BLS WORKING PAPERS

U.S. Department of Labor
U.S. Bureau of Labor Statistics
Office of Prices and Living Conditions

Early Adopters of New Supermarket Products

Brian Adams, U.S. Bureau of Labor Statistics
Hyunchul Kim, Sungkyunkwan University

Working Paper 501
June 2018

Early Adopters of New Supermarket Products

Brian Adams
US Bureau of Labor Statistics*

Hyunchul Kim
Sungkyunkwan University

April 3, 2018

Abstract

New goods and expanding product variety are thought to provide enormous welfare gains. New products can influence the pricing of competing products, but often the most important way that new products improve the welfare is through their direct consumption value. The demographic profile of the buyers of new goods suggests those welfare gains are unequally distributed. For supermarket products in the US, expenditures on new goods are disproportionately concentrated among high earners and younger consumers.

Keywords: new products, product adoption, consumer spending
JEL classification: D12, M31

1 Introduction

New goods and expanding product variety are thought to provide enormous welfare gains (Petrin, 2002; Broda and Weinstein, 2006). New products can influence the pricing and availability of competing products (as in Eizenberg (2014)). Yet, new products most directly improve the welfare of those who choose to buy them. We describe the demographic profile of the buyers of new goods; it suggests those welfare gains are unequally distributed.

Using the Nielsen Homescan, we calculate purchases of recently introduced products as a percentage of supermarket expenditure. We define "recently introduced" several ways; doing so allows us to profile very early adopters and later adopters. Simple regressions reveal the demographic profile of new product purchasers.

Early adoption of new supermarket goods varies across age groups and income groups in the United States. Higher spending on new goods is positively associated with income and negatively associated with age. Larger households spend disproportionately more on newly introduced products; households with only a male head spend less. Adoption patterns are similar for most broad product categories. They are also robust to several ways of defining a product as new.

*All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the US Bureau of Labor Statistics. All estimates and analyses in this paper based on SymphonyIRI or Nielsen data are by the author and not by the data providers. Corresondence: adams.brian@bls.gov and hchkim@skku.edu

The adoption of new products and processes is the subject of a vast, multidisciplinary literature pioneered in Ryan and Gross (1943) and Rogers (1962) and surveyed by Hauser, Tellis, and Griffin (2006). Many of these studies focus on a single product or innovation and identify which demographic or psychological characteristics predict adoption. Income and age effects are often noted but the magnitudes and directions of their effects on adoption vary. Younger consumers were more likely to adopt consumer electronics (Venkatraman and Price, 1990; Venkatraman, 1991; Im, Bayus, and Mason, 2003), female clothing (Midgley and Dowling, 1993), self-service gasoline (McClurg and Andrews, 1974), toll-free information services (McEwen, 1978), and solar energy systems (Labay and Kinnear, 1981), but not rotary-engines Mazdas (Feldman and Armstrong, 1975), personal computers (Dickerson and Gentry, 1983), nor dessert products (Ostlund, 1974). High incomes were associated with adoption of hybrid-seed corn (Ryan and Gross, 1943), electronic goods (Im, Bayus, and Mason, 2003) or home computers (Dickerson and Gentry, 1983), rotary-engined Mazdas (Feldman and Armstrong, 1975), but not solar energy systems (Labay and Kinnear, 1981). Venkatraman and Price (1990) find an inverse relationship between income and adoption of electronic durables such as the personal computer, food processor, and VCR. Steenkamp and Gielens (2003) use actual purchases of 239 new products by 3,687 consumers to find demographic and personality characteristics associated with adoption. Our analysis, focused exclusively on demographic characteristics, uses data from 60,629 households and 6,828 new product introductions in 2010. The main findings are similar, but category-by-category analysis also provides further information on the variation in age and income effects.

Jaravel (2017) uses data similar to ours to show that product variety is expanding most in categories with more high-income consumers. In his model with nested-CES utility, higher welfare gains and lower price inflation for high-income consumers result. We complement these findings by showing that high-income consumers not only buy in categories with more new products, but they also disproportionately buy the new products themselves. More generally, we complement a literature using detailed microdata to document household variation in consumption patterns and opportunities exemplified by Hobijn and Lagakos (2005), Handbury, Rahkovsky, and Schnell (2016), and Kaplan and Schulhofer-Wohl (2017).

Section 2 describes our data. Section 3 describes our regression models and their results. Section 4 concludes by discussing the causes and implications of the patterns we find.

2 Data

Nielsen Homescan records the supermarket purchases for a large and diverse set of households. Responding panelists are sent a barcode scanner and instructed to scan everything they buy. Thus, purchases are recorded to the exact Universal Product Code (UPC) level and linked to a specific household with known demographic characteristics. Its coverage is not limited to purchases at stores that use loyalty cards or otherwise release detailed sales data.

We define a good as new for a set period after its first recorded purchase. This period is 30, 60, or 90 days in different specifications. Obscure products might not be purchased by a Homescan panelist until well after their introduction, so we only consider products purchased on at least 60 different days between January 2008 and December 2010. We sum the expenditures on new goods and continuing goods for all purchases from May 2010 through October 2010. This limited period avoids some anomalous UPC changes associated with the new calendar year and prevents mistaking seasonal items for new products. We sum 25,371,611 item purchases by 60,629 households. We observe 123,013 products, of which 6,828 were new for part of the study period.

Most Homescan panelists are adopters of some new product; 90.1% buy at least one product that debuted within the last 60 days. However, expenditures on new product are small on average, as shown in Table 1. In our regression analysis, the dependent variable will be 100 times the sum of expenditures on new products divided by the sum of expenditures on all products.

Many new products are minor variations of existing products. For example, the cherry blast flavor of Tums antacid and calcium supplement, the 13 ounce (not 8 ounce) size of Pepperidge Farm Pretzel Goldfish, and a store branded version of panko bread crumbs for the chain Stop & Shop were all among products first purchased in June 2010. We therefore also use a more restrictive, alternative definition for new products. IRI identifies the bestselling newly launched product lines as "New Product Pacesetters."[1] We observe 61 food products associated with Pacesetter lines. In a robustness check, we define a product as new only if it is part of a Pacesetter product line. As before, it is counted as new in 60 days following its first purchase by a Homescan panelist.

Several of the known deficiencies of Homescan data are less relevant for our exercise. Einav, Leibtag, and Nevo (2010) document that Homescan panelists often omit items and even whole shopping trips; Homescan prices disagree with retailers' records of price in about half of the observations. Panelists self-select into Homescan participation, and Lusk and Brooks (2011) suggest they may be especially price sensitive. In many studies, such as those attempting demand estimation, these would be critical shortcomings. However, we only need for Homescan participants to be representative in their willingness to buy new goods and for their unrecorded purchases to have their usual proportion of new goods. Homescan participants are older than the national population, and the Homescan data includes projection weights that we use.

[1] IRI is one of the two major vendor of scanner data in the United States along with Nielsen. Pacesetters include the list of top new products at the brand level screened by sales ($7.5 million per year) and national distribution (30%).

3 Estimation and Results

We calculate the proportion of a respondent's spending on new goods. We regress these proportions on demographic characteristics, using the sampling weights Homescan provides. The results, using three definitions of new goods, are displayed in Table 2.

The overall demographic profile is similar for those who adopt in the first 30 days, 60 days, and 90 days after a product's introduction. The results suggest that the instant adopters and the moderately early adopters of new goods have similar demographic profiles. The proportion spent on new goods declines with age and increases in household income. Households with a female head and a larger number of family members tend to spend more on newly available goods, but these patterns emerge more clearly for the moderately early adopters. The results also show that expenditures on new goods are associated with racial demographics. Asians spend more on new products relative to whites in the first 60 or 90 days after introduction, and Blacks tend to spend slightly less for the first 30 days after introduction. We also find that expenditures on new products are higher in the Midwest and South.

Table 3 presents the results for top new products with more novel innovations based on the IRI's Pacesetter reports. The results indicate demographic profiles of new product buyers, which are largely consistent with those from the more inclusive definition of new products. Younger households, households with a female head, and household with more family members tend to spend more on Pacesetter products. However, most racial and geographic patterns are not robust using this more exclusive measure of new products.

Individual products often attract their early adopters from different groups, as evidenced by the contrasting results in the previous literature mentioned in Section 1. Varying demographic patterns are found even when aggregating all new product introductions in narrowly-defined categories. In 36 of the 100 highest grossing four-digit Homescan product modules, consumers over age 50 spend a high proportion of their category expenditures on new goods, for example. Yet, profiles of early adopters converge as categories are aggregated further. Table 4 shows regression results for nine one-digit product categories. Most coefficients for age and income group indicators have the same signs as in a regression using all categories. Liquor (in column 7) is an exception; lower income is associated with higher spending on recently introduced liquor products as a proportion of all liquor expenditures.

4 Discussion and Conclusion

Because the distribution of adopters varies between demographic groups, it is plausible that the welfare impact of new goods and expanding variety are also unequally distributed. The demographic profile of early adopters varies from product to product, but across almost all supermarket categories younger and higher-income households spend more on new products.

New product adoption is positively associated with income. Perhaps new products are designed for (or predominately marketed to) consumers who have more to spend. Whatever the cause, high income consumers receive more of the direct benefits of new product introductions, potentially exacerbating the effects of income inequality.

Younger consumers also adopt more new products. Younger consumers are nearer the beginning of a lifelong search for products that match their tastes and needs. They are less likely to have already found the best match they can expect, and the benefits on finding better matches may accrue over a longer remaining lifespan. Thus, younger consumers may more actively search for new products when qualities are unknown and costly to sample. It may also be that more new products are designed for them, again because they have less established product loyalties and potentially more time as a locked-in customer.

References

Broda, C., and D. E. Weinstein (2006): "Globalization and the Gains From Variety," *Quarterly Journal of Economics*, 121(2), 541–585.

Dickerson, M. D., and J. W. Gentry (1983): "Characteristics of Adopters and Non-Adopters of Home Computers," *Journal of Consumer Research*, 10(2), 225–235.

Einav, L., E. Leibtag, and A. Nevo (2010): "Recording discrepancies in Nielsen Homescan data: Are they present and do they matter?," *Quantitative Marketing and Economics*, 8(2), 207–239.

Eizenberg, A. (2014): "Upstream Innovation and Product Variety in the U.S. Home PC Market," *Review of Economic Studies*, 81(3), 1003–1045.

Feldman, L. P., and G. M. Armstrong (1975): "Identifying Buyers of a Major Automotive Innovation," *Journal of Marketing*, 39(1), 47–53.

Handbury, J., I. Rahkovsky, and M. Schnell (2016): "Is the Focus on Food Deserts Fruitless? Retail Access and Food Purchases Across the Socioeconomic Spectrum," NBER Working Paper no. 21126.

Hauser, J., G. J. Tellis, and A. Griffin (2006): "Research on Innovation: A Review and Agenda for Marketing Science," *Marketing Science*, 25(6), 687–717.

Hobijn, B., and D. Lagakos (2005): "Inflation inequality in the United States," *Review of Income and Wealth*, 51(4), 581–606.

Im, S., B. L. Bayus, and C. H. Mason (2003): "An Empirical Study of Innate Consumer Innovativeness, Personal Characteristics, and New-Product Adoption Behavior," *Journal of the Academy of Marketing Science*, 31(1), 61–73.

Jaravel, X. (2017): "The Unequal Gains from Product Innovations: Evidence from the US Retail Sector," Working Paper, Stanford University.

Kaplan, G., and S. Schulhofer-Wohl (2017): "Inflation at the household level," *Journal of Monetary Economics*, 91, 19 – 38.

Labay, D. G., and T. C. Kinnear (1981): "Exploring the Consumer Decision Process in the Adoption of Solar Energy Systems," *Journal of Consumer Research*, 8(3), 271–278.

Lusk, J. L., and K. Brooks (2011): "Who Participates in Household Scanning Panels?," *American Journal of Agricultural Economics*, 93(1), 226–240.

McClurg, J. M., and I. R. Andrews (1974): "A Consumer Profile Analysis of the Self-Service Gasoline Customer," *Journal of Applied Psychology*, 59(1), 119–121.

McEwen, W. J. (1978): "Bridging the Information Gap," *Journal of Consumer Research*, 4(4), 247–251.

Midgley, D. F., and G. R. Dowling (1993): "A Longitudinal Study of Product Form Innovation: The Interaction betweenPredispositions and Social Messages," *Journal of Consumer Research*, 19(4), 611–625.

Ostlund, L. E. (1974): "Perceived Innovation Attributes as Predictors of Innovativeness," *Journal of Consumer Research*, 1(2), 23–29.

Petrin, A. (2002): "Quantifying the Benefits of New Products: The Case of the Minivan," *Journal of Political Economy*, 110(4), 705–729.

Rogers, E. M. (1962): *Diffusion of Innovations*. New York: The Free Press.

Ryan, B., and N. C. Gross (1943): "The Diffusion of Hybrid Seed Corn in Two Iowa Communities," *Rural Sociology*, 8(1), 15–24.

Steenkamp, J.-B. E. M., and K. Gielens (2003): "Consumer and Market Drivers of the Trial Probability of New Consumer Packaged Goods," *Journal of Consumer Research*, 30(3), 368–384.

Venkatraman, M. P. (1991): "The Impact of Innovativeness and Innovation Type on Adoption," *Journal of Retailing*, 67(1), 51–67.

Venkatraman, M. P., and L. L. Price (1990): "Differentiating Between Cognitive and Sensory Innovativeness Concepts, Measurement, and Implications," *Journal of Business Research*, 20, 293–315.

Table 1: Household characteristics

	Mean	Weighted mean
Age		
Under 35 years	0.041	0.126
35-49	0.251	0.318
50-64	0.443	0.364
Over 65	0.265	0.193
Income		
Less than $40,000	0.347	0.384
$40,000-69,999	0.313	0.256
$70,000-99,999	0.197	0.159
$100,000 or more	0.142	0.201
Head		
Male and female heads	0.652	0.493
No female head	0.097	0.205
No male head	0.250	0.302
Household size		
1 person	0.255	0.263
2 persons	0.420	0.325
3 persons	0.142	0.172
4 or more persons	0.183	0.240
Race		
White	0.838	0.770
Black	0.092	0.118
Asian	0.027	0.032
Other	0.043	0.080
Region		
Northeast	0.176	0.183
Midwest	0.268	0.225
West	0.195	0.216
South	0.362	0.376
Expenditures (May 1 - Oct 31, 2010)		
on all surveyed products	$1,627.47	$1,589.78
on products introduced in the last 30 days	$8.15	$7.96
on products introduced in the last 60 days	$23.69	$23.37
on products introduced in the last 90 days	$41.49	$41.23
Households	60629	

Weighted mean uses projection factors provided by Homescan.

Table 2: Regression results for spending on new UPCs as a share of total expenditures

	(1) Within first 30 days		(2) Within first 60 days		(3) Within first 90 days	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Age						
Under 35 years	0.089***	0.024	0.230***	0.043	0.497***	0.070
35-49	0.036*	0.015	0.101***	0.026	0.174***	0.038
50-64	0.013	0.013	0.042	0.024	0.063	0.034
Over 65	-	-	-	-	-	-
Income						
Less than $40,000	-0.087***	0.017	-0.203***	0.031	-0.300***	0.044
$40,000-69,999	-0.048**	0.017	-0.100***	0.029	-0.114**	0.043
$70,000-99,999	-0.044*	0.017	-0.054	0.031	-0.021	0.045
$100,000 or more	-	-	-	-	-	-
Heads						
Male and female heads	-	-	-	-	-	-
Only male head	-0.024	0.018	-0.098**	0.033	-0.196***	0.056
Only female head	0.017	0.015	0.035	0.027	0.081*	0.040
Household size						
1 person	-	-	-	-	0	-
2 persons	-0.007	0.017	-0.020	0.031	0.047	0.050
3 persons	0.010	0.020	0.075	0.039	0.150**	0.058
4 or more persons	0.014	0.020	0.060	0.038	0.130*	0.057
Race						
White	-	-	-	-	-	-
Black	-0.043**	0.016	-0.037	0.034	-0.046	0.046
Asian	0.066	0.034	0.302***	0.083	0.440***	0.114
Other	0.026	0.024	0.050	0.043	0.045	0.061
Region						
Northeast	-	-	-	-	-	-
Midwest	0.060***	0.014	0.079**	0.028	0.119**	0.041
South	0.049***	0.014	0.090***	0.027	0.114**	0.039
West	-0.007	0.017	-0.013	0.032	-0.051	0.048
Constant	0.482***	0.025	1.403***	0.046	2.412***	0.069
Obs. (households)	60629		60629		60629	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Regression results for spending on products in their first 60 days as a share of total expenditures

	(1) All new UPCs		(2) Pacesetters	
	Coeff.	SE	Coeff.	SE
Age				
Under 35 years	0.230***	0.043	0.015***	0.003
35-49	0.101***	0.026	0.016***	0.002
50-64	0.042	0.024	0.003*	0.001
Over 65	-	-	-	-
Income				
Less than $40,000	-0.203***	0.031	-0.003	0.002
$40,000-69,999	-0.100***	0.029	0.000	0.002
$70,000-99,999	-0.054	0.031	-0.001	0.002
$100,000 or more	-	-	-	-
Heads				
Male and female heads	-	-	-	-
Only male head	-0.098**	0.033	-0.010***	0.002
Only female head	0.035	0.027	0.000	0.002
Household size				
1 person	-	-	-	-
2 persons	-0.020	0.031	0.002	0.002
3 persons	0.075	0.039	0.004	0.003
4 or more persons	0.060	0.038	0.008***	0.002
Race				
White	-	-	-	-
Black	-0.037	0.034	-0.009***	0.002
Asian	0.302***	0.083	-0.007	0.003
Other	0.050	0.043	-0.008***	0.002
Region				
Northeast	-	-	-	-
Midwest	0.079**	0.028	-0.003	0.002
South	0.090***	0.027	-0.006**	0.002
West	-0.013	0.032	-0.011***	0.002
Constant	1.403***	0.046	0.023***	0.003
Observations (households)	60629		60629	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Regression results for spending on new UPCs as a share of category expenditures

	All	Dry Goods	Frozen	Dairy & Meat	Produce	Liquor	Laundry & Office	Soap & Household	Pharmacy
Age									
Under 35 years	0.230***	0.151**	0.194	0.121**	0.0883	0.206	1.389**	-0.0817	1.112***
	(0.0435)	(0.0468)	(0.114)	(0.0409)	(0.118)	(0.120)	(0.484)	(0.151)	(0.192)
35-49	0.101***	0.117***	0.0918	0.165***	-0.0293	0.117	0.804*	-0.130	0.497***
	(0.0264)	(0.0316)	(0.0621)	(0.0303)	(0.0608)	(0.0827)	(0.315)	(0.104)	(0.116)
50-64	0.0423	0.0351	0.0616	0.103***	-0.0280	0.108	0.464	-0.129	0.0882
	(0.0239)	(0.0278)	(0.0560)	(0.0311)	(0.0545)	(0.0647)	(0.272)	(0.0924)	(0.0984)
Over 65	-	-	-	-	-	-	-	-	-
Income									
Less than $40,000	-0.203***	-0.0777*	-0.179**	-0.106***	-0.206**	0.0817	0.723*	-0.588***	-0.388**
	(0.0308)	(0.0350)	(0.0670)	(0.0312)	(0.0657)	(0.0994)	(0.357)	(0.114)	(0.133)
$40,000-69,999	-0.0999***	-0.0514	-0.0767	-0.0567	-0.0919	0.122	0.503	-0.400***	-0.00289
	(0.0290)	(0.0337)	(0.0701)	(0.0314)	(0.0726)	(0.0845)	(0.343)	(0.111)	(0.127)
$70,000-99,999	-0.0542	-0.0187	-0.0882	-0.0289	0.0133	0.0198	0.573	-0.295*	-0.182
	(0.0313)	(0.0363)	(0.0666)	(0.0341)	(0.0692)	(0.0754)	(0.389)	(0.119)	(0.131)
$100,000 or more	-	-	-	-	-	-	-	-	-
Heads									
Male and female heads	-	-	-	-	-	-	-	-	-
Only male head	-0.0977**	0.00197	0.00920	-0.0819*	-0.00556	0.158	0.198	-0.342*	0.188
	(0.0334)	(0.0388)	(0.0878)	(0.0379)	(0.0733)	(0.144)	(0.428)	(0.134)	(0.160)
Only female head	0.0350	-0.00362	-0.0942	0.00806	0.00357	0.0832	0.448	0.0139	-0.00116
	(0.0273)	(0.0303)	(0.0503)	(0.0271)	(0.0582)	(0.124)	(0.362)	(0.0948)	(0.110)
Race									
White	-	-	-	-	-	-	-	-	-
Black	-0.0372	-0.157***	-0.0548	-0.0385	0.0286	-0.00131	0.270	-0.0360	-0.448***
	(0.0339)	(0.0327)	(0.0572)	(0.0413)	(0.0709)	(0.163)	(0.440)	(0.111)	(0.124)
Asian	0.302***	0.0752	-0.167	-0.0179	-0.0214	-0.00331	0.618	0.433	0.685
	(0.0835)	(0.0809)	(0.114)	(0.0550)	(0.103)	(0.178)	(0.767)	(0.266)	(0.357)
Other	0.0498	-0.110*	0.0957	-0.0748*	0.175	-0.0714	0.765	0.367*	0.0184
	(0.0428)	(0.0436)	(0.153)	(0.0363)	(0.132)	(0.109)	(0.603)	(0.185)	(0.173)
Household size indicators	yes	yes	yes	yes	yes	yes	yes	yes	yes
Region indicators	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs. (households)	60629	60582	59576	60268	60159	28359	39501	60474	59903

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$