The Surprising Breadth of Harbingers of Failure

WEB APPENDIX

June 2019

Contents

Demographic Variables: Definitions and Summary Statistics

Variable	Definition	Mean	Std. Dev.
Age	Average age of head of household	53.27	3.61
Home Value	Estimated home value	$278,868	$185,177
Income	Est. household income in the zip code	$83,213	$52,577
Single Family	% of households in single family homes	0.78	0.24
Multi-family	% of households in multi-family homes	0.22	0.24
Distance	Distance to nearest MassStore store	9.88	7.72
Comp. Distance	Distance to nearest competitors' store	13.42	13.38
Nbr Households	Number of households in the zip code	7,485	6,541
% Urbananized	% households classified as "Urbanized"	0.67	0.42
% Urban Clusters	% households in "Urban Clusters"	0.06	0.18
High School	% of households whose highest educational attainment is graduating high school	0.25	0.09
Bachelors	% of households whose highest educational attainment is a bachelor degree	0.20	0.09
White	% of households that are identified as "White"	0.81	0.21
African American	% of households that are identified as "African American"	0.13	0.18
Asian	% of households that are identified as "Asian"	0.05	0.07
Hispanic	% of households that are identified as "Hispanic or Latino (of any race)"	0.11	0.14
Coupon Discount	% households classified as "Urbanized"		
Coupon Frequency	% households in "Urban Clusters"		
Unit Price Paid	% households not classified as urban		

The unit of analysis is a zip code and the sample size for each of these measures is 4,689 zip codes. The summary statistics for the *Coupon Discount*, *Coupon Frequency* and *Unit Price Paid* are confidential and are omitted. The urban, ethnic, educational attainment, coupon and unit price paid measures are discussed in greater detail on the following pages.

How does the Census Bureau define "urban"?

The Census Bureau's urban classification is a delineation of geographical areas, identifying both individual urban areas and the rural areas of the nation. The Census Bureau's urban areas represent densely developed territory, and encompass residential, commercial, and other non-residential urban land uses. For the 2010 Census, an urban area will comprise a densely settled core of census tracts and/or census blocks that meet minimum population density requirements, along with adjacent territory containing non-residential urban land uses as well as territory with low population density included to link outlying densely settled territory with the densely settled core. To qualify as an urban area, the territory identified according to criteria must encompass at least 2,500 people, at least 1,500 of which reside outside institutional group quarters.

The Census Bureau identifies two types of urban areas:

- Urbanized Areas (UAs) of 50,000 or more people;
- Urban Clusters (UCs) of at least 2,500 and less than 50,000 people.

"Rural" encompasses all population, housing, and territory not included within an urban area.

Source: https://www.census.gov/geo/reference/ua/uafaq.html

Education and Ethnicity Data

This data was obtained from the US Census Bureau's American Fact Finder. The data is for 2016 and is obtained from the 2012-2016 American Community Survey 5-year estimates.

The data is aggregated to the "Zip Code Tabulation Area", which are generalized areal representations of United States Postal Service (USPS) ZIP Code service areas. The USPS ZIP Codes identify the individual post office or metropolitan area delivery station associated with mailing addresses. USPS ZIP Codes are not areal features but a collection of mail delivery routes. The ZCTAs are labeled to identify the most frequently occurring zip code in an area for each ZCTA code.

Source: https://www.census.gov/geo/reference/zctas.html

The education data we use describes the highest level of educational attainment for the population 25 years and over. We use two measures of educational achievement:

- High School: % of the ZCTA population with a regular high school diploma
- Bachelor Degree: % of the ZCTA population with a Bachelor's degree

We use four measures of ethnicity:

- White: % of the ZCTA population that is identified as "White"
- African American: % of the ZCTA population that is identified as "African American"
- Hispanic: % of the ZCTA population that is identified as "Hispanic or Latino (of any race)"
- Asian: % of the ZCTA population that is identified as "Asian"

For the *White*, *African American* and *Asian* measures of ethnicity we use a measure of that race "alone or in combination with one or more other races".

Coupon Discount, Coupon Frequency and Unit Price Paid

These three variables are constructed using all of the transactions from each zip code in 2013. For each zip code we calculate the number of items purchased, the total amount spent, the number of coupons used, and the total value of the discounts received from the use of coupons. We then calculated the following zip code level measures:

$$Coupon\ Discount_z = \frac{Total\ Value\ of\ Discounts_z}{Total\ Value\ of\ Discounts_z + \ Total\ Amount\ Spent}$$

$$Coupon\ Frequency_z = \frac{Number\ of\ Coupons\ Used_z}{Number\ of\ Items\ Purchased_z}$$

$$Unit\ Price\ Paid_z = \frac{Total\ Amount\ Spent_z}{Number\ of\ Items\ Purchased_z}$$

Number of Purchases from Group 2, Group 3 and Group 4 Customers: Products That Succeeded and Failed

	Products that Failed	Products that Succeeded	Difference
Log Group 2 Orders	100.00	97.73	2.27** (0.54)
Log Group 3 Orders	100.00	96.09	3.90** (0.59)
Log Group 4 Orders	100.00	93.83	6.17** (0.72)

The table reports the mean of (the log of) the number of purchases from Group 2, Group 3 and Group 4 customers for products that succeeded and failed. The analysis restricts attention to new products for which the number of orders from Group 1 customers is within half a standard deviation of the mean of (the log of) the number of orders from Group 1 customers. These 927 products include 361 products that failed and 566 products that succeeded. To preserve confidentiality, for each group we index the log of the number of orders at 100 among the products that failed.

Coefficients for the Control Variables

Age	2.60% (4.85%)	High School	-1.78% (4.07%)
Home Value $10,000s	-1.81% (2.41%)	Bachelors	0.40% (4.78%)
Income $10,000s	-0.01% (9.56%)	White	-2.70% (3.11%)
Single Family	19.60% (17.15%)	African American	-4.80% (3.14%)
Multi-family	19.79% (17.06%)	Asian	-8.74%* (3.69%)
Distance	17.64%** (4.61%)	Hispanic	-3.08%** (0.94%)
Comp. Distance	-8.17%** (1.96%)	Coupon Discount	12.44% (10.73%)
Nbr Households 1,000s	1.51% (3.05%)	Coupon Frequency	5.06% (6.05%)
Urban	-1.51% (1.01%)	Unit Price Paid	4.79% (6.06%)
Urban Clusters	-1.71% (1.88%)		

The table reports the coefficients for the control variables from estimating Equation 2. The unit of analysis is a new product and the sample size is 2,388. The coefficients of interest are reported in the table above. Standard errors are in parentheses.

The coefficients estimated for the control variables reported above reveal that if new products are purchased by households in zip codes living closer to the retailer's stores and further from a competitor's store then the product is more likely to survive. Notice that this does not require that there are systematic differences in tendencies of customers living close to the firm's stores versus close to the competitor's stores. It is sufficient that there is random variation, and that some new products match the tendencies of customers living closer to the firm's stores (than the competitors' stores).

Variation in *Average Success Rate* Explained by Control Variables

	% of Variance Explained
Age, Income, Home Value, House Type	24.92%
Distance to Competitors	20.05%
Housing Density	18.95%
Education	2.99%
Ethnicity	34.28%
Coupon Use and Price Paid	14.69%
All Control Variables	45.20%

The table reports the reports the percentage of variance explained in an OLS model where the dependent variable is the *Average Success Rate* of new product purchases in a zip code. The OLS model is estimated separately using each group of control variables. The unit of analysis is a zip code. The sample size in all models is 4,689 zip codes.

Coefficients from Regressing *Average Success Rate* on the Control Variables By Harbinger Group

	Group 1	Group 2	Group 3	Group 4
Age	0.027%	-0.003%	-0.014%	-0.059%
Home Value $10,000s	0.013%	0.002%	-0.001%	0.003%
Income $10,000s	-0.026%	0.003%	0.001%	-0.011%
Single Family	1.589%	0.531%	-0.325%	3.865%
Multi-family	2.185%	0.545%	-0.248%	3.286%
Distance	0.013%	0.002%	0.003%	-0.018%
Comp. Distance	-0.012%	0.002%	-0.002%	-0.031%
Nbr Households 1,000's	-0.006%	-0.001%	0.002%	0.043%
Urban	-0.615%	-0.077%	-0.012%	0.344%
Urban Clusters	-0.407%	-0.167%	0.039%	0.063%
High School	1.505%	0.048%	-0.122%	-0.021%
Bachelors	0.174%	-0.103%	0.059%	-0.397%
White	-2.199%	0.355%	0.618%	2.243%
African American	-1.343%	0.617%	0.308%	1.238%
Asian	0.776%	0.970%	0.973%	1.685%
Hispanic	2.159%	0.930%	0.437%	0.376%
Coupon Discount	4.582%	-1.401%	0.903%	-2.553%
Coupon Frequency	-3.687%	0.396%	-0.558%	-1.779%
Unit Price Paid	0.005%	-0.089%	-0.123%	-0.209%
Sample size	1,172	1,173	1,171	1,173

The table reports the OLS coefficients from regressing *Average Success Rate* on the control variables (separately by harbinger group zip code group). The unit of analysis is a zip code.

Alternative Controls for Income

In this analysis we investigate an alternative approach for controlling for differences in average incomes across zip codes. Under this approach, we group the zip codes into quartiles using the average income variable. We then calculate the number of orders from each income quartile and add these counts as control variables in the models. This is analogous to the approach we used to identify the harbinger effect.

To ensure the variables controlling for income are not confounded with the variables measuring the harbinger effect, we use the following approach:

- In Equation 2 the harbinger effect is estimated using the number of orders contributed by each harbinger group (measured by new product success in the classification set). In this model we control for income effects using the % of sales contributed by each income group.
- In Equation 3 the harbinger effect is estimated using the % of sales contributed by each harbinger group. In this model we control for income effects using the number of orders contributed by each income group.

When estimating these models, we omit the income variable from the standard list of control variables.

		Equation 2
Purchases by Harbinger Group (in Classification Set)	Log Orders Group 1	161.08%** (16.25%)
	Log Orders Group 2	-16.75% (19.11%)
	Log Orders Group 3	-32.51% (19.90%)
	Log Orders Group 4	-105.61%** (14.95%)
Purchases by Income Group	% Income Group 2	-99.14% (65.15%)
	% Income Group 3	-86.49% (70.04%)
	% (Lowest) Income Group 4	-68.77% (81.01%)
	R^2	0.2197

The table reports the coefficients from estimating Equation 2 with the addition of controls for income groups. The unit of analysis is a new item and the sample size is 2,388. Fixed effects at the 3-digit zip code together with coefficients for the control variables (except income) are estimated but omitted from the table. Standard errors are in parentheses.

		Equation 3
Purchases by Harbinger Group (in Classification Set)	% Group 2	-158.85%** (50.82%)
	% Group 3	-268.52%** (50.24%)
	% Group 4	-636.67%** (56.15%)
Purchases by Income Group	(Highest) Income Group 1	30.32% (24.57%)
	Income Group 2	-22.38% (20.95%)
	Income Group 3	-9.58% (21.16%)
	(Lowest) Income Group 4	6.18% (22.14%)
	R^2	0.2255

The table reports the coefficients from estimating Equation 3 with the addition of controls for income groups. The unit of analysis is a new item and the sample size is 2,388. Fixed effects at the 3-digit zip code together with coefficients for the control variables (except income) are estimated but omitted from the table. Standard errors are in parentheses.

The findings are robust to using this alternative approach to control for income differences. Moreover, the coefficients on the income variables are not statistically significant. These results confirm that variation in the income of households that purchased the new product in its first 90 days does not help to explain variation in new product success.

Including Controls for Average Price Paid and Number of Stores

In our analysis we include variables measuring the average price paid for each new product and the number of stores each new product was sold in.[1] These measures are also constructed using transactions in the first 90 days after each new product was introduced. We re-estimate Equations 1, 2, and 3 with the addition of these two control variables. The findings are robust to the addition of these additional controls.

	Equation 1	Equation 2	Equation 3
Log Total Orders	14.71%** (2.03%)		6.84%** (2.06%)
Log Orders Group 1		173.72%** (15.93%)	
Log Orders Group 2		-21.85% (19.08%)	
Log Orders Group 3		-40.61%* (19.74%)	
Log Orders Group 4		-101.92%** (14.97%)	
% Group 2			-169.48%** (50.71%)
% Group 3			-292.75%** (49.01%)
% Group 4			-656.90%** (54.44%)
R^2	0.1728	0.2218	0.2262

The table reports the coefficients of interest from estimating Equations 1, 2 and 3. Fixed effects at the 3-digit zip code together with coefficients for the control variables are estimated but omitted from the table. The unit of analysis is a new item and the sample size in all models is 2,388. Standard errors are in parentheses.

[1] We also investigated controlling for the number or depth of discounts (coupons) offered in the first 90 days. However, our data does not allow coupons to be matched to specific products.

Varying the Threshold Used to Define New Product Survival

Classifying new products as successful using an 18 month survival period is somewhat arbitrary. We investigated the robustness of our analysis by labelling new products in the holdout set as successful using alternative survival thresholds. In particular, we measured success using 12 month, 15 month and 21 month survival windows.

Equation 2

	12 Month Survival	15 Month Survival	21 Month Survival
Log Orders Group 1	136.30%**	155.11%**	168.38%**
	(14.28%)	(15.02%)	(15.66%)
Log Orders Group 2	-14.64%	-13.79%	-16.59%
	(17.35%)	(18.25%)	(19.02%)
Log Orders Group 3	-25.48%	-32.82%†	-36.83%†
	(17.97%)	(18.90%)	(19.70%)
Log Orders Group 4	-93.34%**	-104.57%**	-109.09%**
	(13.49%)	(14.20%)	(14.79%)
R^2	0.2179	0.2123	0.2188

The table reports the coefficients of interest from estimating Equation 2. Coefficients for the control variables are omitted from this table. The unit of analysis is a new item and the sample size in all models is 2,388. Standard errors are in parentheses.

Equation 3

	12 Month Survival	15 Month Survival	21 Month Survival
Log Total Orders	1.52%	2.38%	4.30%**
	(1.46%)	(1.53%)	(1.60%)
% Group 2	-114.94%**	-155.30%**	-165.09%**
	(46.22%)	(48.61%)	(50.70%)
% Group 3	-211.48%**	-266.70%**	-287.58%**
	(44.60%)	(46.90%)	(48.91%)
% Group 4	-549.37%**	-625.57%**	-661.21%**
	(49.24%)	(51.78%)	(54.01%)
R^2	0.2239	0.2193	0.2246

The table reports the coefficients of interest from estimating Equation 3. Coefficients for the control variables are omitted from this table. The unit of analysis is a new item and the sample size in all models is 2,388. Standard errors are in parentheses.

Number of Stores New Items are Sold In

In our analysis we focus on items sold in at least 25% of the retailer's stores in the first 90 days after the item was introduced. This restriction was designed to ensure that the item was not just a regional item (such as Red Sox hats) and that it had graduated beyond initial market testing. As a robustness check we repeated the analysis using the following thresholds:

- 50% of stores
- 75% of stores
- 95% of stores
- 100% of stores

The results confirm that the findings are robust to varying this restriction.

Sold in at Least 50% of Stores

	Equation 1	Equation 2	Equation 3
Log Total Orders	11.97%** (1.82%)		4.90%* (1.92%)
Log Orders Group 1		168.78%** (20.95%)	
Log Orders Group 2		21.31% (26.49%)	
Log Orders Group 3		-29.01% (26.53%)	
Log Orders Group 4		-155.79%** (20.39%)	
% Group 2			-56.86% (66.01%)
% Group 3			-240.16%** (64.42%)
% Group 4			-707.51%** (74.01%)
R^2	0.2116	0.2525	0.2529

The table reports the coefficients of interest from estimating Equations 1, 2 and 3. Fixed effects at the 3-digit zip code together with coefficients for the control variables are estimated but omitted from the table. The unit of analysis is a new item and the sample size in all models is 2,036. Standard errors are in parentheses.

Sold in at Least 75% of Stores

	Equation 1	Equation 2	Equation 3
Log Total Orders	6.63%** (2.38%)		0.45% (2.40%)
Log Orders Group 1		192.85%** (26.06%)	
Log Orders Group 2		54.20% (33.87%)	
Log Orders Group 3		-50.13% (33.78%)	
Log Orders Group 4		-195.98%** (27.43%)	
% Group 2			-78.21% (80.21)
% Group 3			-321.37%** (83.67%)
% Group 4			-833.09%** (92.59%)
R^2	0.2397	0.2832	0.2821

The table reports the coefficients of interest from estimating Equations 1, 2 and 3. Fixed effects at the 3-digit zip code together with coefficients for the control variables are estimated but omitted from the table. The unit of analysis is a new item and the sample size in all models is 1,630. Standard errors are in parentheses.

Sold in at Least 95% of Stores

	Equation 1	Equation 2	Equation 3
Log Total Orders	10.53%** (3.97%)		6.13% (4.02%)
Log Orders Group 1		173.47%** (42.62%)	
Log Orders Group 2		79.55% (57.74%)	
Log Orders Group 3		-132.62%* (57.75%)	
Log Orders Group 4		-113.53%* (48.38%)	
% Group 2			37.07% (128.17%)
% Group 3			-392.49%** (138.66%)
% Group 4			-571.06%** (135.65%)
R^2	0.2319	0.2536	0.2534

The table reports the coefficients of interest from estimating Equations 1, 2 and 3. Fixed effects at the 3-digit zip code together with coefficients for the control variables are estimated but omitted from the table. The unit of analysis is a new item and the sample size in all models is 917. Standard errors are in parentheses.

Sold in 100% of Stores

	Equation 1	Equation 2	Equation 3
Log Total Orders	9.50% (7.73%)		9.21% (7.84%)
Log Orders Group 1		-4.38% (78.38%)	
Log Orders Group 2		151.60% (113.93%)	
Log Orders Group 3		46.73%* (121.17%)	
Log Orders Group 4		-184.90%* (85.74%)	
% Group 2			240.40% (247.71%)
% Group 3			125.11% (252.75%)
% Group 4			-499.77%† (261.99%)
R^2	0.2415	0.2556	0.2534

The table reports the coefficients of interest from estimating Equations 1, 2 and 3. Coefficients for the control variables are omitted from this table. The unit of analysis is a new item and the sample size in all models is 334. Standard errors are in parentheses.

Logistic Regression Models

In our estimation we used a linear probability model because the coefficients from this model are directly interpretable. The outcome variable is a binary variable and so we can also use logistic regression. In the tables below we report the coefficients and estimated odds ratios when re-estimating the three models using logistic regression.

	Equation 1	**Equation 2**	**Equation 3**
Log Total Orders	0.6633** (0.0873)		0.2730** (0.0977)
Log Orders Group 1		8.3827** (0.9981)	
Log Orders Group 2		0.2850 (1.1076)	
Log Orders Group 3		-1.6198 (1.1611)	
Log Orders Group 4		-6.7199** (0.9334)	
% Group 2			-11.6676** (3.0706)
% Group 3			-17.0966** (3.0327)
% Group 4			-34.9179** (3.3913)
AIC	2640.0	2527.5	2517.5

The table reports the coefficients of interest from estimating Equations 1, 2 and 3 using a logistic model. Coefficients for the control variables are omitted from this table. The unit of analysis is a new item and the sample size in all models is 2,388. Standard errors are in parentheses.

Logistic Regression Models: Odds Ratios Estimates

	Equation 1	Equation 2	Equation 3
Log Total Orders	0.515 (0.434, 0.611)		0.761 (0.628, 0.922)
Log Orders Group 1		<0.001 (<0.001, 0.002)	
Log Orders Group 2		0.752 (0.086, 6.592)	
Log Orders Group 3		5.052 (0.519, 49.183)	
Log Orders Group 4		828.8 (133.0, >999.9)	
% Group 2			>999.9 (284.1, >999.9)
% Group 3			>999.9 (>999.9, >999.9)
% Group 4			>999.9 (>999.9, >999.9)

The table reports log odds ratios from logistic model estimates of Equations 1, 2 and 3, where the dependent variable is a binary variable indicating whether the new product survived. 95% confidence intervals are reported in parentheses. The unit of analysis is a new item and the sample size in all models is 2,388.

The odds ratio provides a measure of the change in the probability that a new product survived when there is a unit increase in the value of the coefficient. For example, in Equation 1 if *Log Total Orders* increases by 1 (an order of magnitude increase in total orders) then the odds that the new product survived is 0.515 larger than if *Log Total Orders* did not change.

The findings reveal the same pattern of findings as the linear probability models. In Models 2 and 3 we see that the change in the odds of survival depend upon which customers purchased the new product. If the product was purchased by a higher proportion of harbingers, then the product was less likely to survive.

Calculating the *Average Success Rate*
by Weighting Using the Number of Households that Purchased

A key feature of the analysis is the grouping of zip codes using the *Average Success Rate* of new product purchases. Recall that we calculate the *Average Success Rate* for each zip code by observing orders for new products in the classification set and calculating a weighted average of whether the products were successful. We weighted by the number of orders for each new item. This is a natural basis for weighting as it discriminates between zip codes that placed few orders for a new item and zip codes that placed many orders. As an alternative, we investigated constructing the *Average Success Rate* by weighting the new item purchases using the number of households that purchased each item (instead of the number of orders). This means, for example, that zip codes in which 10 households placed a total of 30 orders for a new item are treated the same as zip codes in which 10 households placed a total of 10 orders for the item. Intuitively, it measures how many customers had demand for the new item, rather than measuring total demand for the new item (in each zip code). The findings are reported below. Reassuringly, the coefficients of interest are essentially unchanged.

	Equation 2	**Equation 3**
Log Total Orders		4.45%** (1.60%)
Log Orders Group 1	145.19%** (14.71%)	
Log Orders Group 2	17.75% (19.31%)	
Log Orders Group 3	-62.09%** (20.22%)	
Log Orders Group 4	-94.45%** (14.58%)	
% Group 2		67.16% (52.61%)
% Group 3		-271.74%** (49.69%)
% Group 4		-580.54%** (52.85%)
R^2	0.2148	0.2220

The table reports the coefficients of interest from estimating Equations 2 and 3. In this analysis the *Average Success Rate* used to group zip codes is constructed by weighting the observations using the number of households that purchased the classification items in each zip code (rather than the number of orders for each item). Coefficients for the control variables are omitted from this table. The unit of analysis is a new item and the sample size in all models is 2,388. Standard errors are in parentheses.

Finer Segmentation of *Average Survival Rate*: Deciles

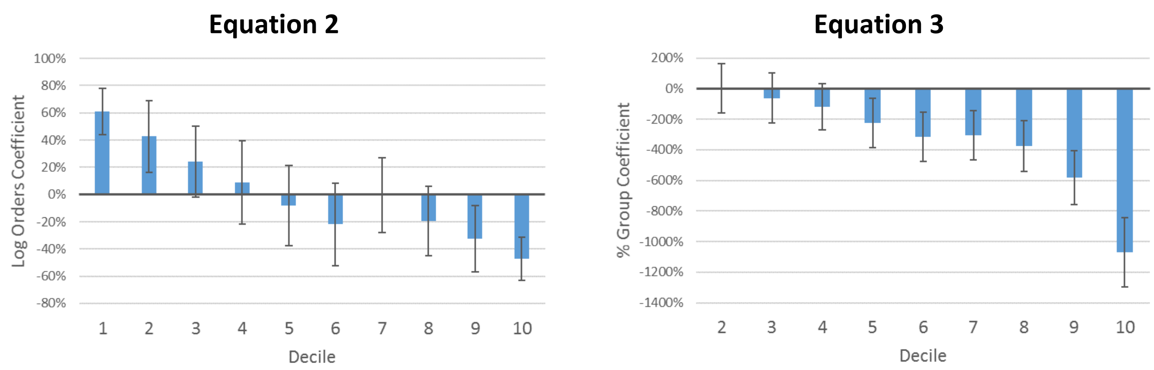
The division of the *Average Success Rate* into quartiles is somewhat arbitrary.[2] For this reason, we investigated using decile buckets instead of quartile buckets. Decile buckets provide a more precise illustration of the relationship between the *Average Success Rate* and new product success. We re-estimated Equations 2 and 3, replacing the variables measuring purchases by the quartile grouping of zip codes, with variables measuring purchases from each decile bucket. We summarize the findings below.

	Equation 2		Equation 3
Log Orders Group 1	60.98%** (8.56%)	Log Total Orders	4.15%* (1.62%)
Log Orders Group 2	42.56%** (13.47%)	% Group 2	2.75% (81.39%)
Log Orders Group 3	23.97%† (13.34%)	% Group 3	-62.03% (84.13%)
Log Orders Group 4	8.91% (15.54%)	% Group 4	-119.44% (76.11%)
Log Orders Group 5	-8.16% (14.96%)	% Group 5	-225.80%** (81.68%)
Log Orders Group 6	-21.86% (15.52%)	% Group 6	-315.72%** (82.12%)
Log Orders Group 7	-0.51% (14.06%)	% Group 7	-305.47%** (83.15%)
Log Orders Group 8	-19.46% (13.10%)	% Group 8	-376.27%** (84.56%)
Log Orders Group 9	-32.44%** (12.54%)	% Group 9	-580.22%** (90.06%)
Log Orders Group 10	-47.14%** (8.01%)	% Group 10	-1069.58% (114.63%)
R^2	0.2226		0.2322

The table reports the coefficients of interest from estimating Equations 2 and 3 using decile instead of quartile splits of the *Average Success Rate* measure. Coefficients are estimated for the control variables but are omitted from this table. The unit of analysis is a new item and the sample sizes are 2,378 (Equation 2) and 2,388 (Equation 3). The difference in sample sizes reflects zero purchases for 10 observations in a zip code x decile (log of zero is undefined). Standard errors are in parentheses.

[2] Chen, McShane and Anderson (2018) propose an approach for endogenously dividing the *Average Success Rate* measure into groups. Somewhat surprisingly, they find that a more sophisticated approach yields only a small performance improvement (measured in the percentage of variance explained).

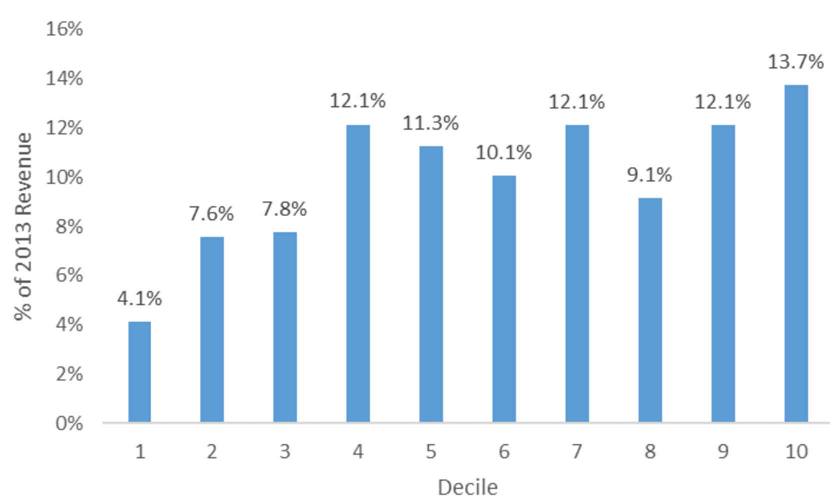
Grouping Zip Codes Using Decile Splits of the Average Success Rate



The figure summarizes the coefficients of interest when estimating Equations 2 and 3 using decile instead of quartile splits of the *Average Success Rate* measure. Error bars indicate 95% confidence intervals.

Zip codes with lower *Average Success Rates* are grouped in higher numbered deciles. More purchases of new products by these zip codes is a clear signal that the new products will fail. Although not perfectly monotonic, the pattern is reassuringly consistent with the previous findings. In the table below we also use this decile analysis to investigate the "buying power" of harbingers. In particular, we calculated the proportion of 2013 sales contributed by each decile. We see that the harbinger deciles contribute a disproportionate percentage of 2013 revenue. The two deciles with the lowest *Average Success Rate* represent 20% of the zip codes but contribute 25.8% of 2013 revenue.

Proportion of 2013 Revenue Contributed by Each *Average Success Rate* Decile



The figure is a histogram summarizing the % of 2013 revenue contributed by each group of zip codes. The columns add to 100%. The zip codes are grouped into deciles according to the *Average Success Rate* calculated using the products in the classification set. The Decile 1 zip codes have the highest *Average Success Rate*.

Differences in Marketing Activities

We collected additional information and conducted additional analysis at MassStore to investigate the possibility that the harbinger effect is due to variation in marketing activities across zip codes. The first step was to understand the degree to which the firm engaged in target marketing during the period in which our data was drawn. We learned that at that time there was little variation in this retailer's marketing activities across zip codes. Existing customers all received direct mail, but the same direct mail piece was sent to every member. The firm had very few online sales and a relatively small digital advertising budget. It did not intentionally vary its digital advertising by geography.[3] When prospecting for new customers the retailer primarily used two marketing activities: mass media advertising and direct mail. The reach of the mass media advertising varied by geographic region. However, within a 3-digit zip code it did not vary, and so our inclusion of 3-digit fixed effects rules out this source of variation as an explanation. The firms' direct mail prospecting also used a single variant (it did not engage in targeting). The only exception were "no mail" control groups, which were randomly assigned.

Although not conclusive, this suggests that the effects we reported are unlikely to be attributable to the firm's marketing activities. To supplement this evidence, we also conducted additional analysis using newly acquired customers. This analysis uses data collected as part of our larger research team's activities with this retailer. In particular, the research team designed a series of direct mail experiments to help the firm target its direct mail prospecting activities (this occurred after the time period used in the paper). During this period our data records the direct mail sent to every prospect. This allows us to identify any variation in marketing activities across zip codes.

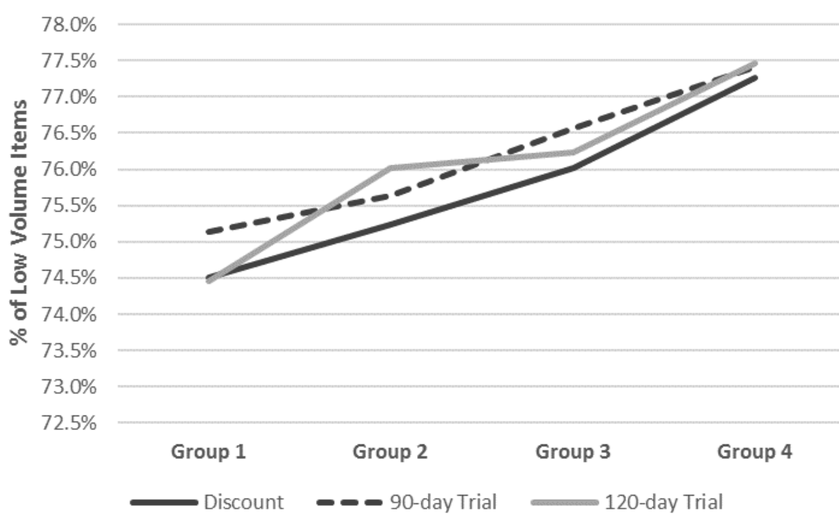
Our analysis focuses on a single six month prospecting "season" and in this season we use the number of orders within a 3-digit zip code to define items that are "low volume". In particular, we rank the items within each 3-digit zip code according to how frequently they were purchased in this six-month season (by both new and existing customers). Within each 3-digit zip code we identify the *Low Volume* items: the lowest volume items that collectively contribute 50% of total orders within a 3-digit zip code. The same approach is used in the main text to investigate the differences between harbinger zip codes and non-harbinger zip codes at MassStore by comparing purchases of existing items (not newly introduced).

We calculate the proportion of *Low Volume* items purchased by new customers acquired in this six month prospecting season. We compare this proportion for new customers acquired using different promotional offers. The promotional offers included a $25 discount (approximately 50% off the membership price), a 90-day free trial, or a 120-day free trial (longer trial). The promotional offers were randomly assigned to different carrier routes. Each carrier route is within a single zip code and includes approximately 400 households. There are an average of 14 carrier routes per zip code. As a result, it was common for different households in a zip code to randomly receive different promotional offers. In the figure and table below we report the proportion of *Low Volume* items purchased by new customers acquired using the different promotional offers. We group the zip codes using the original harbinger

[3] The digital advertising platforms may have varied content by geography, but the inclusion of 3-digit zip code fixed effects are likely to have controlled for most of this effect.

classification calculated using the full sample of 4,712 new products (including both the classification and validation sets).

% of *Low Volume* Items Purchased by New Customers



	Discount	**90-day Trial**	**120-day Trial**
Group 1	74.50% (0.06%)	75.13% (0.16%)	74.45% (0.15%)
Group 2	75.24% (0.07%)	75.63% (0.20%)	76.01% (0.16%)
Group 3	76.02% (0.07%)	76.56% (0.17%)	76.23% (0.17%)
Group 4	77.27% (0.07%)	77.42% (0.18%)	77.83% (0.16%)
Sample Sizes			
Group 1	16,128	2,960	3,545
Group 2	17,794	2,434	3,217
Group 3	16,878	3,001	3,226
Group 4	16,528	2,810	3,494

The figure and table report the proportion the percentage of *Low Volume* items among the items purchased during the fall 2015 prospecting season by new customers acquired during this season. Customers are grouped according to the original harbinger classification of zip codes, and by the type of promotion used to acquire each customer.

There are two findings of interest. First, the results replicate the harbinger effect: new customers in harbinger zip codes are more likely to purchase *Low Volume* items, compared to new customers in non-harbinger zip codes. This replication is reassuring as the both the customers and the time period are different than the results reported in the main text. Second, within a single promotion condition there is strong evidence of a harbinger effect. Notably, within a single promotion condition, the new customers were all exposed to the same marketing actions, and so the effects cannot be attributed to differences in marketing actions. Together, these findings allow us to conclude that the harbinger effect is robust, and is not solely due to variation in the firm's marketing activities.

Do Harbingers Purchase Items that Other Customers Return?

We begin by calculating the average return rate for each item. When calculating the average return rate for an item we exclude return decisions in the focal zip code. This allows us to measure return decisions by "other customers". We then use purchases by customers in each zip code to calculate the average return rate (by other customers) for items purchased in that zip code, weighting by the number of units purchased. We then re-estimate Equation 4 using the *Average Return Rate* (by other customers) as the dependent variable. The coefficients of interest are reported in Table 8.

In this analysis, the coefficient of interest measures how the *Average Return Rate* (by other customers) varies within a 3-digit zip code according to the *Average Success Rate* of new product purchases at MassStore.[4] If harbinger zip codes are more likely to purchase items that other customers return, then we would expect to see a negative coefficient for this variable, indicating a higher *Average Return Rate* when the *Average Success Rate* is lower. The findings confirm that harbinger zip codes are more likely than neighboring zip codes to purchase items that other customers return. A 10% decrease in the *Average Success Rate* in a zip code is associated with an increase of more than 2% in the average return rate (by customers in other zip codes). This effect is almost identical when using transactions from 2010 or 2011.

One interpretation of a high return rate on an item is that it indicates many of the other customers did not like the item. Thus, a tendency to purchase items that other customers return suggests that harbingers purchase items that many others do not like. This argument would be stronger if we knew that other customers returned the item because they did not like it. Fortunately, ApparelCo asks customers to indicate the reason that an item is returned. We group the return reasons into four groups and summarize the frequency of their occurrence in the tables on the following pages.

The most common reason an item is returned is because it is the wrong size. The next most common reason is that the customer did not like the item when it arrived. This category includes returns due to color, material or styling. There are also returns due to quality defects, although these are relatively uncommon. These return reasons allow us to further investigate our interpretation that harbingers have tendencies that are different from other customers. To do so, we separately re-estimate Equation 4 using different dependent variables. The dependent variables measure the proportion of items returned (by other customers) for each of the four return reasons. The coefficients of interest are also reported below.

The analysis of return reasons reveals that the tendency of harbingers to buy items that other customers return is concentrated in returns due to (a) size and (b) because customers did not like the item. Preferences for the color, material or styling, together with the size and fit of an item are idiosyncratic, reflecting customers' body shapes and personal tastes. The evidence that harbingers are more likely to purchase items that other customers return for these idiosyncratic reasons suggests that harbinger tendencies may be associated with differences in some product preferences.

[4] The inclusion of the fixed effects ensures that β_1 is only identified by variation within each 3-digit zip code (and not by regional variation across 3-digit zip codes).

In contrast, quality defects are not idiosyncratic and we would expect returns due to defects to affect all customers in approximately the same way. It is therefore notable that the effects are much smaller for returns due to defects. This is consistent with the interpretation that harbinger tendencies are associated with idiosyncratic product preferences.

We caution that returns due to defects are relatively uncommon, and it is possible that this may have contributed to why we do not see a significant negative coefficient for this return reason. However, the confidence intervals around these parameter estimates are relatively tight. To further investigate this possibility, we re-estimated all of the models when restricting attention to product families that had higher than median returns due to defects. The pattern of findings was unchanged.

Do Harbingers Purchase Items that Other Customers Return?

	***Avg. Success Rate* Coefficient (β_1)**		**R^2 values**	
Dependent Variable	**2010**	**2011**	**2010**	**2011**
All Return Reasons	-2.37%** (0.91%)	-2.11%** (0.94%)	0.2657	0.2985
Did Not Like the Item	-1.02%** (0.31%)	-0.70%* (0.31%)	0.2524	0.2864
Wrong Size	-1.02%* (0.52%)	-1.31%* (0.55%)	0.2711	0.3100
Defective	-0.07%† (0.04%)	0.01% (0.04%)	0.3119	0.3378
Miscellaneous	-0.25%* (0.13%)	-0.11% (0.12%)	0.2785	0.2723

The table reports the *Average Success Rate* coefficients (β_1) and the R^2 values when estimating Equation 4. The unit of analysis is a zip code and the sample size in all of the models is 2,346. The dependent variable measures the *Average Return Rate* by other customers of the products purchased in that zip code. Fixed effects and control variables were included in the model but these coefficients are omitted from the table. Standard errors are in parentheses.

Average Return Rate by Return Reason

Return Reason	2010	2011
Did Not Like The Item	4.13%	4.25%
Item is the Wrong Size	6.72%	7.27%
Item is Defective	0.32%	0.37%
Miscellaneous	2.15%	1.92%
All Reasons	13.32%	13.80%

The table describes the average return rate by return reason. They are calculated separately using return transactions in 2010 and 2011. We only consider transactions in zip codes for which we have *Average Success Rates* from MassStore. Sample sizes are 6,190,833 (2010) and 6,226,019 (2011).

Return Reasons: Average Return Rate

Return Reason	2010	2011
Did Not Like The Item		
Did Not Like Color	0.75%	0.83%
Did Not Like Material	0.42%	0.05%
Did Not Like Styling	1.90%	2.41%
Did Not Like Other	1.06%	0.95%
Any Did Not Like Reason	4.13%	4.25%
Item is the Wrong Size	6.72%	7.27%
Item is Defective	0.32%	0.37%
Miscellaneous	2.15%	1.92%
All Reasons	13.32%	13.80%

The table describes the average return rate by return reason. The sample sizes are 6,190,833 (2010) and 6,226,019 (2011).

Customers that Changed Zip Codes

We can also use households that changed zip codes to address a second question; do households change their purchasing decisions when they move into a harbinger zip code? In particular, we investigate whether households' purchases of niche items changed after they moved zip codes. In this analysis we focus on 13,715 households that changed zip codes between 2007 and 2009 and did not change zip codes between 2009 and 2011.[5] These 13,715 households all satisfy the following criteria:

a. Made at least one order in 2007, 2009 and 2011.
b. Shipped all of their orders to 1 zip code in 2007.
c. Shipped all of their orders to 1 zip code in 2009.
d. Shipped all of their orders to 1 zip code in 2011.
e. The zip code was different in 2007 and 2011.
f. The zip code was the same in 2009 and 2011.

We measure the change in niche item purchases after they moved by comparing the % of niche items purchased in 2011 with the % purchased in 2009. We summarize this identification approach in the figure below.

Composition of the Sample

2007	2008	2009	2010	2011
Moved zip code		Did not move zip code		
		% niche in 2009		% niche in 2011

To compare the % of niche items purchased in 2011 and 2009 we used a multivariate approach that includes the nineteen control variables. In particular, we estimated the following model:

$$\textit{Change in Niche}_i = \alpha + \beta_1 \textit{ Change in Avg Success Rate}_i + \beta_2 \textit{ \% Niche in 2009}_i + \boldsymbol{\beta \Delta X}_z + \varepsilon_z \quad \text{(A1)}$$

The unit of analysis is a customer and the variables in this model are defined as follows:

Change in Niche = % Niche in 2011 - % Niche in 2009

Change in Avg. Success Rate = Avg. Success Rate in 2009 Zip - Avg. Success Rate in 2007 Zip

The $\boldsymbol{\Delta X}_z$ term represents the difference in the 2009 zip code and 2007 zip code for each control variable (for example *Age in 2009 Zip – Age in 2007 Zip*). Notice that every customer in the sample is associated

[5] More precisely, the households had moved by the time of their first purchase in 2009. It is possible that the move occurred in 2009 before their first 2009 purchase. Despite this possibility, our measure of the % of niche items purchased in 2009 only measures purchases after households had moved.

with a different zip code in 2007 and 2009, and so the *Change in Avg. Success Rate* and $\mathbf{\Delta X_z}$ variables are constructed using zip code level measures.

We estimate Equation 6 separately using the *Change in Niche* purchasing and the *Change in Low Volume* purchasing as dependent variables. The coefficients are reported in the table below. We see no evidence that movement from a more harbinger zip code to a less harbinger zip code results in a reduction in the proportion of niche items purchased (or vice versa). The coefficients do not approach statistical significance, and their signs are the reverse of what we would expect if the proportion of niche products decreased when customers moved to a zip code with a higher *Average Success Rate*.

Change in the Percentage of Niche Items Purchased Between 2009 and 2011

Dependent Variable	***Change in Avg. Success Rate* Coefficient (β_1)**	**R^2 Values**
Niche (Bottom 10%)	9.32% (10.00%)	0.4747
Low Volume (Bottom 50%)	3.82% (16.37%)	0.4355

The table reports the *Change in Avg. Success Rate* coefficients (β_1) and R^2 values from estimating Equation A1 with different dependent variables. Control variables are estimated but omitted from the table. The unit of analysis is a customer and the sample size in all of the models is 13,715. Standard errors are in parentheses.

These findings can be compared with an earlier study of purchases of women's shoes. Galak, Gray, Elbert and Strohminger (2016) study shoe purchases by women who moved between zip codes. They find that preferences tend to conform to new local norms when women move from relatively low to relatively high status zip codes. However, when moving to relatively lower status locations they mostly ignore the new local norms.

For completeness, we contrasted customers that changed zip codes but stayed within the same 3-digit zip code, with those that moved zip codes. Recall that whether an item is a niche product is defined within each 3-digit zip code. Therefore, restricting attention to customers who remained within a 3-digit zip code reduces variation in the definition of what is a niche product. The pattern of findings is unchanged; the *Change in Avg. Success Rate* coefficient does not approach statistical significance either when focusing on customers who stayed in the same 3-digit zip code, or when focusing on customers who changed 3-digit zip code.

As an additional robustness check, we investigated including zip code fixed effects identifying either the 2007 or 2009 3-digit zip code. This had almost no impact upon the coefficients of interest. We also investigated replacing the dependent variable with binary variables indicating whether the % of niche items purchased (or % of low volume items purchased) increased from 2009 to 2011. The coefficients of interest were again not significant. We conclude that the data does not indicate that households acquire their harbinger tendencies from their new neighbors.

Zillow House Price Analysis: Robustness Checks

We investigate the robustness of our finding that harbinger zip codes enjoy smaller house price increases during these periods. One explanation for this finding is that these are the zip codes that had lower home values at the start of this period. This turns out to be correct: the house prices of harbinger zip codes at the start of 2002 were lower on average than prices in other zip codes. However, lower prices at the start of 2002 do not imply larger price increases between 2002 and 2006. To understand this relationship, we included starting prices as a control variable in the regressions.[6] The pattern of findings is unchanged (the coefficients of interest from this model are reported in the table below). Moreover, during periods average prices increased, the increases were actually larger in regions with lower initial prices (the *Starting Price* coefficients are negative). This indicates that the smaller increase in house prices in harbinger zip codes occurs despite their lower starting values, not because of it.

Our second robustness check replaces the fixed effects identifying each 3-digit zip code with fixed effects identifying each 4-digit zip code. This reduces the price variation to even smaller regions, with at most ten (5 digit) zip codes within each 4-digit zip code. The pattern of findings is again replicated (the coefficients of interest are also reported in the table below).

	2002 to 2006	**2007 to 2011**	**2012 to 2015**
Controlling for Starting Price	15.50%* (6.74%)	-14.66%† (8.16%)	20.35%** (6.37%)
4-digit Zip Fixed Effects	16.27%* (7.97%)	-24.66%** (9.27%)	16.11%* (0.73%)

The table reports the *Average Success Rate* coefficients and R^2 values when estimating modified versions of Equation 4 using different time periods. The unit of analysis is a zip code and the sample size for all of the models is 3,837. Standard errors are in parentheses.

[6] Starting prices appear in both the left and right hand side variables. This is not unusual in a difference model.

Contributions to Winning vs. Losing Candidates

We constructed a binary variable Win_{cdt} indicating whether a candidate won the election for that congressional district in that electoral cycle. We then calculate the "Winning Percentage" as a weighted average of *Win*. In particular, we average across candidates and congressional districts to calculate a weighted average for each zip code in each election cycle. We weight the total dollar contribution from that zip code to each candidate (*Win %*). To analyze the relationship between *Win %* and *Average Success Rate* of new product purchases at MassStore, we again use Equations 4 and 5. The findings are reported in the table below.

Donations to Political Candidates: % of Winning Candidates

	Equation 4	Equation 5	Equation A2
Average Success Rate	30.82%** (11.38%)		
Group 2		-0.09% (0.62%)	
Group 3		-0.01% (0.68%)	
Group 4		-0.45% (0.74%)	
Percentiles 5% to 10%			-0.13% (0.90%)
Percentiles 0% to 5%			-2.85%** (0.99%)
R^2	0.0597	0.0594	0.0597

The table reports the coefficients of interest from estimating Equations 4, 5 and A2. The dependent variable in both models is *% Win*. Fixed effects at the 3-digit zip code together with coefficients for the control variables are estimated but omitted from the table. The unit of analysis is a zip code x election cycle and the sample size in both models is 24,885. Standard errors are in parentheses.

It is notable that we see a significant coefficient in Equation 4, but the coefficients are not significant in Equation 5. Further investigation reveals that the overall effect (Equation 4) is driven by the 5% of zip codes with the lowest average success rates. To illustrate this, we rank the zip codes using the *Average Success Rate* and construct indicator variables identifying the zip codes with lowest *Average Success Rate*:

- Percentiles 0 to 5 (the 5% of zip codes with the lowest *Average Success Rate*)
- Percentiles 5 to 10

We then re-estimate a modified version of Equation 5 to compare the *% of Winning Candidates* in these two groups of zip codes with the remaining 90% of zip codes.

$$\%\ Win_z = \alpha + \beta_1\ \textit{Percentiles 5 to 10}_z + \beta_2\ \textit{Percentiles 0 to 5}_z + \boldsymbol{\beta}\ \textbf{3-Digit} + \boldsymbol{\beta}\mathbf{X}_z + \varepsilon \qquad \text{(A2)}$$

Under this specification the outcome in Percentiles 10 to 100 serve as the baseline. The coefficients estimated for the *Percentiles 0 to 5* and *Percentiles 5 to 10* indicator variables compare the change in the *% Win* for zip codes with the lowest *Average Success Rate* compared to zip codes with a higher *Average Success Rate*. The model again includes fixed effects identifying each 3-digit zip code, together with the full set of control variables. The findings from this model are also reported in the table below. They reveal a sharp decrease in the probability that donations are made to the winning candidates in the zip codes with the lowest 5% of *Average Success Rates* (in new product purchases at MassStore).