

Demand-Based Pricing Versus Past-Price Dependence: A Cost–Benefit Analysis

The authors develop a conceptual framework of the factors that motivate a retailer's decision to rely on demand conditions and past prices in setting current and future prices. Specifically, they examine the circumstances under which retailers choose demand-based pricing versus past-price dependence for different brands and categories. Given scarce resources and costs of price adjustments, demand-based pricing is more likely when the customer-driven and firm-driven costs of adjusting pricing patterns are low or when the benefits of such adjustments are high. First, the customer-driven benefits of demand-based pricing are expected to be greater in categories with higher penetration and for brands with higher market share and higher demand sensitivity to price. Second, the firm-driven benefits are greater for categories with higher private-label share. Finally, the customer-driven costs are greater for expensive categories, whereas the firm-driven costs are greater for categories with many stockkeeping units. The empirical findings support the conceptual framework, implying that customer-driven and firm-driven benefits are the main stimulants in the retailer's choice of demand-based pricing. In contrast, customer-driven and firm-driven costs significantly hinder retailer implementation of demand-based pricing. These insights enable retailers to identify problem areas and opportunities to improve the allocation of scarce pricing resources. The results also contribute to the ongoing debate in economics and marketing on the rationality of observed past-price dependence. Whereas previous research points to the negative impact on gross margins of this practice, the authors find that retailers weigh the costs and benefits of demand-based pricing rather than adhere to past-pricing patterns.

Keywords: demand-based pricing, past-price dependence, retail-price drivers, time-series models, generalized forecast error variance decomposition

Retailers face the complicated task of setting and changing prices for the many items they carry. A typical grocery store in the United States now carries more than 31,000 items in hundreds of product categories (Kahn and McAlister 1997). Apart from the sheer number of price change possibilities, the considerations that enter retailers' pricing decisions have become very complex. Sophisticated demand forecasts based on scanner data, the push toward category management, and marketing intelligence on competing retailers' prices are all important and

have been incorporated in recent analytical research (e.g., Basuroy, Mantrala, and Walters 2001; Kim and Staelin 1999; Wedel, Zhang, and Feinberg 2004). However, empirical studies have found that retailers often choose not to adapt prices on the basis of demand conditions (Dutta, Bergen, and Levy 2002), leading to past-price dependence and lower category margins (Nijs, Srinivasan, and Pauwels 2007).

Although past-price dependence, or price rigidity, is underexplored in the marketing literature, it is a fundamental issue in pricing (Bergen et al. 2003).¹ Classical economic theory assumes that prices adjust flexibly in response to changes in demand and costs, and most research in marketing adopts this assumption, either directly or implicitly.² The alternative of complete price rigidity is at odds with the large variation in prices that, for example, Bils and Klenow (2004) and Gordon (1981) observe. Other schools of thought in economics, such as new Keynesian macroeco-

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¹We thank an anonymous reviewer for constructive suggestions on the discussion of price rigidity.

²We view the term "pricing rigidity" as an indication that prices are not flexibly adjusted to changes in demand or costs. However, this does not imply that prices never change; rather, pricing patterns follow their usual shape, even in the presence of demand/cost changes. We expand on this definition in the "Methodology" section.

conomic theory (e.g., Blinder 1991; Levy 2007), and work in industrial organization (e.g., Carlton 1986) entertain the possibility that prices are rigid to some degree. The debate of rigid versus flexible prices, which lies at the heart of the theories of firms, markets, industries, and economies (Golosov and Lucas 2007; Zbaracki et al. 2004), has been the subject of empirical and theoretical studies (for an extensive overview, see Wolman 2007). In marketing, however, only a handful of researchers have addressed the issue of price rigidity.

On the one hand, prices may exhibit rigidity because retailers suboptimally anchor their pricing decisions on the past (Krishna, Mela, and Urbany 2001) or simply lack detailed information about market demand (*BusinessWeek* 2000) and appropriate tools for making pricing decisions (AMR Research 2000). On the other hand, retailers may have good reasons to maintain consistent pricing patterns. These may include the high managerial and physical costs of considering and executing alternative pricing patterns (Levy et al. 1997; Slade 1998; Zbaracki et al. 2004), as well as legal, goodwill, and customer reference price issues linked to unexpected price fluctuations (Bergen et al. 2003).

Previous research has mainly focused on the general occurrence of past-price dependence, not on the circumstances that lead a given retailer to behave this way for some categories and brands but not for others, as Nijs, Srinivasan, and Pauwels (2007) report. Nijs, Srinivasan, and Pauwels quantify the relative importance of different drivers of retail prices in a large-scale empirical study. They show that retail prices are driven by, in order of importance, past prices, wholesale prices, brand demand, category management, and store traffic/interretailer price competition. They further demonstrate that the influence of these drivers on retailer pricing tactics varies greatly by category and brand and is linked to retailer category margins. Specifically, of the different drivers, demand-based pricing is most strongly associated with higher retailer margins. In contrast, the most influential price driver, past-price dependence, is linked to lower retailer margins.³ To illustrate the importance of these effects, consider that the average retail margin in the Dominick's Finer Foods database is approximately \$525 per category per store per week. From Nijs, Srinivasan, and Pauwels's (2007) analysis, we calculate that a 10% increase in the influence of past-price dependence on retail price setting will reduce weekly category margins by \$23. However, this increased emphasis on past-price dependence also implies a reduction in the relative influence of another retail-price driver. If the increase in past-price dependence comes at the expense of demand-based pricing, there would be an additional negative margin impact of \$177. The net impact of these two forces would result in a drop in margins of \$200 (38%).

³We define "past-price dependence" as the extent to which variability in retail prices over time can be attributed to past fluctuations in a brand's own price. Past-price dependence can result in everyday same prices or high-low pricing, but without regard for the state of demand or costs. We define the extent of "demand-based pricing" as the variability in retail prices that is attributable to fluctuations in a brand's past sales volume. We provide details in the "Methodology" section and in Technical Appendix A.

Given the theoretical and monetary importance of this phenomenon, "it is unfortunate that so little attention has been given to characterizing the circumstances that give rise to high versus low nominal levels of price inertia" (Andrew Caplin, qtd. in Levy et al. 1998, p. 81). We contribute to this field of inquiry by integrating relevant theories and empirically testing some of their implications. Our key research question is, Under which conditions do retailers rely more heavily on demand-based pricing than past-price dependence in setting prices? Thus, we aim to increase the understanding of demand-based pricing and past-price dependence with an empirical investigation into the variation in both practices across brand and categories.

To this end, we develop a conceptual framework of the cost versus benefit trade-offs between demand-based pricing and past-price dependence in the next section. We then introduce the methodology and report the results of our analysis. We conclude with managerial implications, contributions, and areas for further research.

Conceptual Framework

Previous marketing research has examined sources of price variation from both the manufacturer and the retailer perspective. For manufacturers, Raju, Srinivasan, and Lal (1990) show that brands with lower loyalty have more to gain from promotions, and Kinberg, Rao, and Shakun (1974), Lal (1990), and Rao (1991) argue that promotions by premium brands can keep an intruder, such as a private label, from encroaching on their customers. Retailers may vary prices because of decreasing unit variable costs (Blattberg and Neslin 1990) or a desire to transfer holding costs to consumers (Blattberg, Eppen, and Lieberman 1981). In addition, Varian (1980) shows that retailers may implement sales to price discriminate between informed and uninformed consumers, and Kopalle, Rao, and Assunção (1996) generalize Greenleaf's (1995) result that reference price formation may induce the retailer to vary prices over time. Indeed, when enough consumers weigh price gains more than price losses, the optimal pricing policy is high-low (Kopalle, Rao, and Assunção 1996). Implementing such a pricing policy would require retailers to develop and maintain a thorough understanding of consumers across a multitude of categories. Fader and Lodish (1990, p. 55) argue that retailers are unlikely to go to such lengths, attributing a lack of promotional activity to the observation that many categories "are 'unglamorous' and thus receive no special attention from retailers." They identify determinants of category promotional activity using data from Information Resources Inc.'s (1997) *Marketing Factbook*, but they do not address the extent to which retail pricing in a category is driven by demand-based pricing versus past-price dependence.⁴

⁴Pricing for a category with high promotional activity can be driven by either demand-based pricing or past-price dependence. If the occurrence of promotions follows from changes in consumer demand, demand-based pricing will be more prominent. Conversely, if the pattern of promotions can be predicted from past pricing patterns rather than changes in demand, high past-price dependence will be observed.

Our framework goes beyond the arguments, theories, and variables used in previous research and attempts to explain when and why retailers choose to engage in demand-based pricing versus past-price dependence. Our basic premise is that retailers make a cost–benefit trade-off when deciding whether to rely on demand-based pricing. Although they may not all be directly observable to the researcher, we argue that inferences can be drawn about the nature of these costs and benefits from observable variables.

We distinguish two types of costs and benefits of demand-based pricing: firm driven and customer driven. We consider the material, managerial, and labor costs as well as the margin benefits of pushing the retailer’s private label to be firm driven. Customer-driven costs and benefits, which refer to customers’ reactions to changes in pricing patterns, can include purchase behavior, reference price formation, and the customer’s perception of the retailer. Our conceptual framework integrates each of these forces to provide a

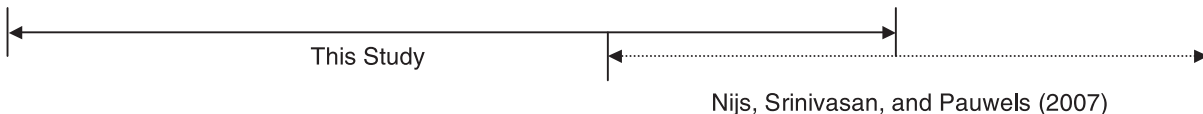
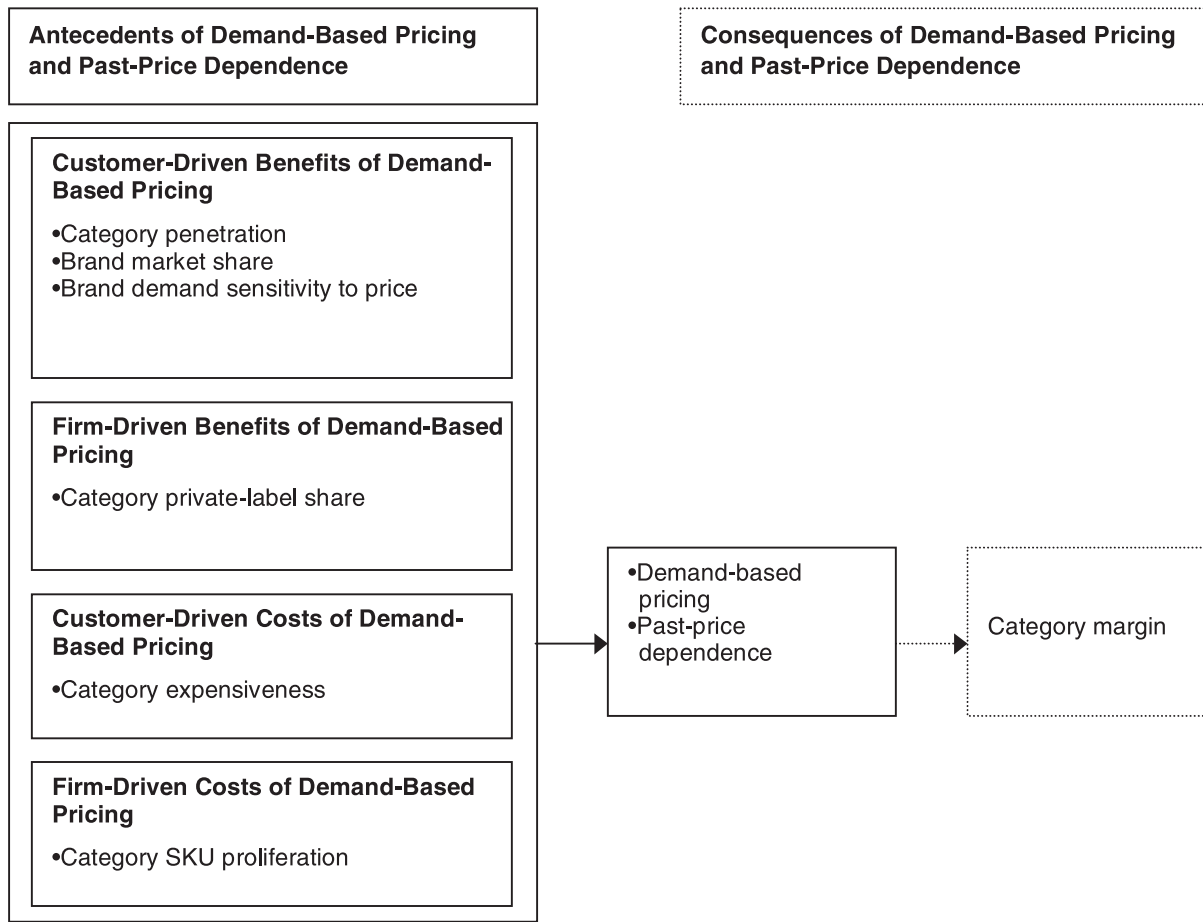
consistent description of how retailers trade off the costs and benefits of demand-based pricing (see Figure 1).⁵

Customer-Driven Benefits of Demand-Based Pricing

Effective pricing requires a retailer to allocate scarce pricing resources for the largest returns. We expect the retailer to do so in accordance with the perceived importance of the category and brand to the retailer’s performance objectives. In particular, we propose that the benefits of demand-based price adjustments are larger in categories with higher penetration and for brands with high market share and demand

⁵Figure 1 also highlights the contribution of the current study over that of Nijs, Srinivasan, and Pauwels (2007). Whereas Nijs, Srinivasan, and Pauwels focus on the consequences of demand-based pricing and past-price dependence, we focus on their antecedents.

FIGURE 1
Conceptual Framework



sensitivity to price. The more pronounced the benefits of demand-based pricing, the more this price driver should override the retailer's use of past-price dependence.

Category penetration. A key issue in pricing is that a retailer must decide on the role of each category in the overall store portfolio (Dhar, Hoch, and Kumar 2001). As McAlister (2008) argues, retailers have scarce resources to engage in demand-based pricing across hundreds of categories and thousands of products. The larger the proportion of households that purchase in the category (i.e., category penetration), the larger is the expected customer purchase reaction, and thus the larger are the revenue benefits of demand-based pricing (Fader and Lodish 1990). Indeed, prior research has suggested that category penetration is the most informative measure of category promotional activity (ibid). Thus, on the basis of the customer benefits of demand-based price adjustments, we expect the following:

H₁: In setting prices of brands in categories with higher penetration rates, retailers place (a) greater emphasis on demand-based price adjustments and (b) less emphasis on past-price dependence.

Brand market share. Both analytical models (e.g., Lal, Little, and Villas-Boas 1996) and empirical evidence (Chevalier and Curhan 1976; Pauwels 2007; Walters 1989) suggest that retailers are more willing to deviate from established pricing patterns for high-share brands than for smaller brands. Leading brands enjoy greater consumer awareness and familiarity (Keller 1993), thus creating a larger customer base that may be affected by the retailer's changes to pricing patterns. Indeed, promotions on leading brands have the power to expand the category (Bronnenberg and Mahajan 2001) and even increase store traffic (Moorthy 2005).

H₂: In setting prices of brands in categories with higher brand market share, retailers place (a) greater emphasis on demand-based pricing and (b) less emphasis on past prices.

Brand demand sensitivity to price. The benefits to demand-based pricing should be higher in categories in which demand is sensitive to changes in price. The retailer is then likely to alter pricing patterns according to perceived differences in consumer preferences and willingness to pay across brands and categories (Levy et al. 1998) and to change prices following shocks to demand.

H₃: In setting retail prices of brands with higher demand sensitivity, retailers place (a) greater emphasis on demand-based pricing and (b) less emphasis on past prices.

Firm-Driven Benefits of Demand-Based Pricing

Category private-label share. An important part of a retailer's business is the private-label program. Some retailers (e.g., Wegman's) successfully use store brands as a source of differentiation and a revenue driver (Dhar, Hoch, and Kumar 2001). For others, the private label offers increased category profits as a result of higher percentage margins and increased bargaining power compared with national brand manufacturers (e.g., Pauwels and Srinivasan 2004). Because the retailer reaps the full rewards from

private-label performance, categories with a higher retailer private-label share tend to get more pricing attention. Therefore, we expect more extensive use of demand-based pricing when firm-driven benefits are higher and less dependent on past prices.

H₄: In setting prices of brands in categories with higher private-label share, retailers place (a) greater emphasis on demand-based pricing and (b) less emphasis on past prices.

Customer-Driven Costs of Demand-Based Pricing

Previous research has argued that the customer-driven costs of pricing adjustments are larger than the firm-driven costs and, thus, more important (Zbaracki et al. 2004). In Rotemberg's (2002) model, a threat of consumers' angry reactions over unfair price increases can lead to price rigidity. In line with this finding, Blinder and colleagues (1998) conclude that firms are less willing to engage in unanticipated changes to price because doing so would antagonize their customers. The more pronounced the customer costs of demand-based pricing, the less we expect retailers to opt for this price driver.

Category expensiveness. Customers are more likely to care about pricing adjustments in expensive categories because such categories consume a larger part of their budgets (Mazumdar and Papatla 2000). Even when justified on the basis of overall demand considerations, some customers may consider these pricing adjustments "unfair," either because they will need to pay more or because they recently paid more for a product that is now cheaper. Retailers may also hesitate to cut prices because "customers will misinterpret the price cuts as reductions in quality" (Blinder et al. 1998, p. 173). Therefore, retailers may adhere to well-established pricing patterns with a consistent pattern of discounts for expensive categories (Fader and Lodish 1990). Thus, the observed past-price dependence may be the result of careful consideration of the long-term pros and cons of consistency in pricing patterns.

H₅: In setting prices of brands in expensive categories, retailers place (a) less emphasis on demand-based pricing and (b) greater emphasis on past prices.

Firm-Driven Costs of Demand-Based Pricing

The firm-driven costs of demand-based pricing have only recently been the subject of academic inquiry. Most important are the management time and attention required to gather the relevant information and to make and implement pricing decisions (Zbaracki et al. 2004). The more pronounced the firm-driven costs of demand-based pricing, the less we expect retailers to rely on this price driver.

Category stockkeeping unit proliferation. A large number of stockkeeping units (SKUs) in a category makes it costly for retailers to evaluate alternative pricing schemes at a weekly level (McAlister 2008). For example, in a Dominick's store in the Chicago area, the oatmeal category has 96 SKUs, whereas shampoo has more than 2500 SKUs. Given the required effort and the pricing complexity in the latter category, we expect the retailer to engage less in demand-based pricing.

H₆: In setting prices of brands in categories with a high degree of SKU proliferation, retailers place (a) less emphasis on demand-based pricing and (b) greater emphasis on past prices.

Table 1 presents an overview of our hypotheses.

Methodology

We obtained estimates of demand-based pricing and past-price dependence, based on generalized forecast error variance decomposition (GFEVD), from Nijs, Srinivasan, and Pauwels (2007). These authors use weekly store-level scanner data from the Dominick's retail chain for 24 product categories in 85 stores. The results are available for the top three brands in each category in each store. In essence, GFEVD quantifies the relative influence on a brand's retail price variation over time of shocks that can be attributed to contemporaneous and past changes in each of the endogenous variables in the vector autoregressive model with exogenous variables (VARX), including brand demand, brand price, brand cost (wholesale price), demand and wholesale prices for competing brands (category management), and store traffic. Although store-level retail scanner data have been used in marketing to study pricing, they have been "rarely used by economists" (Levy, Dutta, and Begeen 2002, p. 202) to study price rigidity (cf. Müller et al. 2006). For estimation details, see Technical Appendix A.

As we described previously, our focus is on two output metrics generated by GFEVD: DBP_{ijk} measures the extent to which current and past changes in demand for brand *i* in category *k* in store *j* drive prices for that same brand (i.e., demand-based pricing), and PPD_{ijk} measures the extent to which past prices for brand *i* in category *k* in store *j* drive prices for that same brand (i.e., past-price dependence). Demand-based pricing and past-price dependence account for 11.4% and 49.6% of the dynamic variation in retail prices, respectively. We report summary statistics per category in Table 2 (for an extensive discussion of other price drivers, see Nijs, Srinivasan, and Pauwels 2007).

We test our hypotheses by linking the estimates of demand-based pricing and past-price dependence to the customer- and firm-driven costs and benefits identified in our conceptual framework. Measurement details on these variables appear in Table 3.

We estimate the following equations:

$$(1) \quad DBP_{ijk} = \gamma_0 + \gamma_1 CPEN_k + \gamma_2 BMS_{ijk} + \gamma_3 BDSP_{ijk} + \gamma_4 CPLS_{jk} + \gamma_5 CE_{jk} + \gamma_6 CSKUP_{jk} + \mu_{ijk}, \text{ and}$$

$$(2) \quad PPD_{ijk} = \beta_0 + \beta_1 CPEN_k + \beta_2 BMS_{ijk} + \beta_3 BDSP_{ijk} + \beta_4 CPLS_{jk} + \beta_5 CE_{jk} + \beta_6 CSKUP_{jk} + \varepsilon_{ijk},$$

where DBP_{ijk} and PPD_{ijk} are as defined previously, μ_{ijk} is the error term for Equation 1, and ε_{ijk} is the error term for Equation 2. The covariates are CPEN (category penetration), BMS (brand market share), BDSP (brand demand sensitivity to price), CPLS (category private-label share), CE (category expensiveness), and CSKUP (category SKU proliferation).⁶ We allow for store fixed effects in both equations.

Estimation of Equations 1 and 2 by ordinary least squares (OLS) provides consistent parameter estimates (see Murphy and Topel 1985). However, parameter standard errors may be biased because demand-based pricing and past-price dependence are estimated quantities. We use a

⁶We acknowledge that several other category and brand characteristics have been examined as moderators of retail price effects on performance (e.g., Srinivasan et al. 2004). These include product storability, category purchase frequency, category growth rate, and manufacturer promotional depth and frequency. Although we do not have a formal expectation of the direction of their effects, we can include them (separately or all together) in Equations 1 and 2 to control for their potential influence. Doing so does not affect our substantive findings, so we focus on the stated equations for clarity and conciseness.

TABLE 1
Overview of Hypotheses

Benefit and Cost Factors	Hypotheses	Category and Brand Characteristics	Effect on Demand-Based Pricing	Effect on Past-Price Dependence
Customer-driven benefits of demand-based pricing	H ₁	Category penetration	+	–
	H ₂	Brand market share	+	–
	H ₃	Brand demand sensitivity to price	+	–
Firm-driven benefits of demand-based pricing	H ₄	Category private-label share	+	–
Customer-driven costs of demand-based pricing	H ₅	Category expensiveness	–	+
Firm-driven costs of demand-based pricing	H ₆	Category SKU proliferation	–	+

TABLE 2
Extent of Demand-Based Pricing and Past-Price Dependence Across Categories

Categories	Demand-Based Pricing (%)			Past-Price Dependence (%)		
	25th	Mdn	75th	25th	Mdn	75th
Analgesics	7.6	10.7	12.8	47.1	48.7	50.7
Beer	11.3	13.8	17.4	48.2	52.2	57.9
Bottled juice	7.7	16.2	19.9	45.7	51.4	57.5
Canned soup	10.0	16.9	20.8	43.3	49.5	53.2
Cereal	16.6	19.9	22.5	44.3	48.0	53.3
Cheese	11.0	17.0	20.3	40.6	45.2	49.9
Cookies	7.2	21.5	24.8	40.8	42.7	47.4
Crackers	8.1	13.5	16.9	40.3	45.8	55.0
Dish detergent	2.2	5.6	10.4	54.7	59.7	64.3
Fabric softeners	5.2	7.7	11.1	51.7	54.5	57.6
Front-end candies	2.4	5.6	9.7	43.1	51.7	56.9
Frozen juice	10.4	13.9	17.9	50.6	55.2	58.8
Laundry detergent	6.6	8.8	13.1	44.9	48.5	51.4
Oatmeal	6.5	9.6	18.7	40.9	45.8	48.8
Paper towels	11.4	15.7	19.6	38.4	41.6	52.3
Refrigerated juice	15.2	18.5	21.0	43.9	49.2	54.5
Shampoos	1.7	3.7	5.8	46.1	52.5	60.1
Snack crackers	9.2	11.8	14.7	46.5	51.5	59.3
Soap	2.3	4.2	9.8	44.2	48.9	52.0
Soft drinks	2.7	5.4	24.3	45.6	47.2	49.0
Toilet tissue	12.3	19.0	22.2	39.4	43.8	53.1
Toothbrush	2.7	4.3	6.7	54.2	56.7	59.7
Toothpaste	2.5	9.1	13.6	49.9	52.7	59.0
Tuna	9.4	12.4	15.5	40.7	43.7	46.4
Total	6.1	11.4	17.3	44.4	49.6	55.7

Notes: The remainder of retail price variation is accounted for by store traffic, wholesale price, and category management considerations, as detailed by Nijs, Srinivasan, and Pauwels (2007).

bootstrap algorithm to obtain unbiased standard errors (for details, see Technical Appendix B).

Results⁷

Customer-Driven Benefits of Demand-Based Pricing

Category penetration. As the standardized coefficients in Table 4 show, in categories with a higher rate of penetration, the extent of demand-based pricing is more pronounced, whereas the extent of past-price dependence is lower, consistent with H_{1a} ($\gamma_1 = .377, p < .01$) and H_{1b} ($\beta_1 = -.241, p < .01$). Among all considered variables, category penetration is the strongest detractor of past-price dependence and the strongest enhancer of demand-based pricing.

Brand market share. In setting retail prices of high-share brands, retailers place greater emphasis on demand-based pricing and less emphasis on past prices, consistent with H_{2a} ($\gamma_2 = .241, p < .01$) and H_{2b} ($\beta_2 = -.181, p < .01$).

Brand demand sensitivity to price. Brands with high demand sensitivity elicit more demand-based pricing and less past-price dependence, consistent with H_{3a} ($\gamma_3 = .181, p < .01$) and H_{3b} ($\beta_3 = -.125, p < .01$).

⁷We generate the results using Ox Version 4.00 (see Doornik 2002).

Firm-Driven Benefits of Demand-Based Pricing

Category private-label share. In support of H_{4a} ($\gamma_4 = .136, p < .01$) and H_{4b} ($\beta_4 = -.135, p < .01$), retailers place greater emphasis on demand-based pricing and less emphasis on past prices in categories in which the retailer's private label commands a larger share.

Customer-Driven Costs of Demand-Based Pricing

Category expensiveness. In setting the prices of brands in expensive categories, retailers place less emphasis on demand-based pricing and greater emphasis on past prices, in support of H_{5a} ($\gamma_5 = -.050, p < .05$). Although the effect on past-price dependence is also in the expected direction, it does not reach traditional significance levels ($\beta_5 = .044, p = .11$).

Firm-Driven Costs of Demand-Based Pricing

Category SKU proliferation. In categories with a large number of SKUs, retailers are less likely to use demand-based pricing, consistent with H_{6a} ($\gamma_6 = -.060, p < .01$). Of the variables considered, category SKU proliferation most strongly hinders demand-based pricing. In contrast to H_{6b} , we find that retailers also rely less on past prices in categories with many SKUs. This might suggest that they use other tactics to simplify pricing in these categories, such as cost-plus and/or category management-based pricing considerations. Overall, our empirical findings support the hypotheses (see Table 5).

TABLE 3
Variable Operationalization

Benefit and Cost Factors	Operationalization
Customer-Driven Benefits of Demand-Based Pricing	
Category penetration	Category penetration is operationalized as the percentage of households that buy this category, obtained from the <i>Marketing Fact Book</i> (Information Resources Inc. 1997)
Brand market share	The brand's market share is operationalized as the average volume-based share of the brand as in Srinivasan and colleagues (2004).
Brand demand sensitivity to price	A brand's demand sensitivity to price is defined as the percentage change in brand sales as a result of a price promotion of 1%.
Firm-Driven Benefits of Demand-Based Pricing	
Category private-label share	This variable is operationalized as the percentage share of the retailer private-label brands in the category.
Customer-Driven Costs of Demand-Based Pricing	
Category expensiveness	Following Raju (1992), we first compute the regular price (highest price over the data period) of each brand. The category-level expensiveness is calculated by the market share weighted average of the regular prices of the brands in the category.
Firm-Driven Costs of Demand-Based Pricing	
Category SKU proliferation	The number of SKUs in the category (Narasimhan, Neslin, and Sen 1996) captures the extent of SKU proliferation.

Managerial Implications and Conclusions

Because considering and executing demand-based price changes are costly, the benefits of doing so should outweigh the costs. In this article, we developed and tested a conceptual framework that outlines the cost–benefit trade-off motivating retailers' choice of demand-based pricing versus past-price dependence.

First, the customer-driven benefits of demand-based pricing are higher for categories with higher penetration, as well as for brands with high market share and high demand sensitivity to price. Because categories with high penetration (e.g., cereals, soft drinks) offer more customer-driven benefits than those with low penetration (e.g., fabric softeners, toothbrushes), they enjoy greater retailer focus on demand-based pricing and less emphasis on past prices. Second, we find that the firm-driven benefits of demand-based pricing are more pronounced for categories with higher private-label share, leading to less emphasis on past-price dependence. Finally, the customer-driven costs of

demand-based pricing are higher for expensive categories, whereas the firm-driven costs are higher for categories with many SKUs. The relative importance of these effects is as follows:

- Category penetration is the strongest positive determinant of demand-based pricing, followed by brand market share. Conversely, category SKU proliferation most severely complicates the implementation of demand-based pricing.
- Category penetration, private-label share, and SKU proliferation all substantially lower the prominence of past-price dependence. The same applies for the brand-level measures: market share and demand sensitivity to price.

Implications for Manufacturers

Our findings may help manufacturers develop a deeper appreciation of retailers' benefits versus costs of demand-based pricing and past-price dependence. Specifically, the estimates suggest scenarios in which pass-through of trade deals is difficult to achieve because of the retailer's reliance on past prices. For example, smaller brands face such pass-through jeopardy because past-price dependence is much stronger for these brands, consistent with Pauwels (2007). Moreover, retailers are less likely to apply demand-based pricing in expensive categories, which represents a hurdle for manufacturers trying to convince retailers to change their established pricing patterns.

Our findings also identify areas in which manufacturers can provide pricing support to the retailer. For categories and brands in which the cost–benefit trade-off does not favor demand-based pricing, manufacturers can work to limit the costs or enhance the benefits. For example, category captains could support retailer pricing policies for categories with many SKUs in a way that leads to a win–win situation for both parties.

Implications for Retailers

Recent research has shown that demand-based pricing is associated with higher retailer gross margins, whereas past-price dependence is associated with lower retailer gross margins (Nijs, Srinivasan, and Pauwels 2007). In the current article, we investigate the conditions under which retailers choose to rely more on the heavy machinery of demand-based pricing than simply sticking with past-pricing patterns by developing and testing a conceptual framework of the customer- and firm-driven benefits and costs of demand-based pricing.

Our framework and findings offer retailers a way to review the allocation of pricing resources systematically across categories according to expected costs and benefits. For example, we show that in categories with high penetration, there are significant benefits to demand-based pricing. A retailer could evaluate whether categories with higher penetration in its stores are getting more attention in terms of demand-based pricing. If some are not, the retailer might want to evaluate whether there are specific costs to demand-based pricing that apply to that category, such as those linked to high SKU proliferation. Moreover, the retailer could choose to build pricing capabilities and/or lower the firm-driven costs of demand-based pricing (e.g., use a better decision support system to support pricing in categories

TABLE 4
Customer- and Firm-Driven Benefits and Costs of Demand-Based Pricing

Benefit and Cost Factors	Demand-Based Pricing (R ² = .30)		Past-Price Dependence (R ² = .16)	
	Standardized Coefficients	SE	Standardized Coefficients	SE
Customer-Driven Benefits of Demand-Based Pricing				
Category penetration	.377**	.019	-.241**	.024
Brand market share	.241**	.025	-.181**	.027
Brand demand sensitivity to price	.181**	.024	-.125**	.025
Firm-Driven Benefits of Demand-Based Pricing				
Category private-label share	.136**	.017	-.135**	.022
Customer-Driven Costs of Demand-Based Pricing				
Category expensiveness	-.050*	.021	.044	.027
Firm-Driven Costs of Demand-Based Pricing				
Category SKU proliferation	-.060**	.023	-.105**	.024

*Significant at the 5% level.

**Significant at the 1% level.

Notes: n = 5190. Parameters are standardized. Store-specific intercepts are not shown for space considerations.

TABLE 5
Overview of Empirical Support for Conceptual Framework

Hypotheses	Demand-Based Pricing	Past-Price Dependence
Customer-Driven Benefits of Demand-Based Pricing		
H ₁ : Category penetration	✓	✓
H ₂ : Brand market share	✓	✓
H ₃ : Brand demand sensitivity to price	✓	✓
Firm-Driven Benefits of Demand-Based Pricing		
H ₄ : Category private-label share	✓	✓
Customer-Driven Costs of Demand-Based Pricing		
H ₅ : Category expensiveness	✓	
Firm-Driven Costs of Demand-Based Pricing		
H ₆ : Category SKU proliferation	✓	

with many SKUs). The retailer could also attempt to control and/or limit costs of demand-based pricing from the customer's perspective. For example, price guarantees could reduce consumer irritation due to changes in established pricing patterns for expensive items.

In Table 6, using estimates from Nijs, Srinivasan, and Pauwels (2007), we show the gross margin impact of changing the level of demand-based pricing (past-price dependence) to the highest (lowest) average level observed in our data. For example, for the analgesics category, the level of demand-based pricing is 10.70%, whereas the score for past-price dependence is 48.70%. If the retailer were to

boost demand-based pricing in this category to 21.50%, the average margin for the category would go up by \$191.01. If the level of past-price dependence could be reduced to 41.60%, margins would increase by \$16.14. The combined gross margin impact of both changes comes to \$207.14. Using in-house cost information, retailers can reevaluate the cost effectiveness of their pricing approaches for different categories and brands. As the example for the analgesics category shows, the retailer has the potential to increase gross category margins by up to 67.33% if the firm and/or customer cost of the altered pricing tactics can be kept low.

If we assume that the mix of price drivers underlying the retailer's pricing patterns is already optimal given its current pricing tools and management practices, the numbers in Table 6 can also be interpreted as cost measures of demand-based pricing (e.g., Slade 1998). Quantifying how substantial these costs are and how they vary across categories informs retailers about consumer and organizational issues that are central to their ability to evaluate the costs and benefits of demand-based pricing versus past-price dependence. As such, our findings give retailers the ability to deal better with these costs and their implications for a variety of decisions, ranging from setting and adjusting prices to interpreting competitive pricing actions to developing improved pricing processes and capabilities.

Contributions to Theory and Empirics

We believe that a central contribution of this article is to the literature on price rigidity and flexibility (Zbaracki et al. 2004). Nijs, Srinivasan, and Pauwels (2007) provide empirical evidence that, at least in retailing, prices are not perfectly flexible. The current research expands on this insight by enhancing the understanding of variation in the patterns of price adjustment. We identify a set of measurable conditions that can enhance or diminish the flexibility of prices to demand shocks. We believe that these insights can be of value in academic research on pricing in both the marketing and the economics literature, offering promising opportuni-

TABLE 6
Margin Impact of Changing the Level of Demand-Based Pricing (Past-Price Dependence) to the Highest (Lowest) Average Level Observed in the Data

Category	DBP (%)	PPD (%)	Impact DBP (\$)	Impact PPD (\$)	Total Impact (\$)	Average Margin (\$)	% Margin Increase
Analgesics	10.70	48.70	191.01	16.14	207.14	307.67	67.33
Beer	13.80	52.20	136.18	24.09	160.27	329.04	48.71
Bottled juice	16.20	51.40	93.74	22.27	116.01	764.70	15.17
Canned soup	16.90	49.50	81.36	17.96	99.31	562.73	17.65
Cereal	19.90	48.00	28.30	14.55	42.84	1,185.26	3.61
Cheese	17.00	45.20	79.59	8.18	87.77	2,092.68	4.19
Cookies	21.50	42.70	.00	2.50	2.50	902.87	.28
Crackers	13.50	45.80	141.49	9.55	151.03	275.30	54.86
Dish detergent	5.60	59.70	281.21	41.14	322.34	254.77	126.53
Fabric softeners	7.70	54.50	244.07	29.32	273.38	89.98	303.83
Front-end candies	5.60	51.70	281.21	22.96	304.16	158.74	191.61
Frozen juice	13.90	55.20	134.41	30.91	165.32	620.71	26.63
Laundry detergent	8.80	48.50	224.61	15.68	240.29	567.13	42.37
Oatmeal	9.60	45.80	210.46	9.55	220.01	193.55	113.67
Paper towels	15.70	41.60	102.58	.00	102.58	234.12	43.81
Refrigerated juice	18.50	49.20	53.06	17.27	70.33	1,059.77	6.64
Shampoos	3.70	52.50	314.81	24.77	339.58	324.52	104.64
Snack crackers	11.80	51.50	171.55	22.50	194.05	490.16	39.59
Soap	4.20	48.90	305.97	16.59	322.56	238.73	135.11
Soft drinks	5.40	47.20	284.74	12.73	297.47	961.45	30.94
Toilet tissue	19.00	43.80	44.21	5.00	49.21	334.76	14.70
Toothbrush	4.30	56.70	304.20	34.32	338.52	92.72	365.11
Toothpaste	9.10	52.70	219.31	25.23	244.53	176.93	138.21
Tuna	12.40	43.70	160.94	4.77	165.71	405.03	40.91

Notes: DBP = demand-based pricing. PPD = past-price dependence. The “Impact DBP” and “Impact PPD” columns show the change in “Average Margin” as a result of improving the DBP and PPD levels in a category to the highest average DBP and lowest average PPD levels reported by Nijs, Srinivasan and Pauwels (2007)—21.50% and 42.70%, respectively. “Average Margin” is the weekly gross margin for a category averaged across stores in the Dominick’s database. Caveats: The “Total Impact” and “% Margin Increase” measures should be interpreted with caution. The underlying assumption is that all model parameters used to generate the reported GFEVD estimates remain constant. The margin impact values can be used as approximate benchmarks of the costs of adjusting pricing to a higher DBP level and/or as the basis for a ranking of the relative potential for profit enhancement across categories.

ties for fundamental contributions to price theory and interdisciplinary research.

The results can be linked to several theories of price rigidity that Blinder and colleagues (1998) summarize and test. Two of these theories (cost-based pricing and constant marginal cost) suggest that rigidity in prices can be caused by cost processes. We can rule out these cost-based explanations as causes of past-price dependence as measured in this study. By including a measure of cost in the VARX model described in Technical Appendix A, we ensure that the stickiness observed in retail pricing patterns is not due to wholesale prices.

Our conceptual model can be linked to the theory of judging quality by price. Price stickiness can result from retailer hesitation to cut prices because “customers will misinterpret the price cuts as reductions in quality” (Blinder et al. 1998, p. 173). We argue that for expensive categories, retailers are likely to adhere to well-established pricing patterns with a consistent pattern of discounts. This theory provides a partial explanation for the strong past-price dependence we observe in these categories.

The strongest link exists with theories of costly price adjustment (Mankiw 1985). Zbaracki and colleagues (2004) enrich this theory by quantifying menu, managerial, and customer costs of price changes in an industrial market.

Although we study stickiness in pricing patterns rather than stickiness in prices, our study provides strong support for the theory that prices often do not adjust flexibly or completely to cost, competitive, or demand shocks. In contrast, our study offers little insight into several other theories of price rigidity (e.g., coordination failure, hierarchical delays, implicit and nominal contracts). Empirical work that studies these theories with appropriate data is an important area for further research.

We also provide insights into the ongoing debate in economics and marketing on the rationality of observed past-price dependence. Whereas Krishna, Mela, and Urbany (2001) and Nijs, Srinivasan, and Pauwels (2007) point to the negative profit impact of this practice, our findings indicate that retailers may well be rationally weighing the costs and benefits of demand-based pricing versus past-price dependence (Carlton 1986). Under the assumption that retailers are able to select the mix of price drivers optimally, we quantify the lower bounds of the costs of demand-based pricing in Table 6.

Our empirical findings are consistent with those of Bills and Klenow (2004), who find that prices vary more for products with more elastic demand and in less expensive categories. The latter result is an unexplained surprise, but it is explained in our cost-benefit framework.

A growing body of research has focused on explaining cross-category differences in price elasticities (e.g., Bell, Chiang, and Padmanabhan 1999; Bolton 1989; Narasimhan, Neslin, and Sen 1996) and promotional activity (Fader and Lodish 1990). Our study complements this line of empirical research by investigating the firm- and customer-driven costs and benefits that determine the retailer's relative use of demand-based pricing versus past-price dependence.

Areas for Further Research

Our research suggests several valuable directions for both theoretical and empirical research. First, given that extant theory focuses on the analysis of single-product settings with few exceptions (e.g., Lach and Tsiddon 1996), it might be fruitful to expand these theories to incorporate benefit and costs dimensions of price adjustments in a multiproduct setting (e.g., Midrigan 2006). Second, research using data from diverse organizational/retailer contexts could also test for the hierarchy theory that organizational inertia is a driver of price rigidity (Blinder et al. 1998). Third, such data sets on heterogeneous firms could also be helpful in testing for the price coordination theory that price leaders (versus price followers) drive patterns of price adjustments (ibid). Fourth, data on promotional calendars set at the start of the year and any adjustments made thereafter might provide insights into the importance of nominal contracts in past-price dependence (ibid). Fifth, whereas we focus on the firm-driven benefits and costs of demand-based pricing from the retailer perspective, it would be desirable to expand this theory to the supply side (i.e., wholesale price rigidity) and to incorporate the firm-driven benefits and costs from the manufacturer perspective. Sixth, whereas we are interested in past-price dependence, which occurs when retailers set prices on the basis of pricing history (whether that is everyday same pricing or alternating discounts), further research could perform a spectral analysis to decompose the nature and direction of autocorrelations in prices for different time frames and frequencies (e.g., Bronnenberg, Mela, and Boulding 2006; Lemmens, Croux, and Dekimpe 2007). Seventh, it would be fruitful to generalize the findings on the patterns of price adjustment to heterogeneous exogenous shocks (e.g., Levy, Dutta, and Bergen 2002) across products, retailers, and markets. Eighth, research in macroeconomics has built models that incorporate menu costs to explain aggregate patterns of price adjustment (e.g., Golosov and Lucas 2007). This research investigates the sensitivity of repricing rates to general inflation and transient monetary shocks. Golosov and Lucas (2007) assume that "under menu costs, any individual price will be constant most of the time and then occasionally jump to a new level" (p. 172), and subsequently, they remove the common sales promotion patterns from their data to obtain a good match between theory and empirics (p. 184). Moreover, they do not consider category- and brand-specific costs and benefits to price changes. Further research seems warranted to develop comprehensive models of price adjustment that account for these microeconomic characteristics. Finally, additional research could generalize our conceptual framework to different retail chains, industries, and countries and could further formalize the empiri-

cally demonstrated phenomena using analytical and structural models.

Technical Appendix A Calculating the Relative Influence of Retail-Price Drivers Using GFEVD

Nijs, Srinivasan, and Pauwels (2007) derive GFEVD estimates from VARX models. These models are well suited to measure the retail-pricing dynamics central to our study.

An 11-equation VARX model was estimated per category per store, with sales volume of the top three brands (S_i , $i = 1, 2, 3$), an other-brands composite (S_4), wholesale and retail prices of the top three brands (WP_i and RP_i , $i = 1, 2, 3$), and store traffic (ST, a proxy for interretailer competition) (Chintagunta 2002). In addition to the intercept (α), five sets of exogenous control variables are included in the model: (1) a deterministic trend t to capture the impact of omitted, gradually changing variables; (2) a set of dummy variables (HD) that equal one in the shopping periods around major holidays (Chevalier, Kashyap, and Rossi 2003); (3) four weekly dummy variables (SD) to account for seasonal fluctuations in sales or prices; (4) a step dummy variable for the impact of new product introductions (NP); and (5) feature (F) and display (D) variables for each brand (for a similar model setup, see Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002; Srinivasan, Popkowski, and Bass 2000).⁸ The VARX is specified in Table A1.

A stepwise procedure is used to determine the appropriate lag-length K , to eliminate redundant parameters, and to ensure that the model residuals are well behaved (for details, see Nijs, Srinivasan, and Pauwels 2007). The VARX parameters are then used to derive GFEVD estimates (Pesaran and Shin 1998). The GFEVD quantifies the dynamic influence of competitive retail prices, brand demand, wholesale price and competitive wholesale price, and category-management considerations on a brand's retail price. In essence, GFEVD provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VARX model, without the need for the researcher to specify a causal ordering among these variables (for a marketing application of FEVD, see Hanssens 1998). We derive the GFEVD estimates using the following equation:

$$(A1) \quad \theta_{ij}^g(n) = \frac{\sum_{l=0}^n [\psi_{ij}^g(l)]^2}{\sum_{l=0}^n \sum_{j=0}^m [\psi_{ij}^g(l)]^2}, \quad i, j = 1, \dots, m,$$

where $\psi_{ij}^g(l)$ is the value of a generalized impulse response function following a one-unit shock to variable i on variable j at time l . By calculating GFEVD in this way, we ensure that the driver estimates are comparable across brands and categories (for details on the calculation, see, e.g., Dekimpe and Hanssens 1999).

⁸To avoid overparameterization, we include feature and display as exogenous variables (Pesaran and Smith 1998).

TABLE A1
VARX Equation

$$\begin{bmatrix} S_{1t} \\ S_{2t} \\ S_{3t} \\ S_{4t} \\ RP_{1t} \\ RP_{2t} \\ RP_{3t} \\ WP_{1t} \\ WP_{2t} \\ WP_{3t} \\ ST_t \end{bmatrix} = \begin{bmatrix} \alpha_{S1} + \delta_{S1}t + \sum_{h=1}^H \theta_{S1}^h HD_t + \sum_{s=2}^S \lambda_{S1}^s SD_t + \eta_{S1} NP_t \\ \alpha_{S2} + \delta_{S2}t + \sum_{h=1}^H \theta_{S2}^h HD_t + \sum_{s=2}^S \lambda_{S2}^s SD_t + \eta_{S2} NP_t \\ \alpha_{S3} + \delta_{S3}t + \sum_{h=1}^H \theta_{S3}^h HD_t + \sum_{s=2}^S \lambda_{S3}^s SD_t + \eta_{S3} NP_t \\ \alpha_{S4} + \delta_{S4}t + \sum_{h=1}^H \theta_{S4}^h HD_t + \sum_{s=2}^S \lambda_{S4}^s SD_t + \eta_{S4} NP_t \\ \alpha_{RP1} + \delta_{RP1}t + \sum_{h=1}^H \theta_{RP1}^h HD_t + \sum_{s=2}^S \lambda_{RP1}^s SD_t + \eta_{RP1} NP_t \\ \alpha_{RP2} + \delta_{RP2}t + \sum_{h=1}^H \theta_{RP2}^h HD_t + \sum_{s=2}^S \lambda_{RP2}^s SD_t + \eta_{RP2} NP_t \\ \alpha_{RP3} + \delta_{RP3}t + \sum_{h=1}^H \theta_{RP3}^h HD_t + \sum_{s=2}^S \lambda_{RP3}^s SD_t + \eta_{RP3} NP_t \\ \alpha_{CP1} + \delta_{CP1}t + \sum_{h=1}^H \theta_{CP1}^h HD_t + \sum_{s=2}^S \lambda_{CP1}^s SD_t + \eta_{CP1} NP_t \\ \alpha_{CP2} + \delta_{CP2}t + \sum_{h=1}^H \theta_{CP2}^h HD_t + \sum_{s=2}^S \lambda_{CP2}^s SD_t + \eta_{CP2} NP_t \\ \alpha_{CP3} + \delta_{CP3}t + \sum_{h=1}^H \theta_{CP3}^h HD_t + \sum_{s=2}^S \lambda_{CP3}^s SD_t + \eta_{CP3} NP_t \\ \alpha_{ST} + \delta_{ST}t + \sum_{h=1}^H \theta_{ST}^h HD_t + \sum_{s=2}^S \lambda_{ST}^s SD_t + \eta_{ST} NP_t \end{bmatrix} = \begin{bmatrix} \beta_{1,1}^k \dots \beta_{1,10}^k \\ \beta_{2,1}^k \dots \beta_{2,10}^k \\ \beta_{3,1}^k \dots \beta_{3,10}^k \\ \beta_{4,1}^k \dots \beta_{4,10}^k \\ \beta_{5,1}^k \dots \beta_{5,10}^k \\ \beta_{6,1}^k \dots \beta_{6,10}^k \\ \beta_{7,1}^k \dots \beta_{7,10}^k \\ \beta_{8,1}^k \dots \beta_{8,10}^k \\ \beta_{9,1}^k \dots \beta_{9,10}^k \\ \beta_{10,1}^k \dots \beta_{10,10}^k \\ \beta_{10,1}^k \dots \beta_{10,10}^k \end{bmatrix} + \sum_{k=1}^K \begin{bmatrix} S_{1t-k} \\ S_{2t-k} \\ S_{3t-k} \\ S_{4t-k} \\ RP_{1t-k} \\ RP_{2t-k} \\ RP_{3t-k} \\ WP_{1t-k} \\ WP_{2t-k} \\ WP_{3t-k} \\ ST_{t-k} \end{bmatrix} + \sum_{l=0}^L \begin{bmatrix} \gamma_{1,1}^l \dots \gamma_{1,6}^l \\ \gamma_{2,1}^l \dots \gamma_{2,6}^l \\ \gamma_{3,1}^l \dots \gamma_{3,6}^l \\ \gamma_{4,1}^l \dots \gamma_{4,6}^l \\ \gamma_{5,1}^l \dots \gamma_{5,6}^l \\ \gamma_{6,1}^l \dots \gamma_{6,6}^l \\ \gamma_{7,1}^l \dots \gamma_{7,6}^l \\ \gamma_{8,1}^l \dots \gamma_{8,6}^l \\ \gamma_{9,1}^l \dots \gamma_{9,6}^l \\ \gamma_{10,1}^l \dots \gamma_{10,6}^l \\ \gamma_{11,1}^l \dots \gamma_{11,6}^l \end{bmatrix} + \begin{bmatrix} F_{1,t-l} \\ F_{2,t-l} \\ F_{3,t-l} \\ D_{1,t-l} \\ D_{2,t-l} \\ D_{3,t-l} \end{bmatrix} + \begin{bmatrix} \varepsilon_{S1,t} \\ \varepsilon_{S2,t} \\ \varepsilon_{S3,t} \\ \varepsilon_{S4,t} \\ \varepsilon_{RP1,t} \\ \varepsilon_{RP2,t} \\ \varepsilon_{RP3,t} \\ \varepsilon_{WP1,t} \\ \varepsilon_{WP2,t} \\ \varepsilon_{WP3,t} \\ \varepsilon_{ST,t} \end{bmatrix}$$

Notes: Σ is the covariance matrix of the residuals $[\varepsilon_{S1,t}, \varepsilon_{S2,t}, \varepsilon_{S3,t}, \varepsilon_{S4,t}, \varepsilon_{RP1,t}, \varepsilon_{RP2,t}, \varepsilon_{RP3,t}, \varepsilon_{WP1,t}, \varepsilon_{WP2,t}, \varepsilon_{WP3,t}, \varepsilon_{ST,t}]'$.

The relative importance of the drivers is established on the basis of the GFEVD values at 26 weeks, which reduces sensitivity to short-term fluctuations. To evaluate the accuracy of our GFEVD estimates, we obtain standard errors using Monte Carlo simulations (see Benkwitz, Lütkepohl, and Wolters 2001).

Technical Appendix B Bootstrap Algorithm to Correct the Standard Error Bias from OLS Estimation

To correct the parameter standard error bias we introduced when estimating Equations 1 and 2 with OLS, we use the following bootstrap algorithm:

Step 1: Select a sample of size n , with replacement, from the GFEVD estimates provided by Nijs, Srinivasan, and Pauwels (2007), where n is equal to the number of observations in the data set.

Step 2: Add measurement error based on Monte Carlo-simulated GFEVD estimates to each element of the sample. This step is repeated 250 times, each time creating a variation of the data set obtained in Step 1.

Step 3: Calculate parameter estimates θ^* for Equations 2 and A1 for each of the 250 augmented data sets created in Step 2.

We repeat Steps 1–3 250 times. The standard deviations across the 62,500 parameter vectors ($\theta^{*1}, \theta^{*2}, \dots, \theta^{*62,500}$) are the unbiased standard errors for θ^{OLS} (for details, see Bradley and Tibshirani 1993).

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