Market Effects of New Product Introduction: Evidence from the Brew-at-home Coffee Market[a]

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Abstract

The introduction of new products has always been an important source of economic development and improvement in consumer welfare. With retail coffee data spanning five years after the single-cup brew coffee pods were introduced to grocery chains, this paper empirically studies the market effects of new product introduction in the brew-at-home coffee market. We use a structural model of demand and supply to capture the changes in consumers' preference for this new product over time. The demand estimates suggest that consumers' relative preference and willingness-to-pay for the new product grew substantially over the sample periods. The analysis reveals the extent to which the introduction and growing presence of the new product simultaneously expanded the relevant market and cannibalized the sales of pre-existing substitute products (traditional auto-drip brew coffee products). Furthermore, we quantify the annually expanding welfare gains of the average consumer attributable to the new product.

Keywords: New product introduction; Willingness-to-pay; Market-expansion; Demand-cannibalization; Brew-at-home coffee market.

JEL Classification Codes: L13; D12; L66

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1. Introduction

New product introduction, which often incorporates new and improved technology, has long played a critical role in influencing not only consumers' tastes, demand, and welfare, but also firms' profitability and even the overall market structure. Firms, especially those in electronics and consumer-packaged goods (CPGs) industries (e.g., food, beverages, cleaning products, etc.), diligently respond to consumers' ever-changing needs and tastes by introducing new products via either line extension or brand extension. Products in the CPGs sectors are primarily channeled through grocery chains to households. According to Gallagher (2011), CPGs manufacturers in the U.S. introduced more than 150,000 new products in 2010 alone.[1] With market-level retail chain packaged coffee sales data available, our empirical analysis focuses on the market of brew-at-home coffee consumption.

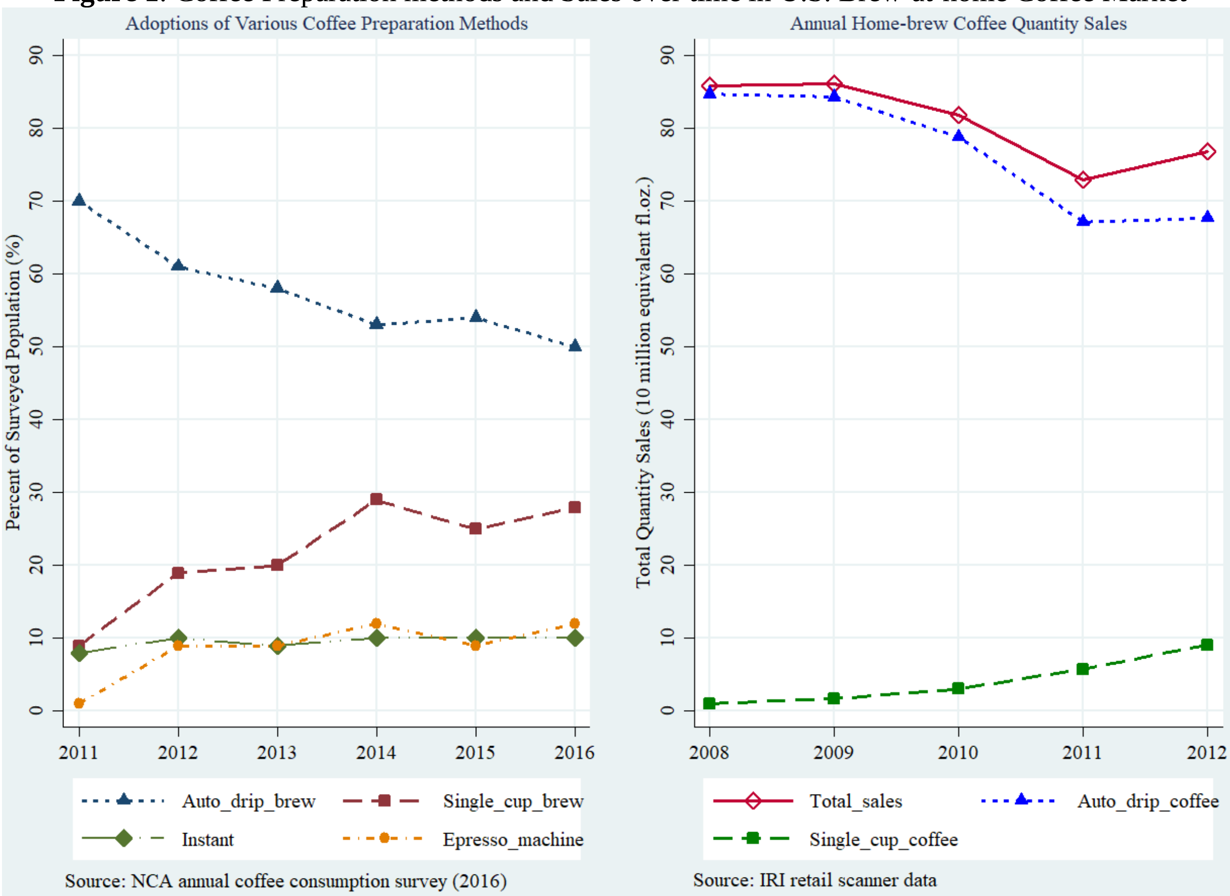
In the retail packaged coffee products sector, single-cup brew coffee products were nearly unavailable in grocery stores for brew-at-home coffee consumers prior to 2008.[2] The introduction of single-cup brewing systems, pioneered by Keurig Green Mountain, introduced a whole new coffee segment by bringing single-cup pods into grocery chains since 2008. The rapid market adoption of single-cup brew method fueled the sales of single-cup coffee pods[3] and significantly influencing the overall landscape of the brew-at-home coffee market.

In Figure 1, on the left panel, National Coffee Association (NCA) annual national coffee consumption survey reveals an increasing popularity of single-cup brew technology among the surveyed population, and a declining trend in the use of traditional auto-drip brewing method from 2011 through 2016.[4] Single-cup brew method has become the second most popular coffee preparation method after the traditional auto-drip brew method, far surpassing the preparation methods of instant coffee and espresso machines. On the right panel of Figure 1,[5] the line plots suggest that total brew-at-home packaged coffee sales in grocery chains began a downward trend

[1] More than ninety percent of new products/brands in the CPG sectors were introduced via extensions of existing brand-name products, according to Hariharan et. al. (2015).
[2] Keurig single-cup brewing systems were available only in some high-end department stores in year 2003. However, they became available to households through grocery stores across the U.S. in year 2008. Since then, single-cup brew became an option for home-brew coffee consumption. See URL link: https://consumergoods.com/gmcrs-path-disruptive-innovation
[3] U.S. consumers bought $3.1 billion worth of coffee pods in 2013 versus $132 million in 2008 (The Seattle Times). See URL link: https://www.seattletimes.com/business/single-serve-coffee-revolution-brews-industry-change/
[4] According to NCA, coffee brew method with single-cup systems was not surveyed until 2011.
[5] The line plots are generated based on our working data sample sourced from Information Resources Inc. (IRI) academic database. Detailed discussion about the construction of the working sample is presented in the data section.

in 2009 and then picked up in 2011. Given the disproportionately large market share of auto-drip coffee relative to single-cup coffee, the trend in the total coffee sales closely followed the sales of auto-drip products even though single-cup sales consistently grew throughout the sample periods.

Figure 1: Coffee Preparation methods and Sales over time in U.S. Brew-at-home Coffee Market



This paper examines the market effects associated with the presence and growing popularity of single-cup brew coffee products in U.S. brew-at-home coffee markets from 2008 through 2012. These market effects are deserving of a better understanding than can be provided by the simple time-series line plots in Figure 1. Unfortunately, due to the unavailability of individual consumer purchase data on coffee brewing machines, we do not incorporate consumers' decisions on hardware adoptions in our demand model.

Specific in this study, we seek answers to the following questions: (1) How and to what extent did the introduction of single-cup brew coffee products expand the U.S. brew-at-home coffee market while at the same time cannibalize the sales of pre-existing substitute coffee products over time? (2) How has consumers' valuation of their coffee consumption experience with the single-cup brew technology evolved over time since it was introduced to the supermarkets? (3) What welfare effects resulted from the presence and increasing popularity of single-cup brew technology?

To examine these questions, our research methodology begins with estimating a random coefficients discrete-choice demand model. Assuming firms compete in prices according to a static Nash equilibrium price-setting game, the demand estimates are subsequently used to compute price-cost margins of the coffee products. These estimates together are used to simulate the new market equilibrium that would result from a counterfactual experiment in which single-cup coffee options are taken away from consumers' choice set. Comparing actual market outcomes when single-cup coffee options are available to consumers with counterfactual market equilibrium outcomes when single-cup coffee options are absent enables us to address the above key research questions.

Results from the demand estimation suggest that the average coffee drinker prefers her coffee consumption using the single-cup brew technology over the traditional auto-drip brew method; and this relative preference increases over time. In addition, the average consumer's willingness-to-pay for the single-cup brew attribute increases by more than 180% from 2008 to 2012. Counterfactually removing single-cup coffee options from consumers' choice set predicts to increase the price level of auto-drip coffee products, effectively suggesting the entry and growing popularity of single-cup brew products caused an average reduction in the price level of auto-drip products. Furthermore, this price effect tends to become larger over time.

Our empirical model predicts that the introduction and growing penetration of single-cup products have an expansionary effect on the overall brew-at-home coffee market by attracting consumers who would have otherwise chosen not to purchase any of the coffee products in our analysis, while also having a demand-cannibalizing effect on the existing auto-drip brew products. Last, the welfare analysis of the new product introduction suggests that the average consumer is predicted to have a welfare gain of about 0.3% in 2008, which substantially increased to a welfare gain of 2.8% in 2012. Results from the estimated compensation variation suggests that, if single-cup coffee options were to be eliminated from consumers' choice sets, then the average coffee drinker needs to be compensated 13 times more in year 2012, compared with the compensation level in year 2008. Accordingly, we monetize these predicted welfare gains and compare them to estimated welfare gains attributable to new product introductions in other industries that are documented in other studies in the literature.

The rest of the paper is organized as follows. Section 2 reviews relevant literature. Section 3 discusses data sources and variables used in the analysis. Section 4 describes the empirical model, as well as the estimation method. Section 5 presents and discusses the empirical results. Section 6 describes the counterfactual procedure and analyzes findings from the counterfactual experiment. Section 7 concludes the paper.

2. Related Literature

The analysis of new product introduction has been the focus of economists' attempts to understand its impacts on the measures of cost-of-living, such as the Consumer Price Index (CPI).[6] As stated in Bresnahan and Gordon (1997), "new goods are the heart of economic progress," and the estimated value created by new goods provides important inference for calculating the CPI. It is therefore important to accurately evaluate the welfare effects of new product introductions. By analyzing the demand and welfare effects associated with the introduction of single-cup coffee products, our paper is related to much of the previous literature examining the economic effects of newly introduced products or technology in various industries. A few well-known papers in this literature include: Hausman (1996); Greenstein (1997); Hausman and Leonard (2002); Petrin (2002); Goolsbee and Petrin (2004); Brynjolfsson et.al. (2003); and Gentzkow (2007).[7]

However, previous literature in evaluating the economic effects of new goods particularly focused on the price effects as well as the welfare impact of new products upon their entry. We, instead, examine the market impacts associated with the introduction of a new product as well as its continuing effects as the new product gradually penetrates the relevant market. Specifically, we model consumers' preference for the new product at each period since the product became available to consumers. In doing so, we are able to understand how consumers' valuation of the new product evolved over time. In addition, we conduct two counterfactual experiments designed

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[6] See relevant discussions in Bresnahan and Gordon (1997), Hausman (1996), and Gentzkow (2007).

[7] Hausman (1996) studied the effect of Apple Cinnamon Cheerios. Greenstein (1997) studied the effect of the technological innovation in the computer industry. Hausman and Leonard (2002) examined the effect of Kimberly-Clark bath tissue product 'Kleenex Bath Tissue'. Petrin (2002) focused on the market effects of minivans' introduction and Goolsbee and Petrin (2004) on the effect of direct broadcast satellites. Brynjolfsson et.al. (2003) examines the welfare effects of increased product varieties at online booksellers. Gentzkow (2007) studied the effects of online newspapers.

to decompose the overall impact of the new product on specific market outcome variables. For example, in the first experiment we use the estimated model to compute the impacts on market outcomes such as quantities demand and consumer welfare after allowing the prices of the pre-existing products to reflect the reduced competition associated with the counterfactual absence of the new product. The second experiment focuses on measuring the impacts on the same market outcomes, i.e., quantities demand and consumer welfare, associated purely with the increased product variety available to consumers due to the market presence of the new product. In order to accurately measure the "variety effects", the second experiment nullifies the impact of the new product introduction on prices of the pre-existing products, i.e., "price effects" are counterfactually nullified in the second experiment.

Our paper is also related to literature on new product introduction via brand extension[8] for multi-product firms. The introduction of new goods is a project with various risks and uncertainty, as it requires substantial investment of time and resources and careful planning at every stage of the new product introduction. Estimating and understanding its impacts on the consumption of existing goods driven by consumers' valuation between the new products and existing products are important for designing optimal business strategies, and for investors seeking to put their resources into projects that maximize return on their investment. For example, Aaker and Keller (1990) studied how consumers' evaluation of the established products/brands influence the effectiveness of multi-product firms' new product line design, and subsequently firms' new product positioning strategies. Cabral (2000) examined various effects on consumers' willingness to pay for a new product associated with a multi-product firm's brand reputation stretching decision, and how these effects together determine the multi-product firm's optimal strategy to launch the new product (under the same brand name vs. create a new brand). Boleslavsky et.al. (2017) studied firms' product demonstration design for learning consumers' valuation when launching new products. Similar works include Choi (1998) and Pepall and Richards (2002).

By analyzing the demand substitution features (or diversions) between the new product and existing products, our paper also fits into the literature that examines diversion ratios, such as Shapiro (1995, 2010) and Conlon and Mortimer (2013, 2021).

[8] Brand extension or brand stretching is a common marketing strategy when a firm tries to introduce a new product under a well-established brand name. There is a large body of marketing literature focusing on the relationship between brand name and brand extension, such as Broniarczyk and Alba (1994), Pitta and Katsanis (1995), Swaminathan et.al. (2001), and Martinez and Chernatony (2004).

Last, our paper is also related to the coffee literature, among which only a few have studied the relatively new single-cup coffee segment, e.g., Chintagunta et. al. (2018), Kong et. al. (2016), Lin (2017), and Ellickson et. al. (2018). Different from previous coffee papers either on auto-drip (ground) coffee or the single-cup system, we examine the interrelationship of the two segments. Furthermore, we are able to provide empirical estimates of the time-varying economic effects of the newly introduced single-cup products on the coffee market, which helps characterize how the market effects evolved over time. The analytical framework outlined in this paper, however, is widely applicable and implementable to other industries with new product/brand introduction, especially in industries with frequent new product launches or product innovations. These industries include consumer-packaged goods (e.g., food, beverages, household products, etc.), electronics, automobiles, and many others.

3. Data

The primary data used in our empirical analysis are retail-level weekly scanner data on consumer purchases of traditional auto-drip brew ground coffee and single-cup brew coffee products, sourced from the Information Resources Inc. (IRI) academic database [Bronnenberg et al. (2008)] for the period of 2008-2012. The data contain weekly observations on packages of coffee products sold at retail grocery stores. Information in the data include: total dollars received by a given retail store for each package of coffee product sold during the relevant week; number of units sold of a given package; net weight of dry coffee (in ounces) contained in each package; and a set of coffee product attributes.

We define a market as the combination of period (year-month) and the retail stores where products are sold. A product within a market is defined as a unique combination of various measurable non-price attributes of the product including the coffee brand to which it belongs.[9] Details of the sample construction and various product attribute definitions are presented in Appendix B.

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[9] For example, Folgers and Maxwell House are two distinct manufacturers of auto-drip products and single-cup products. An example of an auto-drip product sold in January 2008 at retail-store (ID=”689933”) is: Folgers’ auto-drip, non-organic, caffeine content of 1.86 gram per ounce of dry coffee, packed in a light metal tin with a net weight of 34.5 ounces, sold with store featured advertising but no promotional display. Similarly, an example of a single-cup product in the same time period and store is: Maxwell House’s single-cup, non-organic, caffeine of 1.86 gram per ounce of dry coffee, packed in a laminated bag with a net weight of 4.3 ounces, sold without any promotional activities.

To obtain the final working sample, we aggregate the weekly data to monthly frequency; and therefore, the "price" variable for a defined product is the mean of those average unit prices for this product sold during a month, and the "quantity" variable for a defined product is the total equivalent fluid ounces sold during a month. According to the NCA annual coffee consumption survey in 2016, individuals who consume coffee daily varies from 56% to 64% of the surveyed population over the five sampled years, with an average of 59%. We, therefore, assume the actual coffee quantity consumed in the data accounts for 59% of total coffee quantity that could be potentially consumed by the entire population in a defined market. This implies the potential market size (later denoted M_{mt}) in terms of equivalent fluid ounces is equal to the market aggregate quantity consumed in the data multiplied by the inverse of 59%.[10] The observed product share (later denoted S_{jmt}) is computed by dividing the quantity sold of a product in equivalent fluid ounces by the above defined potential market size.

Summary statistics reported in Table 1 suggest that the average price of single-cup brew coffee products is about twice the average price of auto-drip brew products. Product quantity sold during a given month has an average of 7,608 equivalent fl oz, and the average product share is 0.7% in a market. Single-cup Brew is a zero-one dummy variable that takes a value of 1 if a coffee product is designed to use the single-cup brewing technology, and a value of 0 if the product is designed to use the traditional auto-drip brew method. The data summary shows that 12.8% of the coffee products in the data sample are single-cup brew products. Organic is also a zero-one dummy variable that takes a value of 1 only if a product is designated as organic coffee, and 0 otherwise. The average caffeine contained in one ounce of dry coffee grounds is 1.42 grams across all products in the data.[11] Package Weight is a variable that measures the net weight in ounces of dry coffee grounds contained in the package. This variable will be used to capture consumers' preference for the product package size. "Feature" and "Display" are each zero-one dummy variables that describe the marketing strategies used by retail stores for each product during a given period and are considered to influence consumer brand choice and loyalty.[12]

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[10] This method of computing potential market size is similar to the "potential market factor" method in Ivaldi and Verboven (2005).

[11] Caffeine is a major pharmacologically active compound in coffee beans, and it is a mild central nervous system stimulant [de Mejia and Ramirez-Mares (2014)]. Coffee, like other caffeinated soft drinks, acts as a stimulant beverage.

[12] See Hwang and Thomadsen (2015), Bronnenberg et al. (2012) and Boatwright et al. (2004). Coffee is one of the most frequently promoted consumer packaged goods (CPGs) according to Boatwright et al. (2004).

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Price* ($/fl oz across all coffee product types)	0.033	0.017	0.003	0.212
Price* ($/fl oz across all auto-drip brew products)	0.029	0.013	0.003	0.212
Price* ($/fl oz across all single-cup brew products)	0.060	0.018	0.0066	0.171
Quantity (equivalent fluid ounce)	7,608	16,538	80	804,457
Single-cup Brew dummy (single-cup brew products = 1)	0.128	0.335	0	1
Organic dummy (organic coffee products = 1)	0.067	0.251	0	1
Caffeine (gram per ounce of dry coffee grounds)	1.422	0.746	0	2.232
Package Weight (ounces of dry coffee grounds)	15.417	9.963	1.69	80
Feature (e.g., frequent shopper program, store ads)	0.182	0.386	0	1
Display (e.g., promotionally displayed in the lobby, or end aisle)	0.104	0.305	0	1
Product market shares (all inside goods)	0.007	0.013	0.000016	0.488
No. of defined markets	6,002			
No. of retailers	118			
No. of manufacturers	109			
No. of brands	166			
No. of observations	530,172			

* All prices are adjusted to year 2012 dollars.

4. The Model

4.1 Demand

Let m index markets, t index time, i index consumers, and j index products. Consumers in each market are faced with $J_{mt}+1$ choice alternatives indexed by $j=0,\dots,J_{mt}$, where $j=0$ represents consumers' "outside" option.[13] The conditional indirect utility consumer i obtains from choosing product j in market m during period t is:[14]

$$U_{ijmt} = x_{jmt}\beta_i + \sum_{y=1}^{5}\left(\phi_{i,y} SingleCupBrew_{jmt} \times a_y\right) + \alpha_i p_{jmt} + \xi_{jmt} + \varepsilon_{ijmt}, \quad (1)$$

where x_{jmt} is a vector of measured non-price product attributes. $SingleCupBrew_{jmt}$ is a zero-one dummy variable that equals to one only if consumption of coffee product j requires using single-cup brewing technology; and a_y represents a year dummy variable. $\phi_{i,y}$ measures in year y consumer $i's$ preference for the single-cup brew consumption experience relative to the traditional auto-drip brew consumption experience. p_{jmt} represents the price of product j in

[13] In our analysis, consumers' outside option is a composite of several possibilities such as buying other coffee substitutes (e.g. instant coffee, ready-to-drink coffee beverages, or other coffee substitutes) or simply not buying coffee.
[14] This specification of indirect utility may be derived from a quasi-linear utility; thus, consumer demand does not depend on and is not subject to a wealth effect. The likely impact of the investment in a single-cup brewing machine on consumers' purchase of single-cup products requires a different theoretical framework to study the coffee system as tied-goods and availability of brewing machine purchase data, which is beyond the scope of this paper. Thanks to the suggestion of an anonymous referee, the time fixed effects we include do capture likely switching costs resulting from consumers' adoptions of alternative brewing machines.

market m during period t, assumed common to all consumers; and α_i is the consumer-specific taste parameter that measures the consumer's marginal utility of price. ξ_{jmt} is a composite of product characteristics that are observable to consumers and firms, but unobservable to the researchers. ε_{ijmt} is a mean-zero stochastic error term and assumed to be governed by an independent and identically distributed extreme value density. The probability that product j is chosen, or equivalently the *predicted* (by the model) market share of product j is therefore:

$$s_{jmt}\left(x_{jmt}, p_{jmt}, \xi_{jmt}; \beta, \phi_y, \alpha, \Gamma, \Sigma\right) = \int \frac{e^{\delta_{jmt}+\mu_{ijmt}}}{1+\sum_{l=1}^{J_{mt}} e^{\delta_{lmt}+\mu_{ilmt}}} d\widehat{F(D)} dF(v) \quad (2)$$

where δ_{jmt} is the mean utility, while μ_{ijmt} is the deviation from the mean utility that allows for consumer heterogeneity; $\widehat{F(D)}$ and $F(v)$ are population distribution functions for consumer demographics and random taste shocks, respectively, assumed to be independently distributed.[15]

4.2 Supply

We assume coffee manufacturers play a strategic role in setting prices of their coffee products to non-cooperatively maximize firm-level profit in a static Nash equilibrium price-setting game.[16] Let F_{fmt} represent the set of coffee products manufacturer f offers in market m during period t. Suppose manufacturer f sets the prices of these products to maximize the firm's variable profit:

$$\max_{p_{jmt} \forall j \in F_{fmt}} VP_{fmt} = \max_{p_{jmt} \forall j \in F_{fmt}} \sum_{j \in F_{fmt}} \left(p_{jmt} - mc_{jmt}\right) q_{jmt} \quad (3)$$

where in equilibrium the quantity of coffee product j sold in market m during period t, q_{jmt}, is exactly equal to the market demand of this product, i.e., $q_{jmt} = d_{jmt} = M_{mt} \times s_{jmt}(\boldsymbol{p})$; M_{mt} is a measure of the potential size of market m during period t, $s_{jmt}(\boldsymbol{p})$ is product j's predicted market share, and $\boldsymbol{p}$ is a vector of the prices for the J products in the market. mc_{jmt} represents the marginal cost incurred by the firm to provide product j in the market during period t.

4.3 Estimation and Identification

We draw upon the previous discrete-choice literature, following Berry (1994), Berry, Levinsohn and Pakes (1995), Nevo (2000a, 2000b), to estimate the set of demand parameters using

[15] In the actual demand estimation, we use 200 random draws from $F(\cdot)$ for the numerical approximation of $s_{jmt}(\cdot)$.
[16] We make the simplifying assumption that retailers do not play a strategic role in setting retail prices of the coffee products in our analysis, and simply set retail prices just high enough to cover their economic retailing costs and costs to obtain coffee products from coffee manufacturers.

generalized method of moments (GMM).[17] We follow the nonlinear GMM estimation algorithm proposed in Nevo's work to obtain estimates of both the linear and nonlinear parameters of demand. Detailed discussion of the estimation algorithm procedure, as well as the second stage minimum-distance estimation procedure can be found in Nevo (2000b).

Instruments and Identification

The classic econometric problem in logit demand estimation is the endogeneity of prices. One way to partially deal with the endogeneity problem of prices is to account for fixed differences in ξ_{jmt} in a flexible manner by introducing fixed effects dummy variables. We follow Nevo (2000a, 2000b) and include in the mean utility function, time dummies, store dummies, and brand dummies to account for some unobserved product characteristics in ξ_{jmt}.

To further mitigate the endogeneity problem, we construct instruments for product prices using direct components of marginal cost (i.e., manufacturer input prices) interacted with brand fixed effects as in Villas-Boas (2007a, 2007b) and Nakamura and Zerom (2010). The first is time-varying exchange rates between Brazilian real and U.S. dollar, interacted with brand dummies.[18] By interacting the exchange rates and brand dummies, we allow exchange rates to influence coffee products' production costs differently across brands. Similar to Nakamura and Zerom (2010), we consider one-period lagged exchange rates to capture the potential lagged response in coffee products' production costs and its transmission to influence coffee product prices.

Second, we interact the national average electricity prices with the dummy variables for four different packaging materials for coffee products. [19] By interacting electricity price with zero-one dummy variables that correspond to the four different packaging materials, we allow these four instrument variables to capture the likelihood that changes in electricity prices affect coffee products' production costs differently across different packaging processes. Furthermore, in principle this set of instruments is valid since changes in electricity price are unlikely to be driven by changes in coffee markets, making this set of instruments exogenous to coffee markets.

To obtain estimates of random coefficients, we include in the demand model specification an interaction of consumers' observed demographics (D_i) with prices, as well as interactions of

[17] See Conlon and Gortmaker (2020) for a comprehensive review of recent advances related to the estimation of BLP-type problems.
[18] Data on currency exchange rate are obtained from the Federal Reserve Bank of St. Louis Economic Data.
[19] Electricity price is from the US Energy Information Administration.

consumers' unobserved preference shocks (v_i) with prices, the single-cup dummy, and the intercept, respectively.[20] The coefficients of these interaction variables serve to distinguish the estimated substitution patterns from those implied by a simple logit model, and better capture the heterogeneity in preferences across consumers. According to Nevo (2000b), to tie consumer demographic variables to observed purchases, one needs to have in their data several markets with variation in the distribution of demographics. Therefore, the random taste parameters in our demand model can be identified based on the rich distributional variation of the demographics obtained from Census PUMS data on a market-by-market basis, and the assumed standard normal distribution of the unobserved preference shocks.[21]

To identify the coefficient that captures consumers' income-driven heterogeneous preference for price changes, the instrument we use is constructed by interacting the second set of instruments for prices described above with median personal income for the population of aged sixteen and above in the county where the relevant coffee products are sold. It is reasonable to believe that the unobserved product characteristics contained in ξ_{jmt} after controlling for time fixed effects, store fixed effects, and brand fixed effects, are most likely uncorrelated with the county-level average wealth level.

To identify the standard deviations of the random coefficients on price, the single-cup dummy variable, and the constant term, we follow Gandhi and Houde (2020) and construct product differentiation instruments along three dimensions.[22] The differentiation measure along prices is constructed by computing the Euclidian distance between a product's predicted price and predicted prices of rival products, where the predicted prices are generated from an ordinary least squares

[20] A special note regarding the single-cup dummy variable in our demand model specification is that, based on discussions in Conlon and Mortimer (2013), random coefficients on categorical variables may not be identified when there is a lack of variation in price and product dummies are included in the estimation. In our paper, with the richness of price variations across products and markets, we do not have such concern.

[21] Berry and Haile (2014, 2016) raised a concern regarding the identification of parameters that govern the distribution of the random coefficients. In this paper, we believe the richness and the panel structure of our data, as well as the additional information obtained from Census PUMS demographic data across more than 6002 markets makes it possible to have sufficient variations across markets that help identify the substitution parameters in the random component. A careful exploration of our data reveals that the set of available products not only varies by time periods for a given geographic area (zip code and county), but also varies by geographic areas for a given period.

[22] We appreciate an anonymous referee for helpful suggestions on constructing these instrument variables, which help identify the random coefficients. For the construction of these differentiation instruments, we refer the reader to Table 12 in Gandhi and Houde (2020). The predicted prices are obtained from a reduced-form regression of prices on all the non-price product characteristics as well as the exogenous cost-shifters and fixed effects previously discussed.

(OLS) estimated reduced-form price regression.[23] The differentiation instrument for the single-cup dummy is the number of rival products in the market that have the same coffee type attribute (single-cup versus auto-drip) as the given product in question.[24] This instrument proxies the amount of competition faced by each product with respect to its single-cup feature. The differentiation instrument for the intercept is computed by interacting each product's own predicted price with the sum of differences between the product's and rival products' predicted prices.[25] It captures the fact that low quality (priced) products tend to be closer substitutes for the outside good compared to higher quality (priced) products. The variations in these differentiation measures induce consumer substitution along these dimensions, and thus identify the standard deviation preference parameters for the random coefficients.

Last, we also include a standard instrument used by many empirical industrial organization studies: the total number of coffee products offered in a market, which identifies the standard deviation preference parameter on the intercept. The intuition is that as the number of coffee products offered in the market increases (i.e., more inside goods become available in the market), consumers are more likely to be induced away from the outside option to the inside goods.[26]

5. Empirical Results

Demand

The demand model estimates are reported in Table 2. The first column reports parameter estimates from the standard logit model using the ordinary least squares (OLS) estimator, while the second column reports standard logit model parameter estimates using two-stage least squares (2SLS) estimator with product prices instrumented using the set of instruments discussed in the previous section. Parameter estimates from the random coefficients logit demand model using generalized method of moments (GMM) are reported in the last three columns, where consumer heterogeneity is considered by allowing the coefficient on coffee product price and other product characteristics to vary across individual consumers.

[23] As in Gandhi and Houde (2020), the Euclidian distance instrument for prices is defined as: $\sqrt{\sum_{j' \neq j \in J_t} \left(\hat{P}_{j't} - \hat{P}_{jt}\right)^2}$.

[24] The differentiation instrument for the discrete product attribute of whether or not the relevant product in question is single-cup is defined as: $\sum_{j' \neq j \in J_t} 1\{x_{j't,single-cup} = x_{jt,single-cup}\}$.

[25] The differentiation instrument for the intercept is defined as: $\hat{P}_{jt} \times \left(\sum_{j' \neq j \in J_t} \left(\hat{P}_{j't} - \hat{P}_{jt}\right)\right)$.

[26] See a similar argument in Sullivan (2020) and Miller and Weinberg (2017).

Table 2: Demand Estimates

	Standard Logit Model ($\mu_{ij} = 0$)		Random Coefficients Logit Model ($\mu_{ij} \neq 0$)		
	(1) OLS	(2) 2SLS	(3) GMM[b]		
Variables	Mean Coef ($\alpha, \beta's$)	Mean Coef ($\alpha, \beta's$)	Mean Coef ($\alpha, \beta's$)	Standard Deviations (Σ)	Interactions with Income (Γ)
Panel A					
Price ($/fl oz)	-48.81***	-82.6855***	-85.5337***	-1.8606	-339.8212***
	(0.213)	(0.683)	(0.8608)	(11.0556)	(35.7188)
Constant[a]	-4.806***	-6.0860***	-2.9225***	6.6823***	
	(0.136)	(0.0003)	(0.1872)	(0.7651)	
Single-cup Brew				1.1647***	
				(0.1930)	
Panel B					
Single-cup Brew×Y2008	0.721***	1.2903***	0.6134***		
	(0.018)	(0.0211)	(0.1929)		
Single-cup Brew×Y2009	0.865***	1.4794***	0.8229***		
	(0.015)	(0.0193)	(0.1877)		
Single-cup Brew×Y2010	1.046***	1.6283***	1.0242***		
	(0.014)	(0.0177)	(0.1745)		
Single-cup Brew×Y2011	1.296***	2.0176***	1.4461***		
	(0.012)	(0.0180)	(0.1538)		
Single-cup Brew×Y2012	1.360***	2.1951***	1.6737***		
	(0.012)	(0.0196)	(0.1363)		
Panel C					
Organic[a]	-0.521***	-0.0876***	0.1353***		
	(0.0085)	(0.00001)	(0.0079)		
Caffeine	0.407***	0.4010***	0.3994***		
	(0.002)	(0.00205)	(0.0021)		
Package Weight	0.0169***	0.00464***	0.0042***		
	(0.00019)	(0.000293)	(0.0003)		
Feature[a]	-0.117***	0.3171***	0.0288***		
	(0.0042)	(0.00001)	(0.0061)		
Display[a]	0.107***	0.2262***	0.2815***		
	(0.00487)	(0.000009)	(0.0050)		
R-squared	0.487		**M-D weighted R-squared**	0.8027	
Wu-Hausman (F-statistic)		2775.08***	**GMM Objective**	15,925	
Stock and Yogo Weak IV (F-statistic)		341.652***	**IIA joint test on differentiation IVs (Chi-sq)**	7910.76***	
No. of Observations	530,172	530,172	530,172		

***p<0.01; **p<0.05; *p<0.1. Standard errors are in parentheses. All regressions include year, month, store, and brand fixed effects. [a] Estimates with GMM estimator are obtained from a minimum-distance procedure. Details of the minimum-distance procedure can be found in Nevo (2000b). [b] The first column under GMM estimation reports the means of the distribution of marginal utilities ($\beta's$); the second column labeled "Standard Deviations" measures taste variation among consumers for select product attributes driven by unobserved consumer characteristics (v_i); the last column reports the effect of consumer income (D_i) on consumers' marginal utilities of select product attributes.

Comparing OLS estimates without instrumentation with the other columns of estimates when price instruments are used, it is noticeable that the coefficient estimate for price increases in absolute value with instrumentation. The Wu-Hausman test statistic confirms the endogeneity of price by rejecting the exogeneity of price at the 1% level, suggesting that the OLS estimation produces a biased and inconsistent estimate of the price coefficient. Furthermore, the Stock and Yogo (2005) weak instrument test statistic rejects the null hypothesis that the instruments used for price are weak.

To further investigate the possibility of weak identification problems, we follow Gandhi and Houde (2020) and use the differentiation instruments discussed previously to perform the Independence of Irrelevant Alternatives (IIA) hypothesis test.[27] The IIA joint test statistics validates the ability of our product differentiation instruments to identify deviations of the random coefficients from the standard logit preferences. We focus the remainder of our analysis on demand estimates obtained from the random coefficients model using the GMM estimator.

We find the mean coefficient estimate for price is negative and statistically significant at the 1% level, indicating coffee price, on average, has a negative impact on consumers' mean utility. All else equal, an increase in a product's price reduces the probability that a typical coffee drinker chooses this product. The observable variation across markets in consumer demographics (measured by draws of consumers' income in our study) seems to drive deviations from the mean price sensitivity significantly, providing evidence that consumers are heterogeneous with respect to their sensitivity to price changes of coffee products. The parameter estimate for the interaction of unobserved variation in consumers' tastes in the population with the constant term, which measures heterogeneity in consumers' valuation for the outside option, is statistically significant at the 1% level, suggesting statistically discernable heterogeneity across consumers' in their valuation of the outside option.

To assess how much consumers value their coffee consumption experience using the single-cup brewing technology relative to the traditional auto-drip method, and how their valuation varies across time, we focus on the parameter estimates for the interactions of single-cup dummy with the year dummies, reported in Panel B of Table 2. These parameter estimates are all positive and statistically significant at the 1% level, suggesting a relative preference for the single-cup brew attribute over the traditional auto-drip brewing method. In addition, this relative preference increases year after year. To be specific, for the average coffee drinker, the single-cup consumption

[27] See Gandhi and Houde (2020) for details of how to test for weak identification issues in random coefficients demand models.

experience has the greatest positive marginal utility in year 2012, and the smallest in year 2008. This finding holds regardless of the estimators used according to the relevant estimates in columns (1) and (2). What's more, in case of the random coefficients demand model, the parameter estimate on the interaction of unobservable variation in consumers' tastes in the population with the *Single-cup Brew* dummy reported in Panel A is statistically significant, suggesting that there is statistically discernable heterogeneity in preferences for the single-cup brew attribute versus auto-drip brewing method.

We now turn to discuss estimates for other product characteristics that affect consumer choice, reported in Panel C of Table 2. For an average coffee drinker, organic coffee produces a positive marginal utility, suggesting that, holding the impact of other demand factors constant, organic coffee products are favored to non-organic coffee during the sample period. The other demand-shifters all have expected demand impacts and are consistent with findings in previous studies. For example, the coefficient estimate associated with the caffeine content variable is positive and statistically significant, suggesting that, holding all other coffee demand factors constant, consumers prefer coffee products that have higher caffeine content. Bonnet and Villas-Boas (2016) found consumers have significant and negative preference for caffeine-free products; thereby, a typical coffee drinker prefers coffee products that are not decaffeinated.

The package size, measured by the net mass weight of the package, has a statistically significant positive marginal utility for the average consumer. This result is similar to findings in Guadagni and Little (1998) and Ansari et al. (1995). Prendergast and Marr (1997) argue that larger packaged consumer goods normally reflect better value to average consumers, and consumers tend to choose larger packaged products as they are more likely to stand out on the shelf.

Last, the variables capturing the promotional activities (e.g., featured by frequent shopper programs or advantageously displayed at the end of an aisle) both have a positive and statistically significant coefficient estimate, suggesting that these promotional activities for a given coffee product serve to increase consumers' demand for the product. This finding is consistent with results in previous studies such as Guadagni and Little (1998), Gupta (1988), Lattin and Bucklin (1989), Grover and Srinivasan (1992), Boatwright et al. (2004), Ansari et al. (1995).[28]

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[28] These studies all provide empirical evidence that promotional activities have a positive impact on coffee demand. Gupta (1988), for example, argues that promotion enhances a brand's value, which in turn enhances the probability of products of this brand being selected by consumers.

Elasticities of Demand Estimates

Table 3 reports the average own-price elasticities for the auto-drip and single-cup brew coffee products in each sample year. Our demand model yields average own-price elasticity for auto-drip brew coffee products within a given year ranging from -2.22 to -2.51 across the years in our sample, while for single-cup brew coffee products the average own-price elasticity estimate ranges from -2.99 to -5.41, overall greater in magnitude than the mean estimates of auto-drip products. This result is clearly observed from the line charts in Figure 2, where we plot the absolute values of the mean elasticities and the total number of products available in each year. The plots in Figure 2 reveal that consumers' price sensitivity for single-cup coffee products grew at a faster rate than their price sensitivity for auto-drip coffee products, possibly due to the fast growth of single-cup products available in the market. The confidence intervals in the figure show that at a 95% level of statistical confidence our model-predicted own-price elasticities are all different from zero.

The own-price elasticity estimates of traditional auto-drip brew coffee products in this paper tend to be slightly smaller in magnitude compared to analogous estimates obtained in some studies: Krishnamurthi and Raj (1991) (3.6 to 8.2); Broda and Weinstein (2006) (3.1); Foster et al. (2008) (3.65); Villas-Boas (2007b) (5.6 to 6.8); and Nakamura and Zerom (2010) (3.96). Chintagunta et al. (2018) provide an own-price elasticity estimate of 3.6 in absolute magnitude for single-cup brew coffee products in coffee markets in Portugal; and Ellickson et al. (2018) report their own-price elasticity estimate for single-cup products of 2.89 in absolute value. Both estimates are within the range of our estimated own-price elasticities for single-cup coffee products in U.S. markets.

Compared to the own-price elasticity estimates, cross-price elasticity of demand estimates in Table 4 are relatively small in magnitude, but all estimates are positive and statistically different from zero, suggesting that consumers do perceive the coffee products in our sample as substitutable both within and across the two product types.[29]

[29] Cross-price elasticity estimates for consumer-packaged goods sold in grocery chains tend to be relatively small. For example, the estimated cross-price elasticities across ready-to-eat cereal brands in Nevo (2000b) range from 0.05 to 0.4. The cross-price elasticity estimates across bath-tissue brands in Hausman and Leonard (2002) range from 0.01 to 0.7. The cross-price elasticities across yogurt brands estimated in Villas-Boas (2007a) range from 0.018 to 0.032.

Table 3: Mean Own-price Elasticities, by Coffee Type

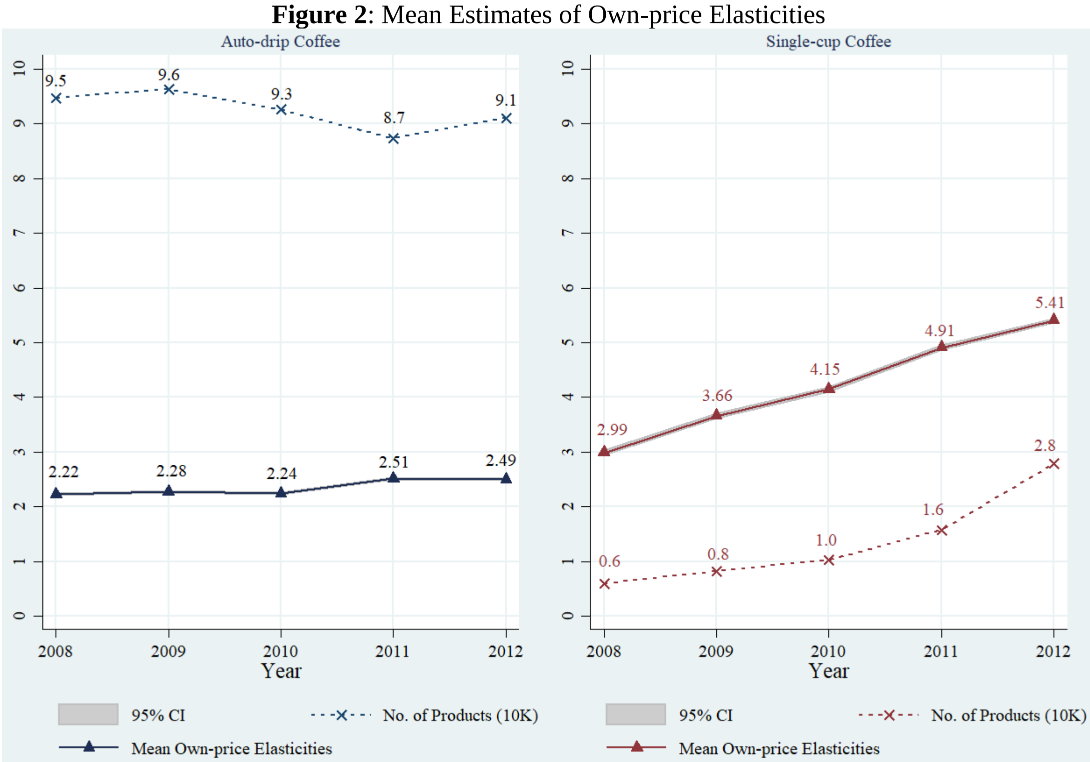
	Auto-drip Brew Products			Single-cup Brew Products		
Year	**Mean**	**Std. Error**	**No. of products**	**Mean**	**Std. Error**	**No. of products**
2008	-2.22	0.0085	94,722	-2.99	0.0219	5,952
2009	-2.28	0.0080	96,377	-3.66	0.0238	8,212
2010	-2.24	0.0083	92,590	-4.15	0.0200	10,277
2011	-2.51	0.0091	87,337	-4.91	0.0190	15,770
2012	-2.49	0.0087	91,079	-5.41	0.0163	27,856

Table 4: Mean Cross-price Elasticities, by Coffee Type

I \ j	Single-cup Brew Products		Auto-drip Brew Products	
	Mean	**Std. Error**	**Mean**	**Std. Error**
Single-cup Brew Products	0.03141	0.00038	0.01428	0.00014
Auto-drip Brew Products	0.01800	0.00024	0.03310	0.00043

Cell entries *I*, *j*, where *I* indexes row and *j* column, gives the percent change in market demand for product *I* due to a 1% change in price of product *j*. Each entry represents the mean of the cross-price elasticities from the 4,179 markets.

Figure 2: Mean Estimates of Own-price Elasticities



Diversion Ratios

Besides estimating the cross-price elasticities between single-cup and auto-drip coffee products, we also compute the diversion ratios to have a more thorough understanding of the substitution characteristics among the two coffee types as well as with the outside option.[30] Though diversion ratios are known to be extensively examined in antitrust analyses,[31] more broadly, they provide an alternative perspective for understanding the substitution attributes in markets with differentiated products, which Conlon and Mortimer (2021) argue cannot be captured by cross-price elasticities.

The diversion ratio from product j to product k, D_{jk}, answers the following question: If the price of product j were to rise, what fraction of the customers leaving product j would switch to product k (Shapiro, 1995, 2010)? For the random-coefficients logit demand model, we compute individual i's diversion ratio from product j to product k as $D_{i,jk} = \left(\frac{\partial s_{ik}}{\partial p_j}\right) \Big/ \left|\frac{\partial s_{ij}}{\partial p_j}\right|$ for a small price change, with individual weight function, w_{ij}, described in Conlon and Mortimer (2021). So, the diversion ratio, D_{jk}, is simply the weighted-average diversion across all the sampled individuals who consumed product j in the given market.[32] For a market with J products, we obtain a $J \times J$ square matrix of weighted-average diversion ratio estimates for each product j with respect to all other products, $k \neq j$, offered in the market, with zeros inserted on the main diagonal of the matrix. The individual diversion ratio from product j to the outside option is given by: $D_{i,j0} = \left(\frac{\partial s_{i0}}{\partial p_j}\right) \Big/ \left|\frac{\partial s_{ij}}{\partial p_j}\right|$, with the above-mentioned individual weights.

For the present paper we are interested in using diversion ratios to answer the following: If the price of a typical single-cup coffee product marginally increases, what fractions of the customers leaving the single-cup coffee product would switch to (*i*) auto-drip coffee products, (*ii*) other single-cup coffee products, and (*iii*) the outside option, respectively? We summarize and plot in Figure 3 the model-predicted mean weighted-average diversion ratios based on the demand parameter estimates.[33] The solid line plots the mean weighted-average diversion ratios of single-cup products to the outside good. It shows a slight declining trend of a typical single-cup product's lost sales diverted to the outside option, driven by a marginal increase in price of the single-cup

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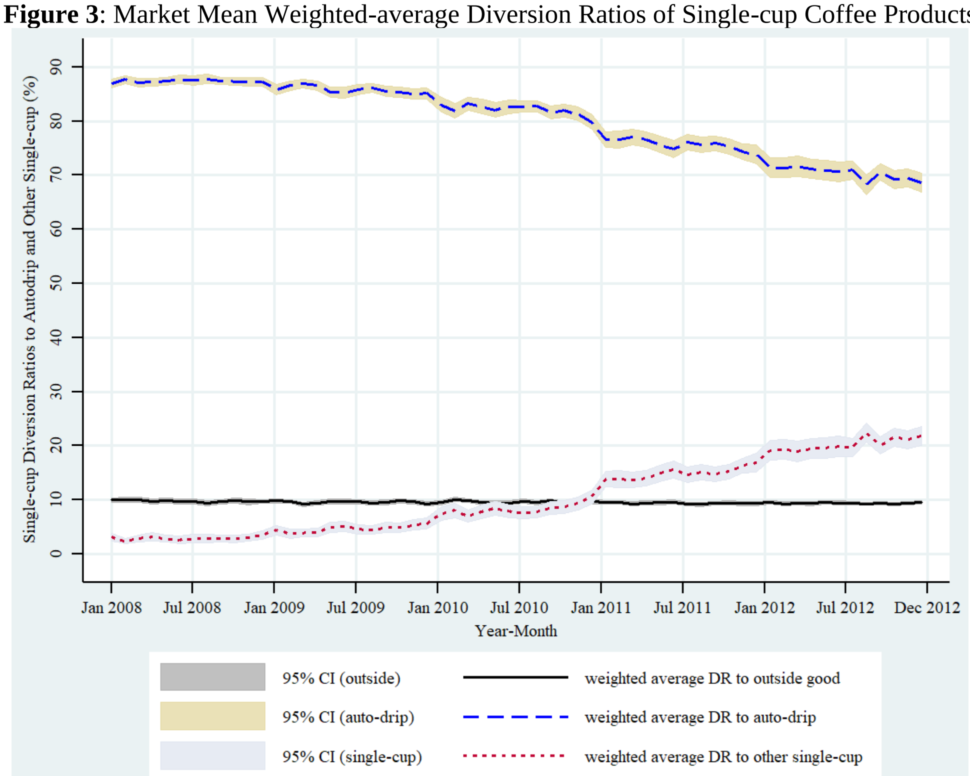
[30] We thank an anonymous referee for suggesting computation of diversion ratios to provide the reader with a more complete picture of product substitution patterns.
[31] For example, see Shapiro (1995, 2010), Farrell and Shapiro (2010), and Conlon and Mortimer (2013).
[32] Recall that the predicted product share integral for each product is approximated by the simulator over 200 individual random draws. Therefore, the weighted-average diversion ratio function is given as: $D_{jk} = \sum_{i=1}^{200}\left(D_{i,jk} w_{ij}\right)$, where w_{ij} is the individual weight function for small price changes as in Table 2 of Conlon and Mortimer (2021, p45).
[33] The corresponding numerical estimates in Figure 3 are reported in Table A1, A2, and A3 in Appendix A.

product. For example, we find the market mean weighted-average diversion of single-cup products' lost consumption to the outside option is approximately 9.8% in 2008, and it declines to 9.4% in 2012, indicating that the fraction of coffee consumers willing to switch from a single-cup product to the outside option (not consuming either coffee type) generally declines over time.

The long-dashed line represents the mean diversions to auto-drip products. During the early years of single-cup product presence through to the end of 2010, lost consumption of this coffee product type diverted to auto-drip products declines slightly from 87% to 82%, with a more precipitous decline thereafter through 2012 to 70%. Meanwhile, the short-dashed line that represents estimated mean diversions of lost consumption of a single-cup product to other single-cup products in the market, increased substantially from 2.9% in 2008 to 8.2% in 2010, surpassing the estimated diversion ratio to the outside option beginning 2011, with a consistent rise to 20% in 2012. The 95% confidence intervals in the figure reveal that the predicted diversion ratios are all statistically different from zero at a conventional level of statistical significance.

Figure 3: Market Mean Weighted-average Diversion Ratios of Single-cup Coffee Products



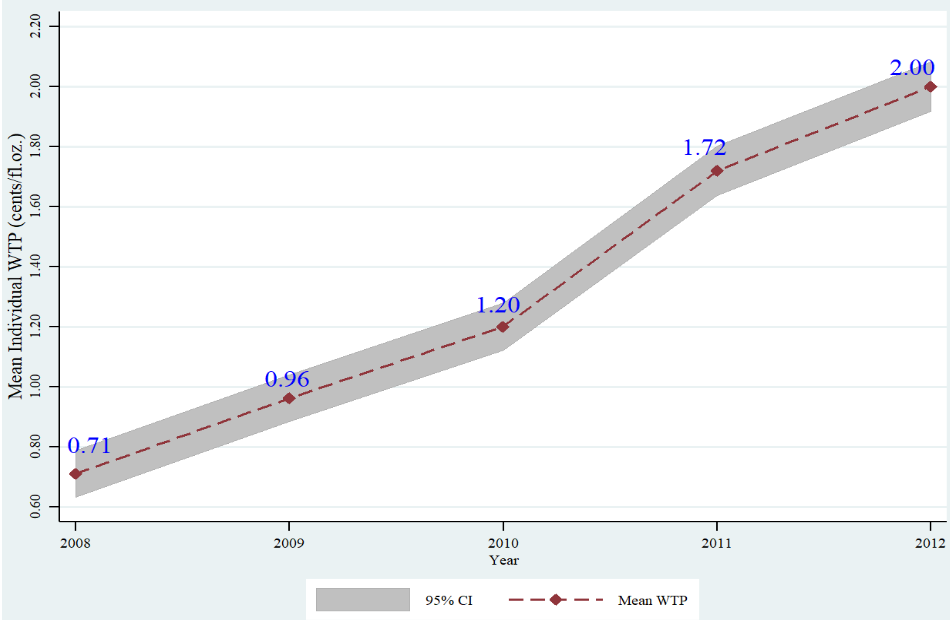
Comparing the three line-plots, for a given period, the lost sales of a single-cup product in response to a marginal price increase of this product are primarily diverted to auto-drip products, followed by diversions to the outside option and other single-cup products, respectively, during the early stage of single-cup products' presence. However, as the single-cup coffee segment gradually becomes mature with increased market presence and penetration over time, beginning in 2011 the lost consumption of a single-cup product is more likely to divert to another single-cup option available in the market rather than to the outside option. The diversion ratio to the auto-drip option, nonetheless, is still the largest. As such, it is reasonable to conjecture that if single-cup coffee products were to be removed from the market, those who initially consume single-cup products are more likely to switch their consumption to auto-drip products offered in the market than to the outside option. This suggests that the presence of single-cup coffee products partially cannibalizes sales of auto-drip coffee products, an inference we further explore in the next section using counterfactual analysis.

Willingness to Pay (WTP)

Discrete choice models have long been widely applied to derive estimates of willingness-to-pay (WTP) for various measured product attributes. The WTP for a product attribute is the ratio of the marginal utility of this attribute to the marginal utility of the cost to obtain this attribute. In the present paper, one of our research objectives is to understand how much consumers are willing to pay for their coffee consumption experience that uses single-cup brewing technology relative to the traditional auto-drip brewing method. An interesting perspective of this WTP measure is to examine how a typical consumer's WTP estimate for this single-cup consumption attribute changes over time. To obtain such estimates, we compute the mean individual WTP across the 200 individuals drawn in each market. The computation uses the individuals' marginal utility coefficient estimates on the interaction terms between the single-cup dummy variable and the year dummies divided by their respective marginal utility coefficient estimates on price across all markets in each of the sample years.

In Figure 4, we plot the estimated yearly mean individual WTP of a typical consumer's single-cup coffee consumption experience relative to their traditional auto-drip coffee consumption experience. The mean individual WTP estimates are measured on the vertical axis in cents per equivalent fluid ounce (fl. oz.). The shaded area around the curve represents the 95% confidence intervals for these WTP estimates. This diagram shows that an average consumer's WTP for her coffee consumption experience using the newly introduced single-cup brewing method increases over time from 0.71 cents/fl. oz in 2008 to 2 cents/fl. oz. in 2012. These WTP estimates imply that in 2008 a typical consumer is willing to pay an extra 7 cents for a standard 10 fl. oz. cup of freshly home-brewed coffee using the single-cup brewing method, but in year 2012 this WTP increases to around 20 cents extra for a standard 10 fl. oz. cup of freshly home-brewed coffee, corresponding to a 180% increase in WTP for the single-cup coffee consumption experience.

Figure 4: Line Plot of Mean Individual Willingness to Pay ($\overline{WTP}$), by Year (all counties)



6. Counterfactual Analysis

To examine the market effects of the introduction and growing presence of single-cup brew coffee products, we follow an approach similar to that in Petrin (2002) by counterfactually removing the single-cup coffee products from each market.[34] This exercise is operationalized by first removing single-cup coffee products from the data sample, and then use the supply side of our model to compute on a market-by-market basis the set of auto-drip product prices that satisfy the remaining set of Nash equilibrium price-setting first-order conditions. By comparing this new model-predicted price vector with the observed price vector of the pre-existing auto-drip coffee products, we are able to understand the "price effects" that resulted from the introduction of a new product, similar to Hausman and Leonard (2002).

To understand the impacts of the new product's introduction and growing presence on quantities of the pre-existing products and the outside option, as well as the associated welfare

[34] Petrin (2002) evaluates the economic effects of the introduction of the minivan by counterfactually removing the minivans from the market.

effects, we undertake two types of comparisons. In the first counterfactual experiment (denoted as "Counterfactual Experiment 1"), we use the new price vector obtained from the Nash-equilibrium that is generated based on the counterfactual absence of single-cup products to compute the model-predicted quantities demand for the auto-drip products and the outside good, respectively. The comparison between the counterfactual equilibrium quantities evaluated at the new price levels based on the absence of the new products and the factual model-precited quantities evaluated at observed price levels, reveals the full demand impacts of the new product introduction on the pre-existing products and the outside good.

In the second counterfactual experiment (denoted as "Counterfactual Experiment 2"), we compute the counterfactual equilibrium quantities of auto-drip products and the outside good with the absence of the new products while holding at their factual observed levels the prices of auto-drip products. We then compare these counterfactual quantities with the factual model-predicted quantities evaluated at observed price levels with the presence of the new products. In this exercise, we aim to understand the pure "variety effects" of the new product introduction by nullifying the "price effects", i.e., in this exercise we impose the restriction that prices of the pre-existing products are unaffected by the market presence of the new product.

In summary, counterfactual experiment 1 captures the full market impacts of the introduction of the new products, where the full market impacts include both "price effects" and "variety effects" as discussed in Hausman and Leonard (2002). However, counterfactual experiment 2 captures only the extent of "variety effects" due to the introduction of the new products. The reader is referred to Appendix C for details on how the counterfactual experiments are formally implemented.

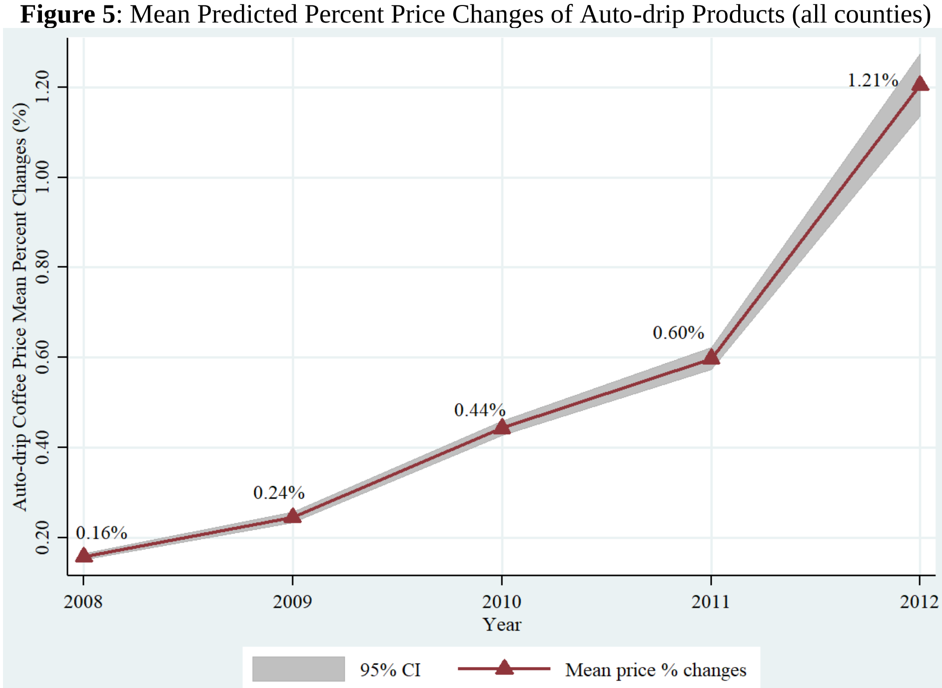
6.1 Predicted Changes in Prices of Auto-drip Coffee

In Figure 5, we summarize and plot the time series variations in the predicted mean percent price changes of auto-drip coffee products after we counterfactually removed the single-cup products.[35] The plot shows that, in general, the prices of auto-drip coffee products are predicted to increase during the sample periods; and the magnitude of the price increase becomes larger over

[35] Readers may refer to Table A4 in the appendix for detailed numerical estimates. We also find the predicted mean percent price changes in each time period for each of the fifteen counties studied in the data sample are all positive. As such, we can infer that the entry and presence of single-cup products is predicted to have reduced the price levels of auto-drip coffee products in each geographic market. Results for individual counties can be made available upon request.

time. The positive values in the plot reveal that the prices of auto-drip brew coffee products, on average, are predicted to increase due to the counterfactual removal of single-cup brew coffee products. Another way of interpreting the positive values in the plot is that auto-drip brew coffee products, on average, are predicted to have experienced decreases in prices driven by the introduction of single-cup brew coffee products. Specifically, the entry and growing presence of single-cup brew coffee products caused the price levels of pre-existing auto-drip coffee products to drop by about 0.2% in 2008 than they would be otherwise, and this downward price effect grew about sixfold up to 1.2% in 2012. This evidence is consistent with findings in Petrin (2002), Hausman and Leonard (2002), and other studies showing that prices of pre-existing products generally decline with new product introduction.

Figure 5: Mean Predicted Percent Price Changes of Auto-drip Products (all counties)

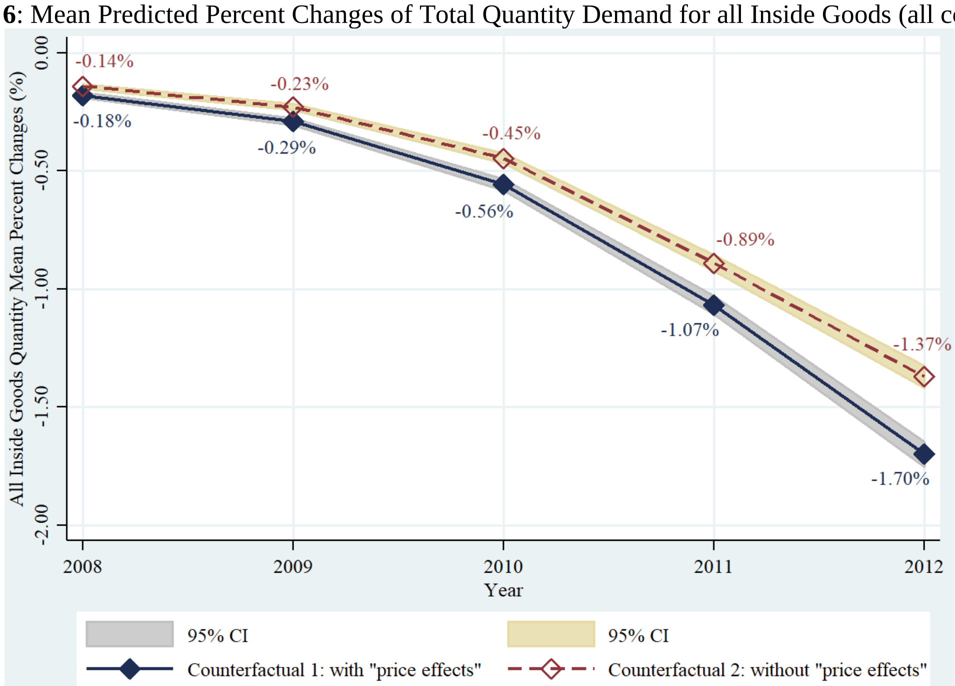


6.2 Predicted Changes in the Total Quantity Demand of All Inside Goods: "Market-Expansionary" Effect vs. "Market-Shrinkage" Effect

To understand whether a new product introduction either expands or shrinks the relevant market, we analyze whether it has a positive or negative impact on the outside good demand or the total demand of all the brew-at-home coffee products (inside goods) after the counterfactual removal of the new product from the relevant market. In Figure 6, we show the mean predicted percent changes in the total quantities of all inside goods in counterfactual experiments 1 and counterfactual experiment 2, respectively.[36] The solid line represents the mean percent changes in the total quantity of all inside goods when allowing the prices of auto-drip products to reflect the reduced competition due to the absence of single-cup products (Counterfactual Experiment 1). The dashed line represents the mean percent changes in total inside goods demand based on nullifying the “price effects” on pre-existing auto-drip products (Counterfactual Experiment 2).

The negative estimated changes of total inside goods demand in both counterfactual exercises reveal predicted shrinking of the brew-at-home coffee market driven by the counterfactual removal of single-cup products. This finding implies that the presence of single-cup products served to expand the total market demand for brew-at-home coffee (or equivalently shrink demand for the outside good). Both lines are downward-sloping, indicating a growing market-expansionary effect over the period as single-cup brew products gained popularity in the brew-at-home coffee market. The solid line lies below the dash line, indicating that the “price effects” increased the market-expansionary effects, i.e., the decline in price levels of auto-drip products driven by the introduction and growing penetration of single-cup products served to make the market-expansionary effects larger.

Figure 6: Mean Predicted Percent Changes of Total Quantity Demand for all Inside Goods (all counties)



The above finding is consistent with what is implied by the positive percent changes in the outside good demand driven by the counterfactual removal of single-cup products in each sample

[36] Detailed numerical estimates are reported in Table A5 in the appendix.

year.[37] We find the introduction of single-cup brew coffee products brings into the brew-at-home coffee market an extra 0.24% more of the potential demand that would otherwise remain outside the brew-at-home coffee market during 2008, and this percentage grew almost tenfold to 2.28% in 2012. As such, the introduction of single-cup brew coffee products expanded the brew-at-home coffee market, and this market-expansionary effect grew substantially over time.

6.3 Predicted Changes in Quantity Demand of Auto-drip Products: "Demand-increasing" Effect vs. "Demand-cannibalizing" Effect

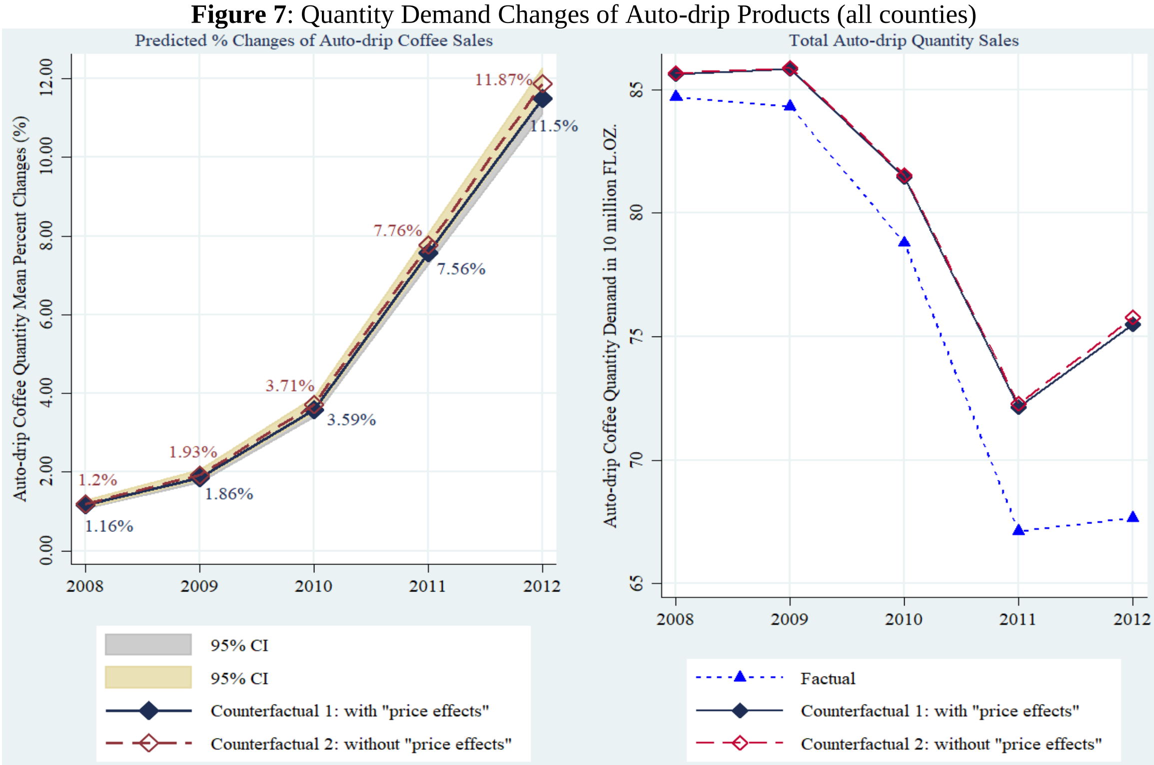
Similarly, to understand whether a new product introduction either increases or cannibalizes the quantity sales of the pre-existing products in the relevant market, we analyze whether the counterfactual absence of the new product negatively or positively impacts demand for the pre-existing products. In the left panel of Figure 7, we plot the mean predicted percent changes in quantity sales of the auto-drip brew products for both counterfactual experiments.[38] The plot shows that quantity sales of the pre-existing auto-drip products are predicted to increase due to the counterfactual removal of single-cup brew coffee products; and the magnitude of the increase becomes larger over time. Therefore, we can infer from this result that the introduction of single-cup brew coffee products cannibalized the sales of the pre-existing auto-drip products; and the size of this cannibalization increased over time. In particular, the solid line in the figure shows that the size of cannibalized auto-drip coffee demand has grown almost tenfold from about 1.16% in 2008 up to 11.5% in 2012. Furthermore, given that the solid line lies below the dash line, it is apparent that the decline in prices of auto-trip products caused by the introduction of single-cup brew products served to mitigate the extent of the sales cannibalization of auto-drip products.

To see how much the introduction of the new goods influenced the sales of the pre-existing coffee segment, in the right panel of Figure 7 we plot the time series of factual and counterfactual demand for auto-drip products over the sample period. The short-dash line of factual aggregate sales of auto-drip products in the right panel of Figure 7 replicates the short-dash line in the right panel of Figure 1, while the model-predicted time series plot of aggregate sales of auto-drip products in the two counterfactual exercises are represented by the solid line and the long-dash line, respectively. These line plots clearly reveal that aggregate sales of the pre-existing auto-drip products would have been at a higher level from 2008 through 2012, and more so toward the end

[37] Readers may refer to Table A6 in the appendix for detailed numerical estimates.
[38] Readers may refer to Table A7 in the appendix for detailed numerical estimates.

of the sample period, if single-cup brew coffee products were not introduced to the brew-at-home coffee market. The two lines representing the quantity sales of auto-drip products obtained from the two counterfactual experiments, however, suggest small quantity differences at the aggregate level regarding whether the "price effects" on auto-drip products are accounted for with the counterfactual absence of single-cup brew products.

Figure 7: Quantity Demand Changes of Auto-drip Products (all counties)



In summary, the evidence provided in Figures 6 and 7 reveal that the introduction and growing popularity of the single-cup coffee prods, which caused the creation of a whole new segment, has not only expanded the brew-at-home coffee market (i.e., a "market-expansionary" effect) but also cannibalized the demand for the pre-existing traditional auto-drip coffee products (i.e., a "demand-cannibalization" effect) in each of the sample periods. Furthermore, both the sizes of market-expansionary effect and demand-cannibalization effect are predicted to have quickly grown over time through the end of sample period.

6.4 Consumer Welfare Analysis

We follow Nevo (2001), McFadden (1984), Small and Rosen (1981), Train (2009), and many others and compute the change in consumer welfare associated with imposing the counterfactual assumption that single-cup coffee products are no longer available in markets, leaving consumers options of either auto-drip products or the outside good.

Table 5 summarizes the model-predicted effects on individual consumer welfare due to the counterfactual elimination of single-cup brew coffee options. Specifically, the table presents the average predicted percent changes of individual consumer surplus in each of the five years across all geographic areas in the data sample. These estimates in the table are all negative, ranging from -0.3% to -2.8%. The decline in estimated consumer welfare is also reflected in Figure 8.[39] The negative percent changes imply that, on average, an individual consumer is predicted to have benefited from the new product introduction, with year-specific increases in consumer surplus that grew ninefold from 0.3% in 2008 to 2.8% in 2012. In dollar term, the mean per-capita welfare gain increases from $0.82 in 2008 to $9.15 in 2012. For comparative purposes, Hausman (1996) reports estimated individual consumer surplus increases for new brand introduction in the ready-to-eat cereal market ranging from $0.268 to $0.3136 per year. Estimated gains in consumer surplus associated with new product introductions in various industries can be found in several studies [e.g., Petrin (2002); and Hausman and Leonard (2002)].

According to Nevo (2000b), the indirect utility function specified in equation (1) can be derived from a quasilinear utility function, free of wealth effects. It is reasonable to assume the wealth effects for the retail-level packaged coffee products are small or negligible, like other consumer packaged goods, for example, ready-to-eat cereals studied in Nevo (2000a). In this case, consumer surplus will be very close to both compensating variation (CV) and equivalent variation, which also means the consumer surplus estimates obtained by equation (6) approximate well the estimates of compensating variation [see Nevo (2000b)].

In Table 5, we also report the estimated change in individual consumer surplus to approximate mean individual compensating variations for a typical coffee drinker from 2008 through 2012. In particular, the estimates reported in the table reveal that if single-cup coffee products are counterfactually removed from markets in year 2008, and given the prices of auto-drip coffee products that would prevail in counterfactual experiment 1, the typical consumer needs to be compensated 0.01 cent per fluid ounce of coffee to maintain their welfare at the level prior

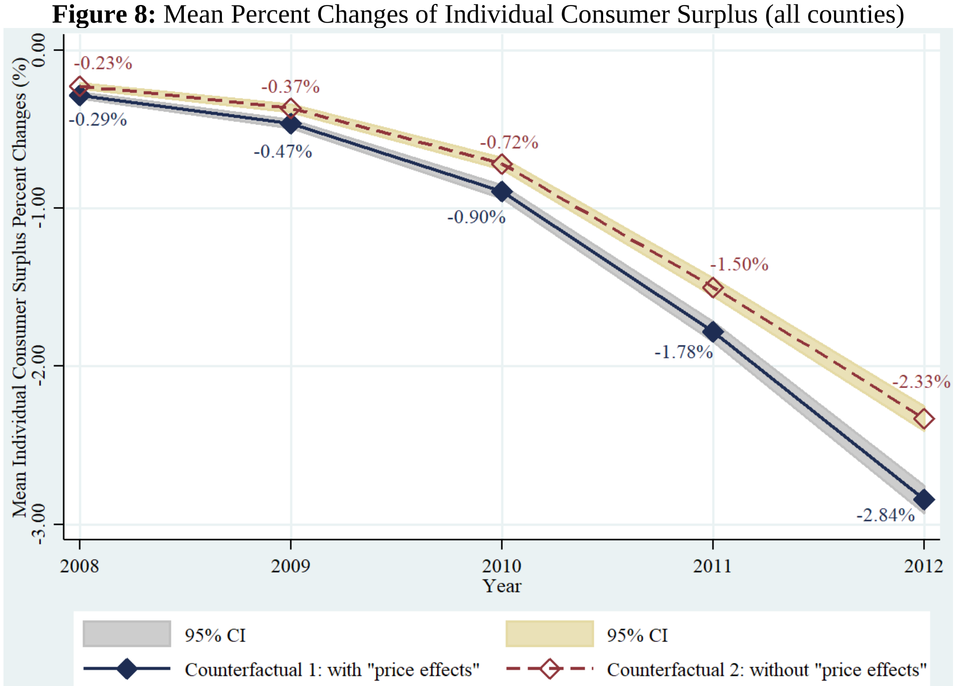
[39] Readers may refer to Table A8 in the appendix for detailed numerical estimates. The predicted changes in mean individual consumers surplus in each county are all negative with a downward sloping trend over the sample periods, implying the entry and presence of single-cup products is predicted to have increasingly benefited consumers in each individual local market. Results for individual counties can be made available upon request.

to the elimination of single-cup coffee products. However, in year 2012 such compensation is 0.13 cent per fluid ounce of coffee, which is 13 times larger compared to the compensation level in year 2008.

Table 5: Mean Predicted Changes in Individual Consumer Surplus (all counties)

Year		2008		2009		2010		2011		2012	
Cups per person per day (NCA 2016)		1.75		1.76		1.79		1.95		1.98	
Total adult population in million (U.S. Census Bureau)		230		232		235		238		240	
		Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
Counter-factual Experiment 1: with "price effects"	% change	-0.29%	0.010	-0.47%	0.013	-0.90%	0.021	-1.78%	0.032	-2.84%	0.045
	Mean change in Individual CS cents/fl. oz.	-0.013	0.0004	-0.021	0.001	-0.040	0.001	-0.079	0.001	-0.127	0.002
	Mean per-capita CV in a year ($)	$ 0.82		$ 1.33		$ 2.59		$ 5.65		$ 9.15	
	Total CVs in the population in a year (million $)	$ 188.03		$ 309.61		$ 609.09		$ 1,344.72		$ 2,196.57	
Counter-factual Experiment 2: without "price effects"	% change	-0.23%	0.009	-0.37%	0.012	-0.72%	0.019	-1.50%	0.029	-2.33%	0.040
	Mean change in Individual CS cents/fl. oz.	-0.010	0.0004	-0.016	0.0005	-0.032	0.0009	-0.067	0.0013	-0.104	0.0018
	Mean per-capita CV in a year ($)	$ 0.64		$ 1.05		$ 2.08		$ 4.76		$ 7.51	
	Total CVs in the population in a year (million $)	$ 147.60		$ 244.27		$ 488.56		$ 1,132.74		$ 1,801.66	

Figure 8: Mean Percent Changes of Individual Consumer Surplus (all counties)



If we nullify the price adjustments of auto-drip products in the absence of single-cup products (counterfactual experiment 2), the estimated mean compensating variation represents the values to an average consumer associated with the additional product variety in the presence of the new products, i.e., the "variety effects" as in Hausman and Leonard (2002).[40] As shown in Table 5, the CV estimates for counterfactual experiment 2 are generally smaller in magnitude than the ones for counterfactual experiment 1. This is because the compensating variations in counterfactual experiment 1 represent the full effect on consumers associated with the presence of new products, which is the sum of the "variety effect" and the "price effect" on pre-existing products.

To better put in context the per capita compensating variation estimates, we can use these per capita estimates to infer the monetary value of the aggregate welfare effects among the adult population in the U.S. Accordingly, we compute the total annual compensating variations across the adult population of the U.S. by multiplying together the following: (*i*) the individual compensating variation estimate for the given year; (*ii*) total adult population;[41] (*iii*) the per capita number of cups (average cup size is 10 fluid ounces) consumed per day;[42] and (*iv*) 365 days. The results for counterfactual experiment 1, reported in Table 5, suggest that the entire adult population need to be compensated by a total amount of $188 million in 2008 at the new equilibrium price levels of traditional auto-drip coffee products in the absence of single-cup products in order to achieve the "standard of living" when the single-cup options are available. The table also shows that this total compensating variation increases each year and reaches a level of $2,196 million in year 2012.

7. Conclusion

New product introductions are particularly proliferating in the "fast-moving" consumer-packaged goods sectors. This paper aims to understand the market impacts of a new product associated with its growing presence in the relevant market over time. Our empirical focus is the U.S. brew-at-home coffee market in which consumers purchase various packaged coffee products from grocery stores and brew coffee at home for their daily coffee consumption. The introduction

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[40] Brynjolfsson et.al. (2003) also provided empirical evidence that consumers gain dramatically with increased product variety.
[41] Total U.S. population data are obtained from the U.S. Census Bureau population and housing unit estimates.
[42] Survey information is obtained from the 2016 report of National Coffee Data Trends from the National Coffee Association (NCA).

of single-cup brew coffee products to the grocery chains has not only changed the way many brew-at-home coffee drinkers brew and consume coffee in daily life, a change from brewing one “pot” at a time to making one cup at a time, but also altered the overall “landscape” of the U.S. brew-at-home coffee market.

We use a structural demand model along with an assumption that coffee manufacturers set prices according to a static Bertrand-Nash equilibrium to enable estimating the economic effects associated with the introduction and growing presence of single-cup brew coffee products in the U.S. brew-at-home coffee market. The estimated model is used to implement two counterfactual experiments that disentangle “price effects” on the pre-existing auto-drip products from pure “variety effects” associated with market presence of the new product. As such, by counterfactually nullifying price effects on pre-existing products, we are able to obtain separate estimates of the impacts of the new product solely due to the product providing an additional variety available to consumers.

From the demand estimates, we find consumers, on average, prefer consuming brewed coffee products using the single-cup brew method instead of the traditional auto-drip brew method; and this relative preference increased substantially over time. In addition, our model predicts that the average coffee drinker’s willingness-to-pay for a cup of freshly brewed coffee with the new brewing method in year 2012 is about 180% more than their willingness-to-pay in year 2008.

The counterfactual experiments predict mean decreases in the total quantity sales of all inside goods (or equivalently increases in the demand for the outside good) and mean increases in the quantity sales of the auto-drip products when we counterfactually eliminated the single-cup brew product options. These predicted changes imply the presence of the single-cup brew products not only has a market-expansionary effect on the brew-at-home coffee market, but also a demand-cannibalization effect on the quantity sales of the pre-existing auto-drip coffee segment. In addition, the size of market-expansionary and demand-cannibalization effects both increase in magnitude over time as single-cup brew products grew in popularity among brew-at-home coffee drinkers. The estimates obtained from the experiment that captures the “variety effects” after nullifying the “price effects” are qualitatively similar to the estimates obtained from the experiment that considers both the “variety effects” and “price effects” associated with the new product introduction.

Last, we compute money-metric welfare changes to individual consumers associated with the introduction and growing presence of single-cup brew coffee options. Our welfare estimates suggest that consumers, on average, benefited from the new coffee product introduction, which is consistent with findings in the literature on new product introductions in other industries. Estimated individual compensation variations obtained from the experiment that allows the prices of the pre-existing auto-drip products to reflect the reduced competition in the absence of the new product suggest that: if single-cup brew options were to be removed from consumers' choice sets, then to maintain consumers' valuation at the level prior to removal of these choice options requires the average consumer be compensated a dollar amount in year 2012 that is 13 times larger than the compensation amount in year 2008. Extending the compensating variation estimates to the entire adult population in the U.S. suggest a compensation amount of $188 million in year 2008 compared to a substantially higher compensation amount of $2,196 million in year 2012. These positive changes in consumer welfare are in large part due to the increased product variety caused by the presence of single-cup products, the "variety effects". Furthermore, the magnitude of the "variety effects" grew over time as the new products become increasingly popular among coffee drinkers.

It is worth pointing out some limitations of our analysis. We simplify modeling the supply side of the market by assuming retailers play a passive role in the price-setting game. Other vertical relationships between coffee manufacturers and retailers can be examined as a potential extension of this current work [see, Villas-Boas (2007b) and Hellerstein and Villas-Boas (2010)]. Another limitation of this study is the inability of modeling consumers' hardware adoption decisions, i.e., consumers purchase decision of coffee brew machines, due to the unavailability of data on purchases of coffee brew machines. Future research may consider investigating whether various vertical contracts between manufacturers and retailers influence counterfactual predicted changes in market outcomes obtained in our study.

Appendix A – Tables

Table A1: Weighted Average Diversion Ratios (measured in %) of Single-cup Products' lost Sales to the Outside Option, by Year-Month (all counties)

Month \ Year	2008		2009		2010		2011		2012	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	9.946	0.224	9.798	0.227	9.505	0.189	9.561	0.182	9.491	0.155
February	9.986	0.216	9.688	0.194	10.056	0.194	9.570	0.174	9.281	0.167
March	10.015	0.218	9.142	0.210	9.853	0.198	9.295	0.174	9.376	0.166
April	9.664	0.234	9.452	0.206	9.493	0.212	9.434	0.208	9.305	0.184
May	9.839	0.221	9.710	0.225	9.448	0.189	9.466	0.177	9.510	0.168
June	9.722	0.229	9.716	0.223	9.462	0.217	9.616	0.184	9.457	0.184
July	9.710	0.224	9.690	0.203	9.733	0.205	9.221	0.183	9.437	0.165
August	9.338	0.222	9.405	0.198	9.490	0.188	9.202	0.205	9.301	0.152
September	9.679	0.207	9.540	0.209	9.847	0.179	9.408	0.179	9.310	0.165
October	9.890	0.235	9.778	0.203	9.350	0.196	9.445	0.174	9.212	0.138
November	9.686	0.281	9.618	0.232	9.359	0.184	9.332	0.183	9.444	0.166
December	9.649	0.174	9.253	0.208	9.706	0.209	9.349	0.188	9.535	0.146
Mean	**9.760**	**0.065**	**9.565**	**0.061**	**9.609**	**0.057**	**9.409**	**0.053**	**9.388**	**0.047**

Table A2 Weighted Average Diversion Ratios (measured in %) of Single-cup Products' lost Sales to Auto-drip Products, by Year-Month (all counties)

Month \ Year	2008		2009		2010		2011		2012	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	86.965	0.426	85.822	0.474	83.033	0.663	76.616	0.732	71.379	0.931
February	87.672	0.353	86.589	0.428	81.910	0.669	76.555	0.779	71.354	0.915
March	87.163	0.398	86.978	0.415	83.221	0.593	77.067	0.717	71.641	0.951
April	87.192	0.391	86.580	0.453	82.691	0.666	76.585	0.690	71.200	0.894
May	87.351	0.376	85.396	0.475	82.083	0.655	75.663	0.752	70.906	0.941
June	87.701	0.408	85.217	0.514	82.667	0.620	74.793	0.784	70.658	0.928
July	87.506	0.414	85.774	0.473	82.696	0.517	76.110	0.714	70.959	0.841
August	87.794	0.418	86.157	0.415	82.745	0.536	75.654	0.709	68.254	0.921
September	87.431	0.351	85.539	0.472	81.614	0.589	75.890	0.707	70.609	0.791
October	87.327	0.375	85.373	0.501	81.949	0.608	75.338	0.700	69.195	0.820
November	87.268	0.431	85.045	0.508	81.316	0.630	74.377	0.687	69.485	0.846
December	87.268	0.431	85.155	0.535	79.789	0.677	73.856	0.864	68.624	0.891
Mean	**87.353**	**0.115**	**85.809**	**0.137**	**82.160**	**0.180**	**75.706**	**0.215**	**70.340**	**0.258**

Table A3: Weighted Average Diversion Ratios (measured in %) of a Single-cup Product's lost Sales to Other Single-cup Products, by Year-Month (all counties)

Year / Month	2008		2009		2010		2011		2012	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	3.088	0.347	4.380	0.445	7.463	0.643	13.823	0.724	19.130	0.937
February	2.341	0.266	3.723	0.412	8.033	0.675	13.875	0.790	19.364	0.932
March	2.822	0.341	3.879	0.400	6.926	0.564	13.637	0.719	18.983	0.954
April	3.144	0.388	3.968	0.424	7.816	0.625	13.981	0.720	19.496	0.890
May	2.811	0.327	4.894	0.486	8.470	0.635	14.870	0.726	19.585	0.965
June	2.576	0.363	5.067	0.475	7.871	0.605	15.592	0.817	19.886	0.947
July	2.784	0.400	4.537	0.412	7.571	0.562	14.670	0.706	19.604	0.841
August	2.868	0.390	4.438	0.391	7.765	0.517	15.145	0.729	22.445	0.904
September	2.891	0.324	4.921	0.449	8.540	0.592	14.702	0.660	20.081	0.814
October	2.783	0.342	4.849	0.453	8.702	0.604	15.217	0.705	21.593	0.837
November	3.046	0.329	5.337	0.480	9.325	0.617	16.292	0.680	21.071	0.847
December	3.498	0.417	5.592	0.511	10.505	0.665	16.795	0.876	21.841	0.896
Mean	**2.887**	**0.102**	**4.626**	**0.129**	**8.230**	**0.177**	**14.886**	**0.215**	**20.273**	**0.260**

Table A4: Mean Predicted Percent Price Changes of Auto-drip Coffee Products, by Year-Month (all counties)

Month / Year	2008		2009		2010		2011		2012	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	0.19%	0.018	0.22%	0.016	0.39%	0.028	0.57%	0.041	0.93%	0.056
February	0.15%	0.011	0.18%	0.016	0.44%	0.029	0.59%	0.043	1.01%	0.057
March	0.16%	0.011	0.20%	0.015	0.43%	0.032	0.60%	0.039	1.00%	0.057
April	0.15%	0.010	0.23%	0.019	0.42%	0.028	0.59%	0.037	1.10%	0.064
May	0.14%	0.011	0.23%	0.017	0.46%	0.031	0.61%	0.043	1.09%	0.060
June	0.14%	0.012	0.23%	0.017	0.44%	0.029	0.59%	0.044	1.14%	0.065
July	0.14%	0.012	0.23%	0.016	0.46%	0.028	0.59%	0.041	1.11%	0.067
August	0.13%	0.010	0.25%	0.018	0.47%	0.025	0.59%	0.043	1.72%	0.345
September	0.16%	0.011	0.22%	0.016	0.48%	0.026	0.53%	0.037	1.25%	0.083
October	0.16%	0.012	0.29%	0.024	0.47%	0.027	0.56%	0.040	1.49%	0.089
November	0.16%	0.011	0.30%	0.025	0.40%	0.027	0.62%	0.046	1.19%	0.062
December	0.18%	0.013	0.35%	0.029	0.45%	0.035	0.72%	0.047	1.40%	0.083
Overall Mean	**0.16%**	**0.003**	**0.24%**	**0.006**	**0.44%**	**0.008**	**0.60%**	**0.012**	**1.21%**	**0.035**

Table A5: Mean Predicted Total Inside Goods Quantity Demand Percent Changes, by Year-Month (all counties)

Month \ Year	2008				2009				2010				2011				2012			
	Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	-0.20%	0.02	-0.15%	0.02	-0.27%	0.02	-0.22%	0.02	-0.49%	0.04	-0.40%	0.04	-1.01%	0.07	-0.86%	0.07	-1.57%	0.09	-1.29%	0.08
February	-0.16%	0.02	-0.13%	0.02	-0.24%	0.02	-0.20%	0.02	-0.57%	0.05	-0.46%	0.04	-0.98%	0.07	-0.83%	0.06	-1.56%	0.08	-1.26%	0.07
March	-0.17%	0.02	-0.13%	0.02	-0.23%	0.02	-0.19%	0.02	-0.50%	0.04	-0.39%	0.03	-0.96%	0.06	-0.79%	0.05	-1.57%	0.09	-1.28%	0.08
April	-0.17%	0.02	-0.13%	0.02	-0.25%	0.02	-0.20%	0.02	-0.54%	0.05	-0.43%	0.04	-0.96%	0.06	-0.79%	0.05	-1.60%	0.09	-1.28%	0.08
May	-0.17%	0.02	-0.13%	0.02	-0.29%	0.02	-0.23%	0.02	-0.56%	0.04	-0.45%	0.04	-1.11%	0.07	-0.93%	0.06	-1.68%	0.10	-1.36%	0.08
June	-0.16%	0.02	-0.12%	0.01	-0.30%	0.03	-0.24%	0.03	-0.52%	0.04	-0.41%	0.03	-1.13%	0.07	-0.95%	0.06	-1.68%	0.10	-1.36%	0.09
July	-0.18%	0.02	-0.14%	0.02	-0.29%	0.02	-0.23%	0.02	-0.52%	0.03	-0.41%	0.03	-1.05%	0.07	-0.86%	0.06	-1.62%	0.08	-1.32%	0.07
August	-0.17%	0.02	-0.14%	0.02	-0.28%	0.02	-0.22%	0.02	-0.53%	0.04	-0.42%	0.03	-1.06%	0.06	-0.86%	0.05	-1.97%	0.11	-1.56%	0.09
September	-0.18%	0.02	-0.15%	0.01	-0.30%	0.02	-0.24%	0.02	-0.61%	0.04	-0.48%	0.04	-1.03%	0.06	-0.86%	0.05	-1.59%	0.08	-1.29%	0.07
October	-0.19%	0.02	-0.15%	0.02	-0.34%	0.03	-0.26%	0.03	-0.58%	0.04	-0.46%	0.04	-1.07%	0.06	-0.90%	0.05	-1.81%	0.08	-1.43%	0.08
November	-0.19%	0.02	-0.15%	0.02	-0.34%	0.03	-0.26%	0.02	-0.57%	0.04	-0.46%	0.03	-1.18%	0.07	-0.98%	0.06	-1.73%	0.09	-1.42%	0.09
December	-0.22%	0.02	-0.17%	0.02	-0.37%	0.03	-0.28%	0.03	-0.72%	0.05	-0.60%	0.05	-1.30%	0.08	-1.07%	0.07	-1.99%	0.10	-1.61%	0.09
Overall Mean	**-0.18%**	**0.01**	**-0.14%**	**0.00**	**-0.29%**	**0.01**	**-0.23%**	**0.01**	**-0.56%**	**0.01**	**-0.45%**	**0.01**	**-1.07%**	**0.02**	**-0.89%**	**0.02**	**-1.70%**	**0.03**	**-1.37%**	**0.02**

Table A6: Mean Predicted Outside Good Quantity Demand Percent Changes, by Year-Month (all counties)

Month \ Year	2008				2009				2010				2011				2012			
	Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	0.28%	0.03	0.21%	0.03	0.36%	0.04	0.28%	0.03	0.66%	0.06	0.52%	0.05	1.35%	0.10	1.14%	0.09	2.11%	0.13	1.71%	0.12
February	0.23%	0.02	0.18%	0.02	0.32%	0.03	0.25%	0.03	0.75%	0.07	0.60%	0.06	1.33%	0.10	1.10%	0.09	2.09%	0.12	1.66%	0.10
March	0.24%	0.02	0.18%	0.02	0.30%	0.03	0.23%	0.02	0.66%	0.06	0.50%	0.05	1.30%	0.08	1.05%	0.07	2.12%	0.12	1.69%	0.11
April	0.24%	0.02	0.19%	0.02	0.33%	0.03	0.25%	0.03	0.70%	0.07	0.55%	0.06	1.30%	0.08	1.05%	0.07	2.14%	0.13	1.68%	0.11
May	0.24%	0.03	0.18%	0.03	0.38%	0.04	0.30%	0.03	0.72%	0.06	0.56%	0.05	1.50%	0.10	1.25%	0.09	2.25%	0.13	1.79%	0.12
June	0.21%	0.02	0.16%	0.02	0.40%	0.04	0.31%	0.04	0.68%	0.05	0.52%	0.05	1.54%	0.10	1.28%	0.08	2.26%	0.14	1.81%	0.12
July	0.23%	0.03	0.18%	0.02	0.38%	0.03	0.29%	0.03	0.67%	0.05	0.50%	0.04	1.41%	0.10	1.14%	0.09	2.15%	0.11	1.71%	0.10
August	0.22%	0.03	0.17%	0.03	0.37%	0.03	0.28%	0.03	0.69%	0.05	0.53%	0.04	1.43%	0.09	1.14%	0.08	2.66%	0.15	2.06%	0.13
September	0.23%	0.02	0.18%	0.02	0.38%	0.03	0.30%	0.03	0.79%	0.06	0.61%	0.06	1.38%	0.08	1.13%	0.07	2.11%	0.12	1.68%	0.10
October	0.24%	0.03	0.18%	0.02	0.44%	0.04	0.34%	0.04	0.74%	0.06	0.57%	0.05	1.41%	0.09	1.17%	0.08	2.43%	0.12	1.89%	0.11
November	0.25%	0.03	0.19%	0.03	0.44%	0.04	0.33%	0.04	0.73%	0.05	0.58%	0.05	1.57%	0.10	1.28%	0.08	2.33%	0.13	1.89%	0.12
December	0.28%	0.03	0.21%	0.03	0.50%	0.05	0.36%	0.04	0.94%	0.07	0.77%	0.07	1.74%	0.12	1.42%	0.10	2.64%	0.14	2.10%	0.13
Overall Mean	**0.24%**	**0.01**	**0.18%**	**0.01**	**0.38%**	**0.01**	**0.29%**	**0.01**	**0.73%**	**0.02**	**0.57%**	**0.02**	**1.44%**	**0.03**	**1.18%**	**0.02**	**2.28%**	**0.04**	**1.81%**	**0.03**

Table A7: Mean Predicted Total Quantity Demand Percent Changes of Auto-drip Products, by Year-Month (all counties)

Month \ Year	2008				2009				2010				2011				2012			
	Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"		Counter-factual 1: with "price effects"		Counter-factual 2: without "price effects"	
	Mean	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**	**Mean**	**Std. Error**
January	1.21%	0.15	1.26%	0.15	1.76%	0.20	1.82%	0.20	3.32%	0.34	3.42%	0.35	7.08%	0.53	7.24%	0.53	10.77%	0.68	11.09%	0.70
February	1.05%	0.13	1.09%	0.14	1.64%	0.21	1.68%	0.21	3.63%	0.36	3.74%	0.36	7.06%	0.56	7.23%	0.57	10.71%	0.63	11.06%	0.64
March	1.11%	0.15	1.15%	0.16	1.57%	0.18	1.62%	0.19	3.04%	0.29	3.16%	0.29	6.92%	0.46	7.10%	0.47	10.75%	0.69	11.09%	0.70
April	1.22%	0.17	1.26%	0.17	1.60%	0.20	1.66%	0.21	3.42%	0.33	3.53%	0.33	6.78%	0.46	6.98%	0.46	10.72%	0.64	11.09%	0.66
May	1.14%	0.17	1.18%	0.17	1.94%	0.24	2.00%	0.24	3.62%	0.36	3.74%	0.36	7.92%	0.53	8.12%	0.53	11.26%	0.70	11.64%	0.71
June	1.04%	0.15	1.07%	0.15	1.95%	0.23	2.01%	0.24	3.38%	0.31	3.50%	0.31	8.06%	0.54	8.26%	0.55	11.62%	0.77	11.99%	0.79
July	1.18%	0.17	1.22%	0.17	1.77%	0.17	1.83%	0.18	3.35%	0.31	3.47%	0.32	7.35%	0.49	7.56%	0.50	10.78%	0.60	11.13%	0.61
August	1.15%	0.18	1.18%	0.18	1.81%	0.18	1.88%	0.18	3.41%	0.28	3.53%	0.28	7.59%	0.50	7.80%	0.51	13.08%	0.75	13.56%	0.76
September	1.16%	0.14	1.20%	0.14	1.93%	0.20	1.99%	0.20	3.70%	0.33	3.84%	0.33	7.09%	0.42	7.28%	0.42	10.87%	0.59	11.21%	0.61
October	1.10%	0.14	1.15%	0.15	2.02%	0.21	2.10%	0.21	3.79%	0.36	3.92%	0.37	7.49%	0.48	7.68%	0.49	12.21%	0.65	12.65%	0.66
November	1.16%	0.15	1.20%	0.15	2.08%	0.21	2.16%	0.21	3.78%	0.31	3.89%	0.32	8.26%	0.46	8.48%	0.47	11.94%	0.71	12.30%	0.72
December	1.39%	0.20	1.44%	0.20	2.32%	0.25	2.42%	0.25	4.74%	0.39	4.87%	0.39	9.08%	0.59	9.34%	0.60	13.10%	0.74	13.54%	0.75
Overall Mean	**1.16%**	**0.05**	**1.20%**	**0.05**	**1.86%**	**0.06**	**1.93%**	**0.06**	**3.59%**	**0.10**	**3.71%**	**0.10**	**7.56%**	**0.15**	**7.76%**	**0.15**	**11.50%**	**0.20**	**11.87%**	**0.20**

Table A8: Mean Predicted Percent Changes in Individual Consumer Surplus, by Year-Month (all counties)

Month \ Year	2008				2009				2010				2011				2012			
	Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"		Counter -factual 1: with "price effects"		Counter -factual 2: without "price effects"	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
January	-0.32%	0.04	-0.24%	0.03	-0.44%	0.04	-0.35%	0.04	-0.81%	0.07	-0.66%	0.07	-1.63%	0.12	-1.40%	0.11	-2.60%	0.15	-2.17%	0.14
February	-0.26%	0.03	-0.21%	0.03	-0.40%	0.04	-0.32%	0.04	-0.89%	0.08	-0.72%	0.07	-1.65%	0.12	-1.41%	0.11	-2.64%	0.14	-2.18%	0.13
March	-0.28%	0.03	-0.22%	0.03	-0.38%	0.04	-0.31%	0.03	-0.78%	0.07	-0.61%	0.06	-1.63%	0.10	-1.37%	0.09	-2.62%	0.15	-2.16%	0.14
April	-0.30%	0.03	-0.24%	0.03	-0.40%	0.04	-0.31%	0.04	-0.86%	0.08	-0.69%	0.07	-1.63%	0.10	-1.35%	0.09	-2.66%	0.15	-2.18%	0.13
May	-0.29%	0.04	-0.23%	0.04	-0.47%	0.05	-0.38%	0.04	-0.89%	0.08	-0.72%	0.07	-1.84%	0.11	-1.56%	0.10	-2.77%	0.16	-2.27%	0.14
June	-0.26%	0.03	-0.20%	0.03	-0.47%	0.05	-0.38%	0.04	-0.87%	0.07	-0.69%	0.06	-1.89%	0.12	-1.61%	0.11	-2.84%	0.17	-2.33%	0.15
July	-0.29%	0.04	-0.23%	0.04	-0.45%	0.04	-0.35%	0.04	-0.84%	0.06	-0.66%	0.06	-1.75%	0.11	-1.46%	0.10	-2.66%	0.14	-2.19%	0.12
August	-0.27%	0.04	-0.22%	0.04	-0.46%	0.04	-0.36%	0.03	-0.85%	0.06	-0.67%	0.05	-1.82%	0.11	-1.51%	0.10	-3.32%	0.17	-2.67%	0.15
September	-0.28%	0.03	-0.23%	0.03	-0.47%	0.04	-0.38%	0.04	-0.96%	0.07	-0.75%	0.07	-1.69%	0.09	-1.41%	0.08	-2.70%	0.14	-2.21%	0.12
October	-0.28%	0.03	-0.22%	0.03	-0.51%	0.05	-0.40%	0.04	-0.95%	0.08	-0.76%	0.07	-1.73%	0.11	-1.46%	0.09	-3.08%	0.15	-2.49%	0.13
November	-0.29%	0.03	-0.22%	0.03	-0.53%	0.05	-0.41%	0.04	-0.93%	0.07	-0.76%	0.06	-1.95%	0.11	-1.65%	0.09	-2.91%	0.15	-2.43%	0.14
December	-0.34%	0.04	-0.27%	0.04	-0.62%	0.06	-0.47%	0.05	-1.15%	0.09	-0.96%	0.08	-2.16%	0.13	-1.80%	0.11	-3.25%	0.16	-2.66%	0.15
Overall Mean	**-0.29%**	**0.01**	**-0.23%**	**0.01**	**-0.47%**	**0.01**	**-0.37%**	**0.01**	**-0.90%**	**0.02**	**-0.72%**	**0.02**	**-1.78%**	**0.03**	**-1.50%**	**0.03**	**-2.84%**	**0.04**	**-2.33%**	**0.04**

Appendix B – Details of Sample Construction

The IRI weekly scanner data sample contains more than 36 million records across 2119 grocery and drug stores in 410 U.S. counties. From an initial examination of the raw data, we find single-cup products are fewer than 3 percent of all coffee products in 2008, but this number increases to 4 percent in 2009, 6 percent in 2010, 11 percent in 2011 and 18 percent in 2012. In addition, exploring the changes of single-cup products revenue in each county during the sample periods, we find single-cup products revenue shares increase over time for each of the 410 counties. Concerning the difficulty of estimating the discrete choice demand model with such a large data set, we select a subsample of these weekly records in 15 counties, with each county satisfying the following conditions: (*i*) contains both single-cup and auto-drip products in each time period; (*ii*) has a total revenue share of all single-cup products in the first time period ranked the highest among all counties; (*iii*) has the largest percent increase in total revenue share of all single-cup product from 2008 to 2012. The resulting subsample has total weekly records of 2.5 million.

When constructing the product attribute variables for the demand estimation, observations due to apparent data entry coding error are removed. Caffeine content is approximated using information from USDA.[1] On average, 0.61 gram of ground coffee contains 40 mg caffeine, equivalently, 1.86 gram caffeine per ounce of dry coffee ground. Product packages for ground coffee include laminated bags (e.g., foil bags), paper bags/boxes, plastic canisters, and light metal tins.[2] We use this information to create package-type dummies used in the demand model.

IRI data contains information on whether the product had a promotion due to the frequent shopper programs or store ads (characterized as "feature" in the data) or displayed in the lobby or end of aisle (characterized as "display" in the data). We use this information to construct dummies, "Feature" and "Display", which are each zero-one dummy variables that capture the marketing strategies used by retail stores for each product during a given period.

In order to construct prices that are comparable across the two coffee segments, we first define an equivalent serving size for each segment, namely, the mass weight of coffee grounds in ounces (oz) to make a standard cup, 10 fluid ounces (fl oz), of brewed coffee. This standard cup size is a product of the NCA survey in 2016. This survey reports that the average number of cups drank per-day per capita is 1.98. This implies a coffee drinker consumes 594 fl oz per month, on

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[1] National Nutrient Database for Standard Reference Release 27, "Basic Report 14209, Coffee, brewed from grounds, prepared with tap water".
[2] More details in URL link: https://plastics.americanchemistry.com/LCI-Summary-for-8-Coffee-Packaging-Systems/

average. For single-cup coffee products, an individual coffee pod contains coffee grounds of 0.14 oz to 0.66 oz varying by brands, with an average of 0.35 oz per coffee pod. We assume each pod makes a standard cup of 10 fl oz of freshly brewed coffee regardless of how much coffee grounds each pod contains.

For auto-drip products, we apply a universal serving size of 0.63 oz coffee grounds per standard 10 fl oz cup of coffee, according to a suggested coffee brew "golden ratio". The coffee-to-water ratio suggested by NCA is one to two tablespoons of ground coffee for every six fluid ounces of water. The coffee-to-water ratio suggested by Specialty Coffee Association (SCA) is 55 grams dry coffee per 1 liter water$\pm$10%. Considering the above two suggested coffee brew ratio, we assume an average coffee drinker follows two tablespoons of dry coffee for every six fluid ounces of water, i.e., 0.063 oz dry coffee grounds makes 1 fl oz brewed coffee. Using this ratio, we then compute the total equivalent fluid ounces for all auto-drip brew product. Given these assumptions, we convert the product quantity measured in ounces of dry coffee grounds in the original IRI data to equivalent fluid ounce measure across the auto-drip brew coffee products and single-cup brew coffee products. Therefore, consumer quantity demanded is measured by how much fluid ounces of brewed coffee can be potentially made from each product given the product's equivalent serving size.

For each observation in the weekly data, we have information on "total dollars received by the retailer for multiple packages sold during a week", "the number of packages sold", "the number of coffee pods in a package", and "ounces of coffee grounds in a package". For each weekly observation in the single-cup category, the total quantity sold in equivalent volume measure in a week is the three-way multiplication of the number of packages sold in that week, the number of pods in a package, and the standard cup size of 10 fl oz.

For each weekly observation in the auto-drip category, we first multiply the number of packages sold in that week with the ounces of coffee grounds in a package to obtain the quantity measure in mass weight, then divide it by the "golden ratio" of "0.63 oz/10 fl oz" to obtain the quantity measure in volume. We then compute the average unit price for each weekly observation by dividing the total dollar received by the retailer for multiple units of same-type packages sold during a week by the total quantity sold during that week in term of the computed volume measure described above.

Appendix C – Formally Implementing the Counterfactual Experiments

Counterfactual Experiment 1: with "price effects"

In this exercise, once single-cup coffee products are counterfactually removed, the new equilibrium price vector, $\boldsymbol{p}^*$, of auto-drip products is obtained by numerically searching for the vector of prices that satisfy the following equation:

$$\boldsymbol{p}^* = \widehat{\boldsymbol{mc}} - [\boldsymbol{\Omega} * \boldsymbol{\Delta}(\boldsymbol{p}^*)]^{-\mathbf{1}}\boldsymbol{s}(\boldsymbol{p}^*) \quad \text{(C1)}$$

where equation C1 is implied by the system of first-order conditions generated by the optimization problem in equation (3) in the paper; $\widehat{\boldsymbol{mc}}$ is the vector of recovered product-level marginal cost estimates based on the demand parameter estimates in Table 2;[3] $\boldsymbol{\Omega}$ is a $J \times J$ matrix of appropriately positioned zeros and ones based on the manufacturers' ownership structure of the J products in the relevant market; $\boldsymbol{\Delta}$ is a $J \times J$ matrix of first-order derivatives of predicted product shares with respect to prices; and $\boldsymbol{\Omega} * \boldsymbol{\Delta}$ is an element-by-element multiplication of the two matrices. A comparison of the actual observed price vector $\boldsymbol{p}$ from the data with the model-predicted new equilibrium price vector $\boldsymbol{p}^*$ reveals how equilibrium prices for auto-drip coffee products are influenced by the introduction of single-cup coffee products to the brew-at-home coffee retail market.

Let AD_{mt} be the subset of brew-at-home coffee products in market m during period t that are auto-drip, while SC_{mt} the subset that are single-cup. We can therefore re-write product shares predicted by the model as follows:

$$s_{jmt}(\boldsymbol{p}; \widehat{\Theta}) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{e^{\delta_{jmt}(p_{jmt})+\mu_{ijmt}(p_{jmt})}}{1+\sum_{l\in AD_{mt}} e^{\delta_{lt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}+\sum_{l\in SC_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}}\right) \quad \text{(C2)}$$

$$s_{0mt}(\boldsymbol{p}; \widehat{\Theta}) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{1}{1+\sum_{l\in AD_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}+\sum_{l\in SC_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}}\right) \quad \text{(C3)}$$

where, conditional on demand parameter estimates in vector $\widehat{\Theta}$, equation (C2) yields the model-predicted share for brew-at-home coffee product j evaluated at the vector of actual prices, $\boldsymbol{p}$; while equation (C3) yields the model-predicted share of the outside good evaluated at the vector of actual prices, $\boldsymbol{p}$.

[3] We assume cost structures of firms are not changed after the counterfactual removal of single-cup products. As stated in Villas-Boas (2007), it is a common limitation that this assumption does not consider the possibility of potential synergy effects due to joint production and distribution of both coffee product types for multi-product firms.

With the model-predicted new equilibrium prices for auto-drip products in hand, we then compute model-predicted shares of auto-drip coffee products and share of the outside good based on the following modified versions of equations (C2) and (C3):

$$s_{jmt}\left(\boldsymbol{p}^*; \widehat{\Theta}\right) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{e^{\delta_{jmt}(p^*_{jmt})+\mu_{ijmt}(p^*_{jmt})}}{1+\sum_{l\in AD_{mt}} e^{\delta_{lmt}(p^*_{lmt})+\mu_{ilmt}(p^*_{lmt})}}\right) \tag{C4}$$

$$s_{0mt}\left(\boldsymbol{p}^*; \widehat{\Theta}\right) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{1}{1+\sum_{l\in AD_{mt}} e^{\delta_{lmt}(p^*_{lmt})+\mu_{ilmt}(p^*_{lmt})}}\right) \tag{C5}$$

where the term, $\sum_{l\in SC_{mt}} e^{\delta_{lmt}(p_{lmt})+\mu_{ilmt}(p_{lmt})}$, is absent from the denominator in equations (C4) and (C5) due to the counterfactual elimination of single-cup products from each market. Using equations (C2) through (C5) along with the measure of the potential size of market *m* during period *t*, M_{mt}, we compute factual model-predicted quantities demand by $d_{jmt} = M_{mt} \times s_{jmt}\left(\boldsymbol{p}; \widehat{\Theta}\right)$ and $d_{0mt} = M_{mt} \times s_{0mt}\left(\boldsymbol{p}; \widehat{\Theta}\right)$, while counterfactual model-predicted quantities demand are obtained by $d^*_{jmt} = M_{mt} \times s_{jmt}\left(\boldsymbol{p}^*; \widehat{\Theta}\right)$ and $d^*_{0mt} = M_{mt} \times s_{0mt}\left(\boldsymbol{p}^*; \widehat{\Theta}\right)$, allowing price responses for auto-drip coffee products with the introduction of single-cup products.

Counterfactual Experiment 2: without "price effects"

In this exercise, we assume the price levels of pre-existing auto-drip coffee products are fixed at their observed price levels after the counterfactual removal of the new products; therefore, the predicted shares of auto-drip coffee products and share of the outside good are given by the following:

$$\tilde{s}_{jmt}\left(\boldsymbol{p}; \widehat{\Theta}\right) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{e^{\delta_{jmt}(p_{jmt})+\mu_{ijmt}(p_{jmt})}}{1+\sum_{l\in AD_{mt}} e^{\delta_{lmt}(p_{jmt})+\mu_{ilmt}(p_{jmt})}}\right) \tag{C6}$$

$$\tilde{s}_{0mt}\left(\boldsymbol{p}; \widehat{\Theta}\right) = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{1}{1+\sum_{l\in AD_{mt}} e^{\delta_{lmt}(p_{jmt})+\mu_{ilmt}(p_{jmt})}}\right) \tag{C7}$$

Using equations (C6) and (C7) along with the measure of the potential market size measure, M_{mt}, we then compute the counterfactual model-predicted quantities demand of the auto-drip and the outside good by $\tilde{d}_{jmt} = M_{mt} \times \tilde{s}_{jmt}\left(\boldsymbol{p}; \widehat{\Theta}\right)$ and $\tilde{d}_{0mt} = M_{mt} \times \tilde{s}_{0mt}\left(\boldsymbol{p}; \widehat{\Theta}\right)$, assuming the prices of auto-drip products remain unchanged with the introduction of single-cup products.

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