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How Much Do Consumers Benefit from New Brand Introductions? The Case of Potato Chips

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This study identifies consumer welfare from new brand introductions in the potato chip market. Price and variety effects of new brand introduction are measured by estimating a demand system underlying an expenditure function. Variety effects are positive in most cities, while price effects are generally negative when consumers exhibit some variety preference. Variety effects dominate price effects in most cities; an opposite effect observed in some cities may indicate high entry barriers or joint brand- and price-based marketing strategies. Results indicate that consumers and producers gain from product innovations, but substantial regional variation exists in the distributional effects of new brand introduction.

Key Words: city-demand system, compensating variation, consumer welfare, new brands, virtual prices

Introduction

New brand introduction alters the nature of competition in a market and has important consequences for producer and consumer welfare (Bresnahan and Gordon, 1997; Hausman and Leonard, 2002; Petrin, 2002). Both demand- and supply-side causes and consequences of such introductions have been explored by several researchers, including Bresnahan and Gordon (1997), Koehn (2001), Bronfer and Chintagunta (2004), and Pofahl and Richards (2009). Given that demand-side explanations often invoke Dixit-Stiglitz or variety-seeking preferences—i.e., consumers prefer small quantities of multiple varieties over a large quantity of any single variety—the impact of an additional variety should therefore be reflected in consumer surplus (a variety effect).[1]

The extent to which an existing brand's price is affected by the introduction of a new brand (a price effect) is a function of the degree of substitutability between the existing and new brands and the form of market competition. The price effect can benefit or harm consumers, depending on manufacturers' market participation in the pre- and post-introduction periods. For instance, if the manufacturer of the new brand does not have brands in the given market, the new brand will typically lead to lower prices for all competing brands. In contrast, a new

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[1] On the supply side, a firm uses brand or variety introduction to attract new consumers and improve its market share. However, a firm's introduction strategy depends on the extent of sunk costs, which may include fixed production and/or marketing costs of each brand or variety (Richards and Hamilton, 2006). Because firms' strategies and pricing are viewed as exogenous to consumer choice, they lie outside the scope of this study's focus on consumer welfare.

brand introduced by a manufacturer already serving the given market in a Nash-Bertrand (price-competition) setting can lead to higher prices among existing brands (Hausman and Leonard, 2002). Hence, the net effect of new brand introduction on consumer welfare can be positive or negative depending on the relative strength of the variety and price effects.

This study assesses the influence of brand introduction and accompanying changes in consumer welfare in geographically separated markets. We draw on Hausman and Leonard's (2002) compensating-variation approach to investigate price and variety effects of new brand introductions in regional markets for potato chips, a market with substantial brand-based competition. Consumer expenditure on potato chips is evaluated before and after a new brand introduction, holding utility constant at the post-introduction level. In addition, the total benefit to consumers, expressed in terms of the compensating variation (expenditure change), is separated into variety and price effects. For this purpose, we estimate brand demand functions, underlying an expenditure function, with pre- and post-introduction data (Pofahl and Richards, 2009). The estimates of demand functions are then employed to directly measure expenditures and compensating variation. In doing so, we avoid instabilities in Hausman and Leonard's formula approach to deriving consumer welfare from new brand introductions. Our focus on consumer welfare abstains from modeling producer behavior for two reasons: (*a*) the form of competition at the retail or manufacturing level remains a subject of debate, and (*b*) the data necessary to understanding producers' welfare changes are proprietary or unavailable (Bronnenberg, Dhar, and Dube, 2009; Dube, 2004; Nevo, 2000; Bresnahan and Gordon, 1997).[2]

Our application focuses on the potato chip market, which has faced significant brand-based competition with the introduction of baked, organic, and flavored potato chips. The empirical analysis uses the ACNielsen Homescan database, from which potato chip purchases of nearly 7,000 U.S. households are tracked between 1998 and 2006. Household data on chip price and quantity purchased by brands or varieties are aggregated to weekly data for 10 major U.S. cities for this analysis.[3] Because of a disclosure issue, we cannot identify brands by name at either the regional or national levels. While the disclosure issue somewhat limits us in reporting brand-specific results, spatial differences highlighted in the study have implications for the heterogeneous effects of national policies (e.g., antitrust regulations).

Research Methods

Using a dual approach, Hausman and Leonard (2002) define compensating variation as the difference in consumer expenditure on the chosen product before and after the introduction of a new brand:

$$CV = E(\mathbf{P}_b^1, \mathbf{P}_n, \mathbf{r}, \bar{U}) - E(\mathbf{P}_b^0, \mathbf{P}_n^*(\mathbf{P}_b^0), \mathbf{r}, \bar{U}), \tag{1}$$

where CV is the compensating variation, or the expenditure (E) adjustment required to ensure utility remains constant after a price change (Just, Hueth, and Schmitz, 2004); $\mathbf{P}_b^0$ and $\mathbf{P}_b^1$ are

[2] Because our data and empirical analysis relate to households, our focus is restricted to consumer welfare. Data on producer costs and supply-chain linkages are not readily available for an analysis of producer welfare. However, the price effects of new brand introductions can provide some insights into producer welfare.

[3] See Pofahl and Richards (2009) for an application to shelf-stable juice products at the national level. Unlike the referenced study, we focus on 10 regional markets and use retail purchase data to identify price, variety, and net effects of brand introduction on consumer welfare. Moreover, our chosen product's bulky nature and possible damage from transportation create a unique market structure (one national firm versus regional firms), making our application a contribution in the spatial dimension to this emerging literature on brand competition.

the price (vector) of existing brands consumed before and after introduction of the new brand; $\mathbf{P}_n$ is the price of the new brand after introduction; and $\mathbf{P}_n^*$ is the "virtual" or inferred price of the new brand prior to introduction. Hausman and Leonard define the virtual price as the price high enough to ensure zero demand for the new brand (also referred to as "choke price"). Prices of other closely related products, $\mathbf{r}$, are also generally included in equation (1), where $\bar{U}$ represents the post-introduction utility level.

Consumers can benefit from either price or variety effect following new brand introduction. The price effect (PE) refers to the possible decline in prices (and thus expenditures) when new brands increase competition among all brands, while the variety effect (VE) is the gain in utility (or expenditure savings) from an increase in the number of varieties available in a given market. Hausman and Leonard show that the total change in expenditure in equation (1), holding utility constant, can be separated into two parts, which are attributable to price and variety effects:

$$CV = \left[E(\mathbf{P}_b^1, \mathbf{P}_n, \mathbf{r}, \bar{U}) - E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U}) \right] + \left[E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U}) - E(\mathbf{P}_b^0, \mathbf{P}_n^*(\mathbf{P}_b^0), \mathbf{r}, \bar{U}) \right], \tag{2}$$

where the terms in the first and second square brackets denote, respectively, the variety and price effect. The first expenditure function in the variety effect of equation (2), $E(\mathbf{P}_b^1, \mathbf{P}_n, \mathbf{r}, \bar{U})$, is actual expenditure in the post-introduction period when all prices are observed. The second term, $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U})$, represents what expenditures would be if new brand consumption were to be zero in the post-introduction period, holding utility constant. In order to compute such expenditures, virtual prices of the new brands must be high enough to ensure zero consumption of new brands. Given such high virtual prices, the reallocation of demand to existing brands leads to higher expenditures than the actual expenditures with observed prices. Hence, the negative of the first term is the variety effect ($-VE$) or the consumer welfare gain as a result of new brand availability, holding the price of existing brands and utility constant at the post-introduction level.

The term in the second square brackets of equation (2) represents price effect, the difference in consumer expenditures due to price change of existing brands after new brand introduction. New brand prices are set at respective virtual prices in both price effect terms, which forces their consumption to zero. Hence, the difference in the two expenditures must arise from a price effect (the influence of new brands on prices of existing brands), which can be either positive or negative. If the new brand competes closely with brands of other manufacturers, the price effect will be negative and consumer welfare gain will be equal to $-PE$. Thus, equation (2) can be rewritten as $CV = -(VE + PE)$.

The Demand System

To measure both price and variety effects, we estimate an almost ideal demand system (AIDS) model.[4] Such AIDS models are compatible with either perfectly or imperfectly competitive

[4] Hausman and Leonard (2002, p. 254, equation 11) rely on an approximating formula, which requires parameters from an upper- and lower-stage demand model. The upper-stage model is used to estimate demand for the product (bath tissue), while the lower-stage model is an LA/AIDS system to estimate demand for the specific brands of the product. A problem with the approximating formula is that it depends on the income elasticity obtained in the upper-stage model. For income elasticities around 0.5 or 0.6, Hausman and Leonard's approximating formula is stable. However, for income elasticities between 0.9 and 1.1, which are entirely reasonable for most food products, the approximating formula is unstable and remains undefined for unitary income elasticity (Klonaris and Hallam, 2003).

suppliers or producers and usually specify shares of various goods in a household's total expenditure as functions of prices, total expenditure, and other control variables. In addition, the AIDS model assumes two-stage budgeting, where the total expenditure on each food group (e.g., potato chips, cheese) is determined in the first stage (Deaton and Muellbauer, 1980; Just, Hueth, and Schmitz, 2004). The second stage of the consumer problem determines allocation of budget among the available brands or choices within each food group. We model up to eight brands of potato chips for each of the 10 major U.S. cities in our sample using weekly data. The typical share equation of an AIDS model is expressed as:

$$S_{it} = a_i + \sum_{j=1}^{n} \beta_{ij} * \ln(P_{jt}) + \lambda_i * \ln(E_t / PI_t) + \varepsilon_{it}, \tag{3}$$

where S_{it} represents the expenditure share of the ith brand of potato chips at time t, P_{jt} is the price of the jth brand of potato chips at time t, and β_{ij} is the corresponding coefficient representing the influence of the jth brand price on the purchase of the ith brand. The term $\ln(E_t)$ represents aggregate expenditures on potato chips, PI_t represents a price index, and ε_{it} is an error term (Asche and Wessels, 1997). Symmetry and homogeneity conditions are imposed by setting

$$\beta_{ij} = \beta_{ji} \text{ and } \sum_j \beta_{ij} = 0.$$

We impose adding-up, which implies that

$$\sum_i \beta_{ij} = 0, \quad \sum_i \lambda_i = 0, \quad \text{and} \quad \sum_i a_i = 1.$$

Specifically, one share equation is dropped from the system to avoid singularity, but the dropped equation's parameters are recovered using the symmetry, homogeneity, and adding-up conditions. The possible endogeneity of P_{jt} and E_t in equation (3) is addressed later.

A common problem while estimating micro-level demand functions is that shares and the underlying consumption can be zero for certain brands and periods. These observations cannot be dropped from estimation because a sample selection bias would arise in the estimated demand coefficients (Heien and Wessels, 1990). Including the zero-consumption observations implies we must fill in the corresponding prices. Alternative methods are available to compute prices when consumption is zero, but we follow Perali and Chavas (2000) in setting the highest observed price in our sample as the price when observed consumption is zero. Since a higher price implies lower quantity demanded, the highest observed price in the sample becomes a proxy for the price that forces consumption to zero.

Shonkwiler and Yen's (1999) two-step procedure is used to estimate the demand system in equation (3). For this purpose, we first estimate probit models for any brand for which consumption is sometimes observed to be zero. The probit model for purchase decisions (zero or one) includes prices, expenditures, and the square of expenditures as explanatory variables (Shonkwiler and Yen, 1999; Perali and Chavas, 2000; Arnade and Gopinath, 2006). Then, the independent variables in equation (3) are transformed using cumulative densities (expected probabilities) at each data point for each equation from the probit estimation. For example, the expected probabilities from the probit model for existing brand I is used to transform the independent variables of the share equation for existing brand 1. Moreover, the inverse Mills ratio from the respective probit model is used as an explanatory variable in the transformed share equation (AIDS model).

Virtual Prices

Once the system of share equations is estimated, the key step in evaluating the effect of new brand introductions on consumer welfare is the derivation of virtual prices.[5] As shown in equations (1) and (2), two sets of virtual prices, $\mathbf{P}_n^*(\mathbf{P}_b^0)$ and $\mathbf{P}_n^*(\mathbf{P}_b^1)$, are necessary to evaluate change in consumer expenditures (compensating variation), which is then attributed to price and variety effects. The first option to compute virtual prices is the Hausman and Leonard (2002) approach, which solves the estimated demand equations to obtain virtual prices. Given estimates of the share equation for the *i*th brand, we can solve for the price of the same brand by inverting equation (3). That is, for observations where consumption is zero ($S_{it} = 0$):

$$P_{it}^{v} = \left(\frac{\hat{a}_i + \sum_{j \neq i}^{n-1} \hat{\beta}_{ij} * \ln(P_{jt}) + \hat{\lambda}_i * \ln(E_t / PI_t)}{-\beta_{ii}} \right), \tag{4}$$

where P_{it}^{v} is the virtual price for the *i*th brand at time *t*, and a caret (^) over a parameter denotes its estimated value. The virtual prices in equation (4) can be sorted for each pre- and post-introduction time period to obtain $\mathbf{P}_n^*(\mathbf{P}_b^0)$ and $\mathbf{P}_n^*(\mathbf{P}_b^1)$ for evaluating compensating variation in equation (2).

We found that this approach can generate estimates with large variance and some prices can be over four or five times the observed new brand price in the post-introduction period. Hence, we also consider using estimated elasticities to project virtual prices as an alternative to the Hausman and Leonard (2002) approach. For example, if the own-price elasticity of demand for a new brand is −2 (−0.5), then increasing prices by 50% (200%) will force quantity demanded to zero, all else constant. The latter approach assumes that demand slopes do not change as they approach the price axis.

Expenditures with Virtual Prices

We employ an elasticity approach with the estimated AIDS model to evaluate expenditures at pre- and post-introduction observed and virtual prices while holding utility constant at the post-introduction level. A key advantage to this approach is that it does not require estimating any parameters of the expenditure function which are not contained in the system of demand equations.[6] Moreover, the elasticity approach allows us to employ consumer variety preference or the Dixit and Stiglitz utility specification similar to Krugman (1980) and Ardelean (2009). In our approach, we employ the variety-loving preferences as follows:

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[5] The derivation of virtual prices, or the choke prices, does not imply that prices are endogenous in our consumer demand model, nor does it mean that this paper attempts to explain firms' pricing behavior. Virtual prices are a hypothetical level of price that choke off demand. How those prices might be arrived at is extraneous to this paper (Nevo, 2000).

[6] All but two parameters of the expenditure function can be recovered from any well-specified LA/AIDS model (Deaton and Muellbauer, 1980). We attempted to recover the remaining two parameters of the expenditure function by regressing the difference between actual expenditures and that component of the expenditure function recovered from the LA/AIDS model on remaining variables in the AIDS expenditure function. In doing so, we regressed the difference on a constant and aggregate *Q* (to represent utility) raised to a power determined by the observed price vector. However, these resulting coefficients are highly unstable to specification changes and create large variation in the computation of price and variety effects. Hence, we chose the elasticity approach to evaluate expenditures.

$$U = \sum q * n^a,$$

where n is the number of brands consumed and a is the love-of-variety parameter. Setting a to zero yields the standard specification of utility in expenditure function estimation. When $a > 0$, consumers prefer varieties. An empirical estimate of a in the neighborhood of 0.4 can be found in Ardelean and Lugovskyy (2010) and Ardelean (2009).

We assume $a = 0$ in evaluating expenditures with virtual prices in the post-introduction period; i.e., $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U})$ [a similar procedure applies for expenditures with virtual prices in the pre-introduction period, $E(\mathbf{P}_b^0, \mathbf{P}_n^*(\mathbf{P}_b^0), \mathbf{r}, \bar{U})$].

- STEP 1. We use estimated AIDS model parameters to calculate own- and cross-price elasticities for existing brands at the data mean.
- STEP 2. We use average quantities after introduction to calculate a base level of utility, i.e., $U = \Sigma_i \bar{q}_i$, where $\bar{q}_i$ is the ith brand's average quantity over the sample period.
- STEP 3. We compute the change in new brand prices required to force new brand demand to zero, i.e., percentage change between post-introduction virtual and observed (average) prices of new brands. With more than one new brand, note that the percentage change in new brand prices is a vector. In every existing-brand demand equation, we introduce the new brand price (vector of) changes. While these higher prices for new brands force their demand to near zero, they also generate changes in quantity demanded of existing brands by way of cross-price elasticities.
- STEP 4. We compare utility using the generated quantities from Step 3 with those in Step 2. To hold utility constant in the post-introduction period, i.e., between Steps 2 and 3, a radial expansion (contraction) of the generated quantity mix in existing-brand space is applied to move utility up (down).
- STEP 5. Holding utility constant (Step 4), we multiply the generated quantities of existing brands by observed prices in the post-introduction period, yielding $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U})$.

The above steps assume the love-of-variety parameter is equal to zero. We compare the base evaluation, $a = 0$, to two alternative values of a (0.25 and 0.50).

Data and Industry Setting

Recent and long-term trends make the potato chip market an interesting case for analyzing consumer welfare changes arising from new brand introductions (Lin et al., 2001). Brand-based and regional competition have been critical features of the potato chip market for many years (see Wolburg, 2005, for a case study of Double-Cola, a regional brand). This competition developed during a decline in the number of plants producing potato chips in the 1960s [U.S. Department of Agriculture/National Agricultural Statistics Service (USDA/NASS), 2007]. An average of six to seven plants have exited the industry annually between 1960 and 2006, but potato chip production increased from 20 to 67 million cwt over the same period (a growth rate of 2.6% per year). Only one company appears to have a national presence with multiple brand offerings, but it faces significant competition from regional brands, some of which are expanding into neighboring regions.

Against this backdrop, firms have introduced new brands to compete with one another or, in several instances, to increase demand for their own existing brands. An increased variety of chip products, such as ridged, low-salt, organic, and baked chips, have been introduced into the market in the last few decades. Regional variation in demand is significant, with a larger share of southern households consuming potato chips (38%), while only 20% of households in other regions consume potato chips. Potato chips produced in the United States are largely consumed within the country. Exports accounted for only 7% of supply ($172 million) in 2007, with major destinations of Canada and Mexico. Imports accounted for only 3% of domestic consumption ($81 million). Per capita consumption of potato chips has risen to 19.3 pounds in 2006, from a low of about 15 pounds in 1998 [USDA/Economic Research Service (ERS), 2008]. We chose the potato chip industry for an analysis of welfare changes from new brand introductions because of the consolidation of the industry, increases in per capita consumption, the rapid rate of introductions of new brands and varieties, and the domestic focus of the market. Potato chips are also a product with a long history of frequent product introduction. This setting is amenable to the analysis of consumer reaction to brand introductions.

Our source of household data, which have only become available for economic analysis in recent years, is the ACNielsen Homescan database. Given regional variations in demand and data availability, we chose 10 major U.S. cities for an analysis covering the period 1998 to 2006—Atlanta, Boston, Chicago, Los Angeles, New York urban, New York suburban, Philadelphia, Phoenix, San Antonio (including Austin), and San Francisco (including Sacramento).[7]

Household data on purchases of bagged potato chips were aggregated into weekly observations for each city, representing 467 weeks beginning in January of 1998 and ending in 2006.[8] The city-level data are the sum of individual households' expenditures and quantities for each brand. The unit price of a brand is the ratio of the corresponding city-level expenditures and quantities. Over the sample period, there is turnover of households participating in the ACNielsen Homescan surveys; e.g., a Boston household in 1999 moved to San Francisco in 2002. In aggregating data to the city level, care was taken to account for households that continued to participate when moving to another sample city. Less than 3% of the sampled households moved from one city to another. Continuing with the example, if a household located in Boston during 1999 moved to San Francisco in 2002, it was included in the 1999 data for Boston and the 2002 data for San Francisco, but not in both cities and both years.

City-specific weekly price and consumption data series were constructed using our sample data for four "top" existing brands and a minimum of two "new" brands of potato chips.[9] A final category, fifth for existing and third or fourth for the new brands, was used to represent all other existing and new brands, respectively. Top brands were chosen by their average market share, measured as a proportion of total purchases over our sample period. Most cities had the same top existing brands, with a few exceptions. For example, two of San Francisco's four top brands were different than those in other cities. Existing brands were included if they

[7] Cities such as Seattle, Denver, Washington, DC, and others are not considered because of the small sample size obtained from the ACNielsen Homescan database.

[8] The ACNielsen Homescan database consists of some observations where expenditures are recorded as zero or reported prices are several times the mean price of the city. We deleted these observations, which represented approximately 0.5% of the sample data.

[9] In the cases of Boston, Chicago, New York (urban), New York (suburban), and San Antonio, we had three top new brands and the "other" new-brand category. San Francisco had only two new brand introductions during the entire sample period. The remainder of the cities had two top new brands and one "other" category.

had an average market share of at least 2% over the entire sample period. This cut-off was necessary because of the proportion of nonzero observations generally required to estimate a censored demand system.

New brands were defined as brands purchased during 2002 and 2006 that had not been observed being sold in the initial year (1998) of the database. Most new brands appear to have been introduced after 2000.[10] Again, top new brands were chosen by their average market share over 2002–2006. As with the existing brands, our choice for the number of new brands depended on the proportion of nonzero observations available for estimating a censored demand system.

Table 1 presents the number of households in our total sample and average shares of existing and new brands in the pre- and post-introduction periods, 1998–2002 and 2002–2006. The cumulative number of households ranges from 48 (Boston) to 1,567 (Los Angeles), with a total of 7,042 households across 10 major U.S. cities.[11] The share of the top brand (index I) ranges from 30.9% in Los Angeles to 8.0% in Philadelphia. In 22 of the 40 instances, top brands realized lower market shares in the post-introduction period in comparison to the pre-introduction period. Moreover, new brands have accounted for 1.9% (Philadelphia) to 9.0% (San Francisco) market share across the 10 cities in our sample during the post-introduction period.

Estimation and Results

The city-specific AIDS models consisted of share equations for four top existing brands, an aggregate of other existing brands, two or three top new brands, and an aggregate of other new brands (dropped equation). In the estimation of the share equations using the ITSUR procedure, we first test for the presence of heteroskedasticity and first-order autocorrelation of ε_{it} in equation (3). The Gleser test failed to reject the null of homoskedasticity in almost all the estimated equations. Statistical evidence of first-order autocorrelation was found in less than 15% of the estimated equations. We therefore proceed to estimate equation (3) after addressing the possibility that prices (P_{jt}) or expenditure (E_t) may be simultaneously determined with brand demand for potato chips.

To test simultaneity between P_{jt} and S_{it} in equation (3), Geroski and likelihood-ratio tests are used. The null hypothesis of $E(P_{jt}, \varepsilon_{it}) = 0$ is not rejected in all cities except Boston. The instruments used to estimate the price equations are lagged brand price and quantity (and quantity squared), raw potato price, and a retail food price index. In the case of Boston, our instrumental equations produced a poor fit (R^2 is about 0.10). While instrumental-variable and other procedures are readily available for estimating equation (3), our sample does not appear to have the price endogeneity issues observed in other studies (Di Giacomo, 2008; Bonfrer and Chintagunta, 2004; Nair, Dube, and Chintagunta, 2005; Nevo, 2000).[12] The lack of price endogeneity issues in our sample can be related to the advantages of using aggregate versus consumer data in the estimation of censored or discrete choice demand systems (Berry, Levinshon, and Pakes, 1998; Petrin, 2002). Such comparisons show that consumer welfare

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[10] Our analysis is not sensitive to the process of choosing new brands. For instance, altering the cut-off period for the choice of new brand yielded very little deviation from the current sample.

[11] Data on all households are not available for all 467 weeks.

[12] Many of these studies model the supply side and assume a degree of mark-up when considering price endogeneity. As noted in the introduction, we abstain from modeling the supply side since the form of competition in the potato chip market is unclear and data on production costs are unavailable.

Table 1. Top Existing and New Brands' Average Share of Purchases in Pre- and Post-Introduction Periods (1998–2002 and 2002–2006)

City	No. of Households		Top Existing Brands I	II	III	IV	Other
Atlanta	736	Before	0.262	0.121	0.066	0.054	0.483
		After	0.243	0.089	0.086	0.046	0.465
Boston	48	Before	0.220	0.051	0.047	0.031	0.640
		After	0.179	0.063	0.048	0.034	0.695
Chicago	1,347	Before	0.180	0.137	0.056	0.086	0.540
		After	0.180	0.146	0.115	0.099	0.404
Los Angeles	1,567	Before	0.309	0.137	0.177	0.030	0.332
		After	0.250	0.097	0.159	0.023	0.401
New York (urban)	251	Before	0.113	0.076	0.022	0.040	0.735
		After	0.110	0.094	0.018	0.025	0.700
New York (suburban)	313	Before	0.110	0.086	0.044	0.051	0.690
		After	0.147	0.072	0.033	0.033	0.640
Philadelphia	736	Before	0.080	0.073	0.030	0.029	0.785
		After	0.094	0.068	0.030	0.016	0.733
Phoenix	198	Before	0.224	0.141	0.071	0.068	0.470
		After	0.196	0.077	0.098	0.066	0.500
San Antonio	391	Before	0.179	0.138	0.056	0.085	0.534
		After	0.187	0.111	0.061	0.097	0.470
San Francisco	1,455	Before	0.209	0.130	0.150	0.013	0.469
		After	0.215	0.126	0.129	0.042	0.396

(extended . . . →)

estimates from new product introductions are lower but more precise when using consumer-based data. It is likely that our use of household data to derive city-level demand aided in minimizing some of the misspecification biases arising from price endogeneity.

Our search for instruments to test whether or not expenditures (E_t) are simultaneously determined with brand demand was limited by data availability. Weekly data on household income, total consumption, or food expenditures are not available at the state or city levels. The ACNielsen database has over 6,000 food products, and the aggregation of food expenditures on a weekly basis would be tedious and beyond the scope of this study. Furthermore, income data in the ACNielsen database are grouped (e.g., between \$25,000 and \$35,000); weekly interpolation of income data will yield an independent variable with little variation. Given the above constraints, we simply replaced E_t with E_{t-1} to lower any bias arising from the possible endogeneity of expenditures in our demand system (LaFrance, 1991).

Table 2 reports the own-price elasticities of brand demand for all brands in each of the 10 cities (cross-price and expenditure elasticities are available from the authors upon request). All own-price elasticities are negative except for new brand III in Chicago and brand II in urban New York. Moreover, about 60% of the own-price elasticities are in the −1.5 to −0.9 range, suggesting highly elastic demand and high substitutability among brands. Not surprisingly, some of the largest own-price elasticities are observed in the case of new brands (e.g., Boston new brand II). Nonetheless, significant differences in own-price elasticities across cities highlight the need to account for regional variation in consumer welfare arising from new brand introductions.

Table 1. Extended

City	No. of Households		New Brands I	II	III	Other
Atlanta	736	Before	—	—		—
		After	0.004	0.014	N/A	0.053
Boston	48	Before	—	—	—	—
		After	0.005	0.005	0.002	0.011
Chicago	1,347	Before	—	—	—	—
		After	0.007	0.003	0.005	0.039
Los Angeles	1,567	Before	—	—		—
		After	0.007	0.006	N/A	0.053
New York (urban)	251	Before	—	—	—	—
		After	0.008	0.004	0.001	0.017
New York (suburban)	313	Before	—	—	—	—
		After	0.005	0.008	0.003	0.018
Philadelphia	736	Before	—	—	—	—
		After	0.005	0.002	0.001	0.011
Phoenix	198	Before	—	—		—
		After	0.008	0.005	N/A	0.048
San Antonio	391	Before	—	—	—	—
		After	0.022	0.005	0.003	0.035
San Francisco	1,455	Before	—	—		
		After	0.052	0.038	N/A	N/A

Table 2. Own-Price Elasticities of Brand Demand

	Top Existing Brands					New Brands			
City	I	II	III	IV	Other	I	II	III	Other
Atlanta	−0.996	−1.680	−1.194	−0.662	−0.678	−0.885	−1.480	—	−0.544
Boston	−0.540	−0.720	−0.550	−0.810	−0.510	−1.390	−2.640	−2.090	−1.210
Chicago	−1.372	−1.277	−1.462	−2.304	−1.020	−0.630	−1.772	0.070	−0.980
Los Angeles	−1.275	−1.201	−1.148	−0.653	−0.996	−1.583	−0.789	—	−0.738
NY (urban)	−0.693	−1.245	−0.558	−1.830	−1.017	−0.203	0.080	−4.190	−0.447
NY (suburban)	−1.011	−0.985	−0.661	−1.461	−1.054	−1.238	−1.425	−0.226	−0.936
Philadelphia	−0.621	−0.960	−0.290	−1.180	−0.893	−0.923	−0.801	−0.495	−0.490
Phoenix	−1.084	−0.846	−0.778	−0.859	−1.000	−0.469	−0.712	−0.853	—
San Antonio	−0.863	−1.041	−0.840	−1.184	−0.835	−0.607	−2.305	−1.471	−0.888
San Francisco	−1.158	−0.755	−1.199	−0.193	−0.845	−0.411	−0.994	—	—

Table 3 presents the virtual prices, which force consumption of new brands to zero, from the elasticity approach noted above. This approach involved the use of estimated elasticities to project virtual prices. For instance, if the own-price elasticity of demand for a new brand is 2, then increasing prices by 50% will force its quantity demanded to zero. Although virtual price estimates from the Hausman and Leonard (2002) approach mostly yielded reasonable

Table 3. Virtual Prices for New Brands (average)

City		New Brands I	II	III	Other
Atlanta	After	0.383	0.439	—	0.516
	Before	0.295	0.465	—	1.008
	Observed	0.180	0.262	—	0.182
Boston	After	0.357	0.551	0.528	0.629
	Before	0.357	0.551	0.528	0.629
	Observed	0.204	0.395	0.347	0.352
Chicago	After	0.466	0.410	0.500	0.696
	Before	0.355	0.517	0.500	0.650
	Observed	0.180	0.262	0.182	0.345
Los Angeles	After	0.416	0.428	—	0.643
	Before	0.435	0.668	—	0.777
	Observed	0.255	0.189	—	0.273
New York (urban)	After	1.360	1.316	0.487	1.428
	Before	0.957	1.316	0.522	1.268
	Observed	0.229	0.420	0.393	0.441
New York (suburban)	After	0.400	0.648	2.074	0.808
	Before	0.427	0.795	1.570	0.827
	Observed	0.221	0.381	0.382	0.391
Philadelphia	After	0.475	0.918	1.190	1.341
	Before	0.476	0.842	1.104	1.045
	Observed	0.228	0.408	0.394	0.441
Phoenix	After	0.589	0.619	0.568	—
	Before	0.524	0.553	0.548	—
	Observed	0.188	0.257	0.262	—
San Antonio	After	0.863	0.505	0.423	0.638
	Before	0.616	0.590	0.370	0.661
	Observed	0.326	0.352	0.252	0.300
San Francisco	After	0.688	0.521	—	—
	Before	0.688	0.501	—	—
	Observed	0.200	0.260	—	—

Notes: The virtual prices reported in this table are obtained using the elasticity method. For example, in Atlanta the observed price per ounce for New Brand I was 18 cents. The virtual price of New Brand I, which would set its demand at 0, was estimated to be 38.3 and 29.5 cents per ounce after and before introduction, respectively.

estimates, about 20% were not plausible. For example, average virtual prices before and after introduction of top new brand II in Chicago were 300 to 400 times average post-introduction prices (0.262).[13] In comparison, the elasticity approach yielded average virtual prices of 0.517 and 0.410 in pre- and post-introduction periods, respectively. With the elasticity approach, we encountered only a dozen virtual prices that were about three times the corresponding observed price in the post-introduction period (e.g., urban New York new brand I, suburban New York new brand III). Given the large variances of virtual prices from the Hausman and Leonard approach, we chose the elasticity-based approach for our welfare analysis. Still, we acknowledge the elasticity approach is limited in that demand slopes do not change when quantity demanded approaches the price axis. Fortunately, our price and demand experience for new brands is not that far from the price axis (market share data for new brands, table 1).

[13] Virtual price estimates from the Hausman and Leonard (2002) approach are available from the authors on request.

Table 4. Observed and Estimated Expenditure in Pre- and Post-Introduction Periods

City	No. of House-holds	Expenditures: Observed Post-Introduction $E(\mathbf{P}_b^1, \mathbf{P}_n, \mathbf{r}, \bar{U})$	Post-Introduction w/Virtual Prices $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U})$	Pre-Introduction w/Virtual Prices $E(\mathbf{P}_b^0, \mathbf{P}_n^*(\mathbf{P}_b^0), \mathbf{r}, \bar{U})$
Atlanta, $a = 0.00$	736	469.39	477.68	483.36
Atlanta, $a = 0.25$			537.39	574.76
Atlanta, $a = 0.50$			604.23	683.56
Boston, $a = 0.00$	48	32.39	31.46	26.72
Boston, $a = 0.25$			31.46	26.72
Boston, $a = 0.50$			31.46	26.72
Chicago, $a = 0.00$	1,347	413.00	410.59	389.60
Chicago, $a = 0.25$			475.58	431.25
Chicago, $a = 0.50$			550.87	477.81
Los Angeles, $a = 0.00$	1,567	315.01	311.48	314.00
Los Angeles, $a = 0.25$			350.42	353.00
Los Angeles, $a = 0.50$			393.95	396.00
New York (urban), $a = 0.00$	251	152.12	183.20	140.42
New York (urban), $a = 0.25$			203.00	171.75
New York (urban), $a = 0.50$			224.70	210.66
New York (suburban), $a = 0.00$	313	181.88	176.16	146.90
New York (suburban), $a = 0.25$			203.83	170.41
New York (suburban), $a = 0.50$			236.47	197.30
Philadelphia, $a = 0.00$	736	515.37	503.70	473.67
Philadelphia, $a = 0.25$			556.80	504.40
Philadelphia, $a = 0.50$			616.90	537.08
Phoenix, $a = 0.00$	198	55.69	55.22	49.33
Phoenix, $a = 0.25$			62.12	55.47
Phoenix, $a = 0.50$			69.76	62.70
San Antonio, $a = 0.00$	391	385.22	387.69	366.70
San Antonio, $a = 0.25$			429.50	405.85
San Antonio, $a = 0.50$			474.90	449.10
San Francisco, $a = 0.00$	1,455	369.98	369.21	344.59
San Francisco, $a = 0.25$			424.69	396.67
San Francisco, $a = 0.50$			488.28	456.12

Notes: Expenditures are dollars spent by all sampled households in a city on a weekly basis. For example, in the 736 households in Atlanta, we observed total average expenditure on potato chips to be \$469.39 a week (column 3). Using virtual prices, the estimated average expenditure would be \$477.68 after introduction (column 4) and \$483.36 before introduction (column 5), when $a = 0$. Parameter a indicates preference for variety; higher values of a indicate higher preference.

Table 4 presents the three expenditures required to compute the compensating variation in equation (2): observed expenditures in the post-introduction period, estimated expenditures in the post-introduction period with virtual prices, and estimated expenditures in the pre-introduction period with virtual prices. The last two columns of table 4 present the expenditures with virtual prices in three alternative ways—setting the love-of-variety parameter a to 0.00, 0.25, and 0.50. The variety effect $(-VE)$ is expected to be positive since consumers prefer more to fewer varieties; i.e., $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U}) > E(\mathbf{P}_b^1, \mathbf{P}_n, \mathbf{r}, \bar{U})$. However, the price effect $(-PE)$ can be either negative or positive depending on the nature of competition. A positive (negative) price effect would imply that the prices of existing brands are reduced (increased) following new brand introductions. Nevertheless, whether the variety effect is larger than the price effect, or vice versa, is an empirical question.

In table 4, we first compare $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U})$ to $E(\mathbf{P}_b^1, \mathbf{P}_n, \mathbf{r}, \bar{U})$, which show the estimated expenditure with virtual prices and observed expenditures, respectively, in the post-introduction period. An interesting feature emerges when comparing these expenditures under alternative values of the love-of-variety parameter. With no preference for varieties ($a = 0$), most cities show negative variety effects as expected; i.e., when consumers do not value variety in consumption, an additional variety does not add to consumer surplus. However, even a small preference for variety ($a = 0.25$) creates positive variety effects in nine out of ten cities (Boston is the exception).[14] As noted earlier, previous studies estimated a to be in the neighborhood of 0.4, but in this case variety effects are positive for most cities even when a is set to 0.15 (Ardelean and Lugovskyy, 2010; Ardelean, 2009). As long as consumers show some variety preference, our findings reveal that new brand introductions create a positive variety effect (Hausman and Leonard, 2002; Pofahl and Richards, 2009).

Similarly, we compare $E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U})$ and $E(\mathbf{P}_b^0, \mathbf{P}_n^*(\mathbf{P}_b^0), \mathbf{r}, \bar{U})$ to evaluate price effects of new brand introductions in the 10 cities under alternative values for a. Results show that consumer expenditures have increased following brand introductions, when evaluated using respective virtual prices ($E(\mathbf{P}_b^1, \mathbf{P}_n^*(\mathbf{P}_b^1), \mathbf{r}, \bar{U}) > E(\mathbf{P}_b^0, \mathbf{P}_n^*(\mathbf{P}_b^0), \mathbf{r}, \bar{U})$), except in Atlanta and Los Angeles for all values of a, and in Boston, urban New York, and Philadelphia for $a = 0.5$. Specifically, the price effect ($-PE$) is negative in 21 of 30 instances, suggesting consumer welfare declined with brand introductions because of the associated increase in the price of existing brands. For our preferred value of a (i.e., 0.25), we find that price effects are negative in eight of the ten cities (Atlanta and Los Angeles are exceptions). Note again that the sign of the net effect of new brand introductions on consumer welfare depends on whether or not positive variety effects offset the negative price effects in our application to potato chips.

Table 5 shows the variety effect, price effect, and total effect for all households per week and per household per year when $a = 0.25$. Variety effects are positive under both methods of measuring total effects in nine cities, with Boston the single exception. Positive variety effects in table 5 range from \$6.43 (Phoenix) to \$67.99 (Atlanta) per week for all households. As a percentage of expenditures, weekly welfare gains range from 8.03% (Philadelphia) to 33.45% (urban New York) for all sampled households. On an annual basis, households' welfare gain from new varieties is equivalent to a reduction in expenditures in the range of \$3.13 (Los Angeles) to \$28.14 (urban New York). Welfare loss in Boston is estimated to be \$2.69 per household on an annual basis.

Price effects are mostly negative except in the cases of Atlanta and Los Angeles. The negative price effects range from \$4.78 (Boston) to \$52.37 (Philadelphia) per week for all households. Weekly welfare losses range from 6.14% (San Antonio) to 20.53% (urban New York) for all sampled households. On an annual basis, households' welfare loss from price increases associated with new brand introduction is equivalent to an increase in expenditures in the range of \$2.67 (San Francisco) to \$17.29 (urban New York). Welfare gains from positive price effects of \$0.23 and \$7.02 per household per year are observed in Los Angeles and Atlanta. The predominantly negative price effects point to producers' welfare gain from new brand introductions. However, we exercise caution in referring to these as producers' welfare gain because relative prices change over time. The differential rate of change in cost of living (inflation) across U.S. cities suggests lower producer gains than those reported in table 5 as price effects.

[14] Due to sample size (48 households) and strong complementarity among new as well as existing brands, there is little variation in Boston's expenditures when the value of a, the variety-preference parameter, is altered.

Table 5. Price, Variety, and Total Effects from New Brand Introductions (*a* = 0.25)

	Variety Effect ($)		Price Effect ($)		Total Effect ($)	
City	All HHs Per Week [1]	Per HH Per Year [2]	All HHs Per Week [3]	Per HH Per Year [4]	All HHs Per Week [5]	Per HH Per Year [6]
Atlanta	67.99 (14.48)	12.77	37.37 (7.96)	7.02	105.39 (22.45)	19.78
Boston	−0.93 (−2.68)	−2.69	−4.78 (−14.63)	−13.69	−5.67 (−17.05)	−16.38
Chicago	62.58 (15.15)	6.44	−44.30 (−10.73)	−4.56	18.25 (4.20)	1.88
Los Angeles	35.36 (11.23)	3.13	2.58 (0.82)	0.23	37.95 (12.04)	3.36
NY (urban)	50.88 (33.45)	28.14	−31.25 (−20.53)	−17.29	19.63 (12.90)	10.85
NY (suburban)	21.95 (12.07)	9.67	−33.42 (−18.38)	−14.73	−11.48 (−6.30)	−5.06
Philadelphia	41.42 (8.03)	7.81	−52.37 (−10.17)	−9.87	−10.97 (−2.28)	−2.07
Phoenix	6.43 (11.57)	4.71	−6.65 (−11.47)	−4.37	−0.22 (−0.40)	−0.16
San Antonio	44.28 (11.94)	15.66	−23.65 (−6.14)	−8.37	20.67 (5.36)	7.30
San Francisco	54.70 (14.79)	5.21	−28.02 (−7.58)	−2.67	26.68 (7.21)	2.54

Notes: Values in parentheses represent percentage of expenditures. Variety, price, and total effects are measured in dollars (expenditure change). For example, in Chicago the welfare gain from variety effect amounted to $62.58 per week (column 1) or $6.44 per year (column 2) per household. Price effects amounted to −$44.30 per week (column 3) or −$4.56 per year (column 4) per household. Total welfare gain was $18.25 per week (column 5) or $1.88 per year (column 6) per household.

The sum of positive variety and negative price effects ranges from −$11.48 (suburban New York) to $105.39 (Atlanta) for all households per week. Four cities with a negative total effect are Boston, suburban New York, Philadelphia, and Phoenix. Note that the total effect for Phoenix is close to zero, while the remaining three cities show welfare gains from new brand introductions. As a percentage of expenditures, weekly welfare gains range from 4.20% (Chicago) to 22.45% (Atlanta) for all sampled households.[15] However, welfare losses per week for all sampled households range from 0.40% to 17.05% of expenditures in Boston, suburban New York, Philadelphia, and Phoenix. Other than Phoenix, the three cities with a significant net welfare loss are in the Northeast, where entry barriers may be high enough to allow current producers and/or retailers to increase the price of existing brands.

In general, the results suggest that consumer welfare improves following new brand introduction. The varying price and variety effects demonstrate alternative competitive forces shaping regional markets. However, some price increases associated with additional brand choices suggest firms' use of multiple strategies, including brand-based competition targeted at specific regional markets. Geographic persistence of top brands is likely associated with brands' city of origin (Bronnenberg, Dhar, and Dube, 2009); that is, markets farther from the

[15] Welfare gains and losses can be projected for the entire city. For example, the net welfare gain of $1.88 per household per year in Chicago translates into $1.13 million annual expenditure savings (about 600,000 consuming households).

brand's city of origin tend to have a lower share of it. Thus, measuring consumer welfare at the regional rather than the national level offers sharper insights into the nature of competition.

Summary and Conclusions

We have applied a compensating-variation approach to measure changes in consumer welfare as a result of new brand introductions in the potato chip market. For this purpose, we estimated an AIDS model and evaluated consumer expenditure before and after a new brand introduction. The resulting measure of compensating variation (expenditure change) identified the total benefit to consumers, which was further separated into variety and price effects. The variety effect of new brand introduction is generally assumed to be positive, indicating consumers prefer more to fewer varieties. However, the price effect can be either negative or positive depending on the nature of competition. A positive (negative) price effect would imply that the prices of existing brands are reduced (increased) following new brand introductions.

The relatively recent introduction of baked, organic, and flavored potato chips has altered the nature of competition in the potato chip market. The ACNielsen Homescan database was used to track potato chip purchases in nearly 7,000 U.S. households between 1998 and 2006. Household data on chip price and quantity purchased by brands or varieties were aggregated to weekly data for 10 major U.S. cities for this analysis.

We estimated brand demand functions, underlying an expenditure function, with pre- and post-introduction data. Consumer expenditures were evaluated in three forms based on the brand demand function estimates: (*a*) using observed post-introduction period prices for existing and new brands, (*b*) using post-introduction period prices for existing brands and virtual prices for new brands, and (*c*) using pre-introduction period prices for existing brands and virtual prices for new brands. The virtual or inferred price of the new brand prior to introduction was defined as a price high enough to ensure zero demand for the new brand. Similarly, the virtual price in the post-introduction period is the price that forced consumption of a new brand to zero. Virtual prices were computed in two alternative ways: Hausman and Leonard's (2002) method and an elasticity approach. The latter approach yielded the least price variance.

Results indicate that variety effects are positive in nine of the ten cities when consumers exhibit a preference for variety, and these welfare gains ranged from 8.03% to 33.45% of expenditures per household. The mostly negative price effects ranged from 6.14% to 20.53% of expenditures per household, pointing to producers' welfare gain from new brand introductions. The sum of positive variety and negative price effects is positive for six of the ten cities. Significant net welfare losses in northeastern cities suggest the presence of high entry barriers. The varying total effects by city demonstrate alternative competitive forces shaping regional markets. Thus, national policies guarding against anti-competitive behavior may have different outcomes depending on the region's characteristics.

In general, the results suggest that consumer welfare improves following brand introductions. Our results also show that prices of existing brands increase following such introductions. The latter result is likely explained by firms' use of joint price- and brand-based strategies to compete against one another and new entrants. Future analysis may focus on the interaction between firms' brand introduction strategies and pricing rules to better understand the nature of competition and the resulting consumer welfare in a market.

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