. Figure [3](#) shows that product innovation happens gradually over the years following the PE buyout.

Overall, private equity firms appear to engage in more creative destruction within their product lines, with introductions of new products outpacing discontinuations, resulting in greater product variety. We also find evidence of expansion into new product categories. Since average category-level prices increase for treated firms, the new products must be slightly more expensive. The higher number of products for sale helps explain why overall

units sold grow for treated firms despite no change in existing product units sold at the store level.

C. Product Availability

Private equity targets increase units sold and revenues more than competitors. In the previous section, we show that introduction of new products contributes to this result. In addition, PE may facilitate geographic expansion.

We report results at the firm-level in Table [V](#), panel A, and at the firm-category-level in panel B. *After* is an indicator variable indicating a post-buyout firm-month or firm-category-month for target firms. Column 1 shows that treated firms increase the number of physical stores in which they sell their products by 25% after the deal, relative to matched untreated firms. This result can happen by selling to more stores within the same retail chain or by entering new retail chains. Column 2 shows that PE firms increase the number of retail chains by 10% post-buyout. How widespread geographically is this expansion? Column 3 shows that PE firms expand to 14% more 3-digit ZIP codes. We obtain similar unreported results for counties, DMAs, and states (see figure [A2](#) in the Appendix for a graphical illustration of these results). The results at the firm-category level (in Panel B) are similar. Figure [4](#) shows that this expansion occurs steadily over the years following the deal.

In the Appendix Table [A7](#), we investigate more formally the timing of the PE effects in all our major analyses, by interacting our treatment variable with each of the four years following the buyout. We find that most of the results are significant starting from the first year post-buyout and that the effects of PE linearly increase over time.

VI. Competitor Response

The results thus far show what happens to private equity treated goods relative to matched competitors. Competitors, however, do not necessarily stand still. In this section, we investigate how competition responds to PE entry. Combined with the relative changes documented in section [V](#), these results paint a more comprehensive picture of the effects of PE on products and, ultimately, consumers.

A. *Competitor Response: Prices*

Prices on existing products taken over by PE increase by about 1% relative to matched products (Table [III](#), Panel C). This result is consistent with private equity firms keeping prices constant while competitors lower prices to run highly leveraged targets out of business. Alternatively, the price effects could be bigger if competitors also increase prices. It is ultimately an empirical question whether rivals match PE price increase behavior—as typical oligopoly models would predict—or seize an opportunity for predation.

To identify the pricing response of competitors to private equity entry, we exploit geographic variation in a given competitor’s exposure to a PE buyout. As an example, assume that Del Monte, a private equity takeover target, sells green beans in store A but not in store B. General Mills, who is not private equity owned, sells green beans in both stores. We compare the price response of General Mills in store A, which faces PE competition, to its response in store B, which does not. We attribute a differential price response following the buyout to the PE deal. The identifying assumption is that absent the deal, the price of this particular green bean product of General Mills would have moved similarly in both stores.

The control firms in previous regressions now become the objects of interest. We first

extract from the same-store analysis of Table III the same non-PE products and store locations that face a PE competitor. We then identify the stores where these non-PE products are sold absent the PE competitor. Given that each product is sold in thousands of stores, we randomly select ten stores, and among these we select the closest match in terms of price level and growth to the non-PE product which does face a PE rival. These two product-stores form a cohort.

In Table VI, *After* is an indicator variable equal to one for non-PE products after their competitors' PE deals, in stores where that newly PE-owned product is sold. As in the previous same-store product analysis, we include product-cohort fixed effects and time-cohort fixed effects. In Panel A, Column 1, the coefficient on *After* is 0.4% and significant, suggesting that private equity leads direct store competitors to marginally raise prices.

A problem for our identifying assumption would be if pricing trends in stores with PE competition are systematically different from trends in stores without PE. For example, PE products could be sold in chains or in geographic areas experiencing differential price changes. We address these possibilities in Column 2 and 3. In Column 2, we require that all eleven stores (ten which sell only the non-PE product, one which also sells the PE entrant) from which the product-store cohorts are drawn are part of the same retail chain. In Column 3 we require that all the stores used to define the cohorts are in the same DMA. The coefficients on *After* in these regressions are 0.4% and 0.3% and still significant. Private equity entry thus leads competitors to marginally raise prices in stores where they directly compete¹¹.

Figure 5 plots the price response over time from Column 1. Price responses for Columns 2 and 3 are in the Appendix, Figure A3. Interestingly, the price change happens very quickly.

¹¹Price changes could be driven by the manufacturer (General Mills in our example) or the individual retail store manager; Levy et al. (1997) notes that both impact final retail pricing. Whether the manufacturer or the retailer is responsible for higher competitor prices when PE is present, however, it is still ultimately the PE buyout that instigated the change.

Added to the relative price increase of approximately 1% for PE-owned goods, the results in panel A suggest the overall PE price increase experienced by consumers could be 1.3 to 1.4%.

B. Competitor Response: Product Mix and Availability

Private equity targets boost product introduction and thus increase variety. How do competitors respond? To address this question we analyze if, after the buyout, there is a change in the number of products these competitors sell in stores where they compete with the PE firms vs. stores where they do not. As an illustrative example, General Mills, which is not PE-owned, sells 10 varieties of green beans in stores A and B prior to the PE buyout of its competitor, Del Monte. Del Monte sells green beans in store A but not store B. What happens to General Mills' green bean variety in store A vs. store B after the PE deal? Our identifying assumption is that any difference in General Mills' store A variety is due to the presence of private equity. The unit of analysis is now a firm's entire product category within a store, not a specific product, since we want to count the number of products in the category. For each store in which a non-PE firm competes with a PE in a given category, we select ten random stores where the non-PE firm does not compete with PE. We form cohorts using all eleven firm-category stores, one treated by a PE entrant and ten untreated. We use all ten control stores because it is not obvious how to identify the best match and because we want to reduce the noise in the measurement of product variety using one single store.

We present these results in Table [VI](#), Panel B. In Column 1, we find that a PE-buyout competitor reduces the number of product offerings by 1.5%. We find similar results in Column 2 where all 11 stores in each cohort are from the same retail chain, and Column 3 where all cohort members are from the same DMA. Unlike with prices, where competitors

respond (marginally) in the same direction as their PE shelf neighbors, product variety responds in the opposite direction. Given that shelf space is finite, more aggressive PE product introduction appears to crowd out competitors.

Our findings are at odds with evidence in Chevalier (1995b) that competitors enter and expand into the LBO grocery chain's markets after the deal. There are key differences between the papers that could help explain the different results. First, Chevalier investigates retail chains, while we focus on manufacturers that sell in these chains. Second, Chevalier's sample is heavily influenced by publicly-traded firms, whereas most of our firms are private. In section VII.B, we split our analyses by public and private firms and find results for public firms at the product-store level that are more consistent with evidence in Chevalier (1995b). Last, supermarket LBOs from the 1980's were undertaken as a takeover defense¹². Decades later, the drivers of PE deals appear starkly different (see our evidence from press releases in section VII.A).

VII. Mechanisms

Private equity deals result in marginally higher prices but significantly higher sales, primarily through aggressive introduction of new products in new locations. How do private equity firms achieve these results? Why is private equity needed? In this section we investigate the potential mechanisms in play. We start by examining cross-sectional and time-series variation in PE impact. Knowing where and when PE is most effective can provide clues to their particular skills and strategy. We study the effects of PE: i) on public versus private

¹²“The vast majority of the leveraged buyouts were not the result of unconstrained decisions by managers and shareholders. Instead, most of them were undertaken in response to unwanted takeover attempts. In fact, all four of the biggest deals (and many of the smaller ones) were undertaken to thwart the unwanted takeover attempts of the Haft family” (Chevalier, 1995b).

targets; ii) around and after the financial crisis; iii) in product categories where target firms have high vs. low market power; iv) in product categories with low vs. high barriers to entry; and v) in categories popular among high-income vs. low-income consumers. We also directly test whether buyout target firms become more acquisitive or increase advertising expenditures. Last, we examine acquisitions of firms by operating companies (i.e., traditional M&As) to test if our results are specific to PE acquisitions or occur whenever there is a change in ownership.

A. Private Equity Deal Press Releases

A starting point for understanding how private equity firms achieve results is to investigate their stated plans and strategies. [Gompers et al. \(2016\)](#) survey PE firms to understand how they might create value. In the same spirit, we collect and analyze the press release announcements for the deals in our sample. With the caveats that PE firms might strategically handle their press and likely overstate positive outcomes (e.g. growth) and downplay negative ones (e.g. layoffs), announcements can still offer insights into the range of strategies employed.

We were able to find press releases for 237 deals.¹³ We categorize the stated reasons for the deals in Table [VII](#). Reasons are not mutually exclusive. Most press releases (69%) generically mention growth; some specifically detail new product development, acquisitions, or access to distribution. Capital infusion and human capital are mentioned as well. Motivations pertaining to cost cutting and financial engineering are hardly present. There is no mention of PE as a takeover defense, as, for example, in the case of supermarket LBOs in [Chevalier](#)

¹³This 237 is out of 297 total firms. The sample here is larger than the final sample in our paper (236 firms) because we include firms here for which we do not have at least one year of data before and after the deal. We have press releases for 184 out of 236 deals in our final sample.

(1995a). Overall, the stated strategies are consistent with our growth results.

B. Public versus Private Targets

Public and private firms may be at different points in their life cycles. They could also have different needs and face different challenges. Private firms are more likely to be small and financially constrained (Farre-Mensa and Ljungqvist, 2016), while public firms are usually larger and more mature and could be more subject to agency and overinvestment problems (Jensen, 1986). In Table VIII, we run our sales and price, product innovation, and product availability tests separately on public and private PE target firms. Of the 236 treated firms, 222 are private and 14 are public. We classify as public to PE those deals where an entire public firm is sold to PE. We do not include in this category the sales of divisions of public firms. We find the impact of private equity is not the same for public and private targets.

In Panel A, the results for private targets match those for the pooled sample (Table III) at the firm level: post-PE prices increase by 5% while sales and units dramatically increase by 52% and 45%. For public firms, however, although the coefficients have the same sign, the magnitudes on sales and units increases are much smaller and not statistically significant. At the firm-category level, the results for private firms are again consistent with the full sample results—significant growth in sales and units and a 4% increase in prices. Directionally, public firm sales and units within a product category fall post-buyout relative to a control. These coefficient are not statistically significant. Public firm buyouts thus do not appear to generate the same growth results.

The within-product-store analyses for the full sample (Table III) document no change in existing product sales and units and a marginal 1% increase in prices. These results mask significant differences between public and private firms. Panel A finishes by showing that for

private firms, existing products increase their sales post-buyout by 6%—a result statistically significant at the 1% level. An increase in units sold, not in price, drives this result. This is consistent with the fact that private targets spend more on advertising after the buyout (see section VII.E). Public firms, instead, raise prices by 2% and see revenues fall by 6%.

In Table IV we find that, in the full sample, product offerings expand within existing categories and into new ones after a private equity buyout. In Table VIII, Panel B, we split these innovation results by public vs. private firms. For private firms, post-buyout behavior mimics the full sample findings: the number of products grows by 11% and categories grows by 6%. There is scant evidence, however, that public firms introduce more new products or enter more new product categories relative to controls in the post-buyout period. The coefficient signs are mixed, and the results are not statistically significant.

In Panel C, we revisit geographic expansion. Private firms drive the strong growth in market penetration in the overall sample (Table V), registering higher growth rates across stores, ZIP codes, and chains relative to matched firms post-buyout. The results hold both at the firm and firm-category level. Public firms again show mixed results with no statistical significance.

This divergence in results between public and private firms suggests the existence of both growth and agency motives for private equity deals. Access to financing, managerial expertise, or business connections can help younger, private firms to expand their product lines. *The New York Times* notes that “business owners with a product to sell often dream of winning shelf space in the Wal-Marts and Targets of the world. But...it is a challenge to get shelf space in any store.”¹⁴ Public firms, in contrast, may be overinvesting in market share by charging prices that are too low. Our results of growth for private targets and

¹⁴“Getting Your Product Onto Retail Shelves” *The New York Times* 10/20/2010

higher prices for public firms are consistent with other studies. For example, [Davis et al. \(2014a\)](#) document that employment grows following private firm buyouts, while it declines after public deals. [Boucly et al. \(2011\)](#) similarly find stronger growth for private target firms. This variation in deal outcomes can also perhaps explain the negative portrayal of private equity in the media: layoffs and contraction are associated with the most visible, well-known targets.

C. Financial Crisis

The financial crisis of the late-2000's provides a setting to investigate how PE treated firms operate when growth is low and capital is scarce, precisely when financial resources and managerial expertise are likely to be important. In [Table IX](#), we split the PE deals into those that close between 2007 and 2010 (during the crisis) and those that close between 2011 and 2015 (after the crisis). Consistent with the full sample results, we find in Panel A that prices, units, and sales increase for PE firm targets in the two time periods, both at the firm and at the firm-category levels. Results at the store level diverge. During the crisis, existing PE products do not gain or lose share relative to shelf neighbors, while their prices fall by 1%. Post-crisis, however, existing products gain share in a given store, even as relative prices increase by 3%. This evidence on prices suggests that PE treated firms could be more responsive to economic conditions in their price setting policies, decreasing prices during the crisis and increasing prices afterward. For product innovation in Panel B, we find that there is more product turnover for PE treated product categories. The product availability results in Panel C show that expansion to new locations is generally similar during the two periods.

There are two main takeaways from these results. First, PE-driven growth occurs in all economic conditions, including during the financial crisis when capital is scarce. This

evidence is consistent with [Bernstein et al. \(2019\)](#). They find that during the crisis UK PE-backed companies decreased investments less and increased their market share more, compared to control firms. They attribute this evidence to the ability of PE firms to raise capital, to assist with operating problems, and to provide strategic guidance. Second, we find evidence that PE strategies change based on general economic conditions. During the crisis greater innovation and product turnover drive sales. After the crisis—in better economic times—PE targets are also able to successfully raise prices and gain market share with their existing products.

D. Industry Structure

In which industries/ product categories are PE firms more successful? We examine: i) the PE target’s market power within an industry; ii) the industry’s overall competitiveness and concentration; and iii) the popularity of an industry among high-income consumers. These cross-sectional tests can provide insights into how PE firms achieve growth.

[Lerner et al. \(2011\)](#) document that, following a buyout, new patent activity becomes more concentrated in “core innovation” areas, i.e., those where there was more patenting prior to the PE deal. Do PE targets in our sample focus their efforts analogously in product categories where they are well-established, or do they direct attention to categories where they have lower penetration and more room to grow? In table [X](#), Panel A, we repeat our main analyses at the product-category level but split the sample by market share. For each firm, each month, we calculate its market share in each product category.¹⁵ A firm’s product category is “high market share” if it is above the median firm market share in that

¹⁵For example, if in a month there are 30 firms nationwide that sell green beans, we divide each firm’s green bean sales by total green bean sales that month. We then categorize these 30 firms into those that are above or below the median green bean market share.

category and “low” otherwise. Growth in sales and units sold and higher average prices all happen in the product-categories where target firms have higher market share. We also find more product churn—introductions and discontinuations—and higher geographic expansion in these higher share categories.

We next analyze whether PE strategies vary based on industry concentration. Low concentration industries are traditionally considered more competitive, but they are also less likely to be dominated by a small number of firms. Do PE-treated firms expand where there are many small sellers and, possibly, lower barriers to entry? Or do they pursue growth in categories where few dominant players (e.g., Coke and Pepsi) have the lion’s share of the market? For each of the 1,127 product categories, each month, we calculate the nationwide Hirfindahl-Hirschman Index value (HHI). Specifically, we compute the revenue market share by firm and then square and sum these shares, resulting in a value between zero and one. Lower HHI values correspond to lower industry concentration. We split categories into those above and below the median HHI each month, labeled respectively “high HHI” and “low HHI”. In Panel B of Table X we run our main specifications separately for these two groups. Many of the results are similar across high vs. low HHI categories. A notable difference is that innovation seems to be concentrated in low HHI categories. Here, target firms introduce more new products and have greater variety.

There is growing evidence that in the past decade product introductions have favored high-income consumers (e.g., Argente and Lee, 2019 and Jaravel, 2018). Do PE-treated firms concentrate their growth efforts in product categories popular among consumers with higher income? We integrate our retail-scanner dataset with the Nielsen Consumer Panel data to address this question. The Consumer Panel Data includes a representative panel of households that provide information about their purchases and, important for our analysis,

demographic information including income. We first classify each product category as high-income consumer appealing if high—that is, above median—income consumers are more likely to buy products in the category. In practice, for each product-category, we compute the average income of the consumers that buy products in the category. We define a category as “high-income” if the average income in the category is above the median income among all categories. In Panel C of Table [X](#) we separately run our main specifications for high vs low-income categories. All our results are stronger, and statistically significant, for the high-income categories.

Overall, the evidence in this section provides insight into where PE finds positive NPV projects. PE firms are more successful when target firms have higher market power and more popularity among high-income consumers. Innovation efforts seem also more pronounced in categories with lower concentration and potentially lower barriers to entry. These results nicely complement our previous evidence on PE deal selection (Table [A5](#)). PE selects categories that are less concentrated and more popular among high-income consumers. In these same categories—as shown in Table [X](#)—PE is able to achieve more innovation and higher growth.

E. Company Strategy and Investments

What specific levers do PE firms pull to spur growth? We examine two specific actions: corporate acquisitions and product advertising. In Table [XI](#), Panel A, we investigate if private equity targets become more acquisitive after the buyout. For the years in our sample period,^{[16](#)} we collect from Capital IQ all M&A transactions where the buyer is one of the 236 firms in our sample or their respective control firms. We find 651 such deals, 361 by

¹⁶Following our empirical specification from equation [1](#), we limit our data collection to two years before and five years after the deal.

target firms and the remaining 290 by control firms. Our outcome variable is the number of monthly acquisitions closed by the firm. We keep in the sample only firms that have made at least one acquisition in Capital IQ. The regression follows equation [1](#). We find that target firms indeed become more active buyers post-buyout, increasing the number of acquisitions per month by 0.016, which translates roughly to one additional deal over the next five years. This result holds whether targets are public or private and during or after the financial crisis. This evidence is consistent with the finding in [Davis et al. \(2014b\)](#) that acquisitions are a driver of growth in buyout deals. We thus investigate further if external growth drives our results. This is an important test, as the growth in sales, innovation, and geographic expansion could be simply driven by redrawing the boundary of the firm rather than by creating new products and markets. In Tables [A9](#), [A10](#), and [A11](#), we repeat our main analyses for price and sales, product innovation, and product availability, excluding the top decile of the most acquisitive target firms. These results are not materially different from those using the entire sample (see Tables [III](#), [IV](#), [V](#)). Similar magnitudes for the effects of PE after excluding the most acquisitive firms suggests that organic, internal expansion is a substantial contributor to PE target growth.

Another channel through which firms can achieve sales growth is investing in advertising. We compile data from AdSpender by Kantar Media, which records the dollar value of monthly advertising expenses for over 3 million brands across 18 major communication media (e.g., television, magazines, radio, newspapers). AdSpender aggregates these brands to the firm level. The data reported by Kantar Media is sparse, with many missing observations for advertising expenditure. To smooth the data, we thus take the average monthly advertising expenditure when reported and annualize it. We keep only firm-year data where the advertising expenditure is reported for at least one month of the year. Overall we are

able to identify monthly spending for 203 out of our 236 treated firms.

We then run a generalized diff-in-diff regression between the treated firms and the matched control firms where the dependent variable is the log of one plus the annualized monthly advertising expenditure. After the buyouts, treated firms increase advertising expenses by roughly 49% compared to their matched control firms. This result is similar across public and private firms, and it is stronger in the years following the financial crisis (2011 to 2015).

PE target firms are more likely to acquire other firms and ramp up advertising following the buyouts. We admittedly cannot disentangle whether PE firms provide managerial expertise or financial resources to make these activities possible. We also cannot comment on the cost-benefit trade-offs of these activities. Nonetheless, these activities are concrete examples of changes to the firm strategy implemented by PE firms.

F. Non-PE Ownership Changes

Are the changes that follow PE buyouts unique to PE buyers, or do acquisitions by operating firms have the same effect? To test if non-PE acquisitions also lead to growth, we repeat our main analyses on sales and prices, product innovation, and product availability, replacing PE buyout targets with merger targets.

We collect from Capital IQ all the target firms of M&A deals during our sample period. Mimicking our process for PE targets, we match these firms first with the GS1 database and then with the Nielsen data. Our final sample of M&A targets consist of 126 firms. For each M&A target firm, we find the closest match using the process described in section [IV.B](#).

Appendix Table [A8](#) mimics Tables [III](#), [IV](#), and [V](#), examining what happens to targets following an acquisition by an operating firm. The results in this setting are quite different compared to PE deals. Most coefficients on the *After* variable are not significantly different

from zero.

In stark contrast to PE buyouts, operational M&As do not seem to lead to growth in our sample. Some M&A deals could happen to eliminate competition. For example, [Cunningham et al. \(2019\)](#) find that pharmaceutical firms discontinue acquired drugs that directly compete with their existing products. One caveat in interpreting these M&A results is that some of the growth prospects that the target would have pursued as a standalone firm could instead be implemented under the acquiring firm brand names. With this caveat in mind, our results suggest that PE firms—and not any change in ownership—spur growth.

VIII. Conclusion

Private equity buyouts often elicit strong negative reactions: a common view is that PE firms try to increase corporate profitability by laying off workers and increasing prices, hurting stakeholders such as workers and consumers. Private equity is undoubtedly exercising a growing influence on consumer products and the purchases of millions of people. Using price and sales data for nearly two million unique UPCs sold in over 41,000 stores, we formally investigate the effects of PE on consumer products.

Retail scanner data has several nice features. First, we are able to study the evolution of pricing strategies, product innovation, and geographic availability following a buyout. Second, we can more precisely identify treated units and their counterfactuals in our empirical analyses. In our difference-in-differences estimations, we analyze firms but also decompose them into product categories and products sold within a particular store. This granularity in the data helps mitigate concerns that selection, not actions of private equity firms, drive our results. Last, thanks to the geographic richness of the data, we can also investigate how

competitors react by comparing price changes in locations with and without a PE brand.

Contrary to the critics' view, we find that target firms raise prices only marginally. Compared to similar products sold in the same store, target firms raise price by about 1.0%. Competitors respond by also marginally raising prices—by roughly 0.4%—only in those stores where they face direct PE competition. An overall potential price increase of 1.4% in the five years following a buyout does not support the view that private equity firms significantly harm consumers on this dimension. Despite the marginal increase in the price of existing products, target firms experience a significant boom in their overall sales of about 50% in the years post-buyout. Compared to matched firms, target firms launch more products, expand more geographically, and enter more retail chains. Target firms become more acquisitive following buyouts, but organic growth is also strong. PE-driven growth is concentrated in product categories popular among high-income consumers. To the extent that consumers value higher product variety and availability (Lancaster (1990), Kahn and Lehmann (1991), Petrin (2002), Brynjolfsson et al. (2003), and Broda and Weinstein (2006)), PE deals appear to benefit consumers. Overall, our evidence is consistent with private equity being an avenue of wealth creation and not simply wealth transfer. How does PE spur growth? To find clues, we explore different PE target types, economic environments, and industry characteristics. Growth is stronger for private targets, firms that likely demand more access to capital and management expertise. PE product strategies vary with the economic environment: there is more product turnover during the financial crisis; normal times bring higher prices. PE firms are particularly successful in product categories where they hold a strong position in a fragmented market. Our findings are limited to one single “industry” and might not necessarily generalize outside of the consumer product space. Nonetheless, households spend a significant fraction of their monthly budget to buy the products in our study.

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Table I. Example of Product Category: Canned Green Beans

List of canned green bean products available in a specific grocery store in Austin, TX, for the month of December 2007.

UPC	Product Details	Firm Name	Size (Oz.)	Units Sold	Sales	Av. Price
2400016286	Cut Green Beans	Del Monte Foods Inc.	14.5	109.43	101.88	0.92
2400016287	Cut Green Beans (No Salt)	Del Monte Foods Inc.	14.5	86.14	81.68	0.92
2400016289	French Style Green Beans	Del Monte Foods Inc.	14.5	51.00	49.89	0.94
2400016293	Whole Green Beans	Del Monte Foods Inc.	14.5	37.29	39.15	1.05
2000011197	Cut Green Beans	General Mills, Inc.	14.5	30.43	30.12	0.99
2400001546	French Style Green Beans	Del Monte Foods Inc.	28.0	16.71	21.90	1.31
3470001219	Cut Italian Green Beans	Sager Creek Vegetable Co.	28.0	11.29	18.96	1.68
3470001211	Cut Italian Green Beans	Sager Creek Vegetable Co.	16.0	21.57	18.34	0.85
3470001211	Cut Italian Green Beans	Sager Creek Vegetable Co.	14.5	21.57	18.34	0.85
2400039364	Pickled Green Beans with Dill Flavor	Del Monte Foods Inc.	14.5	15.29	18.05	1.13
2000011196	French Style Green Beans	General Mills, Inc.	14.5	17.29	17.11	0.99
2400001830	Cut Green Beans	Del Monte Foods Inc.	28.0	5.57	7.30	1.31
2400016290	French Style Green Beans (No Salt)	Del Monte Foods Inc.	14.5	7.14	7.04	0.95
2400001393	Cut Green Beans	Del Monte Foods Inc.	8.0	8.14	5.94	0.73
2400000087	Cut Green Beans (No Salt)	Del Monte Foods Inc.	8.0	3.71	2.71	0.73
2400016292	French Style Green Beans with Onions	Del Monte Foods Inc.	14.5	1.00	1.05	1.05
2400039201	Organic Cut Green Beans	Del Monte Foods Inc.	14.5	0.29	0.49	1.73

Table II. Summary Statistics

This table presents summary statistics for all variables and data used in the paper. Panel A introduces an overview of the number of products, stores, firms, and private equity deals in the overall Nielsen data. Panel B shows the characteristics of the product categories in Nielsen data. We calculate the Hirfindahl-Hirschman Index (HHI) for each of the 1,123 product categories, each month. Panel C presents firm characteristics in the overall Nielsen data. Panels D focuses on product characteristics split by treatment status.

PANEL A: Overall Nielsen Data

	N.		N.
Products	1,977,481	Stores	42,928
Stores per Product	571	Chains	91
Products per Store	18,909	3-Digit ZIP	877
Firms	52,205	Counties	276
PE Deals	236	Designated Market Areas	206
Private Target Deals	222	States	49
Public Target Deals	14		

PANEL B - Product Category Characteristics

	Mean	Median	S.D.
N. Categories	1,127	-	-
N. Products per Category	20.80	8.07	38.04
N. Stores per Category	30,123	36,762	12,821
N. Firms per Category-Store	4.43	2.00	5.94
Herfindahl-Hirschman Index (HHI)	0.60	0.57	0.34

PANEL C - Firm Characteristics

	Mean	Median	S.D.
N. Products per Firm	10.22	3.00	41.22
N. Stores per Firm	1,345.82	62.00	4,177.03
N. Chains per Firm	8.83	3.00	14.78
N. Categories per Firm	2.87	1.00	6.42

PANEL D - Product Characteristics in Our Sample by Treatment

	Control Group			Treated Group		
	Mean	Median	S.D.	Mean	Median	S.D.
Price	5.33	3.99	5.16	5.19	3.76	5.34
Monthly Units Sold per Store	8.51	1.00	42.26	8.62	1.00	39.40
Monthly Sales per Store	20.42	4.96	106.36	19.64	4.99	81.67

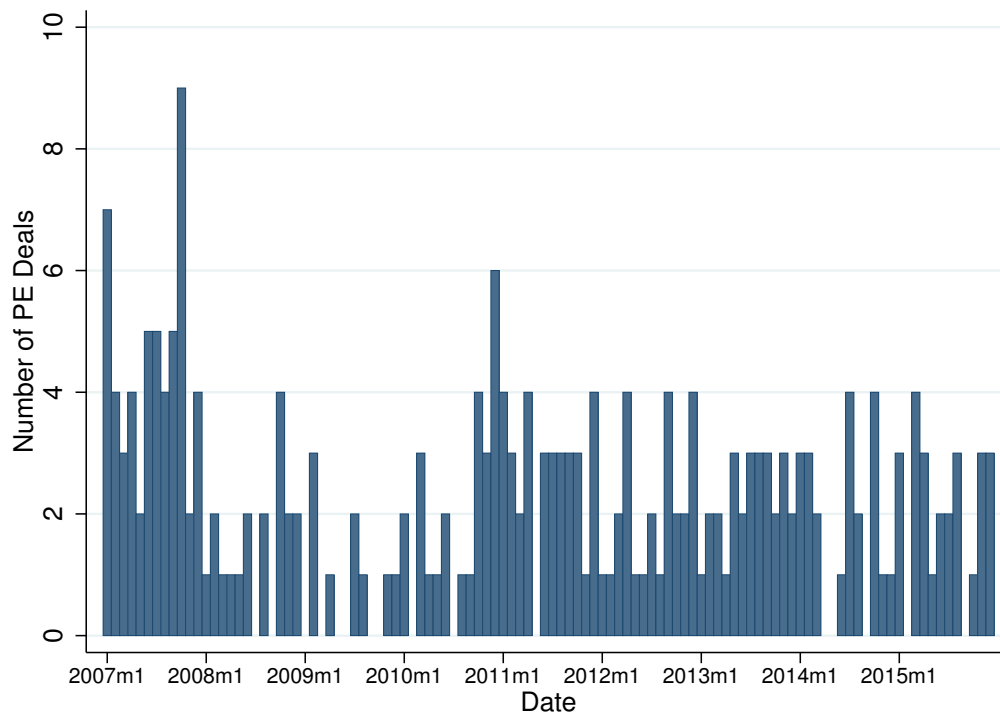


Figure 1. Private Equity Deals over Time

This figure shows the monthly number of private equity deals in our sample from January 2007 to December 2015.

Table III. Private Equity, Sales, and Prices

This table presents OLS coefficient estimates from regressing log of sales, log of average monthly prices, and log of units sold on *After*, a dummy variable equal to one for post-buyout months for firms (Panel A), firm-categories (Panel B), or product-stores (Panel C) that underwent a buyout during our sample period. We use the [Abadie and Imbens \(2006\)](#) distance metric to pair each treated unit with the closest untreated unit. In Panels A and B, we match on sales, unique UPCs sold, and store locations, all during the most recent pre-buyout month, and growth in monthly sales from 12 months before the deal to the most recent pre-buyout month. In Panel C, we match store-products using average price and units sold during the most recent pre-buyout month, and growth in price and units sold from 12 months ago to the most recent pre-buyout month. The unit of analysis is unique at the firm-month-cohort level in panel A, at the firm-product category-month-cohort level in panel B, and at the product-store-month-cohort level in panel C. The estimation period goes from -24 months to +60 months around the private equity deal closing date. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are in parentheses and are double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Within Firm

	Sales	Average Prices	Number of Units Sold
After	0.406*** (3.59)	0.053*** (2.86)	0.355*** (3.43)
Adj. R-Square	0.876	0.933	0.893
N. Obs.	31,596	31,596	31,596
Firm-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes

Panel B: Within Firm-Category

	Sales	Average Prices	Number of Units Sold
After	0.211*** (3.58)	0.032*** (3.76)	0.169*** (3.14)
Adj. R-Square	0.868	0.918	0.884
N. Obs.	224,454	224,454	224,454
Firm-Cat.-Cohort FE	Yes	Yes	Yes
Date-Cat.-Cohort FE	Yes	Yes	Yes

Panel C: Within Product-Store

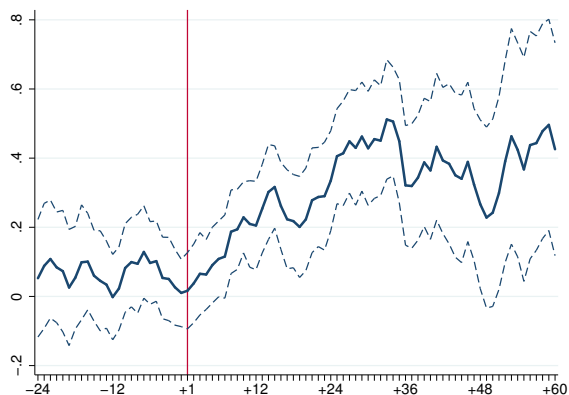
	Sales	Price	Number of Units Sold
After	0.01332 (0.76)	0.01084** (2.35)	0.00213 (0.15)
Adj. R-Square	0.637	0.797	0.773
N. Obs.	880,331,932	880,331,932	880,331,932
Product-Store-Cohort FE	Yes	Yes	Yes
Date-Store-Cohort FE	Yes	Yes	Yes



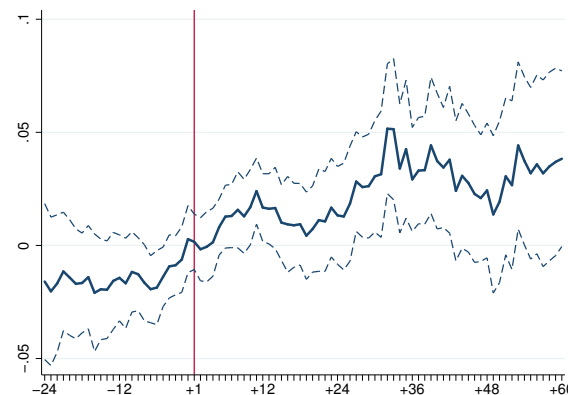
(a) Sales - Within Firm



(b) Price - Within Firm



(c) Sales - Within Firm-Category



(d) Price - Within Firm-Category

Figure 2. Time Trend of Total Sales and Average Price

These graphs plot the coefficient estimates of regressions following equation 2, where the dependent variables are total sales for panels (a) and (c) and average price for panels (b) and (d). The unit of analysis is a firm-month-cohort for panels (a) and (b) and a firm-category-month-cohort for panels (c) and (d). The coefficient estimate at time t represents the difference in the outcome variables between private equity firms/firm-categories and matched non-private equity firms/firm categories t months away from the date of closing of the private equity deal. The estimation period goes from -24 months to +60 months around the date of the closing of the private equity deal. The closing date is indicated by the vertical line. The dotted lines show the 90% confidence interval.

Table IV. Private Equity and Product Innovation

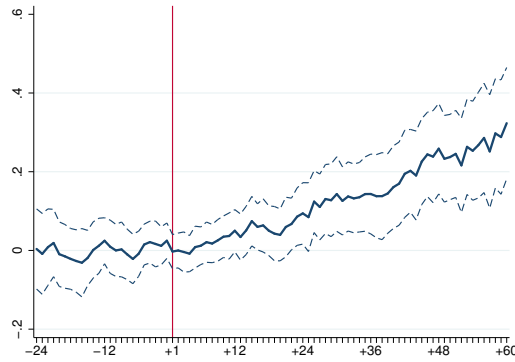
This table presents OLS coefficient estimates from regressing innovation variables on *After*, a dummy variable equal to one for the post-buyout months for firms (Panel A) or firm-categories (Panel B) that underwent a buyout during our sample period. *Number of Products* is the log of the number of unique UPCs a firm or firm-category sells nationwide in month t . *New products* is the number of products introduced by the firm or firm-category in month t , while *Discontinued Products* is the number of products dropped in month t . *Number of Categories* is the log of the number of product categories, out of a total of 1,127 defined by Nielsen, in which a firm sells at time t . Each cohort is a pair of treated-untreated firms (panel A) or firm-categories (panel B). Treated and control are matched as described in Table III. The unit of analysis is unique at the firm-month-cohort level in panel A and at the firm-category-month-cohort level in panel B. The estimation period goes from -24 months to +60 months around private equity deal closing date. The regressions are estimated using the fixed point iteration procedure implemented by Correia (2014). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Within Firm

	Number of Products	New Products	Discont. Products	Number of Categories
After	0.104*** (3.12)	0.393** (2.06)	0.159 (1.11)	0.051** (2.22)
Adj. R-Square	0.942	0.514	0.739	0.950
N. Obs.	31,596	31,596	31,596	31,596
Firm-Cohort FE	Yes	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes	Yes

Panel B: Within Firm-Category

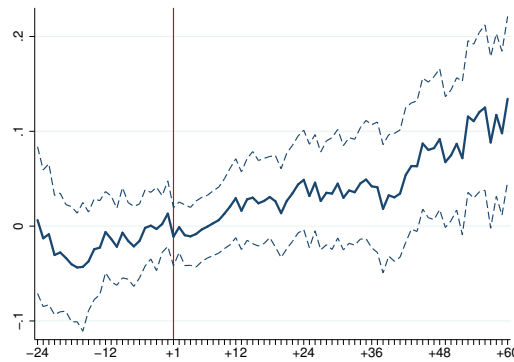
	Number of Products	New Products	Discont. Products
After	0.025** (2.13)	0.048** (2.41)	0.034* (1.77)
Adj. R-Square	0.920	0.530	0.727
N. Obs.	224,454	224,454	224,454
Firm-Cat.-Cohort FE	Yes	Yes	Yes
Date-Cat.Cohort FE	Yes	Yes	Yes



(a) Number of Products - Within Firm



(b) Number of Products - Within Firm-Category



(c) Number of Product Categories - Within Firm

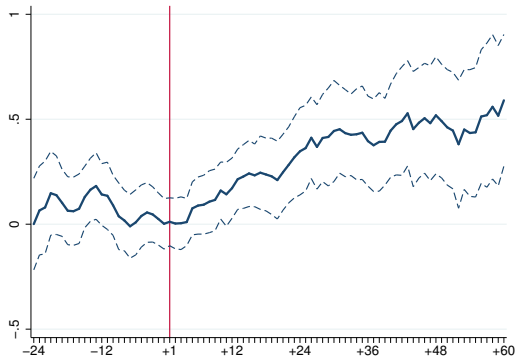
Figure 3. Time Trend of Product Innovation

These graphs plot the coefficient estimates of regressions following equation 2, where the dependent variables are number of products for panels (a) and (b) and number of product categories for panel (c). The unit of analysis is a firm-month-cohort for panels (a) and (c), and a firm-category-month-cohort for panel (b). The coefficient estimate at time t represents the difference in the outcome variables between private equity firms/firm-categories and matched non-PE firms/firm categories t months away from the date of closing of the private equity deal. The estimation period goes from -24 months to +60 months around the closing date of the private equity deal. The closing date is indicated by the vertical line. The dotted lines show the 90% confidence interval.

Table V. Private Equity and Product Availability

This table presents OLS coefficient estimates from regressing the logs of number of stores, retail chains, and 3-digit ZIP codes where a firm or firm-category is present each month on *After*, a dummy variable equal to one for the post-buyout months for firms (Panel A) or firm-categories (Panel B) that underwent a buyout during our sample period. Each cohort is a pair of treated-untreated firms (Panel A) or firm-categories (Panel B). Treated and control are matched as described in Table III. The unit of analysis is unique at the firm-month-cohort level in panel A and the firm-category-month-cohort level in panel B. The estimation period goes from -24 months to +60 months around the private equity deal closing date. The regressions are estimated using the fixed point iteration procedure implemented by Correia (2014). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

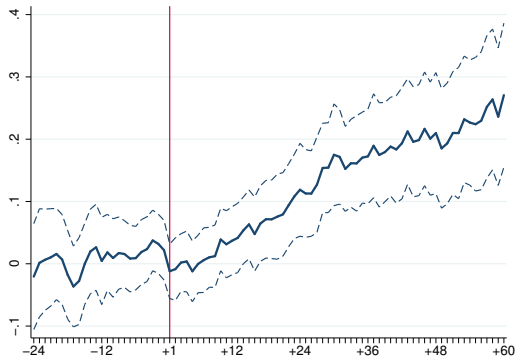
Panel A. Within Firm			
	N. Stores	N. Chains	N. ZIP Codes
After	0.223*** (3.07)	0.098*** (3.28)	0.129** (2.47)
Adj. R-Square	0.907	0.951	0.899
N. Obs.	31,596	31,596	31,596
Firm-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes
Panel B. Within Firm-Category			
	N. Stores	N. Chains	N. ZIP Codes
After	0.130*** (2.93)	0.052*** (2.92)	0.095*** (2.89)
Adj. R-Square	0.889	0.920	0.882
N. Obs.	224,454	224,454	224,454
Firm-Category-Cohort FE	Yes	Yes	Yes
Date-Category-Cohort FE	Yes	Yes	Yes



(a) N. Stores - Within Firm



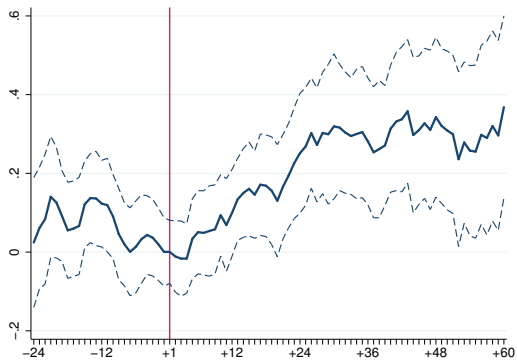
(b) N. Stores - Within Firm-Category



(c) N. Retail Chains - Within Firm



(d) N. Retail Chains - Within Firm-Category



(e) N. 3-digit ZIPs - Within Firm



(f) N. 3-digit ZIPs - Within Firm-Category

Figure 4. Time Trend of Product Availability

These graphs plot the coefficient estimates of regressions following equation 2, where the dependent variables are number of stores for panels (a) and (b), the number of retail chains for panels (c) and (d), and the number of 3-digit ZIPs for panels (e) and (f). The unit of analysis is a firm-month-cohort for panels (a), (c), and (e), and a firm-category-month-cohort for panels (b), (d), and (f). The coefficient estimate at time t represents the difference in the outcome variables between PE firms/firm-categories and matched non-PE firms/firm categories t months away from the closing date of the private equity deal. The estimation period goes from -24 months to +60 months around the date of the closing of the private equity deal. The closing date is indicated by the vertical line. The dotted lines show the 90% confidence interval.

Table VI. Competitor Response

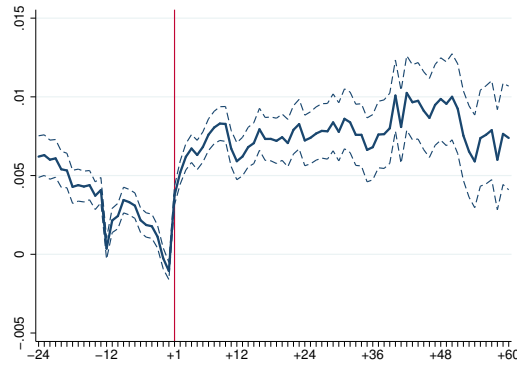
This table presents evidence from product-stores (Panel A) or firm-categories (Panel B) for the competitors of firms that were acquired by a private equity. In Panel A, we present OLS coefficient estimates from regressing the log of average monthly prices on *After*, a dummy variable equal to one in the post-buyout months if the competitor’s product was competing in the same store-category with at least one product that underwent a buyout during our sample period. Each cohort is thus made of a treated product sold in a store with PE competition and a matched control product—with the same UPC—sold in different stores without private equity competition. In practice, for each treated product we randomly select ten of these stores without PE competition. Among these ten stores, we then choose the closest match based on the level and growth in the product-store price before the deal, using the [Abadie and Imbens \(2006\)](#) distance metric. In Column 1, we randomly choose ten among all the US stores to select the match. In Column 2, we choose the ten stores within the same retail chain of the treated product. In Column 3, the ten stores are from the same Designated Market Area of the treated product. In Panel B, we present OLS estimates from regressing the log of number of products on *After*, a dummy variable equal to one if the treated firm-category was competing with at least one product in the same category that underwent a buyout during our sample period. Each cohort is thus made of a treated firm-category sold in a store with PE competition and the same firm-category from ten different stores without private equity competition. In Column 1, we randomly choose the ten stores among all the US stores. In Column 2, we choose the ten stores within the same retail chain of the treated firm-category. In Column 3, the ten stores are from the same Designated Market Area of the treated firm-category. The unit of analysis is unique at the product-store-month-cohort level in Panel A and the firm-category-store-month-cohort level in Panel B. The estimation period goes from -24 months to +60 months around the closing date of the private equity deal. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A. Prices - Within Product-Store

	Full Sample	Same Chain	Same DMA
After	0.004*** (6.06)	0.004*** (8.57)	0.003*** (5.69)
Adj. R-Square	0.987	0.991	0.988
N. Obs.	6,647,108	5,713,080	5,269,109
Product-Store-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes

Panel B. Number of Products - Within Firm-Category-Store

	Full Sample	Same Chain	Same DMA
After	-0.015*** (-10.14)	-0.010*** (-4.30)	-0.021*** (-10.19)
Adj. R-Square	0.924	0.957	0.937
N. Obs.	25,200,128	12,724,588	12,191,146
Firm-Category-Store-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes



(a) Competitor price response



(b) Competitor product mix response

Figure 5. Trend in Competitor Response

These figures plot the coefficient estimates of regressions following equation 2, where the dependent variables are average monthly prices for panel (a) and number of products for panel (b). The coefficient estimate at time t represents the difference in the outcome variables between treated product-stores/firm-category-stores and matched controls t months away from the date of closing of the private equity deal. This sample only includes product-stores/ firm-category-stores for control firms that did not go through a private equity deal. In panel (a), each cohort is made of a treated product that is sold in a store-category where a private equity deal occurred, and the best match (with the same UPC) but selected from ten random stores across the US where there is no private equity competitor. In panel (b), each cohort is made of a firm-category where the PE deal occurred, and the average of the same firm-category from ten random stores across the US where there is no private equity competitor. The estimation period goes from -24 months to +60 months around the date of the closing of the private equity deal. The closing date is indicated by the vertical line. The dotted lines show the 90% confidence interval. Regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#).

Table VII. Mechanism: Press Releases

This table shows the number (and percentage) of press releases that mention a specific reason for the private equity deal. Out of a total of 297 deals, we were able to find press releases for 237 firms. We compute percentages out of these 237 firms. 44 press releases do not mention any specific reason for the deal. Reason are not mutually exclusive and one press release could mention multiple reasons. The total sample of deals used here (297) is larger than the final sample in our analyses (236), because we do not require to have one year of sales data before and after the deal.

Reason	N. Deals	(%)
Expansion Plans/General Growth	163	(69%)
Financial Capital for Growth	63	(27%)
Industry Experience/Expertise	58	(25%)
New Products	49	(21%)
Acquisitions	29	(12%)
Distribution	26	(11%)
New Management/CEO	24	(10%)
Cost Efficiencies	9	(4%)
Access To Talent	2	(1%)

Table VIII. Mechanisms: Public vs. Private Targets

This table presents OLS coefficient estimates from regressing, in Panel A, logs of sales, average monthly prices, and units sold on *After*, a dummy equal to one in the post-buyout months if the firm, firm-category, or product-store underwent a buyout during our sample period. In Panel B we focus on product innovation, in Panel C product availability. All the outcome variables are either indicator variables or in logs. Public targets are those deals where the target was a public company before the private equity acquisition. Each cohort is a pair of treated-untreated firms, firm-categories, or product-stores where the treated unit is matched to the untreated unit using the same methodologies followed in the previous tables. The unit of analysis is unique at the firm-month-cohort, firm-category-month-cohort, or product-store-month-cohort. The estimation period goes from -24 months to +60 months around the closing date of the private equity deal. The regressions are estimated using the fixed point iteration procedure implemented by Correia (2014). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Sales, Pricing, and Units

		Public Target			Private Target		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
Within Firm	Sales	0.214	(0.53)	2,088	0.420***	(3.54)	29,508
	Average Prices	0.046	(0.94)	2,088	0.053***	(2.73)	29,508
	Units Sold	0.119	(0.36)	2,088	0.372***	(3.41)	29,508
Within Firm-Category	Sales	-0.074	(-0.43)	24,820	0.247***	(4.09)	199,634
	Average Prices	-0.014	(-0.72)	24,820	0.038***	(4.16)	199,634
	Units Sold	-0.059	(-0.40)	24,820	0.198***	(3.55)	199,634
Within Product-Store	Sales	-0.063*	(-1.95)	307,133,126	0.055***	(5.01)	554,415,032
	Prices	0.020**	(2.27)	307,133,126	0.007	(1.39)	554,415,032
	Units Sold	-0.059**	(-2.09)	307,133,126	0.035***	(4.67)	554,415,032

Panel B: Product Innovation

		Public Target			Private Target		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
Within Firm	N. of Products	0.060	(0.47)	2,088	0.107***	(3.09)	29,508
	New Products	1.766	(1.12)	2,088	0.296*	(1.78)	29,508
	Discontinued Products	-0.424	(-0.43)	2,088	0.201	(1.48)	29,508
	Number of Categories	-0.078	(-0.90)	2,088	0.060**	(2.53)	29,508
Within Firm-Category	N. of Products	-0.008	(-0.22)	24,820	0.029**	(2.36)	199,634
	New Products	0.181	(1.51)	24,820	0.032**	(1.98)	199,634
	Discontinued Products	0.043	(0.65)	24,820	0.032*	(1.69)	199,634

Panel C: Product Availability

		Public Target			Private Target		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
Within Firm	N. Stores	0.205	(0.98)	2,088	0.224***	(2.93)	29,508
	N. Chains	-0.080	(-1.43)	2,088	0.110***	(3.49)	29,508
	N. Zip	0.057	(0.37)	2,088	0.134***	(2.44)	29,508
Within Firm-Category	N. Stores	-0.116	(-0.97)	24,820	0.161***	(3.52)	199,634
	N. Chains	-0.086	(-1.61)	24,820	0.069***	(3.96)	199,634
	N. Zip	-0.096	(-1.11)	24,820	0.119***	(3.50)	199,634

Table IX. Mechanisms: During (2007-2010) vs. After (2011-2015) the Financial Crisis

This table presents OLS coefficient estimates from regressing, in Panel A, logs of sales, average monthly prices, and units sold on *After*, a dummy equal to one in the post-buyout months if the firm, firm-category, or product-store underwent a buyout during our sample period. In Panel B we focus on product innovation. In Panel C we study product availability. All the outcome variables are either indicator variables or in logs. The columns “2007-2010” and “2011-2015” include results from private equity deals that closed in those years. Each cohort is a pair of treated-untreated firms, firm-categories, or product-stores where the treated unit is matched to the untreated unit using the same methodologies followed in the previous tables. The unit of analysis is unique at the firm-month-cohort, firm-category-month-cohort, or product-store-month-cohort. The estimation period goes from -24 months to +60 months around the closing date of the private equity deal. The regressions are estimated using the fixed point iteration procedure implemented by Correia (2014). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Sales, Pricing, and Units

		2007-2010			2011-2015		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
Within Firm	Sales	0.589***	(2.98)	15,390	0.255**	(2.01)	16,206
	Average Prices	0.057*	(1.84)	15,390	0.049**	(2.23)	16,206
	Units Sold	0.514***	(2.88)	15,390	0.223*	(1.89)	16,206
Within Firm-Category	Sales	0.206*	(1.98)	99,864	0.215***	(3.20)	124,590
	Average Prices	0.035**	(2.25)	99,864	0.030***	(3.11)	124,590
	Units Sold	0.177*	(1.95)	99,864	0.163**	(2.54)	124,590
Within Product-Store	Sales	-0.021	(-0.73)	415,182,486	0.045***	(2.68)	465,149,446
	Prices	-0.011**	(-2.59)	415,182,486	0.031***	(6.04)	465,149,446
	Units Sold	-0.021	(-0.87)	415,182,486	0.024**	(2.22)	465,149,446

Panel B: Product Innovation

		2007-2010			2011-2015		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
Within Firm	N. of Products	0.106*	(1.90)	15,390	0.102**	(2.57)	16,206
	New Products	0.603	(1.59)	15,390	0.220	(1.40)	16,206
	Discontinued Products	0.347	(1.43)	15,390	0.004	(0.02)	16,206
	Number of Categories	0.048	(1.25)	15,390	0.054*	(1.94)	16,206
Within Firm-Category	N. of Products	0.026	(1.35)	99,864	0.024	(1.66)	124,590
	New Products	0.082**	(1.99)	99,864	0.024	(1.34)	124,590
	Discontinued Products	0.087**	(2.14)	99,864	-0.004	(-0.31)	124,590

Panel C: Product Availability

		2007-2010			2011-2015		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
Within Firm	N. Stores	0.308**	(2.50)	15,390	0.153*	(1.82)	16,206
	N. Chains	0.125**	(2.44)	15,390	0.075**	(2.17)	16,206
	N. Zip	0.206**	(2.24)	15,390	0.064	(1.15)	16,206
Within Firm-Category	N. Stores	0.102	(1.43)	99,864	0.150***	(2.73)	124,590
	N. Chains	0.050**	(2.20)	99,864	0.053**	(2.11)	124,590
	N. Zip	0.079	(1.64)	99,864	0.107**	(2.45)	124,590

Table X. Mechanism: Industry Structure

This table presents OLS coefficient estimates from regressing outcome variables on *After*, a dummy equal to one in the post-buyout months if the firm-category underwent a private equity buyout during our sample period. In Panel A, we split results based on the target firm’s market share in the product categories. In Panel B, we separately report results based on the concentration (HHI index) in the product categories. In Panel C, we split the evidence based on the popularity of the product categories among high-end consumers. *Market Share* for each firm is its sales divided by total sales, each month, in a particular category. *High* values of *Market Share* are firms above the median in a category-month. *HHI* is the Herfindahl-Hirschman Index of each product category, each month, calculated by squaring and summing the national market shares of each firm in a given category. *High* values of *HHI* are those categories whose *HHI* is above the median that month. Using the Nielsen Consumer Panel, for each product category, we compute the average income of the consumers that buy products in the category. *High-Income Consumers* categories are those categories that have an average income that is above the median income among of all categories. Each cohort is a pair of treated-untreated firm-categories where the treated unit is matched to the untreated unit with the closest distance at the time of the private equity deal as described in Table III. The unit of analysis is unique at the firm-category-month-cohort level. The estimation period goes from -24 months to +60 months around the private equity deal closing date. The regressions are estimated using the fixed point iteration procedure implemented by Correia (2014). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Market Share in the Product Category

		High Market Share			Low Market Share		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
	Sales	0.265***	(3.13)	92,712	0.109	(1.39)	98,920
	Average Prices	0.055***	(5.07)	92,712	0.013	(0.97)	98,920
	Units Sold	0.208***	(2.73)	92,712	0.089	(1.23)	98,920
Within	N. of Products	0.014	(0.80)	92,712	0.043**	(2.57)	98,920
Firm-Category	New Products	0.107**	(2.53)	92,712	0.005	(0.43)	98,920
	Discontinued Products	0.076*	(1.80)	92,712	0.002	(0.26)	98,920
	N. Stores	0.168***	(3.00)	92,712	0.079	(1.27)	98,920
	N. Chains	0.087***	(4.29)	92,712	-0.007	(-0.26)	98,920
	N. Zip	0.128***	(3.53)	92,712	0.058	(1.21)	98,920

Panel B: Product Category Concentration

		High HHI			Low HHI		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
	Sales	0.186***	(2.72)	109,800	0.243***	(3.60)	114,490
	Average Prices	0.037***	(3.23)	109,800	0.031***	(3.25)	114,490
	Units Sold	0.152**	(2.41)	109,800	0.193***	(3.14)	114,490
Within	N. of Products	0.010	(0.71)	109,800	0.037**	(2.47)	114,490
Firm-Category	New Products	0.013	(0.69)	109,800	0.075**	(2.52)	114,490
	Discontinued Products	0.041	(1.42)	109,800	0.020	(1.11)	114,490
	N. Stores	0.133**	(2.58)	109,800	0.128**	(2.55)	114,490
	N. Chains	0.041*	(1.89)	109,800	0.066***	(3.10)	114,490
	N. Zip	0.106***	(2.73)	109,800	0.087**	(2.36)	114,490

Panel C: Category Popularity Among High-Income Consumers

		High-Income Consumers			Low-Income Consumers		
		After	T-stat	N. Obs.	After	T-stat	N. Obs.
	Sales	0.274***	(3.72)	147,044	0.093	(1.28)	77,410
	Average Prices	0.034***	(3.10)	147,044	0.030***	(2.67)	77,410
	Units Sold	0.231***	(3.51)	147,044	0.051	(0.74)	77,410
Within	N. of Products	0.026*	(1.86)	147,044	0.023	(1.38)	77,410
Firm-Category	New Products	0.063***	(2.84)	147,044	0.020	(0.65)	77,410
	Discontinued Products	0.055**	(2.17)	147,044	-0.008	(-0.39)	77,410
	N. Stores	0.168***	(3.19)	147,044	0.057	(0.99)	77,410
	N. Chains	0.070***	(3.63)	147,044	0.017	(0.61)	77,410
	N. Zip	0.123***	(3.21)	147,044	0.043	(0.99)	77,410

Table XI. Mechanism: Company Strategy and Investments

This table presents OLS coefficient estimates from regressing outcome variables of interest on *After*, a dummy equal to one in the post-buyout months if the firm underwent a private equity buyout during our sample period. In Panel A, we restrict the sample to firms for which we observe at least one acquisition in Capital IQ. The outcome variable *Acquisitiveness* counts the number of acquisitions closed in a month. In Panel B, the unit of analysis is a firm-year. We restrict the sample to firm-years in which we see at least one month of positive advertising expenditure. The outcome variable is *Advertising Expenditures*, the log of one plus the annualized average monthly advertising expenses for all the brands related to the firm as reported in AdSpender by Kantar Media. Each cohort is a pair of treated-untreated firms where the treated unit is matched to the untreated unit with the closest distance at the time of the private equity deal as described in Table III. The unit of analysis is unique at the firm-month level. The estimation period goes from -24 months to +60 months around the private equity deal closing date. The regressions are estimated using the fixed point iteration procedure implemented by Correia (2014). Standard errors are in parentheses and double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Acquisitiveness

	Full	Target		Time Period	
	Sample	Public	Private	2006-2010	2011-2015
After	0.016*** (4.71)	0.017 (1.21)	0.016*** (4.47)	0.014*** (3.25)	0.018*** (3.48)
Adj. R-Square	0.107	-0.016	0.112	0.081	0.120
N. Obs.	26,334	1,770	24,564	12,662	13,672
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes	Yes	Yes

Panel B: Advertising Expenditures

	Full	Target		Time Period	
	Sample	Public	Private	2006-2010	2011-2015
After	0.396** (2.26)	0.499 (1.46)	0.376* (1.84)	0.056 (0.14)	0.330 (1.65)
Adj. R-Square	0.746	0.880	0.721	0.682	0.787
N. Obs.	708	87	621	331	377
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes

Online Appendix for
“Barbarians at the Store?
Private Equity, Products, and Consumers”

by

Cesare Fracassi, Alessandro Previtiero, and Albert Sheen

I. Sample Construction

We follow three steps to create the database used in our analyses. First, we identify private equity deals in the period 2005 to 2017. We rely on *Capital IQ* and *Preqin* as deal sources. Second, we link the products in the Nielsen database to their selling firm names, using their universal product codes (UPCs), and then match these firm names with the PE target firm names. Last, we run robustness checks to ensure that our final sample does not omit major deals and to remove misclassified deals. In the following sub-sections, we review each of these steps in detail.

A. Identifying the Universe of Potential Deals

We first collect information on PE deals from Capital IQ, using the following screens:

1. *Merger/Acquisition Features*: Going Private Transaction OR Leveraged Buy Out (LBO) OR Management Buyout OR Secondary LBO
2. *M&A Announced Date*: [1/1/2005-12/31/2017]
3. *Geographic Locations (Target/Issuer)*: United States and Canada (Primary)
4. *Merger/Acquisition Features*: NOT (Acquisition of Minority Stake).

In particular, we rely on the following fields:

- *TargetName*: the target company name used to match Capital IQ data with GS1 data.
- *State*: the target company state also used in the match.
- *DealCompleted*: the deal date used to create the "After" variable in our main analyses.

- *Buyers*: the name of the PE firms involved in the deal.

We complement the deal information from Capital IQ with deals from the Preqin database. We download private equity buyout deals in North America with deal dates from 2005 to 2017. We use the following fields:

- *Firm*: the target company name used to match Capital IQ data with GS1 data.
- *State*: the target company state also used in the match.
- *Deal Date*: the date used to create the "After" variable in our main analyses.
- *Investors*: the name of the PE firms involved in the deal.

B. *Finding Database Matches*

The most challenging and time-consuming part of our data set construction is to match PE target firms to products in the Nielsen scanner database. We first retrieve from GS1—the organization that assigns UPC codes—the link between UPC numbers and the firms that sell the products associated with these UPCs. We then match these firms to the PE targets from Capital IQ and Preqin. We match across the datasets using *company names* and *States*. In practice, we follow these six steps:

1. We modify the fields "*Target/Issuer*" in Capital IQ and "*CompanyName*" provided by GS1 to remove capital letters.
2. We match these fields ("*Target/Issuer*" and "*CompanyName*") using the Stata user-written command "*reclink*". "Reclink" uses a fuzzy matching algorithm that provides a score between 0 and 1 that expresses the goodness of the match. Based on this score

and the state, firms fall into four groups. The next four steps in the process are based on the inspection of each of these groups.

3. *“Perfect match, same state”*: We include in our sample all firms with a matching score equal to one (i.e., the highest score) and same state across the two data sources. We have 517 of these firms. We visually inspect each of these firms to verify that indeed the names exactly match.
4. *“Perfect match, different state”*: If the match score is equal to one, but the matched company is listed from two different states, a research assistant has conducted a web search to verify that the match is correct and that there are not two firms with similar names but from these two different states. In this and the following web searches the research assistant has relied on information on the target firm from CapitalIQ (fields: “Product Description,” “Primary Sector,” and “Primary Industry”) and Nielsen (“product_module_desc” and “brand_descr”) to verify the actual match between the two firms. We start with 178 of these firms and, after the manual checking process, we add 98 of these firms to our sample.
5. *“Good match, same state”*: For those firms that have a matched score between 0.90 and 1 from the same state, we conduct a web search as in the previous case. We identify 1,535 of these firms. After the clean-up process, we add 794 of these firms to our sample.
6. *“Good match, different state”*: For those firms that have a matched score between 0.99¹⁷ and 1 but with different state information, we conduct our web search. We manually

¹⁷We select a cut-off higher than the one chosen for the previous category to keep the number of firms that we need to manually inspect manageable.

check 1,117 firms in this category. We then include 179 of these firms in our sample.

At the end of this process, we have 1,588 matched firms between Capital IQ and GS1. Note that we follow this same process to match firms that are the target of M&A deals from Capital IQ to firms in GS1. We use these M&A targets in Table [A1](#) and [A8](#).

We then repeat steps #1 to #6 for the PE deals in the Prequin database. The relevant variables for the match in Prequin are “*Firm*” and “*State*.” At the end of this process we have 2,757 matched firms from Prequin. The breakdown of matched firms across the four groups is as follows: 663 “*Perfect match, same state*,” 256 “*Perfect match, different state*,” 1,479 “*Good match, same state*,” and 359 “*Good match, different state*.”

When we consolidate the list of target firms across Capital IQ and Prequin, we obtain 3,563 unique firms. We then merge these firms with Nielsen sales data, using the UPCs that are reported in Nielsen. We are able to match 908 firms. The many firms that drop out sell products with UPCs but not in supermarkets, drug stores, or mass merchandisers.

C. Additional Robustness Checks

We run two additional analyses to complement and verify this list of 908 deals.

If companies are recorded under completely different names in Capital IQ (or Prequin) vs. GS1, we would not be able to match them. To address this concern, we first collect from Capital IQ the largest deals (i.e., top decile by deal size) for each year of our analysis (2007 to 2015). Then, we inspect each of these deals focusing on their “*Product Description*,” “*Primary Sector*,” and “*Primary Industry*.” For the deals that appear to be in the consumer product space, we do a web search to retrieve their most popular brands, potential aliases, and names of subsidiaries or parent companies. Last, we try to match any of the above with the GS1 database following the process previously described. This procedure allows us to

identify 24 companies that were missing from our sample. The major reason for missing these deals was that firms were reported in Capital IQ/Prequin with different names compared to GS1. For example, the target firm Yankee Holding Corp. was recorded in GS1 as The Yankee Candle Company, Inc.

The initial screenings to retrieve PE deals from Capital IQ and Prequin generate a comprehensive list of 932, meant to capture any potential private equity deal. At this point, given that we have Nielsen sales data between 2006 and 2016 and that we require firms to have at least one year of sales data before and after the deal, we drop deals that closed before 2007 or after 2015. We also discovered that some target firms did not have any of their UPCs record sales within one year surrounding the deal closing date. We drop these firms. Next, we do a deep dive into the remaining deals to verify that these are PE deals as commonly defined in the literature. We base our investigation on the deal description and web-based searches. We end up eliminating: i) deals that do not actually result in a change in control; ii) deals where the buyer is a person as opposed to a private equity firm; and iii) deals where the PE targeted firm was mistakenly matched with a similarly named firm in GS1/Nielsen. We also remove add-on deals where the PE target company, not the PE firm, is the buyer. Our final sample consists of 236 firms.

II. Sample Representativeness

How representative are the 236 deals in our sample of typical PE transactions? To address this question, we compare across different samples the deal features available from Capital IQ. We report these results in Table [A1](#). In our sample period there are 17,566 total deals in Capital IQ. The screening criteria to select this sample are reported in subsection [I.A](#).

We classify 4,811 of these deals as “Consumer Goods”, if their primary sector description is “Consumer Discretionary” or “Consumer Staples”. The “Capital IQ–GS1” sample includes those deals whose target firms can be matched to the GS1 database. Details on the matching process are reported in subsection [I.B](#). In this sample, we have 1,588 target firms accounting for 1,839 deals. One target firm could be involved in multiple deals because it is the target of secondary PE buyouts. The “Capital IQ-GS1-Nielsen” sample includes those deals from Capital IQ/ GS1 whose targets have sales data in Nielsen. We identify 536 target firms, accounting for 634 deals. After our manual screening, we are left with a final sample of 216 target firms. Each of these firms appears only in one deal. This sample is different from our final sample of 236 deals, because it only includes deals from Capital IQ. Of these 216 firms, 13 targets were public before the deal. The remaining 203 were private firms. The “M&A Sample” includes firms that were target of M&A deals in our sample period. We collect this deals from Capital IQ and we match them to GS1/ Nielsen data, following the same procedure reported in subsection [I.B](#).

We find that our deals appear to be larger in size and involve older firms compared to the average PE deal in CapitalIQ and, even more so, compared to deals in consumer products. Implied equity valuations and total cash payments are also larger for our sample. There is no significant difference in term of number of PE investors involved. With the caveat that the deal information are not very heavily populated in Capital IQ, our sample seems to represent larger PE deals, between the 75th and the 90th percentile of the overall PE deal size distribution.

Table A1. Deal Characteristics and Sample Selection Process

This table shows descriptive statistics of PE deals across different samples from Capital IQ. Our final sample here includes 216 firms—and not 236 as in the paper—because we include only firms from Capital IQ. We describe these different samples in subsection III. “Deal Value” is defined as the total transaction value (in US \$ Million). “Implied Equity Value” and “Total Cash” are the equity value and the total cash payment of the deal as reported in Capital IQ. “Target Age” is the age, in years, of the target firm when the deal was completed. “Buyer Number” is the number of PE firms involved in each deal.

Variable	Stat.	Capital IQ (17,566)	Consumer Goods (4,811)	Capital IQ-GS1 (1,839)	CIQ/GS1 Nielsen (634)	Final Sample (216)	Final Public (13)	Final Private (203)	M&A Sample (126)
Deal Value	mean	383.9	325.6	573.3	659.5	865.5	1,870.9	521.6	472.9
	sd	1,871.9	1,625.0	1,730.3	1,467.4	1,453.7	1,730.3	1,186.6	1,816.6
	p25	2.4	2.0	9.9	12.6	51.0	702.6	22.0	7.7
	p50	20.0	14.2	78.8	112.6	310.0	1,325.3	149.0	25.5
	p75	161.9	110.1	380.2	415.0	1,009.7	2,239.0	420.0	140.0
N		4,170	1,136	372	122	51	13	38	49
Implied Equity Value	mean	321.7	276.4	501.6	595.6	823.2	1,510.1	535.2	491.5
	sd	1,463.1	1,300.2	1,440.5	1,344.1	1,374.2	1,318.2	1,312.1	1,586.9
	p25	1.9	1.6	8.0	8.5	52.9	476.1	22.0	8.3
	p50	16.0	10.0	73.0	90.0	280.0	1,293.0	100.0	37.0
	p75	139.0	87.5	397.0	420.0	963.9	1,855.2	410.0	173.7
N		3,814	1,041	335	111	44	13	31	49
Total Cash	mean	319.3	273.1	494.1	570.3	771.4	1,510.1	497.1	461.4
	sd	1,433.2	1,281.4	1,419.0	1,309.9	1,323.9	1,318.2	1,234.3	1,440.8
	p25	2.0	1.6	9.5	9.5	50.6	476.1	20.0	5.7
	p50	17.7	11.8	75.0	90.0	205.7	1,293.0	96.5	34.5
	p75	140.0	94.3	327.0	415.0	963.9	1,855.2	410.0	173.7
N		3,875	1,051	347	115	48	13	35	46
Target Age	mean	29.4	34.5	37.3	40.4	43.1	64.9	41.7	33.6
	sd	29.3	33.3	33.3	35.8	40.7	39.5	40.5	28.4
	p25	10	11	15	15	15	33	14	14
	p50	21	25	28	31	31	58	30	23
	p75	38	46	50	57	59	87	57	46
N		11,146	3,050	1,396	495	205	12	193	114
Buyer Number	mean	1.2	1.2	1.2	1.3	1.3	1.4	1.3	1.4
	sd	0.6	0.6	0.6	0.7	0.7	0.7	0.7	0.5
	p25	1	1	1	1	1	1	1	1
	p50	1	1	1	1	1	1	1	1
	p75	1	1	1	1	1	2	1	2
N		9,057	2,115	1,191	430	208	12	196	125

Table A2. List of Largest Product Categories

This table shows the largest product categories by monthly sales in the Nielsen dataset, together with the average number of products in that category nationwide.

Product Category	Monthly Sales (\$)	Av. N. of Products
CIGARETTES	429,254,112	930
SOFT DRINKS - CARBONATED	269,718,144	2,076
CEREAL - READY TO EAT	227,483,344	535
SOFT DRINKS - LOW CALORIE	221,177,712	804
LIGHT BEER (LOW CALORIE/ALCOHOL)	207,607,984	280
WINE-DOMESTIC DRY TABLE	205,774,640	5,258
BEER	176,359,296	1,433
WATER-BOTTLED	175,339,872	1,347
TOILET TISSUE	171,534,576	152
DETERGENTS - HEAVY DUTY - LIQUID	165,413,312	328

Table A3. List of Most Common Private Equity Partners

This table shows the most frequent private equity partners that are involved in the 236 private equity deals in our sample.

General Partner Name	N. of Deals
Sun Capital Partners Inc	9
Encore Consumer Capital	6
Arbor Private Investment Company	5
Wind Point Partners	4
Brazos Private Equity Partners LLC	4
Mason Wells Inc	4
The Riverside Company	4
Brynwood Partners	4
Vestar Capital Partners Inc	4

Table A4. Largest Private Equity Deals

This table shows the largest private equity deals in our sample, sorted by the average monthly sales in the Nielsen dataset. The deal value, from Capital IQ, includes the value of divisions and subsidiaries that do not sell to supermarkets or mass merchandisers.

Target	Deal Date	Monthly Sales (\$)	Deal Value (\$Mil)
Del Monte Foods Inc.	8-Mar-11	59,519,200	5,482
The Nature's Bounty Co.	1-Oct-10	17,472,164	4,078
Pabst Brewing Company	7-Jun-10	13,083,578	250
Evenflo Company, Inc.	8-Feb-07	9,514,464	260
Bradshaw International, Inc.	16-Oct-08	9,313,272	N/A
The Sun Products Corporation	30-Apr-07	8,821,161	1,250
Peet's Coffee And Tea, Inc.	29-Oct-12	7,129,344	1,010
Matrixx Initiatives, Inc.	17-Feb-11	5,734,518	82
Parfums De Coeur Ltd.	5-Sep-12	5,591,422	N/A
Armored Autogroup Inc.	5-Nov-10	4,919,370	755

Table A5. Private Equity Deal Selection

This table presents OLS coefficient estimates from regressing a product category selection dummy, a firm selection dummy, and a product selection dummy on explanatory variables to determine the private equity interest in specific product categories, firms, or products. The sample is restricted to months when a private equity deal occurred. The industry selection dummy is equal to one if there was a private equity deal in that product category in that month. Firm selection dummy is equal to one if the firm was acquired by a private equity company in that month. Product selection dummy is equal to one if the product is acquired by a private equity company in that month. We describe how we construct the "High-Income Category" indicator and how we compute the "Herfindal Index" in section VII.D of the paper. The unit of analysis is unique at the product-category-month for column 1, firm-month for column 2, and product-month for column 3. Standard errors are double-clustered at the firm and time. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Category Selection	Firm Selection	Product Selection
High-Income Category	0.005*** (4.86)		
Herfindal Index	-0.023*** (-11.41)		
Price Av. (log)	-0.003*** (-6.96)	-0.000 (-0.61)	-0.001*** (-21.62)
Sales (log)	0.002*** (9.00)	0.001*** (3.06)	0.000*** (24.10)
Growth N. Products	-0.002 (-0.82)	-0.000 (-1.01)	
Growth Sales	0.002 (1.63)	-0.000 (-1.55)	-0.000*** (-4.51)
Growth Price Av.	-0.002 (-0.66)	0.001* (1.75)	0.001*** (9.32)
Adj. R-Square	0.049	0.019	0.083
N. Obs.	130,053	324,630	2,695,569
Date FE	Yes	No	No
Category-Date FE	No	Yes	Yes

Table A6. Summary Statistics of Matching Procedure

This table presents the summary statistics (Mean and Median) of firm-level characteristics for treated and matched control firms at the time of the private equity buyout. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Treated		Matched Control		Difference	
	Mean	Median	Mean	Median	Diff	t-stat
<i>Matching Variables</i>						
Monthly Sales	1,036,508.44	55,065.39	902,937.81	59,015.72	-133,570.63	(-0.36)
Monthly Sales Growth	27.31	-0.02	4.46	-0.00	-22.85	(-1.23)
N. Products	36.58	11.50	35.12	11.00	-1.47	(-0.23)
N. Stores	5,298.33	1,408.50	5,277.92	1,494.00	-20.41	(-0.03)
<i>Non-Matching Variables</i>						
Monthly Units Sold	396,994.41	12,114.79	332,081.96	12,190.14	-64,912.45	(-0.33)
Average Price	7.85	4.76	7.27	4.31	-0.58	(-0.52)
N. Categories	7.81	3.00	7.71	3.00	-0.09	(-0.07)
N. Chains	24.61	14.00	24.47	14.00	-0.14	(-0.06)
N. 3-digit ZIP Codes	383.67	313.00	378.01	308.00	-5.66	(-0.18)
N. Counties	106.76	117.50	107.84	114.00	1.08	(0.16)
N. States	30.18	36.00	29.02	34.50	-1.16	(-0.66)
N. DMAs	106.15	100.50	103.89	100.00	-2.26	(-0.30)

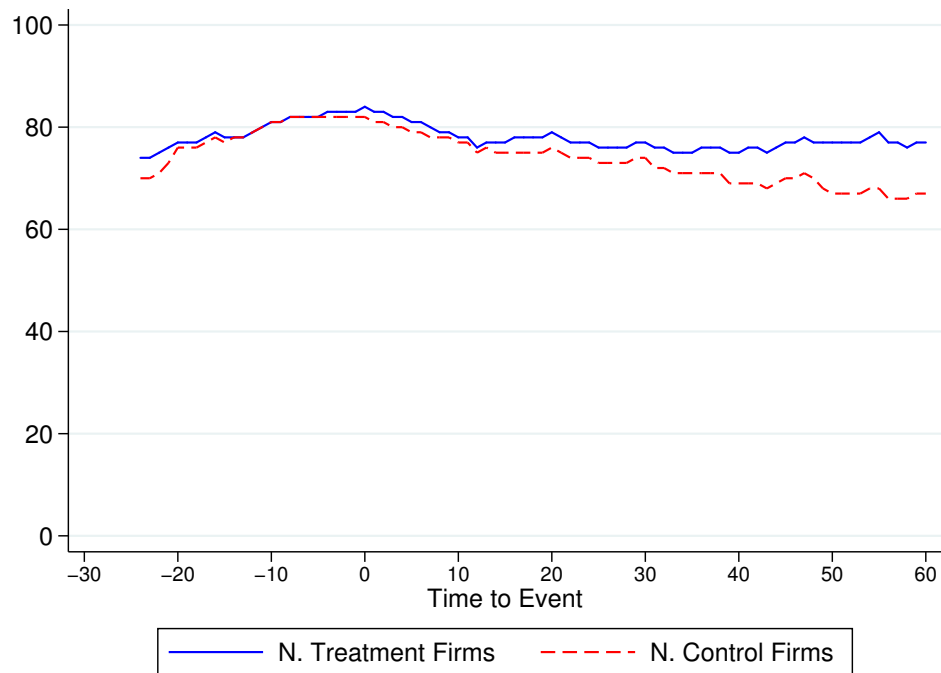
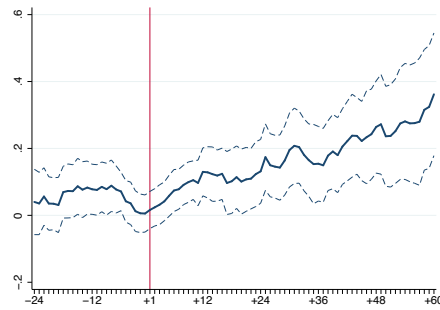


Figure A1. N. of Treated and Control Firms

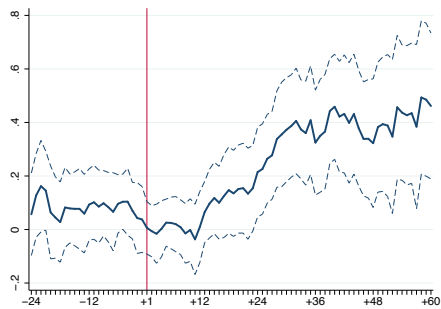
The figure plot the number of treated and control firms in the sample over time relative to the deal close date, only for deal closed in 2008-2011. We limit our analysis to the years 2008 to 2011 to ensure that we have the five full years of data available for all firms (our sample ends in 2015).



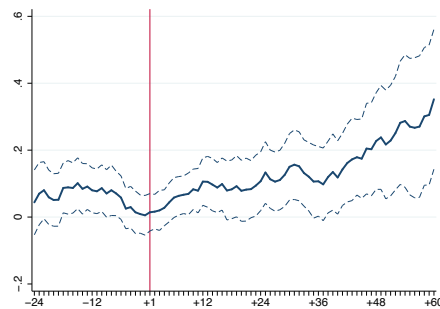
(a) N. of Counties - Within Firm



(b) N. of Counties - Within Firm-Category



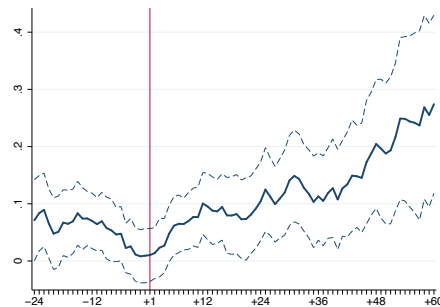
(c) N. of Market Areas - Within Firm



(d) N. of Market Areas - Within Firm-Category



(e) N. of States - Within Firm



(f) N. of States - Within Firm-Category

Figure A2. Time Trend of Product Availability

These graphs plot the coefficient estimates of regressions following equation 2, where the dependent variables are number of counties for panels (a) and (b), the number of designated market areas for panel (c) and (d), and the number of states for panel (e) and (f). The unit of analysis is a firm-month-cohort for panels (a), (c), and (e), and a firm-category-month-cohort for panels (b), (d), and (f). The coefficient estimate at time t represents the difference in the outcome variables between PE firms/firm-categories and matched non-PE firms/firm categories t months away from the date of closing of the private equity deal. The estimation period goes from -24 months to +60 months around the date of the closing of the private equity deal. The closing date is indicated by the vertical line. The dotted lines show the 90% confidence interval.

Table A7. Private Equity and Consumer Goods - Annual Coefficients

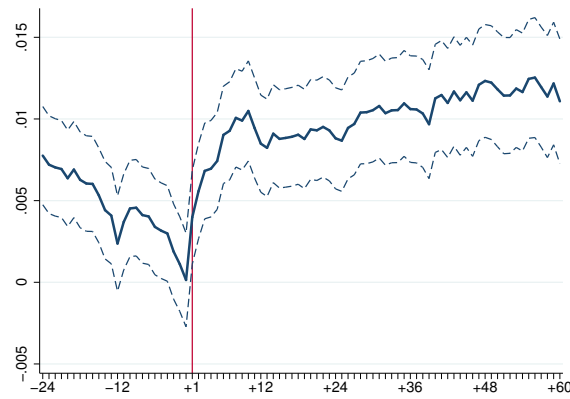
This table presents OLS coefficient estimates from regressing log of sales, log of average monthly prices, log of units sold, number of products, number of stores, number of 3-digit ZIP, and number of categories, on dummies equal to one if the observation month is includes in the year at distance t from the deal close year for firms (Panel A) or firm-categories (Panel B) that underwent a buyout during our sample period. We use the [Abadie and Imbens \(2006\)](#) distance metric to pair each treated unit with the closest untreated unit. We match on sales, unique UPCs sold, and store locations, all during the most recent pre-buyout month, and growth in monthly sales from the past 12 months to the most recent pre-buyout month. The unit of analysis is unique at the firm-month-cohort level in panel A, and at the firm-product category-month-cohort level in panel B. The estimation period goes from -24 months to +60 months around the private equity deal closing date. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are in parentheses and are double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Within Firm

	Sales	Average Price	Units Sold	N. Products	N. Stores	N. Chains	N. ZIP	N. Categories
Year -2	-0.091 (-0.90)	-0.037* (-1.79)	-0.059 (-0.64)	-0.019 (-0.60)	0.038 (0.54)	-0.007 (-0.22)	0.064 (1.19)	-0.027 (-1.12)
Year -1	-0.106 (-1.35)	-0.017 (-1.25)	-0.080 (-1.13)	-0.004 (-0.21)	-0.017 (-0.39)	0.012 (0.69)	0.016 (0.44)	-0.007 (-0.51)
Year +1	0.211** (2.40)	0.023 (1.44)	0.196** (2.55)	0.045** (2.19)	0.170*** (3.35)	0.061*** (3.12)	0.128*** (3.32)	0.028* (1.88)
Year +2	0.492*** (3.63)	0.014 (0.66)	0.454*** (3.72)	0.112*** (3.17)	0.343*** (4.22)	0.141*** (4.94)	0.264*** (4.37)	0.039* (1.72)
Year +3	0.519*** (3.23)	0.046** (2.03)	0.460*** (3.01)	0.169*** (3.58)	0.382*** (3.58)	0.185*** (5.26)	0.273*** (3.57)	0.052* (1.74)
Year +4	0.548*** (2.87)	0.090*** (3.64)	0.523*** (3.00)	0.250*** (4.50)	0.417*** (3.27)	0.219*** (4.89)	0.267*** (2.88)	0.100*** (2.78)
Adj. R-Square	0.876	0.933	0.894	0.943	0.909	0.952	0.900	0.950
N. Obs.	31,596	31,596	31,596	31,596	31,596	31,596	31,596	31,596
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Within Firm-Category

	Sales	Average Price	Units Sold	N. Products	N. Stores	N. Chains	N. ZIP
Year -2	-0.040 (-0.77)	-0.025*** (-2.74)	0.002 (0.05)	0.014 (1.26)	0.058 (1.42)	0.044** (2.44)	0.057* (1.88)
Year -1	-0.044 (-1.36)	-0.020*** (-4.22)	-0.024 (-0.79)	-0.003 (-0.47)	-0.023 (-0.93)	0.003 (0.30)	-0.007 (-0.39)
Year +1	0.146*** (3.76)	0.003 (0.51)	0.139*** (3.91)	0.023*** (2.97)	0.126*** (4.06)	0.061*** (5.31)	0.123*** (4.89)
Year +2	0.330*** (5.40)	0.021** (2.14)	0.295*** (5.55)	0.051*** (4.08)	0.251*** (5.49)	0.119*** (6.49)	0.199*** (5.67)
Year +3	0.252*** (2.84)	0.023* (1.89)	0.229*** (2.90)	0.047** (2.55)	0.235*** (3.57)	0.133*** (5.18)	0.169*** (3.49)
Year +4	0.267** (2.21)	0.022 (1.44)	0.243** (2.26)	0.055** (2.15)	0.221** (2.56)	0.128*** (3.73)	0.167** (2.56)
Adj. R-Square	0.868	0.918	0.884	0.920	0.889	0.921	0.883
N. Obs.	224,454	224,454	224,454	224,454	224,454	224,454	224,454
Firm-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes



(a) Same Retail Chain



(b) Same Designated Market Area

Figure A3. Price Response of Competitors - By Control Type

These figures plot the coefficient estimates of regressions following equation 2, where the dependent variables are product monthly prices. The coefficient estimate at time t represents the difference in the outcome variables between treated products and matched control products, t months away from the date of closing of the private equity deal. This sample only includes products whose firms did not go through a private equity deal. Each cohort is made of a treated product that is sold in a store-category where a private equity deal occurred, and the best match (with the same UPC) but selected from ten random stores where there is no private equity competitor. In Panel (a) we randomly select the ten stores within the same retail chain of the treated product. In Panel (b) we randomly choose the ten stores within the same Designated Market Area of the treated product. The estimation period goes from -24 months to +60 months around the date of the closing of the private equity deal. The closing date is indicated by the vertical line. The dotted lines show the 90% confidence interval. Regressions are estimated using the fixed point iteration procedure implemented by Correia (2014).

Table A8. The Effects of M&A Deals on Consumer Product Firms

This table presents OLS coefficient estimates from regressing, in Panel A, logs of sales (Column 1), average monthly prices (Column 2), and units sold (Column 3) on *After*, a dummy equal to one for the post-M&A months for firms that underwent a M&A during our sample period. In Panel B we focus on product innovation. In Panel C we study product availability. All the outcome variables are either indicator variables or in logs. Each cohort is a pair of treated-untreated firms where the treated unit is matched to the untreated unit with the closest distance at the time of the M&A deal based on sales, unique UPCs sold, and store locations, all during the most recent pre-M&A month, and growth in monthly sales from the past 12 months to the most recent pre-M&A month. For the matching, we use the [Abadie and Imbens \(2006\)](#) distance metric. The unit of analysis is unique at the firm-month-cohort level. The estimation period goes from -24 months to +60 months around the date of the closing of the M&A deal. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Sales, Pricing, and Units

	Sales	Average Prices	Number of Units Sold
After	-0.167 (-0.86)	-0.001 (-0.04)	-0.158 (-0.91)
Adj. R-Square	0.852	0.955	0.867
N. Obs.	13,340	13,340	13,340
Firm-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes

Panel B: Product Innovation

	Number of Products	New Products	Discont. Products	Number of Categories
After	-0.025 (-0.49)	0.099 (1.21)	0.056 (1.44)	-0.027 (-0.82)
Adj. R-Square	0.916	0.381	0.716	0.927
N. Obs.	13,340	13,340	13,340	13,340
Firm-Cohort FE	Yes	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes	Yes

Panel C. Product Availability

	N. Stores	N. Chains	N. ZIP Codes
After	-0.172 (-1.39)	-0.133** (-2.34)	-0.144 (-1.56)
Adj. R-Square	0.895	0.924	0.890
N. Obs.	13,340	13,340	13,340
Firm-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes

Table A9. Private Equity, Sales, and Prices - Excluding Acquisitive Firms

This table presents OLS coefficient estimates from regressing logs of sales (Column 1), average monthly prices (Column 2), and units sold (Column 3) on *After*, a dummy equal to one for the post-buyout months for firms (Panel A) or firm-categories (Panel B) that underwent a buyout during our sample period. The sample excludes firms in the top decile of acquisitiveness. Each cohort is a pair of treated-untreated firms (panel A) or firm-categories (panel B) where the treated unit is matched to the untreated unit with the closest distance at the time of the private equity deal based on sales, unique UPCs sold, and store locations, all during the most recent pre-buyout month, and growth in monthly sales from the past 12 months to the most recent pre-buyout month. For the match, we use the [Abadie and Imbens \(2006\)](#) distance metric. The unit of analysis is unique at the firm-month-cohort level in panel A and at the firm-product category-month-cohort level in panel B. The estimation period goes from -24 months to +60 months around the date of the closing of the private equity deal. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Within Firm

	Sales	Average Prices	Number of Units Sold
After	0.450*** (3.81)	0.058*** (2.98)	0.387*** (3.58)
Adj. R-Square	0.873	0.932	0.891
N. Obs.	30,016	30,016	30,016
Firm-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes

Panel B: Within Firm-Category

	Sales	Average Prices	Number of Units Sold
After	0.188*** (3.06)	0.036*** (3.90)	0.145** (2.59)
Adj. R-Square	0.868	0.916	0.884
N. Obs.	206,730	206,730	206,730
Firm-Cat.-Cohort FE	Yes	Yes	Yes
Date-Cat.-Cohort FE	Yes	Yes	Yes

Panel C: Within Product-Store

	Sales	Price	Number of Units Sold
After	0.01944 (0.95)	0.00733* (1.67)	0.00542 (0.32)
Adj. R-Square	0.885	0.785	0.675
N. Obs.	718,937,916	718,937,916	718,937,916
UPC-Store-Cohort FE	Yes	Yes	Yes
Date-Store-Cohort FE	Yes	Yes	Yes

Table A10. Private Equity and Product Innovation - Excluding Acquisitive Firms

This table presents OLS coefficient estimates from regressing the log of number of products (Column 1), a new product dummy (Column 2), a discontinued product dummy (Column 3), and the log of number of product categories (Column 4) on *After*, a dummy equal to one for the post-buyout months for firms (Panel A) or firm-categories (Panel B) that underwent a buyout during our sample period. The sample excludes firms in the top decile of acquisitiveness. We measure the number of products by counting products that a firm or firm-category has on the shelves in at least one store in that month. The New Products variable is the number of products introduced by the firm or firm-category in that month. The Discontinued Products variable is the number of discontinued products by the firm or firm-category in that month. We measure number of categories by counting the categories in which a firm has at least one product on store shelves in that month. Each cohort is a pair of treated-untreated firms (panel A) or firm-categories (panel B) where the treated unit is matched to the untreated unit with the closest distance at the time of the private equity deal based on sales, unique UPCs sold, and store locations, all during the most recent pre-buyout month, and growth in monthly sales from the past 12 months to the most recent pre-buyout month. For the match, we use the [Abadie and Imbens \(2006\)](#) distance metric. The unit of analysis is unique at the firm-month-cohort level in panel A and at the firm-product category-month-cohort level in panel B. The estimation period goes from -24 months to +60 months around the closing date of the private equity deal. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Within Firm

	Number of Products	New Products	Discont. Products	Number of Categories
After	0.107*** (3.08)	0.404** (2.00)	0.221 (1.51)	0.053** (2.18)
Adj. R-Square	0.940	0.515	0.734	0.948
N. Obs.	30,016	30,016	30,016	30,016
Firm-Cohort FE	Yes	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes	Yes

Panel B: Within Firm-Category

	Number of Products	New Products	Discont. Products
After	0.025** (2.00)	0.053** (2.48)	0.044** (2.19)
Adj. R-Square	0.918	0.534	0.731
N. Obs.	206,730	206,730	206,730
Firm-Cat.-Cohort FE	Yes	Yes	Yes
Date-Cat.Cohort FE	Yes	Yes	Yes

Table A11. Private Equity and Product Availability - Excluding Acquisitive Firms

This table presents OLS coefficient estimates from regressing the logs of number of stores (Column 1), number of retail chains (Column 2), and number of 3-digit ZIP codes (Column 3) where a firm or firm-category is present on *After*, a dummy equal to one for the post-buyout months for firms (Panel A) or firm-categories (Panel B) that underwent a buyout during our sample period. The sample excludes firms in the top decile of acquisitiveness. Each cohort is a pair of treated-untreated firms (Panel A) or firm-categories (Panel B) where the treated unit is matched to the untreated unit with the closest distance at the time of the private equity deal based on sales, unique UPCs sold, and store locations, all during the most recent pre-buyout month, and growth in monthly sales from the past 12 months to the most recent pre-buyout month. For the match, we use the [Abadie and Imbens \(2006\)](#) distance metric. The unit of analysis is unique at the firm-month-cohort level in panel A and the firm-product category-month-cohort level in panel B. The estimation period goes from -24 months to +60 months around the closing date of the private equity deal. The regressions are estimated using the fixed point iteration procedure implemented by [Correia \(2014\)](#). Standard errors are double-clustered by firm and month. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A. Within Firm

	N. Stores	N. Chains	N. ZIP Codes
After	0.254*** (3.36)	0.113*** (3.63)	0.152*** (2.79)
Adj. R-Square	0.906	0.949	0.898
N. Obs.	30,016	30,016	30,016
Firm-Cohort FE	Yes	Yes	Yes
Date-Cohort FE	Yes	Yes	Yes

Panel B. Within Firm-Category

	N. Stores	N. Chains	N. ZIP Codes
After	0.116** (2.50)	0.048*** (2.62)	0.089** (2.59)
Adj. R-Square	0.890	0.921	0.883
N. Obs.	206,730	206,730	206,730
Firm-Category-Cohort FE	Yes	Yes	Yes
Date-Category-Cohort FE	Yes	Yes	Yes