Loss Aversion in Grocery Panel Data: The Confounding Effect of Price Endogeneity[*]

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Abstract

In marketing, there has been extensive empirical research to ascertain whether there is evidence of loss aversion as predicted by several reference price preferences theories. Most of that literature finds that there is indeed evidence of loss aversion for many different goods. I argue that it is possible that some of that evidence seemingly supporting loss aversion arises because price endogeneity is not properly taken into account. Using scanner data I study four product categories: bread, chicken, corn and tortilla chips, and pasta. Taking prices as exogenous, I find evidence of loss aversion for bread and corn and tortilla chips. However, when instrumenting prices, the "loss aversion evidence" disappears.

1 Introduction

Psychology has had a growing influence in economics since the 1970s. In decision-choice models, a landmark paper has been Kahneman and Tversky (1979), which introduced the so-called prospect theory. It revolves around the idea that when making decisions, people value gains and losses differently, i.e. not just to the extent that one is the opposite of the other.[1]

This has lead to the development of a literature, in the 1980s, attempting to incorporate different conceptions of price perception into empirical models. The bulk of the work has been done in marketing by incorporating reference price in the estimation of brand choice models (see among others Winer

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[1]Earlier work on the psychological theory of adaptation level formation dates back to Helson (1964).

(1986) who looks at coffee, and Lattin and Bucklin (1989) who distinguish between the effect of regular prices and promotions on the reference price).

Studies on the topic continued to flourish in the 1990s. In the overwhelming majority, strong evidence was found to favor the importance of reference price formation and the existence of a loss aversion phenomenon, i.e. that losses (prices above the consumer reference point) are more salient than gains (prices below the consumer reference point) such that consumers purchases are more sensitive to them. Given the mounting evidence, Kalyanaram and Winer (1995) and Meyer and Johnson (1995) argued that reference price based decisions and loss aversion had become empirical generalizations.

This view has more recently been contested by Bell and Lattin (2000). They show that, when heterogeneity in consumer price responsiveness is accounted for, the evidence of loss aversion disappears for many products.

In this paper, I consider another potential source of confoundedness in the measure of loss aversion: price endogeneity. Like in every market, prices are here simultaneously determined by supply and demand. Given that most models only estimate demand, taking prices as given might introduce simultaneous equation bias in the estimation. This is precisely what is done in the overwhelming majority of papers in this field. To justify the assumption that prices are exogenous, it is usually argued that the prices for the products studied are determined in a global market, which is little impacted by the consumers under study because they represent only a small subset of that market.

This explanation is not very convincing. There seems to be a strong possibility of store level price adjustments, such as sales, especially in the case of groceries, which are the most studied market in this literature. In that case, there is a strong possibility that prices are somewhat endogenous to the purchasing decisions of customers. Indeed, in a more general random utility model applied to scanner data, Villas-Boas and Winer (1999) find that prices are often endogenous in that context, which leads to significant estimation bias.

To assess this possibility in the context of loss aversion models, I look at the impact of reference price preferences on the demand for four grocery product categories: bread, chicken, corn and tortilla chips, and pasta. Using the theoretical framework developed by Daniel Putler (1992), I test for the presence of loss aversion, both at the extensive and intensive margins. I do this exercise both taking prices as given and instrumenting for them.

I use prices of commodities entering as inputs in the production of the relevant products as instruments. Solis (2009) presents evidence that food commodity prices have little impact on regular shelf prices, but he also reports that higher agricultural commodity prices reduce the frequency and depth of promotions, hence increasing the average net retail price. Therefore, commodity prices has the potential to be a good instrument for net retail prices.

Initially, I find evidence of loss aversion for the bread and corn and tortilla chips categories. However, when instruments are used, most of that evidence disappears.

The next section presents the data used in the estimation, while section 3 and 4 describe respectively the model and the estimation strategy. Finally, results are presented in section 5.

2 Data Set

I use scanner data from a major U.S. supermarket chain. The data set includes all the purchases made from May 2005 to March 2007 at a single store located in California. The neighbourhood in which the store is located is relatively wealthy. The median family income for the subset of the sample for which income data is available is $106,000. The sample is also overwhelmingly composed of Caucasian. The scanner data is combined with agricultural commodity prices obtained from Global Financial Data.

2.1 Scanner Data

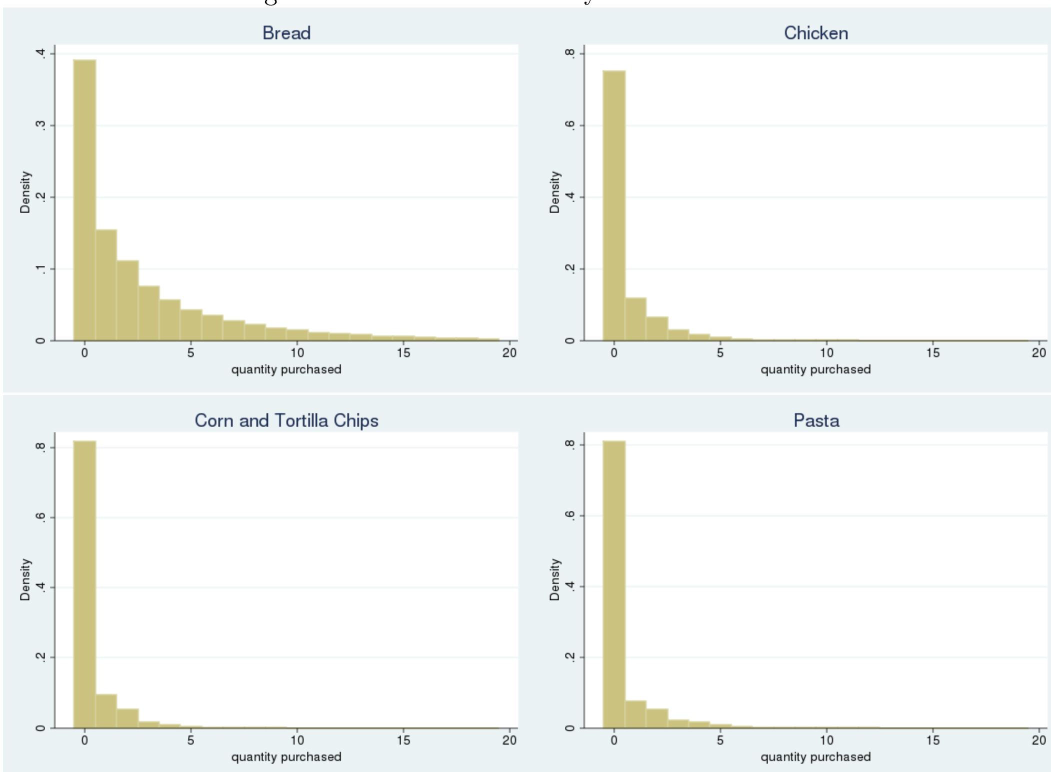
As bar codes and scanner have become almost universal in grocery retailing, the use of scanner data by researchers has exploded. In most cases scanner data sets include a limited range of products and cover a varying number of locations.

The data set used for this paper is on the contrary very thorough. Every single product purchased during the time period is included. In all, it includes more than 18 million observations. An observation is one particular product bought by a given customer at a certain point in time.

Households are tracked over time with their customer fidelity cards. Overall, 96% of the 18 million observations are linked to a specific household through their fidelity card number. This represents 67,000 households making purchases at that supermarket over the two year period. For about 38,000 of those, there is information about their income, which will be important in our estimation.

My analysis focuses on four product categories: bread, chicken, corn and tortilla chips, and pasta. Figure 1 presents the densities of the monthly purchases by product categories. Chicken, corn and tortilla chips, and pasta present very similar patterns. Each of the product is not bought in a given month by about 80% of the households, while very few customers by more than 5 units in the month.

Figure 1: Densities of Monthly Product Purchases



The pattern for bread is markedly different. More people buy it and in greater quantities than for the other three product.

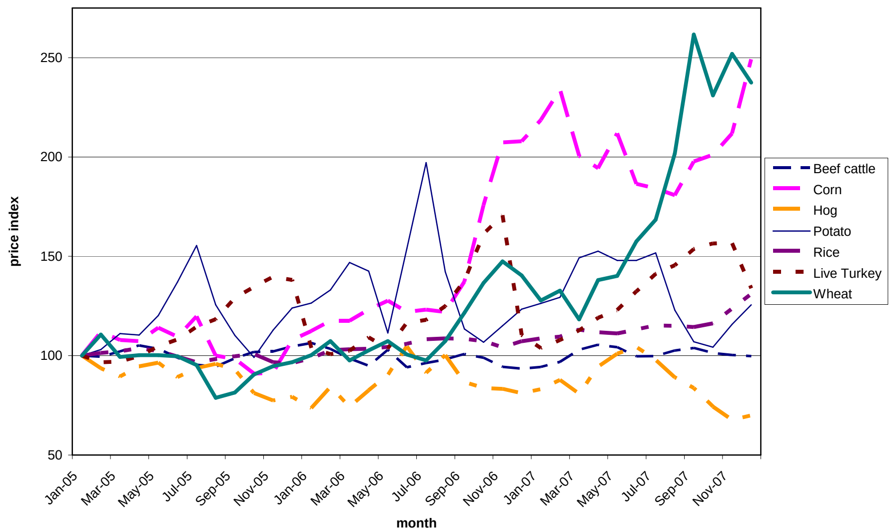
Nevertheless, all product categories display an important proportion of corner solutions. Indeed, a zero can be assimilated to a negative demand that a consumer would have had for that good at a particular purchase occasion. In the data, we define a purchase occasion a period (here a month) in which a household made at least one trip to the store.

Here I must emphasize again that this data is from a single store. The proportion of people who buy of a given category in a given month might seem low, but it does not take into account the fact that people are certainly buying at other stores also.

2.2 Commodity Prices

All the commodity prices needed to instrument the retail prices were available at the daily or monthly interval. Figure 2 presents the monthly evolution of those prices for the period 2005 - 2007. That group of commodities has been chosen because it represents inputs in the production of the four

Figure 2: Commodity Prices



January 2005 Price = 100

product categories of interest as well as of some of their substitutes.

The period that is covered by the scanner data set has been characterized by very volatile commodity prices. That volatility reduces the possibility that some of the commodity prices are collinear. This is confirmed by figure 2 where we can see that there is no commodity that systematically follows the price path of another. There is also very rich variation in that data.

In addition, I never use all the commodities simultaneously as instruments. Relevant products sets are defined and only the appropriate subset of commodities is used.[2]

2.3 Aggregation Issues

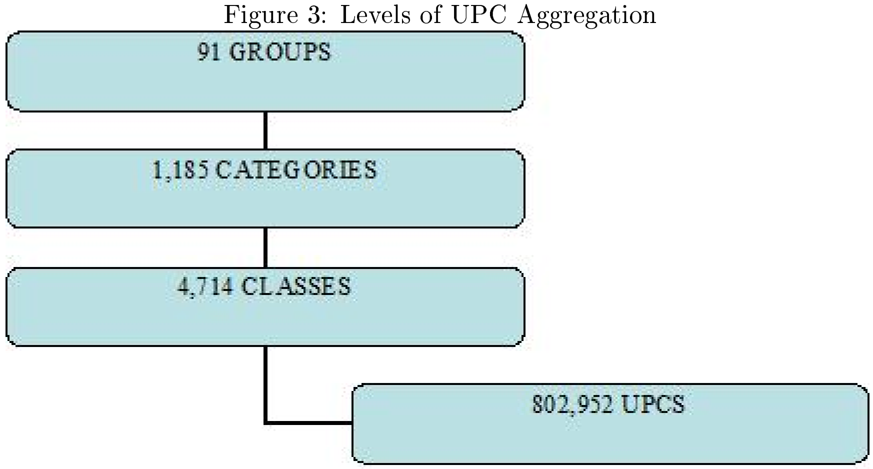
The level of detail at which the data was recorded is very fine. For example, the pasta category counts almost 2,000 UPC codes. To make the data more usable in terms of the question addressed in this paper, I have had to aggregate it both across UPC codes and across time.

Scanners record the exact time of each transaction up to the exact second. There is therefore a complete latitude on the part of the researcher to aggregate the data at whatever level he wishes. The week is the natural time unit in which to conceptualize grocery purchases. Most people buy grocery every week. Aggregating data on a weekly basis gives me 96 periods to work with. However, further

[2]The relevant product sets and appropriate commodity subset are defined in the next section.

examination indicates that weekly aggregation might not be the best way to proceed in this case. Although most people buy groceries every week, some tend not to always shop at the same store. Kim and Park (1997) find that only 30% of grocery shoppers have a relatively high cost of switching store. Even when consumers visit the same store over and over, they do not buy exactly the same products every week. Since I am looking at a relatively small subset of products, this is an important issue. These considerations warrant the use of an alternative monthly aggregation level, which leaves the data set with 22 periods.[3] Any further aggregation would seriously reduce the time dimension of the panel.

Figure 3: Levels of UPC Aggregation



Product aggregation was done along the lines of a classification supplied by the supermarket. Figure 3 presents the different levels of aggregation of UPC codes. The product categories in this paper have been constructed at group and category levels.

Aggregation poses the problem of creating both price and quantity indices. In the data itself, there is actually no price per se. Each transaction recorded includes the quantity of the good purchased and the amount spent to acquire that good. At the UPC level, price can directly be computed by dividing amount spent by quantity. When purchases are aggregated by groups or categories, the creation of a price index is necessary for each aggregation unit. Equation (1) gives the simple formula of how this is done.

$$p_{it} = \frac{\sum_{c=1}^{C}\sum_{n=1}^{N_i} s_{ncit}}{\sum_{c=1}^{C}\sum_{n=1}^{N_i} q_{ncit}} \tag{1}$$

[3] May 2005 has to be dropped because the data set only contains 2 weeks of it.

Where:

p_{it}	is the price index for product category i at time t;
s_{ncit}	is the total amount spent on product n (which is part of category i) by consumer c at time t;
q_{ncit}	is the total quantity of product n (which is part of category i) purchased by consumer c at time t;
C	is the total number of consumers
N_i	is the total number of products in category i.

This procedure is equivalent to creating a quantity weighted price average of all products within a category. Note that this price index also implicitly defines a quantity index, which is the denominator on the right hand side of equation (1).

3 Model

In this section, I present the theoretical model of reference price preferences. This is largely borrowed from Putler (1992) and a more complete exposition can be found in that paper.

The model is constructed around three assumptions. The first, known as temporal separability, implies that the consumer's actions in one period do not directly affect those in other periods. The second, referred to as perfect information, states that consumer are well informed about any product's quality and more specifically that prices are not perceived as conveying information on the level of quality. The last, reference price exogeneity, defines any given reference price as based on past price levels and is therefore exogenous at the time the consumer makes his decision.

The consumer maximizes his utility every periods

$$\max_{x} U(y, L, G) \tag{2}$$

subject to his budget constraint

$$\sum_{i=1}^{I} P_i y_i = M, \tag{3}$$

where:

y	is an I-vector of consumption levels;
L	is an I-vector of perceived losses;
G	is an I-vector of perceived gains;
P_i	is the price of good i;
y_i	is the consumption level of good i;
M	is the predetermined level of expenditures for the current period.

Losses and gains for each individual product are defined as[4]

$$L_i = I_i(P_i - RP_i)y_i \tag{4}$$

$$G_i = (1 - I_i)(RP_i - P_i)y_i, \tag{5}$$

where:

I_i	is an indicator that takes the value 1 if $P_i > RP_i$ and 0 otherwise;
RP_i	is the reference price for good i.

The maximization of (2) subject to (3) leads to Marshallian demand functions that depend not only on prices and budget level, but also on marginal gains and marginal losses.

4 Estimation Strategy

The estimation of the demands implied by the model poses several challenges. First is the choice of an appropriate functional form for the utility function. Because the product categories we look at are somewhat aggregated, a utility function that leads to Marshallian demands that can be easily aggregated over products seems best suited.

[4]Putler discusses a possible monotone nonlinear transformation of the marginal loss (or gain) term.

Second, consumers exhibit a lot of corner solution behaviour, i.e. the demand for a given product in a given period would be negative, but appears as zero in the data. Taking that into account not only improves the validity of the estimation, but also allows to look at the impact of reference price preferences on both the extensive and the intensive margins. At the extensive margin, households decide whether or not to buy the product. This can be represented as the probability of buying the product. At the intensive margin, households decide how much to buy given that they will buy. They is represented by the quantity purchased conditional on purchasing a positive amount.

Finally, because we are dealing with demands, careful attention must be paid to the endogeneity of prices. Preferably, instruments would be use to avoid any simultaneous equation bias.

4.1 Choosing functional forms

The first step of the estimation is to choose appropriate functional forms to be estimated. Functional forms must be chosen for both the reference price formation and the demand equation (through the appropriate choice of a utility function).

The reference price formation we consider is memory based. On any purchase occasion, a consumer compares current prices to previous prices of the same good at the last purchase occasion. We define a purchase occasion as a time period in which the consumer went to the store. By going to the store, the consumer learns about current prices and updates his reference point. If he does not go to the store in a given period, than his reference price does not change. More formally

$$RP_{cit} = S_{ct-1}P_{it-1} + (1 - S_{ct-1})RP_{cit-1}, \tag{6}$$

where:

RP_{cit}	is the reference price about good i of consumer c in period t;
S_{ct}	is an indicator of store visit that takes the value 1 if consumer c visited the store in period t , and 0 otherwise;
P_{it}	is the price of good i in period t.

This is admittedly a very simple reference price concept. Nonetheless, it has its upsides. Most importantly, because it does not depend on specific product chosen by the consumer, it avoids the confounding effects of price-response heterogeneity on estimates of loss aversion as noted by Bell and Lattin (2000).

As proposed by Putler (1992), we consider two different sets of preferences that lead to two distinct functional forms for demand estimation. The first group of preferences is characterized by a modified version of the well-known Klein-Rubin utility function and takes the form

$$U_{cit} = \sum_{i=1}^{I} \rho_i \log \left(y_{cit} - a_i - l_i L_{cit} - g_i G_{cit} \right) \tag{7}$$

where ρ_i, a_i, l_i and g_i are all parameters. This utility function translates into a demand function of the form

$$y_{cit} = \alpha_i^0 + \alpha_i^1 L_{cit} + \alpha_i^2 G_{cit} + \rho_i \frac{M}{P_i} + \sum_{j \neq i}^{I} \frac{P_j}{P_i} \left(\alpha_{ij}^3 + \alpha_{ij}^4 L_{cjt} + \alpha_{ij}^5 G_{cjt} \right) \tag{8}$$

where $\alpha_i^0 = (1 - \rho_i) a_i$; $\alpha_i^1 = (1 - \rho_i) l_i$; $\alpha_i^2 = (1 - \rho_i) g_i$; $\alpha_i^3 = \rho_i a_j$; $\alpha_i^4 = -\rho_i l_j$ and $\alpha_i^5 = -\rho_i g_j$.

This demand specification allows for exact linear aggregation of goods into groups. It is also consistent with the representative consumer hypothesis. It is however inflexible. This inflexibility leads to a potential for confounding the reference price effect with the misspecification of the price response parameters. A more flexible functional form is therefore used to evaluate the potential for this problem to affect the results. It is the translog demand function which can be expressed as

$$y_{cit} = \gamma_i^0 + \sum_{j=1}^{I} \gamma_i^1 \log P_j + \frac{1}{2} \sum_{j=1}^{I} \sum_{k=1}^{I} \gamma_{ij}^2 \log P_j \log P_k + \sum_{j=1}^{I} \gamma_{ij}^3 L_{cit} + \sum_{j=1}^{I} \gamma_{ij}^4 G_{cit} + \gamma_i^5 \log M. \tag{9}$$

This demand specification also allows for exact linear aggregation, but it is not consistent with the representative consumer hypothesis.

To make the number of parameters to estimate manageable, we need to restrict the set of relevant commodities for each product category. Assuming preferences are weekly separable over groups, only prices of products within a given group are relevant for any product of that group (see Deaton and Muellbauer, 1980). Table 1 presents the relevant products for each of the product categories of interest. Those were chosen as obvious potential substitutes for the products analyzed.

Table 1: Products included in the group of each relevant product categories

Product categories	Other products in the group
Bread	Rice, Potatoes, Pasta
Chicken	Beef, Pork, Turkey
Corn and Tortilla Chips	Hard Bites, Potato Chips, Salty Snacks
Pasta	Bread, Potatoes, Rice

4.2 Regression specifications

The equations estimated are (8) and (9), to which I add quarterly dummies, to control for seasonality, and an error term. Those two equations can therefore be rewritten for estimation as follows

$$y_{cit} = \alpha_i^0 + \alpha_i^1 L_{cit} + \alpha_i^2 G_{cit} + \rho_i \frac{M}{P_i} + \sum_{j\neq i}^{I} \frac{P_j}{P_i} \left(\alpha_{ij}^3 + \alpha_{ij}^4 L_{cjt} + \alpha_{ij}^5 G_{cjt}\right) + \sum_{h=2}^{4} \alpha_{ih}^6 q_h + \epsilon_{cit}, \tag{10}$$

$$y_{cit} = \gamma_i^0 + \sum_{j=1}^{I} \gamma_i^1 \log P_j + \frac{1}{2}\sum_{j=1}^{I}\sum_{k=1}^{I} \gamma_{ij}^2 \log P_j \log P_k + \sum_{j=1}^{I} \gamma_{ij}^3 L_{cit} + \sum_{j=1}^{I} \gamma_{ij}^4 G_{cit} + \gamma_i^5 \log M + \sum_{h=2}^{4} \gamma_{ih}^6 q_h + \epsilon_{cit}. \tag{11}$$

The length of a time period is defined as one month. As mentioned previously, this appears as a good compromise. It is long enough such that each product is purchased by a reasonable proportion of households every period.[5]It is also short enough such that short term variation in prices and reference price are not completely smoothed out and that the data retains a reasonable number of periods (22 complete months).

4.3 Estimation techniques

To tackle the issues of corner solutions and endogeneity mentioned at the beginning of this sections while taking into account the potential for simultaneous equations bias, I proceed in several steps.

Given that the data set is primarily composed of corner solutions, I express the general data generating process as

$$y_{cit}^* = \mathbf{X_{cit}}\beta + u_{cit}, \qquad u_{cit}|\mathbf{X_{cit}} \sim \text{Normal}(0, \sigma^2) \tag{12}$$

$$y_{cit} = \max(0, y_{cit}^*) \tag{13}$$

[5]For each category between 15% and 60% of households buy a product during a given month.

where $\mathbf{X_i}\beta$ is the deterministic part of either equation (10) or (11), and y_i is the observed outcome. This formulation lends itself to a pooled Tobit estimation. This seems particularly appropriate to the problem, because it allows to estimate a global effect $\left(\frac{\partial E[y^*|\mathbf{X}]}{\partial x}\right)$, the extensive margin effect $\left(\frac{\partial Pr(y^*>0|\mathbf{X})}{\partial x}\right)$ and the intensive margin effect $\left(\frac{\partial E[y|\mathbf{X}]}{\partial x}\right)$. Some caution against the use of the Tobit model to estimate all these effect nothing that it forces the set of determinants of the extensive and intensive margins to be the same. In the present problem, this appears particularly plausible. The fact that prices and income dictate both whether or not someone buys a given product and if so how much that person buys is quite rational.

The normality and homoskedasticity assumptions are very important to the validity of the estimation. Violation of either assumptions makes the estimator inconsistent. It is unlikely that these assumptions are exactly satisfied, but in the next section, we present evidence that they are not significantly violated. Note however that the model allows for serial correlation of the error term across time within individuals. This is very convenient, because unobserved individual effects are most certainly creating serial correlation at that level.

There are good reasons to suspect that the price variables in equation (12) could be endogenous. To address this problem we use instrumental variables with the twostep Newey's minimum chi-squared estimator (Newey, 1987). This estimator is asymptotically consistent under the normality assumption. However, it does not allow to compute the effects on the intensive and extensive margin. In addition, it is relatively sensitive to the presence of instruments that are somewhat collinear.

The instruments used are prices of commodities entering as inputs in the production of the goods considered in the relevant group. Since those commodities are traded on world markets, consumption of their transformed consumer products in a local market is almost certainly not affecting them. In the other direction however, recent price spikes in the price of many commodities have had impact on the prices of the final goods in which they are production inputs (see among others Solis, 2009).

In addition to the price of commodities themselves, several lags are included in the specification. I do some sensitivity analysis with the number of lags, but beyond 3 or 4 issues of multicollinearity arise. Table 2 present the different commodities of which the prices are used in each group.

To complement the Tobit estimation, I will also report OLS estimates. Although OLS estimates are biased in this context, they can be useful in two settings. First and foremost, whether or not the Tobit model is correctly specified, a regression of y_{cit} on $\mathbf{X_{cit}}$ for positive values of y_{cit} approximates

Table 2: Commodities used as instruments in each group

Product categories of interest in the relevant group	Commodities
Bread	Rice, Potatoes, Wheat
Chicken	Corn, Beef cattle, Hog, Live turkeys
Corn and Tortilla Chips	Corn, Rice, Potatoes, Wheat
Pasta	Wheat, Potatoes, Rice

the intensive margin effects near the mean values of the regressors.[6] Second, it is possible all the OLS coefficients be inconsistent by the same multiplicative factor. Since I am mostly interested in the relative coefficients of Losses and Gains, it would be possible to evaluate that situation with OLS coefficients. However, the assumptions under which the previous result is valid are very restrictive, for example requiring the joint normality of the regressand and the regressors (see Wooldridge, 2002).

5 Results

In this section I present the results of the estimation of both the Klein-Rubin and translog demands. Since the question of interest concerns only the importance of reference price preferences and the prevalence of loss aversion, only the estimates for the coefficients on own losses (losses for the price of the product in question) and own gains are reported. Those correspond respectively to α_i^1 and α_i^2 in equation (10) for the Klein-Rubin utility and to γ_{ii}^3 and γ_{ii}^4 in equation (11) for the translog.

According to the theory, the coefficient on losses should be negative, while the one on gains should be positive. There is loss aversion if the coefficient on losses is of a greater magnitude than the one on gains.

Table 3 presents the results of the pooled regressions for the bread category. The striking result is that the coefficients on own gains has the wrong sign in all the specifications. There is however strong evidence of loss aversion, almost too strong. Looking at the effect of losses on the probability to buy bread, we note the coefficient would mean that if the loss increased by one dollar, the probability to buy bread that month at that given store would decrease by 91%. Although we should expect more responsiveness from consumers given that they likely have the option to go to another store, this appears somewhat high.

Table 4 gives the results for chicken. The sign and magnitude of the coefficients are a little more plausible than for bread. Although the sign of coefficients for losses is almost always positive, it is

[6] Given that all the second moments are finite.

Table 3: Result of the pooled regressions of quantity on prices, gains and losses for Bread

VARIABLES				
Klein-Rubin	OLS	Tobit	ext.	int.
Own Losses	-9.167***	-16.81***	-0.914***	-6.893***
	(0.367)	(0.876)	(0.0477)	(0.359)
Own Gains	-2.487***	-6.547***	-0.356***	-2.684***
	(0.599)	(1.456)	(0.0792)	(0.597)
Observations	188905	188905	188905	188905
R^2	0.024			
Translog				
Own Losses	-9.852***	-17.94***	-0.979***	-7.352***
	(0.425)	(1.036)	(0.0565)	(0.425)
Own Gains	-2.536***	-4.921***	-0.269***	-2.017***
	(0.629)	(1.570)	(0.0857)	(0.644)
Observations	188905	188905	188905	188905
R^2	0.028			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

never significant. There is no evidence of loss aversion. On the contrary, it seems that there might be something like "deal loving" going on.

As for corn and tortilla chips, for which the results are presented in table 5, it is probably the category that exhibits the prototypical expected results. Loss aversion is moderate but significant. For example, consider a one dollar increase in losses. This would reduce average individual monthly purchases by 1.4 units. This effect would materialize both at the extensive margin, by a reduction in the probability to purchase of 12%, and at the intensive margin, by a reduction of average monthly quantity purchased by those who still by the products of 0.3 units.

Note that for the first three categories, the results are very consistent across specifications. In addition, the OLS estimate is often very close to the intensive margin. This should not be surprising because both attempt to evaluate the impact of gains and losses on purchases for the sub-population of households that buy a positive amount of the product.

Pasta is the only group category for which the two demand specifications differ significantly.[7]In table 6 we see that the coefficient on losses goes from negatively significant to insignificant when the demand specification switches from Klein-Rubin to translog. This could be due to the fact that the

[7]Although it conserves the nice symmetry between OLS and intensive margin estimates.

Table 4: Result of the pooled regressions of quantity on prices, gains and losses for Chicken

VARIABLES				
Klein-Rubin	OLS	Tobit	ext.	int.
Own Losses	0.00620	0.0536	0.00507	0.0133
	(0.0154)	(0.0827)	(0.00783)	(0.0206)
Own Gains	0.380***	1.447***	0.137***	0.360***
	(0.0281)	(0.131)	(0.0124)	(0.0327)
Observations	188913	188913	188913	188913
R^2	0.018			
Translog				
Own Losses	-0.00401	0.0323	0.00306	0.00803
	(0.0153)	(0.0832)	(0.00787)	(0.0206)
Own Gains	0.644***	2.714***	0.257***	0.674***
	(0.0312)	(0.166)	(0.0157)	(0.0411)
Observations	188913	188913	188913	188913
R^2	0.020			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Result of the pooled regressions of quantity on prices, gains and losses for Corn & Tortilla Chips

VARIABLES				
Klein-Rubin	OLS	Tobit	ext.	int.
Own Losses	-0.198***	-1.415***	-0.119***	-0.306***
	(0.0315)	(0.231)	(0.0193)	(0.0498)
Own Gains	0.0317	0.377	0.0316	0.0813
	(0.0532)	(0.339)	(0.0284)	(0.0731)
Observations	188904	188904	188904	188904
R^2	0.014			
Translog				
Own Losses	-0.210***	-1.534***	-0.129***	-0.330***
	(0.0334)	(0.251)	(0.0211)	(0.0541)
Own Gains	-0.00343	0.160	0.0134	0.0345
	(0.0543)	(0.343)	(0.0287)	(0.0738)
Observations	188904	188904	188904	188904
R^2	0.015			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Result of the pooled regressions of quantity on prices, gains and losses for Pasta

VARIABLES				
Klein-Rubin	OLS	Tobit	ext.	int.
Own Losses	-0.264***	-1.164**	-0.0742**	-0.256**
	(0.0804)	(0.500)	(0.0318)	(0.110)
Own Gains	0.575***	2.696***	0.172***	0.594***
	(0.0797)	(0.400)	(0.0255)	(0.0881)
Observations	188899	188899	188899	188899
R^2	0.016			
Translog				
Own Losses	-0.116	-0.416	-0.0264	-0.0913
	(0.0822)	(0.526)	(0.0334)	(0.115)
Own Gains	0.517***	2.623***	0.167***	0.576***
	(0.0835)	(0.480)	(0.0305)	(0.105)
Observations	188899	188899	188899	188899
R^2	0.017			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

translog model is more flexible than the Klein-Rubin which may confound the loss term with something else. Note however that this discrepancy does not tell two different stories on the front of loss aversion. Even in the Klein-Rubin specification, the magnitude of the loss coefficients are much smaller than those of the gains. Hence, there is no evidence loss aversion in either cases for pasta.

Before proceeding to the IV estimation, I evaluate the validity of the estimation specification for both demands. As suggested by Wooldridge (2002), I do a probit comparison of the tobit coefficients. This is not an exact test, but it allows to detect if the tobit model is clearly misspecified. The procedure consists in comparing the coefficients obtained from running a probit regression on equations 10 and 11 to the tobit coefficients rescaled by the standard error of their own regressions. If coefficients have different signs or magnitudes, then the tobit model is almost surely misspecified.

Results of this test for all coefficients are reported in the appendix for both demands. In general there is very little concern for misspecification. Virtually all coefficient pairs have the same sign. The vast majority also are very similar in magnitude. The only specification for which some concern arises is the translog for bread. One coefficient pair in particular is very dissimilar. That could explain why some of the results for bread are somewhat surprising.

I now turn to the results of the IV estimations. If results change significantly when prices are

Table 7: Result of the IV regressions of quantity on prices, gains and losses for Bread

	Klein-Rubin		Translog	
VARIABLES	2SLS	Newey's twostep	2SLS	Newey's twostep
Own Losses	1.050	5.173	5.605***	-190.6***
	(0.946)	(3.397)	(1.547)	(43.49)
Own Gains	5.779***	6.740	9.168***	-235.4***
	(1.254)	(4.524)	(2.333)	(53.77)
Observations	188905	188905	188905	188905
R^2			0.020	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

instrument, it gives a good indication that there might be some simultaneous equation bias in the previous results. That is an important point, because most of the research in loss aversion never makes use of instruments. Because the data used is often very disaggregated, researchers just argue that prices are determined at a higher level and hence are exogenous.

In the case of bread, the peculiar results from the original estimation go away in the Klein-Rubin specification. Not only do gains no longer have a negative coefficient, but the magnitude of the coefficient on losses is reduced such that it is no longer significant. As one can see from table 7, the story is not as clear cut for the translog demand. The two stage least squares and twostep Newey's minimum chi-squared estimators tell completely opposite stories, both coefficients being significantly positive in the first case and significantly negative in the second. That might be due to the fact that the translog demand in the case of bread is the most likely to be misspecified of all the specifications for all products (see the appendix).

As for chicken, except in the case of the two stage least squares estimate for losses in the Klein-Rubin specification, all other coefficients are not significant. In the non-instrumented regressions, the gains coefficients were highly significant.

With the same exception for corn and tortilla chips, the significant loss aversion effect previously noted has now disappeared.

Finally, table 10 tells a similar story for pasta. While there was no loss aversion in the Klein-Rubin model but a significant negative coefficient on losses, it becomes insignificant when prices are instrumented. In the case of the translog model, two stage least squares give similar results as those of the Klein-Rubin. The twostep Newey's minimum chi-squared estimators seems to give peculiar results just as in the case of bread. Note however two important differences. For pasta, both coefficients have

Table 8: Result of the IV regressions of quantity on prices, gains and losses for Chicken

	Klein-Rubin		Translog	
VARIABLES	2SLS	Newey's twostep	2SLS	Newey's twostep
Own Losses	-0.164***	-0.290	-0.163	-0.0342
	(0.0359)	(0.209)	(0.103)	(1.469)
Own Gains	-0.0211	-0.345	0.119	1.143
	(0.0631)	(0.359)	(0.161)	(3.632)
Observations	188913	188913	188913	188913
R^2			0.015	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Result of the IV regressions of quantity on prices, gains and losses for Corn and Tortilla Chips

	Klein-Rubin		Translog	
VARIABLES	2SLS	Newey's twostep	2SLS	Newey's twostep
Own Losses	0.196**	-0.509	0.760***	8.265***
	(0.0981)	(3.041)	(0.137)	(2.101)
Own Gains	0.108	11.78	-0.231*	2.241
	(0.107)	(9.447)	(0.127)	(1.421)
Observations	188904	188904	188904	188904
R^2	0.008		0.010	

Newey's twostep
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Result of the IV regressions of quantity on prices, gains and losses for Pasta

	Klein-Rubin		Translog	
VARIABLES	2SLS	Newey's twostep	2SLS	Newey's twostep
Own Losses	0.232	-23.62	-0.251	-30.91***
	(0.161)	(38.16)	(0.250)	(6.994)
Own Gains	0.873***	11.33	1.412***	27.26***
	(0.165)	(17.12)	(0.299)	(5.230)
Observations	188899	188899	188899	188899
R^2			0.015	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

the expected sign. In addition, even if the coefficient on losses is significant, it is not of a significantly greater magnitude than the coefficient on gains. Hence, there is no loss aversion in that case either.

Globally, there is moderate evidence of loss aversion when prices are not instrumented. Bread and corn and tortilla chips display evidence of loss aversion while chicken and pasta do not. However, when the models are estimated in an IV setup, almost all the loss aversion goes away, with the notable exception of the very imprecise twostep Newey's minimum chi-squared estimator in the context of the translog specification for bread. This casts some doubt on the validity of the results of other research that finds strong evidence of loss aversion, but that does not account for the potential endogeneity of prices.

6 Conclusion

In this paper, I have proposed a novel explanation of why appearance of loss aversion in a reference price model might be confounded with other factors. If prices are endogenous, as it is often the case in demand estimation, the loss aversion parameters might just be picking up the bias in the estimation.

The results bring some evidence to support this hypothesis. While standard estimation does not give strong evidence of loss aversion for chicken and pasta, it does for corn and tortilla chips, and bread. When instruments are used to make the prices exogenous, that effect disappears for corn and tortilla chips, and bread, while it still does not show up for chicken and pasta.

These results have two main implications. Empirical estimation of reference price dependent demand ought to pay careful attention to the issue of simultaneous equation bias. Otherwise, reported loss aversion could in fact just be confounded with the bias due to the endogeneity of prices. From a marketing perspective, it is therefore not clear whether supermarkets should pay attention to loss aversion in their pricing strategies. A lot of attention has been devoted to sales pricing and how it should be adjusted in light of reference price preferences. Without loss aversion, it considerably modifies those analysis.

As such, results from this paper should be interpreted with care. Because the sample studied is relatively wealthy, it is possible that it displays less loss aversion than a the overall population. Also, because the extent of the market looked at here is relatively limited, it is not clear whether or not we should expect more or less loss aversion in a broader market.

Future research should off course pay particular attention to those issues. There is no question that behavioural scientist have found that many individuals display loss aversion in several contexts. Does that however necessarily transpose to the marketplace? And if so. Does it depend on the extent of the market? Does it vary across individuals or products, and according to what characteristics? Overall, the debate seems less to be whether loss aversion exist, but whether it plays a significant role in some markets.

Appendix

Table 11: Probit and scaled Tobit estimates for the Klein-Rubin model

	Bread		Chicken		Corn & Tort.		Pasta	
Coefficients	Probit	Sc. Tobit	Probit	Sc. Tobit	Probit	Sc. Tobit	Probit	Sc. Tobit
α_i^1	-2.45	-2.34	0.00608	0.0154	-0.453	-0.431	-0.215	-0.262
α_i^2	-1.13	-0.911	0.375	0.417	0.141	0.115	0.599	0.607
ρ_i	0.00359	0.00367	0.00981	0.00990	0.00407	0.00406	0.00252	0.00257
α_{i1}^3	0.626	0.591	-0.496	-0.474	-0.876	-0.815	0.0371	0.0623
α_{i2}^3	-0.288	-0.193	-0.177	-0.159	-0.752	-0.743	-1.20	-1.15
α_{i3}^3	0.218	0.196	0.00604	0.00567	-0.150	-0.144	-0.786	-0.772
α_{i1}^4	-2.11	-1.66	0.656	0.645	2.46	2.54	-0.879	-0.789
α_{i2}^4	-0.426	-0.349	-0.362	-0.350	-0.486	-0.477	-0.175	-0.165
α_{i3}^4	0.258	0.150	-0.423	-0.406	0.534	0.617	0.150	0.116
α_{i1}^5	-0.383	-0.371	1.79	1.66	-0.115	-0.0919	0.604	0.555
α_{i2}^5	-0.953	-0.873	-0.259	-0.245	-0.0511	-0.0641	-0.228	-0.199
α_{i3}^5	0.842	0.619	-0.164	-0.159	-0.168	-0.175	0.0684	0.0651
α_{i2}^6	-0.0115	0.00858	0.153	0.164	0.164	0.172	-0.0561	-0.0592
α_{i3}^6	0.0925	0.0760	0.0570	0.0564	0.147	0.145	-0.0108	-0.0166
α_{i4}^6	0.140	0.114	0.00203	0.0160	-0.0407	-0.0320	0.0577	0.0450
α_i^0	1.46	0.887	-1.97	-1.92	-1.72	-1.86	-1.23	-1.29

Table 12: Probit and scaled Tobit estimates for the Translog model

	Bread		Chicken		Corn & Tort.		Pasta	
Coefficients	Probit	Sc. Tobit	Probit	Sc. Tobit	Probit	Sc. Tobit	Probit	Sc. Tobit
γ_i^1	1.92	-0.768	22.7	20.7	1.32	0.783	-5.46	-5.47
γ_{i1}^2	0.204	0.456	-1.57	-1.43	-0.378	0.345	0.653	0.638
γ_{i2}^2	0.0222	0.361	-1.47	-1.33	-0.325	-0.233	0.660	0.675
γ_{i3}^2	-1.06	-0.417	-1.62	-1.48	0.242	0.324	0.600	0.647
γ_{i4}^2	-0.470	-0.0485	-1.32	-1.20	-0.124	-0.0364	1.17	1.13
γ_{i1}^3	-2.58	-2.50	-0.00246	0.00935	-0.493	-0.469	-0.0450	-0.0940
γ_{i2}^3	-0.530	-0.351	-0.469	-0.451	-0.734	-0.727	-1.93	-1.85
γ_{i3}^3	-0.317	-0.266	-0.334	-0.328	-0.433	-0.434	-0.286	-0.271
γ_{i4}^3	-0.525	-0.428	-0.294	-0.280	-0.177	-0.211	-0.547	-0.475
γ_{i1}^4	-0.784	-0.687	0.747	0.785	0.0805	0.0489	0.582	0.593
γ_{i2}^4	0.358	0.290	-0.00906	-0.0088	-0.142	-0.153	-1.30	-1.29
γ_{i3}^4	0.146	0.129	-0.0505	-0.490	0.173	0.221	0.312	0.272
γ_{i4}^4	0.587	0.464	-0.108	-0.103	-0.175	-0.181	0.0791	0.0714
γ_i^5	0.254	0.264	0.250	0.251	0.255	0.257	0.290	0.296
γ_{i2}^6	-0.0124	-0.00160	0.142	0.152	0.125	0.133	-0.0756	-0.0785
γ_{i3}^6	0.0897	0.0705	0.0269	0.0234	0.121	0.119	-0.0269	-0.0320
γ_{i4}^6	0.148	0.112	-0.0972	-0.0824	-0.0293	-0.0185	0.0358	0.0233
γ_i^0	-6.21	-1.97	-88.7	-81.7	-6.16	-5.20	4.69	4.64

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