# Market Structure and Cost Pass-Through in Retail

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September 11, 2013

**Abstract**

We examine the extent to which vertical and horizontal market structure can together explain incomplete retail pass-through. To answer this question, we use scanner data from a large U.S. retailer to estimate product level pass-through for three different vertical structures: national brands, private label goods not manufactured by the retailer and private label goods manufactured by the retailer. Our findings emphasize that accounting for the interaction of vertical and horizontal structure is important for understanding how market structure affects pass-through, as a reduction in double-marginalization can raise pass-through directly but can also reduce it indirectly by increasing market share.

*We are greatly indebted to Yuriy Gorodnichenko, Pierre-Olivier Gourinchas, David Romer, Chang-Tai Hsieh and Sofia Villas-Boas for advice, guidance and patience. We also thank Raphael Schoenle, Michael Devereux, Roberto Rigobon, Duncan Simester, Dennis Carlton, Robert Hall, Peter Christoffersen, Gregor Smith, participants of the 2013 NBER Price Dynamics Summer meeting, 2013 Dallas Fed Conference on Globalization and Market Structure, participants of the Bank of Canada Fellowship Exchange Program, and seminar participants at the University of British Columbia, University of Washington, and Carleton University for many helpful comments.
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## 1. Introduction

The degree of pass-through from exchange rates and input cost shocks to prices is a fundamental issue in closed and open economy macroeconomics with implications for relative prices, inflation and real adjustments. A growing body of work in domestic and open economy macroeconomics uses firm and product micro data to shed light on the overall role of nominal rigidities (menu costs), local costs and markups as drivers of incomplete cost pass-through along the production chain (Nakamura (2008), Nakamura and Zerom (2010), Goldberg and Hellerstein (2011), Gopinath et al. (2011)) while a separate literature attempts to explain *variation* in pass-through across products and markets due to firm characteristics and market structure. Recent work on horizontal market structure derives incomplete pass-through as a function of markup adjustment, drawing a positive link between a firm's market share, the size of its markup, and the extent to which it adjusts the markup to dampen pass-through of a cost shock (Atkeson and Burstein (2008), Berman et al. (2011), Auer and Schoenle (2012)). Research on vertical market structure compares arm's-length versus intra-firm transactions within an industry and finds a substantial departure from Coasian bargaining – vertical structure seems to matter for pricing behavior (Bernard et al. (2006), Neiman (2010), Neiman (2011), Hellerstein and Villas-Boas (2010)). The typical finding is that intra-firm transaction prices exhibit greater flexibility and higher exchange-rate pass-through, consistent with models where intra-firm transactions use marginal cost pricing but arm's-length transactions feature double-marginalization and hence greater scope for markup adjustment that dampens cost pass-through.[1]

In this paper we use retail scanner data and a simple model to make two contributions to this literature. First, we analyze the impact of vertical structure in a retail context by comparing pass-through for three classes of goods in multiple product categories – national brands manufactured and marketed outside the retailer, private label (store) brands manufactured externally but marketed by the retailer, and private label (store) brands that are both manufactured and marketed directly by the retailer. By examining two steps in the cost pass-through chain – from commodity prices to wholesale prices, and from wholesale prices to retail prices – we are able to address the concern in the literature regarding the extent to

[1] While the above cited papers find evidence that within-firm and arm's length prices behave differently, the reason that Coasian bargaining fails in some cases is unclear. Hastings (2004) and Hastings and Gilbert (2005) show that vertical organization matters for pricing in the gasoline industry, consistent with a failure of Coasian bargaining. Conversely, Villas-Boas (2007) uses a structural model to show that wholesale prices are close to marginal cost (indicating either non-linear pricing by the manufacturer or retailer market power sufficient to eliminate the vertical pricing externality) for Yogurt sold in several U.S. stores. Anderson et al. (2013) argue that retailer-manufacturer interactions concerning trade promotions in the grocery sector were not incentive compatible during the 1960s and 1970s but that the nature of current contracts allows for a better alignment of incentives. From a legal standpoint, resale price maintenance was illegal in the US during our sample period and the Robinson-Patman Act (which prohibits anti-competitive wholesale price discrimination within a market for goods that cross state lines) also potentially complicated bargaining.

which self-reported cost measures reflect allocative marginal costs, given the potential for non-linear pricing in general and transfer/accounting pricing for intra-firm transactions in particular (Clausing (2003), Nijs et al. (2009) and Anderson et al. (2013)). Second, we present some of the first evidence in the empirical pass-through literature on the interaction between horizontal and vertical market structure.[2] We show theoretically that ceteris paribus vertical integration can lower pass-through directly by eliminating double marginalization but can generate an offsetting effect on horizontal market power, raising market share and markups and lowering pass-through. While under certain conditions either effect could dominate theoretically, we test the empirical prediction that controlling for market share should raise the relative pass-through for vertically integrated products.

Our theoretical framework combines the Spengler (1950) model of vertical price-setting with the Dornbusch (1987) oligopolistic competition model and derives the implications for pass-through from commodity to wholesale to retail prices for the three (vertical) classes of goods in our data. The model highlights the role of the cost structure and the importance of interactions between vertical structure, pricing and horizontal market power. We test the model predictions using data on prices and quantities from a major US retailer (covering thousands of goods in over a hundred product categories) and the Symphony IRI dataset (covering thousands of goods sold by multiple retailers across different product categories). Our empirical analysis using the single-retailer data shows that distinguishing the type of vertical structure – in this case private label brands manufactured by the retailer or externally – is critical for analysis of pricing behavior as we find a much larger and more robust positive effect of vertical integration on commodity to retail pass-through for the fully vertically integrated private labels than the externally manufactured ones. UPC and brand-level market shares tend to be negatively related to pass-through so that consistent with the model, controlling for market share in the pass-through regression increases the magnitude of the vertical (direct) effect because private label goods have larger market shares for a given retailer (a classic omitted variable bias that may be present in the pass-through literature using data with prices but not quantities). We also confirm the model prediction that the effects of vertical integration for pass-through can be different across stages of the cost transmission chain, as vertical integration appears to lower pass-through from wholesale to retail prices while raising it from commodity to wholesale prices. While the standard view (horizontal

[2]The only other paper we are aware of that considers this interaction is Amiti et al. (2013) who analyze a very different setting – the interaction of imported input share and market share on pass-through from exchange rates to export prices for Belgian firms. In their case "vertical" does not refer to intra-firm transactions but rather to the decision of whether to source inputs from domestic or foreign producers, and their model features an interaction between market share and cost sensitivity that is reinforcing rather than offsetting as in our case. A paper that examines vertical structure in a setting with cross-border transactions that can be intra-firm or outside the firm (outsourced) is Hellerstein and Villas-Boas (2010), who find higher pass-through for car manufacturers with more intra-firm (versus outsourced) imports, but the potential interactions with horizontal market structure (of input producing or final assembly firms) is not stressed in the paper.

power lowers pass-through, vertical integration raises it) holds for the typical category, the heterogeneity of estimated pass-through across products and the heterogeneity in the magnitude of private label and market share effects across categories also highlight the need for detailed product classifications and multiple product categories to draw reliable conclusions, and confirms our model's implication that the effects of vertical integration can be ambiguous under certain parameter values. Using our multi-retailer data, we show that the pattern of higher overall pass-through from commodity to retail prices for private label goods is robust across different retailers, and provide insight into how market shares at different levels of the vertical chain (e.g. manufacturer market shares versus retailer market shares) shape product-level pass-through. Finally, we present some evidence on the macro implications of vertical integration in retail by exploring the cyclical properties of private label share and potential to generate counter-cyclical cost pass-through, and by examining differences in more aggregate measures of commodity, wholesale and retail pass-through across European countries with different private label market shares.

While much of the macro literature on pass-through uses exchange rates as a cost-shifter together with import or export price data, domestic retail is an equally important setting to investigate market structure and cost pass-through. In many countries including the United States the majority of products consumed, the majority of products in the CPI, and the majority of product market competition comes from domestic sources. Multi-product manufacturers selling to multi-product retailers are ubiquitous in a domestic grocery retail context and vertical integration thus has significant potential to generate double-marginalization and to interact with horizontal market power to shape pass-through of cost shocks. While retailers have often been treated as passive relative to manufacturers in the macro pass-through literature, entry by big box retailers like Wal-Mart and Target combined with retail consolidation have the potential to reshape pass-through dynamics – the share of grocery sales accruing to the top-5 retailers rose from about 30% to over 60% between 1992 and 2009 (even higher in some areas) and private label market share rose from about 12% to over 20% over the same period.[3] In Europe the top-5 grocery retailer market share is over 80% for countries like Switzerland and Great Britain that also have the highest private label market shares (over 40%) – across 18 European countries the correlation between the top-5 retailer share and the private label share is 0.50 (s.e. 0.04)[4]. The private label share also varies over the business cycle and rose in the US during the Great Recession (Figure 1), and work by Lamey et al. (2007) suggests that asymmetric adjustment in private label share over booms and recessions contributes to the longer term growth trend in private labels. Together, these facts raise the

[3]See research by Cott (http://www.coriolisresearch.com/pdfs/200501_lm_cott.pdf), Symphony IRI "Retail Private Label Brands in Europe: Current and Emerging Trends" (http://www.symphonyiri.eu/Insights/EuropeanWhitepapers/tabid/262/Default.aspx) and Wood (2013).

[4]Author's calculations, sources discussed in Section 5

possibility that the combination of growing retail concentration and private label share may be contributing to the cyclicality of aggregate pass-through in the United States and Europe as well as longer term trends.

At the aggregate level, evidence from BLS data suggests that there have been changes in aggregate pass-through over time – Weinhagen (2002) finds that that between 1974-1989 and 1990-2001, pass-through from crude/intermediate goods prices to finished goods/CPI prices fell, while pass-through from finished goods prices to CPI increased. While a decline in aggregate exchange rate pass-through to import prices has been widely noted for numerous industrialized and emerging countries (see Gagnon and Ihrig (2002) Bailliu and Bouakez (2004), and Frankel et al. (2005)) the potential role of horizontal and vertical market structure in explaining such pattern is still poorly understood. For example, this decline in pass-through seems inconsistent with the rise in intra-firm trade given the findings of Neiman (2010) and others that intra-firm import prices exhibit higher exchange-rate pass-through. Our findings suggest that further analysis of the interactions between horizontal and vertical structure may help resolve this apparent contradiction and provide micro-foundations for differences in aggregate pass-through over time and across countries – the recent trend towards retail consolidation and private label expansion (or in trade, outsourcing to low market power manufacturers by ever more powerful retailers/branders) can be seen as a race between the direct effects of vertical integration and the indirect effects related to horizontal market power.

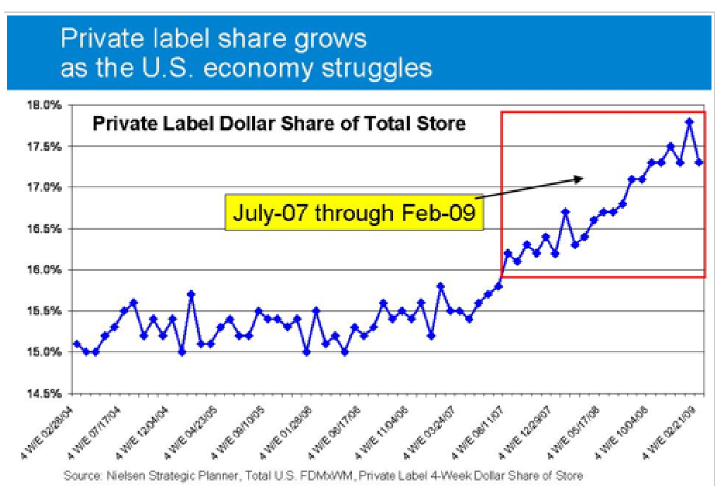



Figure 1: Share of private label goods over the years

Source: AC Nielsen Strategic Planner

The large and growing empirical literature on determinants of incomplete pass-through at the micro level is split between studies that use import or export micro data and those that use retail scanner data. In the trade/open-economy macro literature, Auer and Schoenle (2012) and Neiman (2010) use BLS trade micro data to estimate pass-through differences based on differences in horizontal market share and intra-firm versus arm's-length trades respectively, while Berman et al. (2011) use French export data to look at the effects of market share. Amiti et al. (2013) use Belgian trade and firm micro data to show how market share and use of imported intermediate inputs affect pass-through. Other studies have used the BLS data to document general pricing patterns Gopinath and Rigobon (2008), a positive relationship between long-run pass-through and frequency of price changes (Gopinath and Itskhoki (2010)) and the effects of currency of pricing on pass-through (Gopinath et al. (2010)).

Compared to this literature, our setting has several advantages. We have a precise measure of vertical structure compared to the self-reported intra-firm status of transactions in the BLS data.[5] Because externally manufactured private labels are intermediate on the continuum between national brands and retailer manufactured private labels, we can effectively analyze a "continuum" of potential double-marginalization. Because intra-firm prices are self-reported in the trade data, there is some question about whether these prices can be considered allocative transaction prices or instead contain some element of tax-avoidance (as suggested by Bernard et al. (2006) and Clausing (2003)).[6] Our setting lets us to examine pass-through from one allocative price to another (commodity to retail) and to examine wholesale prices of externally-manufactured private labels that represent a lesser degree of double-marginalization than national brands while being otherwise similar (though still potentially non-allocative). Many trade data sets with price information also lack information on quantities and suffer from product replacement bias due to sampling (see Nakamura and Steinsson (2012) and Gagnon et al. (2011)); our data allows us to measure both product and firm market shares, which is critical for our exploration of interactions between horizontal and vertical market structure, and contains classifications of products and product groupings that are as detailed as any trade data set (e.g. unique Universal Product Codes that can be classified into broad categories like yogurt and milk or very narrow subsubclasses like 32 ounce mainstream white whole milk or 64 ounce 2% reduced fat organic milk). This is important since differences in the share of marginal costs subject to a cost-shifter (e.g. a commodity price or exchange rate) can be another source of incomplete and variable pass-through across products.

The literature using retail pricing data to examine pass-through spans the closed and open-economy macroeconomics, industrial organization and marketing fields. In macroeconomics several studies have looked at wholesale to retail pass-through across many categories

[5]Gopinath and Rigobon (2008) suggest that firms probably use the Bureau of Economic Analysis definition which is a 10% ownership share.

[6]While the BLS classifies intra-firm transactions into "market-based," "cost-based," "other non-market based" and "unknown pricing methods," the precise definition of "price" is just as problematic as the definition of "intra-firm" for the trade data.

domestically (Nakamura (2008), Eichenbaum et al. (2011)) and internationally (Gopinath et al. (2011), Burstein and Jaimovich (2009)), a few studies have linked micro import and retail price data to document pass-through from the dock to the store shelf (Berger et al. (2011)), and others have taken a more structural approach to single categories to examine commodity, wholesale and retail linkages for coffee (Nakamura and Zerom (2010)) and beer (Goldberg and Hellerstein (2011)). These studies generally focus on decomposing the importance of different channels (wholesale versus retail) and different economic forces (nominal rigidities versus markup adjustment versus local non-traded costs) in generating incomplete pass-through of cost shocks. The industrial organization and marketing literature provides rich insights into retailer-manufacturer interactions in general (Kadiyali et al. (2000), Sudhir (2001), Chevalier et al. (2003), Villas-Boas and Zhao (2005), Villas-Boas and Hellerstein (2006), Villas-Boas (2007), Anderson et al. (2013)) and the role private labels for retailers specifically (Hoch and Banerji (1993), Raju et al. (1995), William P. Putsis (1997), Batra and Sinha (2000), Chintagunta et al. (2002) and Chintagunta and Bonfrer (2004)). These studies typically focus on static measures such as prices, profits, and market shares to evaluate outcomes for consumers and firms and to assess the power of retailers versus manufacturers to set prices. There is also a related literature on pass-through, with studies documenting pass-through patterns from commodity to retail prices for chicken and cereals (Berck et al. (2009)), pass-through of (manufacturer) trade promotions from wholesale to retail prices for a single retailer across multiple categories (Besanko et al. (2005), Dube and Gupta (2008)) or across multiple retailers for a single category (Nijs et al. (2009)), and pass-through of commodity/wholesale prices from dairy co-operatives to retail prices (Kanishka Misra and Singh (2010)). We build on this literature by specifically identifying different types of vertical relationships embodied in private label goods (i.e. manufactured externally or internally), examining pass-through at multiple levels (commodity to wholesale and wholesale to retail) to address concerns about self-reported wholesale costs, explicitly analyzing the interaction between horizontal and vertical market structures, and analyzing a wider range of categories (single-retailer data), retailers (multiple retailer data), and market share definitions.

Balanced against these contributions, our study has several limitations. First, the time-series dimension of our data is relatively short for our main sample (41 months) so our focus is on pass-through at modest durations (up to one year). The multi-retailer data, however, provides a longer series, covering 132 months. Second, while the product dimension is very large, our main results only apply to a single retailer. We use supplemental IRI Symphony data that covers multiple US retailers and a longer time period to verify that our main results hold but this restricts the sample to only a few categories and we lose identification of retailer manufactured versus retailer branded goods as well as data on wholesale costs. Finally, our broad focus means that unlike some of the category-specific studies mentioned above that employ structural modeling and/or detailed data on the entire cost structure, we must assume (as an identifying assumption) that the commodity/non-commodity share of marginal costs are similar across products within our narrowly defined categories (e.g. similar sized cartons of 2% organic milk sold by the same retailer) or at least that these differences are small relative to the magnitudes we estimate.[7]

Our paper proceeds as follows. Section 2 presents a model that links horizontal and vertical structure to cost pass-through and encompasses both retailer-manufactured and externally-manufactured private labels to motivate our analysis. Section 3 describes our main data set. Section 4 presents our main empirical findings on pass-through, robustness checks, and a replication of our main findings on a multiple-retailer dataset. Section 5 discusses the macro implications of our findings with respect to the US business cycle and a cross-section of European countries with differing private label market shares. Section 6 concludes.

## 2. Model

### 2.1. Basic setup

We first describe pass-through with horizontal and vertical market power in the simplest partial equilibrium setting with only one retailer and manufacturer that take the cost of competitors as given. Our treatment is similar to the classic double-marginalization problem analyzed in Spengler (1950), which is similar to a Cournot Oligopoly with a Stackelberg leader. The retailer in the model takes its marginal cost as given. The retailer sets the price for brand $i$ as a markup over marginal cost following the conventional formula. We denote the wholesale cost paid by retailer $i$ as $w_i$ and allow for an additional marginal cost of retailing $\theta_i^r$. This additional cost is meant to capture the marginal costs of distribution (between receiving warehouses and retail stores, except in the cases of direct-store-delivery by manufacturers), holding inventory, advertising, along with standard inputs like land, capital, labor, and energy inputs. Although some of these costs can be thought of as fixed costs, at least in the short-run, some of them will likely have a marginal cost component. These additional marginal costs imply that even absent any market power or markup over marginal costs, the pass-through from wholesale to retail prices would be less than complete. Formally, retailer $i$'s price-setting rule is the standard markup over marginal cost based on the elasticity of

[7]Most studies of pass-through make this assumption implicitly, i.e. that cost shares with respect to the cost-shifter are identical across firms – Amiti et al. (2013) and Hellerstein and Villas-Boas (2010) are partial exceptions in allowing for variation in the imported or outsourced share of intermediate inputs, leading to differential cost sensitivity to exchange rate shocks. Even detailed industry studies typically lack cost data detailed enough to rule out differences in cost shares as a source of differences in pass-through across firms/products. The assumption of similar cost shares is consistent with Cobb-Douglas production functions (which automatically imply identical cost shares) and with more general production functions provided the productivity/cost differences are "neutral" with respect to inputs.

demand $\epsilon_i$:

$$p_i = \frac{\epsilon_i}{\epsilon_i - 1}(w_i + \theta_i^r),\ where\ \epsilon_i \equiv -\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_i}. \tag{1}$$

The manufacturer sets the wholesale price taking into account its own demand curve and elasticity, which depend indirectly on retail markups and pricing decisions. Manufacturer $i$ has marginal cost $c + \theta_i^m$ where $c$ is the price of commodity inputs and $\theta_i^m$ represents other marginal costs of the firm, and sets the wholesale price $w_i$ such that

$$w_i = \frac{\mu_i}{\mu_i - 1}(c + \theta_i^m) \tag{2}$$

The elasticity of demand facing manufacturers $\mu_i$ is given by

$$\mu = -\frac{\partial q_i}{\partial w_i}\frac{w_i}{q_i} = -\left(\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_i}\right)\left(\frac{\partial p_i}{\partial w_i}\frac{w_i}{p_i}\right) \tag{3}$$

The first part of this expression is just the demand elasticity with respect to retail price given by $\epsilon_i$ while the second part reflects the pass-through from wholesale to retail prices, i.e. the percent change in retail price $p$ due to a percent change in the wholesale price $w$. The pass-through coefficient is given by

$$\frac{\partial p_i}{\partial w_i}\frac{w_i}{p_i} = \left(\frac{1}{1 + \frac{\partial \epsilon_i}{\partial p_i}\frac{p_i}{\epsilon_i}\frac{1}{(\epsilon - 1)}}\right)\frac{w_i}{w_i + \theta_i^r} \tag{4}$$

The first equality in this equation holds for any demand system and shows how pass-through depends critically on the price elasticity of a price elasticity ($\frac{\partial \epsilon_i}{\partial p_i}\frac{p_i}{\epsilon_i}$) – sometimes called a markup elasticity or "super-elasticity" in the literature – as well as the marginal cost share of the "cost" being passed through ($\frac{w_i}{w_i + \theta_i^r}$).[8] Pass-through from wholesale to retail prices in the model is incomplete ($< 1$) unless there are no additional marginal costs ($\theta_i^r = 0$), there are no markups over marginal cost ($\epsilon \to \infty$) or the markup is invariant ($\frac{\partial \epsilon_i}{\partial p_i}\frac{p_i}{\epsilon_i} = 0$, the case with CES preferences).

Based on equation 3, manufacturers face a lower demand elasticity than retailers ($\mu_i < \epsilon_i$) when retail pass-through is below one. In this case the manufacturer markup and the retailer markup are strategic substitutes. The intuition is that an increase in wholesale price is not fully passed-through to consumers because retailers adjust their markups downward when their costs increase (or have to pay other costs that do not change), making the quantity purchased less elastic to changes in wholesale prices than retail prices. This also implies that

[8]Note that this issue arises in analysis of exchange-rate pass-through as well, often through the form of imported intermediate inputs whose prices are affected when the exchange rate changes (e.g.Gopinath and Itskhoki (2010)) when analyzing at the dock prices and non-traded costs when analyzing exchange-rate pass-through to consumer prices of imported goods.

pass-through from manufacturing cost ($c + \theta_m$) to wholesale price will typically be lower than from wholesale cost to retail price, though the presence of non-commodity retail and manufacturing marginal costs ($\theta_r$ and $\theta_m$) can potentially overturn this when they vary across products.

With both retailing and manufacturing firms following their respective pricing rules, the equilibrium retail price is

$$p_i = \frac{\epsilon_i}{\epsilon_i - 1}\left(\theta_i^r + \frac{\mu_i}{\mu_i - 1}[c + \theta_i^m]\right) \tag{5}$$

Equation 5 makes it explicit that retail and manufacturer markups over marginal cost give rise to double marginalization. Combined with a particular retail demand function, the system of equations for retail and wholesale prices will typically have a unique equilibrium but no closed-form solution.

Now consider the case where the retailer and manufacturer described above decide to vertically integrate. This would imply a pricing rule given by

$$p_i^{VI} = \frac{\epsilon^{VI}}{\epsilon^{VI} - 1}[c + \theta_i^r + \theta_i^m] \tag{6}$$

which eliminates the double marginalization in equation 5 – the integrated firm internalizes the negative pricing externality. This has the implication that the integrated firm will feature lower retail prices and larger total profits:

$$\frac{1}{\epsilon^{VI} - 1}[c + \theta_i^r + \theta_i^m]q_i^{VI} = \pi^{VI} > \pi^r + \pi^m = \left(\frac{1}{\epsilon - 1}\left[\theta_i^r + \frac{\mu}{\mu - 1}(\theta_i^m + c)\right] + \frac{1}{\mu - 1}[c + \theta_i^m]\right) q_i \tag{7}$$

Although under vertical integration the total markup per unit sold is lower, the larger volume sold ($q_i^{VI} > q_i$) results in higher profits.[9]

While the implications of vertical integration for pricing and profits are unambiguous, the implications for pass-through in this model are ambiguous. The rise in volume ($p^{VI}q^{VI} > pq$) generated by vertical integration is central to our analysis as in some commonly used demand systems this rise in market share will generate an increase in horizontal market power and thereby decrease pass-through. Commodity pass-through ($\frac{\partial p}{\partial c}\frac{c}{p}$) under vertical integration is given by:

$$\left(\frac{1}{1 + \frac{\partial \epsilon^{VI}}{\partial p^{VI}}\frac{p^{VI}}{\epsilon^{VI}}\frac{1}{\epsilon^{VI} - 1}}\right)\frac{c}{c + \theta_i^m + \theta_i^r} \tag{8}$$

while under arm's-length pricing it is given by the combined retail and wholesale commodity

[9] Note that under the additional assumption that pass-through is increasing in cost (which applies to the functional form we assume in the next section) we will have $\epsilon^{VI} < \mu < \epsilon$.

price pass-through:

$$\underbrace{\left(\frac{1}{1+\frac{\partial\epsilon}{\partial p}\frac{p}{\epsilon}\frac{1}{(\epsilon-1)}}\right)\frac{w_i}{w_i+\theta_i^r}}_{retail}\underbrace{\left(\frac{1}{1+\frac{\partial\mu_i}{\partial w_i}\frac{w_i}{\mu_i}\frac{1}{(\mu-1)}}\right)\frac{c}{c+\theta_i^m}}_{wholesale}=\frac{1}{1+\frac{\partial\epsilon}{\partial p}\frac{p}{\epsilon}\frac{1}{(\epsilon-1)}}\frac{1}{1+\frac{\partial\mu_i}{\partial w_i}\frac{w_i}{\mu_i}\frac{1}{(\mu-1)}}\frac{c}{c+\theta_i^m+\frac{\mu_i-1}{\mu_i}\theta_i^r} \tag{9}$$

The arm's-length pass-through equation reveals that markup adjustment by manufacturers ($\frac{\partial\mu_i}{\partial w_i}\frac{w_i}{\mu_i}$) can provide an additional source of incomplete pass-through compared to the vertically integrated case; holding retail pass-through constant, this would tend to lower pass-through for the arm's-length case compared to the vertically integrated case. This first force for higher pass-through ("markup adjustment channel") is only relevant when demand elasticities are variable but the economic intuition is fairly simple as the term is completely absent in the vertically integrated case but less than one when the elasticity $\mu$ is finite and increasing in price ($\frac{\partial\mu_i}{\partial w_i}\frac{w_i}{\mu_i}>0$).

Offsetting this first force is the term $\frac{\mu_i-1}{\mu_i}$ in the denominator of the arm's-length pass-through equation. This second force ("cost channel") only arises when there are retail marginal costs, but in this case the level of the manufacturer's markup directly raises pass-through since it increases $w=\frac{\mu}{\mu-1}(c+\theta_m)$ and hence the share of the retailer's marginal cost affected by the shock ($\frac{w}{w+\theta_r}$).[10] Pass-through is rising in the commodity share of total costs – $\frac{c}{c+\theta_m+\theta_r\frac{\mu-1}{\mu}}$ – which in the presence of retail costs is amplified by the degree of double-marginalization. For the vertically-integrated case this is absent (effectively $\mu\to\infty$) which results in lower pass-through. This term also provides insight into how shifting aspects of production between manufacturers and retailers could affect pass-through in the arm's-length case. If private labels are equivalent to a shift from $\theta_m$ and $\theta_r$ to $\theta_m-\delta$ and $\theta_r+\delta$, this raises commodity to wholesale pass-through more than it lowers wholesale to retail pass-through and the net effect is to increase pass-through. Thus while this channel lowers commodity pass-through for retailer manufactured private labels, it always raises it for externally manufactured private labels. Note that in both cases the wholesale to retail pass-through is lower due to this channel.

A third force ("market power channel") is central to our empirical analysis and highlights the interaction between the horizontal and vertical effects of the model – vertical integration affects prices and market shares, which can potentially generate feedback effects on the markup and markup elasticity. Under many demand systems (including the one we investigate in greater detail in the quantitative results below) firms with larger market shares will

[10]This channel does not operate when the retail cost share is constant across products (e.g. Cobb-Douglas production function with wholesale and retail inputs) and could have an opposite effect if retail/wholesale inputs were substitutes. Our model is based on the more plausible case of perfect complementarity (e.g. Leontief production function) between retail and wholesale inputs.

face lower demand elasticities and hence feature higher markups, which could in turn raise the markup elasticity ($\frac{\partial \epsilon}{\partial p}\frac{p}{\epsilon}$ and $\frac{\partial \mu_i}{\partial w_i}\frac{w_i}{\mu_i}$) and lower pass-through. Thus while vertical integration or a shift in costs from the manufacturer to the retailer (e.g. going from $\theta_m$ and $\theta_r$ to $\theta_m - \delta$ and $\theta_r + \delta$) can raise pass-through through the first two forces described above, by raising market share they generate a countervailing force that lowers pass-through.

What determines which of these forces will dominate? We explore this with some quantitative simulations in the next section, but first conclude with a few general observations. The first force we identify (markup adjustment) will be stronger when the markup elasticities are high and markups are highly variable. The second force (cost share) will be stronger when either retail marginal costs ($\theta_r$) and/or the manufacturer markup level ($\mu$) are high. The third force (market power) will be strongest when vertical integration delivers the largest increase in market share and the markup elasticity is most sensitive to market share.

Note that in the case of shifting costs from manufacturer to retailer (e.g. the non-manufactured private label goods where the only difference is the share of total marginal costs paid by the retailer) the first force is absent and the second force strictly increases pass-through. The third force still partly offsets the second, but as an indirect consequence of the second it only generates a second order countervailing effect, and the net effect of shifting from $\theta_m$ and $\theta_r$ to $\theta_m - \delta$ and $\theta_r + \delta$ increases pass-through unambiguously. In the case of full vertical integration all three forces play a role, and the cost channel can be strong enough to outweigh the markup adjustment channel even when the market power channel is absent.

## 2.2. Quantitative analysis

To provide some additional insight we consider a particular version of the previous model along the lines of Dornbusch (1987). Consumer utility is CES and given by

$$C = \left( d_i^{\frac{1}{\eta}} q_i^{\frac{\eta-1}{\eta}} + z^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{10}$$

where $\eta$ is the CES elasticity of substitution, $d_i$ denotes the "quality" of the good (a factor that shifts demand given price) and good $z$ is an "outside good" or the rest of the market, whose price the retailer takes as given. We get the standard CES cost-of-living index $P = \left( d_i p_i^{1-\eta} + p_z^{1-\eta} \right)^{\frac{1}{1-\eta}}$.

The key assumption that allows variable elasticity is that while the retailer of brand $i$ takes $p_z$ and the price of the other brand as given when setting the price, it takes account of the effect of its own price $p_i$ on the overall price index $P$. This implies a simple elasticity of demand formula:

$$-\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_i} = \epsilon_i = (\eta(1 - S_i) + S_i) \tag{11}$$

where the elasticity of demand $\epsilon_i$ is decreasing in the market share ($S_i$) of the firm. Thus firms with more horizontal market power (larger market shares) face less elastic demand and set higher markups. This yields a simple formula for retail pass-through:

$$\frac{\partial p_i}{\partial w_i}\frac{w_i}{p_i} = \left(\frac{\eta(1-S_i)+S_i}{\eta}\right)\frac{w_i}{w_i+\theta_i^r} \tag{12}$$

where we see that a retailer with no market power ($S_i = 0$) only has incomplete pass-through from the presence of local retail costs, but that a retailer with positive market power ($S_i > 0$) has incomplete pass-through due to markup adjustments after a cost shock. Hence this model not only features variable markups that increase in market share, it features a markup elasticity that is increasing in market share (and hence pass-through that is decreasing in market share).

While this model has no explicit solution, we provide some illustrative simulations. We hold set $\eta = 4$, $c = 1$, $\theta_m + \theta_r = 12$ and analyze the effects of a 0.1% increase in the commodity price $c$ to 1.001 in all of our simulations. We picked these parameters to roughly match a few data moments from our data (i.e. low commodity pass-through suggests $\theta_r + \theta_m$ are high relative to $c$, higher pass-through from wholesale to retail implies higher $\theta_m$ than $\theta_r$, the ratio of retail to wholesale costs in our data together with assumptions on $\theta_r$ pin down the elasticity $\eta$, etc.) though our goal here is only to illustrate the quantitative impact of the different forces in the model. We consider three broad scenarios based on different prices of the outside good $z$, setting $p_z$ equal to 50, 25, and 10. For each scenario we calculate five cases:

1. National brand (NB): the arm's-length pricing case (equation 5) where $\frac{\theta_r}{\theta_r+\theta_m} = \frac{1}{6}$ and $d_i = 4$
2. Private-label not vertically-integrated (PL-NVI): the arm's-length case where $\frac{\theta_r}{\theta_r+\theta_m} = \frac{1}{2}$ and $d_i = 4$ (so compared to the first case the retailer has a higher share of the non-commodity cost)
3. Private-label vertically-integrated (PL-VI): pricing based on equation 6 and $d_i = 4$
4. Constant-market share PL-NVI: similar to case 2, but we vary $d_i$ such that the initial market share is exactly equal to case (1)
5. Constant-market share PL-VI: similar to case 3, but we vary $d_i$ such that the initial market share is exactly equal to case (1)

The PL-NVI case captures the idea that private labels that are externally manufactured represent a shifting of some activities (marketing and distribution) to the retailer from the manufacturer, without eliminating the need for these activities or eliminating the ability of the manufacturer to charge a markup over marginal cost. Recall that the three forces in the model are (1)full integration removes markup adjustment by manufacturers (raises pass-through), (2)the presence of retail costs lower's pass-through for the vertically integrated case relative to arm's-length, particularly when the retailer share of retail plus manufacturing marginal costs is higher (the PL-NVI case), and (3)both types of private labels lead to lower prices, higher market shares, higher markups, and lower pass-through when the markup elasticity is increasing in the markup. For the constant-market share cases listed above, the idea is to shut-down the third force in our model (the feedback from vertical integration to horizontal market power due to price reductions and market share increases) to isolate the combined effect of the first two forces.

Table 1 presents the results and reports the price, market share, wholesale to retail pass-through and commodity to retail pass-through for all three broad scenarios and the five cases within each scenario. Scenario 1 illustrates a case where market shares are high because the outside good $z$ is expensive. In this scenario, the first force dominates the second and third forces, so pass-through is increasing from NB to PL-NVI to PL-VI. Holding constant market share (by lowering $d$ for the PL-NVI and PL-VI cases below 4) we see that this effect is even bigger, an illustration of how not conditioning on market share could lead to downward biased estimates of the effect of vertical structure on pass-through. Note also that while commodity to retail pass-through is higher for the PL cases, wholesale to retail pass-through is actually lower than for national brands. The reason for this is clear from equation 12 where even conditional on market share pass-through will be lower when $w$ is lower, which is precisely the case when $w$ contains a lower share of the total marginal costs (the PL-NVI case) or there is no markup on retail inputs (the PL-VI case).[11] This also means that commodity to wholesale pass-through is higher for the PL-NVI and PL-VI cases which can be easily backed out from the two estimates reported in the table.

Scenario 2 illustrates the case with intermediate cost of outside good $z$, so firms start with lower market share. In this case the first force still dominates the second force, but the combined effect of the second and third force yield lower unconditional pass-through for the PL-VI case than the NB case. Pass-through is still higher for the PL-NVI case because in this case the second force works for higher pass-through and the third force is only second order. Note that conditional on market share, pass-through is higher for PL-VI than PL-NVI and NB, confirming that the first force dominates the second. Finally, Scenario 3 illustrates the case with a low cost of the outside good $z$, so market share and markups are smaller and less variable. In this case the second force dominates the first force so that even conditional on market share, PL-VI goods have lower pass-through than NB or PL-NVI goods.

The intuition for the differences between the scenarios is that the first force (markup adjustment channel) depends on the markup elasticity, which is increasing in the initial market

[11]For these simulations we assume that the retailer sets $w = \theta_m + c$.

share and increasing in the gap between the atomistic firm elasticity ($\eta$) and the large firm elasticity (set to 1 in this case though this can be generalized). Otherwise the third force (market share channel) always lowers pass-through for the PL-VI and PL-NVI case. The second force (cost channel) always raises pass-through for PL-NVI compared to NB but lowers it for PL-VI compared to NB – the strength of this channel also depends on $\eta$, as raising $\eta$ raises the elasticity for every term and lowers the degree of double-marginalization ($\frac{\mu}{\mu-1}$) which is what generates the cost channel. Thus raising $\eta$ reinforces the markup adjustment channel and weakens the cost channel, making scenario 1 more likely.

We take four lessons from this simple model that are relevant for our empirical analysis:

- In our setting, unconditional commodity pass-through can be higher or lower for national brands compared to vertically integrated goods (while externally manufactured private labels should always have higher pass-through). Econometrically, we would expect the effect of the "private label" treatment to be quite heterogeneous across categories given the differing strength of the forces we identify.

- Conditioning on market share could raise the commodity pass-through of private labels relative to national brands, because vertical integration/private labels should lead to higher market share which can lower pass-through. Econometrically, omitting market share introduces an omitted variable bias that biases towards zero the positive effect of vertical integration/private labels; similarly omitting vertical structure could bias towards zero the (negative) estimates of the effect of market share.

- Pass-through from wholesale to retail prices should be lower for private labels (vertically integrated or otherwise), though market share should still have a negative effect on pass-through at this level.

- Differences in quality/demand ($d$) or marginal cost shares ($c, \theta_m + \theta_r$) could confound estimation, so looking at similar goods (sold to similar customers, e.g. in the same store) is important. Differences in quality $d$ get absorbed into market shares in our model, so the model's prediction about the direction of omitted variable bias from ignoring market shares relies on the quality of private label goods being similar (or not too far below) that of national brands.

When applying the model to data, we recognize that there are several dimensions of product and consumer heterogeneity that could invalidate the predictions of the model. We think of advertising as a demand-shifter that in an oligopolistic CES model is isomorphic to product quality or consumer taste – it increases market share for a given price. Higher $d_i$ means that empirically, national brands may sometimes have larger store revenue shares than private labels despite higher prices, leading to higher markups and lower pass-through – controlling for market share may then decrease the pass-through for private labels rather than decrease it because we would have expected higher pass-through for private labels solely due to market share. To the extent that advertising is based largely on fixed costs, it is natural to expect many national brands to advertise more heavily than private labels since they reach a larger market. However, to the extent that advertising involves marginal/per unit costs, the cost shares for private label and national brands may differ, which would confound our estimation of commodity or wholesale cost pass-through to retail prices. More generally if national brands are of different quality, then the cost shares of raw materials and manufacturing may differ from those of private label brands. Beyond the cost share effect, advertising and differences in product quality may generate different curvature of demand even conditional on market share – if the consumers who buy private labels are very different than the ones who buy national brands, it may be consumer heterogeneity that is driving our findings and not just the observable dimensions of product heterogeneity that map cleanly on to our model holding constant the demand environment. While this is ultimately a critique that applies to most of the empirical literature on pass-through, we do our best by examining pass-through for products sold by the same retail chain to the same set of consumers (e.g. we are not comparing national brands sold at Wal-Mart to private labels sold at Trader Joe's), controlling for very narrow product classifications, and including price as a control in some specifications which captures at least one dimension important for consumer heterogeneity. Additionally, even if one considered national brands to be too different to compare to private labels, our results provide insight into relative pass-through for retailer manufactured versus externally manufactured private labels – the product quality, cost shares and demand-side for these products- are likely to very similar, which allows for an interpretation of the vertical structure effects that is more robust to these critiques.

### 2.2.1. Multiple products and firms

We focus on the simplest partial equilibrium model since our goal is mainly to motivate the empirical analysis and provide intuition for the results. However, the general insights are robust to other types of market interactions, and we briefly consider the implications of multi-product manufacturers, multi-product retailers and multiple retailers for our analysis.

Multi-product manufacturers are ubiquitous in our data, including our retailer's private label manufacturing division. A simple oligopoly model like ours extended to multi-product manufacturers implies that when a large firm internalizes the effects of its price setting on demand for its other products, it effectively lowers the demand elasticity it faces – it captures some of the positive externality of higher demand for products other than the one whose price it is increasing. This implies that conditional on the product share, a higher brand share (where brand refers to all other similar products produced by the manufacturer) leads to a higher markup and a lower cost pass-through as this captures the extent of cross-product demand externalities internalized by a multi-product manufacturer. We find substantial support in the data for an independent role of brand revenue share (defined at the category level) above and beyond the product revenue share, and consistent with the logic of the model we find that this effect operates largely at the commodity to wholesale channel of pass-through rather than at the wholesale to retail level.[12]

Multi-product retailers in a multiple retailer competitive environment face different issues. While they effectively internalize some of the demand spillovers from raising the price on any product they carry, they potentially lose customers to other retailers when they raise their prices, an effect that diminishes as the retailer's local market power increases. Note that across-retailer spillovers are particularly likely to be the case for national brands where a close substitute exists in the form of purchase from a nearby retail competitor. This has several implications for our empirical analysis, including the possibility that for some national brands the store-level product and brand revenue share is negatively correlated with the pricing power of an individual store or retailer in the local market – Coca-Cola may have a large revenue share at our retailer but is available at virtually every retail outlet which substantially lowers the ability of the retailer to charge a higher markup. This is a common interpretation of the finding in some marketing studies that store-level revenue share is positively correlated with wholesale to retail cost pass-through (Besanko et al. (2005),Nijs et al. (2009), Kanishka Misra and Singh (2010)) which may explain why we sometimes find a positive effect of store-level market share in some of our specifications.[13] We are able to shed some light on these issues with our multiple-retailer data which allows us to examine the effect of store-level, brand-level, and store-brand level local market shares on pass-through.

Note that our simple analysis applies to a firm specific shock – holding $p_z$, the price of other goods, constant. A common shock across firms – like a commodity cost shock – will lead to higher pass-through than an idiosyncratic cost shock. When the price level of the competition $p_z$ is correlated with $c$, it allows the firm to pass on more of the increase in $c$ to consumers. In a more general setting, the entire distribution of other firms matters for the category level pass-through of common cost shocks. For example, Auer and Schoenle (2012) show that the entire distribution of firms can help predict pass-through differences across sectors, trade partners and sector-trade partner pairs. We abstract from these considerations in our empirical analysis by comparing pass-through rates across products with

[12]Except for its private labels, a retailer does not internalize the brand-specific spillovers of raising the retail price of a particular product. Consistent with this we find a stronger role for product revenue share at the wholesale to retail channel of pass-through.

[13]Another explanation they offer is that major national brands drive "category-expansion" – that is, they compete more with products in different categories (Coca-cola vs. chocolate milk) – rather than brand-switching within a category, which could lead to differential pricing. This type of cross-category differential elasticity is clearly ruled out by CES and models with separability across categories but could potentially explain positive effects of market share on pass-through.

different vertical structures and market shares within narrow categories (conditioning on category fixed effects) rather than trying to explain differences in category-level pass-through, which also depends importantly on the (unobserved) commodity share of marginal cost. Our approach is thus similar to the one in Amiti et al. (2013) who compare pass-through of common (exchange-rate) shocks into prices of firms with different characteristics within a category of competing products. A Dornbusch (1987) model suitable for explaining aggregate pass-through dynamics and pass-through levels is straightforward in theory but would require additional assumptions about the nature of the competitive equilibrium (Bertrand vs. Cournot, timing of price-setting by multiple firms), the entire market structure (encompassing multiple multi-product manufacturers and retailers) and data on the cost structure.

### 2.3. Vertical structure and selection

There is a large literature on the boundaries of the firm and vertical relationships but many of the predominant themes in this literature – contractability, moral hazard, and hold-up problems – do not have obvious implications in our setting with regards to which categories feature entry by the retailer's private labels and whether these will be manufactured directly by the retailer or by a third party. In our data private label entry is fairly ubiquitous (there is at 1% private label market share in 155 out of 200 categories) but manufacturing of private labels by the retailer is less common. As many of the typical outsourcing/firm boundary issues are outside the scope of our analysis and data, we consider three factors.

First, the volume of a product that can be sold by the retailer is an important factor in determining whether the retailer undertakes manufacturing. When firms have "core competencies" (in retail or manufacturing), expanding into other areas likely involves additional costs to the firm relative to outsourcing, and many of these costs are likely to have a fixed character. Just as important is the technological dimension of manufacturing which features a declining average cost curve over some region – when a retailer undertakes manufacturing of products exclusively destined for its own stores, it must be able to sell a sufficient volume to produce at a minimum of the average cost curve. As national brands can be sold by many different retailers, they are naturally efficient producers of niche products that only sell in small volumes per retailer. Basic grocery products with high volume – such as bread and milk – are easier for the retailer to manufacture directly at an efficient scale. Thus to the extent that vertical integration raises variable profits by reducing double marginalization but requires fixed costs, we expect retail volume to be an important predictor of manufacturing by the retailer. We later present some evidence that this is in fact the case, and provide additional evidence of a correlation between private label market share and supermarket concentration ratios across European countries consistent with the notion that only large retailers being willing to undertake the fixed costs of launching their own brands.

Second, product categories with low demand elasticities ($\eta$) and hence high markups are choice candidates for vertical integration as the profit gains from integrating (or vertically-integrated entry) are increasing in the extent of double-marginalization, which is increasing in demand elasticity. Because relative pass-through for vertically integrated goods is lower when $\eta$ is lower, we are more likely to see vertically integrated products in categories where vertical integration has a smaller effect on pass-through, biasing down estimates of the effect of vertical integration on pass-through compared to what we would observe in a randomly selected category. While we cannot observe pass-through for private labels (retailer manufactured or otherwise) in categories with no private labels, we do provide evidence that retailer manufactured private labels are more likely in categories with a low elasticity of substitution between varieties.

Finally, comparing across panels of Table 1 indicates that pass-through for vertically-integrated goods will be higher relative to arm's-length goods for products with higher market shares (conditional on $\eta$). Products with very low market share have a lower markup elasticity which shuts down the markup adjustment channel (which raises pass-through for vertically integrated products) more than it shut downs the cost channel (which can lower pass-through for vertically integrated goods). We do not observe hypothetical market shares for private label goods in categories where they are not present but later present some evidence where we compare pass-through for our three vertical classifications and control for market share and the interaction of market share with the vertical classifications.

### 2.4. Frequency of price adjustment

Our last theoretical observation draws on Gopinath and Itskhoki (2010) who document the important linkage between cost pass-through and the frequency of price adjustment for import prices. In a static setting with a menu cost (denoted by $\kappa$), firms face the decision of whether to deviate from their current price when faced with a cost shock. Firms have a profit-maximizing ideal price $p^*(c)$ that depends on the cost shock $c$, and a current price $p^0$ that will be set ex-ante based on the entire expected distribution of cost shocks and the menu cost. After the cost-shock is realized, firms compare

$$\pi(p^*(c), c) - \kappa \; vs. \; \pi(p^0, c) \tag{13}$$

and change their price if the left-hand side exceeds the right-hand side. A key determinant of the gains from changing the price – $\pi(p^*(c), c) - \pi(p^0, c)$ – is the desired pass-through of cost shock $c$, which effectively determines the optimal price $\pi(p^*(c), c)$. When the pass-through from our model above is very small, firms gain much less from changing their prices in response to a given cost shock – $\pi(p^*(c), c) - \pi(p^0, c)$ will be smaller for any $c$. This immediately implies the key finding of Gopinath and Itskhoki (2010) that long-term (desired) pass-through should be positively correlated with the frequency of price changes holding menu costs constant. For any given distribution of costs, the fraction of periods in which the firm will prefer to change its price (relative to the current price) is higher for firms with higher desired pass-through, i.e. firms with lower market shares or greater degrees of vertical integration. Although menu costs could potentially vary with horizontal and vertical structure and firms producing similar products might face different distributions of cost shocks, we see no obvious reasons why this would be the case and hence we examine whether our data are consistent with the ancillary prediction of the model for the frequency of price changes.

# 3. Data Description

## 3.1. Retailer data

We use two rich retail data sets to examine the effects of market structure on pass-through to retail prices. The first data set consists of weekly store-level scanner data on the retail prices, wholesale costs, and quantity sold of individual UPCs for a single large U.S. retailer, while the second data set consists of weekly scanner data on retail prices and quantities for multiple retailers and comes from the marketing agency Symphony IRI.

### 3.1.1. Single retailer data

The first data come from a large retailer and our sample covers operations in 250 stores organized into 10 divisions spanning 19 states for the weeks between January 2004 and June 2007 (178 weeks total).[14] The data cover virtually all of the goods sold by each store, consisting of 200 product categories that span non-durable goods such as food and beverages, magazines, housekeeping supplies, and personal care products. Products are identified by Universal Product Category (UPC) barcodes that identify unique products but the data provided to us also contains coarser categorizations (including the product category measure mentioned above).[15]

As our goal is to analyze pass-through for similar nationally branded and private label goods, we restrict our attention to categories that contain both of these types of goods and to products that are sold frequently enough to avoid truncation and imputation of missing values. We distinguish private label goods from national brand goods by matching the UPC descriptions in our data with the names of private label brand lines. Within this list of private

[14]The data sharing agreement between this retailer and the research community is managed through the SIEPR-Giannini data center.

[15]For more in-depth description of the data set, see Gopinath et al. (2011), Eichenbaum et al. (2011) and Burstein and Jaimovich (2009).

label goods, we distinguish those that are manufactured by the retailer from those that are branded but not manufactured using information from the manufacturing division web-site. We therefore categorize goods into three types: national brands (NB), private label products that are not manufactured by the retailer ('private label branded') and a private label good that is manufactured by the retailer ('private label manufactured'). Our retailer has a significant private label presence across a wide range of categories, spanning relatively unprocessed goods like meat, seafood and coffee to highly processed goods like cookies and cleaning products. There are 175 categories that contain both private label goods and national brand goods. In addition to excluding certain categories, the other main selection criteria we use is that a product must be sold in at least one store/week every month for the 41 months in the sample period. This excludes a substantial number of UPCs that enter or exit during the sample period as well as those that only appear in a few months of data. When we also exclude categories that have a very low private label presence among the remaining UPCs (below 1% of category revenue) we are left with our main sample of 155 product categories, 20 of which contain at least some retailer manufactured products (including dairy, cookies, soft drinks and bread). Although our sample selection leaves us with only 18,941 out of 63,977 UPCs, this subsample represents over 2/3 of revenue.

Our data contain two measures of retail prices: a regular (or list) price and a sales price. The retail list price is calculated by dividing gross revenues by quantities sold. The sales price is calculated by dividing the net revenues (gross revenues net of promotions, coupons, and rebates) by quantities sold. Because of sales promotions, coupon usage, bulk discounts, and membership discounts that do not apply to every customer, it is often the case that different consumers pay different prices for a particular product in a given week. Using these measures, we calculate a national-level monthly (unweighted) price series for each item by averaging across stores and weeks in a month:

$$\overline{p}_{i,m} = \frac{\sum_{j=1}^{J_{i,m}} p_{i,j}}{N_{i,m}} \tag{14}$$

where *i* is product, *m* is the month, $J_{i,m}$ is the set of all store by week observations for product $i$ during month $m$, and $N_{i,m}$ is the number of observations in set $J_{i,m}$.

Our measure of retailer cost comes from the scanner data and is the reported wholesale list price at which the retailer can purchase the product (i.e. the current replacement price). This is the measure of cost used in Eichenbaum et al. (2011), Gopinath et al. (2011), and Burstein and Jaimovich (2009). Note that this cost measure may or may not include associated distribution services since some national brand manufacturers engage in direct-store-delivery (DSD) while others ship to central warehouses owned and operated by the retailer. Furthermore, the extensive use of promotions and contracts means that this cost measure does not always correspond to the marginal cost of the retailer, which may not be constant in quantity given the existence of incentives based on quantity targets. Given the tight relationship between changes in this wholesale list price and the retail price, and the lack of other evidence on the use of manufacturer promotions/incentives as a mechanism of adjustment following manufacturer cost shocks, we follow the previous literature and treat this wholesale list price as a primary component of the retailer's marginal cost ($w_i$ in the model) and as equivalent to a manufacturer/producer price. However, we add an important caveat to the previous literature by recognizing that the wholesale list price for products manufactured directly by the retailer may not be an allocative price for another reason – we recognize that these prices may be accounting fictions rather than representative of the true marginal production costs ($\theta_m + c$) faced by the integrated retailer-manufacturer. This is one reason why our setup, which allows us to examine pass-through from commodity prices to retail prices, bypassing wholesale costs completely, is potentially advantageous for identifying the effects of vertical integration on pass-through.

In addition to the price and cost measures provided by the retailer, we use the quantity measure to construct a product-level share of the retailer's revenue or what we call "market share." While this is not a true market share in that many of these products are sold by other competing retailers in local markets, differences in prices and within-retailer revenue shares are still informative about the implied demand or quality-shifters for a product – a product with high quality can sell more at a given price, and compared to a product with the same marginal cost will receive a higher markup by manufacturers and/or retailers. We construct this revenue share level by taking the total gross revenue from the product over the entire sample period (which necessarily includes an across-store margin). We also construct firm-level market shares to account for multi-product manufacturers (including our retailer). We do this using what is called the "manufacturer code" given by the first five digits of each UPC – these typically identify a unique manufacturer at the time of issuance, but changes in ownership through mergers and acquisitions take place without any change in the UPC. Our measure is thus more likely to be accurate within highly disaggregated product categories where a large manufacturer will not have multiple divisions (leading us to underestimate firm market share) and where ownership is likely to be uniform for UPCs sharing the same manufacturer code (as opposed to across broad categories where manufacturers are more likely to acquire or sell a division). While our measure is noisy, inspection of the UPC descriptions suggests that it provides a reasonably good match.

Finally, the retailer provides classification information that we use to construct appropriate comparison sets for goods. In assessing the effects of different market structures on pass-through, defining the appropriate set of comparison goods is important both for defining the relevant competition and for isolating the effects of observed market structure on pass-through from the effects of unobserved heterogeneity in product characteristics – there is no reason to expect an increase in a meat commodity price to affect the marginal cost of a "steak" and a "frankfurter" product to the same degree, but comparing a nationally branded 6 pack of frankfurters with a private label 6 pack of similar dimensions is likely to be informative. The 155 product categories in the data are often too internally heterogeneous. Fortunately the retailer provides classification information down to a very disaggregate level, from category to class, subclass, and subsubclass. Subsubclass usually contains information on product volume but also modifiers like diet, organic, and flavors. To take a concrete example, a UPC with the description "Northern lights milk 2%" is in the "mainstream white milk" product category, "reduced fat 2%" class, and the "64 ounce reduced fat 2% milk" subclass and subsubclass, while a UPC described as "Hersheys chocolate milk" is in the "mainstream white milk" category, the "flavored milk/milk substitute" class, "chocolate flavored milk/milk substitutes" subclass and "quart chocolate milk/milk substitutes" subsubclass. Thus while in some cases the more disaggregated categories overlap or do not add additional information, typically at the subsubclass level products will be differentiated by product dimension, premium/non-premium dimension, diet/fat-free/health/organic modifiers, and flavor modifiers. We can thus define our comparison sets for pass-through regressions and for definitions of market share at different levels of aggregation – while our results turn out to be qualitatively robust from the category level on, the quantitative findings do depend on the level of disaggregation. We later report results using the most broad (category) and narrow (subsubclass) classifications to show this effect.[16] When a very narrow category does not contain both a national brand and a private label good, we aggregate up to the most disaggregated level that that contains both.

Table 4 presents some descriptive sample statistics from the retailer data. Private label goods that are manufactured by the retailer tend to have a higher revenue share and brand share within a comparison group, while also exhibiting lower prices (70% to 83%) and wholesale costs (50% to 90%) than national brands and higher markups(5% to 30%). The median prices and wholesale costs of retailer manufactured goods are also lower than those for retailer branded goods by 7 to 10%.

### 3.1.2. Multiple retailer data

The second data set comes from Symphony IRI, a market research agency.[17] The data contain weekly scanner price and quantity information covering a panel of stores in 50 metropolitan areas ("markets") in the U.S. in 31 product categories defined similarly to the ones in our retailer data, e.g. beer, yogurt. The data set covers the period from January 2001 to December

[16]Results using intermediate classifications are available by request.
[17]See Bronnenberg et al. (2008) for a detailed discussion of the data.

2011 with multiple retail chains in each market. We restrict our attention to 13 food product categories that we can match to a commodity ingredient to estimate commodity-retail price pass-through.[18] The price and quantity information are available at the UPC level. While brand information is included (e.g. Kellogg's, Coca-Cola), all private-label UPCs have the same brand identification so that the identity of the retailer cannot be recovered from the labeling information. While we were previously able to separately identify private label goods manufactured by the retailer and those that were branded by the retailer but externally manufactured, this information is not available for the IRI marketing data set and our inability to identify particular chains makes it impossible. The IRI data also do not contain any cost measures and does not contain a more disaggregated classification than category.

Retailers report the total dollar value of weekly sales and the total quantity sold for each UPC, along with a flag for goods that are on sale. When the sales flag is equal to zero, in other words, the item was not on sale, we calculate the regular price by dividing weekly revenue by weekly quantity sold. In other case, when the sales flag shows that the item was sold on sale, we assume that the pre-sale regular price persists during the sale and use the pre-sale regular price as the regular price. Using these regular price series, we calculate a store-level monthly (unweighted) price series for each item by averaging across weeks in a month:

$$\overline{p}_{i,c,s,m} = \frac{\sum_{j=1}^{J_{i,c,s,m}} p_{i,c,s,j}}{N_{i,c,s,m}} \tag{15}$$

where all the subscripts are defined as in equation 14 except $c$ which refers to a chain. The subscript $s$ refers to the geographic unit of the price, and we allowed this $s$ to be either national or a city (or an MSA), which allows for variation of prices in different cities. For instance, if s is national, a $\overline{p}_{i,c,s,m}$ would be the average retail price of a particular UPC at a specific chain across cities for the particular month. If s, on the other hand, is an MSA, a $\overline{p}_{i,c,s,m}$ is the average retail price of a particular good at a particular chain in a specific city like Los Angeles for that particular month.

### 3.2. Commodity and wholesale cost indexes

We supplement our product-level data on retailer prices, costs, and quantities with two measures of "common shocks" that should shift the marginal cost of similar goods by a similar amount: (1) commodity prices and (2) wholesale cost index. Commodity prices, like exchange rates, are arguably exogenous sources of cost variation at the product level we can use to examine cost pass-through into both wholesale prices and retail prices. For retail price-commodity and wholesale price-commodity regressions, we collect weekly or monthly prices

[18]The 13 product categories we use are beer, carbonated soft drink, coffee, cold cereal, hotdog, margarine and butter, mayonnaise, milk, mustard and ketchup, peanut butter, saltine crackers, soup and yogurt.

of raw materials (sugar, wheat, corn, meat, milk and coffee) from the Food and Agricultural Organization and the S&P Goldman Sachs Commodity Index and aggregate to the monthly level to be consistent with our price data.[19] Using commodity prices as cost measure ensures that a retail price/cost pass-through regression can be run with an allocative, market-based cost measure. We match product categories with commodities that are likely to be important ingredients (e.g. wheat with bread, milk with yogurt, meat with franks, corn with syrup and soft drinks via high-fructose corn syrup). The idea behind the wholesale cost index is that identifying the appropriate commodities and weights for a category is difficult, but shifts in category-level wholesale prices are likely to be informative of these changes. Unlike the idiosyncratic wholesale price changes, which may reflect individual product demand shocks, shocks to local factor prices, etc. the wholesale cost index for a product category is likely to capture the common cost shocks facing all manufacturers in an industry. We construct this index by using fixed revenue weights to aggregate the wholesale costs for each product in a category.

Figure 2 presents some time-series plots of the commodity indexes we use and the wholesale cost indexes of some associated categories. Commodity prices during this period are generally trending up, particularly in late 2006 and early 2007, but to varying degrees, and there are substantial periods of increase and decrease for most commodities. Commodity price swings are much larger than those of the wholesale cost index, which should not be surprising given that commodity inputs are only a relatively small share of the costs of most products and products that use multiple commodity inputs will have a smoother material cost component over time than any individual component. We see clear co-movement between the commodity and wholesale indexes in some cases (milk and cottage cheese with dairy, coffee with coffee, bread with wheat, sugar with granulated sugar) while in other cases the co-movement appears to be relatively small or close to zero.

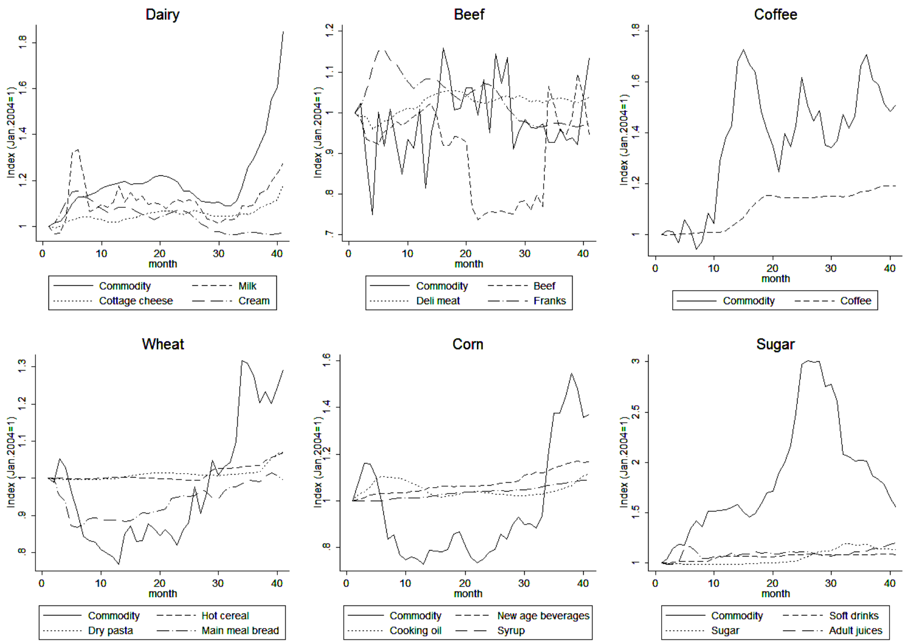
### 3.3. Frequency of price changes

While our pass-through results aggregate across stores and weeks up to the monthly level, when measuring the frequency of price changes one is confronted with a standard problem of incomplete data. The scanner data set that we use only collects prices for a week/store if there are recorded transactions, so there are many missing observations.[20] Although a missing value need not imply a price adjustment, failure to correct for missing values could

[19]The commodity price series from the Food and Agricultural Organization is available at http://www.fao.org/es/esc/prices. There are several price series for some material depending on the country of origin and product characteristics. We use the export price of bovine meat produced in the U.S. as the meat commodity price and the dairy real price index.

[20]This is less of a problem for our subsample since we exclude many goods that are only sporadically purchased, but is still potentially an issue.

Figure 2: Retail and Commodity Price Movements




Note: The commodity price information is from the Food and Agricultural Organization of the United Nations and S&P Goldman Sachs commodity price index. In each plot, we generate a product category level regular price index from a sample of product categories that we use to run commodity-retail price regressions. Both data covers 41 months from January 2004 to May 2007.

bias our measurement of price duration and sale frequency if missing values are correlated with price changes. Another issue, noted by Eichenbaum et al. (2011) in their description of the data set, is that there is potential measurement error in the weekly sale price because not all consumers purchase goods at the same price due to coupons, loyalty cards and promotions – a few consumers who do not take advantage of a promotion could create the appearance of a price change when there is no change in the underlying list and sale price. As in their paper, our estimates of the frequency of weekly price changes should be interpreted as an upper bound.

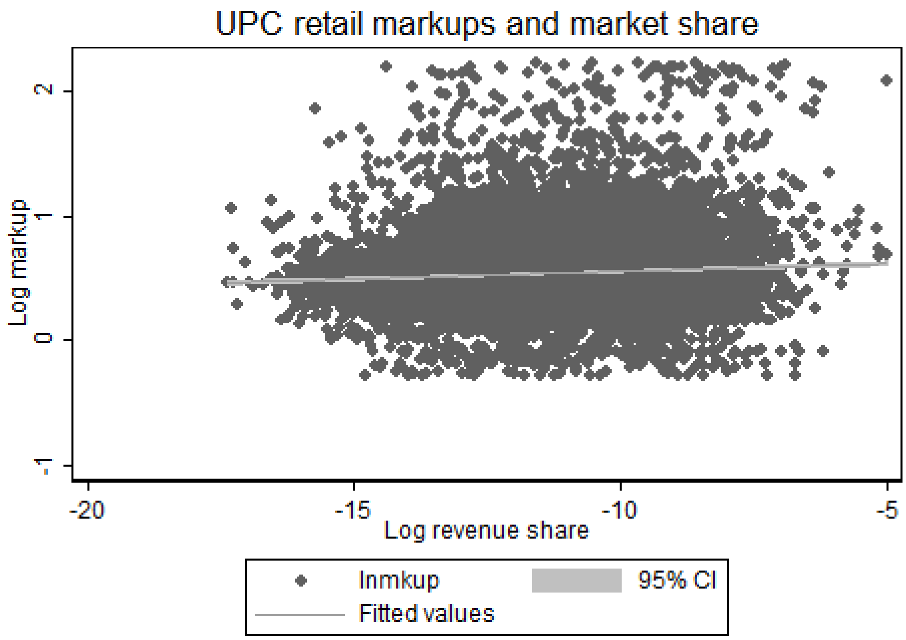
We adopt two different procedures to deal with missing values that are now standard in the literature (see Nakamura and Steinsson (2008) and Kehoe and Midrigan (2008)). They are described in detail in Table 2. The first procedure, referred to as 'spell1' combines spells on both sides of a missing spell provided the price before and after the missing spell is unchanged. Suppose we observe a price of \$1 during weeks 2 to 3 and the price for weeks 4 to 6 missing, but we observe a price of \$1 for week 7 followed by \$1.5 for week 8 and \$1.4 for week 9. The length of the (\$1) spell is 2+1=3 weeks. The second procedure, 'spell2,' imputes the previously observed price to all missing values. In the example above, this means that we include weeks 4 to 6, resulting in a ($1) spell length of $2 + 3 + 1 = 6$. Table 3 shows that the 'spell2' procedure generates slightly longer durations than the 'spell1' procedure but the overall pattern is similar, with fairly similar and lengthy durations for regular prices and wholesale costs and much shorter durations for sales prices, consistent with Eichenbaum et al. (2011). Table 4 shows that using our preferred 'spell2' measure, retailer manufactured goods have the longest regular price durations (7-8 months), while exhibiting the shortest sales price durations (5.2 weeks median).

## 4. Market Share, Vertical Structure and Pass-Through

Before presenting our main pass-through results, we briefly provide some graphical evidence to corroborate two of the implications of our model – that higher market share is related to higher market power and hence higher markups, as in the Dornbusch (1987) framework, and that greater degrees of vertical integration are chosen for product categories that have higher volume and higher degrees of double-marginalization. Figure 3 presents a plot of the log within-category revenue share and the log retail markup (defined here as retail price over wholesale price) for the 18,941 products in our sample. While there is lots of variation along both dimensions for these products and lots of omitted factors relative to the model (e.g. the fundamental parameter $\eta$, the presence of other retail marginal costs $\theta^r$ and multi-product manufacturers) there is clear evidence of a significant and positive relationship between a product's market share and its retail markup - the coefficient is 0.012 at 1% significance level. This implies some retail pricing power that is tied to the popularity of the product (otherwise the markup would be identical across products or unrelated to market share) and suggests that manufacturer markups may have a similar feature. It also corroborates the main feature of the Dornbusch (1987) model that greater market share effectively reduces the demand elasticity of these products leading to higher optimal markups, and our later analysis will show more formally that market share has a negative effect on pass-through as implied by the model.

Although we abstract from the retailer's decision regarding which categories to enter, which mode of entry (direct manufacture or simply branding) to choose and how many products to introduce, Figure 4 provides some evidence in line with the discussion earlier. Aggregating up to the category level, we find that categories in which the retailer has some manufactured private labels tend to have a higher private label market share, consistent with deeper integration leading to lower final prices. Panel A shows that retailer-manufactured private labels tend to be in higher volume categories (measured by total category-level sales) which is consistent with a minimum efficient scale of production for products that are sold

Figure 3: Market share and retail markups




Note: This figure shows the log within-category revenue share and the log retail markup (defined here as retail price over wholesale price) for the UPCs in our sample of 18,941 UPCs that appear every month during the sample period (41 months). The slope coefficient is 0.012 at 1% significance level.

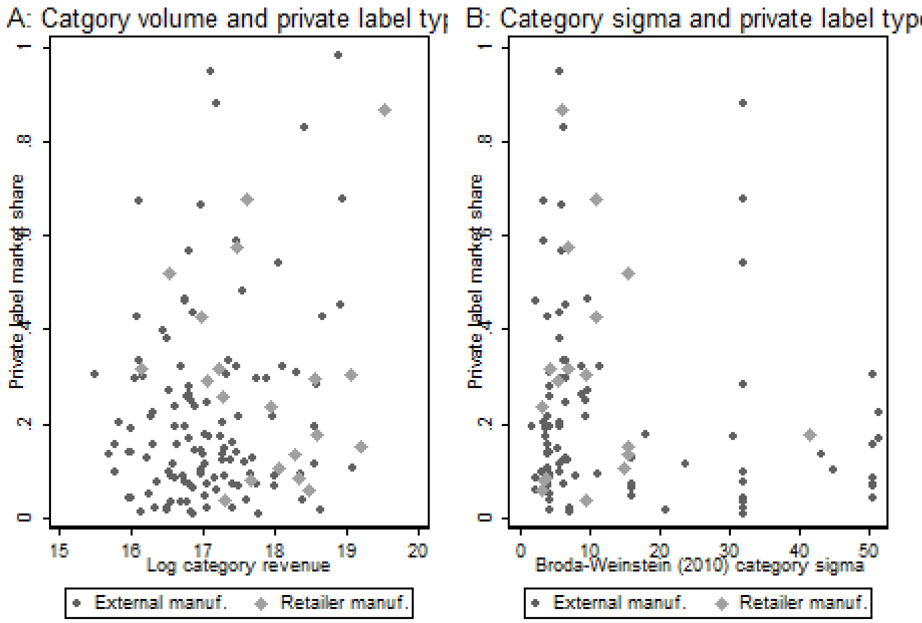
exclusively by the retailer or with a fixed cost for greater integration. Panel B links products to the demand elasticities calculated by Broda and Weinstein (2010) using Nielsen scanner data. While their elasticities are derived from a structural estimator under different preferences, it is interesting to note that in categories with lower demand elasticities (and hence greater potential double-marginalization) (i) private labels gain a higher market share and (ii) direct manufacture is more likely.

### 4.1. Pass-through: empirical approach

We first describe our general empirical approach to estimating cost pass-through. Our preferred pass-through estimator is based on a "rolling-window" regression where we regress a change in price over horizon K against a change in cost over horizon K. That is, we estimate:

$$\Delta^K logP_{i,t} = \alpha_i + \beta_i^K \Delta^K logC_{i,t} + error_{i,t} \tag{16}$$

Figure 4: Choice of vertical structure




Note: Panel A and B show that categories that have manufactured private labels tend to be in higher volume categories and also tend to have lower demand elasticities.

where $i$ is the UPC, $t$ is the month, $P$ is the price measure which is the unweighted monthly average defined in equation 14, $C$ is the cost measure, and $\Delta^K$ is the time-difference operator such that $\Delta^{12}logP_{i,t} \equiv logP_{i,t} - logP_{i,t-12}$. We perform this regression for each UPC separately at different horizons with $K = 4, 8, 12$ for the 41 months in our sample. We choose $K = 12$ or annual windows for our baseline results as our aim is to capture longer-term pass-through, and most products in our sample change prices at least once per year – price-stickiness is more of an issue when looking over shorter horizons. Our measure of pass-through is $\beta^K$, specific to a UPC and a horizon.

An alternate pass-through estimator that has been widely used in the literature (e.g. Gopinath and Itskhoki (2010), Neiman (2010), Nakamura and Zerom (2010)) uses distributed lags, as in:

$$\Delta logP_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_i^k \Delta logC_{i,t-k+1} + error_{i,t} \tag{17}$$

In this regression, we define a "long-term" pass-through for product $i$ equivalent to the one from the rolling window regression as $\beta_i^K = \sum_{k=1}^{K} \beta_i^k$. We also use values of $K = 4, 8, 12$ for this regression. The results from the distributed lag regression are qualitatively similar to those from the rolling-window regression.[21]

We use four main combinations of prices and costs for our analysis: we regress retail prices on wholesale prices, wholesale prices on commodity prices, retail prices on commodity prices, and retail prices on a wholesale price index. Note that for the regressions using commodity prices we often have multiple pass-through coefficient for a UPC corresponding to multiple commodities – for example, we look at pass-through of both dairy and sugar prices into ice-cream prices, of both wheat and corn prices into breakfast cereal prices.

The overall magnitude of cost pass-through appears to be reasonable but very heterogeneous across products and categories. Overall commodity pass-through to products is low, which leads to a substantial number of negative pass-through estimates in our sample. Similar results have been obtained in other studies of commodity pass-through (Dube and Gupta (2008), Kanishka Misra and Singh (2010)) and in studies of the transmission of exchange rate changes to at the dock import prices to consumer prices (Berger et al. (2011)). Figure 5 presents the distribution of pass-through estimates using either the rolling window or lagged specification at the twelve month horizon across UPCs.[22] This reveals very low pass-through from commodity prices to retail or wholesale prices (with many negatives but a positive median) and generally much higher pass-through from wholesale costs or the wholesale price index to retail prices (with some negatives but a substantially higher median). Our results on incomplete wholesale to retail pass-through are consistent with Eichenbaum et al. (2011), who find that *conditional* on a change in the retail "reference price" there is on average 100% pass-through of cumulated changes in "reference cost" but that reference prices frequently do not respond to reference cost changes, resulting in a 9% standard deviation of the "reference markup" for the average UPC over time.[23] When we restrict to products with positive pass-through, we find median pass-through from wholesale prices to retail prices around 70%, while pass-through from commodity prices to wholesale prices is much lower at about 5%. The combination of these effects generates pass-through from commodity to retail prices of a comparable magnitude to the pass-through from commodity to wholesale prices.[24] Pass-through from the wholesale price index to retail prices is much higher than

[21]We do not report and discuss our results using this alternative pass-through measure to save space, but they are contained in the appendix tables. We also experimented with quarterly/monthly seasonal dummies in the pass-through regressions but found that these had only minor effects on the estimated pass-through and omitted them because we have limited degrees of freedom given our short time-series.

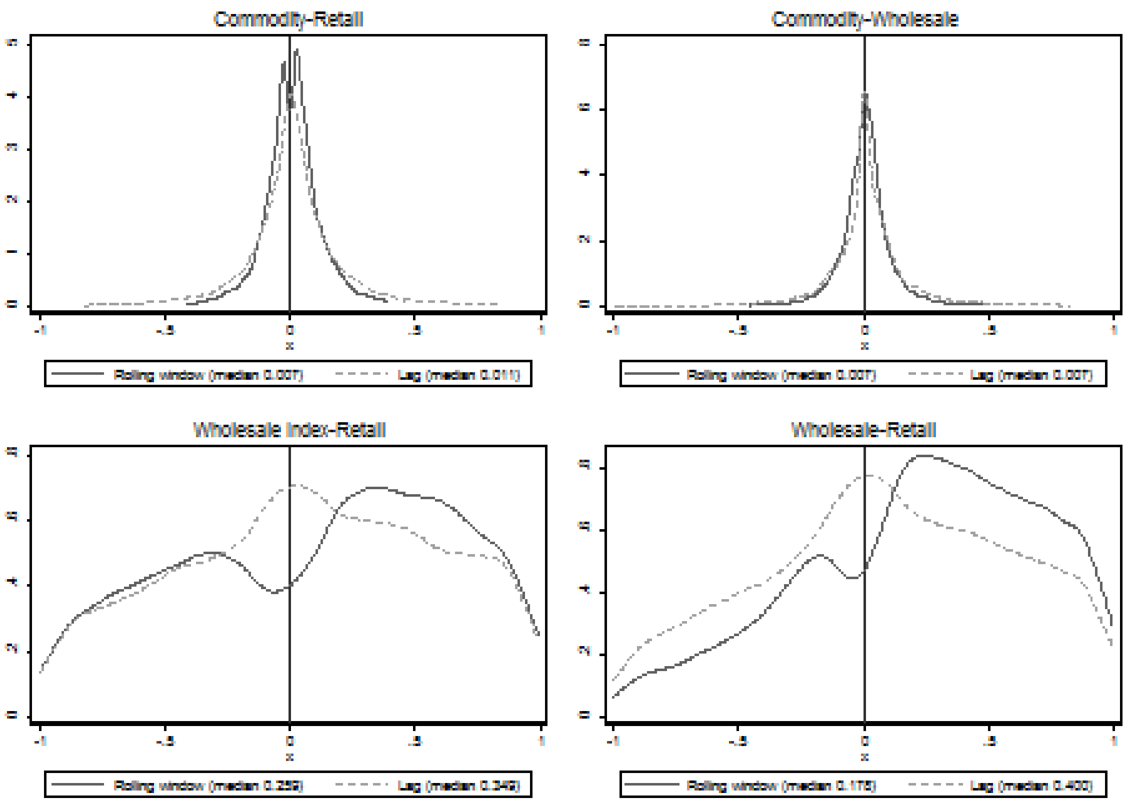
[22]Note that for commodity pass-through we sometimes have multiple commodities per UPC.

[23]For commodity to retail price pass-through 31% are positive and statistically significant at the 5% level and 25% are negative and significant. For wholesale price to retail price pass-through 48% of the coefficients are positive and statistically significant at the 5% level and 13% are negative and significant.

[24]We address the robustness of our results to the use of negative pass-through estimates in section 4.3. We have also explored specifications that allow positive and negative commodity price changes to have different effects, i.e. asymmetric pass-through. While we find that pass-through of negative cost changes is typically smaller in magnitude than pass-through of positive cost changes (similar to Kanishka Misra and Singh (2010) who look at pass-through in liquid milk), allowing for asymmetric pass-through has little impact on our main results.

for commodity prices suggesting that this may provide a better measure of aggregate cost pressures facing UPCs in a particular category, although this measure is arguably less exogenous than commodity prices in the sense that it could be driven by shocks to demand for individual products that have a large weight in a category.

Figure 5: Distribution of first-stage pass-through estimates for 12 month horizon




## 4.2. Pass-through and market structure

With product-level pass-through estimates in hand, we now address our central question – how do vertical and horizontal market structures affect product-level cost pass-through? Our main specification is a regression of the pass-through coefficient on dummies for UPCs that are manufactured or branded by the retailer together with controls for product and brand revenue share and dummies for each comparison group:

$$\begin{aligned}\ln \hat{\beta_i^K} = \alpha_{comparison} + \gamma_1 I[Retail\ Manufactured] + \gamma_2 I[Retail\ Branded] \\ + \gamma_3 Product\ RevShare_i + \gamma_4 Brand\ RevShare_i + \epsilon_i\end{aligned} \tag{18}$$

In this regression, the dependent variable $\ln \hat{\beta_i^K}$ is the estimated pass-through coefficient of item $i$ over horizon K. Note that by comparing pass-through across products within a comparison group, we are adopting a similar strategy to Amiti et al. (2013). Amiti et al. (2013) show that market share and the firm share of imported inputs (in our case, vertical structure) form a sufficient statistic for cross-section variation in pass-through within a sector-market, independently of what shocks hit the economy and the shape the dynamics of commodity prices. The definition of pass-through corresponding to our empirical exercise is the equilibrium co-movement between the price of the product and the commodity price index, not a partial equilibrium response to an exogenous change in costs, and we do not need to assume that movements in commodity prices are exogenous.

In the following tables, Table 5 to Table 7, we focus on the twelve month rolling window pass-through specification (equation 16) and begin with category dummies.[25] We include the vertical (private label) variables in column 1, the horizontal (revenue share) variables in column 2, and then both sets of variables combined in column 3 – the changes from columns 1 and 2 to column 3 reveal the "omitted variable bias" caused by considering only vertical and horizontal market structure in isolation and ignoring the interaction effects we emphasize in the model. In columns 4 through 6 we use subsubclass dummies, which should make the products very comparable, and consider the same three specifications. In column 7 we add the median (across stores and periods) price as a control variable, controlling for another dimension of product heterogeneity and one that may potentially lead to different consumers and hence different demand curvature across apparently similar products sold in the same store. Including price typically lowers the size of the vertical integration dummy but only modestly, which can be interpreted as the effect of controlling for unobserved aspects of consumer or product heterogeneity or as the effect of controlling for one of the main channels (price reduction) through which vertical integration affects pass-through. In column 8 we report results for the 4 month rolling window using the specification in column 6 – in general are results are quite similar using different horizons.[26] In this two-step estimation, the dependent variable in the second stage is a vector of estimated pass-through coefficients from the first stage, which makes heteroskedasticity is a serious concern. Following the suggestion of

[25]In the Appendix we repeat all of our main results using the pass-through estimates based on equation 17 which lead to similar qualitative conclusions.

[26]See Table 8 where we present some results for the lagged pass-through specification and using sales prices instead of regular/list prices.

Lewis and Linzer (2005), we use OLS with Eicker-White robust standard errors.[27] We later report results using alternate specifications including a one-step procedure.

The measures of product and brand share are calculated within the "comparison group" we are considering – $\alpha_{comparison}$ is a set of dummies for each group. We use all products, categories, class, subclass, and subsubclass but only report results using category and subsubclass dummies. Recall that we aggregate up comparison groups if there are no private labels in the group (e.g. we will aggregate up to "class" from "subsubclass" if there are no private labels in a particular "subsubclass" or "subclass"). When considering commodity price regressions, a "comparison group" is for a unique commodity as well, so "Quart chocolate milk/sugar" and "Quart chocolate milk/dairy" would be two separate comparison groups. Starting from our initial sample of 18,941 product-level pass-through coefficients, we drop products where there is no variation in the dependent or independent variable (resulting in $R^2 = 1$ or precisely estimated pass-through coefficients of zero) and trim the 1% tails of the pass-through distribution.

Table 5 presents the results for pass-through of wholesale prices to retail prices, the second and final link in the cost pass-through chain. The results clearly indicate that private labels have lower pass-through that is 40% to 80% lower on this dimension, with generally lower pass-through for the retailer manufactured private labels than the other private labels. Product market share has a large and substantially negative effect on this channel of pass-through – a product with a 50% market share would have pass-through over 25% lower than a product with a 1% market share – but brand share has no additional effect.[28]

Note that these effects of horizontal and market structure are exactly as predicted by the model provided that there are additional retail marginal costs ($\theta^r > 0$) and either (a)wholesale prices are lower for private labels and/or (b)the retail marginal costs are higher for private labels. This is because double-incomplete pass-through plays no role for wholesale to retail pass-through and only the retail market power (which we associate with the product market share) and the wholesale marginal cost share $\frac{w_i}{w_i+\theta_i^r}$ matter. Are these reasonable assumptions? While the size and nature of retail marginal costs over and above the wholesale cost is difficult to measure and substantiate, we know that assumption (a) is true so given any such costs our empirical result has a theoretical foundation. It is also seems reasonable to conclude that for private label goods, where the retailer takes over a larger share of distribution and

[27]Note that while weighted least squares is often used this context, following the work of Saxonhouse (1976), Lewis and Linzer (2005) find that weighted least squares often performs poorly in their simulations leading to inefficient estimates and underestimated standard errors. They suggest a feasible GLS approach that results in standard errors of the right size, and under some circumstances (a high share of the total regression variance due to sampling error) greater efficiency, but they show that OLS with Eicker-White standard errors does not lead to over or under confidence.

[28]Note that theoretically the effect of relative market share on relative pass-through is monotonic in this setting. We have explored including higher order terms in all of our specifications and find no evidence of non-monotonicity, though there is some evidence of curvature.

marketing costs, the "retail" component of marginal costs may be larger than for nationally branded goods but we cannot substantiate this directly.[29] Note also that the absence of brand share effects here is also consistent with theory in that retailers receive the multi-product firm pricing externality for all products – what matters for them in terms of retail pricing is the product share and their overall share of the local market, not the share of particular manufacturers.

In Table 6, we next turn to pass-through from commodity prices to wholesale prices, the first link in the cost pass-through chain. Note that the sample differs from the previous regressions as there are many UPCs that we do not link to any of our six commodity prices, and some UPCs can be linked to multiple commodities. We treat each pass-through separately, even for the same UPC, and compare it to similar UPCs (within a "comparison group") for the same commodity. Here we find that private label UPCs show significantly higher pass-through rates compared to national brands. The effect is larger in most specifications for the retailer manufactured goods, consistent with the theory. Without controls the pass-through for retailer manufactured goods is up to 50% higher, which falls when including category controls but rises when using subsubclass controls. Our preferred specification (column (7)) finds that retailer manufactured goods have 42% higher pass-through while retailer branded goods have 29% higher pass-through.

One of our main results is that the use of market share controls *increases* the size of the retailer brand and manufactured dummies – consistent with the model, the effects of vertical structure are larger once we control for its indirect (and partly offsetting effect) operating through horizontal structure. Comparing private labels with national brands with similar market shares isolates the part of incomplete pass-through coming from double-marginalization from the part that comes from higher market share. We also find that the direct effect of market share for this link of cost pass-through is consistent with the theory – products with larger market share have lower cost pass-through – but that this operates primarily at the brand rather than the product level, though the product coefficient remains negative.

Finally, Table 7 presents our results for overall pass-through from commodity prices to retail prices, combining both of the previous links in the cost pass-through chain. These results provide a cleaner interpretation of the overall effects of vertical and horizontal market structure on pass-through, especially given the potential non-allocativeness of the wholesale price reported for retailer manufactured goods. Our findings are consistent with theory, in that pass-through rates are substantially higher for private label goods – 11% higher for

[29]One obvious channel is distribution given the fairly widespread use of direct-store-delivery by large national brand manufacturers, but if advertising and shelf-placement have some marginal cost component then "marketing" costs broadly understood may also have this feature. Another channel is related to our observation that sales are more frequent for the private label goods – to the extent that sales represent a price discrimination tool or a technology to boost demand and sales, but require some menu cost, more frequent sales will drive up $\theta^r$.

retailer branded goods and 40% higher for retailer manufactured goods over a 12 month horizon in our preferred specification (column (7) of Panel A). Less double-marginalization increases pass-through, and this effect is larger when controlling for indirect effect of double-marginalization operating through market share. Market share also has the expected negative effect on pass-through for both product market share and brand market share, consistent with a multi-product firm version of the Dornbusch (1987) model. We also stress that the including controls for vertical structure affects estimates of the effects of market size on pass-through – since many of the products with larger market share are private labels, including private label dummies typically *increases* the negative effect of product market share on pass-through. Note that the percent changes are fairly similar at four and twelve month horizons but that the absolute effect is bigger at longer horizons where pass-through is higher. Controlling for product heterogeneity also seems to be important and has fairly large effects on the private label dummy coefficients.

Panel B of Table 7 presents results for pass-through from the wholesale price index to retail prices. This allows us to expand the sample though we only have one pass-through coefficient per UPC, and can potentially provide a better picture of common cost shocks at the category level. The results at the 12 month horizon are fairly consistent with the results for commodity prices, with 11% and 34% higher pass-through from retailer branded and manufactured goods respectively. The results for market share are similar for product market share but generally insignificant for brand market share.

Qualitatively our results are in line with our model, in that vertical structure has the expected (differential) effect on different stages of cost transmission, neglecting either the vertical or horizontal characteristic of products biases the coefficients on the other characteristic towards zero due to the interaction effect. Overall our findings suggest that on average the products in our sample behave similarly to the model under the parameters in Scenario 1 in Table 1. We also note that given our parameter estimates, at the individual product level the vertical effect of private labels dominates the horizontal effect, particularly for the retailer manufactured private labels – given the average differences in market shares of private labels and national brands in the data (see Table 4) the average private label product has higher pass-through compared to the average national brand in the same category or subsubclass. However, our results also emphasize that a rise in private labels will have a much weaker effect on pass-through when it replaces competing products with small market shares than when it gains market share at the expense of large national brands.

### 4.3. Robustness

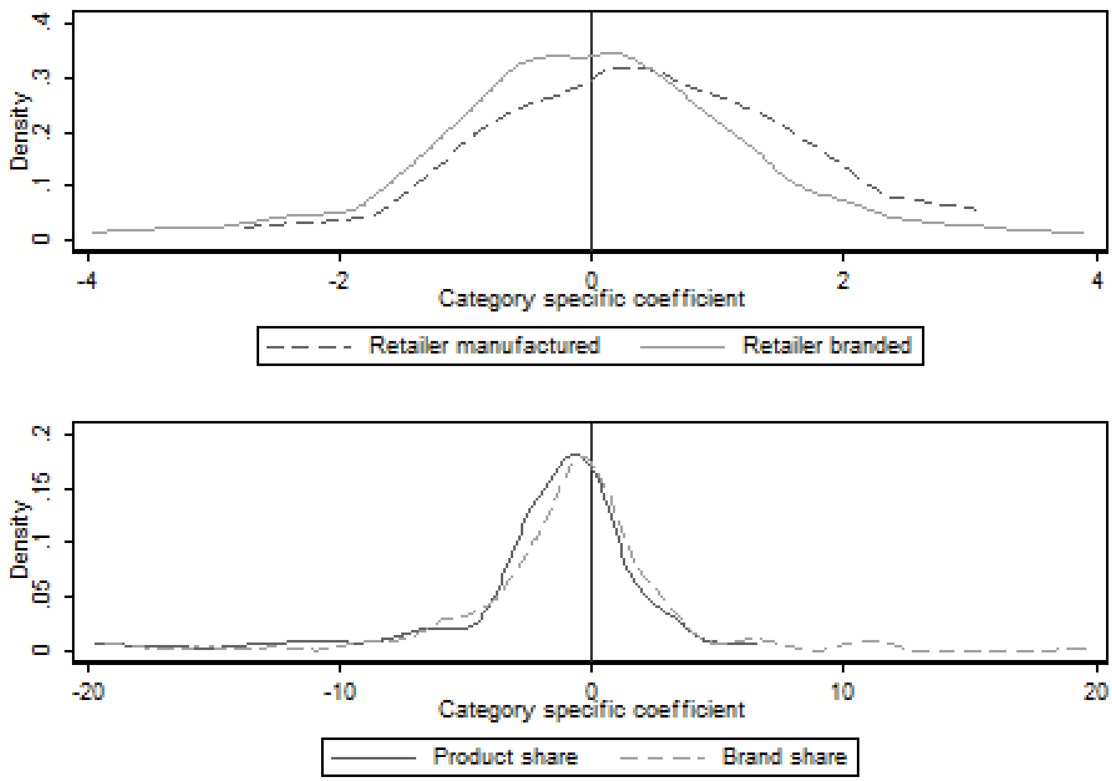
While on average the results conform to the model calibration "Scenario 1" in Table 1, there is considerable heterogeneity across categories. Figure 6 presents the distribution of estimates for the two private label dummies and the two revenue share variables from the specification in column 6 of table 7 (the 12-month rolling window commodity to regular price regression including subsubclass dummies, both private label dummies and both revenue share variables) when these are estimated category by category. While the distributions clearly indicate a general tendency for higher pass-through for private labels and lower pass-through for higher revenue shares, they also indicate that there is significant heterogeneity across product categories. This likely explains why the marketing literature often finds mixed or conflicting results regarding private labels. It also suggests that either the basic model we propose may be overly simple, or that for some product categories the commodity cost share may be lower for private labels, resulting in lower pass-through for externally manufactured private labels even conditional on market shares.[30]

In Table 8 we present several alternative specifications to address some potential concerns. In the first two columns we substitute the monthly average sales price for the monthly average regular price as the dependent variable in the first-stage pass-through regression. There is some debate in the literature about whether sales prices are important for pass-through of cost shocks – Berck et al. (2009) find some evidence that sales frequency declines when commodity prices rise but find that pass-through can be higher (cereals) or lower (chicken) when using sales prices instead of regular prices, while Anderson et al. (2013) look at a large number of product categories and find evidence that regular prices are responsive to wholesale and commodity price movements but temporary sales are not. The sales price is inclusive of all customer loyalty card discounts, coupons and rebates and temporary sales that vary by week and store (along with variable use of available discounts) leads to a much noisier monthly price series that generally co-moves with the regular price over longer horizons. Unless (a) retailers and/or manufacturers use the depth and frequency of sales (reflected in our monthly average sale price) to pass-through cost shocks to consumers over longer horizons and (b) this behavior varies systematically with vertical and horizontal market power, we would expect similar results using either price measure. Our results using sales prices are generally in line with those using the regular prices – pass-through of commodity or wholesale costs is higher for both types of private labels relative to national brands, and although the point estimates are different (and slightly higher for externally manufactured relative to retailer manufactured private labels) they are not significantly different.

In the next two columns of Table 8 we present results where we estimate pass-through separately for each of the ten retail divisions in our sample (each with a 25 store sample), which gives us variation in pass-through and market shares at the division and UPC level.

[30]Note that in our model externally manufactured private labels can never have lower pass-through conditional on market share, unless the cost shares are different. Unconditionally they could have lower pass-through if they are much higher quality (have much higher market shares conditional on price). Our model predicts that for retailer manufactured private labels the pass-through could be higher or lower than for national brands depending on the characteristics of the market.

Figure 6: Coefficients by category




The retail divisions generally correspond to a distribution center area and both retail prices and especially wholesale costs are more highly correlated within areas. Estimating multiple pass-through coefficients per UPC allows us to include UPC fixed effects in the regression and use variation in market shares for the same UPC across divisions to identify the effects of division-level market shares on pass-through. Using this entirely different source of variation provides somewhat conflicting results – while we find a substantial negative effect for the category brand share on the commodity-wholesale pass-through, the effects on commodity-retail and wholesale-retail (not reported) are positive and marginally significant at the 10% level; the effects of subsubclass product share are not statistically significant.[31] Recall that one interpretation for this finding (which is consistent with sometimes zero or positive effects for brand share in some of our main specifications using wholesale to retail pass-through) is that

[31] In Appendix table 17 we present our main specification replicated without the use of UPC dummies and find similar results for private labels as in our earlier regressions. However, we also find a positive effect of brand market share for the wholesale cost to retail price regressions.

within-store market share for national brands may be negatively correlated with the store-brand share within the local market, leading to less retail pricing power/markup and higher pass-through for popular national brands, an interpretation that finds some support using interactions (columns seven and eight) or multiple-retailer data.

In columns five and six we deal with the issue of nominal rigidity by estimating pass-through as the percent change in retail price divided by the percent change in wholesale or commodity price *conditional on a price change.* That is, we identify each price-change spell (the period between two observed price changes in our data) at the store-level and then take the average change in retail, wholesale and commodity prices across all stores and spells in our data for each UPC. We find similar negative effects of the market share variables on pass-through and similar effects of private label dummies for commodity to retail pass-through, but the private label dummies are no longer significant at the wholesale to retail pass-through channel. This suggests that the lower pass-through we observed for private labels in our earlier results is partly a function of the longer price durations (less frequent price changes) we observe in Table 11.

Finally in columns seven and eight we repeat our main specifications but include the full set of interactions between product (within subsubclass) and brand (within category) market share and the two private label dummies. The interactions are generally not significant and the non-interacted coefficients remain similar in magnitude, but the overall direction of the interaction effects hints at the possibility that the positive effect of brand share on pass-through that we sometimes observe at the wholesale to retail level is driven by national brands, where the store-level market share may be inversely related to the retailer's pricing power due to intense competition from other retail outlets.

In Table 9, we explore a different concern – are our results driven by the two-stage estimation procedure, which treats the second-stage dependent variable as data (when it is an estimate) and drops negative pass-through coefficients?[32] While it is difficult to interpret negative pass-through coefficients in the context of standard pricing models, in the empirical literature they are quite common at the product level. For example, Dube and Gupta (2008) find negative pass-through coefficients for over 10% of products when estimating wholesale cost to retail price pass-through for eleven product categories, Kanishka Misra and Singh (2010) find negative wholesale to retail pass-through for liquid milk in up to one third of estimated coefficients, and Berger et al. (2011) find negative pass-through from exchange rates to import or consumer prices for about half of the products they study. In our case, due to the low (expected) pass-through from most commodity prices to retail prices they make up a

[32]Note that the first issue is primarily about statistical significance since the two-step OLS estimator is consistent but less efficient than a one-step estimator, or a two-step estimator that weights the first-step estimates using the first-stage estimated variance-covariance matrix. As previously stated in our main results we use OLS with heteroskedasticity robust standard errors rather than weighted least squares based on the results of Lewis and Linzer (2005).

large share of our sample.

To address this concern we instead consider all products (including those with negative individual pass-through) in the subset of categories that have positive pass-through at the category level. That is, we first regress a category retail price index on the commodity indexes we initially match using the 12-month rolling window pass-through regression, and then restrict the analysis to categories with a positive and statistically significant relationship with the commodity prices. This allows for many individual products with negative pass-through and leaves us with about 7,000 product/category matches using the 1% significance level.[33] We then follow Neiman (2010) and estimate a one-step regression where the coefficients of interest are the interactions between a product's vertical and horizontal variables and the change in the cost variable:

$$\begin{aligned}\Delta^{12}\ln p_{it} = \alpha_t + \alpha_i + \beta_j\Delta^{12}\ln c_{jt} + (\gamma_1 I[Retail\ Manufactured] + \gamma_2 I[Retail\ Branded] \\ + \gamma_3 Product\ RevShare_i + \gamma_4 Brand\ RevShare_i) * \Delta^{12}\ln c_{1t} + \epsilon_{it}\end{aligned} \tag{19}$$

where $i$ and $t$ are individual products and months, $j$ is a product category or subclass by commodity pair, and $c_{jt}$ is a monthly commodity price associated with the UPC. By including UPC and month fixed effects we allow for product specific linear price trends and common shocks, and we allow pass-through to vary for each category/subclass by commodity pairing $j$. The $\gamma$ coefficients of interest are the interactions of changes in commodity prices with market share variables and dummies for private labels. We report heteroskedasticity robust standard errors.[34] While our two-step procedure omits products with negative (or zero) pass-through which could bias estimation, our one-step procedure selects based on categories and not products so should not bias us towards finding relatively higher or lower pass-through for private labels or products with larger market shares within categories.[35]

Panel A of Table 9 presents the results, which are consistent with our main finding – the retailer manufactured private label manufactured goods on average have a higher level of pass-through than national brands and externally manufactured private labels – but generally indicate a zero effect of retailer branded private labels on commodity to retail price pass-through. This is similar to some of our two-stage specifications, e.g. Table 7 columns 1 and 3 and columns 6-8 of Appendix Table 3. These results highlight the importance of distin-

[33]The results we present are robust to using a 5% significance cutoff for category-commodity pass-through, which increases the sample by roughly 1500.

[34]Where possible we also calculated Driscoll and Kraay (1998) standard errors that allow for arbitrary cross-sectional dependence of the error terms and autoregressive error terms up to order 12. Where we could calculate them, Driscoll and Kraay (1998) standard errors resulted in similar or smaller standard errors. However, perhaps due to the large number of observations and dummy variables, our software had trouble with matrix inversion and was unable to calculate Driscoll and Kraay (1998) standard errors in many cases.

[35]The composition of products with negative pass-through is fairly similar (4.3% vs. 4.8% for retailer manufactured private labels, 11.2% vs. 9.2% for externally manufactured private labels, 0.46% vs. 0.50% for average product category share and 14.3% vs. 15.1% for average brand category share).

guishing between the two types of private labels. We are able to reproduce the basic patterns from our earlier regressions for different levels of pass-through, with private labels featuring higher pass-through from commodity to wholesale prices but lower pass-through from wholesale to retail prices. Note that the magnitude of the coefficients varies more here across stages because the coefficients reflect level and not percentage differences in pass-through and pass-through is much lower for commodity prices than wholesale prices. Our results for the market share variables in Panel A of Table 9 are less consistent with our main findings, with a zero or even positive effect for product market share, and a consistently positive effect for brand share.[36] Note that a positive effect of market share implies that the combined effect of horizontal and vertical structure results in even higher pass-through for retailer manufactured private labels. Overall we conclude that our results for vertical structure are quite robust but that the effects of market share (particularly brand share) are less so, as the results using one-step estimation or using market share differences across retail chain divisions within a UPC sometimes yield positive and statistically significant pass-through coefficients for some stages of pass-through.

### 4.4. Extension to Multi-Retailer Data

Another limitation of our main results using single retailer data is that the pricing behavior we observe may be specific to a particular retailer. To address this concern, we replicate our analysis of commodity pass-through into retail prices using data from multiple retail chains – while we no longer have wholesale costs, detailed product classifications, or identification of retailer manufactured versus retailer branded private labels, and only have 13 product categories, we can now examine different measures of market share and test the generalizability of our previous results. Similar to our earlier exercise, we estimate pass-through from commodity to retail prices at the product (UPC)-chain level using monthly average prices. We take the average price for a product-chain over all of the week/store observations within a month at the MSA-level or nationally.

While we only have one definition of private label goods now, we are able to calculate several different measures of market share by MSA or nationally. These can be lumped into three broad categories:

1. The revenues of a product/brand relative to total category revenue *within a particular retail chain*: these two measures are exactly analogous to the ones we can calculate using the single-retailer data

2. The revenues of a product/brand/category sold by a particular retail chain relative to

[36]We have investigated this discrepancy and find that while part of it comes from the use of levels rather than logs, most of it is driven by products with negative estimated pass-through.

total revenue for the same product/brand/category *sold by all retail chains*: this captures the relative market power of different retailers

3. The revenues of a product/brand sold by all retail chains (hence for a particular manufacturer) relative to total category revenues for all retail chains: this captures the relative market power of different manufacturers

Otherwise the analysis is similar to earlier, and we use a two-step procedure with rolling window pass-throughs followed by regressions of chain-product (or chain-product-MSA) pass-through coefficients on the private label dummy and various market share measures described below; we also use the one-step estimation procedure described above.[37] We use several different specifications of the dummy variables for category and chain. Category dummies enter into each specification separately or interactively with chain dummies, while our MSA-level results also include MSA dummies. When considering the retail market power variables we also sometimes drop chain dummies because otherwise all identification of retailer-size/market power effects comes from relative differences across categories.

The average pass-through from commodity to retail prices using the IRI data is 11% (ranging from 5% to 20% depending on the product category) which is higher than for our retailer (median of 4.1% to 8.3% depending on the specification) but the set of products is different and there is significantly more time variation. The regression results from the second stage are reported in Table 10 for the national-level aggregation (the results for MSA-level aggregation are reported in Appendix Table 18). The market share variables described above are classified as within-chain, retailer market power and manufacturer market power respectively. The first column essentially replicates our findings for the single retailer data on the multiple retailer data including chain fixed effects; the second column uses chain-category fixed effects. Consistent with our earlier results we find higher pass-through for the private label goods – about 30% using national-level pass-throughs and about 20% using MSA pass-through, somewhere between our estimates for retailer manufactured and retailer branded private labels. Product market share has a positive effect on pass-through while brand market share has a negative effect on pass-through. Turning to the retailer market power measures in columns 3 and 4, we find that a chain's share of sales within a category lowers the retail pass-through significantly only when we do not include chain fixed effects – including chain fixed effects removes much of the variation across chains in terms of chain size and only uses variation in category/brand/product shares within chain for identification, leading to insignificant or even positive effects. Manufacturer market power results on columns 5 and 6 indicate that brands with a large market share (across all retailers in our sample) tend to have lower pass-through,

[37] In both cases we make a restriction similar to our single retailer results, which only used products that appeared in all 41 months in the sample. In this case we only used products that were sold in 66 out of 132 possible months over the sample period.

while there is little effect for individual products. Finally, the last two columns include all of our market share measures simultaneously and shows that while the magnitudes vary, the sign and significance of the coefficients is similar.

In Panel B of Table 9 we also apply the one-step procedure used with single-retailer data to our multi-retailer data. Once again we restricted to category-commodity combinations that featured positive and significant (1% level) pass-through for the category price index, but otherwise allowed for the inclusion of product-chain combinations with negative pass-through. We include product-chain-commodity fixed effects (allowing for differential price trends over the sample period) and allow pass-through to vary by category-commodity in all specifications and additionally by chain in some specifications. Overall, the results are mostly consistent with our two-step results for the effect of private labels (positive), within-chain product share (positive), category share of retailer (negative) and brand share of manufacturer (negative) but the results differ somewhat for within-chain brand share (zero in columns 1 and 2 but positive in columns 5 and 6) and product share of manufacturer (positive).

Looking at the correlations across market share measures, we find that within-chain and (across-chain) manufacturer product shares are highly positively correlated, with positive but somewhat weaker correlations with the within-chain and manufacturer brand shares. Thus the fact that we sometimes find a positive conditional effect of one or more of the four product/brand within-chain/manufacturer on pass-through could still be consistent with lower overall pass-through for that product after factoring in all of the market share measures. Moreover, and in line with our earlier conjecture, retail power tends to be lower for products that are popular overall – products like Coca-cola that have high within-store shares and high overall market shares tend to be sold in many retail outlets resulting in a lower revenue share for a particular retailer for that specific product. Thus while our overall results from both single and multiple retailer data find very strong support for higher cost pass-through for private labels (particularly at the commodity to wholesale price stage), the fact that not all market share variables have a negative effect on pass-through – as predicted by the simple oligopoly model we developed in the theory section – highlights both the potential for omitted variables that might affect demand elasticities (including both demand factors like different preferences as well as omitted supply factors like different definitions of market share) as well as the possibility that some retailers and manufacturers may use more complex pricing strategies than the simple static optimization model.

## 4.5. Price durations and sales

Finally, we examine whether price durations are related to long-term pass-through as in Gopinath and Itskhoki (2010), consistent with a fixed menu cost and larger profit loss from not adjusting prices of goods with high desired pass-through. Does the higher level of pass-through rates from commodity prices to retail prices for private label goods coincide with more flexible price movements for the private label goods? Our evidence here is somewhat mixed. Table 11 presents our results and shows that for regular prices, there is not much difference in price durations for retailer manufactured and branded goods – in fact the duration is slightly higher for retailer branded goods (3.6%). The effects of market share are also mixed, with a positive effect of product market share on duration and a negative effect of brand market share. Our pass-through results suggest that durations should be higher for goods with higher market share (and lower pass-through). Some of this ambiguity may arise because the source of cost shocks to retailers matters for the effect of the private label dummy on pass-through – the effect is negative for wholesale prices but positive for commodity prices, so the precise size and distribution of cost shocks arising from these two different sources may matter. We also cannot rule out that menu costs differ for private label and national brands, which would break the link posited in Gopinath and Itskhoki (2010).

When we turn to sales prices and wholesale costs, we find that sales price durations are 40% shorter for retail manufactured goods and 30% lower for retailer branded goods, while wholesale cost durations are 30% lower for retailer manufactured goods and 60% lower for retailer branded goods. An increase in market share on sales price duration reduces the price duration or increases the frequency of sales price changes. This is opposite to the theoretical link between pass-through rates and frequency of price changes in the model which shows an increase in market share lowers the pass-through rate which may also leads to higher duration given the duration of the cost. To understand this finding we turn to the recent literature arguing that sales price-setting mechanisms and motives are different from regular price setting mechanisms and motives by nature, which results in different cyclical properties (Coibion et al. (2012), Anderson et al. (2013)). Interestingly, our finding is consistent with a story in which sales are not used for cost pass-through but rather as part of a price discrimination scheme by retailers. Guimaraes and Sheedy (2011) and Chevalier and Kashyap (2011) consider models where retailers face different types of consumers with different demand elasticities, with some consumers acting as price-sensitive “bargain-hunters” and others as less price-sensitive “loyals.” Given that private label goods are typically cheaper than national brand goods, and the retailer manufactured ones are even cheaper than the externally-manufactured ones, the higher ratio of price-sensitive consumers who prefer private label brands may increase the incentive of the retailer to offer frequent sales.

## 5. Macroeconomic implications

## 5.1. Cyclicality

While the rise in private label brands in the US market is part of a longer secular trend that is likely related to retail consolidation and may eventually lead to convergence with European levels of private label market share, Figure 1 hints that private label share may also be driven by demand-side considerations over the business-cycle, with households substituting towards "better value" private label alternatives to national brands.

To examine the cyclical sensitivity of private label market shares, we use the store-time panel dimension of our data, aggregating products across our product categories to form an aggregate store/month level private label market share from 2004 to 2007. We regress this measure of private label share on a local zipcode level measure of median household income from the 2000 Census and local (MSA or county level) measures of time-varying gas prices and unemployment rates; following Gicheva et al. (2010) we interpret a rise in gas prices as a negative disposable income shock to households given the very low price elasticity of gasoline.

Table 12 presents our results. The mean private label share for our sample stores is 0.24 (standard deviation 0.07). Most of the variation is cross-sectional, across stores. While private label shares vary over time during our sample period, this variation is small. The first column presents the cross-section from the first month of 2004, and reveals that our three variables explain 21% of the cross-sectional variation. For our retailer, private label goods seem to be inferior in the sense that lower income leads to substitution towards them and away from national brands. These effects are quite large – doubling local incomes lowers the private label share by 8 percentage points and doubling gas prices raises the private label share by 13.5 percentage points. One extra percentage point of unemployment raises the private label share by 0.43 percentage points. These effects are generally smaller when we use the time-series variation as well in column 2. When we control for store and month fixed effects, the impacts of unemployment and gas prices are smaller still but they remain statistically significant. Going from the lowest to highest county-level unemployment rate in our sample would raise the private label share by 4 percentage points (0.2 x 0.211) while going from the lowest to highest gas price raises private label share by 1 percentage point (1 log point x 0.01).

Given our earlier findings on the greater pass-through of private labels compared to national brands, our results suggest that the types of cyclical shifts in private label share we observe in the data – around 4 percentage points based on Figure 1 and Table 12 – could increase commodity to retail pass-through by about 1.2 percent (4 x 0.3). While this effect strikes as quite small (absent other estimates of the cyclicality of commodity price pass-through), it suggests that retail prices should be more sensitive to input costs during recessions and less sensitive during booms due to this demand channel, a novel implication to the best of our knowledge.

Moreover, the much larger trend and cross-sectional differences in private label market share observed in the US and Europe could have much bigger effects. We explore some of these cross-sectional in the next subsection.

### 5.2. Cross-country commodity pass-through and private labels

While the market share of private label goods does not vary enough over the business cycle to have substantial implications for the cyclicality of pass-through, the market share of private label goods varies significantly over longer horizons and across countries. Around 2009 the private label market share for supermarkets varies from as high as 46% in Switzerland or 42% in the United Kingdom to as low as 15% in Italy, 10% in Iceland and Romania and 4% in Bulgaria.[38] For the 18 European countries we could match with comparable market share data (we use the CR5, the market share of the five largest supermarket chains) the correlation of private label shares with market concentration is 0.50 (s.e. 0.04). Our micro estimates indicate that the net effect of a higher private label share could go either way when private labels are also associated with greater market power as appears to be the case in Europe, particularly since most private label goods in Europe are not manufactured directly by the retailer.

To explore whether this has any implications for pass-through we use data from the Eurostat Food supply chain monitor, which collects monthly consumer prices, producer prices, and agricultural commodity prices for 32 European countries in 17 categories between January 2005 and March 2013. Some of the categories are composites of others, and we focus on 11 distinct (non-overlapping categories) – beef, bread and cereals, cheese, eggs, fruit, milk, oils and fats, pork, poultry, confectionery, and vegetables. Note that the database tries to match the most important commodity to each category. We found private label market share data for 22 countries at the country level for the year 2009, so our final sample consists of 22 countries in up to 11 categories. We also estimate commodity to producer price pass-through regressions but due to lack of data we can only include 7 countries and 10 categories for these regressions.

To examine whether the private label shares are correlated with the strength of pass-through we pool the countries ($i$) and categories ($j$) and run the following regression:

$$\Delta^T \ln p_{ijt} = \alpha_t + \alpha_{ij} + \beta_j \Delta^T \ln c_{ijt} + \gamma \Delta^T \ln c_{ijt} * plshare_i + \epsilon_{ijt} \quad (20)$$

where $t$ is month and $T$ is the horizon over which we are differencing. We consider a twelve month horizon for comparability with our earlier micro results as well as one month changes. This specification allows average inflation within a category to vary by country and

[38]Sources: Nielsen, IGD, Business Review (Romania), USDA FAS (Bulgaria).

allows for common time-varying price shocks across countries/categories. It also allows for differential pass-through rates across categories ($\beta_j$ varies with $j$). Our focus is on estimating the common "average" effect of the country private label share on commodity to retail price pass-through (the coefficient $\gamma$). The results are presented in Table 13. We use Driscoll and Kraay (1998) standard errors that allow for arbitrarily correlated error terms in the cross-section and autoregressive errors up to twelve lags.

Our results show that private label share is associated with lower pass-through of commodity prices to consumer prices across the European countries in our sample for the period and categories we study (Panel A). A one standard deviation increase in the private label share from 0 to 0.1 would lower the pass-through from 0.044 for the mean category to 0.028 for the twelve month pass-through and from 0.102 to 0.077 for the one month pass-through. The higher commodity pass-through over shorter (1 month) than longer (12 month) horizons is different than our results for the US retailer, but it is important to keep in mind that the consumer prices here are indexes/aggregates across different products and retailers – overall commodity pass-through is still quite low. Similar to our micro results, the effects appear to be heterogeneous across categories – while no categories have a significant and positive coefficient on the interaction of commodity price and private label share, only four categories (bread and cereals, fruit, milk, and vegetables) had a negative and significant coefficient at the 5% level, indicating that the country-level private label share was negatively associated with pass-through across countries. Turning to producer prices, we see a positive association of private label share with pass-through from commodity to producer prices. Taken together, these results are consistent with story in which European countries with highly concentrated retail sectors have a large role for private label goods resulting in low market power for producers (high pass-through of their cost shocks) and high market power for retailers (low pass-through to final consumers). We view these results as suggestive but hope to more fully explore the cross-country implications of vertical and horizontal structure in retail in future work as more micro data becomes available.

### 5.3. Discussion

Our results for the macro implications of retail market structure have many parallels to the international trade literature on vertical integration and pricing. While the available data do not reveal significant changes at business cycle frequencies, when we look across countries and over longer horizons there have been significant changes in the vertical organization of relationships between sellers and buyers. While our micro-level findings and those of Neiman (2010) suggest that a rise in vertical integration could raise pass-through by reducing double-marginalization created by the market power of upstream firms, our results for market share and those from a separate international trade literature imply that interactions between vertical and horizontal market structure are critical. If rising private label penetration and rising intra-firm trade are associated with greater market power for downstream firms, which appears to be the case for retail, it is not obvious theoretically or empirically whether pass-through will increase or decrease. Indeed the rise in intra-firm trade in the United States appears to coincide with a decrease in the pass-through of exchange rates to import prices, and the rise in private labels that accompanies greater market power for retailers appears to be associated with lower pass-through of commodity prices across European countries.

Before concluding, we briefly discuss some testable hypotheses about the macroeconomic forces that shape private label market share based on our empirical findings. First, the longer-run evolution of market share for private label goods – rising in the United States and Canada, very high in some advanced European economies, and generally much lower in Asia and the developing world – is consistent with changes in technology, particularly scale effects associated with retail consolidation and advances in supply-chain management and marketing technologies. The relatively small scale and limited managerial capacities of the retail sector in lower income countries is likely to be a major impediment to the introduction and growth of private label store brands. Low private label share in middle-income and developing countries may also be related to legal and regulatory policies that limit foreign direct investment or retail consolidation. These size constraints are likely to be relaxed as distribution, marketing, and managerial technology improves in these countries and the legal and regulatory policies converge towards what we observe in the rich, advanced economies. Regardless of the precise source of this ongoing evolution of private label market share, the implication of this supply-driven phenomenon is that manufacturers will lose market power resulting relative to retailers, which our results indicate could have ambiguous effects on pass-through and potentially the frequency of price adjustment because vertical integration driven by the growing horizontal market power of retailers generates countervailing effects.

Second, the inflationary aspect of commodity price pass-through into retail prices has received more attention during the recent period of volatility associated with the Great Recession. In general, the relevance of commodity prices as a reliable source of inflation forecasting is still under debate. While there are empirical studies that show the lack of a meaningful relationship between commodity price movements and core inflation since 1980s in the United States (for instance, Evans (May 2011)), other recent studies also suggest a prominent role for commodity prices in predicting a broad set of macroeconomic and financial variable (see Edelstein (2007)) and there is substantial micro evidence. The sharp increases in commodity prices – especially food and energy – account for most of the rising inflation in emerging market economies for a variety of reasons.[39] An obvious explanation for the greater inflationary pressure from commodity prices in developing countries is that the share of household ex-

[39]See http://www.imf.org/external/np/seminars/eng/2011/lic/index.htm for reports and discussion from the International Monetary Fund.

penditures on food and energy are greater in low-income countries. As countries get richer, the food and energy share in the consumption basket may fall, lowering the sensitivity of inflation to commodity prices. However, our findings suggest that as countries get richer the growth in private label brands may partly offset this effect by increasing commodity price pass-through within narrow food categories, unless this is accompanied by rising horizontal market power. Our findings also suggest that commodity price pass-through may be more counter-cyclical than otherwise due to the private label margin but this effect is small. Furthermore, even if firms prefer not to alter regular prices in response to rising commodity and energy prices due to reputation concerns or staggered contracts, pressure from consumers during bad states of the economy may incentivize firms to implement more frequent and deeper sales.[40]

## 6. Conclusion

We provide evidence on the effects of horizontal and vertical market structure on two links of the commodity to retail price pass-through chain. Our evidence is generally consistent with the previous literature – greater double-marginalization reduces pass-through (vertical effect) and firms with larger market shares have lower pass-through (horizontal effect). However, we stress that the interaction of these two effects is important; since reducing double-marginalization simultaneously increases pass-through directly while increasing market share, the positive effect of greater control of the value chain by the downstream party on pass-through is larger when conditioning on market share. We also show that accounting for multi-product firms is important for estimating the effects of horizontal market structure and that the effects of vertical integration on pass-through hold when considering two allocative prices in lieu of an intra-firm price. Finally, while the effects of vertical structure on commodity to retail price pass-through are quite large – 10% higher for retailer branded private labels and 40% higher for retailer manufactured brands – the cyclicality of the private label share appears quite modest. Thus the channel we study suggests that cost pass-through will be higher during recessions (with higher private label share) and lower during booms but this effect is modest given the observed cyclical fluctuations of private label revenue share which is about 4 percentage points.

Our findings suggest several avenues for future research. While the cyclical macro effects we identify are modest, longer-term trends in retail consolidation and market power generate much larger differences in private label shares, most notably in the large differences across countries. Several European countries have private label shares around 50%. While this would seem to suggest a much higher pass-through rate, our results on the interplay be-

[40]See Coibion et al. (2012).

tween horizontal and vertical structure highlight the danger of considering only one of these channels. If private label dominance in Europe is driven by huge market shares of the retailer brands, this anti-competitive effect could potentially reduce pass-through. Understanding how the forces we identify in this paper contribute to differences in commodity price pass-through across countries is thus a promising direction. Similarly, our results are likely to be relevant in an international context where existing studies have typically examined only horizontal or vertical structure in isolation. The rise of intra-firm transactions highlighted in Neiman (2010) is undoubtedly an important part of the story, but the general trend of declining exchange rate pass-through into US import prices seems to pose a puzzle in this regard. This puzzle could potentially be resolved by recognizing that the rise of intra-firm transactions is connected to the growth and dominance of large multinational corporations that have sufficient market share that their pass-through is lower, as in Berman et al. (2011). While many of the existing trade micro data sets have limitations in terms of measuring horizontal market structure (lacking quantity data or multi-product firm identifiers) we believe this is another track worth pursuing. Vertical integration in an international context takes numerous forms, so being able to parse out the importance of distribution and marketing aspects of production from production aspects would also be interesting. Finally, we provide some preliminary evidence that private label sales frequency is higher than for national brands. We speculate that this may be a feature of menu cost technology and the nature of retailer-manufacturer contracts and promotions, or may be the result of optimal price discrimination by the retailer given heterogeneous consumers. We would like to explore why this is the case and its implications for price rigidity over the business cycle and over the long-term.

## References

Amiti, Mary, Oleg Itskhoki, and Jozef Konings, "Importers, Exporters, and Exchange Rate Disconnect," *Working Paper*, 2013.

Anderson, Eric, Emi Nakamura, Duncan Simester, and Jon Steinsson, "Informational Rigidities and the Stickiness of Temporary Sales," *Working Paper*, 2013.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 2008, *98(5)*, 1998–2031.

Auer, Raphael and Raphael Schoenle, "Market Structure and Exchange-Rate Pass-Through," *Swiss National Bank Working Papers*, 2012, *2012-14.*

Bailliu, Jeannine and Hafedh Bouakez, "Exchange Rate Pass-Through in Industrialized Countries," *Bank of Canada Review Article*, 2004.

Batra, R. and I. Sinha, "Consumer-level factors moderating the success of private label brands," *Journal of Retailing*, 2000, *76* (2), 175–191.

Berck, Peter, Ephraim S Leibtag, Alex Solis, and Sofia Berto Villas-Boas, "Patterns of Pass-through of Commodity Price Shocks to Retail Prices," *American Journal of Agricultural Economics Papers and Proceedings*, 2009, *91(5)*, 1456–1461.

Berger, David, Jon Faust, John H. Rogers, and Kai Steverson, "Border prices and retail prices," *Journal of International Economics*, 2011, *88*, 62–73.

Berman, Nicolas, Philippe Martin, and Thierry Mayer, "How do different exporters react to exchange rate changes? Theory and empirics," *Quarterly Journal of Economics*, 2011, *127(1)*, 4437–4493.

Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott, "Transfer pricing by U.S.-based multinational firms," *NBER Working Paper Series*, 2006, *w12493.*

Besanko, David, Jean-Pierre Dube, and Sachin Gupta, "Own-Brand and Cross-Brand Retail Pass-Through," *Marketing Science*, 2005, *24(1)*, 123–137.

Broda, Christian and David E. Weinstein, "Product Creation and Destruction: Evidence and Price Implications," *American Economic Review*, 2010, *100(3)*, 691–723.

Bronnenberg, Bart, Michael Krueger, and Carl Mela, "Database Paper: The IRI Marketing Data Set," *Marketing Science*, 2008, *27(4)*, 745–748.

Burstein, Ariel and Nir Jaimovich, "Understanding Movements in Aggregate and Product-Level Real-Exchange Rates," *Unpublished*, 2009.

Chevalier, Judith A. and Anil K. Kashyap, "Best Prices," *NBER Working Paper*, 2011, *w16680.*

Chevalier, Judith, Anil Kashyap, and Peter Rossi, "Why Don't Prices Rise During Periods of Peak Demand?," *American Economic Review*, 2003.

Chintagunta, Pradeep and Andre Bonfrer, "Store Brands: Who Buys Them and What Happens to Retail Prices When They Are Introduced?," *Review of Industrial Organization*, 2004, *24(2)*, 195–218.

_ , _ , and Inseong Song, "Investigating the Effects of Store-Brand Introduction on Retailer Demand and Pricing Behavior," *Management Science*, 2002, *48(10)*, 1242–1274.

Clausing, Kimberly, "Tax-Motivated Transfer Pricing and U.S. Intrafirm Trade Prices," *Journal of Public Economics*, 2003, *87(9)*, 2207–2223.

Coibion, Olivier, Yuriy Gorodnichenko, and Gee Hee Hong, "The Cyclicality of Regular, Sales and Effective Prices: Business Cycle and Policy Implications," *NBER Working Paper Series*, 2012, *w18273.*

Dornbusch, Rudiger, "Exchange Rates and Prices," *American Economic Review*, 1987, *77*, 93–106.

Driscoll, J.C. and Aart C. Kraay, "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data," *Review of Economics and Statistics*, 1998, *80*, 549–560.

Dube, Jean-Pierre and Sachin Gupta, "Cross-Brand Pass-Through in Supermarket Pricing," *Marketing Science*, 2008, *27(3)*, 324–333.

Edelstein, Paul, "Commodity Prices, Inflation Forecasts, and Monetary Policy," *Working Paper*, 2007.

Eichenbaum, Martin, Nir Jaimovich, and Sergio Rebelo, "Reference Prices, Costs, and Nominal Rigidities," *American Economic Review*, 2011, *101(1)*, 234–262.

Evans, Charles, "What are the implications of rising commodity prices for inflation and monetary policy?," *Chicago Fed Letter*, May 2011, *286.*

Frankel, Jeffrey, David Parsley, and Shang-Jin Wei, "Slow Passthrough Around the World: A New Import for Developing Countries?," *NBER Working Paper Series*, 2005.

Gagnon, Etienne, Benjamin Mandel, and Rob Vigfusson, "Don't Panic: The Hitchhiker's Guide to Missing Import Price Changes," *Working Paper*, 2011.

Gagnon, Joseph and Jane Ihrig, "Monetary Policy and Exchange Rate Pass-Through," *Board of Governonrs of the Federeral Reserve System, International Finance Discussion Paper*, 2002, *2001-704.*

Gicheva, Dora, Justine Hastings, and Sofia Berto Villas-Boas, "Revisiting the Income Effect: Gasoline Prices and Grocery Purchases," *American Economic Review Papers and Proceedings*, 2010, *100(2)*, 480–484.

Goldberg, Pinelopi K and Rebecca Hellerstein, "A Structural Approach to Identifying the Source of Local-Currency Price Stability," *Working Paper*, 2011.

Gopinath, Gita and Oleg Itskhoki, "Frequency of Price Adjustment and Pass-through," *Quarterly Journal of Economics*, 2010.

— and Roberto Rigobon, "Sticky Borders," *Quarterly Journal of Economics*, 2008, *123 (May)*, 531–575.

—, Oleg Itskhoki, and Roberto Rigobon, "Currency Choice and Exchange Rate Pass-Through," *American Economic Review*, 2010, *100(1)*, 304–336.

—, Pierre-Olivier Gourinchas, Chang-Tai Hsieh, and Nicholas Li, "International Prices, Costs, and Markup Differences," *American Economic Review*, 2011, *101*, 1–40.

Guimaraes, Bernardo and Kevin D. Sheedy, "Sales and Monetary Policy," *American Economic Review*, 2011, *101(2)*, 844–76.

Hastings, Justine, "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California," *American Economic Review*, 2004, *94(1)*, 317–328.

Hastings, Justine S. and Richard J. Gilbert, "Market Power, Vertical Integration and the Wholesale Price of Gasoline," *Journal of Industrial Economics*, 2005, *53(4)*, 469–492.

Hellerstein, Rebecca and Sofia Berto Villas-Boas, "Outsourcing and Pass-through," *Journal of International Economics*, 2010, *81*, 170–183.

Hoch, S.J. and S. Banerji, "When do private labels succeed?," *Sloan Management Review*, 1993, *34*, 57–57.

Kadiyali, Vrinda, Pradeep Chintagunta, and Naufel Vilcassim, "Manufacturer-Retailer Channel Interactions and Implications for Channel Power: An Empirical Invetsigation of Pricing in a Local Market," *Marketing Science*, 2000, *19(2)*, 127–148.

Kehoe, Patrick and Virgiliu Midrigan, "Temporary price changes and the real effects of monetary policy," *Federal Reserve Bank of Minneapolis Working Paper*, 2008, *661.*

Lamey, Lien, Barbara Deleersnyder, Marnik G. Dekimpe, and Jan0Benedict E.M. Steenkamp, "How Business Cycles Contribute to Private-Label Success: Evidence from the United States and Europe," *Journal of Marketing*, 2007, *71*, 1–15.

Lewis, Jeffrey B. and Drew A. Linzer, "Estimating Regression Models in Which the Dependent Variable Is Based on Estimates," *Political Analysis*, 2005, *13*, 345–364.

Misra, Romana Khan Kanishka and Vishal Singh, "Asymmetries and Dynamics of Cost pass through in the US Milk Market," *Working Paper*, 2010.

Nakamura, Emi, "Pass-Through in Retail and Wholesale," *American Economic Review*, 2008, *98*, 430–437.

— and Dawit Zerom, "Accounting for Incomplete Pass-Through," *Review of Economic Studies*, 2010, *77(3)*, 1192–1230.

— and Jon Steinsson, "Five Facts About Prices: A Re-evaluation of Menu Cost Models," *Quarterly Journal of Economics*, 2008, *123 (November)*, 1415–1464.

— and — , "Lost in Transit: Product Replacement Bias and Pricing to Market," *American Economic Review*, 2012, *102(7)*, 3277–3316.

Neiman, Brent, "Stickiness, Synchronization, and Passthrough in Intrafirm Trade Prices," *Journal of Monetary Economics*, 2010, *57(3)*, 295–308.

— , "A State-Dependent Model of Intermediate Goods Pricing," *Journal of International Economics*, 2011.

Nijs, Vincent, Kanishka Misra, Eric T. Anderson, Karsten Hansen, and Lakshman Krishnamurthi, "Channel Pass-Through of Trade Promotions," *Marketing Science*, 2009, *Online*, 1–18.

Putsis, Jr. William P., "An Empirical Study of the Effect of Brand Proliferation on Private Label - National Brand Pricing Behavior," *Review of Industrial Organization*, 1997, *12*, 355–371.

Raju, J.S., R. Sethuraman, and S.K. Dhar, "The introduction and performance of store brands," *Management Science*, 1995, pp. 957–978.

Saxonhouse, Gary, "Estimated Parameters as Dependent Variables," *American Economic Review*, 1976, *66*, 178–183.

Spengler, Joseph J., "Vertical Integration and Antitrust Policy," *Journal of Political Economy*, 1950, *50(4)*, 347–352.

Sudhir, K., "Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer," *Marketing Science*, 2001, *20(3)*, 244–264.

Villas-Boas, Sofia and Rebecca Hellerstein, "Identification of Supply Models of Retailer and Manufacturer Oligopoly Pricing," *Economics Letters*, 2006, *90(1)*, 132–140.

— and Ying Zhao, "Retailer, Manufacturers and Individual Consumers: Modeling the Supply Side in the Ketchup Market Place," *Journal of Marketing Research*, 2005, *42*, 83–95.

Villas-Boas, Sofia Berto, "Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data," *Review of Economic Studies*, 2007, *74(2)*, 625–652.

Weinhagen, Jonathan, "An empirical analysis of price transmission by stage of processing," *Monthly Labor Review*, 2002, *November*, 3–11.

Wood, Steve, "Revisiting the US food retail consolidation wave: regulation, market power and spatial outcomes," *Journal of Economic Geography*, 2013, *13*, 299–326.

Table 1: Model simulations

| Case | Price | Share | $\frac{\partial p}{\partial w}\frac{w}{p}$ | $\frac{\partial p}{\partial c}\frac{c}{p}$ |
|---|---|---|---|---|
| Scenario 1: $p_z = 50$ | | | | |
| NB | 79.59 | 0.554 | 0.559 | 0.021 |
| PL-NVI | 76.57 | 0.582 | 0.484 | 0.024 |
| PL-VI | 45.70 | 0.868 | 0.302 | 0.027 |
| Constant market share | | | | |
| PL-NVI | 60.63 | 0.554 | 0.484 | 0.030 |
| PL-VI | 22.71 | 0.554 | 0.495 | 0.045 |
| Scenario 2: $p_z = 25$ | | | | |
| NB | 43.52 | 0.431 | 0.627 | 0.037 |
| PL-NVI | 41.06 | 0.475 | 0.490 | 0.044 |
| PL-VI | 28.74 | 0.725 | 0.386 | 0.035 |
| Constant market share | | | | |
| PL-NVI | 35.88 | 0.431 | 0.497 | 0.050 |
| PL-VI | 20.62 | 0.431 | 0.573 | 0.052 |
| Scenario 3: $p_z = 10$ | | | | |
| NB | 26.60 | 0.175 | 0.777 | 0.070 |
| PL-NVI | 24.68 | 0.210 | 0.551 | 0.079 |
| PL-VI | 19.63 | 0.346 | 0.627 | 0.057 |
| Constant market share | | | | |
| PL-NVI | 23.82 | 0.175 | 0.561 | 0.083 |
| PL-VI | 18.25 | 0.175 | 0.735 | 0.067 |

Note: All simulations use $eta = 4$, $c = 1$, and $\theta_r + \theta_m = 12$.The first three cases in each scenario use $d = 4$ while the constant market share cases vary $d$ to match the market share of the $NB$ case under that scenario. Under NB there is arm's-length pricing but $\theta_r = 2$ and $\theta_m = 10$, while under PL-NVI there is arm's-length pricing but $\theta_r = \theta_m = 6$. Under PL-VI there is full vertical integration. The pass-through is calculated based on a 0.1% increase in the commodity price, i.e. $c$ increases to 1.001.

Table 2: Treatment of Missing Values

| | • | • | • | X | X | • | • | • |
|---|---|---|---|---|---|---|---|---|
| Time | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Price | 2 | 1 | 1 | | | 1 | 1.5 | 1.4 |
| Spell1 | 1 | 2 | 2 | | | 2 | 3 | 4 |
| Spell2 | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 4 |

Note: The dots represent the observations that are missing from the data set, while the crosses represent the observations in the data set. Spell1 counts value at t=6 as the same price spell as the spell before the missing values, but missing values are not counted as part of the spell. Spell2 is similar to Spell1, but differs in that Spell2 takes the missing values as part of the spell. Naturally, prices seem to be stickier using Spell2 than Spell1.

Table 3: Duration of prices and costs (weeks)

| Spell1 | | |
|---|---|---|
| | Mean | Median |
| Regular Price | 25.85 | 26.4 |
| Sales Price | 8.27 | 3.97 |
| Wholesale Cost | 23.39 | 21.48 |
| Spell2 | | |
| Regular Price | 30.24 | 31.82 |
| Sales Price | 10.13 | 5.16 |
| Wholesale Cost | 27.67 | 26.71 |

Note: The sample is restricted to UPCs that appear every month from January 2004 to May 2007 (41 months) and product categories that contain both national brands and private label goods. Depending on our measure of price spells, the regular price changes every 6-8 months. Our Spell2 measure of median sales price duration is comparable to Kehoe and Midrigan (2008) who report sales price durations of 3 weeks using a grocery store data set. Regular price spells are shorter than Nakamura and Steinsson (2008) (10 to 12 months)) and import data (Gopinath and Rigobon (2008) find a median price duration 10.6 months for imports and 12.8 months for exported goods), but longer than Kehoe and Midrigan (2008) that uses Dominick's supermarket data set.

Table 4: Summary Statistics: Private Label Goods, National Brands

| | | Single-Retailer Data | | | Multi-Retailer Data | |
|---|---|---|---|---|---|---|
| | | Manufactured PL | Branded PL | NB | PL | NB |
| Number of UPCs | | 674 | 2,314 | 15,953 | 13,533 | 32,786 |
| Number of UPCs in a subsubclass | Median | 5 | 5 | 13 | | |
| | Mean | 10.6 | 6.7 | 23.1 | | |
| Number of UPCs in a category | Median | 64 | 33 | 188 | 1,214 | 1,890 |
| | Mean | 64.3 | 43.6 | 237.9 | 1,353 | 3,279 |
| Product RevShare in a subsubclass (%) | Median | 6.8 | 4.6 | 2.8 | | |
| | Mean | 17.9 | 11.9 | 10.5 | | |
| Brand RevShare in a subsubclass (%) | Median | 62.4 | 35.2 | 29.0 | | |
| | Mean | 62.9 | 44.5 | 35.5 | | |
| Product RevShare in a category (%) | Median | 0.3 | 0.3 | 0.1 | 0.1 | 0.1 |
| | Mean | 0.8 | 0.9 | 0.5 | 0.3 | 0.2 |
| Brand RevShare in a category (%) | Median | 28.6 | 21.2 | 4.0 | 10.6 | 9.7 |
| | Mean | 35.8 | 28.6 | 12.8 | 19.5 | 17,9 |
| Ratio of regular price (PL/NB) in a subsubclass | Median | 0.73 | 0.79 | | | |
| | Mean | 0.73 | 0.84 | | | |
| Ratio of wholesale cost (PL/NB) in a subsubclass | Median | 0.52 | 0.58 | | | |
| | Mean | 0.58 | 0.94 | | | |
| Chain RevShare in a category (%) | Median | | | | 1.0 | 1.0 |
| | Mean | | | | 1.0 | 1.0 |
| Brand-Chain Rev/Brand Rev (%) | Median | | | | 1.1 | 1.0 |
| | Mean | | | | 1.0 | 2.3 |
| Product-Chain Rev/Product Rev (%) | Median | | | | 2.4 | 1.0 |
| | Mean | | | | 9.8 | 3.7 |
| Product RevShare in a category (%) | Median | | | | 0.01 | 0.03 |
| | Mean | | | | 0.16 | 0.16 |
| Brand RevShare in a category (%) | Median | | | | 9.0 | 10.1 |
| | Mean | | | | 13.1 | 18.5 |

Note: The single retailer data sample is restricted to UPCs that appear every month from January 2004 to May 2007 (41 months) and categories that contain both national brands and private label goods (minimum 1% revenue share). This leaves 155 product categories and 4,472 subsubclasses. For duration calculation we report measures using 'spell2.' The multi-retailer data covers from January 2001 to December 2011 (132 months). The summary statistics are of UPCs from a category that contain both national brands private label goods (minimum 1% revenue share), with 11 product categories.

Table 5: Retail Price and Wholesale Cost Pass-through

| Dependent Variable (Log Pass-through of Wholesale Cost to Regular Price) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Window | 12 months | | | | | | | 4 months |
| Median | 0.695 | | | | | | | 0.569 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | -0.394*** | | -0.404*** | -0.810*** | | -0.799*** | -0.815*** | -0.632*** |
| | (0.071) | | (0.074) | (0.089) | | (0.095) | (0.096) | (0.084) |
| RetailBranded | -0.437*** | | -0.443*** | -0.506*** | | -0.511*** | -0.523*** | -0.472*** |
| | (0.038) | | (0.039) | (0.048) | | (0.049) | (0.049) | (0.047) |
| Product RevShare | | -3.439*** | -3.680*** | | -0.519*** | -0.543*** | -0.526*** | -0.643*** |
| | | (0.824) | (0.818) | | (0.106) | (0.105) | (0.106) | (0.100) |
| Brand RevShare | | -0.118* | 0.123* | | -0.311*** | 0.100 | 0.101 | -0.013 |
| | | (0.068) | (0.068) | | (0.088) | (0.090) | (0.090) | (0.088) |
| Log(Med. Price) | | | | | | | -0.050 | |
| | | | | | | | (0.035) | |
| Obs. | 10939 | 10939 | 10939 | 10939 | 10939 | 10939 | 10939 | 10541 |
| $\bar{R}^2$ | 0.102 | 0.088 | 0.104 | 0.237 | 0.212 | 0.239 | 0.239 | 0.253 |
| Category | Y | Y | Y | N | N | N | N | N |
| Subsubclass | N | N | N | Y | Y | Y | Y | Y |

Note: The dependent variable is the logarithm of estimated product-level pass-through using the rolling window specification given by equation 16. This pass-through variable is first calculated by regressing the 12 month change in log average monthly retail regular price on the 12 month change in the log average monthly wholesale price. The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each observation corresponds to an individual product pass-through coefficient, and use heteroskedasticity robust standard errors.

Table 6: Wholesale Cost and Commodity Price

| Dependent Variable (Log Pass-through of Commodity Price to Wholesale Cost) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Window | 12 months | | | | | | | 4 months |
| Median | 0.047 | | | | | | | 0.037 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | 0.211*** | | 0.318*** | 0.347*** | | 0.416*** | 0.392*** | 0.392*** |
| | (0.045) | | (0.046) | (0.067) | | (0.068) | (0.069) | (0.082) |
| RetailBranded | 0.292*** | | 0.343*** | 0.264*** | | 0.288*** | 0.271*** | 0.300*** |
| | (0.042) | | (0.043) | (0.055) | | (0.056) | (0.056) | (0.061) |
| Product RevShare | | -1.960 | -1.817 | | -0.452*** | -0.454*** | -0.440*** | -0.372*** |
| | | (1.366) | (1.293) | | (0.096) | (0.095) | (0.095) | (0.099) |
| Brand RevShare | | -0.512*** | -0.668*** | | -0.129 | -0.290*** | -0.280*** | -0.687*** |
| | | (0.074) | (0.075) | | (0.088) | (0.089) | (0.090) | (0.110) |
| Log(Med. Price) | | | | | | | -0.072** | |
| | | | | | | | (0.035) | |
| Obs. | 12757 | 12757 | 12757 | 12757 | 12757 | 12757 | 12757 | 10326 |
| $\bar{R}^2$ | 0.270 | 0.270 | 0.276 | 0.470 | 0.468 | 0.472 | 0.472 | 0.548 |
| Category | Y | Y | Y | N | N | N | N | N |
| Subsubclass | N | N | N | Y | Y | Y | Y | Y |

Note: The dependent variable is the logarithm of estimated product-level pass-through using the rolling window specification given by equation 16. This pass-through variable is first calculated by regressing the 12 month change in log average monthly wholesale price on the 12 month change in the log commodity index for a linked commodity. The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each individual observation is a product x commodity pass-through coefficient, and use heteroskedasticity robust standard errors. Because there are sometimes multiple commodities linked to an individual product, we include commodity dummies in this regression interacted with category or subsubclass dummies where applicable.

## Table 7: Regular Price and Commodity Price/Wholesale Cost Index Pass-through

| Panel A: Dependent Variable (Log Pass-through of Commodity Prices to Regular Price) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Window | 12 months | | | | | | | 4 months |
| Median | 0.064 | | | | | | | 0.050 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | 0.389*** | | 0.456*** | 0.306*** | | 0.416*** | 0.350*** | 0.418*** |
| | (0.039) | | (0.040) | (0.059) | | (0.061) | (0.062) | (0.071) |
| RetailBranded | 0.028 | | 0.055 | 0.120** | | 0.150*** | 0.100** | 0.205*** |
| | (0.036) | | (0.036) | (0.050) | | (0.050) | (0.051) | (0.049) |
| Product RevShare | | -5.373*** | -5.234*** | | -0.928*** | -0.918*** | -0.873*** | -1.113*** |
| | | (1.061) | (1.055) | | (0.087) | (0.086) | (0.086) | (0.104) |
| Brand RevShare | | -0.273*** | -0.393*** | | -0.285*** | -0.431*** | -0.414*** | -0.473*** |
| | | (0.058) | (0.058) | | (0.085) | (0.087) | (0.085) | (0.094) |
| Log(Med. Price) | | | | | | | -0.208*** | |
| | | | | | | | (0.044) | |
| Obs. | 12627 | 12627 | 12627 | 12627 | 12627 | 12627 | 12627 | 9951 |
| $\bar{R}^2$ | 0.195 | 0.195 | 0.202 | 0.303 | 0.309 | 0.313 | 0.316 | 0.324 |
| Category | Y | Y | Y | N | N | N | N | N |
| Subsubclass | N | N | N | Y | Y | Y | Y | Y |

| Panel B: Dependent Variable (Log Pass-through of Wholesale Index to Regular Price) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Window | 12 months | | | | | | | 4 months |
| Median | 1.006 | | | | | | | 0.783 |
| RetailManufactured | 0.216*** | | 0.254*** | 0.265*** | | 0.320*** | 0.289*** | -0.055 |
| | (0.070) | | (0.072) | (0.098) | | (0.102) | (0.103) | (0.085) |
| RetailBranded | 0.148*** | | 0.156*** | 0.103*** | | 0.105*** | 0.077* | 0.111*** |
| | (0.033) | | (0.033) | (0.040) | | (0.039) | (0.041) | (0.041) |
| Product RevShare | | -2.916*** | -2.712*** | | -0.855*** | -0.840*** | -0.793*** | -0.686*** |
| | | (0.844) | (0.830) | | (0.100) | (0.099) | (0.098) | (0.096) |
| Brand RevShare | | 0.035 | -0.073 | | 0.153* | 0.021 | 0.022 | 0.195** |
| | | (0.065) | (0.066) | | (0.079) | (0.081) | (0.081) | (0.087) |
| Log(Med. Price) | | | | | | | -0.113*** | |
| | | | | | | | (0.043) | |
| Obs. | 9653 | 9653 | 9653 | 9653 | 9653 | 9653 | 9653 | 8805 |
| $\bar{R}^2$ | 0.323 | 0.322 | 0.324 | 0.429 | 0.432 | 0.433 | 0.434 | 0.381 |
| Category | Y | Y | Y | N | N | N | N | N |
| Subsubclass | N | N | N | Y | Y | Y | Y | Y |

Note: The dependent variable is the logarithm of estimated product-level pass-through using the rolling window specification given by equation 16. The pass-through variable is first calculated by regressing the 12 month change in log average monthly retail regular price on the 12 month change in the log commodity index for a linked commodity (Panel A) or the category-level wholesale cost commodity index (Panel B). The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each individual observation is a product x commodity pass-through coefficient, and use heteroskedasticity robust standard errors. Because there are sometimes multiple commodities linked to an individual product, we include commodity dummies in this regression interacted with category or subsubclass dummies where applicable. For panel B, the wholesale cost index measures are calculated using the change in log average wholesale cost for every UPC in the category that appears in all 41 months, using fixed aggregate revenue weights to aggregate up to the category level.

Table 8: Robustness

| Dependent Variable (Log 12-month Pass-through) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Sales price | | Regions & UPC FE | | Cond. on $\Delta p$ | | Interactions | |
| Pass-through dep. var. | Retail | Retail | Retail | Whole. | Retail | Retail | Retail | Retail |
| Pass-through ind. var. | Comm. | Whole. | Comm. | Comm. | Comm. | Whole. | Comm. | Whole. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | 0.169*** | -0.505*** | | | 0.443*** | 0.063 | 0.318*** | -0.772*** |
| | (0.053) | (0.091) | | | (0.09) | (0.101) | (0.112) | (0.182) |
| RetailBranded | 0.248*** | -0.246*** | | | 0.126** | -0.087 | 0.117 | -0.341*** |
| | (0.035) | (0.051) | | | (0.059) | (0.059) | (0.094) | (0.095) |
| Product RevShare | -0.284*** | -0.125 | -0.028 | 0.003 | -0.607*** | -0.335*** | -0.970*** | -0.609*** |
| | (0.074) | (0.108) | (0.073) | (0.057) | (0.127) | (0.117) | (0.093) | (0.12) |
| Brand RevShare | -0.221*** | -0.118 | 0.177* | -0.297*** | -0.198* | -0.162 | -0.461*** | 0.218** |
| | (0.083) | (0.101) | (0.107) | (0.073) | (0.118) | (0.107) | (0.102) | (0.032) |
| (RetailManufactured x | | | | | | | 0.206 | 1.31*** |
| Product RevShare) | | | | | | | (0.355) | (0.358) |
| (RetailBranded x | | | | | | | 0.277 | -0.334 |
| Product RevShare) | | | | | | | (0.259) | (0.269) |
| (RetailManufactured x | | | | | | | 0.322 | -0.581 |
| Brand RevShare) | | | | | | | (0.342) | (0.376) |
| (RetailBranded x | | | | | | | 0.065 | -0.626* |
| Brand RevShare) | | | | | | | (0.302) | (0.326) |
| Obs | 11278 | 9596 | 47783 | 48111 | 12036 | 8288 | 12627 | 10989 |
| $\bar{R}^2$ | 0.282 | 0.281 | 0.432 | 0.807 | 0.188 | 0.153 | 0.313 | 0.240 |
| Controls | Subsub | Subsub | UPC | UPC | Subsub | Subsub | Subsub | Subsub |

Note: In columns 1-2 and 7-8 the dependent variable is the logarithm of estimated product-level pass-through using the 12-month rolling window specification as in previous tables. In columns 3-4 the dependent variable is the log of product-region pass-through and we use UPC fixed effects (forcing us to drop the private label dummies). In columns 5-6 the dependent variable is the store-level percent change in regular retail price divided by the percent change in commodity price or wholesale cost between two observed price changes, taking an average for each product across all weeks and stores. The results reported here are for estimation of equation 18 (modified to include interactions in columns 7-8) where each observation corresponds to the pass-through defined above. All regressions use heteroskedasticity robust standard errors.

## Table 9: One-step estimation

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Panel A:Single-Retailer Data | | | | | |
| Pass-through | Commodity-Retail | | Commodity-Wholesale | | Wholesale-Retail | |
| RetailManufactured | 0.0268*** | 0.0175*** | 0.0320*** | 0.0163*** | -0.4284*** | -0.5266*** |
| | (0.0058) | (0.0065) | (0.0053) | (0.0063) | (0.0785) | (0.0728) |
| RetailBranded | -0.0045 | 0.0004 | -0.0020 | -0.0101 | -0.4718*** | -0.3841*** |
| | (0.0049) | (0.0053) | (0.0107) | (0.0086) | (0.0896) | (0.0731) |
| Product Share | 0.1903* | -0.0231 | 0.5078** | 0.0633** | -0.2851 | -0.0447 |
| | (0.1095) | (0.0169) | (0.2092) | (0.0315) | (0.3668) | (0.0842) |
| Brand Share | 0.0600*** | 0.0762*** | 0.0211 | 0.0270* | 0.8815*** | 0.7190*** |
| | (0.0086) | (0.0102) | (0.0166) | (0.0141) | (0.1922) | (0.1663) |
| Obs. | 203479 | 203479 | 203076 | 203078 | 203077 | 203077 |
| $R^2$ within | 0.0273 | 0.0455 | 0.0127 | 0.1365 | 0.1063 | 0.1744 |
| PT varies by | Category | Subclass | Category | Subclass | Category | Subclass |
| | Panel B: Multi-Retailer Data, commodity-retail pass-through only | | | | | |
| PrivateLabel | 0.007*** | 0.007*** | 0.007*** | 0.008*** | 0.007*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Within-Chain | | | | | | |
| ProductShare | 0.344*** | 0.347*** | | | 0.234*** | 0.251*** |
| | (0.034) | (0.035) | | | (0.048) | (0.049) |
| BrandShare | 0.000 | 0.001 | | | 0.007** | 0.007** |
| | (0.001) | (0.001) | | | (0.003) | (0.003) |
| Retail Market Power | | | | | | |
| CategoryShare | | | -0.164*** | | -0.137*** | -0.053 |
| | | | (0.029) | | (0.030) | (0.135) |
| BrandShare | | | 0.018*** | | 0.018*** | 0.016*** |
| | | | (0.005) | | (0.005) | (0.006) |
| ProductShare | | | 0.009*** | | 0.011*** | 0.009** |
| | | | (0.003) | | (0.003) | (0.003) |
| Manufacture Market Power | | | | | | |
| ProductShare | | | | 0.465*** | 0.205*** | 0.187*** |
| | | | | (0.049) | (0.071) | (0.072) |
| BrandShare | | | | -0.003* | -0.007** | -0.007** |
| | | | | (0.001) | (0.003) | (0.003) |
| Obs. | 11394428 | 11394428 | 11394428 | 11394428 | 11394428 | 11394428 |
| $R^2$ within | 0.0045 | 0.005 | 0.0044 | 0.0045 | 0.0045 | 0.005 |
| PT varies by | Category | Category, chain | Category | Category | Category | Category, chain |

Note: The reported coefficients in Panel A are the interaction terms from estimation equation 19 using the 12-month rolling window specification where the dependent variable is the 12-month change in log average monthly price and the independent variable is the 12-month change in log average monthly cost, using UPC-commodity and month fixed effects. Panel B is similar but uses the multi-retailer data and calculates pass-through at the UPC-chain level, using UPC-commodity-chain and month fixed effects. The sub-panels divide the different market share variables in the multi-retailer data (described in the text). We allow pass-through to vary by category-commodity (Panel A and Panel B) and by chain (Panel B only) by including interactions of dummies with the commodity price change. In both cases we restrict the sample to category/commodity pairs that feature a positive and significant pass-through from commodity to retail prices at the 1% level. Robust standard errors in parentheses.

Table 10: Multiple-retailers: Regular Price and Commodity Price Pass-through

| | Dependent Variable (Log Pass-through of Commodity Prices to Regular Price) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Median | 0.079 | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PrivateLabel | 0.303*** | 0.314*** | 0.301*** | 0.281*** | 0.292*** | 0.306*** | 0.319*** | 0.303*** |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| Within-Chain | | | | | | | | |
| ProductShare | 1.467*** | 1.852*** | | | | | 2.232*** | 1.845*** |
| | (0.448) | (0.467) | | | | | (0.623) | (0.642) |
| BrandShare | -0.325*** | -0.305*** | | | | | -0.387*** | -0.461*** |
| | (0.037) | (0.039) | | | | | (0.06) | (0.061) |
| Retail Market Power | | | | | | | | |
| CategoryShare | | | -1.547*** | 5.425 | | | -1.627*** | 5.743** |
| | | | (0.621) | (2.865) | | | (0.627) | (2.865) |
| ProductShare | | | 0.039 | 0.092 | | | 0.004 | 0.0064 |
| | | | (0.075) | (0.075) | | | (0.076) | (0.076) |
| BrandShare | | | 0.104 | 0.098 | | | 0.083 | 0.084 |
| | | | (0.115) | (0.115) | | | (0.116) | (0.116) |
| Manufacturer Market Power | | | | | | | | |
| ProductShare | | | | | 0.905 | 1.602 | -1.29 | -0.653 |
| | | | | | (0.695) | (0.696) | (0.998) | (1.002) |
| BrandShare | | | | | -0.218*** | -0.187*** | -0.149*** | -0.207*** |
| | | | | | (0.042) | (0.044) | (0.069) | (0.07) |
| Obs | 51630 | 51630 | 51630 | 51630 | 51630 | 51630 | 51630 | 51630 |
| $R^2$ | 0.142 | 0.184 | 0.127 | 0.141 | 0.141 | 0.184 | 0.128 | 0.142 |
| Dummies | Category,Chain | Category+Chain | Category | Category, Chain | Category,Chain | Category+Chain | Category | Category,Chain |

Note: The dependent variable is the logarithm of estimated UPC-chain level pass-through using the lagged specification given by equation 17. This pass-through is calculated regressing the dependent variable, the change in log average monthly regular price at UPC-chain level, on the independent variable, the change in the log commodity index for a linked commodity or the category-level wholesale cost commodity index and its lags up to 12 months, and then summing up the coefficients of each independent variable. The sample comprises the 132 months from January 2001 to December 2011. The results reported here are for estimation of equation 18 where each individual observation is a product x commodity pass-through coefficient, and use heteroskedasticity robust standard errors. Category FE is included for all specifications.

## Table 11: Duration of Prices changes (logs)

| Dependent Variable (Log Duration of Regular Price) | | | | | (Log Duration of Sales Price)) | | | | (Log Duration of Wholesale Price) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Median | 31.9 weeks | | | Median | 6.49 weeks | | | Median | 37.25 weeks | | |
| RetailManufactured | 0.043 | 0.032 | 0.041 | 0.037 | -0.783*** | -0.733*** | -0.599*** | -0.381*** | -0.292*** | -0.239*** | -0.308*** | -0.323*** |
| s.e. | (0.023) | (0.024) | (0.028) | (0.029) | (0.049) | (0.047) | (0.054) | (0.053) | (0.028) | (0.027) | (0.032) | (0.032) |
| RetailBranded | 0.021 | 0.044*** | 0.051*** | 0.052*** | -0.487*** | -0.404*** | -0.356*** | -0.299*** | -0.525*** | -0.531*** | -0.574*** | -0.578*** |
| s.e. | (0.014) | (0.014) | (0.015) | (0.015) | (0.028) | (0.027) | (0.028) | (0.028) | (0.017) | (0.014) | (0.017) | (0.017) |
| Product RevShare | | | | 0.136*** | | | | -1.302*** | | | | 0.065 |
| s.e. | | | | (0.044) | | | | (0.08) | | | | (0.047) |
| Brand RevShare | | | | -0.021*** | | | | -0.569*** | | | | 0.048** |
| s.e. | | | | (0.022) | | | | (0.04) | | | | (0.024) |
| Category | N | Y | N | N | N | Y | N | N | N | Y | N | N |
| Subsubclass | N | N | Y | Y | N | N | Y | Y | N | N | Y | Y |
| Obs | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 | 14896 |
| $R^2$ | 0.0004 | 0.1617 | 0.3903 | 0.3936 | 0.0359 | 0.2126 | 0.5001 | 0.542 | 0.0608 | 0.3706 | 0.5897 | 0.5901 |

Note: The dependent variables are the log of regular, sales, and wholesale price duration using Spell2. The sample is over 41 months from January 2004 to May 2007.

## Table 12: Dependent variable: store/month private-label market share

| | (1) | (2) | (3) | Mean |
|---|---|---|---|---|
| Log median household income | $-0.078^{***}$ | $-0.081^{***}$ | | 10.90 |
| s.e. | (0.014) | (0.002) | | (0.343) |
| Log gas price | $0.135^{*}$ | $0.023^{***}$ | $0.009^{***}$ | 0.616 |
| s.e. | (0.082) | (0.003) | (0.004) | (0.225) |
| Unemployment rate | $0.428^{*}$ | $0.266^{***}$ | $0.211^{***}$ | 0.049 |
| s.e. | (0.227) | (0.039) | (0.030) | (0.017) |
| Months | Jan.2004 | All | All | All |
| Store and month FE | No | No | Yes | |
| Obs | | | | |
| $R^2$ | 0.21 | 0.21 | 0.96 | |

Robust standard errors and standard deviations in parentheses. Private label share is aggregated across of 124 product categories. There are 41 months and up to 250 stores per month. Private label share and unemployment rate are measured out of 1. Private label share has mean 0.24 and standard deviation of 0.07.

Table 13: European country-level pass-throughs and private label shares

| Panel A: Pooled country/category commodity to consumer price pass-through (2005:1-2013:3) | | |
|---|---|---|
| T difference | 12 months | 1 month |
| Median category pass-through when PL=0 | 0.041 | 0.109 |
| $\Delta \ln c * plshare_j$ | -0.163** | -0.250** |
| s.e. | (0.077) | (0.105) |
| Obs. | 12154 | 15175 |
| $\bar{R}^2$ | 0.011 | 0.027 |
| Countries | 22 | 22 |
| Categories | 11 | 11 |
| Country x category | 210 | 210 |

| Panel B: Pooled country/category commodity to producer price pass-through (2005:1-2013:3) | | |
|---|---|---|
| T difference | 12 months | 1 month |
| Median category pass-through when PL=0 | 0.031 | 0.024 |
| $\Delta \ln c * plshare_j$ | 0.146** | 0.204*** |
| s.e. | (0.069) | (0.053) |
| Obs. | 4725 | 5499 |
| $\bar{R}^2$ | 0.013 | 0.047 |
| Countries | 7 | 7 |
| Categories | 10 | 10 |
| Country x category | 61 | 64 |

Note: This table reports the coefficient $\gamma$ from estimation of equation 20. Regressions include country by category dummies, period dummies, and allow for separate coefficients for each of the eleven categories. Standard errors in parentheses are calculated using Driscoll and Kraay (1998) standard errors with lag order 12. Column (1) differences prices and commodities by twelve months while column (2) uses monthly differences.

# A Appendix: Results from the Long-Run Pass-Through Regressions

Table 14: Retail Price and Wholesale Cost Pass-through

| Dependent Variable (Log Pass-through of Wholesale Cost to Regular Price) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 4 months | | | | 12 months | | | |
| Median | 0.481 | | | | 0.981 | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | -0.341*** | -0.561*** | -0.659*** | -0.587*** | -0.242*** | -0.139 | -0.34** | -0.236* |
| s.e | (0.069) | (0.079) | (0.096) | (0.099) | (0.095) | (0.105) | (0.137) | (0.14) |
| RetailBranded | -0.489*** | -0.411*** | -0.403*** | -0.391*** | -0.239*** | -0.376*** | -0.419*** | -0.396*** |
| s.e | (0.042) | (0.044) | (0.052) | (0.052) | (0.055) | (0.057) | (0.068) | (0.069) |
| Product RevShare | | | | -0.551*** | | | | -0.303 |
| s.e. | | | | (0.149) | | | | (0.203) |
| Brand RevShare | | | | -0.063 | | | | -0.218** |
| s.e. | | | | (0.075) | | | | (0.104) |
| Category | N | Y | N | N | N | Y | N | N |
| Subsubclass | N | N | Y | Y | N | N | Y | Y |
| Obs | 10586 | 10586 | 10586 | 10586 | 9646 | 9646 | 9646 | 9646 |
| $R^2$ | 0.0142 | 0.0933 | 0.3327 | 0.3344 | 0.0025 | 0.0949 | 0.3581 | 0.3591 |

Note: The dependent variable is the logarithm of estimated product-level pass-through using the lagged specification given by equation 17. This pass-through is calculated by regressing the dependent variable, the change in log average monthly retail regular price, on the independent variable, the change in the log average monthly wholesale price and its lags (4 months and 12 months respectively), and then summing up the coefficients of each independent variable. The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each observation corresponds to an individual product pass-through coefficient, and use heteroskedasticity robust standard errors.

Table 15: Wholesale Cost and Commodity Price Pass-through

| Dependent Variable (Log Pass-through of Commodity price to Wholesale Cost) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 4 months | | | | | | | |
| Median | 0.03 | | | | 0.063 | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | 0.692*** | 0.616*** | 0.664*** | 0.707*** | 0.355*** | 0.425*** | 0.439*** | 0.517*** |
| s.e | (0.071) | (0.066) | (0.087) | (0.087) | (0.067) | (0.062) | (0.07) | (0.079) |
| RetailBranded | 0.197*** | 0.279*** | 0.301*** | 0.325*** | 0.231*** | 0.207*** | 0.221*** | 0.246*** |
| s.e | (0.047) | (0.046) | (0.053) | (0.053) | (0.045) | (0.043) | (0.048) | (0.048) |
| Product RevShare | | | | 0.099 | | | | -0.119 |
| s.e. | | | | (0.142) | | | | (0.137) |
| Brand RevShare | | | | -0.6*** | | | | -0.456*** |
| s.e. | | | | (0.07) | | | | (0.068) |
| Category | N | Y | N | N | N | Y | N | N |
| Subsubclass | N | N | Y | Y | N | N | Y | Y |
| Obs | 13633 | 13633 | 13633 | 13633 | 14682 | 14682 | 14682 | 14682 |
| $R^2$ | 0.0079 | 0.2509 | 0.5215 | 0.5252 | 0.0035 | 0.2628 | 0.5159 | 0.5185 |

Note: The dependent variable is the logarithm of estimated product-level pass-through using the lagged specification given by equation 17. This pass-through is calculated by regressing the dependent variable, the change in log average monthly retail wholesale price, on the independent variable, the change in the log commodity index for a linked commodity and its lags (4 months), and then summing up the coefficients of each independent variable. The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each individual observation is a product x commodity pass-through coefficient, and use heteroskedasticity robust standard errors. Because there are sometimes multiple commodities linked to an individual product, we include commodity dummies in this regression interacted with category or subsubclass dummies where applicable.

## Table 16: Regular Price and Commodity Price/Wholesale Cost Index Pass-through

| Panel A: Dependent Variable (Log Pass-through of Commodity Prices to Regular Price) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 4 lags | | | | 12 lags | | | |
| Median | 0.041 | | | | 0.083 | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | 0.046 | 0.115* | 0.126 | 0.204** | 0.255*** | 0.358*** | 0.199** | 0.284*** |
| s.e | (0.064) | (0.063) | (0.084) | (0.084) | (0.063) | (0.063) | (0.085) | (0.085) |
| RetailBranded | 0.272*** | 0.018 | 0.038 | 0.049 | 0.208*** | 0.051 | 0.034 | 0.051 |
| s.e | (0.042) | (0.044) | (0.051) | (0.051) | (0.042) | (0.043) | (0.057) | (0.051) |
| Product RevShare | | | | -0.667*** | | | | -0.342** |
| s.e. | | | | (0.145) | | | | (0.148) |
| Brand RevShare | | | | -0.256*** | | | | -0.355*** |
| s.e. | | | | (0.073) | | | | (0.074) |
| Category | N | Y | N | N | N | Y | N | N |
| Subsubclass | N | N | Y | Y | N | N | Y | Y |
| Obs | 13527 | 13527 | 13527 | 13527 | 14222 | 14222 | 14222 | 14222 |
| $R^2$ | 0.0031 | 0.1458 | 0.3896 | 0.393 | 0.0027 | 0.136 | 0.3788 | 0.3814 |

| Panel B: Dependent Variable (Log Pass-through of Wholesale Cost Index to Regular Price) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 4 lags | | | | 12 lags | | | |
| Median | 0.649 | | | | 1.473 | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RetailManufactured | 0.21*** | 0.077 | 0.053 | 0.169 | 0.113 | -0.066 | 0.026 | 0.21* |
| s.e | (0.028) | (0.088) | (0.104) | (0.107) | (0.086) | (0.087) | (0.112) | (0.113) |
| RetailBranded | -0.03 | 0.233*** | 0.218*** | 0.239*** | -0.181*** | 0.131*** | 0.106** | 0.141*** |
| s.e | (0.045) | (0.045) | (0.052) | (0.052) | (0.046) | (0.046) | (0.053) | (0.053) |
| Product RevShare | | | | -0.599*** | | | | -0.714*** |
| s.e. | | | | (0.154) | | | | (0.162) |
| Brand RevShare | | | | 0.205*** | | | | -0.431*** |
| s.e. | | | | (0.079) | | | | (0.081) |
| Category | N | Y | N | N | N | Y | N | N |
| Subsubclass | N | N | Y | Y | N | N | Y | Y |
| Obs | 10175 | 10175 | 10175 | 10175 | 10265 | 10265 | 10265 | 10265 |
| $R^2$ | 0.0007 | 0.1985 | 0.4185 | 0.4211 | 0.0018 | 0.2234 | 0.4535 | 0.459 |

Note: The dependent variable is the logarithm of estimated product-level pass-through using the lagged specification given by equation 17. This pass-through is calculated regressing the dependent variable, the change in log average monthly retail wholesale price, on the independent variable, the change in the log commodity index for a linked commodity or the category-level wholesale cost commodity index and its respective lags and then summing up the coefficients of each independent variable. The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each individual observation is a product x commodity pass-through coefficient, and use heteroskedasticity robust standard errors. Because there are sometimes multiple commodities linked to an individual product, we include commodity dummies in this regression interacted with category or subsubclass dummies where applicable. For panel B, the wholesale cost index measures are calculated using the change in log average wholesale cost for every UPC in the category that appears in all 41 months, using fixed aggregate revenue weights to aggregate up to the category level.

Table 17: Operating area pass-through

| | Retail-Comm. | | Wh.-Comm. | | Retail-Wh. | | Retail-Wh. Index | |
|---|---|---|---|---|---|---|---|---|
| RetailManufactured | 0.316*** | 0.276*** | 0.565*** | 0.545*** | -0.500*** | -0.745*** | 0.152*** | 0.179*** |
| s.e. | (0.031) | (0.042) | (0.024) | (0.037) | (0.045) | (0.058) | (0.054) | (0.060) |
| RetailBranded | 0.078*** | 0.124*** | 0.444*** | 0.544*** | -0.400*** | -0.434*** | 0.170*** | 0.100*** |
| s.e. | (0.021) | (0.026) | (0.022) | (0.029) | (0.023) | (0.028) | (0.020) | (0.022) |
| Product RevShare | -0.191 | -0.105** | -0.779** | -0.198*** | -0.581** | 0.049 | 0.658** | -0.105** |
| s.e. | (0.406) | (0.044) | (0.365) | (0.041) | (0.294) | (0.051) | (0.329) | (0.052) |
| Brand RevShare | -0.251*** | -0.253*** | -0.574*** | -0.220*** | 0.231*** | 0.114** | -0.084** | -0.075 |
| s.e. | (0.033) | (0.046) | (0.037) | (0.043) | (0.037) | (0.049) | (0.036) | (0.046) |
| Category | Y | N | Y | N | Y | N | Y | N |
| Subsubclass | N | Y | N | Y | N | Y | N | Y |
| Obs | 47783 | 47783 | 48111 | 48111 | 37502 | 37502 | 33064 | 33064 |
| $R^2$ | 0.194 | 0.308 | 0.311 | 0.546 | 0.103 | 0.234 | 0.215 | 0.324 |

Note: The dependent variable is the logarithm of estimated product-operating area level pass-through using the rolling window specification given by equation 16, where the dependent and independent variables are the log average monthly price within an operating area (for columns 1-4 we use the national commodity price and for columns 7-8 we use operating level wholesale cost indexes). The sample comprises the 41 months from January 2004 to May 2007. The results reported here are for estimation of equation 18 where each individual observation is a product x operating area x commodity pass-through coefficient. All results use heteroskedasticity robust standard errors and include operating area fixed effects. Because there are sometimes multiple commodities linked to an individual product, we include commodity dummies in this regression interacted with category or subsubclass dummies where applicable.

Table 18: Multiple-retailers: Regular Price and Commodity Price Pass-through

| Dependent Variable (Log Pass-through of Commodity Prices to Regular Price (MSA-level)) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Median | 0.079 | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| PrivateLabel | 0.185*** | 0.196*** | 0.205*** | 0.166*** | 0.196*** | 0.204*** | 0.167*** | 0.157*** | |
| | (0.019) | (0.019) | (0.019) | (0.021) | (0.02) | (0.019) | (0.021) | (0.022) | |
| es1 | 0.726* | 0.863** | | | | | 4.306*** | 4.175*** | 4.389*** |
| | (0.439) | (0.439) | | | | | (0.776) | (0.777) | (0.776) |
| es2 | -0.247*** | -0.201*** | | | | | -0.262*** | -0.253*** | -0.269*** |
| | (0.04) | (0.04) | | | | | (0.068) | (0.069) | (0.068) |
| es3 | | | -0.467*** | 1.502 | | | -0.495** | 1.754 | 1.891 |
| | | | (0.181) | (1.511) | | | (0.207) | (1.511) | (1.511) |
| es4 | | | 0.273*** | 0.201*** | | | 0.118 | 0.125 | 0.058 |
| | | | (0.078) | (0.082) | | | (0.086) | (0.086) | (0.085) |
| es5 | | | 0.187*** | 0.229*** | | | 0.144** | 0.177*** | 0.024*** |
| | | | | (0.055) | (0.056) | | (0.056) | (0.058) | (0.056) |
| es6 | | | | | -1.827** | -1.718** | -7.16*** | -7.063*** | -6.261*** |
| | | | | | (0.781) | (0.779) | (1.403) | (1.405) | (1.405) |
| es7 | | | | | -0.129*** | -0.069* | 0.163** | 0.101 | -0.125** |
| s.e. | | | | | (0.04) | (0.039) | (0.065) | (0.066) | (0.065) |
| Obs | 38140 | 38140 | 38140 | 38140 | 38140 | 38140 | 38140 | 38140 | 38140 |
| $R^2$ | 0.145 | 0.1458 | 0.145 | 0.149 | 0.145 | 0.145 | 0.146 | 0.140 | 0.147 |
| Dummies | MSA, Chain | MSA, Cat+Chain | MSA | MSA, Chain | MSA,Chain | MSA, Cat+Chain | MSA | MSA, Chain | UPC, MSA, Chain |

Note: The dependent variable is the logarithm of estimated UPC-chain-MSA level pass-through using the lagged specification given by equation 17. This pass-through is calculated regressing the dependent variable, the change in log average monthly regular price at UPC-chain-MSA level, on the independent variable, the change in the log commodity index for a linked commodity or the category-level wholesale cost commodity index and its lags up to 12 months, and then summing up the coefficients of each independent variable.The sample comprises the 132 months from January 2001 to December 2011. The results reported here are for estimation of equation 18 where each individual observation is a product x commodity pass-through coefficient, and use heteroskedasticity robust standard errors. Category FE is always included either separately or interactively with chain FE, in which case, the controls are described as 'Cat+Chain.'