CORE
Metadata, citation and similar papers at core.ac.uk
Provided by DSpace@MIT

Submitted to *Marketing Science*
manuscript (Please, provide the manuscript number!)

Authors are encouraged to submit new papers to INFORMS journals by means of a style file template, which includes the journal title. However, use of a template does not certify that the paper has been accepted for publication in the named journal. INFORMS journal templates are for the exclusive purpose of submitting to an INFORMS journal and should not be used to distribute the papers in print or online or to submit the papers to another publication.

Decision Stages and Asymmetries in Regular Retail Price Pass-through

Blakeley B. McShane, Chaoqun Chen, Eric T. Anderson
Kellogg School of Management, Northwestern University, b-mcshane@kellogg.northwestern.edu, c-chen@kellogg.northwestern.edu, eric-anderson@kellogg.northwestern.edu

Duncan I. Simester
Sloan School of Management, Massachusetts Institute of Technology, simester@mit.edu

We study the pass-through of wholesale price changes onto regular retail prices using an unusually detailed dataset obtained from a major retailer. We model pass-through as a two-stage decision process that considers both whether and how much to change the regular retail price. We show that pass-through is strongly asymmetric with respect to wholesale price increases versus decreases. Wholesale price increases are passed through to regular retail prices 70% of the time while wholesale price decreases are passed through only 9% of the time. Pass-through is also asymmetric with respect to the magnitude of the wholesale price change, with the magnitude affecting only the response to wholesale price increases but not decreases. Finally, we show that covariates such as private label versus national brand, ninety-nine cent price endings, and the time since the last wholesale price change have a much stronger impact on the first stage of the decision process (i.e., whether to change the regular retail price) than the second stage (i.e., how much to change the regular retail price).

Key words: regular, retail, price, pricing, pass-through

1. Introduction

How retail prices adjust to wholesale price changes is of fundamental interest to both practitioners and academics. Brand managers want to understand how changes in wholesale prices affect downstream retail prices, while academics have made price pass-through a cornerstone of theory in both marketing (Tyagi 1999) and economics (Bils and Klenow 2004, Eichenbaum et al. 2011, Nakamura and Steinsson 2008). Despite the importance of retail price pass-through, the empirical literature is scant. In this paper, we use a novel dataset that consists of 11,852 wholesale price change events faced by a very large national

retailer to study regular retail price pass-through. We develop a flexible statistical model that allows for a rich characterization of how managers adjust the regular retail price in response to a wholesale price change.

We find that, following 44% of wholesale price changes, managers make no change to the regular retail price. Further, we find that their response is strongly asymmetric with respect to wholesale price increases versus decreases. Wholesale price increases result in regular retail price increases 70% of the time while wholesale price decreases result in regular retail price decreases only 9% of the time.

The large fraction of non-responses to wholesale price changes is broadly consistent with menu cost models of price adjustments (Barro 1972, Sheshinski and Weiss 1977). These models argue that changing prices is costly and therefore managers will not respond to every wholesale price change. If a firm faces menu costs and managers believe that future wholesale price changes are more likely to be increases rather than decreases, then menu cost models can also explain the asymmetric response we observe (Laurence and Mankiw 1994). Expected future wholesale price increases would negate at least partially any windfall arising from a current wholesale price decrease. On the other hand, they would exacerbate the effects of a current wholesale price increase. Thus, an extension of the menu cost model is consistent with an asymmetric response.

Empirically, the large fraction of non-responses suggests that retail pass-through is best characterized as a two-stage decision process: managers first decide whether to change the regular retail price, and then, conditional on this decision, they decide the magnitude of the price change. To our knowledge, other empirical models of pass-through have not considered this two-stage process (Besanko et al. 2005, Nijs et al. 2010, Gopinath and Itskhoki 2010).

When we consider the magnitude of pass-through, we also find tremendous asymmetry. When managers increase the regular retail price following a wholesale price increase, the increase in the regular retail price is a roughly linear function of the increase in the wholesale price. However, when they respond to a wholesale price decrease, the regular retail price adjustment is uncorrelated with the magnitude of the wholesale price decrease.

When we examine the magnitude of the regular retail price increase in response to a wholesale price increase, we find that pass-through generally exceeds 100%. More specifically, the dollar increase in the regular retail price is greater than the dollar increase in the

wholesale price in 96% of cases where managers decide to pass a wholesale price increase through to the regular retail price. Thus, pass-through that exceeds 100% is the norm rather than the exception in our data. Relatedly, we show that small regular retail price increases are rare events: when the regular retail price does increase, the change tends to exceed 5% of the prior retail price even for marginal increases in the wholesale price.

Theoretical models of pass-through suggest that the magnitude of the price adjustment should be influenced by factors such as the wholesale price (Besanko et al. 2005, Nijs et al. 2010), the shape of the demand curve (Tyagi 1999), competitive factors (Levy et al. 1998, Slade and G.R.E.Q.A.M. 1998), and category management concerns (Zenor 1994, Basuroy et al. 2001). We include covariates, such as the wholesale price, directly in our empirical model and specify a very flexible model that can accommodate a wide variety of potential managerial behaviors.

Overall, our two-stage model captures three key features of the data: (i) non-response to wholesale price changes, (ii) asymmetry in both response incidence and magnitude, and (iii) pass-through that exceeds 100%. Using out-of-sample data, we show that more restrictive (e.g., single-stage) models of pass-through perform much more poorly than our model.

We also compare our flexible model with managerial heuristics. First, we consider a price maintenance policy under which the regular retail price always remains unchanged. Second, we consider a percentage margin maintenance policy under which the regular retail price after the wholesale price change is set so as to maintain the percentage margin in place before the wholesale price change. Third, we consider a dollar margin maintenance policy. The first heuristic clearly fails to explain the managerial response to wholesale price changes while the latter two cannot explain the non-response. In sum, all three heuristics perform quite poorly on the overall dataset. However, when we restrict our attention to an important subset of the data, namely wholesale price increases that are followed by regular retail price increases, the percentage margin maintenance rule performs reasonably well and offers a parsimonious explanation for why we observe pass-through rates that nearly always exceed 100%.

Two additional heuristics we consider are hybrid policies that we refer to as minimum percentage margin maintenance and minimum dollar margin maintenance. Under the minimum percentage (dollar) margin maintenance heuristic, managers seek to maintain percentage (dollar) margins at or above a target level. We assume that the current percentage

(dollar) margin is the target. When faced with a wholesale price decrease, the margin increases if regular retail prices are left unchanged and hence minimum percentage (dollar) margin maintenance predicts non-response (i.e., it is equivalent to price maintenance). When faced with a wholesale price increase, minimum percentage (dollar) margin maintenance predicts that managers should always respond and increase the retail price so as to maintain the percentage (dollar) margin (i.e., it is equivalent to percentage (dollar) margin maintenance). We note that while the minimum percentage margin maintenance heuristic does a good job at characterizing the non-response to wholesale price decreases as well as the magnitude of the response to wholesale price increases, it cannot explain why managers do not respond to 29% of the wholesale price increases in our data.

On the surface, it may appear that the heuristics that we consider are non-rational. However, the percentage margin maintenance heuristic is identical to the widely applied monopoly mark-up pricing rule. Under this rule, the price is proportional to marginal cost times a markup that is a function of demand elasticity. Faced with a wholesale price increase, the mark-up rule implies that managers should use the same percentage markup. We note that percentage margins vary widely among categories and items, which suggests that managers are not using a single, naïve markup rule to price all items in the store. We also note that this rule may not be fully rational as it ignores competitive factors and other considerations such as product line effects.

Our analysis explicitly focuses on regular retail prices and excludes promoted prices. We believe that there are several factors that make our focus on regular retail prices appropriate. First, unlike promoted prices, regular retail price changes are persistent: a single regular retail price change event has implications for many subsequent periods (Kehoe and Midrigan 2015; forthcoming). Second, most revenue is earned at the regular retail price. In particular, transactions at the regular retail price account for 77% of this retailer's total revenue. Although the proportion of revenue generated at the regular price varies across SKUs, it is generally quite high: 61% of SKUs generate over 90% of their revenue at the regular retail price while 77% of SKUs generate over 80% of their revenue at the regular retail price. Similar facts hold for the unit volume at the regular retail price. Transactions at the regular retail price account for 70% of this retailer's unit volume with most SKUs having a large amount of volume at the regular retail price: 49% of SKUs generate over 90% of their unit volume at the regular retail price while 67% of SKUs generate over 80%

of their unit volume at the regular retail price. Consequently, potential changes to the regular retail price are very high-profile decisions and are carefully scrutinized by senior management (see Section 3.1 for details).

We believe our focus on regular retail prices (and exclusion of promoted priced) helps explain why some of our findings conflict with prior empirical results. Given that managers treat regular and promoted prices differently, we would expect different results. We also believe the unparalleled breadth of our dataset helps explain these conflicts. We have a census of pricing decisions across a wide range of categories and products. Finally, we believe our extremely high-quality data also helps explain any conflict. We observe discrete wholesale price change events along with the actual managerial decision about whether and how much to respond to the wholesale price change. Thus, we measure pass-through directly from these observations. Most previous studies have had to infer pass-through from patterns in historical data, which may introduce considerable noise. As a final comment, we note our data allows us to build a multi-stage model of pass-through; the data considered in previous studies have typically limited researchers to single-stage models of pass-through whereas the multi-stage model we consider yields many new results.

Because we focus on the regular retail price, our study should not be interpreted as either a comparison of regular and promoted pass-through rates or a criticism of studies of promoted price pass-through. Instead, we remain silent on the issue of promoted price pass-through. Additionally, we note a limitation of our study is that our data come from a single retailer, which is common among studies that analyze detailed proprietary data. Acquiring such data requires building a close relationship with a retailer, and the effort required to establish these relationships makes it unrealistic to analyze data from multiple retailers. Although our data is from a single retailer discussions with managers and merchants at the firm reveals an organizational structure and pricing processes that are typical of other consumer packaged goods retailers such as supermarkets, drug stores, mass merchandisers, and convenience stores. Across all SKUs in the store, the median (mean) regular retail price is \$6.04 (\$9.07) while the twenty-fifth and seventy-fifth percentiles are \$3.64 and \$10.19 respectively. The retailer follows a Hi-Lo pricing policy with a median (mean) promotion depth of 27% (29%) while the twenty-fifth and seventy-fifth percentiles are 20% and 37% respectively. We believe our findings would generalize to other consumer packaged goods retailers that sell products in a similar price range.

The remainder of this paper is organized as follows. We discuss the extant literature in Section 2. We then discuss institutional details, describe our unique dataset, and perform some exploratory analyses in Section 3. In Sections 4-5, we describe our model for regular retail price pass-through and discuss our results respectively. Finally, in Section 6, we discuss the implications of our work.

2. Literature Review

Our paper contributes to three broad literatures in marketing and economics: price pass-through, menu costs, and managerial rules. We discuss each of these and our contribution to them in turn.

Several empirical papers have investigated price pass-through in the consumer packaged goods industry, beginning with the seminal work of Chevalier and Curhan (1976) who observe (i) zero pass-through on a substantial fraction of trade promotions, (ii) average overall pass-through of 35%, and (ii) average pass-through of 126% excluding the zero pass-through events. While our empirical approach differs, our results are similar in that we find, for example, a substantial fraction of zero pass-through events and that average pass-through exceeds 100% when regular retail prices are increased in response to a wholesale price increase.

A major challenge in estimating pass-through is obtaining accurate cost data and, broadly speaking, there have been three approaches in the literature: working closely with a single firm, using aggregate data, or building a structural model. The first approach was used by Nijs et al. (2010), who worked closely with a single manufacturer to obtain detailed cost data throughout the manufacturer's vertical channel thereby allowing for the study of pass-through across multiple layers of the channel. They find that pass-through from wholesalers to retailers averages 106%. They also find that pass-through from retailers to consumers averages 69%, which is similar to the estimates reported by Besanko et al. (2005) and Pauwels (2007) for a broader set of product categories within the Dominick's Finer Foods retail chain.

The aggregate data approach to estimating pass-through was employed by Ailawadi and Harlam (2009) who examined the annual pass-through of trade promotion dollars. In particular, they calculated the annual total dollars spent by the manufacturer in the form of trade promotions and divided this by the annual dollars spent by the retailer in the form

of temporary price discounts to obtain an overall annual measure of pass-through. Under this approach, Ailawadi and Harlam (2009) found that (i) $20\% - 35\%$ of observations have zero pass-through of trade promotion dollars and (ii) there is substantial heterogeneity in annual trade promotion dollars pass-through across categories with several categories showing annual pass-through in excess of 100%.

Finally, a structural modeling approach to estimating pass-through was used by Meza and Sudhir (2006) who investigated the timing of pass-through. They found that retailers tend to pass through a smaller amount in peak demand periods but that pass-through for loss leaders exceeds 160% in non-peak demand periods.

Given both the difficulty of empirically measuring pass-through and the variety of approaches used to do so, it is perhaps not surprising that there is considerable controversy over some findings. For example, a key finding of Besanko et al. (2005) is that discounts offered on one brand may affect the prices offered on competing brands, an effect termed cross-brand pass-through. This effect has also been studied in a specific case by Anderson et al. (2013) who find that a retailer adjusts the private label price when a national brand is promoted. While there is some support for this concept of cross-brand pass-through, the empirical evidence is mixed as both McAlister (2007) and Duan et al. (2011) find little to no evidence of it.

In addition to the empirical literature on pass-through, there is also a considerable theoretical literature (Tyagi 1999, Moorthy 2005) that focuses on the derivative of the retail price with respect to the wholesale price. Tyagi (1999) characterizes conditions (e.g., properties of the demand function) that lead to pass-through that is greater than or less than 100% while Moorthy (2005) generalizes these findings to include cross-brand pass-through showing that it can be positive or negative. Our paper complements these theoretical papers by providing empirical evidence that pass-through is a two-stage rather than one-stage process; this suggests that new theoretical models of pass-through may need to be developed in order to explore the theoretical implications of a two-stage decision process.

The two-stage decision process, while relatively unexamined in the marketing literature, has been widely considered in the theoretical macroeconomics literature. For example, menu costs, which impact whether to change prices but not how much to change them, are often cited as a key source of price stickiness (Barro 1972, Sheshinski and Weiss 1977). Despite the prominence of menu costs in theory, there is comparably less empirical evidence

of them with notable exceptions being research on how managers set prices (Levy et al. (1997), Levy et al. (1998), and Dutta et al. (1999)).

The paper is also related to work by two different (though overlapping) research teams using data from the same retailer. The results of the first study are described in Anderson, Simester, and Jaimovich (2015; forthcoming). They use a subset of the data used in this paper and focus on the role of menu costs. In particular, they investigate whether a wholesale price increase is less likely to result in a regular retail price change if the menu costs of changing regular retail prices are higher. Because they focus on the role of menu costs, they only consider whether the regular retail price changes. In contrast, this paper considers both whether and how much the regular retail price changes and employs a more flexible statistical model. This allows us to characterize the asymmetric response to wholesale price increases versus wholesale price decreases and variables that moderate both stages.

Work-in-progress by Anderson, Nakamura, Simester, and Steinsson (2014) uses a different sample of data from a different set of stores. They obtained data describing the quantities purchased at both the regular retail price and at the discounted or promoted price (if any). They combine this with unemployment data and commodity price data to study the retail price response to demand or supply shocks. In particular, they study whether the retailer responds to supply or demand shocks using regular retail prices or promoted prices.

Another area of focus in the macroeconomics literature has been studying the effects of large-scale macroeconomic events such as recessions on retail margins, with early work suggesting that retail margins may be counter-cyclical (Pigou 1927, Keynes 1939). Several explanations have been offered to explain this type of pricing behavior (Bils 1989, Rotemberg and Saloner 1986, Greenwald et al. 1984). We contribute to this literature by studying a time period that spans one of the largest recessionary periods in U.S. history and observing how all retail prices within a chain are affected. While retail managers face an unprecedented number of wholesale price increases at the beginning of the recession and a large number of wholesale price decreases soon thereafter, we find that their pricing behavior is remarkably stable. In other words, retail managers do not seem to modify their price setting behavior during the recession.

3. Data and Exploratory Data Analysis

3.1. Institutional Details

We study the pricing behavior of a retailer that operates a large number of stores across the United States and sells a broad mix of consumer packaged goods. Like many retailers, the firm sells a mix of national brands and private label products. The private label products typically carry the retailer's name but are produced by either a contract manufacturer or a national brand manufacturer. As noted earlier, a subset of this data is utilized by Anderson et al. (2015; forthcoming) and additional details can be found in that paper.

To set the stage for our analysis, we briefly summarize important institutional facts regarding the pricing process of consumer packaged goods manufacturers and retailers. Many of these facts are also discussed in Anderson et al. (2014). First, nearly every major consumer packaged goods manufacturer and retailer engage in some type of annual planning process that leads to a promotion calendar (Blattberg and Neslin 1990, p. 392). Second, manufacturers establish trade promotion budgets that are used to fund price discounts, in-store merchandising, and other retailer activities. Financial transfers from manufacturers to retailers are somewhat flexible, which allows retailers to execute different pricing policies (e.g., Hi-Lo versus EDLP). Third, manufacturers establish a wholesale price, which is the long-run wholesale price for a product, and nearly every retailer faces this same wholesale price. Fourth, changes in the wholesale price are infrequent events and are often affected by input costs, such as crude oil; these changes are unplanned, are not part of the annual promotion calendar, and are highly disruptive to the supply chain, which explains in part why they are so infrequent.

We now consider how these facts manifest themselves in our data. The retailer that provided the data for our study maintains a wholesale price (or vendor list price) for every product; this is viewed as the marginal cost of acquiring the product. The wholesale price tends to be stable: only very infrequently does a manufacturer adjust the wholesale price and then, in turn, the retailer decides whether to adjust the regular retail price. It is unusual to change the wholesale price more than once a year and typically wholesale price changes are announced thirty to sixty days in advance, although this varies by manufacturer. When faced with a wholesale price change, the retail category manager and corporate pricing team jointly determine the best response. If they decide to make a regular retail price change, it is often coordinated with the wholesale price change so that both occur on the

same day. These are very high-profile decisions that are carefully scrutinized by senior management via a monthly report that summarizes the expected profit implications of the decisions.

In contrast, price promotions, which are studied by Ailawadi and Harlam (2009) and Nijs et al. (2010), are managed via an entirely different process at this retailer. Promoted price changes often occur several times per year and are heavily influenced by trade promotion funds. At the retailer we study, these financial flows are distinct from the wholesale price and reside in a dedicated IT system. As we do not have access to these financial flows, we do not have a measure of wholesale price for promotion and therefore cannot study promoted price pass-through.

Given that there is some flexibility in the allocation of trade promotion funds, one may be concerned whether changes in the wholesale price may affect the depth or frequency of trade promotions. Our conversations with many managers suggest that this is very unlikely. Similar to industry norms, this retailer jointly plans price promotions with manufacturers well in advance because they require tremendous coordination and lead-time. In-store merchandising activities that generate demand (e.g., special displays, weekly features, television advertising) must be coordinated with supply (e.g., inventory), and promotions featured in store flyers each week are finalized at least twelve weeks in advance. Canceling or changing a promotion at the last-minute is both difficult and costly. Given these facts, we believe that the wholesale price change events that we observe in our data have no immediate impact on promotions or temporary discounts. Additional research by Anderson et al. (2014) on the same retail chain is consistent with this assumption.

One factor that may affect the decision to change the regular retail price at this retail chain is a capacity constraint on the number of price changes each day. This is analyzed in detail by Anderson et al. (2015; forthcoming) who provide details on this policy. The rationale for this capacity constraint is to avoid excessive use of in-store labor that is required to change each regular retail price. For completeness, we also examine whether this capacity constraint affects whether and how much to pass through wholesale price changes.

3.2. Data

Our data consist of $n = 11,852$ wholesale price change events faced by the retailer from January 2006 through September 2009. For each event i, we observe four variables of

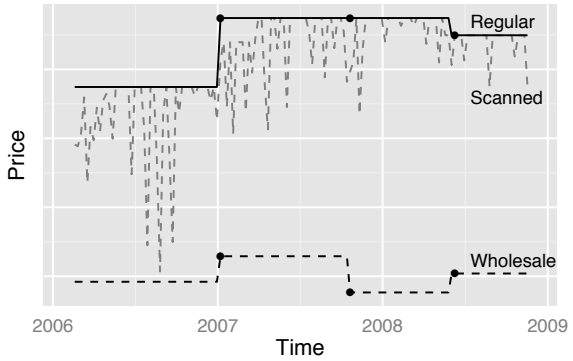


Figure 1 **Time Series of Prices for a Single SKU. Scanned prices change frequently relative to wholesale prices and regular retail prices. Wholesale prices co-vary with regular retail prices but not scanned prices. Observation of wholesale prices and regular retail prices allows us to model the managerial decision process more accurately. We note that, while we observe these three time series for this single SKU, in general we possess only the data described in Section 3.2 and indicated by the six points in the figure; we also emphasize that this figure plots data for a single SKU and thus serves only for illustration.**

principal interest: (i) $c_{0,i}$, the wholesale price charged to the retailer by the manufacturer *before* the wholesale price change; (ii) $c_{1,i}$, the wholesale price charged to the retailer by the manufacturer *after* the wholesale price change; (iii) $p_{0,i}$, the regular retail price (i.e., shelf price) charged to consumers by the retailer *before* the wholesale price change; and (iv) $p_{1,i}$, the regular retail price charged to consumers by the retailer *after* the wholesale price change.

An event in our data is an aggregate for all related flavors or variants of an SKU. For example, the wholesale prices of all flavors of single serve Snapple always change at exactly the same time. Thus, while Snapple may have many single serve SKUs (e.g., single serve Lemon Iced Tea, single serve Raspberry Iced Tea, etc.), a change in the wholesale prices of these SKUs constitutes a single event in our study. Unfortunately, we do not have data on how wholesale price changes affect other retailers. However, conversations with retail managers suggest that competing retailers generally face the same wholesale price change. For example, if the wholesale price of single serve Snapple changes at the retailer in our study, then it is very likely that competing retailers also face a similar wholesale price change.

To demonstrate how the price variables contained in our dataset have a number of unique advantages relative to the data used in prior research, consider Figure 1, which provides a time series of prices for a single SKU. Prior research (Besanko et al. 2005, Bils

Variable	**25%**	**Median**	**75%**	**Mean**	**Std.Dev.**
Market Share (Percent)	0.61	1.83	5.03	4.88	8.67
Promotion Frequency (Percent)	0.00	2.27	21.74	15.12	23.78
Promotion Depth (Percent)	0.00	20.40	48.07	25.10	26.01
Shelf Time (Days)*	795	1771	3890	2241.30	1638.74
Time Since Last Wholesale Price Change (Days)*	266	478	959	746.32	741.56
Proliferation (No. of Brands)*	217	521	1254	739.96	601.71
Revenue (Dollars)*	221.37	550.24	1299.40	1288.86	2959.54
Number of Same Week Wholesale Price Changes (Number)*	52	88	151	105.42	68.82

Table 1 Continuous Covariate Summary Statistics. Variables marked with a star enter into our model logarithmically.

and Klenow 2004, Dubé and Gupta 2008) has typically worked with the full time series of scanned prices which, as demonstrated in the figure, is typically noisy. Our data contrasts in two notable ways. First, we possess accurate observations of both the regular retail price and the wholesale price; the wholesale price is the current base cost for the item and is not confounded by trade promotions or adjustments for the historical price paid for current inventory. Second, we isolate the points in time for which there is a change in the wholesale price. More concretely, rather than working with the full time series of scanned prices in the figure, we are able to work with the wholesale and regular retail prices immediately before and after the wholesale price changes indicated by the points in the figure. These observations allow us to model the managerial decision process more accurately (see Sections 3.3 and 4 for details).

In addition to information about wholesale and regular retail prices, we observe several auxiliary variables as well as ten covariates. Our auxiliary variables include: (i) SKU_i, the stock keeping unit associated with event i; (ii) $d[i]$, the department of SKU_i (e.g., beauty, snacks, etc.); and (iii) the date associated with event i. Among our ten covariates, there are two binary covariates, namely (i) whether SKU_i is private label or national brand (24.9% of all events are for private label SKUs) and (ii) whether or not $p_{0,i}$ ends in ninety-nine cents (55.4% of all events are for SKUs with ninety-nine cent price endings). Finally, our eight

Wholesale Price	**Regular Retail Price**		
	Decrease	No Change	Increase
Decrease	2.4%	22.7%	1.2%
Increase	0.4%	21.5%	51.7%

Table 2 Frequency of the Direction of Changes in Wholesale Price and Regular Retail Price. Decreases in the wholesale price are less frequent and are more often followed by no change in regular retail price whereas increases in the wholesale price are more frequent and more often followed by increases in regular retail price.

continuous covariates are: (i) market share, the dollar sales of SKU$_i$ in the ninety-days prior to the wholesale price change divided by the dollar sales in the department of SKU$_i$ in the ninety-days prior to the wholesale price change; (ii) promotion frequency, the number of units of SKU$_i$ sold when SKU$_i$ is offered at a promoted price in the ninety-days prior to the wholesale price change divided by the total number of units sold in the ninety-days prior to the wholesale price change; (iii) promotion depth, the average discount of SKU$_i$ on days it is offered at a promoted price in the ninety-days prior to the wholesale price change; (iv) shelf time, the number of days between the date of event i and the date on which SKU$_i$ was first sold by the retailer; (v) time since last wholesale price change, the number of days between the date of event i and the date of the most recent prior wholesale price change; (vi) proliferation, the number of brands offered by the retailer in the department to which SKU$_i$ belongs; (vii) revenue, the dollar sales of SKU$_i$ in the ninety-days prior to the wholesale price change; and (viii) number of same week wholesale price changes, the number of wholesale price changes across all SKUs occurring in the same week as event i. We present summary statistics for these variables in Table 1. Of note is the relative infrequency of wholesale price changes with the median (mean) time between such changes being 478 (746) days.

3.3. Exploratory Data Analysis

Consider $s_i^c = \text{sgn}(c_{1,i} - c_{0,i})$ and $s_i^p = \text{sgn}(p_{1,i} - p_{0,i})$, the direction of the change in the wholesale price and regular retail price associated with event i respectively, which we summarize in Table 2. Nearly three-quarters of our observed wholesale price changes are increases in the wholesale price and these wholesale price increases are typically followed by increases in the regular retail price. Nonetheless, a large fraction of our observed wholesale price increases are followed by no change in the regular retail price. On the other hand,

about one-quarter of our observed wholesale price changes are decreases in the wholesale price and these wholesale price decreases are typically followed by no change in the regular retail price. This portends two features of the managerial decision-making process. First, the large fraction of wholesale price change events with no change in the regular retail price suggests managers may be adopting a two-stage approach in setting prices: after observing a change in wholesale price, they first determine whether and in what direction to change the regular retail price, and then they determine the magnitude of the change in regular retail price. Second, the asymmetry of responses suggests managers may use a different process when responding to wholesale price increases versus decreases.

Table 2 also shows a curious behavior: sometimes the retailer increases (decreases) the regular retail price after a decrease (increase) in the wholesale price. We believe that changes to the wholesale price prompt the retailer to re-evaluate their regular retail price, and, consequently, they sometimes react in the unexpected (i.e., opposite sign) direction.

To more deeply examine the relationship between wholesale and regular retail price changes, we plot the change in regular retail price (i.e., $p_{1,i} - p_{0,i}$) versus the change in wholesale price (i.e, $c_{1,i} - c_{0,i}$) in Figure 2. The observations fall into two distinct groups, a group of observations for which the change in the regular retail price is zero (and for which the points lie on the $y = 0$ line in the plot) and a group of observations for which the change in the regular retail price is non-zero (and which tend to be strongly positively correlated with the wholesale price change).

Key features of the relationship between wholesale and regular retail price changes are highlighted by the solid smoothing curve. First, there appears to be an asymmetric price response: for wholesale price increases that are small to moderate the smooth curve overlaps the gray 45° line while for wholesale price decreases the smooth curve is well above the 45° line. This suggests that managers might pass wholesale price increases through on a one-to-one basis but that they decrease regular retail prices commensurately less when faced with wholesale price decreases. Second, for relatively small decreases in wholesale price, the smooth curve essentially lies on the $y = 0$ line suggesting that relatively small decreases in wholesale prices are generally not passed through to consumers.

The solid smooth curve is fit to all observations and thus ignores a key feature of the data, namely that the data falls into two distinct groups (i.e., those with zero and non-zero changes in regular retails prices). By examining the curve alone, one cannot determine

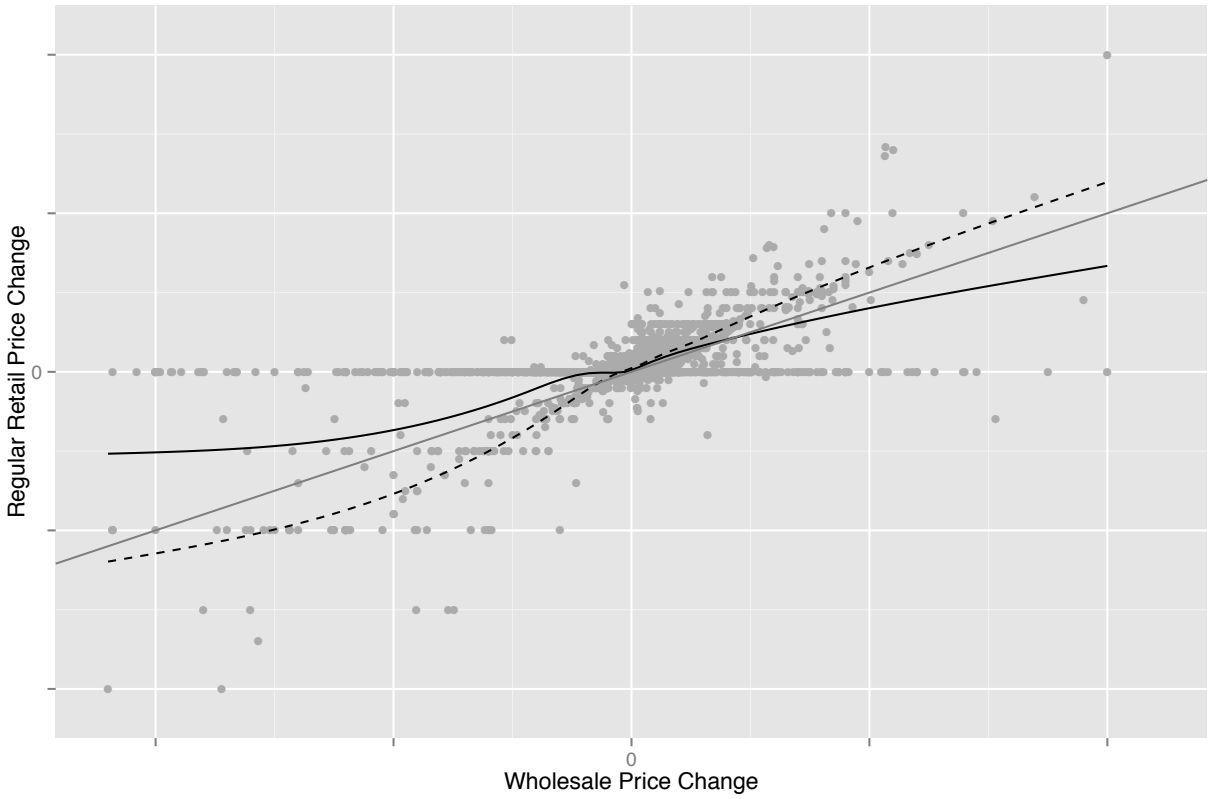


Figure 2 **Regular Retail Price Change versus Wholesale Price Change. The smooth curves provide the fit of a generalized additive model with the degree of smoothness estimated from the data using all events (solid curve) and excluding zero regular retail price change events (dashed curve) respectively. The gray line is the 45° line. Excluding zero regular retail price change events results in a relatively symmetric price response curve. Including zero regular retail price change events results in an asymmetric price response curve: for wholesale price increases the smooth curve overlaps the 45° line while for wholesale price decreases it is well above it. Axis values have been removed to protect confidentiality.**

whether the price changes are a result of (i) a relatively smooth relationship between wholesale price changes and regular retail price changes or (ii) a mixture of a relatively smooth relationship between wholesale price changes and regular retail price changes with a probability of no change in regular retail price that varies with the direction and size of the change in wholesale price. The large number of data points on the $y = 0$ line suggest the latter is indeed the case and thus we refit our smooth curve excluding these observations; the resulting curve is the dashed curve and it differs considerably from the solid one. The dashed curve is relatively symmetric with respect to wholesale price decreases and increases. Further, it lies beyond the 45° line suggesting that pass-through, when it occurs, occurs on a greater than one-to-one basis. In sum, this suggests that the second explanation

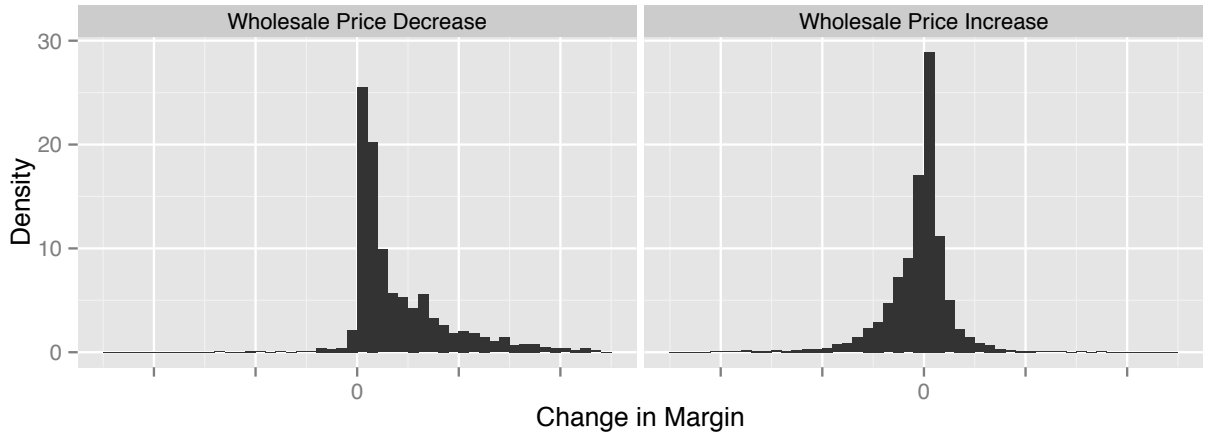
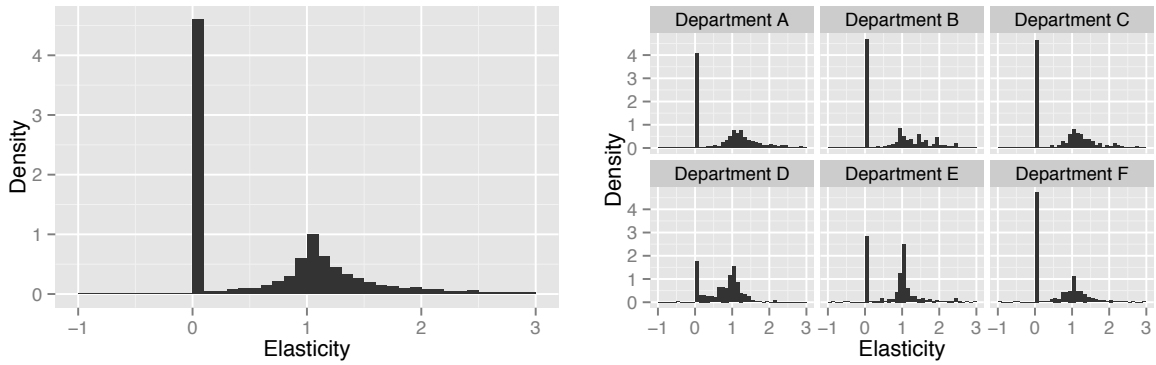


Figure 3 **Change in Margin by Direction of Wholesale Price Change. The distributions have large mass near zero suggesting a margin maintenance policy while the distribution associated with wholesale price decreases has more mass in the right tail due to the large fraction of observations with zero associated change in regular retail price. Axis values have been removed to protect confidentiality.**

mentioned in this paragraph is at play: (i) after observing a change in wholesale price, managers choose whether and in what direction to change the regular retail price and this decision is impacted by both the size and direction of the change in wholesale price; then (ii) they determine the magnitude of the change in regular retail price in a manner which may also depend on the size and direction of the change in wholesale price.

We define the retail percentage margin before and after the wholesale price change as $m_{j,i} = \frac{p_{j,i} - c_{j,i}}{p_{j,i}}$ for $j \in \{0, 1\}$ and the change in margin as $m_{1,i} - m_{0,i}$, and we plot the changes in margin conditional on the direction of the change in wholesale price in Figure 3. As can be seen, both distributions feature a large mass near zero. This suggests that retailers are setting prices in a manner that roughly maintains percentage margin. Nonetheless, the distribution associated with wholesale price decreases has more mass in the right tail because there is a large fraction of observations with zero associated change in regular retail price, and a zero change in the regular retail price in combination with a decrease in the wholesale price leads to a potentially large increase in margin.

We define pass-through elasticity as $e_i = \frac{(p_{1,i} - p_{0,i})/p_{0,i}}{(c_{1,i} - c_{0,i})/c_{0,i}}$ and we plot the elasticities in Figure 4. The left panel provides the elasticities for the entire dataset. This distribution has mass at zero reflecting the large number of observations with zero change in regular retail price; the distribution with non-zero support is centered around one reflecting margin maintenance. The right panels plot the elasticities by department for the top six departments in terms



(a) Entire Dataset (b) Top Six Departments

Figure 4 **Pass-Through Elasticity. The left panel gives the distribution of pass-through elasticity for the entire dataset. The distribution has mass at zero reflecting the large number of observations with no change in the regular retail price; the distribution with non-zero support is centered around one. The right panels give the distribution of pass-through elasticity for the six departments with the greatest number of wholesale price changes. Different patterns of pass-through elasticity indicate department heterogeneity. Department names have been removed to protect confidentiality.**

of the number of wholesale price changes. There is considerable heterogeneity in shape across departments. For instance, departments A, B, C, and F have a comparably large mass at zero (i.e., no change in the regular retail price) while departments D and E have a comparably smaller mass at zero. Further, departments A, B, and C seem to have a more uniform distribution of the non-zero elasticities while department D has more mass between zero and one and department E is more sharply peaked at one. These different patterns of pass-through suggest considerable heterogeneity across departments, a key feature of our model.

As a final consideration, we note that a salient feature of the data is an unprecedented number of wholesale price increases in the second half of 2008 followed by a large number of wholesale price decreases in the first half of 2009 and we believe that both are due to the economic recession (Anderson et al. 2014). As managers are faced with an increasing number of wholesale price change events in these time periods and, further, the relative balance of wholesale price increases and decreases deviates strongly from the norm in these time periods (the ratio of wholesale price increases to decreases is 2.5, 2.4, 7.4, and 1.3 and for each year 2006 - 2009 respectively), one may wonder whether pass-through decisions also deviate strongly from the norm. Consequently, our model allows for heterogeneity

in pass-through across time; this allows us to detect whether pass-through decisions vary along with the incidence and direction of wholesale price changes.

4. Model

We model $p_{1,i}$, the regular retail price charged by the retailer *after* the wholesale price change, as a function of $c_{0,i}$, $c_{1,i}$, $p_{0,i}$, and X_i, the vector of ten covariates discuss in Section 3, using a two-stage, asymmetric Bayesian hierarchical model. The two-stage approach allows us to account for key features of the data: the large fraction of wholesale price change events with no change in the regular retail price (Table 2), asymmetry in both whether and how much to change the regular retail price (Table 2 and Figure 2 respectively), and different shapes for decreases versus increases in the wholesale price (Figures 2 and 3).

The basic form of our two-stage model is a multinomial logistic regression in the first stage and a truncated regression in the second stage. The first stage models the direction of the change in the regular retail price while the second models its magnitude; both stages are asymmetric with respect to wholesale price increases versus decreases.

Before formally introducing our model, we introduce some basic principles for notation. First, we let α and β denote parameters for the first and second stage of our model respectively. Second, we use superscripts to denote the various classes of our model parameters (e.g., intercept, covariates, etc.). Third, parameters have subscripts that refer to direction of the wholesale price change and the regular retail price change; in cases where an additional subscript is needed, its role will be clear from context.

In the first stage of our model, we model s_i^p, the direction of the regular retail price change. In particular, we let

$$\log\left(\frac{\mathbb{P}(s_i^p = k)}{\mathbb{P}(s_i^p = 0)}\right) = \alpha_{s_i^c,k}^{Intercept} + \alpha_{d[i],s_i^c,k}^{Department} + \alpha_{t[i],s_i^c,k}^{Time} + f_{\alpha,s_i^c,k}^{Price}(c_{0,i}, c_{1,i}, p_{0,i}) + X_i' \, \alpha_{s_i^c,k}^{Covariate}$$

for $k \in \{-1, 1\}$ and where (i) $\alpha_{s_i^c,k}^{Intercept}$ is an intercept term for which k varies in the usual multinomial logistic manner for the specification of the logarithm of the probability of a regular retail price increase ($k = 1$) or decrease ($k = -1$) relative to no change ($k = 0$), (ii) $\alpha_{d[i],s_i^c,k}^{Department}$ is a department-specific intercept term that depends on $d[i]$, the department of the SKU$_i$, (iii) $\alpha_{t[i],s_i^c,k}^{Time}$ is a time-specific intercept term that depends on $t[i]$, the week of event i, (iv) $f_{\alpha,s_i^c,k}^{Price}$ is a function to be specified below, and (v) $\alpha_{s_i^c,k}^{Covariate}$ is a vector of coefficients that model the impact of our covariates X_i. These equations allow us to obtain

$\boldsymbol{p}_i = (\mathbb{P}(s_i^p = -1), \mathbb{P}(s_i^p = 0), \mathbb{P}(s_i^p = 1))$ and we then let $s_i^p \sim \text{Multinomial}(1, \boldsymbol{p}_i)$ with support $\{-1, 0, 1\}$.

In the second stage, we model $p_{1,i}$, the regular retail price following the wholesale price change conditional on the direction of the regular retail price change (i.e., conditional on stage one of the model). In particular, we let

$$p_{1,i} \sim \text{Truncated Normal}(\mu_i, \sigma^2_{s_i^c, s_i^p} | l_i, u_i).$$

The use of a truncated normal reflects the fact that, in the second stage, we know s_i^p (i.e., whether the change in regular retail price was an increase, decrease, or no change) and, thus, we can bound $p_{1,i}$. In particular, when $s_i^p = 1$ (reflecting an increase in regular retail price) we set the lower and upper bounds to $l_i = p_{0,i}$ and $u_i = \infty$ respectively. Similarly, when $s_i^p = -1$ (reflecting a decrease in regular retail price) we set the lower and upper bounds to $l_i = -\infty$ and $u_i = p_{0,i}$ respectively. Finally, when $s_i^p = 0$ (reflecting no change in regular retail price) we set $p_{1,i} = \mu_i = l_i = u_i = p_{0,i}$ and $\sigma_{s_i^c,0} = 0$ reflecting no change in regular retail price with probability one (which is true conditional on the first stage of the model). Our specification for μ_i mirrors our specification for the relative log probabilities above. In particular,

$$\mu_i = \beta^{Intercept}_{s_i^c, s_i^p} + \beta^{Department}_{d[i], s_i^c, s_i^p} + \beta^{Time}_{t[i], s_i^c, s_i^p} + f^{Price}_{\beta, s_i^c, s_i^p}(c_{0,i}, c_{1,i}, p_{0,i}) + X_i' \beta^{Covariate}_{s_i^c, s_i^p}$$

as above.

At the heart of our model lies the specification of (i) a hierarchical Bayesian prior for $\alpha^{Department}$ and $\beta^{Department}$ as well as α^{Time} and β^{Time} and (ii) a functional form for $f^{Price}_{\gamma,j,k}$. We proceed by first discussing the former. The $\alpha^{Department}$ and $\beta^{Department}$ terms in our model allow for heterogeneity across departments, an important feature as suggested by Figure 4. We go beyond department-specific heterogeneity by also allowing the pass-through decision to be heterogenous in time via the α^{Time} and β^{Time} terms. To define the prior, let us first define

$$\begin{aligned}\gamma^{Department}_{d[i]} = (&\alpha^{Department}_{d[i],-1,-1}, \alpha^{Department}_{d[i],-1,1}, \alpha^{Department}_{d[i],1,-1}, \alpha^{Department}_{d[i],1,1}, \\ &\beta^{Department}_{d[i],-1,-1}, \beta^{Department}_{d[i],-1,1}, \beta^{Department}_{d[i],1,-1}, \beta^{Department}_{d[i],1,1})\end{aligned}$$

$$\gamma^{Time}_{t[i]} = (\alpha^{Time}_{t[i],-1,-1}, \alpha^{Time}_{t[i],-1,1}, \alpha^{Time}_{t[i],1,-1}, \alpha^{Time}_{t[i],1,1}, \beta^{Time}_{t[i],-1,-1}, \beta^{Time}_{t[i],-1,1}, \beta^{Time}_{t[i],1,-1}, \beta^{Time}_{t[i],1,1})$$

as the vectors of all eight department-specific and time-specific terms. We then use the priors

$$\gamma_d^{Department} \sim \text{Multivariate Normal}(0, \Sigma^{Department}) \quad , \quad \gamma_t^{Time} \sim \text{Multivariate Normal}(0, \Sigma^{Time})$$

where $\Sigma^{Department}$ and Σ^{Time} are arbitrary matrices thus implying a joint prior on the respective elements of $\gamma_d^{Department}$ and γ_t^{Time}; with this specification for $\Sigma^{Department}$ and Σ^{Time}, the two stages of our model are linked not only by the fact that the second stage is conditional on the first stage but also through the joint prior on the respective elements of $\gamma_d^{Department}$ and γ_t^{Time}.

We now discuss the functional form of $f_{\gamma,j,k}^{Price}$. Prior literature has typically focused on modeling the regular retail price as a function of the wholesale price (Besanko et al. 2005). An advantage of our unique dataset is the ability to observe changes in both regular retail prices and wholesale prices. Consequently, modeling the change in the regular retail price as a function of the change in the wholesale price would be a natural analogue of prior models. This model, $(p_1 - p_0) \sim \gamma(c_1 - c_0)$ implies $p_1 \sim p_0 - \gamma c_0 + \gamma c_1$ which is a restricted linear model with the coefficient on p_0 fixed to one and the coefficients on c_0 and c_1 fixed to be of the same magnitude but opposite in sign. Thus, our restricted linear specification for $f_{\gamma,j,k}^{Price}$ is

$$f_{\gamma,j,k}^{Price}(c_{0,i}, c_{1,i}, p_{0,i}) = -\gamma_{j,k,1}^{Price} c_{0,i} + \gamma_{j,k,1}^{Price} c_{1,i} + p_{0,i}$$

where $\gamma \in \{\alpha, \beta\}$ and $j, k \in \{-1, 1\}$. This naturally suggests our second specification for $f_{\gamma,j,k}^{Price}$ which is simply the unrestricted linear specification

$$f_{\gamma,j,k}^{Price}(c_{0,i}, c_{1,i}, p_{0,i}) = \gamma_{j,k,1}^{Price} c_{0,i} + \gamma_{j,k,2}^{Price} c_{1,i} + \gamma_{j,k,3}^{Price} p_{0,i}.$$

Our third and final specification for $f_{\gamma,j,k}^{Price}$ allows for a more flexible form, in particular a response surface of order two

$$\begin{aligned} f_{\gamma,j,k}^{Price}(c_{0,i}, c_{1,i}, p_{0,i}) = & \gamma_{j,k,1}^{Price} c_{0,i} + \gamma_{j,k,2}^{Price} c_{1,i} + \gamma_{j,k,3}^{Price} p_{0,i} \\ & + \gamma_{j,k,4}^{Price} c_{0,i} c_{1,i} + \gamma_{j,k,5}^{Price} c_{0,i} p_{0,i} + \gamma_{j,k,6}^{Price} c_{1,i} p_{0,i} \\ & + \gamma_{j,k,7}^{Price} c_{0,i}^2 + \gamma_{j,k,8}^{Price} c_{1,i}^2 + \gamma_{j,k,9}^{Price} p_{0,i}^2. \end{aligned}$$

We explore these models in full in the next section.

Given the likelihood presented in this section (i.e., the product of the multinomial distribution for stage one and the truncated normal distribution for stage two conditional on stage one), all that remains to be specified are our priors for our parameters and hyper-parameters. Simply put, we use standard ones for Bayesian hierarchical models; full details can be found in Appendix A.

In addition to the principal model presented above, we consider two simplifications of our model. First, we consider a version of the model that is symmetric with regards to wholesale price increases versus decreases. This model is identical to that presented above except that all model parameters with a subscript for the sign of the wholesale price change (i.e., with a subscript s_i^c) are set equal for $s_i^c = -1$ (i.e., wholesale price decrease) and $s_i^c = 1$ (i.e., wholesale price increase); in particular, we set $\alpha^{Intercept}_{-1,s_i^p} = \alpha^{Intercept}_{1,s_i^p}$, $\alpha^{Department}_{d[i],-1,s_i^p} = \alpha^{Department}_{d[i],1,s_i^p}$, and so on. Second, we also consider a one stage version of the model. This model is identical to the second stage of the model presented above except that conditional on the incidence or direction of the regular retail price change and thus uses a normal distribution (as opposed to a truncated normal distribution) to model $p_{1,i}$, the regular retail price following the wholesale price change. In particular, we let $p_{1,i} \sim \text{Normal}(\mu_i, \sigma^2_{s_i^c})$ where the specification for μ_i is as above but does not depend on the direction of the regular retail price change (i.e., $\mu_i = \beta^{Intercept}_{s_i^c} + \beta^{Department}_{d[i],s_i^c} + \beta^{Time}_{t[i],s_i^c} + f^{Price}_{\beta,s_i^c}(c_{0,i}, c_{1,i}, p_{0,i}) + X_i' \beta^{Covariate}_{s_i^c}$).

5. Results

5.1. Model Evaluation

The key findings of our the paper are that (i) managers respond to a wholesale price change by first deciding whether and in what direction to change the regular retail price and then by deciding on the magnitude of the change and (ii) managers make these decisions asymmetrically with respect to whether the wholesale price is increased or decreased. Therefore, our analysis focuses on validating the claim that retail managers use a two-stage asymmetric approach rather than one-stage or symmetric approaches when deciding how to respond to wholesale price changes. To do so we will compare the twelve model specifications discussed in Section 4 (i.e., three specifications for f_γ crossed with the symmetric versus asymmetric version of the model crossed with the one-stage versus two-stage version of the model).

We compare these models both in-sample and out-of-sample. To assess in-sample fit, we use the deviance information criterion (DIC) (Spiegelhalter et al. (2002)). Out-of-sample

Stages	**Assymetry**	$f^{Price}_{\gamma,j,k}$	**In-sample**	**Out-of-Sample**					
			DIC	**RMSE**	**MAE**	**Sign%**	**Zero%**	**Cov%**	**Avg. Width**
One	No	Restricted Linear	29454.6	0.95	0.19	51	0	96	3.67
One	No	Linear	29165.2	0.96	0.19	51	0	96	3.62
One	No	Response Surface	27419.4	0.81	0.18	51	0	96	3.34
One	Yes	Restricted Linear	24653.2	0.89	0.21	51	0	96	3.20
One	Yes	Linear	24258.4	0.88	0.20	51	0	96	3.14
One	Yes	Response Surface	22221.3	0.79	0.18	51	0	96	2.83
Two	No	Restricted Linear	19963.1	1.04	0.09	78	73	97	1.66
Two	No	Linear	19394.7	1.01	0.08	78	71	98	1.65
Two	No	Response Surface	18758.8	0.68	0.08	79	73	98	1.62
Two	Yes	Restricted Linear	17579.9	0.82	0.09	80	72	98	1.63
Two	Yes	Linear	17189.3	0.91	0.08	80	73	98	1.58
Two	Yes	Response Surface	16753.7	0.64	0.07	81	73	98	1.54
Price Maintenance			NA	1.11	0.20	46	100	NA	NA
Percentage Margin Maintenance			NA	1.69	0.15	52	0	NA	NA
Dollar Margin Maintenance			NA	1.06	0.19	52	0	NA	NA
Minimum Percentage Margin Maintenance			NA	1.52	0.08	74	52	NA	NA
Minimum Dollar Margin Maintenance			NA	1.13	0.14	74	52	NA	NA

Table 3: Model Evaluation Metrics for Various Model Specifications. DIC denotes deviance information criterion, RMSE root mean square error, MAE median absolute error, Sign% the percentage of sign changes in the regular retail price correctly forecast by the model, Zero% the percentage of zero regular retail price changes correctly forecast by the model, Cov% the coverage percentage of the 95% predictive intervals, and Avg. Width the average width of the 95% predictive intervals. More flexible models typically perform better and the most flexible one performs the best. The managerial heuristics generally perform poorly except minimum percentage margin maintenance which is quite competitive in terms of MAE.

fit is assessed using a holdout sample of 1,000 randomly selected observations, and we compare model performance using six different metrics:

1. RMSE: Root mean square error.
2. MAE: Median absolute error.
3. Sign%: The percentage of sign changes in the regular retail price correctly forecast by the model.
4. Zero%: The percentage of zero regular retail price changes correctly forecast by the model.
5. Cov%: The coverage percentage of the 95% predictive intervals.
6. Avg. Width: The average width of the 95% predictive intervals.

Our findings are reported in Table 3. We see that the asymmetric two-stage models consistently perform better than either the one-stage or symmetric models. This holds not just for the in-sample metric but also the out-of-sample metrics where the larger number of parameters associated with the most flexible asymmetric two-stage model could potentially (but do not in practice) lead to over-fitting.

The relatively poor performance of the various models in comparison to the two-stage, asymmetric model is not particularly surprising given the data presented in Table 2 and Figure 2. First, Table 2 shows that nearly 45% of wholesale price changes are met with no change in regular retail price. Thus, any model that does not allow for substantial mass on this single outcome will provide a poor fit to our data. Consequently, one-stage models (which necessarily place zero mass on this outcome) fare poorly in comparison to two-stage models. Second, Table 2 reveals that managers make dramatically asymmetric decisions about whether and in what direction to adjust regular retail prices: no change in the regular retail price is much more likely for wholesale price decreases versus increases; third, the smooth curves in Figure 2 suggest asymmetries in the magnitude of changes in regular retail prices. In tandem, these two points means that symmetric models that do not allow for this possibility fare poorly relative to asymmetric models. We conclude that both in-sample and out-of-sample fit measures together with very obvious features of the data call for a two-stage, asymmetric model.

We also evaluate our models relative to five managerial heuristics:

1. Price Maintenance: A policy under which the regular retail price always remains unchanged. Formally, $p_{1,i} = p_{0,i}$.

2. Percentage Margin Maintenance: A policy under which the regular retail price after the wholesale price change is set so as to maintain the percentage margin in place before the wholesale price change. As noted, this policy is equivalent to the monopoly mark-up pricing rule. Formally, $p_{1,i} = p_{0,i}\frac{c_{1,i}}{c_{0,i}}$ which is equivalent to $p_{1,i} = \frac{\epsilon_{0,i}}{1+\epsilon_{0,i}}c_{1,i}$ where the markup $\frac{\epsilon_{0,i}}{1+\epsilon_{0,i}}$ is determined based on the mark-up prior to the wholesale price change (i.e., $\epsilon_{0,i} = p_{0,i}/(c_{0,i} - p_{0,i})$).
3. Dollar Margin Maintenance: A policy under which the regular retail price after the wholesale price change is set so as to maintain the dollar margin in place before the wholesale price change. Formally, $p_{1,i} = p_{0,i} + (c_{1,i} - c_{0,i})$.
4. Minimum Percentage Margin Maintenance: A hybrid policy under which Price Maintenance is followed for wholesale price decreases and Percentage Margin Maintenance is followed for wholesale price increases. Formally, $p_{1,i} = 1(c_{1,i} < c_{0,i}) \cdot p_{0,i} + 1(c_{1,i} > c_{0,i}) \cdot p_{0,i}\frac{c_{1,i}}{c_{0,i}}$
5. Minimum Dollar Margin Maintenance: A hybrid policy under which Price Maintenance is followed for wholesale price decreases and Dollar Margin Maintenance is followed for wholesale price increases. Formally, $p_{1,i} = p_{0,i} + 1(c_{1,i} > c_{0,i}) \cdot (c_{1,i} - c_{0,i})$.

As can be seen in Table 3, these heuristics generally fare poorly relative to our asymmetric two-stage models. A notable exception, however, is the minimum percentage margin maintenance heuristic which is quite competitive in terms of MAE. We believe this heuristic is particularly accurate for small to moderate wholesale price changes and but much less accurate for large wholesale price changes; this combined with the fact that RMSE is more sensitive to large errors than MAE helps explain the discrepant performance of this heuristic in terms of these two metrics. We note the perfect Zero% achieved by the price maintenance heuristic is by definition and is thus trivial.

To further examine model performance, we compare in Table 4 our various models specifications and heuristics on an important subset of the data, namely wholesale price increases followed by regular retail price increases which account for 51.7% of the data. While the most flexible asymmetric two-stage model still performs the best, the various model specifications differ little with respect to all but the average width metric. This is not unsurprising: by conditioning on wholesale price increases followed by regular retail price increases, this subset of the data is necessarily "one-stage" and "symmetric"; further, empirically it is roughly linear as indicated by the dashed curve in Figure 2. The

Stages	**Assymetry**	$f^{Price}_{\gamma,j,k}$	**Out-of-Sample**			
			RMSE	**MAE**	**Cov%**	**Avg. Width**
One	No	Restricted Linear	0.49	0.15	99	3.66
One	No	Linear	0.47	0.16	99	3.62
One	No	Response Surface	0.55	0.16	99	3.34
One	Yes	Restricted Linear	0.50	0.16	97	2.35
One	Yes	Linear	0.49	0.14	97	2.31
One	Yes	Response Surface	0.45	0.14	97	2.14
Two	No	Restricted Linear	0.41	0.16	97	1.61
Two	No	Linear	0.41	0.14	98	1.59
Two	No	Response Surface	0.40	0.14	98	1.56
Two	Yes	Restricted Linear	0.48	0.15	98	1.48
Two	Yes	Linear	0.45	0.14	98	1.42
Two	Yes	Response Surface	0.40	0.14	98	1.42
Price Maintenance			1.06	0.50	NA	NA
Percentage Margin Maintenance			0.51	0.09	NA	NA
Dollar Margin Maintenance			0.51	0.22	NA	NA

Table 4: Model Evaluation Metrics for Various Model Specifications Conditional on a Wholesale Price Increase Followed by a Regular Retail Price Increase. RMSE denotes root mean square error, MAE median absolute error, Cov% the coverage percentage of the 95% predictive intervals, and Avg. Width the average width of the 95% predictive intervals. Minimum Percentage (Dollar) Margin Maintenance is equivalent to Percentage (Dollar) Margin Maintenance conditioning on a wholesale price increase followed by a regular retail price increase so it is omitted from the table. The model specifications generally perform similarly except in terms of Avg. Width because this subset of the data is necessarily "one-stage" and "symmetric." The Percentage Margin Maintenance heuristic (which is equivalent to minimum percentage margin maintenance for this subset of the data) is competitive in terms of RMSE and has the best MAE.

performance of the managerial heuristics is much more interesting. Unsurprisingly, the price maintenance policy performs quite poorly. However, percentage margin maintenance (which is equivalent to minimum percentage margin maintenance for this subset of the data) is competitive in terms of RMSE and has the best MAE suggesting that percentage margin maintenance (i.e., the monopoly mark-up pricing rule) provides a reasonable description of this large subset of the data. Dollar margin maintenance (which is equivalent to minimum dollar margin maintenance for this subset of the data) is not particularly competitive in terms of either RMSE or MAE.

As an additional consideration, we performed an additional series of model fits, refitting our full suite of model specifications but replacing $c_{0,i}$, $c_{1,i}$, $p_{0,i}$, and $p_{1,i}$ with their natural logarithms. Again, the two-stage, asymmetric, response surface model was the best performing model. Further, differences in interpretation of results between this logarithmic model and the original model were comparatively minor so we proceed with results from the original model.

As a final consideration, beyond linking the two stages of our model via the conditionality of the second stage on the first stage and via the joint prior on the respective elements of $\gamma_d^{Department}$ and γ_t^{Time}, we also sought to link them by allowing for non-zero covariance among the error terms implicit in the model specification. Interval estimates of such covariances both overlapped zero and were relatively narrow thereby supporting the assumption of zero covariance made in our original model specification.

5.2. Pass-through Elasticity

While our principal coefficient estimates appear in Appendix B, we devote this section to discussion of the most salient and important results. In particular, we discuss the effect of changes in wholesale prices on the direction and magnitude of changes in regular retail prices. We also highlight the importance of our most impactful covariates as well as department heterogeneity.

We illustrate our findings via Figures 5-7, which all have three panels. In the top panel of each figure, we show results from the first stage of the model; the x-axis gives the percentage change in the wholesale price while the y-axis gives the probability of a regular retail price change. Recall that there are three possible events for any wholesale price change: no change in regular retail price, a regular retail price increase, and a regular retail price decrease. We plot the probability of each of these three events for wholesale

price changes ranging from -10% to $+10\%$ and note that empirically 74% of the observed wholesale price changes lie in this range. In the second panel of each figure, we show results from the second stage of the model; the x-axis again gives the percentage change in the wholesale price while the y-axis gives the percentage change in the regular retail price, conditional on the direction of the change in regular retail price. Finally, in the third panel of each figure, we show results that aggregate across both stages of our model thus giving the overall effect of whether and how much is passed through; the axes are as in the second panel but are not conditional on the direction of the change in regular retail price.

To obtain the results presented in each panel of the figures, we use our model to compute, conditional on a given change in the wholesale price, an average (i) probability for the change in direction of the regular retail price, (ii) magnitude of the change of the regular retail price conditional on the direction, and (iii) overall change averaging both over direction and magnitude. In particular, for event i and posterior draw j, we can calculate $\boldsymbol{p}_{i,j}^{c_1}$ which gives the probability of each of the three outcomes (i.e., increase, decrease, or no change in regular retail price) given a change in wholesale price implied by setting the new wholesale price equal to c_1 (i.e., by using c_1 in place of $c_{1,i}$ and $s_i^{c_1} = \text{sgn}(c_1 - c_{0,i})$ in place of s_i^c). We can then draw $s_{i,j}^{p,c_1,\star} \sim \text{Multinomial}(1, \boldsymbol{p}_{i,j}^{c_1})$. Similarly, we can use c_1 in place of $c_{1,i}$, $s_i^{c_1}$ in place of s_i^c, and $s_{i,j}^{p,c_1,\star}$ in place of s_i^p to calculate $\mu_{i,j}^{c_1}$ and then draw $p_{1,i,j}^{c_1,\star} \sim \text{Truncated Normal}(\mu_{i,j}^{c_1}, \sigma^2_{s_i^{c_1}, s_{i,j}^{p,c_1,\star}} | l_{i,j}^{c_1}, u_{i,j}^{c_1})$ where $l_{i,j}^{c_1}$ and $u_{i,j}^{c_1}$ are defined as described in Section 4. In order to make wholesale price comparisons comparable across different SKUs, we successively set c_1 proportional to c_0. Finally, we obtain results by computing various functions of the $s_i^{p,c_1,\star}$ and $p_{1,i,j}^{c_1,\star}$ and summarizing them over posterior draws j by computing quantiles.

We begin by examining the direction of the regular retail price change conditional on the change in wholesale price implied by c_1. In particular, for each j, we calculate the fraction of $s_i^{p,c_1,\star}$ equal to -1, 0, and 1 respectively and then take quantiles over j. We show such results in the top panel of Figure 5. For wholesale price decreases, we estimate that there is an 80% chance of no pass-through and that this probability is relatively invariant to the size of the wholesale price decrease. On the other hand, for even nominal wholesale price increases, there is a 60% chance of a regular retail price increase and this probability rises with the size of the wholesale price increase. In sum, the probability of the direction of the

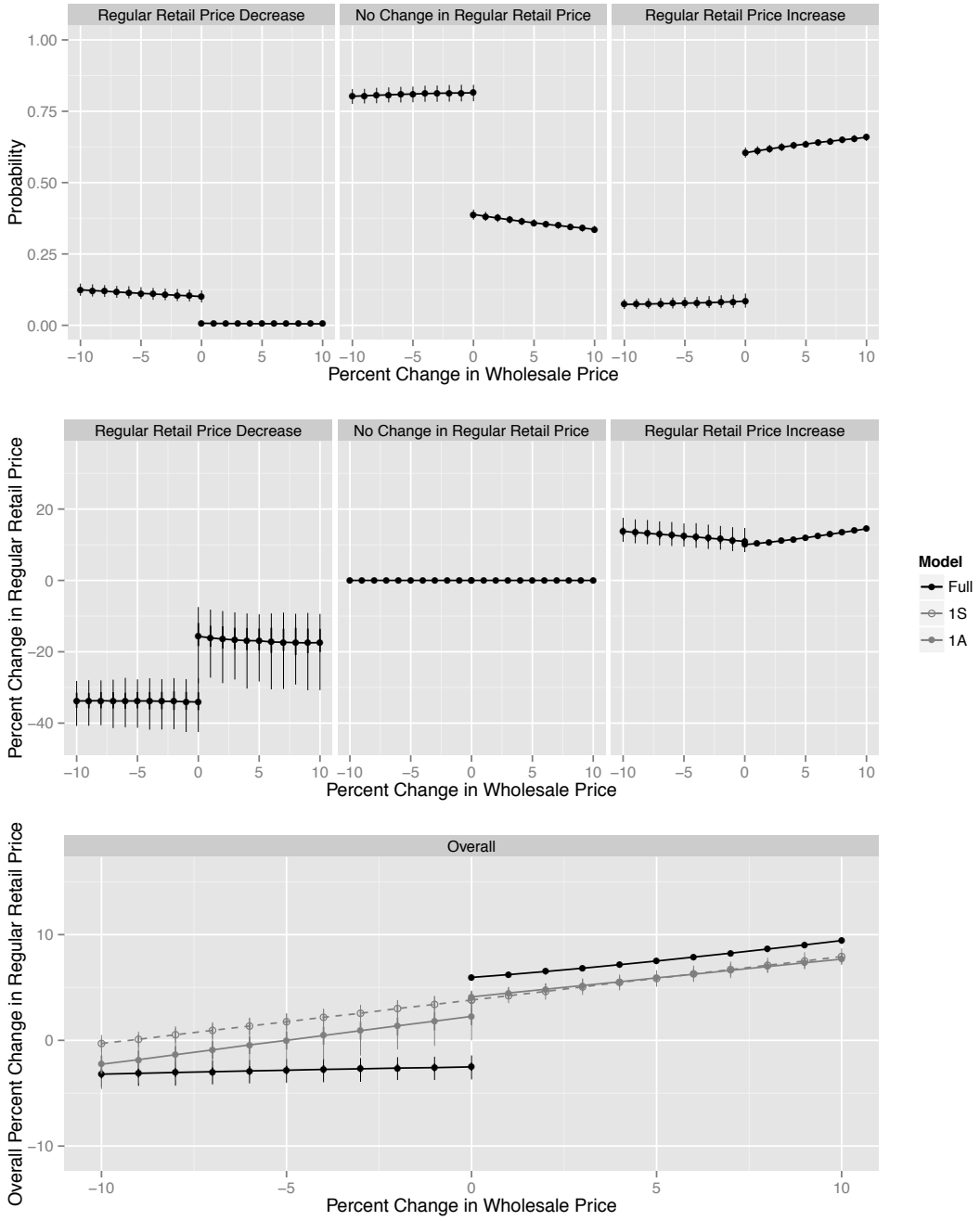


Figure 5 **Model Estimate of the Average Effect of Wholesale Price Changes. Posterior predictive medians are given by the points and 50% and 95% posterior predictive intervals are given by the thick and thin lines respectively. The top panel plots the probability of the direction of the change in the regular retail price, the middle panel plots the percentage change in the regular retail price conditional on the direction of the change, and the bottom panel plots the overall average change in the regular retail price. The probability of the direction of the change in the regular retail price shows an asymmetric response to wholesale price increases versus decreases while the magnitude of the change in the regular retail price conditional on the direction of the change does not; overall, there is an asymmetric response. The line labeled 1S (1A) in the bottom plot gives the estimated price response from the one-stage, symmetric (asymmetric), non-hierarchical restricted linear model common in the literature; it provides a substantially different estimate particularly for wholesale price decreases.**

change in regular retail price shows an asymmetric response to wholesale price increases versus decreases.

We next examine the magnitude of regular retail price changes conditional on their direction. In particular, for each j, we select the observations with $s_i^{p,c_1,\star} = k$ for $k \in \{-1, 0, 1\}$, compute the proportional regular retail price change $\frac{(p_{1,i,j}^{c_1,\star} - p_{0,i})}{p_{0,i}}$, and take quantiles over j. We show such results in the middle panel of Figure 5. Again, for wholesale price decreases, when regular retail prices are also decreased (which occurs only about 10% of the time as per the top panel of the figure), they are decreased roughly 35% and this decrease is relatively insensitive to the size of the wholesale price decrease. For wholesale price increases, when regular retail prices are also increased (which occurs over 60% of the time as per the top panel of the figure), they are increased by about 10% for nominal wholesale price increases and this percentage rises with the size of the wholesale price increase. Due to the large standard errors associated with (i) regular retail price increases following wholesale price decreases and (ii) regular retail price decreases following wholesale price increases (note, there is little data in these regions as shown in Table 2), we conclude that the magnitude of the change in regular retail price conditional on the direction of the change does not show an asymmetric response to wholesale price increases versus decreases.

Finally, we examine what happens overall by looking at $\frac{(p_{1,i,j}^{c_1,\star} - p_{0,i})}{p_{0,i}}$ unconditional on $s_i^{p,c_1,\star}$ and taking quantiles over j. We show such results in the bottom panel of Figure 5. In sum, wholesale price decreases are followed by a roughly 2% decrease in regular retail price and this decrease is relatively insensitive to the size of the wholesale price increase while even nominal wholesale price increases are followed by a 6% increase in regular retail price and this percentage rises with the size of the wholesale price increase. The average change in regular retail price shows an asymmetric response to wholesale price increases versus decreases, and, putting all three panels together, this asymmetry appears to be driven by the first stage of the decision-making process.

In order to compare our model results to those of models more typical in the literature, we fit a one-stage, symmetric, non-hierarchical restricted linear model as described above. As this model has only one stage, it can only appear in the bottom panel of Figure 5. The fact that wholesale price increases followed by regular retail price increases dominate the dataset (they are over half of all observations and indicated by Table 2) makes this model severely biased upwards for wholesale price decreases: it predicts an increase in

regular retail price even for a large wholesale price decrease. On the other hand, it performs relatively similarly to our model for wholesale price increases. In sum, this relatively simple model cannot accommodate the complex patterns demonstrated in Section 3 (and, in particular, in Table 2 and Figure 2). We also generalized this model to allow for asymmetry, but this did not substantially improve model fit or add new insights.

Another strategy that is common in the literature is to model the natural logarithm of the regular retail price as a linear function of the natural logarithm of the wholesale price (Besanko et al. 2005). Because our data allows us to fit richer models we do not fit this model. Further, the bottom panel Figure 5 reveals that the log-linear would be inadequate because it implies a constant pass-through elasticity whereas the elasticity in the figure is indeed very non-constant. We note that a constant pass-through elasticity is similar to what is actually estimated by the one-stage, symmetric, non-hierarchical restricted linear model in Figure 6.

In addition to the overall assessment discussed above, we also investigated the impact of our various covariates on regular retail price pass-through. Our most impactful covariates were (i) the binary covariate indicating whether SKU_i is private label or national brand, (ii) the binary covariate indicating whether or not $p_{0,i}$ ends in ninety-nine cents, and (iii) the time since the last wholesale price change for SKU_i. We discuss the impact of these covariates beginning with the former. The impact of private label versus national brand SKUs is shown in Figure 6 which generates estimates using the same procedure as Figure 5 but setting each private label indicator to zero and one respectively. As can be seen, private label SKUs are more likely than national brands to have no change in the regular retail price following a change in the wholesale price (top panel of Figure 6). Nonetheless, private label and national brand SKUs do not differ in terms of the magnitude of the change in the regular retail price conditional on the direction of the change (middle panel of Figure 6). The two features aggregate together to yield lower overall pass-though for private label SKUs (bottom panel of Figure 6).

This finding is interesting in light of prior work which has found that retailers are more likely to pass through price promotions for private label products (Ailawadi and Harlam 2009). Together, these results suggest that the retailer is quite sensitive to the price of private label products. Since the majority of our events are wholesale price increases, less frequent regular price pass-through leads to lower regular prices for private label items.

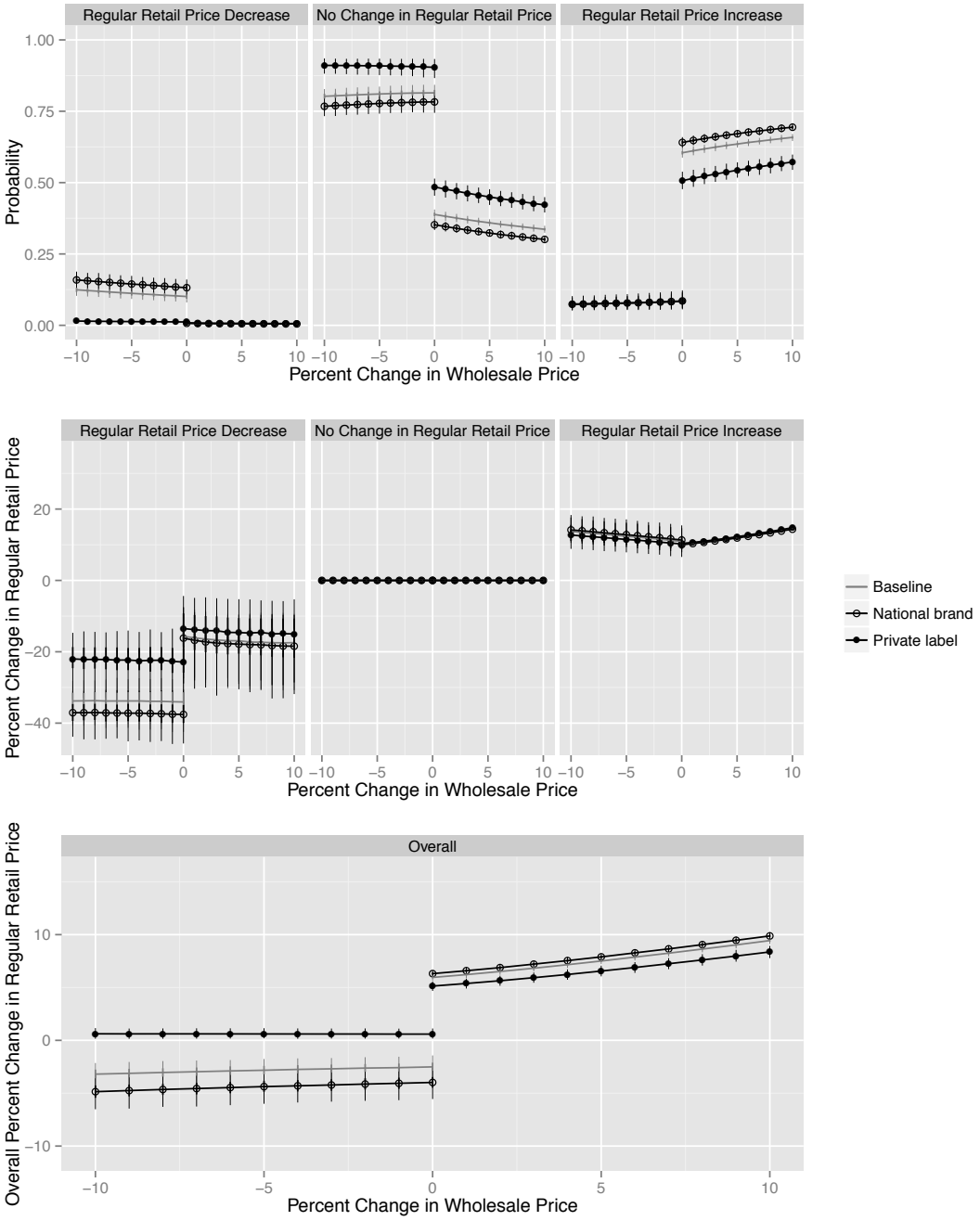


Figure 6 **Model Estimate of the Average Effect of Wholesale Price Changes for Private Label and National Brands. For interpretation, see the caption for Figure 5. Private label SKUs are more likely than national brands to have no change in the regular retail price following a change in the wholesale price, but private label and national brand SKUs do not differ in terms of the magnitude of the change in the regular retail price conditional on the direction of the change; consequently, private label SKUs have lower overall pass-through. The principal estimates from Figure 5 are provided in gray for purposes of comparison.**

But, a high promotional pass-through would lead to deep discounts on these items. This paints a picture of the retailer focusing on both low regular prices and deep discounts for private label items.

The binary ninety-nine cent ending covariate had an impact similar to the binary private label covariate. SKUs with ninety-nine cent price endings were less likely to have a change in regular retail price followed by a change in wholesale price (as in Anderson et al. (2015; forthcoming)), but the magnitude of the change in regular retail price conditional on the direction of the change did not vary depending on whether or not the price ended in ninety-nine cents. Thus, the plot for the binary ninety-cent ending covariate (not shown) looks very similar to Figure 6 although the magnitude of the differences in the top and bottom panels is somewhat attenuated. This finding reflects price ending preservation, an important real-world pricing practice (Anderson and Simester 2003).

We present the impact of the time since the last wholesale price change for a given SKU in Figure 7. We generate estimates using the same procedure as Figure 5 by respectively adding and subtracting one standard deviation to each time since the last wholesale price change. SKUs that have not had a wholesale price change in a comparably long time are more likely to have a regular retail price increase (decrease) following a wholesale price price increase (decrease), a finding that makes a great deal of intuitive sense (top panel of Figure 7). Nonetheless, there is no effect for the magnitude of the change in regular retail price conditional on the direction of the change (middle panel of Figure 7). These two features aggregate together to yield higher overall pass-though for SKUs that have not had a wholesale price change in a comparably long time (bottom panel of Figure 7).

We also investigated the effect of department heterogeneity as captured by the $\gamma_d^{Department}$ and temporal heterogeneity as captured by the γ_t^{Time} and the number of same week wholesale price changes covariate. As suggested by Figure 4, patterns of pass-through vary considerably across departments and this variation, unlike the impact of covariates, is not limited to the first stage of the model: the various departments differ in terms of both the likelihood and magnitude of pass-through in response to both wholesale price increases and decreases. In contrast, managers' pass-through decisions did not vary all that much at least over the four-year period of our data. This result is interesting given the debate on the cyclicality of markup in macroeconomics (Bils 1987, Nekarda and Ramey 2010,

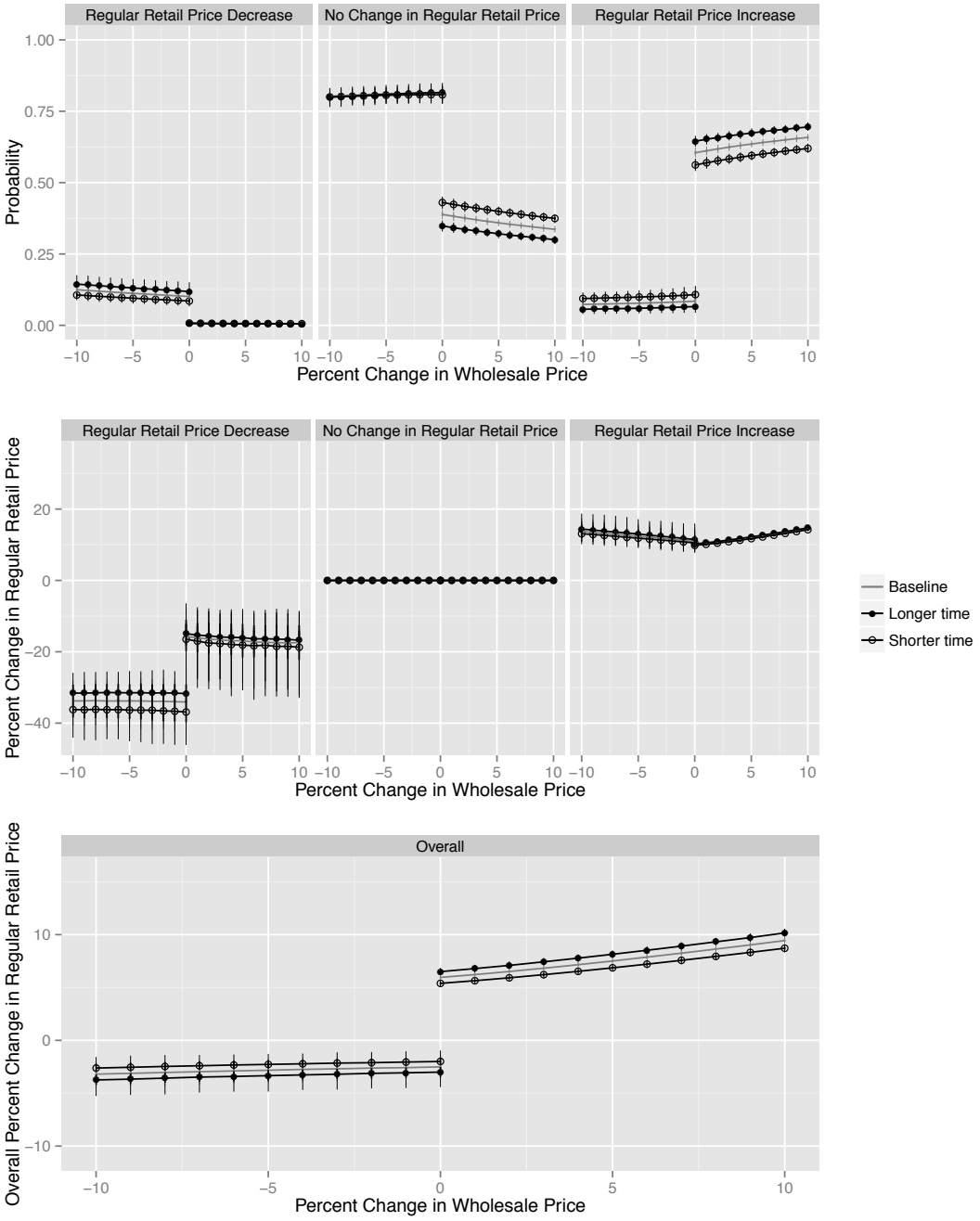


Figure 7 **Model Estimate of the Average Effect of Wholesale Price Changes by Time Since Last Wholesale Price Change. For interpretation, see the caption for Figure 5. When the most recent wholesale price change prior to the current one is large, regular retail prices are more likely to be adjusted upward (downward) following an increase (decrease) in the wholesale price but there is no difference for the magnitude of the change in the regular retail price conditional on the direction of the change; consequently, SKUs with wholesale prices that have not been recently changed have higher overall pass-through. The principal estimates from Figure 5 are provided in gray for purposes of comparison.**

Eichenbaum et al. 2011). Our finding contributes to this literature by suggesting that pass-through decision behavior is relatively stable despite the macroeconomic fluctuations in evidence during our four-year period.

One potential concern with the results presented above is that the retailer limits the number of price adjustments to one hundred per day Anderson et al. (2015; forthcoming). To investigate the extent to which our findings are influenced by this constraint, we repeated our analysis but omitting weeks in the top decile of number of cost changes from our dataset; reassuringly, there was no substantive difference in the results.

5.3. Explaining the Empirical Findings

In this subsection, we relate our empirical findings to various theoretical models of price adjustment. When faced with a change in marginal cost, single-state economic models predict that there should always be a price adjustment and that the adjustment should be proportional in magnitude to the cost change. Our data clearly reject these models on two grounds: (i) we find that non-response is common and (ii) we find considerable asymmetry in response with respect to the direction of the cost shocks. These two empirical facts are inconsistent with this class of economic models.

In contrast, menu cost models are broadly consistent with several empirical facts. In particular, non-response to cost shocks is a key feature of these models. If managers also have expectations that future cost increases are more likely than future cost decreases, then these models also predict asymmetry in whether to respond to a cost shock.

A limitation of menu cost models is that they are largely silent on the magnitude of price response. Here, menu cost models typically revert to a one-stage model where the magnitude of price adjustment is dictated by demand elasticity, the size of the cost change, competitive prices, product line considerations, and many other factors. While these factors may clearly play a role in price adjustment, we believe that managerial heuristics also play an important role. When we consider only wholesale price increases that are followed by regular retail price increases, we showed that the percentage margin maintenance heuristic is a reasonably good predictor of the magnitude of price adjustment. When we consider the entire dataset, we find that the minimum percentage margin maintenance heuristic is a good predictor of both non-response and the magnitude of response.

An alternative explanation for our findings, which was offered by the review team, is driven by consumer attention. Retailers may want to make infrequent, large regular retail

price decreases so that consumers notice the price change. In contrast, regular retail price increases may be masked via frequent, small adjustments. While this theory is plausible, it offers only a partial explanation of the data. For example, it is true that we observe infrequent regular retail price decreases and that when they occur they tend to be large; this fits the attention theory well. However, we do not observe frequent, small regular retail price increases. Indeed, if anything, we see the opposite: when a regular retail price increase occurs, there is a discrete jump in price and then a linear relationship with the size of the wholesale price increase. The attention theory fails to explain these empirical patterns that represent the bulk of our data.

An additional explanation suggested by the review team is that the patterns we observe could be driven by the retailer utilizing a dynamic strategy. For example, a retailer may not pass through a current wholesale price decrease if a future wholesale price increase is expected. This dynamic theory could explain the non-response to wholesale price decreases. Similarly, a retailer may not pass through a small wholesale price increase today but then take a larger price adjustment on a subsequent wholesale price increase. This dynamic theory could explain pass-through rates that exceed 100%.

We readily concede that these dynamic theories are plausible. However, we are unable to investigate them with our data. First, we have no measures of managers' future price expectations though we speculate that these expectations are likely to play at least some role in explaining the non-response to wholesale price decreases. Second, while our data span every wholesale price change in the entire store over four years, there are very few items with numerous wholesale price changes (recall the median (mean) number of days between wholesale price changes is 478 (746)). If managers are employing a dynamic adjustment strategy in this setting, then the dynamics must extend beyond the four-year horizon of our data. Given the institutional memory of most firms, we speculate that dynamic adjustments are unlikely for this firm but may apply in other contexts.

When considering the full set of explanations for these findings, we believe that no single theory is adequate. This suggests an opportunity for future researchers to develop a new theoretical model that can capture our key empirical findings. Importantly, a theory of regular retail price adjustment may need to be distinct from theories of temporary price adjustments.

General Finding	**Empirical Fact From This Study**
The decision regarding whether to pass a wholesale price change through to the regular retail price is asymmetric with respect to the direction of the wholesale price change.	70% (9%) of wholesale price increases (decreases) result in a regular retail price increase (decrease).
The decision regarding whether to pass a wholesale price change through to the regular retail price is moderated by: (i) Whether or not a product is private label. (ii) Whether or not it has a ninety-nine cent price ending. (iii) The amount of time since the product's last wholesale price change.	(i) Private label products are 12% (13%) more likely to have no change in regular retail price following a wholesale price increase (decrease). (ii) Products with a regular retail price that ends in ninety-nine cent are 7% (5%) more likely to have no change in regular retail price following a wholesale price increase (decrease). (iii) A one standard deviation increase in the time since the last wholesale price change is associated with a -4% (0%) change in the likelihood of no change in regular retail price following a wholesale price increase (decrease).
The decision regarding how much to pass a wholesale price change through to the regular retail price is asymmetric with respect to the direction of the wholesale price change.	Regular retail price increases (increases) are approximately linear (flat) with respect to the wholesale price increase (decrease).
Small regular retail price adjustments are rare.	Less than 3% of all regular retail price changes are less than or equal to ten cents. Less than 19% of all regular retail price changes are less than or equal to 5% of the original retail price.
Regular retail price pass-through is typically larger than 100%	96% (81%) of regular retail price increase (decreases) events have pass through greater than 100%.
Wholesale price increases are more frequent than wholesale price decreases.	There are 2.8 times as many wholesale price increases as decreases (2.5, 2.4, 7.4, and 1.3 and for each year 2006 - 2009 respectively.).
Wholesale price changes are infrequent.	The median (mean) number of days between wholesale price changes is 478 (746).
The majority of store revenue is earned at the regular retail price.	75% of store revenue is earned at the regular retail price.

Table 5 Summary of Findings.

5.4. Summary of Empirical Findings

A summary of our findings is presented in Table 5. Each row of the table gives a general finding about regular retail price pass-through as well as an empirical fact from this study. A potential concern with any empirical study is the extent to which the results generalize to other settings. While our study is limited in that we consider only a single large retail chain, it is extensive in that we cover every regular retail price change across a broad set of products (i.e., the entire store) over a long time horizon (i.e., four years). This extensive coverage across products and time is rarely seen in empirical studies of pass-through. Consequently, we believe that our results are thus comparably quite generalizable.

6. Discussion

We have built a flexible two-stage asymmetric statistical model to characterize how managers adjust the regular retail price in response to a wholesale price change. We show that our model performs better relative to both restricted versions of it (i.e., one-stage or symmetric models) as well various managerial heuristics that reflect at least in part theoretical considerations (e.g., menu costs, monopoly mark-up). The strong performance of our model suggests important implications for both academic research and management practice.

For academics, one of the key insights is that regular retail price pass-through is best characterized by a two-stage process. In the first stage, one must consider whether to make a retail price change. In the second stage, one must consider how much to change the retail price. This contradicts with the standard approach in marketing and economics, which has characterized the managerial decision as a single stage model in which pass-through is measured as a single derivative. This type of model does not capture some of the salient features of managerial behavior. For example, small price changes are rarely observed in our data. If a manager changes the price, then the price change is likely to be substantial even if the wholesale price change is small. This type of behavior is consistent with macroeconomic models that include menu costs. Our results suggest a need to incorporate features of these models in order to more accurately capture how managers make decisions.

A second result that is of importance to academics is that regular retail price pass-through is highly asymmetric. When there are wholesale price increases, managers are substantially more likely to increase the regular retail price. But, when there are wholesale price decreases, managers are more likely to pocket the additional margin and leave regular retail prices unchanged. While these asymmetries have been found in other industries, such as gasoline, they have not been found in frequently-purchased consumer packaged goods. Again, we have few theories that can account for this type of asymmetry in price pass-through, and, thus, models such as those of Tyagi (1999) and Moorthy (2005) need to be extended to incorporate this type of asymmetry.

Manufacturers that we have worked with indicate that they exert considerable effort forecasting how a retailer will respond to a wholesale price change. Our results suggest that whether to respond is asymmetric and depends on whether the wholesale price change is an increase or decrease. But, conditional on a retailer responding to a wholesale price

increase, the regular retail price increase is approximately linear. Combining this with our observation that managers tend to maintain retail price margins, one can develop a reasonably good model of how a retailer is likely to respond to a wholesale price increase. For wholesale price decreases, a surprise is that prices are relatively sticky and invariant to the magnitude of the decrease. This suggests that manufacturers may want to pursue levers other than wholesale price for reducing the regular retail price.

Acknowledgments

Appendix A: Priors and Sampling

The priors used for the model of Section 4 are, simply put, standard non-informative ones. We provide full details of our prior specification and sampling strategy below.

Our priors for the intercept terms $\alpha^{Intercept}_{s^c_i,k}$ and $\beta^{Intercept}_{s^c_i,s^p_i}$ are

$$\alpha^{Intercept}_{s^c_i,k} \sim \text{Normal}(0, 100^2) \quad , \quad \beta^{Intercept}_{s^c_i,s^p_i} \sim \text{Normal}(0, 100^2)$$

where $s^c_i, s^p_i, k \in \{-1, 1\}$. As mentioned in Section 4, the prior for our heterogeneous department-specific and time-specific terms $\gamma^{Department}_d$ and γ^{Time}_t are

$$\gamma^{Department}_d \sim \text{Multivariate Normal}(0, \Sigma^{Department}) \quad , \quad \gamma^{Time}_t \sim \text{Multivariate Normal}(0, \Sigma^{Time}).$$

We let $\Sigma^{Department}$ and Σ^{Time} be arbitrary matrices thus implying a joint prior on the respective elements of $\gamma^{Department}_d$ and γ^{Time}_t; this requires a prior for $\Sigma^{Department}$ and Σ^{Time} and we use the standard

$$\Sigma^{Department} \sim \text{Inverse Wishart}(10 \cdot I_8, 8) \quad , \quad \Sigma^{Time} \sim \text{Inverse Wishart}(10 \cdot I_8, 8)$$

where I_8 is the eight-dimensional identity matrix. Under this final specification, the two stages of our model are linked not only by the fact that the second stage is conditional on the first stage but also through the joint prior on respective elements of $\gamma^{Department}_d$ and γ^{Time}_t.

For each $\alpha^x_{s^c_i,k}$ and $\beta^x_{s^c_i,s^p_i}$ where $s^c_i, s^p_i, k \in \{-1, 1\}$ and $x \in \{Price, Covariate\}$, we use the same prior as the intercept, namely

$$\alpha^x_{s^c_i,k,p} \sim \text{Normal}(0, 100^2) \quad , \quad \beta^x_{s^c_i,s^p_i,p} \sim \text{Normal}(0, 100^2)$$

where p indexes the components of $\alpha^x_{s^c_i,k}$ and $\beta^x_{s^c_i,s^p_i}$. Finally, our prior for the standard deviations of the truncated normal distributions in stage two of our model is

$$\sigma_{s^c_i,s^p_i} \sim \text{Uniform}(0, 100)$$

for $s^c_i, s^p_i \in \{-1, 1\}$.

We sample from the full posterior distribution using Markov Chain Monte Carlo (Chib and Greenberg 1995, Gelfand 1996, Gelman et al. 2003). We implement the MCMC algorithm in WinBUGS (Spiegelhalter et al. 1999) running four independent chains each for 80,000 iterations, discarding the first 30,000 as burn-in, and thinning every 200 iterations. Convergence was assessed via the Gelman-Rubin $\hat{R}$ statistic (Gelman and Rubin 1992).

Appendix B: Coefficient Estimates

Coefficient	$\boldsymbol{\alpha}_{-1,-1}$		$\boldsymbol{\alpha}_{1,1}$		$\boldsymbol{\beta}_{-1,-1}$		$\boldsymbol{\beta}_{1,1}$	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Intercept	-2.56	1.68	-0.91	1.33	-2.70	2.01	0.88	0.94
p_0	0.04	0.05	-0.24	0.03	0.62	0.07	1.04	0.00
c_0	0.55	0.13	-0.96	0.19	-0.68	0.16	-1.36	0.03
c_1	-0.60	0.12	1.34	0.18	1.22	0.13	1.31	0.03
p_0^2	-0.00	0.00	0.01	0.00	-0.00	0.00	-0.00	0.00
c_0^2	-0.03	0.01	-0.13	0.03	-0.02	0.01	-0.07	0.01
c_1^2	0.00	0.01	-0.05	0.03	-0.02	0.00	-0.04	0.00
p_0c_0	0.02	0.01	0.05	0.01	0.01	0.01	0.02	0.00
p_0c_1	-0.01	0.01	-0.07	0.01	-0.01	0.01	-0.02	0.00
c_0c_1	0.02	0.01	0.19	0.05	0.03	0.01	0.10	0.01
Private Label	-3.02	0.34	-0.81	0.10	1.82	0.56	0.04	0.02
Ninety-nine Cent Ending	-0.39	0.22	-0.48	0.06	0.07	0.31	0.06	0.01
Market Share	-2.13	1.39	-0.97	0.51	5.29	1.90	-0.17	0.11
Promotion Frequency	0.01	0.39	-0.10	0.16	0.27	0.51	0.02	0.03
Promotion Depth	-0.14	0.40	-0.11	0.13	0.20	0.56	0.07	0.02
Shelf Time	-0.33	0.09	0.07	0.03	0.02	0.14	-0.00	0.01
Time Since Last Wholesale Price Change	0.19	0.08	0.24	0.03	0.24	0.12	0.01	0.01
Proliferation	0.22	0.23	-0.06	0.22	0.05	0.23	-0.09	0.17
Revenue	0.14	0.07	-0.03	0.02	0.02	0.10	-0.02	0.00
Number of Same Week Wholesale Price Changes	-0.14	0.16	0.15	0.14	0.17	0.24	-0.00	0.03

Posterior Means and Standard Deviations of Coefficients. Most coefficients pertaining to wholesale and regular retail prices attain statistically significance thus suggesting the importance of the flexible response surface. Most coefficients pertaining to our ten covariates, in contrast, fail to attain statistical significance thus suggesting that pass-through decisions are more strongly related to wholesale and regular retail prices. For simplicity, coefficients for which the direction of the change in the wholesale and regular retail price do not match are omitted.

References

Ailawadi, Kusum L., Bari A. Harlam. 2009. Retailer promotion pass-through: A measure, its magnitude, and its determinants. *Marketing Science* **28**(4) 782–791.

Anderson, Eric T., Karsten T. Hansen, Duncan I. Simester. 2013. Shielding store brands: A large scale field experiment. Tech. rep., Kellogg School of Management.

Anderson, Eric T., Emi Nakamura, Duncan I. Simester, Jon Steinsson. 2014. Informational rigidities and the stickiness of temporary sales. Tech. rep., Kellogg School of Management.

Anderson, Eric T., Duncan I. Simester. 2003. Effects of $9 price endings on retail sales: Evidence from field experiments. *Quantitative Marketing and Economics* **1**(1) 93–110.

Anderson, Eric T., Duncan I. Simester, Nir Jaimovich. 2015; forthcoming. Price stickiness: Empirical evidence of the menu cost channel. *Review of Economics and Statistics* .

Barro, Robert J. 1972. A theory of monopolistic price adjustment. *The Review of Economic Studies* **39**(1) 17–26.

Basuroy, Suman, Murali K. Mantrala, Rockney G. Walters. 2001. The impact of category management on retailer prices and performance: Theory and evidence. *Journal of Marketing* **65**(4) 16–32.

Besanko, David, JeanPierre Dubé, Sachin Gupta. 2005. Own-brand and cross-brand retail pass-through. *Marketing Science* **24**(1) 123–137.

Bils, Mark. 1987. The cyclical behavior of marginal cost and price. *American Economic Review* **77**(5) 838–55.

Bils, Mark. 1989. Pricing in a customer market. *The Quarterly Journal of Economics* **104**(4) 699–718.

Bils, Mark, Peter J. Klenow. 2004. Some evidence on the importance of sticky prices. *Journal of Political Economy* **112**(5) 947–985.

Blattberg, Robert C., Scott A. Neslin. 1990. *Sales Promotion: Concepts, Methods, and Strategies*. Prentice Hall, Englewood Cliffs, NJ.

Chevalier, Michel, Ronald C. Curhan. 1976. Retail promotions as a function of trade promotions: A descriptive analysis. *Sloan Management Review* **18**(3) 19–32.

Chib, Siddhartha, Edward Greenberg. 1995. Understanding the metropolis algorithm. *The American Statistician* **49**(4) 327–335.

Duan, Jason A., Leigh McAlister, Shameek Sinha. 2011. Reexamining bayesian model-comparison evidence of cross-brand pass-through. *Marketing Science* **30**(3) 550–561.

Dubé, JeanPierre, Sachin Gupta. 2008. Cross-brand pass-through in supermarket pricing. *Marketing Science* **27**(3) 324–333.

Dutta, Shantanu, Mark Bergen, Daniel Levy, Robert Venable. 1999. Menu costs, posted prices, and multiproduct retailers. *Journal of Money, Credit, and Banking* **31**(4) 683–703.

Eichenbaum, Martin, Nir Jaimovich, Sergio T Rebelo. 2011. Reference prices, costs, and nominal rigidities. *American Economic Review* **101**(1) 234–262.

Gelfand, Alan E. 1996. *Markov Chain Monte Carlo in Practice*, chap. Model Determination Using Sampling Based Methods. Chapman and Hall (CRC), 142–162.

Gelman, A., D. B. Rubin. 1992. Inference from iterative simulation using multiple sequences. *Statistical Science* **7** 457–472.

Gelman, Andrew, John B. Carlin, Hal S. Stern, Donald B. Rubin. 2003. *Bayesian Data Analysis*. 2nd ed. Chapman and Hall/CRC, Boca Raton, FL.

Gopinath, Gita, Oleg Itskhoki. 2010. Frequency of price adjustment and pass-through. *Quarterly Journal of Economics* **125**(2) 675–727.

Greenwald, Bruce, Joseph E. Stiglitz, Andrew Weiss. 1984. Informational imperfections in the capital market and macroeconomic fluctuations. *The American Economic Review* **74**(2) 194–199.

Kehoe, Patrick, Virgiliu Midrigan. 2015; forthcoming. Prices are sticky after all. *Journal of Monetary Economics* .

Keynes, John Maynard. 1939. Relative movements of real wages and output. *The Economic Journal* **49**(193) 34–51.

Laurence, Bill, N. Gregory Mankiw. 1994. Asymmetric price adjustment and economic fluctuations. *The Economic Journal* **104**(23) 247–261.

Levy, Daniel, Mark Bergen, Shantanu Dutta, Robert Venable. 1997. The magnitude of menu costs: direct evidence from large us supermarket chains. *The Quarterly Journal of Economics* **112**(3) 791–824.

Levy, Daniel, Shantanu Dutta, Mark Bergen, Robert Venable. 1998. Price adjustment at multiproduct retailers. *Managerial and Decision Economics* **19**(2) 81–120.

McAlister, Leigh. 2007. Cross-brand pass-through: Fact or artifact. *Marketing Science* **26**(6) 876–898.

Meza, Sergio, K. Sudhir. 2006. Pass-through timing. *Quantitative Marketing and Economics* **4**(4) 351–382.

Moorthy, Sridhar. 2005. A general theory of pass-through in channels with category management and retail competition. *Marketing Science* **24**(1) 110–122.

Nakamura, Emi, Jon Steinsson. 2008. Five facts about prices: A reevaluation of menu cost models. *The Quarterly Journal of Economics* **123**(4) 1415–1464.

Nekarda, Christopher J, Valerie A Ramey. 2010. The cyclical behavior of the price-cost markup. Tech. rep., University of California.

Nijs, Vincent, Kanishka Misra, Eric T. Anderson, Karsten T. Hansen, Lakshman Krishnamurthi. 2010. Channel pass-through of trade promotions. *Marketing Science* **29**(2) 250–267.

Pauwels, Koen. 2007. How retailer and competitor decisions drive the long-term effectiveness of manufacturer promotions for fast moving consumer goods. *Journal of Retailing* **83**(3) 297–308.

Pigou, Alfred C. 1927. The laws of diminishing and increasing cost. *The Economic Journal* **37**(146) 188–197.

Rotemberg, Julio J., Garth Saloner. 1986. A supergame-theoretic model of price wars during booms. *The American Economic Review* **76**(3) 390–407.

Sheshinski, Eytan, Yoram Weiss. 1977. Inflation and costs of price adjustment. *The Review of Economic Studies* **44**(2) 287–303.

Slade, Margaret E., G.R.E.Q.A.M. 1998. Optimal pricing with costly adjustment: Evidence from retail-grocery prices. *Review of Economic Studies* **65**(1) 87–107.

Spiegelhalter, David J., Nicola G. Best, Bradley P. Carlin, Angelika van der Linde. 2002. Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **64**(4) 583–639.

Spiegelhalter, David J., Andrew Thomas, Nicky G. Best. 1999. *WinBUGS Version 1.2 User Manual*. MRC Biostatistics Unit.

Tyagi, Rajeev K. 1999. A characterization of retailer response to manufacturer trade deals. *Journal of Marketing Research* **36**(4) 510–516.

Zenor, Michael J. 1994. The profit benefits of category management. *Journal of Marketing Research* **31**(2) 202–213.