

The Impact of Private Label Introduction on Assortment, Prices, and Profits of Retailers

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Abstract

We study how the introduction of private-label brands (PLs) affects retailers' prices, demand, and profits, accounting for rich assortment adjustments of national brands (NBs) in retail stores. Using scanner data on the U.S. beef market and an event-study framework, we find that stores reposition NBs to further differentiate them from the PL and remove NBs from the same segment, when PLs are added to the low-priced market segment but not the high-priced segment. These findings are robust to a generalized synthetic control estimator and a large set of sensitivity tests. PL introduction and PL-driven assortment changes of NBs impose a small effect on NB prices, but strongly cannibalize NB demand and steer consumers toward PLs, which tends to increase store-level profits.

Keywords: Prices and demand of national brands, Private label, Retailer assortment decisions.

JEL codes: D22, L66, L81

* Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. The authors thank two anonymous reviewers and the editor, Professor Ryan McDevitt, for constructive feedback.

1. Introduction

Over decades, firms have introduced many new products into the retail. For example, the number of unique products offered by an average supermarket in the U.S. grew from 9,000 in 1975 to 47,000 in 2008 (Consumer Reports, 2014). The substantial product expansion is partly explained by the introduction of private-label brands (hereafter, PLs), also known as store brands (Pauwels and Srinivasan, 2004), which are developed and marketed by retail chains (Morton and Zettelmeyer, 2004; ter Braak et al., 2014). Theoretically, assuming fixed positioning and/or a fixed set of incumbent products, PL introduction may impose negative (Connor and Peterson, 1992) or positive effects (Hotelling, 1929; Salop, 1979; Gabrielsen and Sorgard, 2007) on national brands' (NBs') product prices in the market. The effects on prices and consumer surplus can be large, which explains why PL introduction attracts a lot of attention among scholars and policy makers. Relatedly, empirical studies find mixed results on the effect PL introduction has on NB prices (e.g., Bontemps et al., 2008). These studies evaluate price effects, under the assumption that the store's assortment of NBs remains fixed.

Our study highlights a novel aspect in evaluating the effects of PL introduction – the assortment of NBs. The introduction of PLs can intensify intra-store brand competition and enhance the store's inter-store competence in variety. Under these competitive forces, retail stores can make assortment adjustments (e.g., Draganska et al., 2009; Draganska and Jain, 2010). Using scanner data of a large number of multi-brand stores, we explicitly account for NB assortment adjustments in the store's product portfolio in response to introducing PL into the store and evaluate PL effects on NB prices, NB sales, and store profits.

We concentrate on two research questions: (1) How do retail stores change the positioning and the number of NBs, after PLs are introduced; and (2) How do those assortment changes affect

prices and demand of NBs and store-level profits? One of our main insights is that, though the direct price effect of selling PLs is limited, PL introduction increases a store's profits via assortment changes that strongly divert consumers from purchasing less profitable NBs toward more profitable PL products. The findings shed new light on the effects of PLs and, more broadly, on how multi-product firms may use assortment adjustments as a strategic tool for altering within-store product differentiation and steering consumers to certain products. These assortment and price changes also leave PL impacts on consumer surplus harder to estimate than often thought.

In the late 1970s, retail stores introduced PLs that were considered discount brands to their NB counterparts (Janofsky, 1993). In the early 1990s, the retail market experienced an expansion of PLs that were introduced into the economy, standard, and premium market segments. PL is under control of the retailer, and PL products are acquired by retailers from manufactures close to marginal costs of manufacturing (Connor and Peterson, 1992). Selling PLs is likely more profitable for retailers compared with NBs, because PLs eliminate double margins (Mills, 1995; Raju et al., 1995; Narasimhan and Wilcox, 1998). The elimination of double margins allows retailers to sell PLs for low prices which, in turn, imposes downward pressure on NB prices, especially on NBs that are relatively less differentiated from the PL.¹ Even if the price of a PL is higher than the price of NBs, adding a PL as a new brand intensifies within-store competition among brands (Shaked and Sutton, 1982; Connor and Peterson, 1992; Siebert, 2015). Selling a PL can hence cannibalize the demand of existing NBs and cause a “business stealing effect” (Connor and Peterson, 1992; Hamilton and Richards, 2009; Ellickson et al., 2018).

¹ For more reasons to sell store brands, such as gaining more bargaining power, improving store image, etc., see Scott-Morton and Zettelmeyer (2004), Steiner (2004), and Draganska et al. (2010).

To reduce price competition and the stealing effect, NBs may be further differentiated from PLs in the variety space (MacDonald, 1998; Nijssen and Van Trijp, 1998). Stores may even withdraw less differentiated NBs. Such assortment adjustments can soften internal competition among brands (Hotelling, 1929; Shaked and Sutton, 1982) and result in relatively high equilibrium prices of all brands and, hence, higher store profits (Scott-Morton and Zettelmeyer, 2004; Draganska et al., 2009; Draganska et al., 2010).

We estimate the effect of PL introduction on assortment, prices, demand, and profits of retail stores in the context of the U.S. fresh beef retail market from 2006 to 2016. The beef market is the highest-valued meat market in the U.S. and is especially well suited for our study for the following reasons: (1) The number of stores selling PLs has grown considerably over the period of interest, and the stores start selling PLs at different time periods; (2) Stores carry a wide range of PLs and NBs and a fairly large set of varieties (e.g., ground beef and ribeye steak), leaving room for assortment changes; (3) Beef varieties and prices vary over time and across brands, retail stores, and market segments; and (4) Most importantly, beef brands rarely change their available variety offerings that retailers pick from. This differs from other widely studied food categories (e.g., yogurt and cereals) and non-food categories (e.g., automobiles) where manufacturers make frequent and considerable offering changes (e.g., Draganska et al., 2005, 2009) in response to competitive forces. In terms of fresh beef, a store selects NBs and varieties of each NB from a common and stable pool in the integrated U.S. beef market. The stylized fact helps isolate assortment decisions by retailers from those made by manufacturers in identifying the effect of PL.

We use a big database—the Nielsen Retail Scanner Data. The database contains sales information collected from more than 28,000 retail stores in 49 U.S. states. The database includes 1,000+ unique beef products and 200+ beef brands, suggesting considerable room for assortment

adjustments by retail stores. Each brand offers several beef varieties that differ by their cuts (such as fillet steak, ground/patties, ribeye steak, striploin steak, etc.) and packaging sizes (measured in pounds). We classify beef products into 21 varieties, as explained in Section 2.

Descriptive analyses show that PLs are sold by an increasing number and proportion of stores from 2006 to 2016. By 2016, more than 75% of the market by volume sales was occupied by PLs. We consider two assortment adjustments that can be made by stores. First, stores can reposition NBs, that is, they change the beef varieties offered by an NB. Second, stores can remove an entire NB. Controlling for a full set of fixed effects and other variables, we rely on the timing of store-level assortment changes and PL introductions under an event-study framework as well as a novel generalized synthetic control estimator to identify the causal effect of selling PLs. Our econometrics results show heterogeneous reactions by stores to PLs: stores further differentiate NBs from PLs in the variety space and reduce the number of NBs, when PLs are added to the low-priced market segment and NBs in the same segment; when PLs are added to the high-priced market segment, store reactions are insignificant.

Increased NB-PL differentiation and the heterogeneity in store responses across market segments indicate multiple economic forces at work rather than merely a shelf-space constraint. Limited shelf space is unlikely to be a major constraint, especially given that we find the total number of unique beef products carried by store increases post the PL introduction (with the number of unique products as a proxy for shelf space following Ackerberg and Rysman, 2005). As discussed in Section 3, heterogeneous assortment responses across segments suggest that inter-store variety competition, which is particularly intensive for the high-priced segment, is a relevant force and NB-PL differentiation is likely driven by the cannibalization effect among brands.

Next, we conduct regressions to evaluate direct price effects of PL introductions as well as indirect effects via assortment changes in NBs. Our results show that PL introductions have an insignificant direct effect on NB prices. We then turn to the novelty of our study and argue that assortment adjustments change the degree of product differentiation in the store and may affect equilibrium prices and sales of NBs and, consequently, store-level profits.

Econometrics results show that PL-induced assortment changes impose indirect effects on NB prices, which are ignored in prior studies. First, repositioning NBs against the PL increases intra-store product differentiation and NB prices. Second, stores may remove NBs, which softens competition and also increases NB prices. Though the net price effect is small, the PL-driven assortment changes enable stores to steer a considerable portion of consumers toward PL products, implying that retailers use assortment changes as a strategic tool (Heidhues et al., 2021). Steering consumers to the PL may generate more profits for the store, because PLs products tend to be more profitable due to eliminated double margins under vertical integration or cost savings due to vertical coordination.

We make two major contributions to the literature. First, we show the relevance of considering NB assortment changes caused by selling PLs and emphasize the heterogeneity in the assortment effect of PLs across market segments. Second, we show the relevance of assortment changes in evaluating PL impacts on NB prices and sales. Assortment changes serve as a strategic instrument for a retail store in altering the degree of product differentiation within the store and steering consumers toward purchasing PL products. Prior studies do not explicitly consider NB assortments and, thus, overlook an important channel through which the PL affects NBs and store profits. Various assortment changes and their use as a strategic instrument in response to new products are broadly relevant to multi-product firms carrying differentiated products.

1.1 Related Literature

Our study is mainly related to three areas of research described below.

(1) There is a rich empirical literature on the price effect of selling PL products on NBs. These studies cover a wide range of product categories and make no explicit consideration of NB assortments when estimating price effects. Some studies show that prices decline (Putsis, 1997; Cotterill and Putsis, 2000; Sayman et al., 2002; Choi and Coughlan, 2006; Chung and Lee, 2017), while other studies provide evidence that prices increase (Ward et al., 2002; Pauwels and Srinivasan, 2004; Bontemps et al., 2008).

(2) A group of studies investigate the non-price effects and aspects of selling PLs. For instance, a few empirical studies find mixed evidence on the PL effect on market shares of existing brands (Sethuraman, 2009; Geyskens et al., 2010). There are only a few empirical studies on the effect of PLs on the assortment of NBs. One rare example is the study by Pauwels and Srinivasan (2004) that shows NBs may add products in response to PL introductions. Conditional on the presence of PL, Akcura et al. (2019) study how sales performance of PLs in different market segments affect occupation of NB products differently using observations of multiple categories of goods. They find that increasing market shares of standard (low-priced) PLs correlate with a decreasing number of NB products out of total products in a category, while rising shares of premium (high-priced) PLs go along with an increasing number of NB products relative to category total products.

A few theoretical models discuss the optimal positioning of PLs in the variety space and given NB positioning (Choi and Coughlan, 2006; Chung and Lee, 2017; Li et al., 2022). ter Braak et al. (2014) conduct a survey on factors that determine stores' decisions to sell a PL in the low- (standard) or the high-priced (premium) market segment. They find that PLs are more likely to

enter the high segment if the category has a higher need for variety and if NBs in the category spend relatively little on advertising.

(3) There is an extensive literature on product assortment under competition. Borenstein and Netz (1999) and Davis (2006) study product assortments in the context of airline departure times and movie theater showtimes. They consider the fact that closer departure times and showtimes reduce product differentiation, toughen price competition, and increase demand cannibalization effects. Gandhi et al. (2008) use a theoretical model to show that firms reposition products post-merger to reduce the cannibalization effect, an effect that we study as well. Mazzeo et al. (2018) study retail stores' joint product and price decisions after a merger. They examine firms' assortment decisions, including the number of products offered, which also interests us.

An active literature shows that firms adjust product assortments to change the degree of product differentiation, which affects price competition, demand, and cannibalization (Richards and Hamilton, 2015). For example, Sweeting (2010) studies mergers in the music radio industry and finds that music stations under common ownership are repositioned to reduce overlap in their playlists. In a recent study, Atalay et al. (2020) examine a large number of mergers and acquisitions in retail markets. They find that merging firms reduce the number of products to strengthen core competencies in particular segments of the market. Other important studies that address repositioning and cannibalization effects include Berry and Waldfogel (2001), Berry et al. (2004), Draganska et al. (2009) Einav (2010), and Johnson and Rhodes (2021).

2. Data

Our study concentrates on the U.S. fresh beef market—the highest-valued meat market in the nation. In 2016, the retail equivalent value of beef produced in the U.S. was worth more than \$100 billion. Our data come from the Nielsen Retail Scanner Data and contain monthly product-level

sales information on more than 28,000 beef-selling stores in 49 U.S. states from 2006 to 2016.² A variety of stores, including grocery stores and mass merchandisers, enter the database. References confirm that the dataset is nationally representative (Atalay et al., 2020).

Table 1 displays a few key statistics of our data. The number of retail chains that sold beef ranged from 82 to 101 in 2006 to 2016 (see column 2). During this period, the number of stores selling beef increased from 9,134 to 26,452 (column 3), part of the increase is driven by Nielsen's adjustments of store selection. During that time, the number of NBs increased from 51 in 2006 to 114 (see column 4). PLs are developed by retail chains (ter Braak et al., 2014), and the number of retailers offering PLs increased from 38 to 60 throughout our study's time span (see column 5). The number of stores that sold PLs increased from 5,436 to 16,978 (see column 6), which translates to an increase in the proportion of PL-selling stores from 59% to 64%. The collective market share of PLs increased from 59% in 2006 to 77% in 2016 (see column 7). Not surprisingly, some large NBs experienced steady declines in market shares over the same period (see Table A1).

[Table 1 approximately here]

The timing of introducing PLs in specific stores of a retail chain varies considerably, reflecting the influence of local market conditions on the chain-level strategy of marketing PLs. The standard deviation of the timing of PL introductions is as large as 15 months for one retail chain on average. Figure 1 shows that PLs are introduced to some stores almost every month; at least one store started selling the PL in all but four months from 2006 to 2016.

² The original Nielsen dataset contains weekly observations of a beef product in a store if it is sold at least once in the week. For the remainder of the study, we aggregate weekly observations to the month level, which helps avoid missing brands due to zero weekly product sales. If we used weekly observations instead, we risked undercounting the number of brands due to zero sales in some weeks. Because fresh beef is perishable, brands without at least one transaction in a month would most likely not be available in the store.

[Figure 1 approximately here]

The Nielsen database contains more than 1,100 unique beef products belonging to various PLs and NBs. Every beef product is denoted by a universal product code (UPCs). Fresh beef products involve little processing other than cutting and packaging, and the only ingredient is the flesh itself. Thus, beef varieties are straightforward to define based upon the sizes and cuts. Specifically, beef cuts include ribeye steak, fillet steak, striploin steak, round, ground, patties, and so on. In terms of package sizes, the majority of beef UPCs weigh less than three pounds. Given the cuts and package sizes, we can group the beef UPCs into 21 varieties (see Table A2).

Importantly, our data show that NB manufacturers rarely adjust variety offerings (e.g., a NB consistently offers 2 out of the 21 beef varieties); nearly 95% of NBs offer the same set of varieties from month to month during the period of interest. The stylized fact ensures that the significant, monthly changes in NB variety offerings that we identify in Section 3 are driven primarily by retail stores instead of by manufacturers or NB brand managers.³

2.1 National Brand and Private Label Prices

For our empirical analysis, we use information on brand prices and brand assortments at the store-market-month level. Local markets are defined by three-digit zip codes, which indicate the smallest geographic boundary in the Nielsen database. We begin with computing the price of each brand

³ The literature also generally considers retailers as the decision makers of retail product offerings (e.g., Scott-Morton and Zettelmeyer, 2004; Dekimpe et al., 2011; Richards and Hamilton, 2015). Our data show, stores that do not sell PLs rarely change the varieties that they offer from month to month. Upon the month of PL introduction, in contrast, more than 36% of stores change the set of varieties. In Section 2.2., we introduce a sophisticated and informative measurement of variety offerings for NBs and PLs.

carried by a store for every month, measured in dollars per pound.⁴ The average price of NBs is \$5.74 and the median price is \$4.94 with a standard deviation of \$2.88 (see Table 2).

[Table 2 approximately here]

Figure A2 shows the average prices of beef products for NBs and PLs across the 132 months in our dataset. The average NB beef price began to increase significantly after 2009 and reached a peak in 2015; it began to decline thereafter. A similar trend is observed for the average PL beef price. The PL price lies below the NB price, which might be indicative of PLs being characterized by lower quality or PLs being produced at lower marginal costs by eliminating double marginalization and, if passed on to consumers, sold at lower prices. The price gap between NBs and PLs narrows over time, which likely reflects an upgrading strategy of retailers—PL introduction is not limited to low market segments, but also occurs in high market segments.

Beef varieties are priced differently. Ground beef varieties cover more than 80% of all beef UPCs and hold large market shares (in volume or revenue), accounting for 85% of the total beef sales. Ground beef is relatively inexpensive (\$3-\$5 per pound, see Table A2); this especially applies to ground beef with a fat content greater than 15%. Various high-priced steak products (\$6-\$11 per pound) cover only small shares of volume and revenue.

Figure 2 illustrates average store-level NB prices for several months before and after the introduction of PLs in stores. Note, month “0” refers to the month in which the store introduces the PL. Negative numbers denote months before PL introduction, and positive numbers refer to

⁴ The price is calculated by dividing the monthly store-level revenue by the volume sales of the brand. All monetary values are measured in 2015 dollars.

months after PLs are introduced. The figure shows a 10-15% increase in the average price of NBs during the first 12 months of selling the PL without controlling for other factors determining prices.

[Figure 2 approximately here]

2.2 Assortment: Brand Proximity and Brand Numbers

After a PL is introduced, a store has opportunities to adjust the NB product assortment. The NB assortment adjustment can soften price competition against the store's own PL products. The adjustment can also be useful in limiting the extent to which NBs cannibalize the demand of PLs.

Specifically, we consider two NB assortment adjustments. First, a store can change positions of NBs in the variety space and, hence, alter the proximity between NBs and the PL. For example, consider a store that carries one NB offering two beef varieties, including low-fat ground beef. If the store introduces a PL variety of the low-fat ground beef, it may withdraw the NB's low-fat ground beef variety. Hence, while this NB is still sold in the store, it offers only one variety and is further differentiated from the PL. Second, the store would have the opportunity to withdraw all varieties offered by an NB, namely, removing the NB. These two adjustments have different implications on the degree of product differentiation, price competition, and the extent to which the demand of the PL is cannibalized by NBs. We measure the change in assortment—repositioning and withdrawal of NBs—using two variables specified below.

Brand Proximity

We measure the change of NB positions in the variety space using the uncentered correlation coefficient, also frequently referred to as the Jaffe (1986) index. This index is used widely (Bloom et al., 2013; Harris and Siebert, 2017). It is especially appropriate in our context since it allows us to measure the closeness or proximity between national and private brands offering different beef

varieties. We consider the 21 beef varieties as introduced earlier and construct for each NB a 21-dimensional vector. Each element of the vector indicates the proportion of UPCs that the NB offers in a specific variety. The vector is built at the store-month level.

For example, let brand i in store s sell m_{ist} different UPCs in month t . Among the m_{ist} UPCs, $m_{ist}^1 \geq 0$ UPCs belong to variety 1, $m_{ist}^2 \geq 0$ variety 2, and so on and so forth until $m_{ist}^{21} \geq 0$. The variety vector for brand i in store s and month t is specified as $v_{ist} = \left(\frac{m_{ist}^1}{m_{ist}}, \frac{m_{ist}^2}{m_{ist}}, \dots, \frac{m_{ist}^{21}}{m_{ist}} \right)$ and describes the brand's location in the 21-dimensional variety space.⁵

Similarly, we construct the variety vector for another brand j carried by store s in t , v_{jst} . The Jaffe index describes the proximity between two brands i and j in store s at time t and is calculated as the uncentered correlation between brand i and brand j :

$$V_{ijst} = \frac{v_{ist}v'_{jst}}{(v_{ist}v'_{ist})^{\frac{1}{2}}(v_{jst}v'_{jst})^{\frac{1}{2}}}$$

This index ranges from 0 to 1. When $V_{ijst} = 0$, the vectors v_{ist} and v_{jst} are orthogonal, namely, the two brands offer completely different sets of varieties in the store. When $V_{ijst} = 1$, the variety distributions of the two brands overlap perfectly, and they offer identical varieties. A larger V_{ijst} indicates that brands i and j offer more similar varieties, implying a lower degree of brand-level differentiation, more intense price competition, and higher cannibalization effects.

Since we are interested in evaluating the assortment changes of NBs after PL introduction, we compare the Jaffe index of NB-PL pairs in a store before and after PLs are introduced. When computing the Jaffe index for NB-PL pairs before PL introduction, we face the caveat that the

⁵ Note that the index is not weighted by UPC sales because the sales are endogenous to positioning of products. If the index were weighted by sales, we would not be able to determine if the changes are driven by repositioning of brands or different sales of UPCs after a PL is introduced.

variety vector of the PL is unobserved. Hence, we declare a hypothetical or “forthcoming” PL as a benchmark, so we are able to compute the Jaffe index between NBs and a PL before the PL is actually sold. More specifically, the “forthcoming” PL variety vector, v_{jst} , is set to be the same as the PL variety vector in the first month of selling the PL.

Next, we average the brand proximities between each NB (brands i) and the PL (brands j) in store s in a month t to obtain:

$$V_{st} = \frac{\sum_i V_{ijst}}{n_{st}},$$

where n_{st} is the number of NBs in the store and in the month. Again, this store-level Jaffe index varies from 0 to 1. If the store carries only the PL, the index is set to 0, meaning that the PL is unique in the variety space. Table 2 shows that this store-level Jaffe index (referred to as *Jaffe Index NB-PL* from now onward) has a mean of 0.34 and a standard deviation of 0.42.

Figure 3 shows the *Jaffe Index NB-PL* for the months before and after PL introduction. After a PL is introduced, the *Jaffe Index NB-PL* declines drastically, implying that NBs are further differentiated from the PL in the variety space. The index falls by more than 80% in the first year of selling a PL. Repositioning and further differentiating NBs from the PL could be rationalized by softening price competition against the PL and reducing the extent to which NBs cannibalize PL demand in the store. We empirically test the conjecture later.

[Figure 3 approximately here]

Brand Numbers

Beyond changing the varieties offered by an NB, the store has the opportunity to withdraw all varieties belonging to the NB. The withdrawal of an entire NB from a store affects the degree of product differentiation, price competition, and cannibalization of PL demand. If the NB is removed

entirely, we are not able to compute the *Jaffe Index NB-PL* due to missing observations. Hence, we establish an alternative measure that accounts for the *Number of NBs* in a store across market segments, which enables us to incorporate the proximity between NBs and the PL.

Market segments are supposed to capture quality differences across brands in varieties (e.g., a brand selling low-fat ground beef *versus* a brand selling high-fat ground beef) and other horizontal differences (e.g., different steak cuts or package sizes). Brands in the same market segment are considered less differentiated from each other. The market segments are constructed as follows: Every brand is categorized into a low-priced (L) or high-priced (H) segment by comparing its annual average store-specific price with the median nationwide brand-store prices in a year.⁶ Brands with average store-specific prices below (above) the median nationwide brand-store price are then classified as L- (H-) segment brands.

Figure 4 shows the brand-store price distribution, where the vertical solid line indicates the median price. The skewed distribution implies that the price range below the median price is much smaller compared with the price range above the median price. Since brands characterized by prices below the median belong to the L-segment, we expect this segment to be characterized by a smaller degree of product differentiation, more intense price competition, and potentially higher cannibalization effects. Table 2 shows that the majority of PLs (68.5%) are introduced into the L-segment. This finding confirms that PLs are frequently inexpensive alternatives for NBs, not premium brands (Scott-Morton and Zettelmeyer, 2004).

[Figure 4 approximately here]

⁶ The market segment is a comprehensive, though rough, indicator of brand proximity in the variety space. The average prices are computed by dividing a brand's annual revenue by its annual volume sold in store. Yearly average prices limit mismeasurement caused by confounded effects such as temporary discounts or other price shocks.

Figure 5 illustrates the change in the number of NBs in a market segment before and after PL introduction. The right panel shows that the number of NBs declines strongly (by almost 40%), after a PL has been added to the same segment of the NBs. The smaller number of NBs persists throughout the first year of selling the PL. The sizable reduction could be driven by the store's effort to increase product differentiation, which would result in lower price competition and cannibalization effects. The left panel of the figure, in contrast, shows that a PL introduction only modestly reduces the number of NBs in the other market segment. One reason why few NBs are withdrawn from the other segment could be that the competition across segments is weak.

[Figure 5 approximately here]

2.3 Other Variables

Stores' assortment decisions depend on variety competition across stores within a market highlighted in earlier studies (Sweeting, 2010). We construct control variables that describe the intensity of variety competition in the local market. A competitor store is defined as a store of a different retail chain within the same local market. Nielsen does not survey all stores in a local market, making the number of competitor stores in the local market *per se* a suboptimal measurement of competition. We compute the average number of brands carried by a competitor store in a particular market segment as a more precise measurement of the intensity of local competition in variety. Table 2 shows that a competitor store carries on average 1.3 brands per segment with a standard deviation of 0.7-0.8.

3. Empirical Models and Results

Our goal is to examine how the introduction of PLs affects the store-level NB assortment and how the assortment adjustments impact NB prices and demand. To achieve this goal, we first identify

the PL effects on NB assortment, accounting for proximities between NBs and PLs and the number of NBs. Once we have evaluated the assortment effects, we estimate the PL effects on NB prices and demand.

3.1 Identification

We rely on the variation in the timing of PL introductions (see Figure 1) to identify its effect on NB assortment at the store level; even stores belonging to the same chain or in the same local market introduce PLs in different months. The variation in timing creates difficulty in establishing counterfactuals, which rules out some common estimators like a standard difference-in-differences (DID) that work with one common treatment on all agents of interest. In the baseline, we use an event-study framework to identify the causal effect of PL introductions.

The timing of each PL introduction may, of course, depend on store features, local market conditions, and retail-chain business strategies that are unobserved to researchers. In reality, the exact timing of PL introduction is likely subject to many idiosyncratic factors. To address the potential endogeneity of PL introduction to stores, we control for a complete set of store format, retailer-year, market-year, and month fixed effects in the regressions. The retailer-year specific effects should absorb each retailer's underlying year-specific business strategy on the PL. Other general trends of assortment, including an increasing number of organic brands on the market and changes in consumer preferences, are captured by the retailer-year, market-year, and monthly fixed effects.⁷ With this set of fixed effects and control variables (specified in the next subsection), we

⁷ We regressed a dummy for whether a store ever sells the PL, the store-specific timing of PL introduction, and the store-specific segment of PL on pre-PL *Jaffe Index NB-PL* and the *Number of NBs* and found that the store-level, pre-PL NB assortment has little to zero impacts on whether a store ever sells PL, the timing of PL introduction, or the segment that a PL enters. Concerns on inverse causality in our baseline identification are hence limited.

control for unobserved covariates that would explain store-specific timings of PL introductions and also affect store assortment, ensuring the identification of causal effects for PL introductions.

Under an event-study framework, we empirically evaluate PL effects within one year before and one year after PL introduction. Choosing this relatively short window around the PL introduction helps mitigate unobserved confounding effects that may affect NB assortment and not captured by the set of fixed effects (e.g., changes in consumer taste or competition). A key advantage of the event-study framework is that it does not require a group of stores that never introduce PL and hence allows examining all the dependent variables of interest. For example, the *Jaffe Index NB-PL* can only be computed for stores that sell PLs for at least one month; there is no control store, ruling out synthetic control estimators or DID.

In Section 3.3, furthermore, we employ a counterfactual estimation procedure for causal inference proposed by Liu et al. (2022) to strengthen the baseline identification (see also Linde and Siebert, 2021). This interactive fixed-effect estimator identifies the treatment effect of introducing PL on the treated stores. It avoids the strict exogeneity and parallel trends assumptions. It allows for PL introductions to occur in different periods and imposes heterogeneous treatment effects across stores in each period. As detailed in Section 3.3, the estimator controls for observables as well as store- and time-specific latent factors that capture store-level unobservables affecting the PL introduction and the potential outcomes. The estimated PL effects align with the baseline. A large set of sensitivity tests in Section 3.4 further confirm the baseline results.

3.2 Empirical Model: Assortment Effects

First, we empirically evaluate the impact of PL introduction on brand proximity between NBs and PLs using the *Jaffe Index NB-PL*. The baseline specification is:

$$V_{srt} = \alpha_0 + \alpha PL_{srt} + \gamma X_{srt} + W_{rt} + Z_s + T_t + \epsilon_{srt}, \quad (1)$$

where V_{srt} refers to the *Jaffe Index NB-PL* in store s , retail chain r , and month t . The indicator variable PL_{srt} equals 1 if a PL has been introduced to the store, and 0 otherwise. The control variable X_{srt} refers to the *Average Number of Brands Carried by a Competitor Store* in the local market, W_{rt} contain retailer-year fixed effects, Z_s represents store format (e.g., grocery store) and local market fixed effects, T_t contains month fixed effects, and ϵ_{srt} is the error term.

We consider the fact that stores of the same retail chain tend to experience similar demand (e.g., due to chain-level marketing activities) and supply shocks (e.g., due to chain-level cost changes) and make similar pricing and other non-price decisions, including NB assortment (DellaVigna and Gentzkow, 2019; Hitsch et al., 2019). Standard errors are hence clustered at the chain level to account for potential correlations of errors across stores within the same chain and autocorrelated errors within a store.

The OLS (ordinary-least-squares) estimation results are shown in column 1 of Table 3. The R-squared is high, suggesting a good fit of our specification. Selling PLs has a negative effect on the *Jaffe Index NB-PL*. The *Jaffe Index NB-PL* decreases by 0.28 on average or by 0.67 of its standard deviation, which is economically significant. The result echoes Figure 3 and supports that stores reposition NBs to further differentiate NBs from PLs, which softens price competition and diminishes cannibalizing the PL demand. We also distinguish between stores selling a PL in the L-segment from stores selling a PL in the H-segment and show the results in columns 2 and 3, respectively. The estimation returns a significantly negative coefficient for a PL that enters the L-segment, but not the H-segment. We further discuss the differential assortment responses to PL introductions when interpreting the PL effect on the number of NBs.

[Table 3 approximately here]

We evaluate the evolution of the proximity effect before and after PL introduction by decomposing the variable PL_{srt} into a series of two-month indicator variables. Taking the 11th and 12th months prior to the PL introduction as the benchmark, the two-month indicators include PL_{srt}^{-10} (i.e., the 9th and 10th months prior to PL introduction), ..., PL_{srt}^0 (i.e., the month of PL introduction), ..., PL_{srt}^{12} (i.e., the 11th and 12th months after PL introduction). The model specification is rewritten as:

$$V_{srt} = \alpha_0 + \sum_{\tau} \alpha_{\tau} PL_{srt}^{\tau} + D_{\tau} + \gamma X_{srt} + W_{rt} + Z_s + T_t + \epsilon_{srt}, \quad (2)$$

where $\tau \in \{-10, -8, \dots, 0, \dots, 10, 12\}$ indicates the two-month window relative to PL introduction; other variables are defined in equation (1). The index τ is positive (negative) for months after (prior to) the introduction. D_{τ} includes dummy variables that take on a value of 1 if the observation falls within a specific two-month window indicated by τ .

The evolution of the proximity effect over time is shown in Panel A of Figure 6. The solid line depicts the point estimates of PL_{srt}^{τ} , while the dashed lines represent the corresponding 95% confidence intervals. The reduction in the *Jaffe Index NB-PL* is significant and fairly stable throughout the first year of selling the PL. Importantly, there is no significant trend in the index prior to PL introduction, suggesting that potential confounding factors related to the endogeneity of PL introduction are largely absorbed by the control variables and fixed effects.

[Figure 6 approximately here]

We now consider the PL effect on the number of NBs in the L- and H-segments. The number of NBs in segment g store s and month t is denoted as n_{gsrt} . Remember, Figure 5 shows that PLs have a stronger impact on the number of NBs in the same market segment. Hence, we add an indicator variable SS_{gsrt} , which equals 1 if the PL and NBs are in the same segment. Note

that since $Same_{gsrt}$ is specified only if the store sells a PL for at least one month, stores that never sell PLs do not enter the estimation. We include an interaction term between PL_{srt} and $Same_{gsrt}$ denoted by PS_{gsrt} . The interaction term shows differential PL effects on the *Number of NBs* in the same and different segments. The specification is:

$$n_{gsrt} = \beta_0 + \beta_1 PL_{srt} + \beta_2 PS_{gsrt} + \gamma_1 SS_{gsrt} + \gamma_2 X_{gsrt} + W_{rt} + Z_s + T_t + \epsilon_{gsrt}. \quad (3)$$

The PL effect on the number of NBs in the different segment is β_1 , and the effect on NBs in the same segment equals $\beta_1 + \beta_2$. Control variables, X_{gsrt} , include two measures of local competition: the *Average Number of Brands in the Same Segment of a Competitor Store*, and the *Average Number of Brands in the Other Segment of a Competitor Store*. Other variables are defined in equation (1).

The estimation results of equation (3) are displayed in column 4 of Table 3. The R-squared is fairly high, suggesting a good fit of the model specification. Selling a PL leads to a significant reduction in the number of NBs in the same segment. On average, every three stores remove one NB. Column 5 of Table 3 displays the estimation results for stores introducing a PL into the L-segment. PLs sold in the L-segment reduce the *Number of NBs* in the same segment by 0.62, while the impact on the *Number of NBs* in the H-segment is positive and much smaller. This result is consistent with what is shown in Figure 4: The L-segment is characterized by a denser price distribution, which is indicative of less differentiated products and tougher price competition. The addition of a PL to the L-segment tends to largely intensify internal brand competition and incentivize assortment adjustments of NBs aimed at reducing price competition and alleviating cannibalization of the PL demand.

The decrease in the number of NBs after PL introduction does not merely reflect a “crowd-out effect” due to limited shelf space. In fact, the shelf space does not seem to be strictly fixed,

because our econometric tests show that the total numbers of UPCs per market segment and per store increase significantly after PL introduction; there is room to expand the shelf space (see online Table B4 for estimated PL effects on the number of UPCs).⁸

Column 6 of Table 3 shows that a PL introduced into the H-segment exerts no significant impact on the number of NBs in either segment. This result coincides with Figure 4, which shows a wider price range in the H-segment. This is indicative of the product space in the H-segment being less crowded, and price competition is not as intense as in the L-segment. For a store selling the PL in the H-segment, the value of the PL in enriching the brand portfolio tends to outweigh its cost of intensifying competition with the store's NBs.

Evidence suggests that variety competition is more intense in the H-segment. First, the significantly positive coefficient on the *Number of Brands in the Same Segment in a Competitor Store* implies that stores adding PLs to the H-segment are likely to carry more NBs as competitors enlarge brand offerings in the same segment, which is not the case for stores selling L-segments PLs. Second, there is a strong general trend of adding brands in the H-segment. Figure A1 shows that the number of NBs in the H-segment increases consistently over time. In 2006, stores sold on average 1.5 NBs in the H-segment, and this number increased to 2.5 by the end of 2016, representing an increase of 66%. More broadly, Jaravel (2019) shows that stores significantly enlarge high-priced product portfolios in response to the increasing size of market segments for high-income consumers.

Again, we estimate an extended specification of equation (3) and include a series of two-month indicator variables as in equation (2). Panel B of Figure 6 shows the evolution of the PL

⁸ One UPC typically takes one slot on the shelf, and the number of UPCs is a good proxy for shelf space (Ackerberg and Rysman, 2005).

effect on the *Number of NBs in a Segment* same as the PL. Prior to PL introduction, the effect is statistically zero, suggesting, again, limited endogeneity concerns using OLS. Once a PL is introduced, the point estimates become significantly negative and level off around -0.4.

Overall, the estimation results show that stores make differential assortment adjustments depending on whether PLs are introduced into the L- or the H-segment. PL introduced in the L-segments triggers removal of NBs from the same segment and separation of NBs from the PL in the variety space to soften price competition, while PL introduced in the H-segment does not eliminate NBs in the H-segment likely due to intensive cross-store variety competition.

3.3 Alternative Identification Strategy

One may be concerned that the variable PL_{srt} remains endogenous despite the control variables and fixed effects. Some unobserved factors could influence the introduction of a PL as well as the NB assortment decision in a store. Baseline outcomes already provide support for no systematic changes in *Jaffe Index NB-PL* and *the Number of NBs* prior to PL introduction (Figure 6). We adopt an alternative estimation method to confirm the causal effects of PL introduction.

One common estimation method for identifying causal effects is a DID approach. This method is rather difficult to apply in our context, since the “treatments,” or PL introductions, take place at different months across stores (see Figure 1). Hence, a control group would likely be confounded by the choice of different timing decisions. Alternatively, one could adopt an instrumental variable (IV) estimation method. This technique requires the use of a variable that is strongly correlated with the PL introduction decisions, but uncorrelated with the potentially endogenous variables—that is, the *Jaffe Index NB-PL* and the *Number of NBs*. The difficulty in finding an appropriate IV is confirmed by the fact that we are not aware of a prior empirical study on PL effects that employs the IV method.

To strengthen the identification of PL effects, we employ a generalized synthetic control method recently developed by Liu et al. (2022). The method builds an interactive fixed effects (IFE) estimator to evaluate the treatment effect for each “treated” store (here, a store that introduces a PL) in each period. The method has three major advantages over alternative estimators such as DID and IV. First, the IFE estimator returns individual treatment effects for treated subjects in each period. It corrects biases induced by heterogeneity in the treatment effects across treated subjects and enables us to study the determinants of store-period-specific treatment effects. Second, the estimator uses a latent factor approach to adjust for potential time-varying unobserved confounders regarding each subject (i.e., store in our context). Such confounders are decomposed into time-specific factors interacted with subject-specific factor loadings. Third, the IFE estimator accounts for treatments taking place at different timings for different subjects during the period of interest (see Appendix 3 for details).⁹

Within a two-year window, the IFE method requires that PL-introducing stores are observed continuously. After excluding stores observed infrequently, the IFE sample is considerably smaller than the one used in our baseline regressions. The IFE method also requires the inclusion of a control group—that is, stores that never sell PLs. Since stores that never sell PLs cannot be characterized by a *Jaffe Index NB-PL*, this rules out the inclusion of this measure as the dependent variable. Thus, we focus on the *Number of NBs* as the dependent variable.

The IFE method returns individual treatment effects, $\widehat{\beta}_{gsrt}$, which we use as the dependent variable in the following regression:

$$\widehat{\beta}_{gsrt} = \theta_0 + \theta_1 SS_{gsrt} + \epsilon_{gsrt}, \quad (4)$$

⁹ One may wonder whether the variety competition across stores may render our identification assumption of no spillover effect of the treatment. Yet this concern is rather limited, because variety competition is realized in the local market, while we select treatment stores from all local markets.

where the same segment indicator, SS_{gsrt} defined in equation (3), is the main explanatory variable for the variation in $\widehat{\beta}_{gsrt}$. We conduct the estimation for stores introducing the PL into the L- and H-segments, respectively.

The estimation results are shown in Table 4. Column 1 reports the basic results from equation (4). Standard errors are computed using bootstrapping method. The positive and small coefficient estimate on the constant represents the effect of introducing a PL into the L-segment on the number of NBs in the H-segment (i.e., the constant term in column 1 is comparable to the coefficient of the PL indicator in column 5 of Table 3). The significantly negative coefficient estimated for SS_{gsrt} shows that introducing a PL into the L-segment reduces the number of NBs in the L-segment (i.e., this coefficient corresponds with the interaction term, PS_{gsrt} , in column 5 of Table 3).

[Table 4 approximately here]

The estimation results in column 2 of Table 4 are comparable to the ones in column 6 of Table 3. When introducing a PL into the H-segment, there is a significantly negative effect on the number of NBs in the L-segment (i.e., the constant term in column 2), while the effect on NBs in the H-segment is statistically zero (i.e., the coefficient of SS_{gsrt} plus the constant term). Consistent with our baseline results, we find that a PL introduced into the H-segment does not crowd out NBs in the same segment, which is likely explained by intense competition in variety in the H-segment. The results in columns 3 and 4 of Table 4 account for store-format, retailer, market, and time fixed

effects and control variables. The results show that the coefficients on SS_{gsrt} stay robust at the values in columns 1 and 2.¹⁰

3.4 Sensitivity Tests

Though we have shown evidence that beef category leaves little room for manufacturers to adjust product offerings, one might still be concerned that the PL effects identified are partly driven by manufacturers, especially those process PLs (Chen et al., 2010; Dekimpe et al., 2011). To further eliminate the concern, we conduct a robustness test where brands owned by the four predominate beef processors, Tyson, Cargill, JBS, and National Beef (the “Big 4” process some 80% of cattle in the US beef industry), are excluded from estimation. The “Big 4” are excluded because they most likely have advantageous positions in bargaining with retail chains and so they are the potential manufacturers that could potentially decide on assortments of their products and sub-brands in a store. Non-Big 4 NBs occupy small market shares and are unlikely to affect store-level product offerings, especially brand choices of a store. Online Table B1 confirms Table 3, suggesting that the role played by manufacturers in retailer assortment is limited if any.

We perform several other robustness tests regarding the causal effects of PL introduction. (1) We use alternative samples to estimate the baseline models, including shortening the window from one year to half a year around the PL introduction, excluding a small number of drug stores from the sample, and dropping stores that do not sell any NBs prior to introducing a PL. The estimation results closely resemble our earlier results (see online Table B2). (2) We conduct a placebo test and randomly assign a month of PL introduction and a segment of PL to stores that never sell any PLs. Estimation results of the placebo test show no significant effects of the fake

¹⁰ The constant of columns 3 and 4 have no straightforward interpretation given all the fixed effects included in the regression.

PL on the *Number of NBs in a Segment* (see online Table B3). (3) We test the sensitivity of measuring brand proximity with the Jaffe index; the *Uniqueness Index NB-PL* is used as an alternative measure of brand proximity (Sweeting, 2010). Online Figure B1 confirms Figure 6 panel A that NBs are pushed away from the location in the variety space occupied by the PL after PL is added to the shelf. More details are in the online Appendix.

3.5 Price and Sales Effects

We use the impact of PL introductions on assortment changes to deepen our understanding of PL effects on NB prices and demand. Prior studies on PL introduction ignore assortment changes and estimate the direct effect of the PL on NB prices by regressing the logarithm of store-specific NB prices on a PL dummy variable. We specify this benchmark price regression as:

$$\log(p_{bsrt}) = \xi_0 + \xi_1 PL_{srt} + \gamma X_{gsrt} + B_b + W_{rt} + Z_s + T_t + \epsilon_{bgsrt}, \quad (5)$$

where the subscript b indicates NBs and B_b is a vector of NB fixed effects. The corresponding estimation results in column 1 of Table 5 show no significant price effect on NBs.

[Table 5 approximately here]

The benchmark specification ignores the PL effect on prices via assortment changes. As shown earlier, a PL induces significant changes in the proximity and the number of brands in the store. To explicitly consider the price effect through changing brand proximity and brand number, we consider the specification in equation (6). We use observations post PL-introduction for estimation to filter out the direct effect of PL introduction, so that we focus on indirect price effects due to induced assortment changes.

$$\log(p_{bsrt}) = \xi_0 + \xi_1 V_{srt} + \xi_2 n_{srt} + \gamma X_{gsrt} + B_b + W_{rt} + Z_s + T_t + \epsilon_{bgsrt}, \quad (6)$$

where n_{srt} denotes the number of NBs in a store and other variables are defined in equation (3). The mean of n_{srt} is 2.78 with a standard deviation of 2.04.

Column 2 of Table 5 shows that a reduction in the *Jaffe Index PL-NB* (i.e., larger differentiation between NBs and PLs) increases NB prices, which is explained by softened price competition within the store. Given our earlier finding that PL introduction on average reduces the *Jaffe Index PL-NB* by 0.29 (i.e., the PL effect in column 1 of Table 3), the price is expected to increase on average by $0.29 \times 0.05 = 1.5\%$ due to the change in brand proximity. Given the positioning of NBs, the estimated coefficient of the *Number of NBs in the Store* is insignificant in column 2 of Table 5. These two positive price effects add up small and echo the upward price trend captured by Figure 2.

The effects on prices stemming from the assortment changes help reconcile the mixed evidence of the price effect of selling PLs as discovered in prior studies (e.g., Cotterill and Putsis, 2000; Ward et al., 2002; Bontemps et al., 2008). The net price effect of selling PLs depends on the magnitude and the direction of NB assortment adjustments made by the store and is case specific.¹¹

Next, we evaluate the extent to which PL introduction impacts NB demand via assortment changes. Using the volume share of NBs as the dependent variable, we re-estimate equations (5) and (6). The volume share equals NBs' volume divided by the store's total volume sold and ranges from 0 to 1. We focus on stores that sell a positive volume of NBs in a month.

The estimation results are shown in columns 3 and 4 of Table 5. After the PL introduction, the NB volume share is reduced by 24 percentage points due to cannibalization effects of the PL.

¹¹ Gabrielsen and Sorgard (2007) offer another theoretical explanation why NB prices may go up or down after adding the PL. In particular, their model allows NBs to offer exclusivity contracts to the retailer, which makes a positive price effect possible. Offering exclusivity contracts due to a PL are unlikely in the beef market because our data show that NBs are carried by a highly stable number of retailers over time, regardless of the PL expansion. Indeed, the proportion of NBs that are carried by only one retailer even declined slightly from 2006 to 2016.

Given the previous finding that the PL introduction results in a reduction of the *Jaffe Index NB-PL* of 0.29 (i.e., the PL effect in column 1 of Table 3), the change in brand proximity further reduces the NB volume share by $0.29 \times 0.15 = 4.4$ percentage points. We have also shown that PL introduction induces NB removals by 0.36 (i.e., the PL effect in column 4 of Table 3), which reduces the volume share of NBs by another $0.36 \times 0.04 = 1.4$ percentage points. The two indirect sales effects due to assortment adjustments add up to 5.8 percentage points of NB volume sales transferred to the PL. This finding suggests that stores change NB assortment after PL introductions to steer a sizable portion of consumers toward purchasing PL products.

One explanation as to why the stores have incentives to steer consumers toward the PL could be that PLs benefit from eliminating double margins due to vertical integration or saving costs due to vertical coordination. Consequently, marginal retail costs of selling PL products are relatively low. Stores can hence increase profit margins and total profits by steering more consumers toward PLs.

To evaluate the impact of PLs on store profits, it would be natural to examine store revenues and costs. However, retail costs of beef products are rarely observed. Wholesale prices are usually private information. In case they are published, they would be available only as nationwide averages, which do not serve our purpose of comparing store-brand specific profits using store brand-level wholesale costs.

Given the data limitations, we consider a different strategy to infer the impact of PL on store profits. Based on prior studies, we operate under the assumption that PL products are characterized by lower marginal costs than comparable NBs. We then evaluate changes in store-level revenues due to PL introduction, and those results will provide the necessary conditions that apply to store-level profits. More specifically, if store-level revenues increased or remained

constant after PL introduction, the store-level profits must have increased given that PL marginal costs do not exceed those of NBs and the average costs of the store would be lower with PLs.

We estimate the PL effect on store-level revenues using the same specification as equation (1). Table 5, column 5, reports the results. The store-level revenue is significantly higher after selling the PL. The store-level profits likely have increased because PLs are vertically integrated with retailers and eliminate double margins or save costs. Furthermore, based on the assortment and price effects identified earlier, we may draw a few welfare implications with caution. For H-segment consumers, adding a H-segment PL seems to be benefiting because brand variety increases without price increases. For L-segment consumers, the welfare implication is mixed because adding an L-segment PL induces small price increases and may drive out a NB (which could eliminate the benefit from brand diversification due to PL). Estimation of consumer demand for variety is needed to obtain more rigorous welfare impacts.

4. Concluding Remarks

Our study evaluates the impact of PL introduction on NB assortment, prices, and demand in retail stores. Prior studies typically evaluate the direct effect of PL introduction on prices, ignoring or fixing NB assortment; they find mixed effects. The novelty of our study is considering PL effects on NB assortments that have impacts on prices and demand of NBs. Our new insights have important implications for how to think about adding PLs in differentiated product markets and regarding multi-product firms.

Using data on the U.S. beef market, we find that PL introductions have differential effects on NB assortment. When a PL is added to the low-price market segment, stores reposition NBs by changing some of the NB varieties to further differentiate NBs from PLs. Stores may also remove all varieties of some NBs—that is, withdraw entire NBs from the same segment. Increased brand

differentiation and reduced NB numbers relax price competition within the store and diminishes cannibalizing the PL demand. Though PL introductions have insignificant direct price effects on NBs, they push up NB prices via assortment changes. Furthermore, despite a small direct price effect, the assortment changes serve as an instrument to steer a considerable portion of consumers to purchasing PL products.

Our study provides new insights into the store-level impact of PL introductions. We find evidence that PL introductions may impose limited effects on prices, but exert strong effects on the assortment of NBs that reduce NB demand. It implies that stores do not use price as the main device to increase profits after PLs are added; rather, they use assortment changes as the key strategic instrument to steer consumers to more profitable PL products.

The impact on NB assortment adds complexity to the evaluation of welfare changes of PL introduction. While adding a PL expands consumers' choice sets, which benefits consumers *ceteris paribus*, the repositioning and removals of NBs create ambiguous effects on consumer welfare. To evaluate the net welfare effect accurately, consumers' preferences for quality and love of variety should be considered. It should be noted that retail stores' assortment changes likely go beyond the beef market and also apply to other product categories. It is of interest to study PL-driven assortment changes in categories of processed goods (e.g., beer, cereal, ice cream, and yogurt) for which branding matters more strongly than for fresh beef. In these cases, though, the evaluation of assortment changes becomes more complex, because there are larger sets of product varieties and both manufacturers and retailers make considerable assortment adjustments under competition. We leave these questions for future research.

References

- Akerberg, D. A. and Rysman, M., 2005, 'Unobserved Product Differentiation in Discrete-Choice Models: Estimating Price Elasticities and Welfare Effects,' *RAND Journal of Economics*, 36(4), pp. 771-788.
- Akcura, M. T.; Sinapuelas, I. C. and Wang, H. M. D., 2019, 'Effects of Multitier Private Labels on Marketing National Brands,' *Journal of Product & Brand Management*, 28(3), pp. 391-407.
- Atalay, E.; Sorensen, A.; Zhu W. and Sullivan C., 2020, 'Post-Merger Product Repositioning: An Empirical Analysis,' FRB of Philadelphia Working Paper No. 20-36. Available at: <https://ssrn.com/abstract=3696732>.
- Berry, S. and Waldfogel, J., 2001, 'Do Mergers Increase Product Variety? Evidence from Radio Broadcasting,' *Quarterly Journal of Economics*, 116(3), pp. 1009-1025.
- Berry, S.; Levinsohn, J. and Pakes, A., 2004, 'Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market,' *Journal of Political Economy*, 112(1), pp. 68-105.
- Bloom, N.; Schankerman, M. and Van Reenen, J., 2013, 'Identifying Technology Spillovers and Product Market Rivalry,' *Econometrica*, 81(4), pp. 1347-1393.
- Borenstein, S. and Netz, J., 1999, 'Why Do All the Flights Leave at 8 Am: Competition and Departure-Time Differentiation in Airline Markets,' *International Journal of Industrial Organization*, 17(5), pp. 611-640.
- Bontemps, C.; Orozco, V. and Réquillart, V., 2008, 'Private Labels, National Brands and Food Prices,' *Review of Industrial Organization*, 33(1), pp. 1-22.
- Choi, S. C. and Coughlan, A. T., 2006, 'Private Label Positioning: Quality versus Feature Differentiation from the National Brand,' *Journal of Retailing*, 82(2), pp. 79-93.
- Chung, H. and Lee, E., 2017, 'Store Brand Quality and Retailer's Product Line Design,' *Journal of Retailing*, 93(4), pp. 527-540.
- Connor, J. M. and Peterson, E. B., 1992, 'Market-Structure Determinants of National Brand-Private Label Price Differences of Manufactured Food Products,' *Journal of Industrial Economics*, 40(2), pp. 157-171.
- Consumer Reports, 2014, 'What to Do When There Are Too Many Product Choices on the Store Shelves?,' Available at: <https://www.consumerreports.org/cro/magazine/2014/03/too-many-product-choices-in-supermarkets/index.htm>.
- Cotterill, R. W. and Putsis, W. P., 2000, 'Market Share and Price Setting Behavior for Private Labels and National Brands,' *Review of Industrial Organization*, 17(1), pp. 17-39.
- Davis, P., 2006, 'Measuring the Business Stealing, Cannibalization and Market Expansion Effects of Entry in the U.S. Motion Picture Exhibition Market,' *Journal of Industrial Economics*, 54(3), pp. 293-321.
- DellaVigna, S. and Gentzkow, M., 2019, 'Uniform Pricing in U.S. Retail Chains,' *Quarterly Journal of Economics*, 134(4), pp. 2011-2084.
- Draganska, M. and Jain, D. C., 2005, 'Product-Line Length as a Competitive Tool,' *Journal of Economics & Management Strategy*, 14(1), pp. 1-28.
- Draganska, M.; Klapper, D. and Villas-Boas, S. B., 2010, 'A Larger Slice or a Larger Pie? An Empirical Investigation of Bargaining Power in the Distribution Channel,' *Marketing Science*, 29(1), pp. 57-74.

- Draganska, M.; Mazzeo, M. and Seim, K., 2009, 'Beyond Plain Vanilla: Modeling Joint Product Assortment and Pricing Decisions,' *Quantitative Marketing and Economics*, 7(2), pp. 105-146.
- Einav, L., 2010, 'Not All Rivals Look Alike: Estimating an Equilibrium Model of the Release Date Timing Game,' *Economic Inquiry*, 48(2), pp. 369-390.
- Ellickson, P. B.; Kong P. and Lovett, M. J., 2018, 'Private Labels and Retailer Profitability: Bilateral Bargaining in the Grocery Channel,' Available at SSRN: <https://ssrn.com/abstract=3045372>.
- Gandhi, A.; Froeb, L.; Tschantz, S. and Werden, G. J., 2008, 'Post-Merger Product Repositioning,' *Journal of Industrial Economics*, 56(1), pp. 49-67.
- Gabrielsen, T. S. and Sørgaard, L., 2007, 'Private Labels, Price Rivalry, and Public Policy,' *European Economic Review*, 51(2), pp. 403-424.
- Geyskens, I.; Gielens, K. and Gijsbrechts, E., 2010, 'Proliferating Private-Label Portfolios: How Introducing Economy and Premium Private Labels Influences Brand Choice,' *Journal of Marketing Research*, 47(5), pp. 791-807.
- Harris, J. and Siebert, R., 2017, 'Firm-Specific Time Preferences and Post-Merger Firm Performance,' *International Journal of Industrial Organization*, 53, pp. 32-62.
- Heidhues, P.; Köster, M. and Kőszegi, B., 2022, 'Steering Fallible Consumers,' Working paper. Available at: http://www.personal.ceu.hu/staff/Botond_Koszegi/steering.pdf.
- Hitsch, G. J.; Hortacsu, A. and Lin, X., 2019, 'Prices and Promotions in U.S. Retail Markets: Evidence from Big Data,' National Bureau of Economic Research, No. w26306.
- Hotelling, H., 1929, 'Stability in Competition,' *Economic Journal*, 39(153), pp. 41-57.
- Jaffe, A. B., 1986, 'Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value,' *American Economic Review*, 76(5), pp. 984-1001.
- Janofsky, M., 1993, 'Discount Brands Flex Their Muscles,' *New York Times*, Section 1, p. 37.
- Johnson, J. P. and Rhodes, A., 2021, 'Multiproduct Mergers and Quality Competition,' *RAND Journal of Economics*, 52(3), pp. 633-661.
- Judd, K. L., 1985, 'Credible Spatial Preemption,' *RAND Journal of Economics*, 16(2), pp. 153-166.
- Li, X.; Cai, X. and Chen, J., 2022, 'Quality and Private Label Encroachment Strategy,' *Production and Operations Management*, 31(1), pp. 374-390.
- Linde, S. and Siebert, R. B., 2021, 'Exploring the Heterogeneous Effects of State Price Transparency Laws on Charge Prices, Negotiated Prices, and Operating Costs,' CESifo Working Paper No. 9348.
- Liu, L.; Wang, Y. and Xu, Y., 2022, 'A Practical Guide to Counterfactual Estimators for Causal Inference with Time-Series Cross-Sectional Data,' Available at SSRN: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3555463.
- MacDonald, J. M., 2000, 'Demand, Information, and Competition: Why Do Food Prices Fall at Seasonal Demand Peaks?' *Journal of Industrial Economics*, 48(1), pp. 27-45.
- Mazzeo, M. J.; Seim, K. and Varela, M., 2018, 'The Welfare Consequences of Mergers with Endogenous Product Choice,' *Journal of Industrial Economics*, 66(4), pp. 980-1016.
- Mills, D. E., 1995, 'Why Retailers Sell Private Labels,' *Journal of Economics and Management Strategy*, 4(3), pp. 509-528.
- Scott Morton, F. and Zettelmeyer, F., 2004, 'The Strategic Positioning of Store Brands in Retailer–Manufacturer Negotiations,' *Review of Industrial Organization*, 24(2), pp. 161-194.

- Narasimhan, C. and Wilcox, R. T., 1998, 'Private Labels and the Channel Relationship: A Cross-Category Analysis,' *Journal of Business*, 71(4), pp. 573-600.
- Nijssen, E. J. and Van Trijp, H. C., 1998, 'Branding Fresh Food Products: Exploratory Empirical Evidence from the Netherlands,' *European Review of Agricultural Economics*, 25(2), pp. 228-242.
- Pauwels, K. and Srinivasan, S., 2004, 'Who Benefits from Store Brand Entry?' *Marketing Science*, 23(3), pp. 364-390.
- Raju, J. S.; Sethuraman, R. and Dhar, S. K., 1995, 'The Introduction and Performance of Store Brands,' *Management Science*, 41(6), pp. 957-978.
- Richards, T. J. and Hamilton, S. F., 2015, 'Variety Pass-Through: An Examination of the Ready-To-Eat Breakfast Cereal Market,' *Review of Economics and Statistics*, 97(1), pp. 166-180.
- Salop, S. C., 1979, 'Monopolistic Competition with Outside Goods,' *Bell Journal of Economics*, 10(1), pp. 141-156.
- Sayman, S.; Hoch, S. J. and Raju, J. S., 2002, 'Positioning of Store Brands,' *Marketing Science*, 21(4), pp. 378-397.
- Sethuraman, R., 2009, 'Assessing the External Validity of Analytical Results from National Brand and Store Brand Competition Models,' *Marketing Science*, 28(4), pp. 759-781.
- Shaked, A. and Sutton, J., 1982, 'Relaxing Price Competition through Product Differentiation,' *Review of Economic Studies*, 49(1), pp. 3-13.
- Steiner, R. L., 2004, 'The Nature and Benefits of National Brand/Private Label Competition,' *Review of Industrial Organization*, 24(2), pp. 105-127.
- Sweeting, A., 2010, 'The Effects of Mergers on Product Positioning: Evidence from the Music Radio Industry,' *RAND Journal of Economics*, 41(2), pp. 372-397.
- ter Braak, A.; Geyskens, I. and Dekimpe, M. G., 2014, 'Taking Private Labels Upmarket: Empirical Generalizations on Category Drivers of Premium Private Label Introductions,' *Journal of Retailing*, 90(2), pp. 125-140.
- Ward, M. B.; Shimshack, J. P.; Perloff, J. M. and Harris, J. M., 2002, 'Effects of the Private-Label Invasion in Food Industries,' *American Journal of Agricultural Economics*, 84(4), pp. 961-973.

Tables

TABLE 1: Numbers and Volume Shares of Beef Brands and Stores

	<i>Value</i> <i>(Bil \$)</i>	<i>#Retail</i> <i>Chains</i>	<i>#Store</i>	<i>#NB</i>	<i>#PL</i>	<i>#Stores</i> <i>Selling</i>	<i>PL Vol</i> <i>(%)</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2006	71.2	82	9,134	51	38	5,436	59.0
2007	74.4	83	9,600	59	36	5,487	60.2
2008	75.9	84	9,520	60	32	4,890	62.8
2009	73.0	90	10,001	61	31	5,189	62.2
2010	75.8	92	10,433	65	51	5,836	65.5
2011	79.3	101	13,746	67	55	6,100	67.8
2012	84.7	101	21,773	80	56	7,860	64.1
2013	88.2	95	21,242	88	52	8,416	69.2
2014	96.9	99	26,235	97	55	13,264	74.8
2015	104.9	95	26,647	110	59	17,015	76.9
2016	103.3	97	26,452	114	60	16,978	77.0

Note: The table reports key summary statistics of our baseline dataset. Column 1 reports the annual retail equivalent value of beef produced in the United States in nominal \$billion. PL vol (%) is the collective volume market share of all PLs in the U.S. in each year.

Sources: Nielsen Retail Scanner Data and <https://www.ers.usda.gov/topics/animal-products/cattle-beef/statistics-information.aspx>

TABLE 2: Summary Statistics of Key Variables

	Mean	SD	Min	Max
<i>NB Price (\$/lb.)</i>	5.74	2.88	1.76	14.41
<i>Jaffe Index NB-PL</i>	0.34	0.42	0	1
<i>No. NBs/H-Segment/Store</i>	0.85	0.94	0	9
<i>No. NBs/L-Segment/Store</i>	0.99	1.13	0	12
<i>PL Introduced (1, if yes)</i>	0.38	0.49	0	1
<i>No. Brands/L-Segment/Competitor Store</i>	1.26	0.66	0	8
<i>No. Brands/H-Segment/Competitor Store</i>	1.27	0.82	0	6

Note: The table reports summary statistics of key variables. Statistics are weighted by observations in column 1 or 3 of Table 3. Prices in the lower and upper one percentiles are excluded.

TABLE 3: Determinants of PL Effects on Assortment of National Brands

<i>Dependent Variable</i>	<i>Jaffe Index NB-PL</i>			<i>No. NB/Segment</i>		
	<i>All PL</i>	<i>PL in L</i>	<i>PL in H</i>	<i>All PL</i>	<i>PL in L</i>	<i>PL in H</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>PL Introduced (PL)</i>	-0.29*	-0.41***	-0.18	0.09	0.20***	-0.07
<i>(1, if yes)</i>	(0.15)	(0.13)	(0.13)	(0.07)	(0.05)	(0.16)
<i>PL Introduced Interacted</i>				-0.36***	-0.82***	0.19
<i>with Same Segment (PS)</i>				(0.11)	(0.12)	(0.13)
<i>No. Brands/Cmp Store</i>	0.02*	0.01	0.03***			
	(0.01)	(0.01)	(0.003)			
<i>No. Brands/Cmp Store</i>				0.05	0.01	0.12*
<i>Same Segment</i>				(0.03)	(0.01)	(0.06)
<i>No. Brands/Cmp Store</i>				-0.02	-0.01	-0.02
<i>Diff Segment</i>				(0.01)	(0.01)	(0.04)
<i>Control Variables</i>	Y	Y	Y	Y	Y	Y
<i>Trends and FE</i>	Y	Y	Y	Y	Y	Y
<i>R²</i>	0.88	0.88	0.89	0.64	0.62	0.63
<i>No. Observations</i>	284,305	156,447	127,858	587,198	319,172	254,152

Note: This table reports the estimation results of equations (1), (3), and (4). “PL in L (H)” means PL introduced in the L (H)-segment. “Cmp” stands for competitor. Stores that introduced PLs before November 2006 or after February 2016 are excluded to ensure at least 10 months of observations before and after PL introduction. *Trends and FE* refer to retailer and market specific trends and month fixed effects. *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.10.

TABLE 4: Determinants of Individual PL Effects

	<i>PL in L</i>	<i>PL in H</i>	<i>PL in L</i>	<i>PL in H</i>
	(1)	(2)	(3)	(4)
<i>PL in the Same Segment</i> <i>(1, if yes)</i>	-0.17** (0.08)	0.20*** (0.04)	-0.17** (0.07)	0.20*** (0.04)
<i>Constant</i>	0.03 (0.03)	-0.28*** (0.02)	0.58** (0.28)	0.88*** (0.27)
<i>Control Variables</i>	N	N	Y	Y
<i>Format/Retailer/Market/Time FE</i>	N	N	Y	Y
<i>R</i> ²	0.01	0.01	0.17	0.25
<i>No. Observations</i>	24,690	34,062	24,690	34,062

Note: The table reports the estimation outcomes of equation (5). “PL in L (H)” means PL introduced in the L (H)-segment. Bootstrapping is used to obtain standard errors. *** p -value < 0.01, ** p -value < 0.05, * p -value < 0.10.

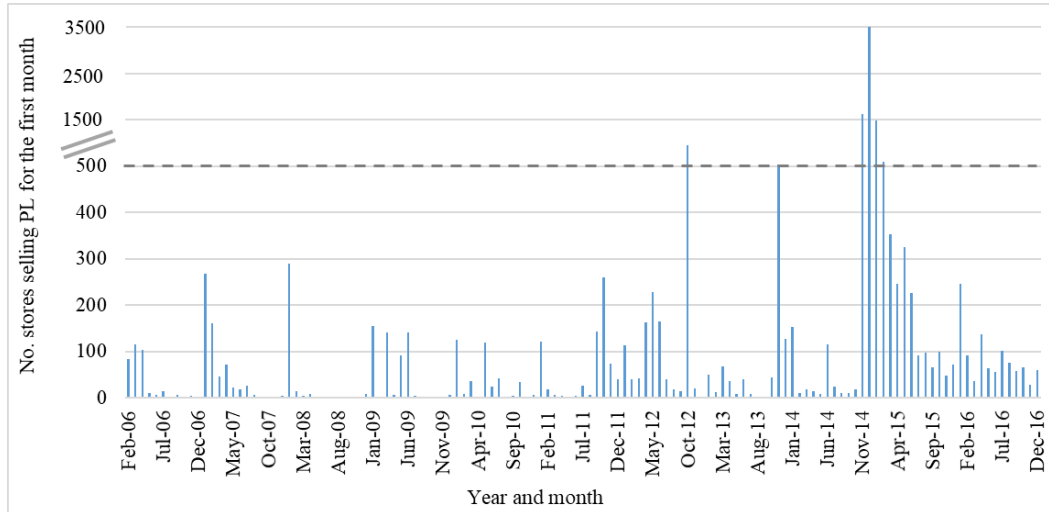
TABLE 5: Effects of Assortment on Prices and Sales of National Brands

<i>Dependent Variable</i>	<i>Log(NB Price)</i>	<i>Log(NB Price)</i>	<i>NB Vol Share (>0%)</i>	<i>NB Vol Share (>0%)</i>	<i>Log(Store Revenue)</i>
	(1)	(2)	(3)	(4)	(5)
<i>PL Introduced (PL)</i> <i>(1, if yes)</i>	-0.001 (0.01)		-0.24*** (0.08)		0.23*** (0.07)
<i>Jaffe Index NB-PL</i>		-0.05* (0.03)		0.15* (0.10)	
<i>No. NB in the Store</i>		0.01 (0.01)		0.04*** (0.01)	
<i>Control Variables</i>	Y	Y	Y	Y	Y
<i>Trends and FE</i>	Y	Y	Y	Y	Y
<i>R</i> ²	0.89	0.90	0.81	0.86	0.89
<i>No. Observations</i>	1,206,59	199,570	202,896	67,523	732,641

Note: The table reports the estimation results of equations (5) and (6). Prices in the lower and upper one percentiles are excluded. *Trends and FE* refer to retailer and market specific trends and month fixed effects. *** p -value < 0.01, ** p -value < 0.05, * p -value < 0.10.

Figures

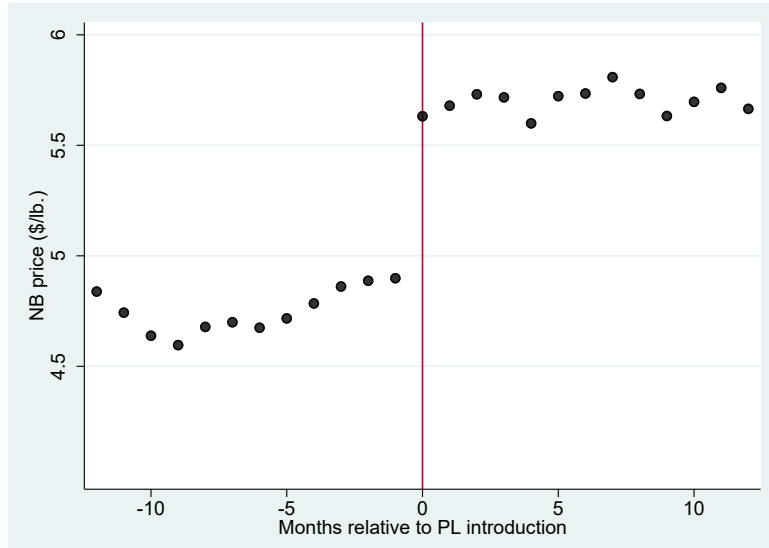
FIGURE 1: Number of Stores Introducing Private Labels over Time



Note: The figure displays the number of stores that introduced PLs over time. The vertical axis is broken at 500 to provide a more condensed view. We exclude a large number of stores that started selling PLs in January 2006 because that is the first month of the Nielsen database, and we are unable to tell if those stores introduced PLs before or in January 2006.

Source: Nielsen Retail Scanner Data.

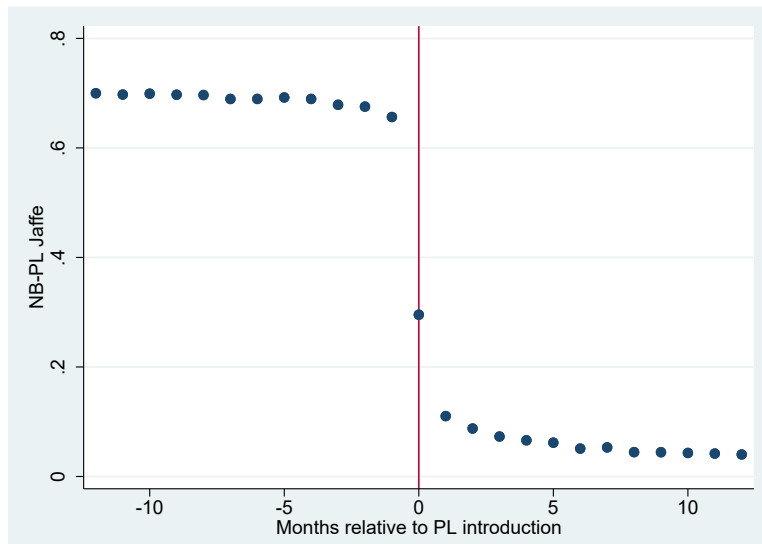
FIGURE 2: Average National Brand Prices in a Store over Time



Note: The figure depicts the average price of NBs against the PL over time. The horizontal axis shows the months relative to the introduction of the PL and covers 12 months before and 12 months after PL introduction. For example, 0 is the month of PL introduction, -10 means 10 months before the introduction, and 10 means 10 months after the introduction.

Source: Nielsen Retail Scanner Data.

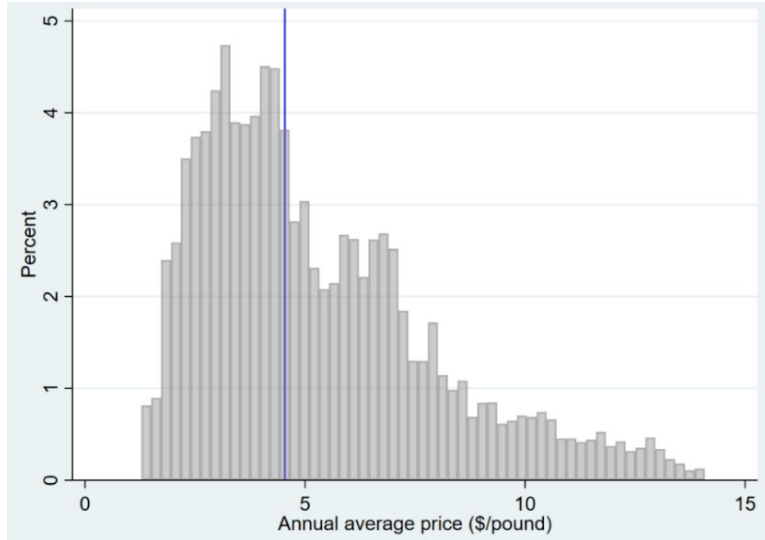
FIGURE 3: Evolution of Jaffe Index NB-PL over Time



Note: The figure depicts the Jaffe index for NBs against the PL over time. Other notes are the same as in Figure 2.

Source: Nielsen Retail Scanner Data.

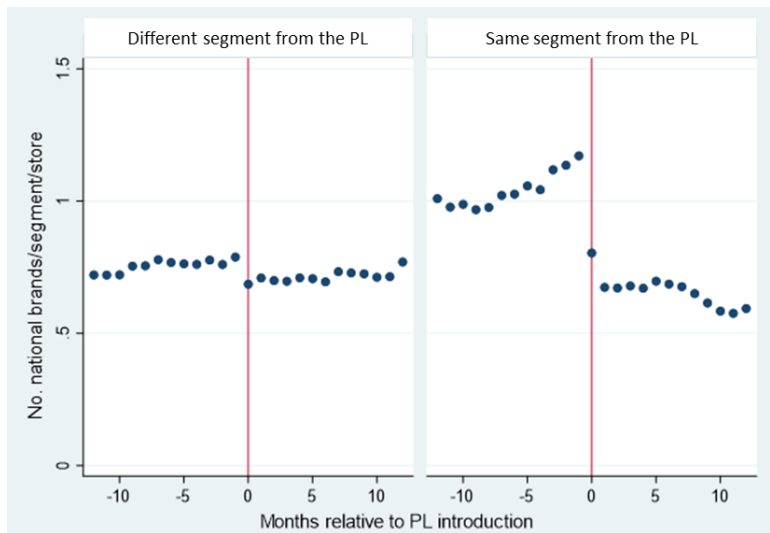
FIGURE 4: Distribution of Store-Level Brand Prices



Note: The figure shows the distribution of store-specific, annual average prices of all brands 2006 to 2016. The vertical line indicates the median of all prices. The upper and lower one percentiles of the price distribution are excluded.

Source: Nielsen Retail Scanner Data.

FIGURE 5: Number of National Brands over Time

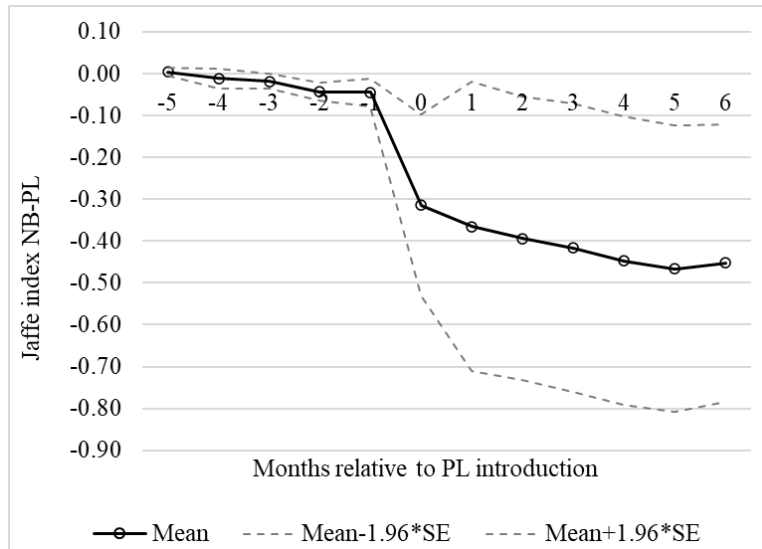


Note: The left panel depicts the average number of NBS in the different price segment compared with the PL. The right panel depicts the average number of NBS in the same price segment with the PL. Other notes are the same as in Figure 2.

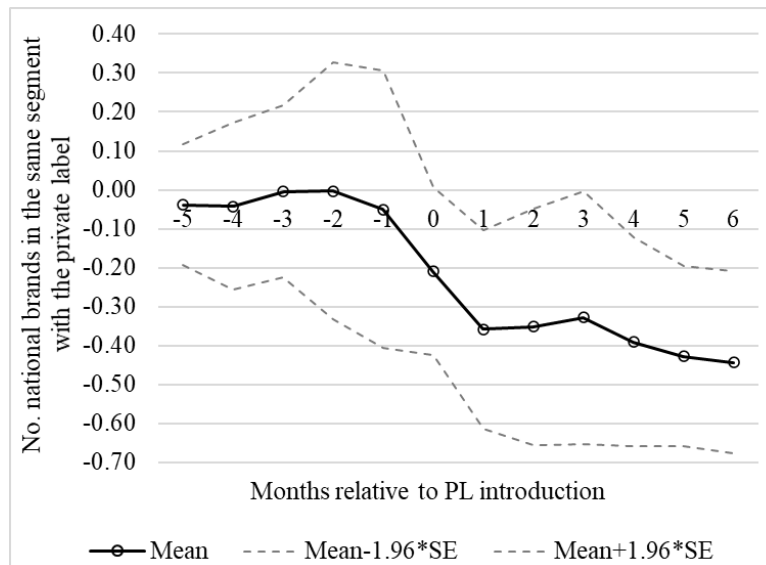
Source: Nielsen Retail Scanner Data.

FIGURE 6: Evolution of Brand Proximity and Brand Numbers

Panel A: Evolution of Jaffe Index NB-PL



Panel B: Evolution of Number of National Brands in a Segment



Note: The two figures summarize the evolution of the estimated PL effects. Points along the upper dotted curve equal the point estimate plus 1.96 multiplied by the corresponding standard error of the point estimate. Points on the lower dotted curve equal the point estimate minus 1.96 multiplied by the standard error. The dotted curves generate a 95% confidence interval for each point estimate.

Appendix 1. Beef Market Overview

The U.S. beef market contains a large number of national brands. Table A1 shows the top NBs and their corresponding market shares by volume (in %) over the years. Tyson has been consistently one of the three largest NBs. Several NBs lost market shares after 2012, which echoes the rapid expansion of PLs in the market during that period.

TABLE A1: Market Shares by Volume for Top National Beef Brands

	Tyson	Excel	Laura's Lean	Cargill	Moran's
	Brand Market Shares by Volume (%)				
<i>2006</i>	5.67	5.89	6.06	2.88	4.87
<i>2007</i>	5.29	6.23	6.16	3.00	4.80
<i>2008</i>	6.29	5.15	5.89	3.49	3.31
<i>2009</i>	6.22	6.45	2.51	3.59	2.79
<i>2010</i>	6.50	6.05	1.90	3.88	1.93
<i>2011</i>	6.17	5.70	1.81	4.19	1.13
<i>2012</i>	5.85	6.44	2.06	4.71	0.26
<i>2013</i>	4.29	4.85	2.74	3.38	0.21
<i>2014</i>	3.86	2.83	3.02	2.61	0.10
<i>2015</i>	4.76	0.71	3.13	0.57	0.10
<i>2016</i>	4.43	0.76	2.70	0.23	0.11
<i>Average</i>	5.39	4.64	3.45	2.96	1.78

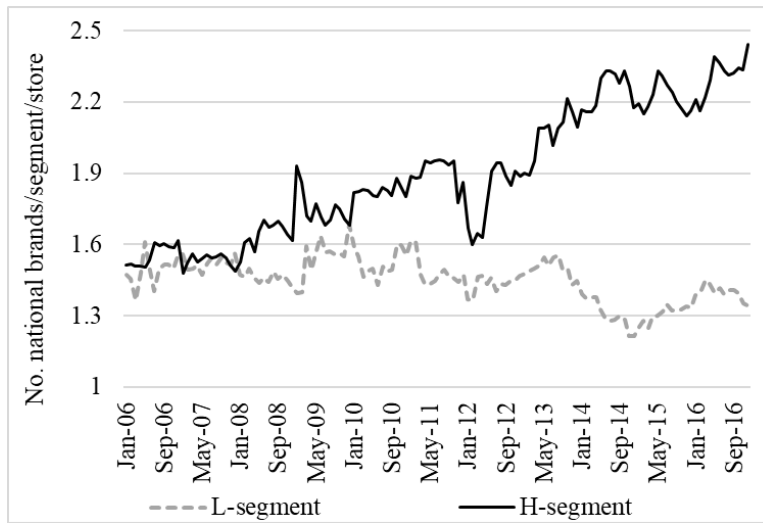
Note: The table reports volume market shares of major beef NBs in each year. All months from 2006 to 2016 are included to generate the statistics.

Source: Nielsen Retail Scanner Data.

Richness of brand variety is different for low- and high-priced market segments. Figure A1 shows that the number of beef NBs in the high-priced segment increases consistently over time. In 2006, stores sold on average 1.5 NBs in the high-priced segment, and this number increased to 2.5 by the end of 2016, representing an increase of 66%. Worth pointing out that this increase is

not driven by stores carrying more organic beef brands which are typically more expensive. More statistics are available upon request.

FIGURE A1: Number of National Brands by Segment and Store over Time

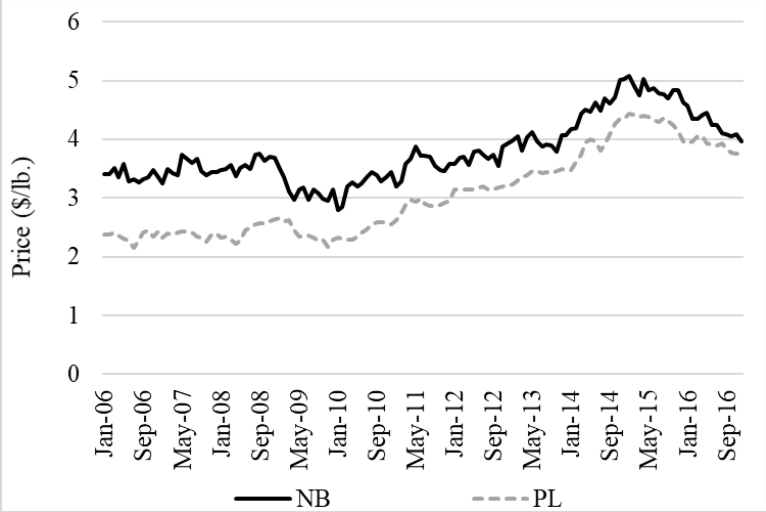


Note: The figure draws the number of NBs in L- and H-segments of a store over time.

Source: Nielsen Retail Scanner Data.

Figure A2 shows the average prices of beef products for NBs and PLs across the 132 months in our dataset. PL prices are always lower than NB prices. From 2006 to 2016, the gap between PL and NB prices gradually narrowed. More discussion is available in Section 2.1.

FIGURE A2: Monthly Average Prices for National Brands and Private Labels over Time



Note: The figure summarizes NB and PL price patterns over time. The solid black curve refers to market-level average prices of NB products, while the gray curve stands for market-level average prices of the PL products.

Source: Nielsen Retail Scanner Data.

Appendix 2. Varieties of Beef Products

The table summarizes all beef varieties recorded in the Nielsen database. A variety is defined by the cut and size. Different varieties are sold at different prices.

TABLE A2: List of Beef Varieties and Summary Statistics

	Cut	Size	Avg. Price	UPC Share	Revenue Share	Volume Share	Notes
1	Beef rolls	≤ 3 lb.	3.39	0.3	0.03	0.03	
2	Beef rolls	> 3 lb.	2.63	0.2	0.07	0.10	
3	Ground, fat	≤ 3 lb.	3.29	35.0	53.36	56.28	Lean ≤ 85%
4	Ground, fat	> 3 lb.	2.23	4.7	13.17	20.52	Lean ≤ 85%
5	Ground, lean	≤ 3 lb.	4.96	15.2	19.85	13.91	Lean > 85%
6	Ground, lean	> 3 lb.	2.86	0.3	0.23	0.28	Lean > 85%
7	Others	≤ 3 lb.	2.32	0.9	0.16	0.24	Sliced sirloin, tripe, etc.
8	Others	> 3 lb.	2.77	0.6	0.03	0.03	Sliced sirloin, tripe, etc.
9	Patty, fat	≤ 3 lb.	4.30	18.9	6.57	5.31	Lean ≤ 85%
10	Patty, fat	> 3 lb.	3.45	1.5	0.35	0.35	Lean ≤ 85%
11	Patty, lean	≤ 3 lb.	5.57	4.4	1.79	1.12	Lean > 85%
12	Patty, lean	> 3 lb.	5.03	0.1	0.01	0.01	Lean > 85%
13	Roast	≤ 3 lb.	7.57	0.5	0.04	0.02	Bulk, round, etc.
14	Roast other	≤ 3 lb.	8.37	1.2	0.15	0.06	
15	Roast tndl.	≤ 3 lb.	5.20	1.1	0.21	0.14	Tenderloin pieces for roast

(TABLE A2 Continued)

	Cut	Size	Avg. Price	UPC Share	Revenue Share	Volume Share	Notes
16	Steak fillet	≤ 3 lb.	10.63	4.6	2.06	0.67	
17	Steak other	≤ 3 lb.	6.16	1.8	0.57	0.32	Flank, skirt, round, chuck, cube, etc.
18	Steak ribeye	≤ 3 lb.	9.46	2.1	0.16	0.06	
19	Steak sirloin	≤ 3 lb.	8.66	2.6	0.76	0.30	Top sirloin steak included
20	Steak slice	≤ 3 lb.	4.55	1.9	0.25	0.19	Shaved and diced steak included
21	Steak strip	≤ 3 lb.	12.22	2.1	0.18	0.05	Shortloin steak included

Note: The table summarizes all beef varieties recorded in the Nielsen database. There are 1,117 unique UPCs in the data over all years. The prices are measured in the unit of real 2015 U.S. dollars per pound.

Source: Nielsen Retail Scanner Data.

Appendix 3. Interactive Fixed Effects Model

We provide more information on the Interactive Fixed Effects (IFE) estimator developed by Liu et al. (2022) that enables us to address potential endogeneity concerns on PL introduction. This estimator builds upon a generalized synthetic control approach (Xu, 2017). Below, we summarize the key steps and defer readers to Xu’s original article for further details.¹²

For simplicity, the retailer subscript r is suppressed. In period $t \in \{1, \dots, T\}$ after the PL introduction, each “treated” store (here, a store that sells a PL) has an unobserved potential outcome that relates to the untreated event, $n_{gst}(0)$, and is used to obtain the causal effect of the treatment (i.e., selling a PL). The counterfactual number of NBs in segment g needs to be computed. The actual outcome value of the store is denoted by $n_{gst}(1)$. A set of period-specific, latent factors are f_t . Observed control variables are denoted by Y_{st} . The identification condition is:

$$\{n_{gst}(1), n_{gst}(0)\} \perp PL_{st} | Y_{st}, f_t,$$

where PL_{st} is the PL indicator and equals 1 if the PL has been introduced. Note that the standard unconfoundedness assumption of Rosenbaum and Rubin (1983) is relaxed by including store- and time-specific factor components.¹³ The latent factors ameliorate the unconfoundedness assumption since they capture additional unobserved store- and time-specific heterogeneities. For additional information on how factor structures ameliorate endogeneity concerns caused by omitted variables see Eberhardt et al. (2013).¹⁴

¹² Xu, Y., 2017, ‘Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models,’ *Political Analysis*, 25(1), pp. 57-76.

¹³ Rosenbaum, P. R. and Rubin, D. B., 1983, ‘Assessing Sensitivity to An Unobserved Binary Covariate in An Observational Study with Binary Outcome,’ *Journal of the Royal Statistical Society: Series B (Methodological)*, 45(2), pp. 212-218.

¹⁴ Eberhardt, M.; Helmers, C. and Strauss, H., 2013, ‘Do Spillovers Matter When Estimating Private Returns to R&D?’ *Review of Economics and Statistics*, 95(2), pp. 436-448.

The IFE specification is given by:

$$n_{gst} = \theta_{st}PL_{st} + \Lambda Y_{st} + \lambda_s f_t + \epsilon_{gst},$$

where λ_s refers to the unknown factor loadings specific to a store and $\lambda_s f_t$ is the interactive FE that captures a wide range of unobserved heterogeneities. This setup effectively allows for unit-specific intercepts interacted with time-varying coefficients.

To estimate the treatment effect, we first estimate the counterfactual outcomes for each “treated” store, $\widehat{n_{gst}(0)}$, using the control stores (i.e., stores never selling PLs from 2006 to 2016).

Next, we compute the treatment effect by:

$$\widehat{\beta}_{gst} = n_{gst}(1) - \widehat{n_{gst}(0)}, \quad \forall t \geq t_s,$$

where t_s is the first month of selling the PL for store s . The average treatment effect in period t can be computed by taking the average across all stores:

$$\widehat{ATT}_t = \frac{1}{N_t} \sum_s \widehat{\beta}_{gst}, \quad \forall t \geq t_s,$$

where N_t is the number of treated stores in period t .

To apply the IFE estimator, we need to sort out treated as well as control stores that are observed continuously over a series of months. It turns out that less than 8% of the stores provide information in all months from 2006 to 2016. To avoid dropping the majority of stores in the database, we separate the 10-year period from 2007 to 2016 into five two-year windows: 2007-2008, 2009-2010, 2011-2012, 2013-2014, and 2015-2016. In each window, 60 to 80% of the stores are observed for at least 20 months.

Given the existence of L- and H-segments, we effectively have four PL effects to estimate and need four subsamples in each two-year window: the effect of selling the L-segment PL on the L-segment NB number (the LL subsample), selling the L-segment PL on the H-segment NB number (the LH subsample), selling the H-segment PL on the L- as well as H-segment NB numbers,

respectively (the HL and HH subsamples, respectively). The LL subsample, for instance, includes treated stores that sell PL in the L-segment for at least one month and control stores that never sell PL. Similarly, we find stores appropriate to include in the other three subsamples.

In total, the four subsamples provide more than one million observations to conduct the estimation. Summary statistics of the subsamples are displayed in Table A3 and show no significant differences compared with the statistics of the full dataset (see Table 2).¹⁵ Estimation is performed for each subsample and two-year each window. Combining the estimated individual effects, we obtain the full set of outcomes covering 2007 to 2016 and all treated stores. The full set of outcomes is used for estimating equation (5).

¹⁵ When using the IFE, the exact number of unobserved factors is determined by a cross-validation procedure. The procedure relies on the information on the control group as well as the treatment group in the pretreatment periods (Xu, 2017). We perform the procedure whenever feasible. When we do not have a sufficiently large number of pretreatment observations in a certain subsample, we set the number of unobserved factors to what the cross-validation suggests in other subsamples. In the LL and LH subsamples, the cross-validation tests suggest that the number of unobserved factors is 2. In HL and HH subsamples, the cross-validation tests suggest that the number of unobserved factors is 1. Changing the number of unobserved factors makes little impact on the outcomes.

TABLE A3: Summary Statistics of the Subsample

	Mean	SD	Min	Max
L-Segment PL				
<i>No. NB/Segment/Store</i>	0.98	1.11	0	10
<i>PL Introduced (1, if yes)</i>	0.33	0.47	0	1
<i>No. Observations</i>	1,053,336			
H-Segment PL				
<i>No. NB/Segment/Store</i>	1.20	1.13	0	12
<i>PL Introduced (1, if yes)</i>	0.27	0.44	0	1
<i>No. Observations</i>	1,054,508			
<i>No. Observations Never PL</i>	490,932			

Note: The table reports summary statistics of observations used for estimating the IFE model. “No. NB/segment/store” is the number of NBs in one segment and a store. “No. Observations Never PL” is the number of observations of stores that never sell PLs and is the same for all subsamples. The upper panel includes observations of subsamples for the L-segment PL, while the lower panel is for the H-segment PL.

Source: Nielsen Retail Scanner Data.