

Does Wal-Mart Sell Inferior Goods?

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Abstract

I estimate the aggregate income elasticity of Wal-Mart's and Target's revenues using quarterly data for 1997–2006. I find that Wal-Mart's revenues increase during bad times, whereas Target's revenues decrease, consistent with Wal-Mart selling “inferior goods” in the technical sense of the term. An upper bound on the aggregate income elasticity of demand for Wal-Mart's wares is -0.5 .

JEL Codes: L81, D12

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“I feel we are well positioned for an economic downturn. Our low prices and low-cost business model should give us an advantage over other retailers if things get more difficult for consumers.”

— Wal-Mart's CEO Lee Scott, quoted by CNNMoney, October 2007

1 Introduction

In this paper, I test for the aggregate-income elasticity of revenues at Wal-Mart and Target using panel data for 1997-2006. I find that Wal-Mart's revenues fall during good times whereas Target's rise during good times. Inferring income elasticities of demand from these estimated income elasticities of revenue, consumers view purchases at Wal-Mart as inferior goods whereas purchases at Target are normal goods.

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A well-established cross-sectional fact is that Wal-Mart’s shoppers have relatively low incomes compared to, say, Target’s shoppers.¹ In a 2005 survey by the Pew Research Center for the People and the Press, 53 percent of respondents reporting annual earnings below \$20,000 said they shopped at Wal-Mart “regularly,” compared with 33 percent of respondents earning more than \$50,000 (Pew Research Center for the People and the Press, 2005). The average annual household income among Wal-Mart shoppers is \$40,000-45,000, roughly equal to the U.S. median household income, compared with \$60,000 for Target shoppers (Mui, 2005). Confirming this pattern, Figure A plots the frequency of shopping at Wal-Mart (and Target) — “often,” “sometimes,” or “never,” based on survey evidence — for households with incomes below \$40,000 and above \$70,000.² Shopping frequencies at Wal-Mart are higher for all income groups because the chain’s penetration is higher, but the likelihood of shopping at Wal-Mart “often” falls with income whereas the likelihood of shopping at Target “often” rises with income.

This cross-sectional evidence does not establish that a given household will increase its shopping at Target and decrease its shopping at Wal-Mart as its income rose. If Wal-Mart stores are located in lower-income areas, for example, shopping at Wal-Mart may be a normal activity and still consistent with the cross-sectional evidence. Despite this distinction, the claim has been made that Wal-Mart sells inferior goods in the technical sense of the term — goods for which demand increases when income falls. The goal of this paper is to evaluate the “inferiority” of Wal-Mart’s goods using appropriate data and methods.

I use aggregate data on personal disposable income as a measure of consumer income and publicly-available data on sales per store at both Wal-Mart and Target. By construction, the aggregate elasticity I estimate is a weighted average of individual households’ elasticities of expenditure and can be interpreted as the “average” household’s income elasticity of

¹Target’s “upscale discounter” brand positioning and its tendency to locate in higher-income markets (Rowley, 2003; Zhu, Singh, and Manuszak, 2005) have contributed to this difference.

²See Basker, Gil, and Kendall (2008) for details about the data.

expenditure on Wal-Mart's and Target's wares. This elasticity of expenditure is an upper bound on the elasticity of demand at Wal-Mart if Wal-Mart's prices are not any more elastic with respect to income than other stores' prices. Evidence presented in the Appendix to this paper suggests Wal-Mart's prices are, if anything, less elastic with respect to income than prices at other stores, which implies that the income elasticity of expenditure for Wal-Mart's goods is even more negative than my estimates suggest.

Holding relative prices constant, two effects of income on store revenues work in opposite directions. On the one hand, a negative income shock may send some shoppers who normally shop at more upscale retailers to discounters, thus increasing revenue at the discount retailers. On the other hand, people who already shop at discounters curtail their spending as well. The aggregate effect depends both on the proportion of households of the two types and on the income elasticity of demand for each group. If the income shocks are not uniform across types, the relative size of the income shock matters, too.

Ideally, this question would be addressed using household panel data in which household's time-invariant characteristics as well as shoppers' choice sets are controlled for and changes in income are matched with changes in purchasing patterns. Unfortunately, I am not aware of a panel large enough for such analysis; since household income is highly auto-correlated, a long panel would be necessary to capture the effect of changes in income.

I estimate the aggregate income elasticity of revenue at Wal-Mart to be negative, with an upper bound around -0.5 . This implies that *ceteris paribus*, a 1% decrease in personal disposable income *increases* Wal-Mart's revenues by 0.5%, either because there are more households that view shopping at Wal-Mart as an inferior activity or because those households that view it as inferior have a larger (absolute) elasticity of demand than households that view it as normal. The income elasticity of demand is, if anything, larger in absolute terms (more negative); the same upper bound applies but a realistic (still conservative) value is -0.7 . By contrast, shopping at Target is a normal activity with an aggregate income elasticity between 0.8 and 0.9.

2 Data

I combine data from Wal-Mart Stores, Inc. and Target Corporation with data on personal disposal income from the Bureau of Economic Analysis.³

For Wal-Mart, I obtained Annual Reports, 10-Q and 10-K filings with the Securities and Exchange Commission (SEC) to calculate Wal-Mart's store count and quarterly revenue from 1997 to the present. Because Wal-Mart Stores operates in two other market segments — Sam's Clubs, which cater primarily to small-business owners, and the international market, which follows different cyclical and seasonal patterns — I relied on the quarterly reports to parse out the Wal-Mart segment's store count and revenue. Quarterly data prior to 1997 do not distinguish between Wal-Mart and the other segments. (The Wal-Mart segment's revenues as a fraction of all revenues range between 63–72% over this period.) Within the Wal-Mart segment, the retailer operates three store types: Discount Stores, Supercenters, and Neighborhood Markets.

Target Corporation currently operates only Target stores, having sold its two other segments, Mervyn's and Marshall Field's department stores, in 2004. Prior to mid-2004 I obtain Target stores' share of revenue and store count from the company's 10-Q filings and Annual Reports. I was able to obtain data for Target back to 1994, but I use only the 1997–2006 sample for comparability with Wal-Mart.

Both firms' fiscal years start at the beginning of February (Wal-Mart's fiscal year starts on February 1 each year; Target's fiscal year starts on the Sunday following the Saturday nearest to January 31). I use the average CPI for all items from the Bureau of Labor Statistics over the three months constituting each quarter to deflate the firms' revenue figures.

By the mid-1990s, each of these two chains operated more than 1,000 stores in the seg-

³Kmart, the third major discount retailer and a natural candidate to be included in this analysis is excluded because it underwent two major structural changes during this period resulting in inconsistent financial data over time. After emerging from Chapter 11 bankruptcy protection in the early 00s, in November 2005 Kmart Holding Corporation merged with Sears to become Sears Holding Corporation.

ment of interest and had a presence in most states. I use quarterly estimates of aggregate personal disposable income from the Bureau of Economic Analysis as my measure of consumer income for the quarter, and divide by annual estimates of the U.S. population from the Census Bureau to obtain a measure of per-capita disposable income.⁴

The quarterly data from the BEA is off by one month from the quarterly data for the firms. For example, the first quarter in the BEA data runs January-March whereas the first quarter of the firms' fiscal years is February-April. This seems appropriate, given the fact that past income largely fuels current spending, but I also construct an adjusted measure of disposable income using a weighted average of disposable income in the current quarter and the next quarter.

3 Implementation and Results

I index retailers (Wal-Mart and Target) by i and quarters by t . The main specification is:

$$\ln(\text{StoreRevenue}_{it}) = \alpha + \beta \cdot \ln(\text{Income}_t) + \omega \cdot \text{Wal-Mart}_i + \theta \cdot \ln(\text{Income}_t) \cdot \text{Wal-Mart}_i + \sum_{s=2}^4 \gamma_s \cdot \text{Season}_{st} + \delta \cdot \text{Trend}_t + \phi \cdot \text{Trend}_t \cdot \text{Wal-Mart}_i + \varepsilon_{it} \quad (1)$$

where **StoreRevenue** is real revenue per store in quarter t ; **Income** is real disposable income per capita in quarter t ; **Wal-Mart** is a dummy for Wal-Mart; **Season** are a set of quarter (season) dummies, with the first quarter excluded; **Trend** is a linear time trend; and ε is the error term which is assumed to be normal, and is adjusted for heteroskedasticity.

⁴State-level estimates of personal income are also available. In the case of Wal-Mart, I could use supplementary information on the number of stores in each state at the end of each quarter to construct a weighted average of state-level per-capita personal income, but I do not have comparable data for Target. In addition, this measure is not qualitatively different from the national figures since the chain was already operating in most, and then all, states by the sample period. Finally, state-level estimates are only available for personal income, not for personal disposable income, which is arguably the better measure of income for this analysis.

The coefficient δ captures the common trend in sales per store across the two firms, while, ϕ , the coefficient on the interaction term, captures any differential trend for Wal-Mart.

The coefficient β on log disposable income is intended to capture the cyclical nature of revenues common to Wal-Mart and Target; if β is positive, then consumers view Target’s products as normal goods, and if β is negative, the goods are viewed as inferior. The coefficient θ captures the differential effect of log disposable income on Wal-Mart’s revenue; a positive estimate of θ would indicate that Wal-Mart’s products are “more normal” than Target’s, and a negative coefficient would indicate that they are “less normal” (more inferior). The interpretation of β is subject to the objection that purchases in general merchandise are often durable, at least for a few quarters: clothing, electronics, toys, and housewares are obvious examples. These purchases may be procyclical simply because of liquidity constraints, even if consumers smooth actual consumption. For this reason I focus on the estimate of θ , which captures the difference between the two chains, given that they sell very similar baskets of goods. The trend variables allow (different) linear trends for the two retailers, and season fixed effects capture the Christmas rush and other seasonal fluctuations in purchasing common to both chains. The reason for including a separate intercept and time trend for Wal-Mart (ω and ϕ) is that Wal-Mart stores are, on average, larger than Target’s, and have been growing — most notably due to the rapid expansion of the “Supercenter” format, which includes a full line of groceries — at a faster rate.⁵

As an alternative specification, I also estimate the model with time fixed effects,

$$\ln(\text{StoreRevenue}_{it}) = \alpha + \omega \cdot \text{Wal-Mart}_i + \theta \cdot \ln(\text{Income}_t) \cdot \text{Wal-Mart}_i + \sum_{s=2}^{39} \delta_s \text{Time}_t + \phi \cdot \text{Trend}_t \cdot \text{Wal-Mart}_i + \varepsilon_{it} \quad (2)$$

⁵Basker, Klimek, and Van (2008) discuss the general trend of general-merchandisers adding product lines to their stores. Basker and Noel (2008) provide background on Wal-Mart’s entry into the supermarket industry.

where **Time** is a vector of time dummies. The common trend variable, season dummies, and the direct effect of log disposable income cannot be estimated in this specification, but it allows us to estimate θ , Wal-Mart's differential reaction to income fluctuations, with fewer functional form restrictions. (The coefficient on Wal-Mart's differential trend can still be estimated.)

The results are shown in Table 1. Columns (1) and (2) show estimates of Equation (1), with a common time trend and season fixed effects, as well as a Wal-Mart-specific time trend; columns (3) and (4) show estimates of Equation (2), with a full set of time fixed effects and a Wal-Mart-specific trend. In columns (1) and (2) I calculate the total income effect for Wal-Mart as the sum of the coefficients on $\ln(\mathbf{Income})$ and $\ln(\mathbf{Income}) \cdot \mathbf{Wal-Mart}$, and show the p-value from a t test for this sum equaling zero. These tests show that, with confidence levels around 95%, the effect of an increase in personal disposable income on Wal-Mart's revenue is negative, whereas the effect on Target's revenue is positive and highly significant. The difference between these two income elasticities is large, around 1.3-1.4, and statistically significant at the 1% confidence level.

Columns (1) and (3) use unadjusted log disposable income, while columns (2) and (4) use adjustment income (the weighted average of disposable income in the current quarter and the next quarter). The adjusted income is available for one fewer quarters than the unadjusted income because it is a weighted average of two observations. The coefficients on $\ln(\mathbf{Income})$ and the interaction term with Wal-Mart are slightly larger in absolute term with the adjustment, consistent with the presence of measurement error in the original variable.

I also estimated these models in first differences:

$$\Delta \ln(\text{StoreRevenue}_{it}) = \alpha + \beta \cdot \Delta \ln(\text{Income}_t) + \omega \cdot \text{Wal-Mart}_i + \theta \cdot \Delta \ln(\text{Income}_t) \cdot \text{Wal-Mart}_i + \sum_{s=2}^4 \gamma_s \cdot \text{Season}_{st} + \varepsilon_{it} \quad (3)$$

where Δ indicates the quarter-to-quarter change. The equation no longer includes time

trends and the Wal-Mart variable is interpretable as the differential trend for Wal-Mart. (I also estimate a variant of this equation with quarter fixed effects.) The results are shown in Table 2: both income elasticities are larger in absolute terms, with Target's positive and Wal-Mart's negative. The difference between them is estimated to be in the range of 1.7–2.7.

Despite the negative aggregate elasticity of demand for Wal-Mart's products, these results imply that a decline in Wal-Mart's revenues during economic booms is a rare event. Holding income constant, Wal-Mart's (real) revenue increases, on average, by about 5.2% a year (summing the two coefficients on the time trend in column (1) or (2)).⁶ An income shock would have to be twice that size before the negative elasticity of demand dominated the trend, or about 2.6% in a single quarter. Such a large positive quarter-to-quarter increase in income is relatively rare; in the detrended and seasonally-adjusted income series I use here it occurred three times over a 10-year period (in the second and fourth quarter of 1998 and again in the first quarter of 2006).

A possible simultaneity problem arises because income, the LHS variable of interest, may be endogenous to Wal-Mart's revenues. There is some evidence that Wal-Mart pays lower wages than other retailers, so its expansion could lower income for retail workers.⁷ In practice, this effect, if present, is likely to be very small. Even given its size, total earning of Wal-Mart employees are not a significant share of personal disposable income.

In addition, the number of stores — which is used to calculate the LHS variable — may be endogenous to income. In that case the LHS variable may move with income, but for the wrong reasons. For example, if Wal-Mart opens more stores during good economic times, an increase in the number of stores may come at the same time that consumers' disposable income rises, creating a spurious negative relationship between sales per store and income. To address this problem I replace the LHS with total revenue and add the log of number

⁶The trend variable increases by 0.25 per quarter.

⁷See Dube, Eidlin, and Lester (2007); Neumark, Zhang, and Ciccarella (2005). Basker (2006) questions the methodological assumptions underlying to reach these estimates.

of stores as an explanatory variable, which I instrument with one-quarter lagged number of stores. The regression equation is

$$\begin{aligned} \ln(\text{TotalRevenue}_{it}) = & \alpha + \beta \cdot \ln(\text{Income}_t) + \omega \cdot \text{Wal-Mart}_i + \theta \cdot \ln(\text{Income}_t) \cdot \text{Wal-Mart}_i \\ & + \sum_{s=2}^4 \gamma_s \cdot \text{Season}_{st} + \delta \cdot \text{Trend}_t + \phi \cdot \text{Trend}_t \cdot \text{Wal-Mart}_i + \sigma \cdot \ln(\text{Stores}_{it}) + \varepsilon_{it} \quad (4) \end{aligned}$$

with first-stage equation

$$\begin{aligned} \ln(\text{Stores}_{it}) = & \tilde{\alpha} + \tilde{\beta} \cdot \ln(\text{Income}_t) + \tilde{\omega} \cdot \text{Wal-Mart}_i + \tilde{\theta} \cdot \ln(\text{Income}_t) \cdot \text{Wal-Mart}_i \\ & + \sum_{s=2}^4 \tilde{\gamma}_s \cdot \text{Season}_{st} + \tilde{\delta} \cdot \text{Trend}_t + \tilde{\phi} \cdot \text{Trend}_t \cdot \text{Wal-Mart}_i + \tilde{\sigma} \cdot \ln(\text{Stores}_{i,t-1}) + \tilde{\varepsilon}_{it} \end{aligned}$$

The results of this specification are shown in Table 3. (The fixed-effect version of the model is also shown.) The first stage is uniformly strong, with F statistics for $\tilde{\sigma}$ well into the double digits. Estimates of the income elasticity of Target's revenues are around 0.9–1.2, but estimates of the income elasticity of Wal-Mart's revenue are virtually identical to those in Table 1, though some statistical significance is lost.

The RHS variable throughout this analysis has been revenue, not quantity of goods purchased; log of revenue per store is really $\ln(P) + \ln(Q)$. If (CPI-adjusted) prices at Wal-Mart and Target were constant over the study period coefficient estimates would be unaffected, but if prices fluctuate over time coefficient estimates could be biased. Prices at Wal-Mart have been falling relative to the CPI, so even the deflated revenues may be inflated, but if the downward trend in prices is constant the two trend variables would be sufficient to capture it. However, if Wal-Mart's prices are counter-cyclical relative to the rest of the economy — for example, if it lowers its markup when consumers' disposable income is low — the relationship between real revenue per store and income could reflect price changes rather than quantity changes. Decomposing $\frac{d \ln(PQ)}{d \ln(I)}$ into an income elasticity of demand, an income elasticity of price (cyclicality measure), and a price elasticity of demand, and solving

for the income elasticity of demand $\frac{\partial \ln(Q)}{\partial \ln(I)}$, we get:

$$\frac{\partial \ln(Q)}{\partial \ln(I)} = \frac{d \ln(PQ)}{d \ln(I)} - \frac{d \ln(P)}{d \ln(I)} \cdot \left(1 + \frac{\partial \ln(Q)}{\partial \ln(P)} \right) \quad (5)$$

Assuming demand for Wal-Mart's products is elastic, $\frac{\partial \ln(Q)}{\partial \ln(P)} < -1$, the estimated quantity $\frac{d \ln(PQ)}{d \ln(I)}$ is an *upper bound* on $\frac{\partial \ln(Q)}{\partial \ln(I)}$ if $\frac{d \ln(P)}{d \ln(I)} < 0$, and a lower bound otherwise. Since all dollar amounts are CPI-deflated, the question is how Wal-Mart's prices respond to changes in aggregate income relative to the CPI. Appendix A reports regressions using auxiliary data which suggest that Wal-Mart's prices vary less with income than the rest of the economy, implying that the estimate estimates reported above, -0.5 , are an *upper bound* on the income elasticity of demand for Wal-Mart's products.

4 Conclusion

In this note, I estimate the income elasticity of revenue for Wal-Mart and Target over the last ten years. Because some consumers are likely to view each discounter's products as normal while others view them as inferior, the aggregate relationship could go either way and depends on the size of the two groups as well as on the magnitude of their elasticities of demand (positive and negative). I find that demand for Wal-Mart's products exhibits a negative income elasticity and Target's demand exhibits a positive income elasticity. An upper bound on the income elasticity of demand for Wal-Mart's products is -0.5 , with more realistic (still conservative) values closer to -0.7 . For the average consumer, then, it appears that shopping at Target is perfectly normal, but shopping at Wal-Mart is not.

A Price vs. Revenue Elasticities

To assess the relative cyclicity of Wal-Mart’s prices I use auxiliary data from the American Chamber of Commerce Research Association (ACCRA). The data include prices at both Wal-Mart Supercenters and a wide variety of other grocery stores and supermarkets for 24 products in 175 cities in 40 states at the beginning of the third quarter of each year for 2001–2004.⁸ Although the product set is limited to groceries, the results are suggestive for other products sold by Wal-Mart. Because the time-series data comprise only four data points a regression of the sort in Equation (1) using average prices is not informative, but we can use variation in income across states and over time to estimate how Wal-Mart’s prices vary relative to other stores’ prices as state-level incomes change.

For each product, state, and year, I calculate the average log (real) price at Wal-Mart and at other grocery stores and use the state’s real per-capita income from the BEA to estimate Wal-Mart’s relative price sensitivity to income variations. Letting p index products, g index stores (Wal-Mart or non-Wal-Mart), s index state and t index year, I estimate:

$$\begin{aligned} \ln(\text{Price}_{pgst}) = & \alpha + \beta \cdot \ln(\text{Income}_{st}) + \omega \cdot \text{Wal-Mart}_g + \theta \cdot \ln(\text{Income}_{st}) \cdot \text{Wal-Mart}_g \\ & + \sum_p \gamma_p \cdot \text{Product}_p + \sum_s \psi_s \cdot \text{State}_s + \sum_{t=2001}^{2004} \delta_t \text{Time}_t + \varepsilon_{pgst} \quad (6) \end{aligned}$$

where **Product** is a set of product fixed effects, **State** is a set of state fixed effects, **Time** are time fixed effects, and **Wal-Mart** is a Wal-Mart fixed effect; $\ln(\mathbf{Income})$ is log of real per-capita personal income by state and quarter.⁹ The time fixed effects capture any across-the-board price changes from year to year due to aggregate inflation. The coefficient β captures the degree to which overall prices move with income, whereas θ captures the differential movement of Wal-Mart’s prices, a proxy for $\frac{d\ln(P)}{d\ln(I)}$ in Equation (5). Neither

⁸See Basker and Noel (2008) for details about the data.

⁹Unlike in the earlier regressions, it is not disposable income because these figures are not available at the state level.

coefficient is statistically different from zero but the point estimate of θ is around -0.11 , suggesting that, if anything, Wal-Mart's prices are countercyclical relative to the rest of the economy.¹⁰

To account for the possibility that Wal-Mart's prices vary less with state-level conditions because of uniform pricing, I also estimate Equation (6) using only prices from Wal-Mart and the "Big Three" supermarket chains (Albertson's, Kroger, and Safeway) which had similar national markets.¹¹ Coefficient estimates are virtually unchanged.

Taking this point estimate at face value we can calculate the income elasticity of demand at Wal-Mart from Equation (5). To be conservative, I assume that the price elasticity of demand at Wal-Mart is -3 and that $\frac{d\ln(PQ)}{d\ln(I)} = -0.5$ (based on the results in Tables 1 and 3).¹² In that case the income elasticity of demand for Wal-Mart's wares is approximately -0.72 . Thus, if personal incomes fall by 2%, this would cause revenues at each of Wal-Mart's stores to increase, on average, by 1.44%.

¹⁰Results are not sensitive to adding interactions of Wal-Mart with each product fixed effect, allowing product fixed effects to differ by year, and adding state-specific trends.

¹¹Uniform pricing could be motivated by managerial "menu costs" involved in price setting (see, e.g., Levy, Bergen, Dutta, and Venable, 1997), or by strategic considerations as a device to "soften" competition in contested markets (see Dobson and Waterson, 2005, for a model of this phenomenon).

¹²Basker and Van (2008) calibrate the aggregate price elasticity of demand at Wal-Mart to be approximately -3.2 . This number is in keeping with estimated price elasticities for various items at Dominick's Finer Foods grocery stores reported by Chevalier, Kashyap, and Rossi (2003). Chiou (2005) estimates the price elasticity of demand for DVDs at Wal-Mart to be about -2 .

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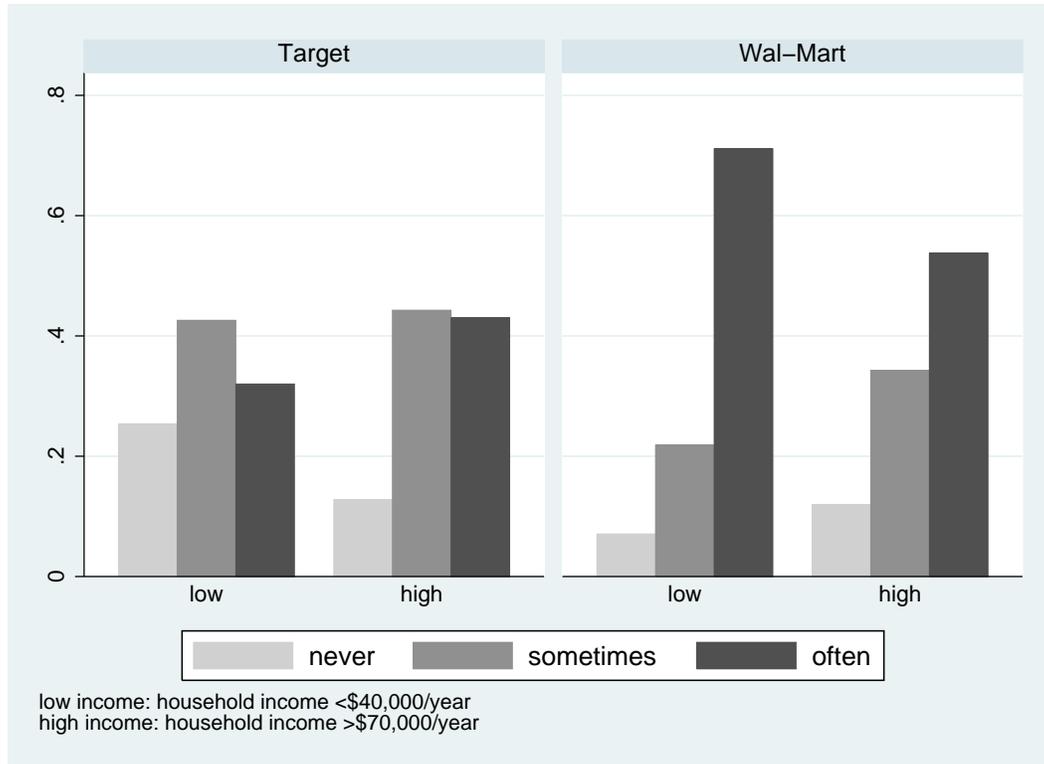


Figure 1. Shopping Frequency at Wal-Mart and Target by Income

Table 1. Coefficient Estimates, Equations (1) and (2)

	(1)	(2)	(3)	(4)
Wal-Mart	37.1501*** (5.7646)	40.0570*** (6.7904)	37.1501*** (7.1184)	40.0570*** (8.1598)
ln(Income)	0.8153*** (0.2506)	0.9088*** (0.2575)		
ln(Income) · Wal-Mart	-1.3240*** (0.2072)	-1.4289*** (0.2442)	-1.3240*** (0.2559)	-1.4289*** (0.2935)
Time Trend	0.0092** (0.0044)	0.0069 (0.0046)		
Trend · Wal-Mart	0.0420*** (0.0043)	0.0464*** (0.0049)	0.0420*** (0.0049)	0.0464*** (0.0057)
Time Dummies	N	N	Y	Y
Season Dummies	Y	Y	N	N
Income Adjusted	N	Y	N	Y
Total Income Effect for Wal-Mart	-0.5087**	-0.5200*		
p-value	0.0424	0.0539		
Observations	78	76	78	76

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2. Coefficient Estimates, Equation (3)

	(1)	(2)	(3)	(4)
Wal-Mart	0.0136 (0.0085)	0.0212** (0.0081)	0.0136 (0.0106)	0.0212** (0.0099)
$\Delta \ln(\text{Income})$	1.0644*** (0.2614)	1.7534*** (0.3684)		
$\Delta \ln(\text{Income}) \cdot \text{Wal-Mart}$	-1.7227*** (0.1155)	-2.7314*** (0.2123)	-1.7227*** (0.1407)	-2.7314*** (0.2653)
Time Dummies	N	N	Y	Y
Season Dummies	Y	Y	N	N
Income Adjusted	N	Y	N	Y
Total Income Effect for Wal-Mart	-0.6583**	-0.9780**		
p-value	0.0206	0.0183		
Observations	78	76	78	76

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. Coefficient Estimates, Equation (4)

	(1)	(2)	(3)	(4)
$\ln(\text{Stores})$	1.6929 (1.0234)	2.4386* (1.3632)	2.0044 (1.5598)	2.9119 (1.9584)
Wal-Mart	39.8258*** (6.5808)	44.8324*** (7.9153)	40.6323*** (8.1812)	46.0322*** (10.4069)
$\ln(\text{Income})$	0.9586*** (0.2697)	1.1981*** (0.3488)		
$\ln(\text{Income}) \cdot \text{Wal-Mart}$	-1.4480*** (0.2547)	-1.6587*** (0.3050)	-1.4897*** (0.3204)	-1.7210*** (0.4043)
Time Trend	-0.0423 (0.0748)	-0.1003 (0.1007)		
Trend \cdot Wal-Mart	0.0628** (0.0310)	0.0904** (0.0416)	0.0726 (0.0471)	0.1049* (0.0595)
Time Dummies	N	N	Y	Y
Season Dummies	Y	Y	N	N
Income Adjusted	N	Y	N	Y
Total Income Effect for Wal-Mart	-0.4849*	-0.4606		
p-value	0.0638	0.1596		
First-Stage F Statistic	66.6761	32.4257	49.8181	19.0429
Observations	77	75	77	75

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%