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Decision Stages and Asymmetries in Regular Retail Price Pass-Through

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We study the pass-through of wholesale price changes onto regular retail prices using an unusually detailed data set obtained from a major retailer. We model pass-through as a two-stage decision process that reflects both whether as well as 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 the response to wholesale price increases but not decreases. Finally, we show that covariates such as private label versus national brand, 99-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 on the second stage (i.e., how much to change the regular retail price).

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0947.

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1. Introduction

How retail prices adjust to wholesale price changes is of fundamental interest to 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 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 data set consisting of 11,852 wholesale price change events faced by a major national retail chain 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. Furthermore, 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 nonresponses to wholesale price changes is broadly consistent with menu cost models of price adjustment (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 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 and 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 nonresponses 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, based on this decision, they determine the magnitude of the price change. To our knowledge, other empirical pass-through models 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 find that small regular retail price increases are rare: When the regular retail price increases, 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 1998), and category management concerns (Zenor 1994, Basuroy et al. 2001). We include covariates such as the wholesale price directly in our empirical model to create a 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) nonresponse to wholesale price changes, (ii) asymmetry in 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) pass-through models 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 fail to explain the nonresponse. In sum, all three heuristics perform quite poorly on the overall data set. However, when we restrict our attention to an important subset of the data, i.e., wholesale price increases 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%.

We also consider two hybrid heuristics, which we call 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 a minimum percentage (dollar) margin maintenance predicts nonresponse (i.e., it is equivalent to price maintenance). When faced with a wholesale price increase, a minimum percentage (dollar) margin maintenance predicts that managers 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 can characterize the nonresponse to wholesale price decreases as well as the magnitude of the response to wholesale price increases, it fails to 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 nonrational. 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 there are several factors that make this focus appropriate. First, unlike promoted price changes, regular retail price changes are persistent: A single regular retail price change event has implications for many subsequent periods (Kehoe and Midrigan 2015). 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 stockkeeping units (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 §3.1 for details).

We believe our focus on regular retail prices (and exclusion of promoted prices) 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 data set 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 a wholesale price change. Thus, we measure pass-through directly from these observations. Most previous studies have inferred pass-through from patterns in historical data, which may introduce considerable noise. Finally, our data allows us to build a multistage pass-through model. Data considered in previous studies have typically limited researchers to single-stage pass-through models whereas our multistage model yields many new results.

Because we focus on the regular retail price, our study should not be interpreted as a comparison of regular and promoted pass-through rates or a criticism of studies of promoted price pass-through. We remain silent on the issue of promoted price pass-through. In addition, 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; 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 reveal 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 25th and 75th 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 25th and 75th 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 §2. We then discuss institutional details, describe our unique data set, and perform some exploratory analyses in §3. In §§4 and 5, we describe our model for regular retail price pass-through and discuss our results, respectively. Finally, in §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 observed (i) zero pass-through on a substantial fraction of trade promotions, (ii) average overall pass-through of 35%, and (iii) 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. Broadly speaking, there have been three approaches in the literature: working closely with a single firm, using aggregate data, or building a structural model. Nijs et al. (2010) used the first approach. In particular, they 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 channel layers. They found that pass-through from wholesalers to retailers averages 106%. They also found 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.

Ailawadi and Harlam (2009) used the aggregate data approach to examine the annual pass-through of trade promotion dollars. In particular, they calculated the annual 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 pass-through of trade promotion dollars across categories with several categories showing pass-through in excess of 100%.

Finally, Meza and Sudhir (2006) used the structural modeling approach to examine pass-through timing. They found that retailers tend to pass through a smaller amount during peak demand periods but that pass-through for loss leaders exceeds 160% during nonpeak demand periods.

Given both the difficulty of empirically measuring pass-through and the variety of approaches used to do so, it is 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. Anderson et al. (2015a) also studied this effect in a specific case; they found that a retailer adjusts the private label price when a national brand is promoted. Thus, while there is some support for this concept of cross-brand pass-through, the empirical evidence is mixed as 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 a considerable theoretical literature (Tyagi 1999, Moorthy 2005) 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%. 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 a one-stage process. This suggests that new theoretical pass-through models may need to be developed 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, 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. Notable exceptions include research on how managers set prices (Levy et al. 1997, 1998; Dutta et al. 1999).

Our paper is also related to work by two different (though overlapping) research teams using data from the same retailer. Anderson et al. (2015b) use a subset of the data used in this paper to study 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 cost of changing the regular retail price is higher. Because they focus on the role of menu costs, they only consider whether the regular retail price changes. By contrast, this paper considers whether and how much the regular retail price changes and uses 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 et al. (2015c) uses a different data sample from a different set of stores. They obtained data describing the quantities purchased at the regular retail price and at the discounted or promoted price (if any). They combine this with unemployment 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 the effects of large-scale macroeconomic events such as recessions on retail margins. Early work suggested that retail margins may be counter-cyclical (Pigou 1927, Keynes 1939). Several explanations have been offered for 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 were 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, Anderson et al. (2015b) used a subset of this data; additional details can be found there.

To set the stage for our analysis, we briefly summarize important institutional facts about the pricing process of consumer packaged goods manufacturers and retailers. Many of these facts are also discussed in Anderson et al. (2015c). First, nearly every major consumer packaged goods manufacturer and retailer engages 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 to fund price discounts, in-store merchandising, and other retail activities. Financial transfers from manufacturers to retailers are somewhat flexible, which allows retailers to execute different pricing policies (e.g., Hi-Lo versus Everyday Low Price). Third, manufacturers establish a wholesale price, which is the long-run wholesale price for a product; nearly every retailer faces this same wholesale price. Fourth, changes in the wholesale price are infrequent and are often associated with changes in 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 (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; 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. Typically wholesale price changes are announced 30 to 60 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 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 high-profile decisions that are carefully scrutinized by senior management via a monthly report that summarizes the expected profit implications of the decisions.

By contrast, price promotions, studied by Ailawadi and Harlam (2009) and Nijs et al. (2010), are managed via a different process at the retailer we study. Promoted price changes often occur several times per year and are heavily influenced by trade promotion funds. 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 the 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 concern may be whether changes in the wholesale price 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 plans price promotions jointly 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, etc.) must be coordinated with supply (e.g., inventory); promotions featured in store flyers each week are finalized at least 12 weeks in advance. Canceling or changing a promotion at the last minute is 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. (2015c) 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. Anderson et al. (2015b) carefully analyze the capacity constraint, and provide details on the policy. The rationale for the 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.

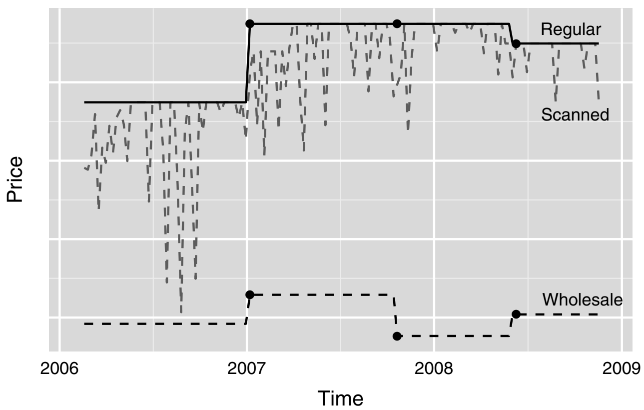
3.2. Data

Our data consist of 11,852 wholesale price change events faced by the retailer from January 2006 through September 2009. For each event i, we observe four principal variables of 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 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 data set are advantageous 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 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 provides two notable contrasts. First, we have accurate observations of 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 work with the wholesale and regular retail prices immediately before and after the wholesale price changes indicated by the

Figure 1 Time Series of Prices for a Single SKU



Notes. Scanned prices change frequently relative to wholesale prices and regular retail prices. Wholesale prices co-vary with regular retail prices but not with scanned prices. Observation of wholesale prices and regular retail prices allows us to more accurately model the managerial decision process. Note that, while we observe these three time series for this single SKU, in general we only have the data described in §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.

points in the figure. These observations allow us to more accurately model the managerial decision process (see §§3.3 and 4 for details).

In addition to information about wholesale and regular retail prices, we observe several auxiliary variables as well as 10 covariates. Our auxiliary variables include: (i) SKU_i, the SKU associated with event i; (ii) the department of SKU_i (e.g., beauty, snacks, etc.); and (iii) the date associated with event i. Among our 10 covariates, two are binary, i.e., (i) whether SKU_i is a private label or a national brand (24.9% of all events are for private label SKUs), and (ii) whether $p_{0,i}$ ends in 99 cents (55.4% of all events are for SKUs with 99-cent price endings). Finally, our eight continuous covariates are: (i) market share, the dollar sales of SKU_i in the 90 days before the wholesale price change divided by the dollar sales in the department of SKU_i in the 90 days before 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 90 days before the wholesale price change divided by the total number of units sold in the 90 days before the wholesale price change; (iii) promotion depth, the average discount of SKU_i on days it is offered at a promoted price in the 90 days before 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 90 days before 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 and note the relative infrequency of wholesale price changes; the median (mean) time between such changes is 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. 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. 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 that managers may be adopting a two-stage approach in setting prices: After observing a wholesale price change,

Table 1 Continuous Covariate Summary Statistics

Variable	25%	Median	75%	Mean	Std. dev.
Market Share (%)	0.61	1.83	5.03	4.88	8.67
Promotion Frequency (%)	0.00	2.27	21.74	15.12	23.78
Promotion Depth (%)	0.00	20.40	48.07	25.10	26.01
Shelf Time (Days)*	795	1,771	3,890	2,241.30	1,638.74
Time Since Last Wholesale Price Change (Days)*	266	478	959	746.32	741.56
Proliferation (Number of Brands)*	217	521	1,254	739.96	601.71
Revenue (Dollars)*	221.37	550.24	1,299.40	1,288.86	2,959.54
Number of Same Week Wholesale Price Changes (Number)*	52	88	151	105.42	68.82

Note. Variables marked with a star enter into our model logarithmically.

Table 2 Frequency of the Direction of Changes in the Wholesale Price and the Regular Retail Price

	Regular retail price		
Wholesale price	Decrease	No change	Increase
Decrease	2.4	22.7	1.2
Increase	0.4	21.5	51.7

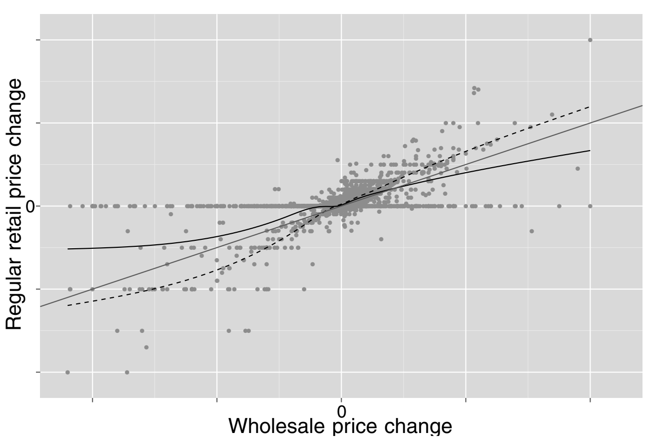
Notes. Cells give the percentage of wholesale price change events. Decreases in the wholesale price are less frequent and are more often followed by no change in the regular retail price whereas increases in the wholesale price are more frequent and more often followed by increases in the regular retail 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 that 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 the regular retail price, and consequently, they sometimes react in the unexpected (i.e., opposite sign) direction.

For a more detailed examination of 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 wholesale price change (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 for which the change in the regular retail price is nonzero (and which tend to be strongly positively correlated with the wholesale price change).

Figure 2 Regular Retail Price Change vs. Wholesale Price Change



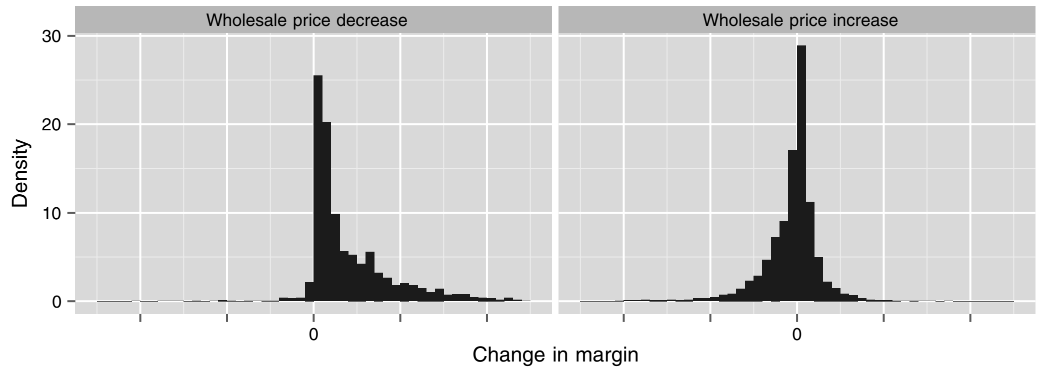
Notes. The smooth curves provide the fit of a generalized additive model with the degree of smoothness estimated from the data using all events (solid curve) and excluding zero regular retail price change events (dashed curve), respectively. The gray line is the 45° line. Excluding zero regular retail price change events yields a relatively symmetric price response curve. Including zero regular retail price change events provides an asymmetric price response curve: For wholesale price increases the solid curve overlaps the 45° line, while for wholesale price decreases it is well above it. Axis values have been removed for reasons of confidentiality.

Key features of the relationship between wholesale and regular retail price changes are indicated by the solid smoothing curve. First, there appears to be an asymmetric price response: For small to moderate wholesale price increases the solid curve overlaps the gray 45° line while for wholesale price decreases it 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 solid 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 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 change and those with nonzero change in the regular retail price). By examining the curve alone, one cannot determine 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 wholesale price change. The large number of data points on the $y = 0$ line suggest that the latter is the case; thus we refit our smooth curve excluding these observations. The result is the dashed curve, which differs considerably from the solid curve. The dashed curve is relatively symmetric with respect to wholesale price decreases and increases. Furthermore, 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 mentioned in this paragraph is at play: (i) After observing a wholesale price change, managers first choose whether and in what direction to change the regular retail price and this decision is impacted by the size and direction of the wholesale price change; (ii) Then they determine the magnitude of the change in regular retail price in a manner that may also depend on the size and direction of the wholesale price change.

We define the retail percentage margin before and after the wholesale price change as $m_{j,i} = (p_{j,i} - c_{j,i})/p_{j,i}$ for $j \in \{0, 1\}$ and the change in margin as $m_{1,i} - m_{0,i}$, and we plot the change in margin conditional on the direction of the wholesale price change in Figure 3. Clearly, both distributions feature a large mass near zero. This suggests that retailers are setting prices in a manner that roughly maintains percentage margin.

Figure 3 **Change in Margin by Direction of Wholesale Price Change**



Notes. The distributions have large mass near zero suggesting a margin maintenance policy. 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 for reasons of confidentiality.

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 the regular retail price. A zero change in the regular retail price combined with a decrease in the wholesale price leads to a potentially large increase in margin.

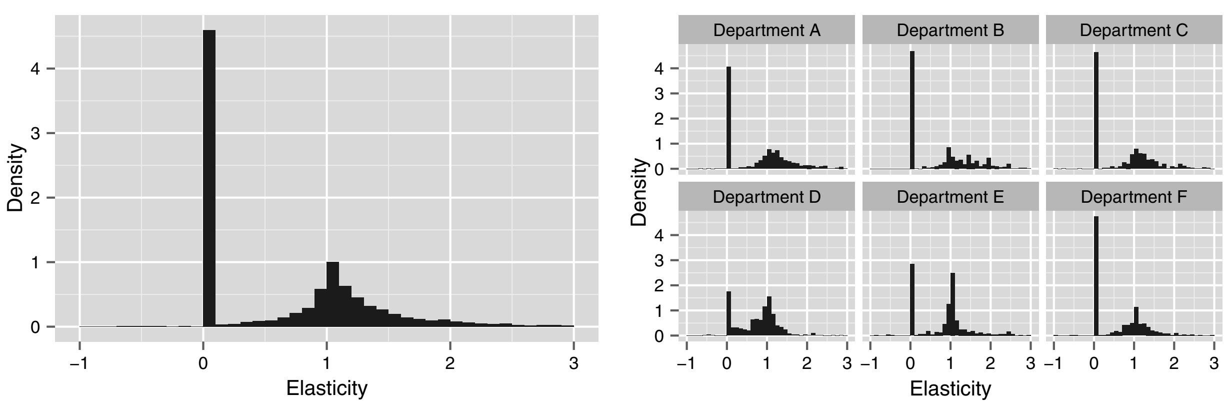
We define pass-through elasticity as

$$e_i = \frac{(p_{1,i} - p_{0,i})/p_{0,i}}{(c_{1,i} - c_{0,i})/c_{0,i}}.$$

We plot the elasticities in Figure 4. The left panel provides the elasticities for all wholesale price change events. This distribution has large mass at zero reflecting the large number of observations with zero change in the regular retail price; the distribution with nonzero support is centered around one reflecting margin maintenance. The right panels plot the elasticities by department for the top six departments in terms of the number of wholesale price change events. 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. Furthermore, departments A, B, and C seem to have a more uniform distribution of the nonzero 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, 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. We believe that both are due to the economic recession (Anderson et al. 2015c). As managers faced an increasing number of wholesale price change events

Figure 4 **Pass-Through Elasticity**



(a) Entire data set

(b) Top six departments

Notes. The left panel gives the distribution of pass-through elasticity for all wholesale price change events. The distribution has large mass at zero reflecting the large number of observations with no change in the regular retail price; the distribution with nonzero support is centered around one reflecting margin maintenance. The right panels give the distribution of pass-through elasticity for the six departments with the greatest number of wholesale price change events. Different patterns of pass-through elasticity indicate department heterogeneity. Department names have been removed for reasons of confidentiality.

in these time periods and, further, the relative balance of wholesale price increases and decreases deviated, 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, for each year 2006–2009, respectively), one might wonder whether pass-through decisions also deviated 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 the 10 covariates discussed in §3, using a two-stage, asymmetric Bayesian hierarchical model. The two-stage approach allows us to account for key features of the data, i.e., 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

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

for $k\in\{-1,1\}$ and where (i) $\alpha^{\text{Intercept}}_{s_i^c,k}$ 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) $\alpha^{\text{Department}}_{d[i],s_i^c,k}$ is a department-specific intercept term that depends on $d[i]$, the department of the SKU_i, (iii) $\alpha^{\text{Time}}_{t[i],s_i^c,k}$ is a time-specific intercept term that depends on $t[i]$, the week of event i, (iv) $f^{\text{Price}}_{\alpha,s_i^c,k}$ is a function to be specified below, and (v) $\alpha^{\text{Covariate}}_{s_i^c,k}$ is a vector of coefficients that model the impact of our covariates X_i. These equations allow us to obtain $\mathbf{p}_i=(\mathbb{P}(s_i^p=-1),\mathbb{P}(s_i^p=0),\mathbb{P}(s_i^p=1))$. We then let $s_i^p\sim\text{MNom}(1,\mathbf{p}_i)$ with support $\{-1,0,1\}$ where MNom is the multinomial distribution.

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

$$p_{1,i}\sim\text{TN}(\mu_i,\sigma^2_{s_i^c,s_i^p}\mid l_i,u_i)$$

where TN is the truncated normal distribution. 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); 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 log relative probabilities above. In particular,

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

as above.

At the heart of our model lies the specification of (i) a hierarchical Bayesian prior for $\alpha^{\text{Department}}$ and $\beta^{\text{Department}}$ as well as α^{Time} and β^{Time} and (ii) a functional form for $f^{\text{Price}}_{\gamma,j,k}$. First, we discuss the former. The $\alpha^{\text{Department}}$ and $\beta^{\text{Department}}$ 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, we first define

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

$$\begin{aligned}\gamma^{\text{Time}}_{t[i]} &= (\alpha^{\text{Time}}_{t[i],-1,-1},\alpha^{\text{Time}}_{t[i],-1,1},\alpha^{\text{Time}}_{t[i],1,-1},\alpha^{\text{Time}}_{t[i],1,1},\\ &\qquad \beta^{\text{Time}}_{t[i],-1,-1},\beta^{\text{Time}}_{t[i],-1,1},\beta^{\text{Time}}_{t[i],1,-1},\beta^{\text{Time}}_{t[i],1,1})\end{aligned}$$

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

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

where MN is the multivariate normal distribution; and $\Sigma^{\text{Department}}$ and Σ^{Time} are arbitrary matrices thus implying a joint prior on the respective elements of $\gamma_d^{\text{Department}}$ and γ_t^{Time}. With this specification for $\Sigma^{\text{Department}}$ 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 $\gamma_d^{\text{Department}}$ and γ_t^{Time}.

We now discuss the functional form of $f_{\gamma,j,k}^{\text{Price}}$. 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 data set is the ability to observe changes in 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 $f_{\gamma,j,k}^{\text{Price}}$ is

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

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

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

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

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

We explore these specifications in detail in §5.

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 the priors for our parameters and hyperparameters. Simply put, we use the standard priors for Bayesian hierarchical models. Full details are presented 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 regard 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 decreases) and $s_i^c = 1$ (i.e., wholesale price increases). In particular, we set $\alpha_{-1,s_i^p}^{\text{Intercept}} = \alpha_{1,s_i^p}^{\text{Intercept}}$, $\alpha_{d[i],-1,s_i^p}^{\text{Department}} = \alpha_{d[i],1,s_i^p}^{\text{Department}}$, and so on. Second, we consider a one-stage version of the model. This model is identical to the second stage of the model presented above except that it is not 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 $p_{1,i} \sim \text{N}(\mu_i, \sigma_{s_i^c}^2)$ where the specification for μ_i is as above but does not depend on the direction of the regular retail price change (i.e., $\mu_i = \beta_{s_i^c}^{\text{Intercept}} + \beta_{d[i],s_i^c}^{\text{Department}} + \beta_{t[i],s_i^c}^{\text{Time}} + f_{\beta,s_i^c}^{\text{Price}}(c_{0,i}, c_{1,i}, p_{0,i}) + X_i' \beta_{s_i^c}^{\text{Covariate}}$).

5. Results

5.1. Model Evaluation

The key findings of our 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 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. To validate our 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, we compare the 12 model specifications discussed in §4 (i.e., three specifications for f_γ crossed with the symmetric versus asymmetric model specification crossed with the one-stage versus two-stage model specification).

We compare these models both in-sample and out-of-sample. We assess in-sample fit using the deviance information criterion (DIC) (Spiegelhalter et al. 2002). We assess out-of-sample fit using a holdout sample of 1,000 randomly selected observations and 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. The asymmetric two-stage models consistently perform better than

Table 3 **Model Evaluation Metrics for Various Model Specifications and Managerial Heuristics**

			In-sample	Out-of-sample					
Stages	Asymmetry	$f^{\text{Price}}_{\gamma,j,k}$	DIC	RMSE	MAE	Sign%	Zero%	Cov%	Avg. width
One	No	Restricted linear	29,454.6	0.95	0.19	51	0	96	3.67
One	No	Linear	29,165.2	0.96	0.19	51	0	96	3.62
One	No	Response surface	27,419.4	0.81	0.18	51	0	96	3.34
One	Yes	Restricted linear	24,653.2	0.89	0.21	51	0	96	3.20
One	Yes	Linear	24,258.4	0.88	0.20	51	0	96	3.14
One	Yes	Response surface	22,221.3	0.79	0.18	51	0	96	2.83
Two	No	Restricted linear	19,963.1	1.04	0.09	78	73	97	1.66
Two	No	Linear	19,394.7	1.01	0.08	78	71	98	1.65
Two	No	Response surface	18,758.8	0.68	0.08	79	73	98	1.62
Two	Yes	Restricted linear	17,579.9	0.82	0.09	80	72	98	1.63
Two	Yes	Linear	17,189.3	0.91	0.08	80	73	98	1.58
Two	Yes	Response surface	16,753.7	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

Notes. DIC, 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; Avg. Width, the average width of the 95% predictive intervals. More flexible models typically perform better; the most flexible model performs best. Managerial heuristics generally perform poorly except for minimum percentage margin maintenance, which is quite competitive in terms of MAE.

the one-stage or symmetric models. This holds not just for the in-sample metric but also for the out-of-sample metrics, where the larger number of parameters associated with the most flexible asymmetric two-stage model could (but do not in practice) lead to over-fitting.

The relatively poor performance of the various models compared 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 the 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 compared 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 mean that symmetric models that do not allow for this possibility fare poorly relative to asymmetric models. We conclude that 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, $p_{1,i} = p_{0,i}(c_{1,i}/c_{0,i})$, which is equivalent to $p_{1,i} = (\epsilon_{0,i}/(1+\epsilon_{0,i}))c_{1,i}$, where the mark-up $\epsilon_{0,i}/(1+\epsilon_{0,i})$ is determined based on the mark-up before 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, $p_{1,i} = 1(c_{1,i} < c_{0,i}) \cdot p_{0,i} + 1(c_{1,i} > c_{0,i}) \cdot p_{0,i}(c_{1,i}/c_{0,i})$.

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 shown in Table 3, these heuristics generally fare poorly relative to our asymmetric two-stage models. A notable exception 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

Table 4 **Model Evaluation Metrics for Various Model Specifications and Managerial Heuristics Conditional on a Wholesale Price Increase Followed by a Regular Retail Price Increase**

			Out-of-sample			
Stages	Asymmetry	$f^{\text{Price}}_{\gamma,j,k}$	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

Notes. RMSE, root mean square error; MAE, median absolute error; Cov%, the coverage percentage of the 95% predictive intervals; 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; thus, 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 is competitive in terms of RMSE and has the best MAE.

changes 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. Note that the perfect Zero% achieved by the price maintenance heuristic is by definition and is thus trivial.

To further examine model performance, in Table 4 we compare our various model specifications and heuristics on an important subset of the data, i.e., 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 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." Furthermore, empirically it is roughly linear as indicated by the dashed curve in Figure 2. The performance of the managerial heuristics is much more interesting. Not surprisingly, the price maintenance policy performs 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 RMSE or MAE.

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 performed best. Furthermore, differences in interpretation of results between this logarithmic model and the original model were comparatively minor. Thus we proceed with results from the original model.

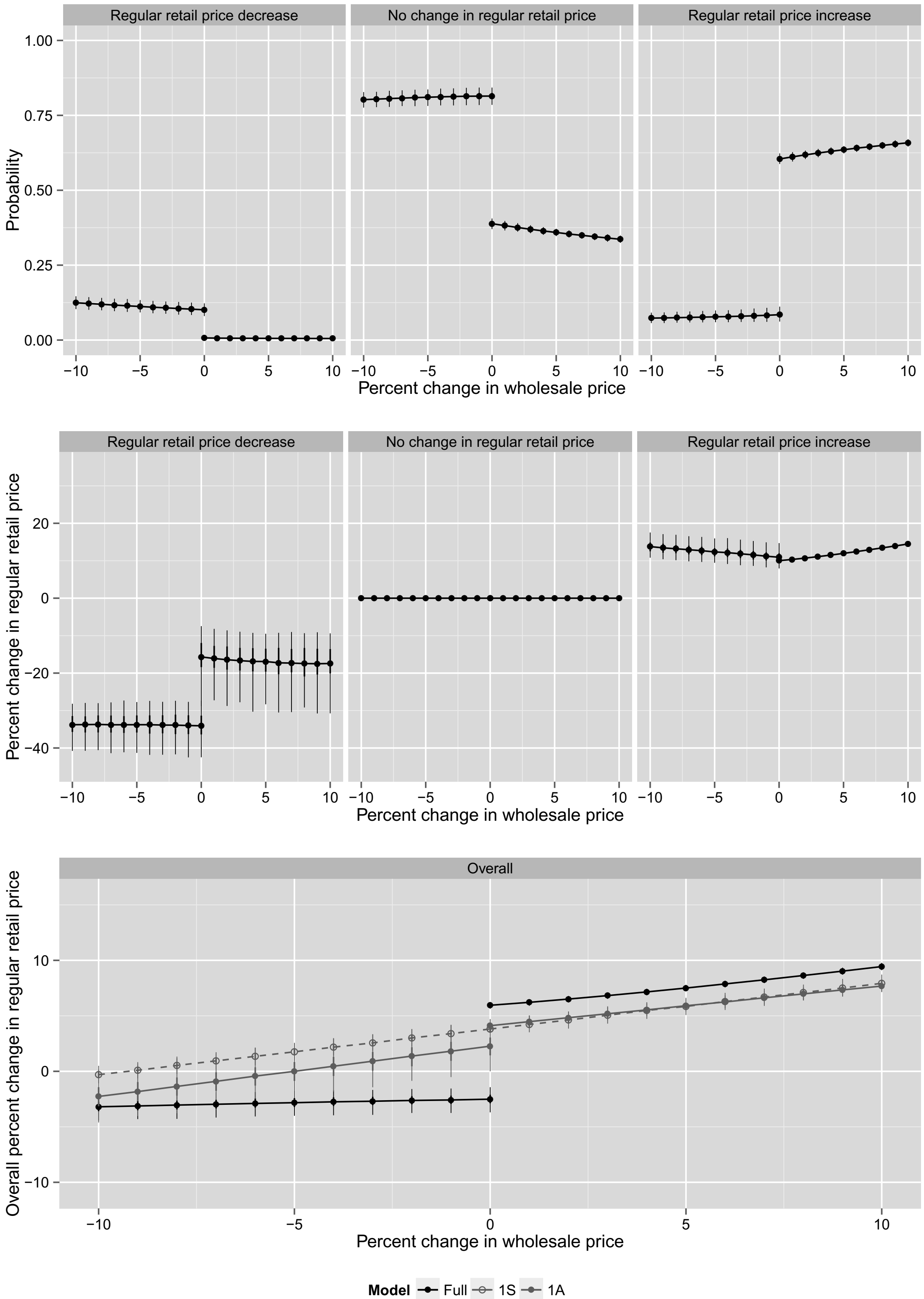
As a final consideration, beyond linking the two stages of our model via the conditionality of the second stage on the first stage and via the joint prior on the respective elements of $\gamma_d^{\text{Department}}$ and γ_t^{Time}, we also sought to link them by allowing for nonzero covariance among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

5.2. Pass-Through Elasticity

While our principal coefficient estimates are presented in Appendix B, we devote this section to discussion of our 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 covariates with the greatest impact as well as department heterogeneity.

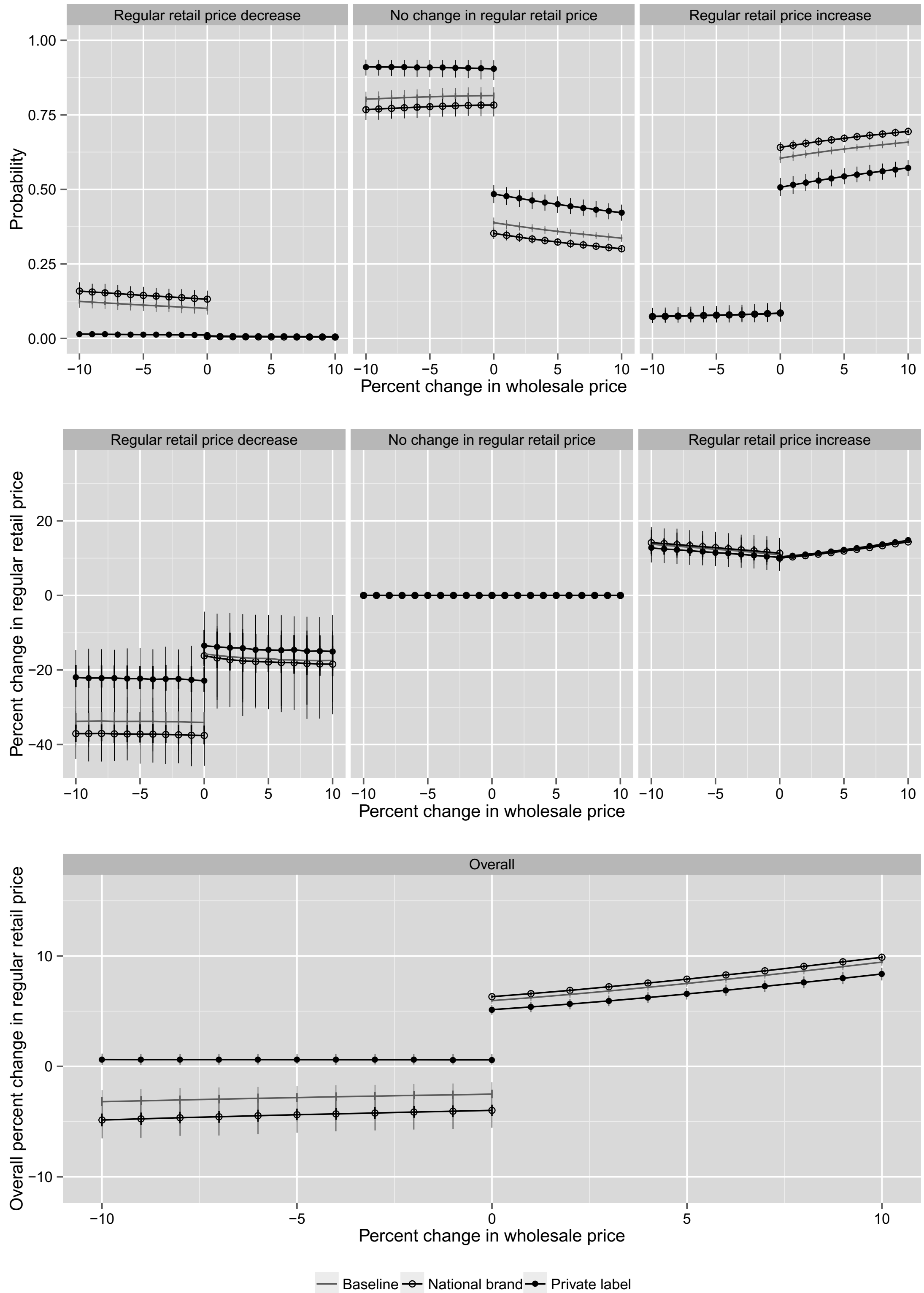
We illustrate our findings in Figures 5–7. Each has three panels. In the top panel of each figure, we show results from the first stage of the model; the x-axis gives the percentage change in the wholesale price while the y-axis gives the probability of a regular retail price

Figure 5 Model Estimate of the Average Effect of Wholesale Price Changes



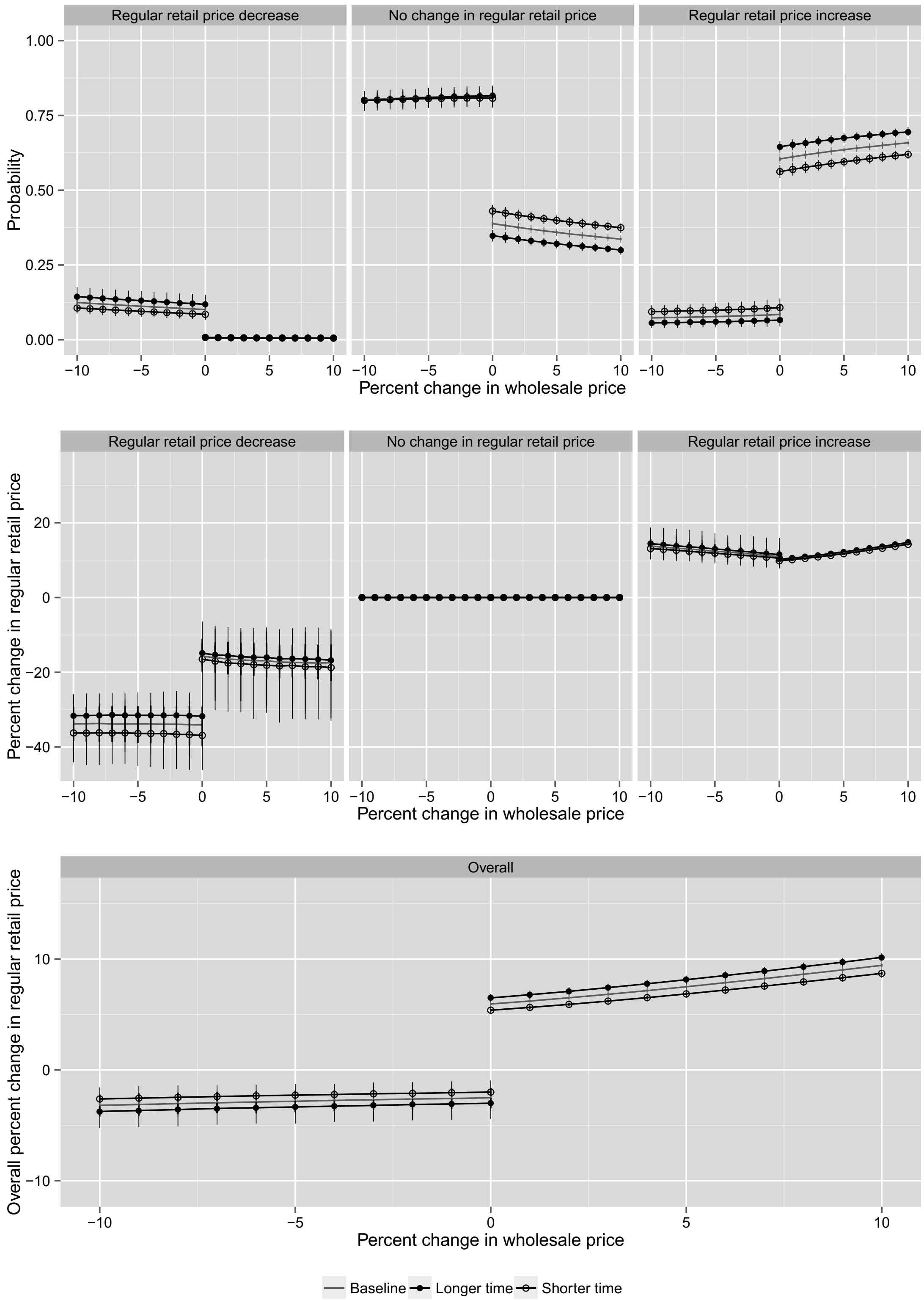
Notes. Posterior predictive medians are given by the points; 50% and 95% posterior predictive intervals are given by the thick and thin lines, respectively. The top panel plots the probability of the direction of the change in the regular retail price; the middle panel plots the percentage change in the regular retail price conditional on the direction of the change; 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), nonhierarchical restricted linear model common in the literature; it provides a substantially different estimate particularly for wholesale price decreases.

Figure 6 Model Estimate of the Average Effect of Wholesale Price Changes for Private Label and National Brands



Notes. 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.

Figure 7 Model Estimate of the Average Effect of Wholesale Price Changes by Time Since Last Wholesale Price Change



Notes. For interpretation, see the caption for Figure 5. When the most recent wholesale price change before the current one was a longer time ago, 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.

change. Recall that there are three possible events for any wholesale price change, i.e., 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 middle 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 bottom 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. Here 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 over direction and magnitude. In particular, for event i and posterior draw j, we can calculate $\mathbf{p}_{i,j}^{c_1}$, which gives the probability of each of the three outcomes (i.e., increase, decrease or no change in regular retail price) given a wholesale price change implied by setting the new wholesale price equal to c_1 (i.e., 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 then draw $s_{i,j}^{p,c_1,\star} \sim \text{MNom}(1, \mathbf{p}_{i,j}^{c_1})$. Similarly, we 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 $p_{1,i,j}^{c_1,\star} \sim \text{TN}(\mu_{i,j}^{c_1}, \sigma^2_{s_i^{c_1}, s_{i,j}^{p,c_1,\star}} \mid l_{i,j}^{c_1}, u_{i,j}^{c_1})$ where $l_{i,j}^{c_1}$ and $u_{i,j}^{c_1}$ are defined as described in §4. 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 $s_{i,j}^{p,c_1,\star}$ 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 wholesale price change implied by c_1. In particular, for each j, we calculate the fraction of $s_{i,j}^{p,c_1,\star}$ equal to −1, 0, and 1, respectively, and then take quantiles over j. We show these 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 the 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 change in the 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 $s_{i,j}^{p,c_1,\star} = k$ for $k \in \{-1, 0, 1\}$, compute the proportional regular retail price change $(p_{1,i,j}^{c_1,\star} - p_{0,i})/p_{0,i}$, and take quantiles over j. We show these 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%; 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; this percentage increase rises with the size of the wholesale price increase. Because of 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 cannot conclude that the magnitude of the change in the regular retail price conditional on the direction of the change shows an asymmetric response to wholesale price increases versus decreases for this subset of the data.

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

To compare our model results to those of more typical models in the literature, we fit a one-stage, symmetric, nonhierarchical 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 data (they are over half of all observations as indicated by Table 2) makes this model severely biased upwards for wholesale price decreases: It predicts an increase in the regular retail price even for large wholesale price decreases. 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 §3 (and, in particular, in Table 2 and Figure 2). We also generalized this model to allow for asymmetry. This did not substantially improve model fit or add new insights.

Another common strategy 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. Furthermore, the bottom panel in Figure 5 shows that the log-linear model would be inadequate because it implies a constant pass-through elasticity whereas the elasticity in the figure is very nonconstant. Note that a constant pass-through elasticity is similar to what is actually estimated by the one-stage, symmetric, nonhierarchical restricted linear model in Figure 5.

In addition to the overall assessment discussed above, we investigated the impact of our various covariates on regular retail price pass-through. The covariates with the greatest impact were (i) the binary covariate indicating whether SKU_i is a private label or a national brand, (ii) the binary covariate indicating whether $p_{0,i}$ ends in 99 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. Clearly, private label SKUs are more likely than national brand SKUs 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 differ very little 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). These 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 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 sensitive to the price of private label products. Because the majority of our events are wholesale price increases, less frequent regular price pass-through leads to lower regular prices for private label items. Yet a high promotional pass-through would lead to deep discounts on these items. This shows the retailer focusing on low regular prices and deep discounts for private label items.

The impact of the binary 99-cent ending covariate was similar to the binary private label covariate. SKUs with 99-cent price endings were less likely to have a change in the regular retail price after a wholesale price change (as in Anderson et al. 2015b), but the magnitude of the change in the regular retail price conditional on the direction of the change did not vary depending on whether or not the price ended in 99 cents. Thus, the plot for the binary 99-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 illustrate the impact of the time since the last wholesale price change 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 increase (decrease), a finding that makes a great deal of intuitive sense (top panel of Figure 7). Nonetheless, there is hardly any 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 (i) department heterogeneity as captured by the $\gamma_d^{\mathrm{Department}}$ and (ii) temporal heterogeneity as captured by the γ_t^{Time} and the number of same week wholesale price changes covariate. As suggested by Figure 4, pass-through patterns vary considerably across departments. This variation, unlike the impact of covariates, is not limited to the first stage of the model: The various departments differ in terms of the likelihood and magnitude of pass-through in response to wholesale price increases and decreases. By contrast, managers' pass-through decisions did not vary much at least over the four-year period of our data. This result is interesting given the debate on the cyclicality of mark-up in macroeconomics (Bils 1987, Nekarda and Ramey 2013, 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 100 per day (Anderson et al. 2015b). To investigate the extent to which our findings are influenced by this constraint, we repeated our analysis, but omitted weeks in the top decile of number of cost changes from our data set. 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 nonresponse 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.

By contrast, menu cost models are broadly consistent with several empirical facts. In particular, nonresponse 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 considered 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 data set, we find that the minimum percentage margin maintenance heuristic is a good predictor of nonresponse 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. By 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. 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. Thus, 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 using a dynamic strategy. For example, a retailer may not pass through a current wholesale price decrease if a future wholesale price increase is expected. 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. Thus, this dynamic theory can explain the nonresponse to wholesale price decreases as well as 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 nonresponse to wholesale price decreases. Second, while our data span every wholesale price change in the entire store over four years, there are few items with numerous wholesale price changes (recall that the median (mean) number of days between wholesale price changes is 478 (746)). If managers are using 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 new theoretical models that can capture our key empirical findings. Significantly, theories of regular retail price adjustment may need to be distinct from theories of temporary price adjustment.

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 comparably quite generalizable.

6. Discussion

We have built a flexible two-stage asymmetric model to characterize how managers adjust the regular retail

Table 5 **Summary of Findings**

General finding	Empirical fact from this study
The decision about 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 about whether to pass a wholesale price change through to the regular retail price is moderated by: (i) Whether a product is private label. (ii) Whether it has a 99-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 the regular retail price following a wholesale price increase (decrease). (ii) Products with a regular retail price that ends in 99 cents are 7% (5%) more likely to have no change in the 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 the regular retail price following a wholesale price increase (decrease).
The decision about 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 (decreases) 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 10 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 (decrease) 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.	77% of store revenue is earned at the regular retail price.

price in response to a wholesale price change. We show that our model performs better than restricted (i.e., one-stage or symmetric models) versions of it as well as 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 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 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 to more accurately capture how managers make decisions.

A second result 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. Yet 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. Thus models such as those of Tyagi (1999) and Moorthy (2005) need to be extended to incorporate this type of asymmetry.

Manufacturers with whom we have worked 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. Yet, 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 the wholesale price for reducing the regular retail price.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0947.

Appendix A. Priors and Sampling

The priors used for the model of §4 are, simply put, standard and noninformative. We provide full details of our prior specification and sampling strategy below.

Our priors for the intercept terms $\alpha^{\text{Intercept}}_{s_i^c, k}$ and $\beta^{\text{Intercept}}_{s_i^c, s_i^p}$ are

$$\alpha^{\text{Intercept}}_{s_i^c, k} \sim \mathrm{N}(0, 100^2), \quad \beta^{\text{Intercept}}_{s_i^c, s_i^p} \sim \mathrm{N}(0, 100^2)$$

where $s_i^c, s_i^p, k \in \{-1, 1\}$. As mentioned in §4, the prior for our heterogeneous department-specific and time-specific terms $\gamma_d^{\text{Department}}$ and γ_t^{Time} are

$$\gamma_d^{\text{Department}} \sim \mathrm{MN}(0, \Sigma^{\text{Department}}),$$

$$\gamma_t^{\text{Time}} \sim \mathrm{MN}(0, \Sigma^{\text{Time}}).$$

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

$$\Sigma^{\text{Department}} \sim \mathrm{IW}(10 \cdot I_8, 8),$$

$$\Sigma^{\text{Time}} \sim \mathrm{IW}(10 \cdot I_8, 8)$$

where IW is the Inverse Wishart distribution and where I_8 is the eight-dimensional identity matrix. Under this 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 $\gamma_d^{\text{Department}}$ and γ_t^{Time}.

For each $\alpha^x_{s_i^c, k}$ and $\beta^x_{s_i^c, s_i^p}$, where $s_i^c, s_i^p, k \in \{-1, 1\}$ and $x \in \{\text{Price}, \text{Covariate}\}$, we use the same prior as the intercept, i.e.,

$$\alpha^x_{s_i^c, k, p} \sim \mathrm{N}(0, 100^2), \quad \beta^x_{s_i^c, s_i^p, p} \sim \mathrm{N}(0, 100^2)$$

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

$$\sigma_{s_i^c, s_i^p} \sim \mathrm{U}(0, 100)$$

for $s_i^c, s_i^p \in \{-1, 1\}$.

We sample from the full posterior distribution using Markov Chain Monte Carlo (MCMC) (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

	$\boldsymbol{\alpha}_{-1,-1}$		$\boldsymbol{\alpha}_{1,1}$		$\boldsymbol{\beta}_{-1,-1}$		$\boldsymbol{\beta}_{1,1}$	
Coefficient	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
99-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

Notes. Posterior Means and Standard Deviations of Coefficients. Most coefficients pertaining to wholesale and regular retail prices attain statistical significance, thus suggesting the importance of the flexible response surface. Most coefficients pertaining to our 10 covariates, by 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.

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