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Essays on Price Dynamics

by

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Abstract

Essays on Price Dynamics

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Doctor of Philosophy in Economics

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Standard macro models typically assume that producers sell goods directly to final consumers, while, in reality, the distribution network or vertical structure from a manufacturer to a consumer takes various forms. The boundary of firms, or to what extent a firm wishes to extend its distribution or manufacturing process is not a trivial issue when firms develop sourcing strategies. A substantial number of recent studies in international trade have demonstrated systematic patterns in intra-firm trade patterns and price patterns. Inclusion of vertical chains possibly generates frictions by means of double-marginalization problem, asymmetric information and coordination issues, while the choice of vertical structure is an endogenous choice of transaction cost minimization and contractibility.

The first part of work discusses the price patterns by documenting several facts about price rigidity using a large grocery retail data set. The role of retailers has been completely neglected in standard macro pricing models. However, consumers seldom interact with manufacturers directly, especially for grocery items. The assumption that retail level is negligible would be innocuous only if the wholesale price dynamics is similar to retail price dynamics. That is, only when retailers fully pass through the wholesale price to consumers and do not influence the prices that have been set by manufacturers would this assumption make sense. Using detailed information of weekly price and cost from a major retailer store that operates across the United States, we find strong evidence that retail price dynamics are completely different from manufacturer price dynamics. We find two main reasons for why retail prices cannot fully reflect wholesale prices. First, retailers cannot do so because retailers face costs of their own aside from wholesale price. Second, retailers react to variations in demand more directly than wholesalers. Pass-through rate of retailer cost (including wholesale price and extra costs to retailers) to retail price is incomplete. We also find that (1) retail pass-through rate is incomplete, (2) retail pass-through rate and retail price rigidity is negatively correlated, (3) categories with higher retail mark-up show lower pass-through rate, (4) price rigidity is heterogeneous across categories, (5) competition within a category shows positive

correlation with pass-through rate, but the correlation is less obvious in the scatter plots and (6) retail price duration is shorter than wholesale price duration, while retail price duration is longer than retail cost duration. In a simple model where retailers play non-neutral role, we can successfully explain the empirical findings, while models with neutral retailers or no retailers fail to explain the findings.

The second part of work discusses the relationship between the vertical structure and the price rigidity. In the job market paper, Vertical Integration and Retail Pricing Facts for Macroeconomists: Private Label vs. National Brand (co-authored with Nicholas Li), we propose to extend this analysis to retail behavior and also into closed economy using a data set that contains prices and wholesale costs for a retail chain that operates in the United States. The retailer owns numerous brands that are sold in its stores ownership in this case implies control over branding, marketing and packaging in all cases and in many cases control over manufacturing as well. We call these private labels and consider equivalent to intra-firm in open macro literature. Beyond generalizing the findings of previous studies to the retail sector and a different data set, the significant growth of store-brands makes the impact of vertical integration in retail on intra and inter-national pricing behavior of independent interest. By analyzing the main dimensions of pricing (duration, cost pass-through and synchronization), we find that the private label goods show shorter price duration, greater cost shock pass-through and greater synchronization of price changes than national brands counterpart. These findings are consistent with previous literature using trade dataset. We compare two existing models that can potentially explain these facts one featuring symmetric retail demand but different vertical structures/double-marginalization, and the other featuring demand asymmetry and price discrimination as a motive for sales to find evidence that two models are complementary. If vertical structure is endogenous, with vertically integrated lower-priced products gaining market share for product categories, we argue that it can serve as a potential multiplier for demand-based induced changes in retail pricing behavior.

One example that shows retailers non-neutral role in price-setting mechanism is the existence of sales at retail level. With a recent surge of micro-level data sets from various sources, researchers have been able to examine price dynamics at a disaggregate level and to test previously established macro-pricing models. A notable feature of price dynamics across all of these data sets is significant heterogeneity across products and sectors in measured pass-through and frequency due to temporary discounts, or sales. Previous studies have demonstrated that the retailer is largely responsible for the timing and size of temporary discounts.

Sales prices behave qualitative and quantitatively different from regular prices. Yet, researchers have not reached a conclusion whether or not and how to incorporate intermittent price into crucial issues, such as, macro price-setting models and price index constructions. The core of the question is whether sales have any implications for business cycle and monetary neutrality. The question is also intimately related to how economic agents respond to shocks how retailers adjust their profit-maximizing strategies, how consumers adjust their consumption patterns in response to cost shocks.

The third chapter of work, On the Cyclicality of Effective Prices with Professors Yuriy Gorodnichenko and Olivier Coibin directly tackles this issue. We study the cyclical properties of sales, regular price changes and average prices paid by consumers in a dataset containing prices and quantities sold for numerous retailers across a variety of U.S. metropolitan areas. Both the frequency and size of sales fall when unemployment rates rise and yet the inflation rate of average prices paid by consumers declines with higher unemployment. This discrepancy can be reconciled by consumers reallocating their expenditures across retailers, a feature of the data which we document and quantify. The results point toward a cyclical mis-measurement of inflation which can account for part of the missing disinflation during the Great Recession.

Professor Yuriy Gorodnichenko
Dissertation Committee Chair

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This is dedicated to the ones I love.

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Chapter 1

Introduction

1.1 Overview

Standard macro models typically assume that producers sell goods directly to final consumers, while, in reality, the distribution network or vertical structure from a manufacturer to a consumer takes various forms. The boundary of firms, or to what extent a firm wishes to extend its distribution or manufacturing process is not a trivial issue when firms develop sourcing strategies. A substantial number of recent studies in international trade have demonstrated systematic patterns in intra-firm trade patterns and price patterns. Inclusion of vertical chains possibly generates frictions by means of double-marginalization problem, asymmetric information and coordination issues, while the choice of vertical structure is an endogenous choice of transaction cost minimization and contractibility.

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1.2 Dissertation Outline

The dissertation consists of 3 chapters.

- Chapter 2 analyzes the price patterns by documenting facts about price rigidity using a large grocery retail data set.
- Chapter 3 discusses how vertical structure may influence price patterns. We document price pattern differences of store brands and national brands.
- Chapter 4 discusses the cyclical behavior of sales empirically.

Chapter 2

The Role of Retailers: Incomplete Pass-Through at the Retail Level

2.1 Introduction

In standard pricing models, the role of retailers is completely neglected. Often, we assume the manufacturers to be price setters, while consumers take these prices to maximize their utility. In reality, however, consumers seldom interact directly with manufacturer. This becomes even more likely in the case of necessity goods such as grocery items, clothing. Consumers often purchase necessity goods from retail stores, taking retail price, not wholesale price. Therefore, the assumption that the role of retailer in price setting is negligible would be innocuous only if the price observed at wholesale level is similar to the price observed at retail level. In other words, such an assumption would be correct only when retailers fully pass through the wholesale price to consumers and do not influence the prices that have been set by manufacturers.

In this paper, using detailed information of weekly price and cost from major retailer store that operates across the United States, we find strong evidence that retail price dynamics are completely different from manufacturer price dynamics. This result implies that ignoring the role of retailers in pricing models would be hugely misleading. In a nutshell, wholesale prices are a lot more rigid (average duration is close to 7 months), while retail prices are a lot more volatile (average duration is less than 4 months, similar to the duration of sales price in Klenow and Kryvtsov (2008)). We find two main reasons for why retail prices cannot fully reflect wholesale prices. First, retailers cannot do so because retailers face costs of their own aside from wholesale price. These extra costs (captured as various allowances, such as scanner allowances, freight allowance or extra labor cost) are often more volatile than wholesale prices (average duration for these costs are 2 months at most) and retail price pass-through to these costs are incomplete (ranging from 0.29 0.33 depending on the measure of pass-through rate). Therefore, the retail prices are influenced by existence of such costs, not being able to fully reflect wholesale prices. Second, retailers interact with consumers directly. Demand variations that are unobservable to manufacturers are observable to retailers, making retailers to be in better positions to reprice in the face of demand variation. It has been documented in a number of marketing journals that manufacturers, knowing that retailers are better observers of consumers, set a special fund called trading promotions, to pay for temporary discounts at retail level (Besanko and S.Gupta (2005)). Although it is difficult to argue who is actually in charge of setting the retail price in this case (manufacturers are paying for temporary discounts, while retailers are more in charge of timing and depth of discounts; therefore, both are in charge setting the prices), the role of retailers cannot be ignored.

To further understand the behavior of retail prices, we specifically pay attention to retail pass-through rates. Also we study price rigidity, for pass-through rates are closely linked to price rigidity. Complete pass-through, conditioned on non-zero cost change, implies flexible price movement, which also implies constant mark-up. On the other hand, zero pass-through with the same volatility in cost implies rigid price movement, implying variable mark-up.

Using unique price and cost information of a major retailer store across the United States, we establish the following facts. (1) retail pass-through rate is incomplete, (2) retail pass-through rate and retail price rigidity is negatively correlated, (3) categories with higher retail mark-up show lower pass-through rate, (4) price rigidity is heterogeneous across categories, (5) competition within a category shows positive correlation with pass-through rate, but the correlation is less obvious in the scatter plots and (6) retail price duration is shorter than wholesale price duration. We assess the implications of our empirical findings for four macro workhorse pricing models: two Time-Dependent Pricing Models (Calvo and Taylor) and two State-Dependent Pricing Models (Golosov and Lucas (2007), Dotsey et al. (1999)).

The contributions of our work are three-fold. First, the role of retailers in macro price settings is emphasized. The assumption that manufacturers interact directly with consumer demands could be seriously misleading, especially for grocery items. This becomes a serious issue in understanding monetary shock transmission to prices. According to the weights of components in the Consumer Price Index 2002, the sheer size of grocery expenditure in an economy comprises about 10.3% of total expenditure (food at home (8.338), other food at home (1.771), Personal care products such as hair, dental and shavings (0.362)). Misunderstanding the transmission of monetary shocks to 10% of consumer expenditure will lead to serious mis-measurement of the real effect of monetary policy.

Second, we provide information on pass-through rates. The popular setting for research in pass-through rates has been importing manufacturers, who set prices in response to exchange rate shocks (Engel (1995), Campa and Goldberg (2006)). However, studies of pass-through rates in other settings, especially in retail market have been seriously limited. This was mainly due to lack of dataset that enables such rigorous analysis. Widely used Dominicks Fine Food dataset does provide both retailer price and retail margin information. This imputed wholesale price (retail price minus retail margin), however, may suffer from serious measurement error, because the variable constructed can be complicated by the allowances that retailers provide to agents other than manufacturers (such as freight allowances, scanner usage allowances), thereby underestimating the actual wholesale prices. Our data set provides unique information about cost that incorporates allowances and other sources of cost that retailers face each week. Because these costs are in accounting terms, the variable may also be different from the perfect definition of cost in models. However, same caveat about the variables to our research as in previous research using this variable from same dataset (Eichenbaum et al. (2011), Gopinath et al. (2011)).

Finally, despite the natural relation between price rigidity and pass-through rates as mentioned above, efforts to understand these two variables in a single framework, both theoretically and empirically, have been rare. Often, research on price rigidity has been independent from research on pass-through rates. Gopinath and Itskhoki (2011), Goldberg and Hellerstein (2006) and Eichenbaum et al. (2011) are rare exceptions. Gopinath and Itskhoki (2011) acknowledge this missing link and establish positive relation between frequency of price adjustment (inverse of price duration) and exchange rate pass-through using information of U.S. imported goods. Goldberg and Hellerstein (2006) provide a useful estimation strategy to identify the sources of incomplete exchange rate pass-through. Incomplete pass-through can be decomposed into three components: mark-up adjustment, price adjustment cost and local non-traded cost. This paper uniquely incorporates retail level price setting, who directly interacts with consumers. Note that the relation between price rigidity and pass-through rates are distinct for these two papers: Price rigidity is the source of incomplete pass-through in Goldberg and Hellerstein setting, while price rigidity and pass-through rates are jointly influenced by a common factor in Gopinath and Itskhoki setting. Finally, Gopinath and Itskhoki (2011) do not provide information on price rigidity and pass-through, per se, but focus on price and cost movements by documenting several facts about mark-up movement.

The rest of the paper is organized as follows. Section 2 provides detailed information on dataset, definition of variables and treatment of missing values. Section 3 compares the behavior of wholesale prices and retail prices. Section 4 defines pass-through rate using three different definitions and find that pass-through rates are incomplete (ranging from 0.29 to 0.33 depending on the definition). Section 5 provides empirical evidence that link pass-through rates defined in the previous section with other variables, such as average mark-up, competition and price rigidity. Also, measures of price rigidity are related to these variables as well. Section 6 compares these empirical findings using standard macro pricing models. Section 7 concludes.

2.2 Data Description, Definition of Variables and Treatment of Missing Values

2.2.1 Data Description

Our analysis is based on scanner dataset from a large retail grocery chain that operates in the United States and Canada. This dataset has been used by Eichenbaum et al. (2011) and Gopinath et al. (2011) and recent work by Burstein and Jaimovich (2009) (hereafter, BJ) used in their respective research.
The dataset contains information on weekly total sales, quantities sold, wholesale unit cost as well as a measure of per-unit gross profit for each item for roughly over 178 weeks from the beginning of 2004 to mid 2007. By item, we mean a specific good defined in Universal Product Code (abbreviated as UPC). Most of the observations are concentrated in the food items (processed and unprocessed) and beverage categories, books and magazines, and personal care products. As noted in GGH in detail, the information that a UPC contains is extremely specific: for example, 25 fl.oz Perrier Mineral Water with a Lemon Twist and a 25 fl.oz Perrier Mineral Water with a Lime and 10 fl.oz Perrier Mineral Water with a Lemon Twist would have separate UPC. Table 1 in the Appendix reports number of items in each product category of the entire dataset.
Here, we focus our research on transactions carried out in 2004 alone. The total number of observations in this sample for one year is over 33 million. This data covers 73,764 items for 250 stores in 19 states. Unlike GGH who focused on the matching items of US and Canada, and unlike BJ who focused on wholesale prices in US and Canada, we exploit the entire information on wholesale, retail cost and prices.
Another feature of the dataset is the availability of aggregation levels. The store classifies each item in hierarchical order subsubclass, subclass, class, category, group and department. A specific apple would belong to a subsubclass Imported Bulk Red Delicious Apple, which belongs to subclass Bulk Red Delicious Apples, which belongs to class Red Delicious Apples, which belongs to category Apples, which belongs to group Fresh Produce which finally belongs to department Produce. Table 2.1 reports the number of UPCs that belongs to each subgroup of aggregation. This enables us to examine demand side fluctuations later in the paper. The rationale behind is that any price fluctuations coming from products within a subsubclass would not come from

manufacturers, for manufacturers are same for the products. Therefore, a shock to the manufacturer would be reflected similarly, while any shock to demand would generate price fluctuations in items within subsubclass.

2.2.2 Definition of Variables

Now, we would like to explain how we defined variables. We construct measures for price, cost and mark-up. It is important to denote that all of these measures are for retailers. Therefore, cost must be interpreted as what retailers pay to manufacturers or for other weekly allowances. Similarly, mark-up defined here reflects the mark-up for specific item at that specific week to retailers. We use quantity and volume provided in the dataset to compute two different measures for prices. There are two measures of quantity; gross quantity and net quantity. The gross quantity is the total gross revenue from sale of the good at its non-sale (or pre-sale) price. It is the sum total of the value of all purchases in that week, calculated based on the non-sale sticker price, exclusive of sales taxes. Net quantity, on the other hand, is the same value except that it is calculated based on the actual price paid, again exclusive of sales taxes. Put differently, net quantity differs from gross quantity in that the gross quantity excludes sales or temporary discounts. Using sales volume measure and two different information on quantity, we define regular price (P_R) using gross quantity and sales price (P_S) using net quantity. Sales price is always smaller than or equal to the regular price. Also, as can be shown in the analysis and previous literature, sales price has greater size change and shorter duration than regular price.

Also we have two different measures for cost: regular cost and sales cost. The data contains information on the whole-sale cost, which refers to the list price at which the retailer purchases to the wholesaler. These costs need not represent the true cost to the retailer. These costs are typically manufacturer allowances (rebate provided by the wholesaler to the retailer or vice versa) or freight and transport cost. Based on this information, two measures of costs differ in that one excludes manufacturer allowances and the other does not. Regular cost (C_R) is the measure which excludes manufactures allowances. It refers to the average wholesale cost paid by the retailer store per unit. This is the same wholesale price that Burstein and Jaimovich (2009) used in their analysis to gauge the international relative price movements. The second measure of cost Sales cost (C_S), we believe, is closer measure to the actual cost. The sales cost is different from regular price in that it includes manufactures allowances.

Finally, we look into mark-up. EJR points to the markup as an important measurement to understand how prices are related to cost. Specifically, they find that there is a narrow bound for the actual markup within plus/minus twenty percent of the desired markup over reference cost. Because of sales promotion, coupon uses or membership discounts that do not apply to every customer, it is often the case that there are multiple prices for a single product. Therefore, net quantity, which we used to construct retail price,P_S, combines product that was purchased at sales price and regular price. What we have, as a result, is a linear combination of actual sales price and regular price, weighted by the proportion of people purchased at each price level. To get a rough idea of measurement error, we count the observations of sales prices, where the size of discount is less than 5% (or 10%) of regular price. These observations are clear suspects of measurement error. That is, for a 1.00 dollar item, we do not suppose that a discount would have been less than 5 cent. Conditional on price change, 2% of total observations have less than 5% deviation from regular price, while 6% of total observations have less than 10% deviation from regular price.

2.2.3 Treatment of Missing Values

Because the data is collected at transaction level, missing values could arise when there is no purchase of the item at that week. Although observations do not imply price adjustment, without correcting for such missing values, we could bias frequency of price adjustment upward, or drive down the estimation of duration of each variables. Price duration or frequency can be sensitive to how we define missing values. As EJR noted in describing the dataset, measurement errors can be potentially be aroused in weekly price measures, due to irregular discount from promotions, loyalty card and usage of coupons. Thus, the same argument holds for us, as it did it EJR paper, that our estimates of duration of weekly prices provide an upper bound of the true duration. We have carefully adopted three different approaches in dealing with missing values, for how we define the spell of a time series is crucial in determining the behavior of duration and frequency of variables. The procedure is described in detail in Figure 3.1. In the analysis, we confirm that the duration of variables is highly sensitive to how we treat the missing values. The first treatment, referred to as spellA, takes the dataset as it is. The dataset, as in the dataset used by similar studies (Nakamura and Steinsson (2008), Kehoe and Midrigan (2008) and Kehoe and Midrigan (2010) to name a few), suffers from several issues; possible truncation of spell and potentially missing records. Therefore, we adopt two other methods. First of all, no correction for missing values as long as the price is the same, which results in the price spell being simply the number of weeks with weeks observed with same price. For instance, if price was \$1 during weeks 2 3 and the prices for week 4 6 are missing. The price continues to be is \$1 for week 7, jumps to \$1.5 for week 8 and declines to \$1.4 for week 9. The length of the spell is 2+1=3 weeks. We call this treatment SpellB. Notice that weeks 4 to 6 where there were no records, are not counted in the spell. The second method in defining spell is to include weeks 4 to 6 in the previous example. In other words, here the spell

is the number of weeks between the first and last occurrence of the observation of same price. We refer to this spell as SpellC, which would yield 6-2+1=5 week spell in the previous example.
Although we do not provide criterion as to assess which one of these spells is correct, we rely more on spellB and spellC than spellA. Not treating for missing values and taking the raw dataset as it is, as in spellA, can lead to serious measurement error, because it does not capture the missing price observation arising from non-purchase at particular week. For instance, using spellA, magazines are captured as one of the categories with highest price frequency. Looking close at the price path, it has been found that there were certain weeks that magazines were not purchased. Frequency of price adjustment, in this case, is exaggerated, not because of price adjustment, but because of missing values due to the nature of dataset collected at transaction level. Therefore, we rely more on spellB and spellC than spellA. The following histograms provide distribution of price duration. We can observe more density in lower frequency of price adjustment in histograms of price frequency in spellB and spellC.

2.2.4 Some Facts about Duration

- Wholesale price duration shows the longest price duration (ranging from 2 months to 8 months depending on the spell and the aggregation level). Retail price as sales price shows shorter price duration (ranging from 1 month to 3 months depending on the spell and the aggregation level). Finally, the retail cost duration is the shortest of all.
- It is unclear how the aggregation level influences the spell. For most of the duration, the aggregation from UPC to category increases the duration. However, for spells of sales price and sales cost, the opposite seems to be true. Table 2.3 and Table 2.4 report the unweighted and weighted duration of each variable, respectively.
- We observe heterogeneity of frequency of price adjustment.

In numerous studies using micro-level dataset, it is reported that frequency of price adjustment is heterogeneous across product categories. According to Bils and Klenow (2004) (2004, hereafter, BK), the average frequency is 26 percent for all product categories in the BLS dataset. The most frequently changing product category is transportation costs (cars and airfares) (40 percent of prices changing monthly), while the least frequently changing product category is medical cost with about 10 percent changing monthly. Also, Gopinath and Rigobon (2008) (2007, hereafter, GR) document a large amount of heterogeneity in the level of price stickiness across goods for both import and export goods, using micro data on U.S. import and export prices at the dock.

Understanding heterogeneity of price duration has important implications for real effects of monetary policy. It has been studied that heterogeneity in price stickiness across sectors induces nominal rigidity and real rigidity compared to identical-firms model, requiring the identical firm models to have a frequency of price changes up to three times lower than the average of the heterogeneous economy to match the real effect of monetary shock for the U.S. economy (Carvalho and Schwartzman (2008)).
Here, we find heterogeneity of frequency of price adjustment of retail prices across product categories within the range of grocery items. Using SpellA, frequency of price adjustment ranges from 0.04 to 0.66 (Beverage ice being the category with the longest duration of 25 weeks, while refrigerated juice blends being the category with the shortest duration of less than 2 weeks). Using SpellB, the frequency of price adjustment ranges from 0.03 to 0.56 (sushi being the category with longest duration of nearly 33 weeks, while refrigerated juice blends show the shortest duration of less than 2 weeks). Finally, using SpellC, the frequency of price adjustment ranges from 0.02 to 0.52 (pet food being the category with longest duration of nearly 50 weeks, while refrigerated juice blend category shows the shortest duration). To provide the distribution of frequency measures, figure 2.1 in the Appendix is provided.
The data set that we use in this paper differs from the previous work in that it covers only grocery items. The frequency of price adjustments of grocery items in both BK and GR is close to the average frequency across all products or higher than average: in BK, food items have frequency of 25.5%, while in GR, vegetable and fruit products have frequency of 20% and prepared food show 40% frequency.

2.3 Wholesale Price vs. Retail Price

The goal of this section is to provide insight why retail prices are different from wholesale prices. Here, we consider three different cases to emphasize the role of (non-neutral) retailer in modeling. The model that include (non-neutral) retailer induces different price dynamics for wholesaler and retailer, especially in terms of frequency of price adjustment and successfully explains the empirical predictions. The key role that non-neutral retailer plays in price dynamics is that the existence of stochastic retail cost derives the wedge between the retail price dynamics and wholesale price dynamics, making retail prices more volatile than wholesale prices. The underlying price adjustment mechanism follows Calvo style, where every period, t, manufacturer (wholesaler) receives a signal with probability (1-λ) to re-optimize its price.

2.3.1 Case 1: Without a retailer

Here we present the usual setting, where consumers respond to the prices set by manufacturers, without intermediary (retailer). At time t, in a perfectly competitive market, firm produces a final good, Y_t, by combining intermediate goods, indexed by $j \in [0,1]$ using a constant returns to scale technology. The producer of intermediate good is a monopolist using the following technology:

$$Y_{jt} = A_t k_{jt}^{\alpha} L_{jt}^{1-\alpha} \tag{2.1}$$

where $0 < \alpha < 1$, while k_{jt} and L_{jt} denote capital and labor service the firm used at time t to produce j th intermediate goods, borrowing capital and labor in perfectly competitive factor markets. Finally, A_t refers to time-varying technology. With c_t as the representative firm's marginal cost, the firm's time t profit is given by:

$$[\frac{P_{jt}}{P_t} - c_t] P_t Y_{jt}. \tag{2.2}$$

Using the mechanism by Calvo (1983), firms face a constant probability, 1-λ each period, to reoptimize its nominal price. In expectation, each firm re-optimizes its price every $(1-\lambda)^(-1)$ periods, $P_{j,t}^{*}$. With probability ? each period, the firm does not readjust its price and updates the price according to the rule:

$$P_{j,t} = \bar{\pi} P_{j,t-1} \tag{2.3}$$

Here, we assume that inflation is constant, so that price of previous period is equal to the price at time t, with probability λ. Under such mechanism, the aggregate price level can be expressed as:

$$P_t = [(1-\lambda)(P_{jt}^{*})^{\frac{1}{1-\theta}} + \lambda (P_{j,t-1})^{\frac{1}{1-\theta}}]^{\frac{1}{1-\theta}} \tag{2.4}$$

where $\theta \in [1, \inf]$ implies the degree of substitutability of intermediate goods.

2.3.2 Case 2: With a neutral retailer

Here, we consider the case where we take into account the retailer where retailer merely passes through the wholesale price (or price set by manufacturers). We assume that $P_{it}^{S} = P_{it}^{W} + \mu_i$, where P_{it}^{S} is the retail price of item i at time t, P_{it}^{W} is the wholesale price of item i at time t and μ_i implies good-specific, time-invariant mark-up. Here, the retailer does not face costs of their own, and sets price as constant mark-up over wholesale price. The pass-through rate, from here on, is how much wholesale price (cost to the retailer) is passed through retail price, which matches the pass-through rates calculated in this paper. Calvo mechanism in this model feeds into the manufacturer price, P_{it}^W.

Now let's assume that the mark-up is time-varying, that is, $P_{it}^S = P_{it}^W + \mu_{it}$. Differencing P_{it}^s leads to:

$$\triangle P_{it}^S = \triangle P_{it}^W + \triangle \mu_{it} \tag{2.5}$$

Here, the last term $\triangle \mu_{it}$ does not vanish by differencing. Let's suppose μ_{it} to be i.i.d random shock. Positive correlation between frequency of price adjustment and pass-through rate is possible, but unlikely. In order to induce price fixed for some periods with stochastic cost, the mark-up should be negatively correlated with stochastic cost. That is, whenever there is a cost decrease, mark-up should increase and exactly offset any price change, otherwise, price at time t will differ from the price in the previous period. In order for this model to be plausible, we need to put unrealistic restrictions on the movement of $\triangle \mu_{it}$, that is, $\triangle \mu_{it}$ cannot be positive and at the same time, cannot be negative by large margin: positive $\triangle \mu_{it}$ leads to pass-through rate greater than 1, which is not observed in the dataset, and too small value of $\triangle \mu_{it}$ leads to pass-through rate less than 0.

2.3.3 Case 3: With a non-neutral retailer

Finally, lets suppose retailer influences wholesale price, with stochastic retail cost. Here, the role of retailer is non-neutral. The retail price is set as follows: $P_{it}^S = P_{it}^W + C_{it}^R + \mu_{it}$, where C_{it}^R is good-specific, time-variant retail cost, while other variables are exactly same as above.
At time t, P_{it}^W andC_{it}^R are revealed to the retailer. Then, retailer sets the price $(P_{it}^S)^*$. Wholesale price follows Calvo pricing mechanism, resetting price to optimal level $(P_{it}^W)^*$ with probability (1-λ) and maintaining its previous price with probability λ. The model presented in this section will show how retail price change frequency is different from wholesale price frequency with non-neutral retailer. We consider two different cases: (1) without menu cost and (2) with menu cost.

No Menu Cost

Consider a retail firm that sells all of the markets J differentiated products. The profits of the retail firm associated with selling product j at time t are given by:

$$\pi_{jt}^R = (P_{jt}^S - P_{jt}^W - C_{jt}^R)Q_{jt}(P_t^S) \tag{2.6}$$

where P_{jt}^S represents the retail price of item j at time t, P_{jt}^W represents wholesale price of item j at time t, C_{jt}^R represent retail cost aside from the wholesale price of item j at time t and $Q_{jt}(P_t^S)$ is the demand which is function of retail price vector at time t, P_t^S. Here, the optimal price, $(P_{it}^S)^* = (1-1/\epsilon)^(-1)(P_{jt}^W + C_{jt}^R)$. Let Ψ denote the frequency of retail price adjustment.

$$\Psi = Pr(P_{jt}^S \neq P_{j,t-1}^S) = Pr(P_{jt}^S \neq P_{j,t-1}^S, P_{jt}^W = P_{j,t-1}^W + Pr(P_{jt}^S \neq P_{j,t-1}^S, P_{jt}^W \neq P_{j,t-1}^W) \tag{2.7}$$

In the above equation, we can observe Ψ can be decomposed into retail price change conditional on no change in wholesale price and retail price change conditional on wholesale price change. It is easy to observe that ? is different from the probability of wholesale price change, (1-λ): in fact, Ψ is higher than (1-λ), because even without wholesale price change, retail price will change as long as $C_{jt}^R \neq C_{j,t-1}^R$.

Lemma 1. (1) As long as $C_{jt}^R \neq C_{j,t-1}^R$, and wholesale price maintains its previous level with probability λ, retail price P_{jt}^S is different from $P_{j,t-1}^S$. (2) Unless $\triangle C_{j,t}^R + \triangle P_{j,t}^W = 0$, retail price P_{jt}^S is different from $P_{j,t-1}^S$ when wholesale price readjusts to optimal level, $(P_{j,t}^W)^*$ with probability (1-λ). Therefore, retail price is likely to change with or without wholesale price change, leading wholesale price frequency (1-λ) is lower than Ψ.

Menu Cost

Although no-menu cost model discussed above fully explains the frequency of price adjustment of wholesale price differing from that of retail price, it does not explain why retail price maintains certain level of price rigidity. A study by Kehoe and Midrigan (2008) reports that prices take V-shape: over 50 weeks, prices spend most of their time in its modal price, while making temporary jumps frequently. Also, these temporary jumps, mostly associated with sales, tend to return to pre-sales price. According to no-menu cost model, as long as $C_{jt}^R \neq C_{j,t-1}^R$, retail price adjusts its level to optimal level at time t, contrasting the empirical finding that retail price stays at its modal price. Here, in an effort to induce price rigidity at retail price level, we introduce $A_{j,t}^R$, cost that retailers bear when changing its nominal price of item j at time t. The profit for the retailer is, therefore:

$$\pi_{jt}^{R} = (P_{jt}^{S} - P_{jt}^{W} - C_{jt}^{R})Q_{jt}(P_{t}^{S}) - A_{j,t}^{R} A_{j,t}^{R} = 0 if P_{jt}^{S} = P_{j,t-1}^{S} A_{j,t}^{R} > 0 if P_{jt}^{S} \neq P_{j,t-1}^{S} \quad (2.8)$$

Here, retailers readjust prices only when gains from doing so outweigh the cost. Formally, $\pi_{jt}^{R}((P_{jt}^{S})^{*}|P_{jt}^{W}, C_{jt}^{R}, A_{j,t}^{R})$ should exceed $\pi_{jt}^{R}(P_{j,t-1}^{S}|P_{jt}^{W}, C_{jt}^{R})$. We consider two cases: first consider the case where $P_{jt}^{W} = P_{jt-1}^{W}$ with probability λ, and second, consider the case where $P_{jt}^{W} = (P_{jt}^{W})^{*}$ with probability (1-λ).
Let Ψ_1 denote the frequency of price adjustment in the first case, where Ψ_2 denote the frequency of price adjustment in the second case. Formally, we can write each variable as follows:

$$\begin{aligned} \Psi_1 &= Prob(\pi_{jt}^{R}((P_{jt}^{S})^{*}|P_{jt}^{W}, C_{jt}^{R}, A_{j,t}^{R}) - \pi_{jt}^{R}(P_{jt-1}^{S}|P_{jt}^{W}, C_{jt}^{R}). > A_{j,t}^{R}|P_{jt}^{W} = P_{jt-1}^{W}) \\ \Psi_2 &= Prob(\pi_{jt}^{R}(P_{jt}^{S})^{*}|P_{jt}^{W}, C_{jt}^{R}, A_{j,t}^{R}) - \pi_{jt}^{R}(P_{j,t-1}^{S}|P_{jt}^{W}, C_{jt}^{R}). > A_{j,t}^{R}|P_{jt}^{W} = (P_{jt}^{W})^{*}) \end{aligned} \quad (2.9)$$

Ψ_1 and Ψ_2 can be re-written as follows:

$$\begin{aligned} \Psi_1 &= Prob(\pi_{jt}^{R}((P_{jt}^{S})^{*}|P_{jt}^{W}, C_{jt}^{R}, A_{j,t}^{R}) - \pi_{jt}^{R}(P_{j,t-1}^{S}|P_{jt}^{W}, C_{jt}^{R}) > A_{j,t}^{R}|P_{jt}^{W} = P_{jt-1}^{W}) \\ &= Prob([(P_{jt}^{S})^{*} - P_{jt-1}^{W} - C_{jt}^{R}]Q_{j,t}^{'} - A_{j,t}^{R} - [P_{jt-1}^{S} - P_{jt-1}^{W} - C_{jt}^{R}]Q_{j,t}^{''} > 0) \\ &= Prob((P_{jt}^{S})^{*}Q_{j,t}^{'} - P_{j,t-1}^{S}Q_{j,t}^{''} - [P_{jt-1}^{W} + C_{jt}^{R}](Q_{j,t}^{'} - Q_{j,t}^{''}) > A_{j,t}^{R}) \end{aligned} \quad (2.10)$$

$$\begin{aligned} \Psi_2 &= Prob(\pi_{jt}^{R}((P_{jt}^{S})^{*}|P_{jt}^{W}, C_{jt}^{R}, A_{j,t}^{R}) - \pi_{jt}^{R}(P_{jt-1}^{S}|P_{jt}^{W}, C_{jt}^{R}). > A_{j,t}^{R}|P_{jt}^{W} = (P_{jt}^{W})^{*}) \\ &= Prob([(P_{jt}^{S})^{*} - (P_{jt}^{W})^{*} - C_{jt}^{R}]Q_{j,t}^{'''} - A_{j,t}^{R} - [P_{jt-1}^{S} - P_{jt}^{W})^{*} - C_{jt}^{R}]Q_{j,t}^{''''} > 0) \\ &= Prob((P_{jt}^{S})^{*}Q_{j,t}^{'''} - P_{jt-1}^{S}Q_{j,t}^{''''} - [(P_{jt}^{W})^{*} + C_{jt}^{R}](Q_{j,t}^{'''} - Q_{j,t}^{''''}) > A_{j,t}^{R}) \end{aligned} \quad (2.11)$$

Here, $Q_{j,t}^{'}$ and $Q_{j,t}^{'''}$ are the quantity induced by new optimal price, while $Q_{j,t}^{''}$ and $Q_{j,t}^{''''}$ can be interpreted as counterfactual quantity level if the retailer decides to maintain the previous retail price level. It is easy to find that both Ψ_1 and Ψ_2 are mainly composed of two factors: how much the retailer revenue increases by adjusting retail price and how much the cost share changes due to quantity changes induced by the new price level. The first component depends on how elastic the demand function is, while the

second component depends on whether quantity change is positive or negative, which ultimately depends on the sign of price change at time t.
These result in the following lemmas:

Lemma 2. $((P^S_{j,t})^* > P^S_{j,t-1})$ In the case where new optimal price is greater than the previous price level, Ψ_1, Ψ_2 depend on the elasticity of demand. If the demand is not elastic so that the retailer revenue with the new price is greater than retail revenue with previous price level, this unambiguously increases Ψ_1 and Ψ_2. If the demand is highly elastic so that retailer revenue with the new price level is smaller than retailer revenue with previous price level, the effect onΨ_1 and Ψ_2 is ambiguous.

Lemma 3. $((P^S_{j,t})^* < P^S_{j,t-1})$ In the case where new optimal price is smaller than the previous price level, Ψ_1 and Ψ_2 depend on the elasticity of demand. If the demand is not so elastic so that the retailer revenue with the new price level is smaller than retail revenue with previous price level, this unambiguously decreases Ψ_1 and Ψ_2. If the demand is highly elastic so that retailer revenue with the new price level is greater than retailer revenue with previous price level, the effect on Ψ_1 and Ψ_2 is ambiguous.

In summary, the standard model with the retailer playing neutral role predicts same price dynamics (in terms of price rigidity and price fluctuation) between wholesale price and retail price. Pass-through rate at retail level (understood as wholesale price passed through retail price) is complete. On the other hand, model with non-neutral retailer who faces time-varying retail cost of its own, predicts that price dynamics are quite different for retailer price and wholesale price. In fact, in this model, pass-through rates at retail level are incomplete.
As non-neutral retailer models predict, the data set clearly shows drastically different price rigidity for wholesale price C^R_t and retail price P^S_t. Also we see different price rigidity for retail cost C^S_t and retail price.

In addition to models above, we qualitatively present two main reasons why wholesale price is not fully reflected in retail prices, that is, why "$P^R or P^S = C^R + constant$" does not hold, when $P^(RorS)$ is retail regular or sales price and C^R refers to wholesale price. If the relation holds, then, any change in retail price from time t to t+1 would be completely reflecting any cost change from time t to t+1, because constant terms become eliminated by differencing. However, because (1) retailers face time-varying cost of their own, aside from whatever amount the retailers are paying to wholesalers, and (2) retailers interact directly with consumers, wholesale price is not reflected fully into retail price. With this, we can argue that ignoring retailer level in pricing models could generate discrepancy.

To be more specific, first, lets decompose P_t^R, the regular price before discount. Regular price at time t is sum of wholesale price and extra cost, $P_t^R = C_t^R + \epsilon_t$. The extra cost, ϵ_t, can be understood as retail margin and other costs that retailers have to pay. For instance, the retailers have to bear the cost of delivery, scanner or extra labor costs. If these extra costs were time-invariant, pass-through rate, defined as price change regressed on cost change, would be one, implying complete pass-through rate.

What complicates the matter more is that retail price is regular price minus discount, that is, $P_t^S = P_t^R - \tau_t$, when $\tau_t$refers to the size of discount. Combining with the expression for regular cost, the retail price can be expressed in the following equation.

$$P_t^S = P_t^R - \tau_t = C_t^R + \epsilon_t - \tau_t \tag{2.12}$$

In this case, P_t^S would fully reflect the wholesale price C_t^R only if $\epsilon_t - \tau_t$ were not time-varying, so that pass-through rate of wholesale price to retail price would be 1. The figures 2.2 show the distribution of standard deviation of ϵ_t and $\epsilon_t - \tau_t$ for each products for each store. If there is no time variation of ϵ_t or $\epsilon_t - \tau_t$ for an item for a specific store, the standard deviation is going to be zero or close to zero. The distribution of ϵ_t actually shows that there is a huge mass concentrated at 0. In fact, 25% of observations have 0 standard deviation, implying that pass-through rate of wholesale price to regular price could be 1 for 25% of the items. However, the distribution of $\epsilon_t - \tau_t$ is more skewed to the right. Less than 5% of observations have 0 standard deviation, implying that complete pass-through rate of wholesale price to retail price cannot be justified, for there is too much time variation in $\epsilon_t - \tau_t$.
Another reason why retail prices do not fully reflect the wholesale prices is that retail price interacts with demand directly. In the face of demand variation, retailers are in better position than wholesalers to reprice. To understand this price adjustment at retail level in reaction to demand variation, we employ the method in Zhao (2006) on computing price dispersion in the grocery market. The data contains information on the exact location of the store. The measure of price dispersion across stores for a certain UPC, i, in category j at time t, at store s is computed as follows:

$$DISP_{it} = \frac{S_{it}}{P_{it}} * 100 \tag{2.13}$$

where S_{it} is the standard deviation of P_{ist} and P_{it} is the mean price of the product across category at time. There is a great variation in the dispersion of the sales prices across stores. The range of $DISP_{it}$ is from 0 to 0.50, with average 0.34. This dispersion, however, can be due to the local cost that has little to do with demand variation. To substantiate the argument, we carry out another analysis where we construct the relative price of individual item over the average price of the same item within a city. Relative price is calculated as follows, where N_c refers to the number of stores in the city.

$$REL_{it} = (\frac{P_{its}}{\overline{P_{it}}}) \tag{2.14}$$

where $\overline{P_{it}} = \frac{1}{N_c}\sum P_{ist}$. The same exercise is carried out across district and operating area. As the retail store operates across the United States, there are 9 operating areas that manage the stores at local level (Texas, Portland, Seattle, East Coast, Northern California, Southern California, Denver, Chicago and Phoenix). District level is smaller geographical unit than operating areas, comparable to county level. The Table 2.5 documents the findings of the variation of standard deviation at city, district and operating area levels. Relative measure shows that price dispersions across city, district, and operating areas are little. The average of relative measure is close to 1, while median is also 1. However, there is a great variation in REL, implying that there are significant numbers of observations where retail prices are highly deviant from the average price across region. Therefore, from this finding, we conclude that most of the prices are controlled at city, district and operating area level. However, there exist prices that retailers choose independently at individual stores and deviate from the average item price across set by managers at operating area, district or city. This, we believe, is reflective of retailers response to local demand shocks.

2.4 Incomplete Pass-Through

The goal of this section is to provide careful definition of pass-through rates of sales cost to sales price. Sales cost comprise of wholesale price (which is a cost to the retailers) plus extra costs that retailers bear every week. As mentioned in the previous section, one of the reasons why retailers do not fully reflect wholesale price is existence of sales cost. Variation in sales cost create wedge between wholesale cost and retail price, especially because sales cost is not fully passed through retail prices. Therefore, establishing that sales cost pass-through to sales price is essential in establishing that retailers follow pricing mechanism that creates discrepancy between retail prices and wholesale prices. The figures 2.3 in the Appendix provide motivation for this section. Items in different categories show starkly different movements of prices in response to costs. In the line graphs, the cost movements of lettuce track closely the movements of prices, while price movements are stickier than cost movements for the case of a breakfast item. The scatter plots capture the differences in the line graph to motivate for regression approach to measure pass-through rate. In fact, the pass-through rate

(using fixed-effect regression) for lettuce is close to 0.9 while the pass-through rate (using fixed-effect regression) for this breakfast item is close to 0.3.
Our measures of pass-through rates are the slopes in these scatter plots: the size of price change over the size of cost change. Scatter plots in 2.3 in the Appendix motivate this. We provide three different measures of pass-through rates: OLS, fixed-effect (controlling for item-specific, location-specific and time-specific variations) and long-run pass-through, often used in previous literature. We fully recognize the endogeneity issue that arises from OLS regressions. The pass-through rate, which is the coefficient of the slope, reflects the correlation between the two variables of interest (the size of price change and the size of cost change). We employ fixed-effect regressions to control for time-variant omitted variable and time-invariant (item-specific, store-specific). If there are other factors that can cause the bias, this measure may not solve the endogeneity issue completely. However, pass-through rates from OLS regressions are highly correlated to those from fixed-effect regressions (correlation: 0.98). Finally, long-run pass-through rate over 52 weeks is used. This captures the cumulative changes of price and cost, rather than weekly variations of those variables. Because this measure also suffers from endogeneity issue, we use fixed-effect (time-specific, store-specific, and item-specific) to control, at best, for the problem.
For all of these three measures, we find strong evidence for incomplete pass-through (ranging from 0.29 to 0.33, depending on the definition of pass-through rate). In other words, sales cost is not fully reflected in the retail prices.

2.4.1 Price and Cost Co-Movements

Pass-Through Rate captures how price responds to cost shocks. Empirical studies of pass-through rates, to my knowledge, have been mainly in two settings: (1) exchange rate shocks to the price of imported goods (Engel (1995), Campa and Goldberg (2006), Goldberg and Hellerstein (2008)), (2) commodity shocks to wholesale prices (Nakamura and Zerom (2010)), Goldberg and Hellerstein (2008)). A common assumption in the literature is that movements in the exchange rate or commodity price are disconnected from most macro-variables, making it orthogonal to other shocks that effect the firms pricing decision. Also firms inability to influence pricing decision obviates the argument of reverse causality, leading to an unbiased, consistent estimate of pass-through rate β. Standard pass-through regression is as follows :

$$\triangle P_t = \alpha + \beta \triangle FX_t + \epsilon_t \tag{2.15}$$

We face the similar issue in estimating pass-through rate. In estimating for pass-through rates, we first employ simple OLS regression. For instance, there are ample examples that could influence both firms cost shocks and price decision, making the coefficient suffer from omitted variables bias. Also, price decision could also factor into cost, resulting in reverse causality. Fortunately, unlike the previous literature on pass-through rate, we can identify the cost to specific location, item and time benefiting from disaggregated feature of the dataset. We employ item-specific, time-specific and store-specific fixed effects that could control for both time-invariant and time-variant factors that might bias the estimate. This fixed-effect regression can capture bias arising from variations from those factors specified in the regression (although we cannot say that this fixed-effect regression fully eliminates any source of bias). Third, we estimate fixed-effect long-run pass-through rate, implemented by many researchers like Gopinath and Itskhoki (2008). Long-Run Pass-Through rate can be obtained by regressing cumulative price, defined as change of price from the beginning of the observation to the end of observation, on cumulative cost, defined similarly The benefit of this approach is that by widening the window, we can ensure that goods have indeed changed their price.

Although it is the standard in the literature to assume that β is unbiased estimate of pass-through rate, possible sources of endogeneity still exist in this regression, as well. Especially when real exchange rate is used as the regressor, there are rooms for factors such as inflation rate, country income growth in the error term that are correlated with both dependent and independent variable. Usual control variables such as local shocks do not control for these endogeneity either.

2.4.2 Pass-Through Regressions and Results

First, we run the following simple OLS regression for each product category.

$$\triangle P_t = \alpha + \beta \triangle C_t + errorterm \tag{2.16}$$

The average of pass-through across product categories is 0.31, ranging from nearly 0 to 0.98. The items with highest pass-through rates are orange juice, potato chips, juice blends (lettuce also being one of categories with highest pass-through rates), while the items with lowest pass-through rates are pet food, greeting cards, magazines and shrimp. The following histogram 2.4 represent the distribution of pass-through rates using OLS regression. This measure, however, suffers from serious endogeneity problem. Unlike exchange rate pass-through regression, where exchange rate shocks are arguably exogenous, there could be various scenarios where factors in the error terms influence both sales cost and sales price in retail setting. This problem is especially likely, since there is ample evidence that both retailers and manufacturers are responsible for retail prices (through trading promotions, for instance).

To treat for the endogeneity issue of estimate from OLS regression, we run fixed-effect regression using location-specific, item-specific and time-specific controls. Although there still could be elements that could bias the pass-through rate coefficient from fixed-effect regressions, we can control for time-varying and time-invariant (item, location) factors that can both influence sales cost and sales price in error terms. We carry out the following regression for each category:

$$P^{(RorS)}_{(i(t+k)s)} - P^{(RorS)}_{i(t-1)s} = \alpha_i + \gamma_s + \delta_t + \beta_j \triangle C^{(RorS)}_{its} + errorterm \tag{2.17}$$

where the subscript i represents item (or UPC), t represent time and s represent store and k=0,1,2,...
As mentioned before, we focus at category (e.g. apples) level, because comparison between observations within a category naturally leads to a sensible interpretation, where different items that belong to different firms within this subgroup operate in a same industry producing differentiated products.

Average pass-through rate across categories in this exercise is 0.2696, ranging from close to 0 to 0.984. The categories with highest pass-through rates are similar to OLS regressions, orange juice, juice blends and potato chips, while the categories with lowest pass-through rates are also similar to OLS regressions, shrimp, greeting cards and magazines.
The figure 2.5 in Appendix provides histogram to capture the distribution of coefficients. The pass-through rate we consider last is Long-Run Pass-Through. Long Run Pass-Through Rates defined here are similar to the LRPT by Gopinath and Itskhoki (2008). Specifically, for the first Long Run Pass-Through measure, we take the cumulative change in the price (averaged across items within a category) taken from the beginning of the series to its last observation. Then, this measure is related to cumulative change in the cost measured in similar manner. The benefit of this approach, as they argue, is that the measure ensures a cost change by widening the time window. This benefit, however, is not so apparent in our paper, for both OLS and fixed-effect regressions are carried out, conditional on cost change. Therefore, the measures that we have explored earlier also ensure cost change. However, long-run pass-through is attractive, for it captures a general trend of cost and price movement over a year, obviating from possible noise that arise from weekly variations. These measures are referred to as LRPT and can be estimated from the following regressions.

$$\triangle P^{(j,RorS)}_{LR} = \alpha_j + \gamma_s + \triangle C^{(j,RorS)}_{LR} + errorterm \tag{2.18}$$

As a result, LRPT provides slightly higher pass-through rates than previous approach. On average, the pass-through rates are 0.33 across categories. The rate ranges from -0.011 to 0.989. Categories with highest pass-through rates are ramen, ready-to-serve-soups, condiments, while those with lowest pass-through rates are shrimp, flower bouquets and pet food. The histogram, figure 2.6 provides a distribution of LRPT. The clear difference from figure 2.4 and 2.5 is the shift of distribution to the right, implying higher pass-through rates.

We do not provide criterion as to which of the three measures are most reliable than the others. We find that all of these three matters are highly correlated. The following table 2.6 provides the correlation between the pass-through rates, and shows that the correlation is high. In the later analysis, we are going to use all three measures to relate to other important variables, such as mark-up and proxy for competition.

2.5 Facts About Pass-Through Rates

The goal of this section is to use carefully defined pass-through rate and price rigidities and view them in perspective of competition, mark-up. Here, we focus our attention at aggregation level of category, for this aggregation level is directly comparable to industry classification. Therefore, we claim that comparing measures at category level enables us to compare patterns across industries.

- Pass-Through Rates (β) and the frequency of price adjustment (Ψ) are Positively Correlated.
- Average mark-up of a product category is negatively correlated with pass-through rates.
- Competition within a product category is not strongly correlated with pass-through rates.

The first result exhibits the positive correlation between the pass-through rates and the frequency of price adjustment. Theoretically, pass-through rates and frequency of price adjustment is closely related. In this subsection, we establish this empirically. Measures of pass-through rate are regressed on frequency of price adjustment (refer to the equation (1) below). We find that strong positive correlation with 1% significance level and this is true for all three measures of pass-through rates.

$$Pass - throughrates(\beta) = constant + \delta * \Psi + errorterm \tag{2.19}$$

Table 2.7 provides regression coefficients δ. Consistent with the findings of Gopinath and Itskhoki, We see strong positive coefficients for all three measures of pass-through. To recall the definition of spells, SpellA treats the data set as it is. SpellB and SpellC interpolate the price series with missing values: SpellB does not take into account the missing observations as a part of price series, while SpellC does. Price duration with SpellC, therefore, is longer than that with SpellB. This finding is further substantiated with scatter plots in figures 2.7, 2.8 and 2.9.

However, this positive correlation does not hold when we run separate regressions of frequency of price adjustment and pass-through rates in two separate frequency bins. Here, we separate the categories with frequency higher than median frequency from those with frequency lower than median. First, we take the average of pass-through rates in each bin. Table 2.8 reports the result. For all pass-through rate measures and duration measures, we find higher average pass-through rates for high frequency categories. When we run regression (3) in each bin, however, there is no clear pattern of correlation between two variables. Table 2.9 reports that most of the coefficients are non-significant, while for those coefficients with high significance show higher pass-through rates for low-frequency bins.

The second set of results establishes a correlation between mark-up level and pass-through rates. Usually, mark-up level implies the degree of competition. In perfect competition, mark-up is average zero, while monopolists garner the maximum rent (mark-up). Melitz and Ottaviano (2008) provide a formal setting where mark-up is endogenously determined by firm competition. They derive endogenous mark-up in international trade model, where firms with productivity higher than a threshold level enter the market. They allow for firm heterogeneity in monopolistically competitive market to induce endogenous mark-up. Mark-up observed here, however, cannot be interpreted as competition. Actually, it is unclear how to interpret these measures. Retail mark-up could reflect bargaining powers between manufacturer and retailers, or could be related to manufacturer competition. These assumptions, however, are not based on formal theories.

Using the identity:

$$\log(P_t^S) = \log(C_t^S) + \log(\mu_t) \tag{2.20}$$

where P_t^S is the retail price of a particular product at time t, C_t^S is the retail cost of a particular product at time t and μ_t is the mark-up, we calculate the average mark-up for each category. It is important to remember that the mark-up established here is for the retailer, not for manufacturers.

We find that categories with higher average mark-up show lower pass-through (we cannot disclose the information about mark-up level). That is, categories that have higher mark-up pass through costs less. Table 2.10 report the result. The coefficients are negative with 1% significance level for all measures of pass-through rate. Scatter plots in figure 2.10 further substantiate this negative correlation.

$$Pass - throughrates(\beta) = constant + \gamma * \mu + errorterm \tag{2.21}$$

Finally, the third result attempts to establish the relation between the competition level and pass-through rates. To get a sense of degree of competition in each product categories, we carry out the following exercise where we proxy the degree of competition with number of items in the category and number of brands in the category. The rationale behind this is that more items reflect more choice for consumers, making the environment more intense for manufacturers to appeal to consumers. It has been standard in literature of differentiated goods in monopolistically competitive market that number of firms in the market reflects the degree of competition. Here, we assume such environment. It should be noted that such explanation would not be applicable for oligopolistic market: in oligopolistic market where small number of agents competes with each other, such as airplane manufacturer, number of players in the market does not reflect the degree of competition.

$$Pass - throughrates(\beta) = constant + \theta * (degreeofcompetition) + errorterm \tag{2.22}$$

Table **??** shows the results.

2.6 Further Results

In this section, we provide further results using the data set. Because of the apparent positive relation between price rigidity and pass-through rates, we compare if same patterns exist between price rigidity measure and variables of interest in the previous section. Overall, the correlations between price rigidity and these variables become weak. In most cases, the correlations are still statistically significant, but very difficult to substantiate the findings with scatter plots.

- Product categories with more competition show more price rigidity (although the relation is weaker than Fact 2.
- Product categories with higher average mark-up show more price rigidity (although the relation is weaker than Fact 1.

First, we find that product categories with more competition, measured by the number of items in the category, exhibit higher price rigidity. Gopinath and Itskhoki (2008) highlight that in order to discern what the frequency of price adjustment implies for the transmission of shocks or why certain categories adjust prices more frequently than others, it is crucial to relate frequency of price adjustment with other meaningful variables. They relate frequency of price adjustment to exchange rate pass-through to highlight the role of curvature of profit function. Here, we relate price rigidity with degree of competition, proxied by number of items within a category. The exercise is similar as before with pass-through rate. We find that categories with more items, thereby, more competition, adjust their prices less frequently than the categories with less competition. How should we interpret this? One possible explanation is provided by Blanchard (1983). He provides a model that highlights the role of relative prices, in the absence of perfect synchronization of price decision, in explaining price inertia. The process of price adjustment with imperfect synchronization of price decision will lead to temporary movements in relative prices. Firms, trying to avoid huge changes in relative price that might decrease demand drastically, they adjust prices slowly. Because every price setter does this, this creates substantial inertia of price level. Applying this framework, the categories with more competing items, decrease in demand due to temporary changes in relative price could be greater. That is, the tension between competitors creates greater force of inertia of the price level. Such negative correlation is significant, but weaker than the correlation between competition and pass-through rates. Tables 2.12 provide the regression coefficient, with scatter plots in figure 2.11.

Second, we compare the price rigidity with mark-up level. We establish the fact that product categories with higher average mark-up adjust their prices less frequently. That is, the retailer adjusts price less frequently for categories that allow higher returns to the retailer. Why is this the case? One possible explanation for this can be that there is asymmetric information between manufacturers and retailers. If high mark-up level is sustainable, this is hard to reconcile with perfect information case where manufacturers know retailers mark-up. We do not know if this finding can be generalized to other retailers that we do not have information of. In other words, we cannot discern if this case we observe is an anomaly or a generalizable fact for retail price setting. Together with Fact 5, this implies that categories with higher average mark-up tend to have more number of items within a category. This is quite contrary to what we would expect at manufacturers. As the market becomes more competitive, the returns to individual firms (mark-up) become smaller. One extreme of perfect competition, price is equal to marginal cost. The other extreme case of monopoly setting, the monopolist gain maximum rent (mark-up). However, we find that for retailers, more competition of producers, measured as the number of items, lead to higher mark-up for retailers. Table 2.13 provides the regression coefficient, while figure 2.12 provides scatter plots.

2.7 Reconciling Findings with Models

We abstract from general equilibrium model. The empirical findings that the models will be tested against are the following: (1) retail pass-through rate is incomplete, (2) retail pass-through rate and retail price rigidity is negatively correlated, (3) categories with higher retail mark-up show lower pass-through rate, (4) price rigidity is heterogeneous across categories, (5) competition within a category shows positive correlation with pass-through rate, but the correlation is less obvious in the scatter plots and (6) retail price duration is shorter than wholesale price duration. Since our objective here is to compare the testable implications of the models, we do not characterize general equilibrium model.

Case 1: No Retailer Here, the pass-through rate is 0 with probability λ and 1 with probability (1-λ), each period. Should the firm readjusts its price to the optimal level, the new price level incorporates the cost, C_t, fully. In the remaining period without price adjustment, the pass-through rate is 0, for the price at time t is independent of stochastic cost, since the price at time t is equal to the price at time t-1. Overall, the oscillations between 0 and 1 leads to (1-λ) pass-through rate in expectation, implying incomplete pass-through. Here, frequency of price adjustment (1-λ) is in one-to-one relation with pass-through rates (1-λ), leading to positive correlation. If we allow the probability to vary by product category, λ_i, where subscript i refers to product category, this model predicts that categories with higher frequency of price adjustment having higher pass-through rate. Also, allowing for λ_i easily induces heterogeneity of frequency of price adjustment across product categories. Mark-up level and pass-through rate in this setting is independent. This is because mark-up level is not only determined by price, but also by stochastic cost. Stochastic cost is unrelated to (1-λ), which induces mark-up level stochastic, as well, at the time of readjustment. Pass-Through rates and the degree of competition in the market are generally uncorrelated in Calvo model, unless if (1-λ) is not exogenous, and endogenously determined by the degree of competition. If we specify in the model that frequency of price adjustment increases or decreases with market competition, this will lead to correlation between the two variables. Another possible channel that two variables could be correlated is through variability of cost: the degree of competition influences the variability of cost. This, however, is not plausible, for the pass-through rate in Calvo model is unaffected by variability of cost. Finally, the comparison between the duration of price and cost would depend on the assumption on the distribution of C_t. Figures 2.13 show the simulated price movement following this model, while figures 2.14 show scatter plots of price change of cost change, generated by the simulations. Finally, figure 2.15 represents the negative relation between pass-through rate and price rigidity; or positive relation between pass-through rate and frequency of price adjustment. Costs are assumed to follow AR(1) distribution with autoregressive coefficient 0.9.

Case 2: Neutral Retailer

The prediction for the pass-through under this scenario of "neutral retailer" is that retail level pricing decision is solely dependent on the pricing decision of manufacturer (or wholesale) level. Therefore, pass-through rate in this setting is always complete, regardless of the pricing mechanism of the wholesale price, P^w_{it}. This results to a perfect correlation between mark-up and pass-through rates, since both are constant. This is opposite to our findings. If we allow for the mark-up to time-vary, μ_{it}, There is no relation between market competition among manufacturers and pass-through rate, for pass-through rate at retail level is always complete, although market competition among manufacturers surely influences the wholesale price dynamics. In this setting, duration of wholesale price is exactly the same as the duration of retail price, which contradicts our finding. However, heterogeneity of price rigidity across product categories can be induced with category-specific probability of price readjustment, λ_i.

2.8 Discussion and Conclusion

In this paper, we looked for evidence how retailer price dynamics differ from wholesale price dynamics. Two main reasons why retail prices cannot fully reflect wholesale prices are (1) volatile costs to retailers and (2) demand variation that yields more volatile retail prices. For further evidence, we have looked at pass-through rate of retail cost to retail prices, finding that the pass-through rate is incomplete. We found several facts about pass-through rate and price rigidity movements at retail level, some of which are not consistent with the dynamics at manufacturer level. The biggest drawback of standard macro models in explaining our findings is that these models do not incorporate retail level. Comparing models of differing role of retailer using Calvo Pricing Model, we find that the case with non-neutral retailer or retailer with time-varying mark-up can match the data set.

This paper does not discuss the competition between retailers. Villas-Boas highlights the retail competition in retail prices. Here, we take the prices in the dataset as sufficient statistics that reflect the competition environment and abstract from the details to focus on the price dynamic differences at retail level and manufacturer level. But an ideal model should incorporate the role of retailer competition in retailer price. One final concern is the variable that we use as wholesale prices. Although our measure of wholesale price (C^R) is of good quality and is more accurate than other wholesale price measures in other dataset, it might also have some measurement error, for it is an accounting term. That is, wholesale price measure would be sum of the actual wholesale price (C^A) and measurement error (ϵ).

$$C^R_{its} = C^A_{its} + \epsilon_{its} \tag{2.23}$$

Unless the error term, ϵ_{its} is time-invariant, (time) differencing C^R_{its} would be different from differencing the actual wholesale price C^A_{its}. This is an issue that we have to still be cautious about.

Table 2.1: Number of UPCs in Each Subgroup

Subgroup	UPC	Subsubclass	Subclass	Class	Category	Group	Department
Number of UPCs	73,764	5,440	3,736	1,633	429	85	43

Note: The data covers 178 weeks from January 2004 to July 2007.

Table 2.2: Treatment of Missing Values

	•	•	•	X	X	•	•	•
Time	1	2	3	4	5	6	7	8
Price	2	1	1			1	1.5	1.4
SpellA	1	2	2			3	4	5
SpellB	1	2	2			2	3	4
SpellC	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. SpellA takes the data set as it is, taking the observation after the missing value (t=6) as a beginning of a new spell. SpellB 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. SpellC is similar to SpellB, but differs in that SpellC takes the missing values as part of the spell. Naturally, prices seem to be stickier using SpellC than SpellB, and using SpellA results in the shortest measured price duration.

Table 2.3: Average Duration of Variables Using Different Spell (Unweighted)

	SpellA	SpellB	SpellC
P^R	7.7	16.1	23.52
P^S	4.4	8.4	13.6
C^R	8.4	18.6	27.3
C^S	1.4	1.8	4.2
P^R	12.9	22.9	27.3
P^S	5.1	7.7	9.6
C^R	14.2	26.7	32.2
C^S	1.4	1.5	2.2

Note: The first panel exhibits average unweighted durations of each variable at UPC level in weeks and the second panel exhibits average unweighted durations of each variable at category level.

Table 2.4: Average Duration of Variables Using Different Spell (Weighted)

	SpellA	SpellB	SpellC
P^R	8.7	15.3	24.5
P^S	3.4	8.5	12.5
C^R	7.7	17.5	22.7
C^S	1.4	1.8	3.9
P^R	16.3	24.9	27.9
P^S	5	6.6	7.6
C^R	18.3	29.4	33.1
C^S	1.6	1.6	1.9

Note: The first panel exhibits average weighted durations of each variable at UPC level in weeks and the second panel exhibits average weighted durations of each variable at category level.

Table 2.5: Relative price comparisons within a region

	City	District	Operating Areas
Mean	0.99	0.99	0.99
Median	1	1	1
S.D	24	58	21

Note: The data covers 178 weeks from 2004 to mid-2007 across 50 stores in the United States. Relative price captures how dispersed prices are within selected region (city, district or operating area).

Table 2.6: Correlation Between Different Measures of Pass-Through Rates

	OLS	Fixed-Effects	LRPT
OLS	1	0.98	0.715
FE	0.98	1	0.73
LRPT	0.715	0.73	1

Note: Across 200 categories, three different measures of pass-through rates are calculated. Correlations between OLS, Fixed-Effect coefficient, LRPT show that OLS and Fixed-Effect pass-through are highly correlated. Both measures are positively, but not as highly correlated with LRPT.

Table 2.7: Pass-through rates and frequency of price adjustment

	SpellA	SpellB	SpellC
OLS	0.29**	0.96**	1.58**
	(2.16)	(5.89)	(8.41)
FE	0.24**	0.84**	1.43**
	(1.84)	(5.28)	(7.65)
LRPT	0.39**	0.72**	1.14**
	(3.23)	(4.62)	(6.04)

Note: Pass-through rates are regressed on price rigidity. ** implies 1% significance level. T-statistics are provided in the parentheses.

Table 2.8: Average Pass-Through Rates in High Frequency and Low Frequency Bins

	SpellA		SpellB		SpellC	
	High	Low	High	Low	High	Low
OLS	0.35	0.28	0.39	0.24	0.41	0.23
FE	0.33	0.27	0.37	0.22	0.38	0.21
LRPT	0.38	0.29	0.39	0.27	0.39	0.27

Notes: Pass-through rates are averaged in high frequency bins and low frequency bins using different measures of price rigidity. High frequency bins include product categories with frequency higher than median frequency, while low frequency bins include product categories with frequency lower than median frequency.

Table 2.9: Pass-Through Rates in High Frequency and Low Frequency Bins

	SpellA		SpellB		SpellC	
	High	Low	High	Low	High	Low
OLS	0.14	-0.07	0.67**	0.57	1.38**	2.1**
	(0.62)	(0.16)	(2.30)	(0.84)	(4.28)	(2.61)
FE	0.12	-0.06	0.53**	0.56	1.2**	1.95**
	(0.45)	(0.15)	(1.87)	(0.85)	(3.75)	(2.51)
LRPT	0.27	0.06	0.43	0.11	0.97**	1.47**
	(1.1)	(0.14)	(1.55)	(0.17)	(3.06)	(1.81)

Notes: After putting product categories according to their frequency of price adjustment into high and low frequency bins, we run regressions to obtain pass-through rates for each bin. ***: 1% significant level, **: 5% significant level, *: 10% significant level .

Table 2.10: Pass-through rates and mark-up

	OLS	Fixed-Effects	LRPT
Average Mark-up	-1.62**	-1.49**	-0.99**
	(12.2)	(11.5)	(6.8)

Note: ** implies 1% significance level. T-statistics are provided in the parentheses.

Table 2.11: Pass-through rates and competition

	OLS	Fixed-Effects	LRPT
Number of items in a category	-344.28**	-307.46**	-316.26**
	(2.67)	(2.30)	(2.28)
	-0.726**	-0.588**	-0.435
	(2.55)	(1.99)	(1.42)

Note: The first panel shows the coefficient when both the dependent and independent variables are in numbers. The second panel runs the same regression with the dependent variable in logs. ** implies 1% significance level. T-statistics are provided in the parentheses.

Table 2.12: Frequency of price adjustments and competition

	SpellA	SpellB	SpellC
Competition	0.016	-0.01	-0.014**
	(1.78)	(1.05)	(2.57)

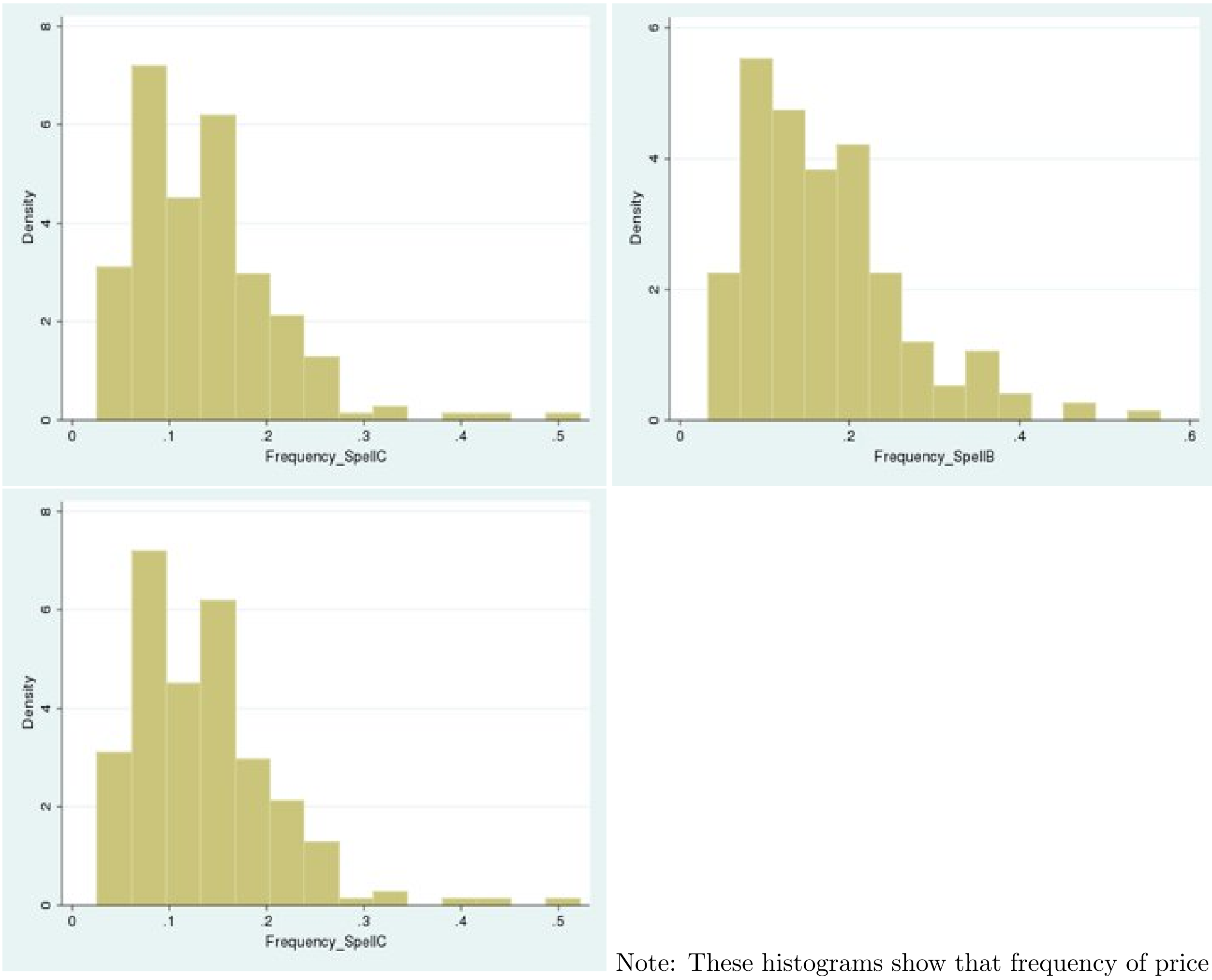
Note: The degree of competition is measured as the log of number of items within a category. ** implies 1% significance level. T-statistics are provided in the parentheses.

Table 2.13: Average mark-up and frequency of price adjustments

	SpellA	SpellB	SpellC
Average mark-up	0.45**	0.042	-0.18**
	(5.33)	(0.60)	(2.04)

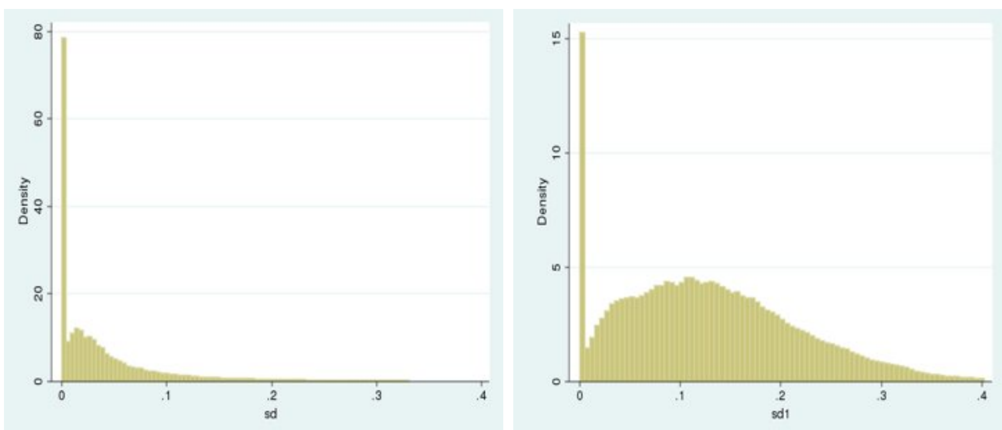
Note: ** implies 1% significance level. T-statistics are provided in the parentheses.

Figure 2.1: Frequency of Price Adjustments of Sales Using SpellA, SpellB and SpellC



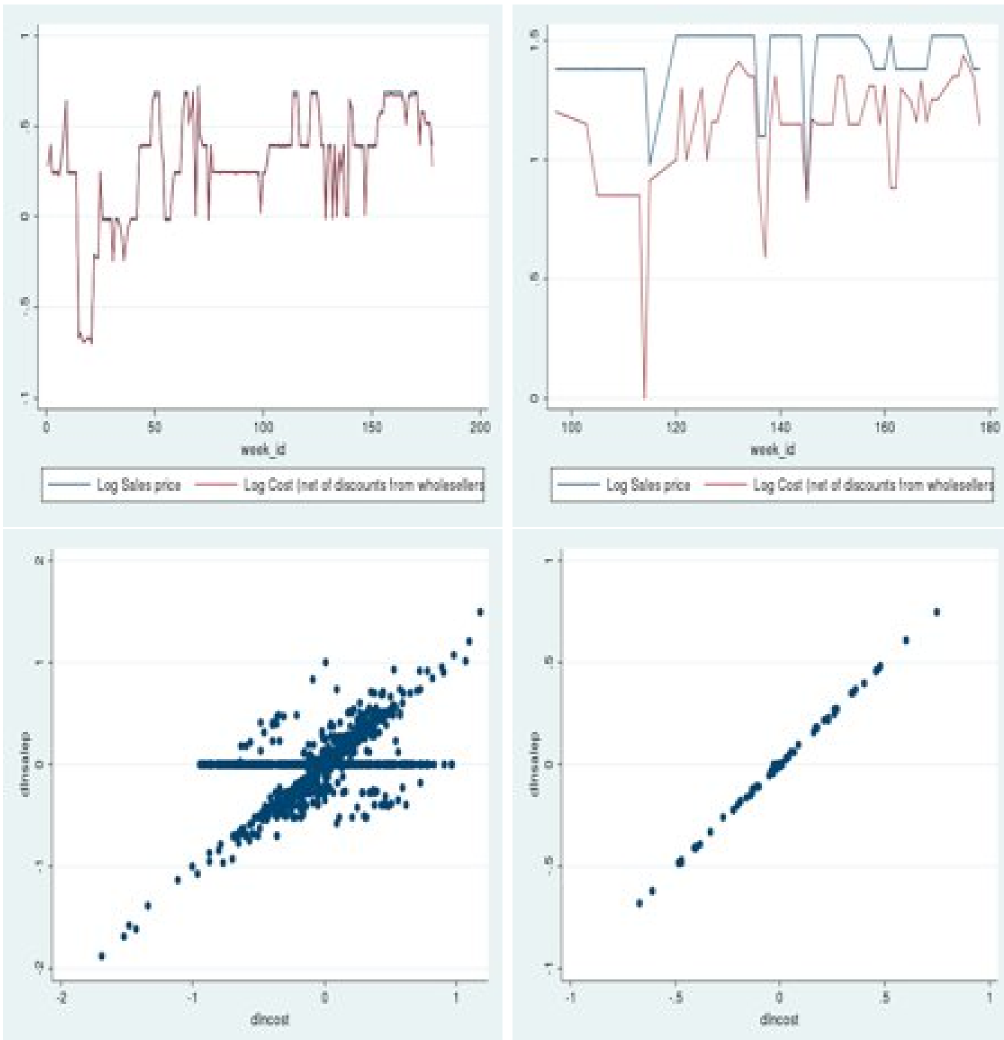
Note: These histograms show that frequency of price adjustment is quite heterogeneous across different categories. Also, the distribution shifted toward left using SpellC compared to other spells, implying longer duration using this spell.

Figure 2.2: Distribution of Standard Deviation of ϵ_t and $\epsilon_t - \tau_t$



Note: These histograms show that retail prices do not fully reflect the wholesale price because of volatile(time-varying) retail cost. Histogram on the left show that wholesale price can be similar to regular price, since the residuals are not volatile. Histogram on the right, however, shows that sales price can be drastically different from wholesale price, implying highly variable residual.

Figure 2.3: Price and Cost Movement in Different Product Categories



In both graphs in the first row, the blue lines represent logged sales price over the period at a particular store (over the entire sample of 178 weeks), while the red lines represent logged sales cost over the same period at a particular store. Unlike the case of lettuce, where the cost closely tracks the retail price, the price is stickier than cost in the case of a breakfast item. Cost pass-through to price at retail level has starkly different implications for lettuce and breakfast items. While retail price of lettuce fully reflects the retail cost changes (implying complete pass-through), the retail price of a breakfast item does not fully reflect the retail cost changes (implying incomplete pass-through). This is represented well in the scatter plots in the second row.

Figure 2.4: Histogram of Category-Level Pass-Through Rates: OLS

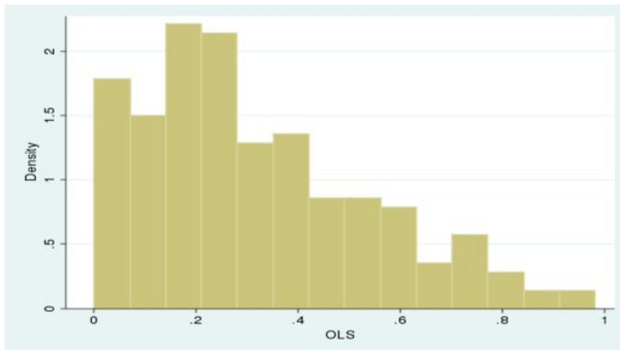


Figure 2.5: Histogram of Category-Level Pass-Through Rates: Fixed-Effects

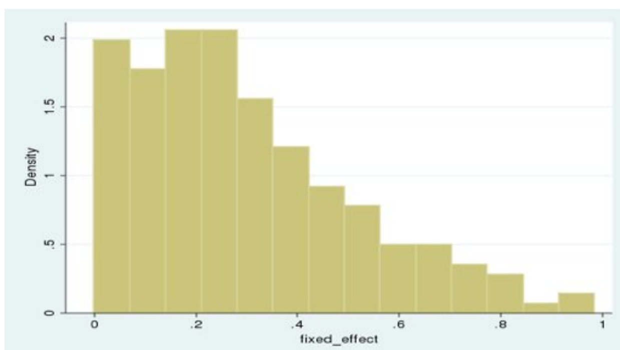


Figure 2.6: Histogram of Category-Level Pass-Through Rates: Long-Run Pass-Through

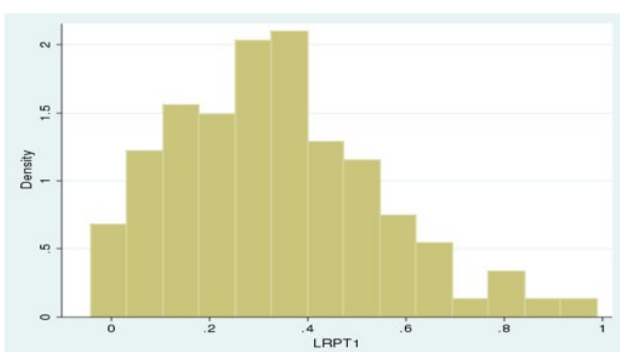


Figure 2.7: Scatter Plots: Pass-Through rates (OLS) and frequency of price adjustments

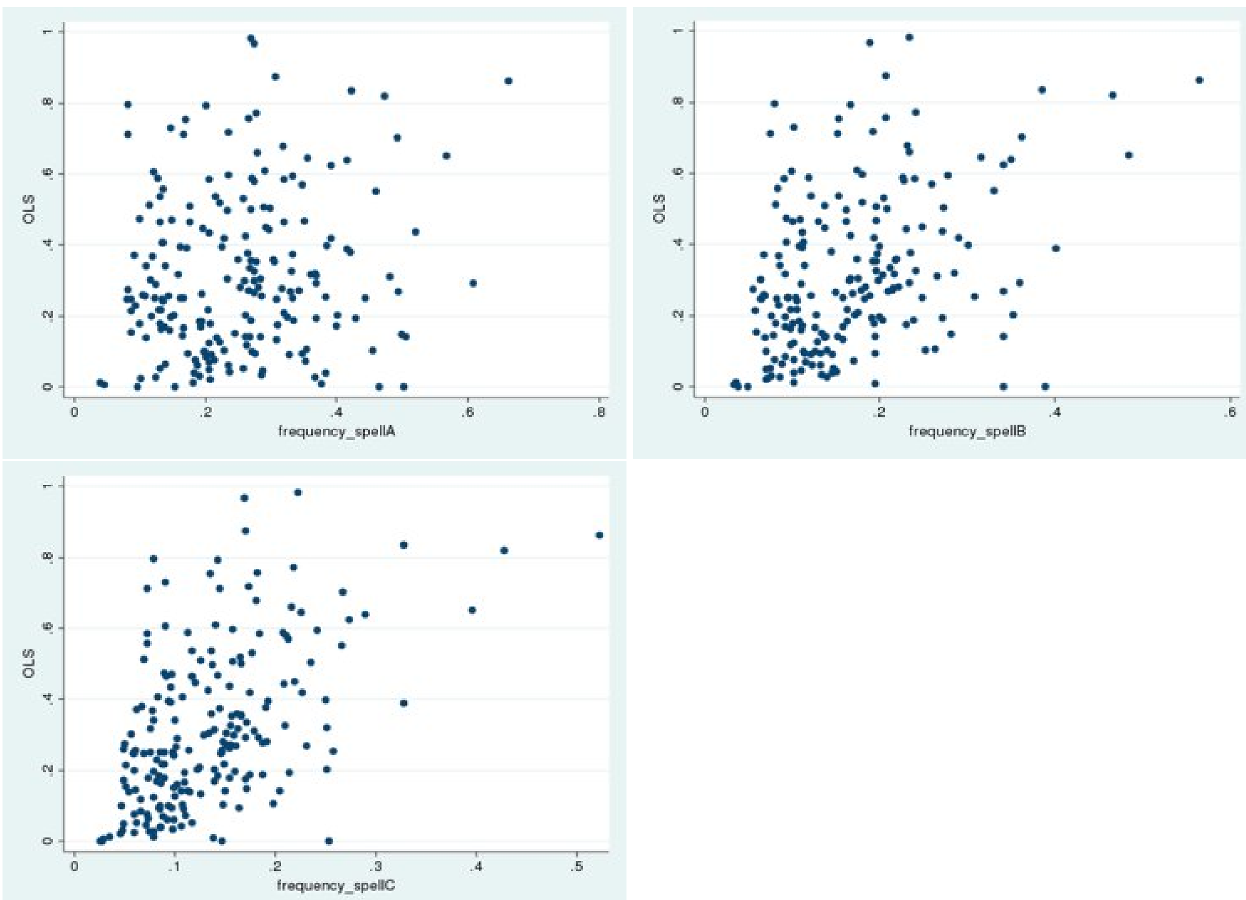


Figure 2.8: Scatter Plots: Pass-Through rates (Fixed-Effects) and frequency of price adjustments

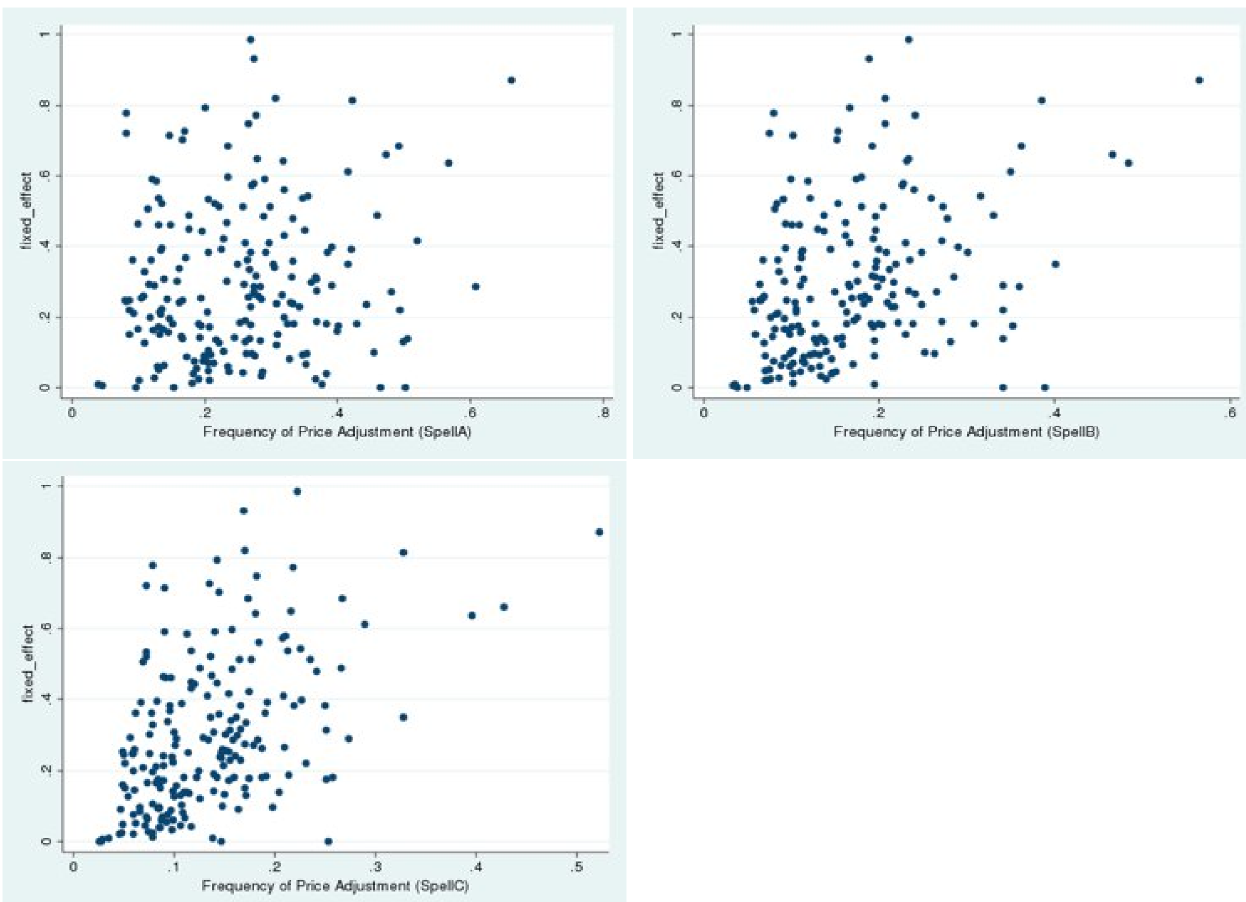


Figure 2.9: Scatter Plots: Pass-Through rates (LRPT) and frequency of price adjustments

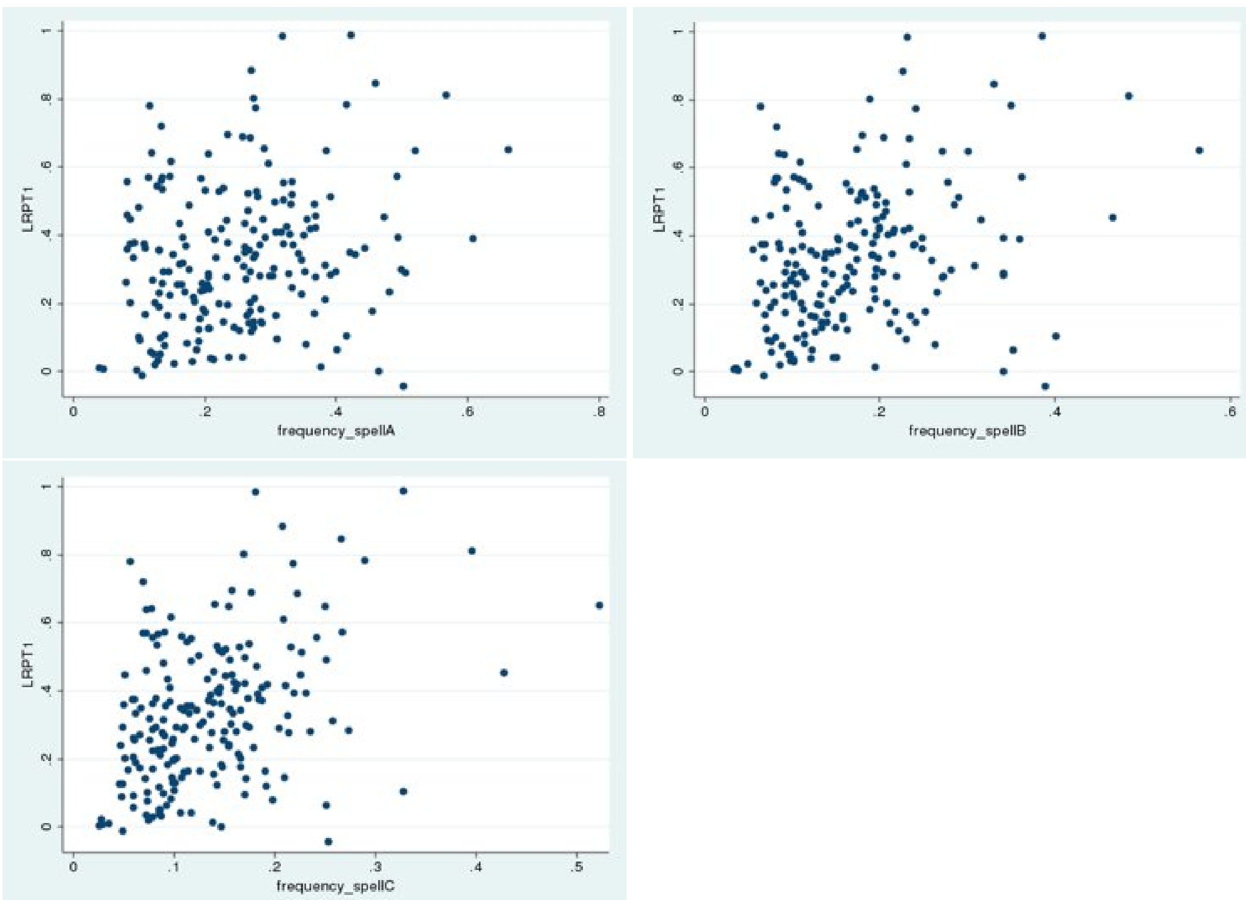


Figure 2.10: Scatter Plots: Pass-Through rates and average mark-up

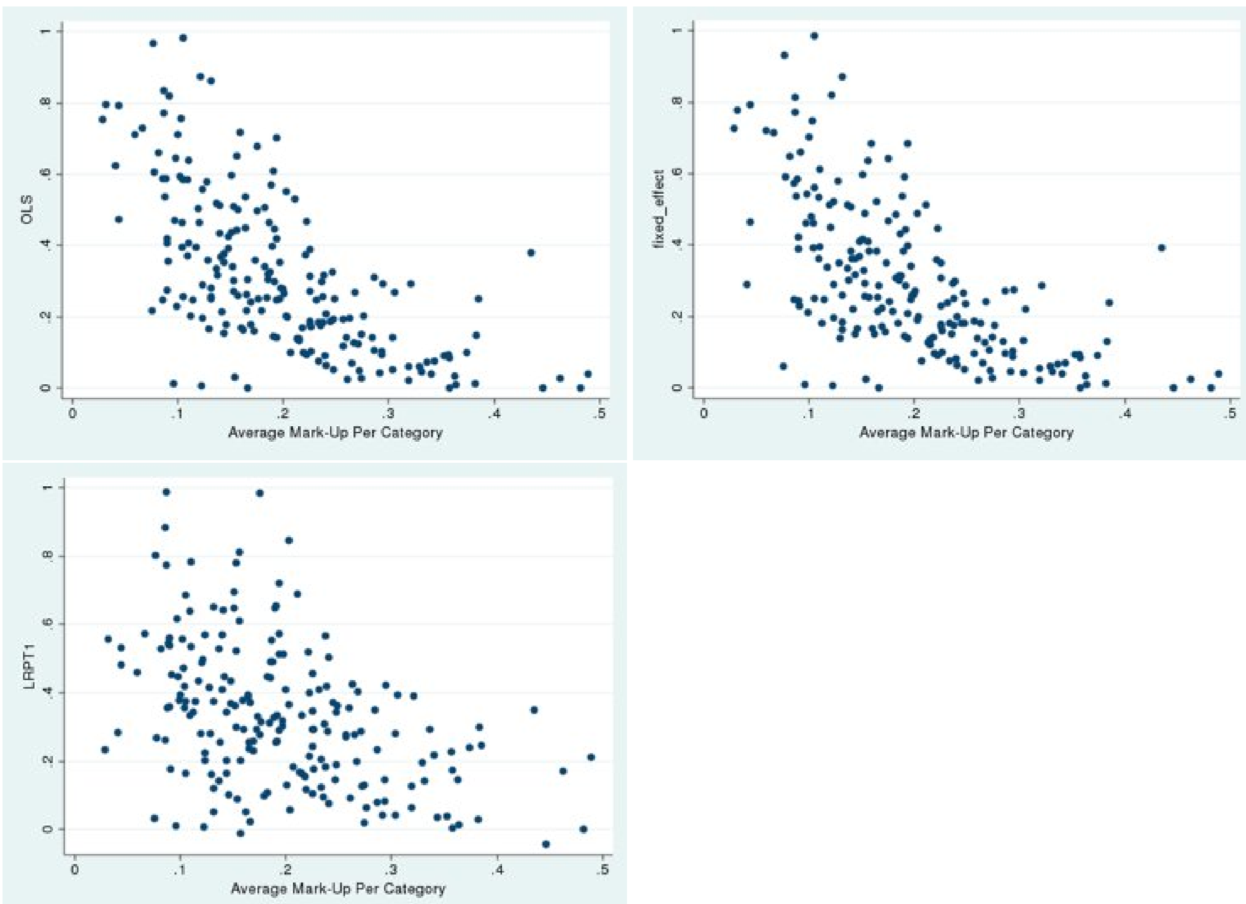


Figure 2.11: Scatter Plots: Pass-Through rates and competition

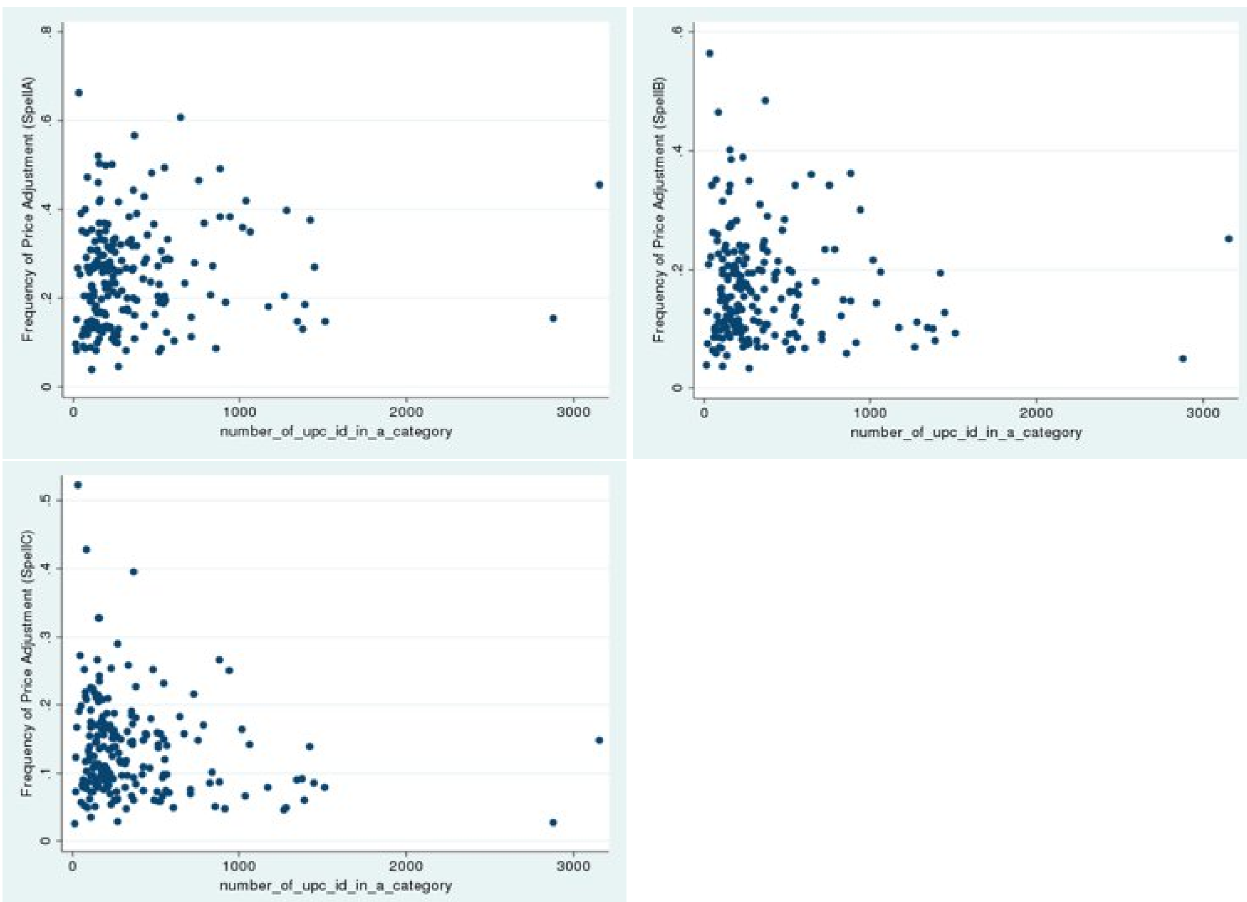


Figure 2.12: Scatter Plots: Frequency of price adjustments and average mark-up

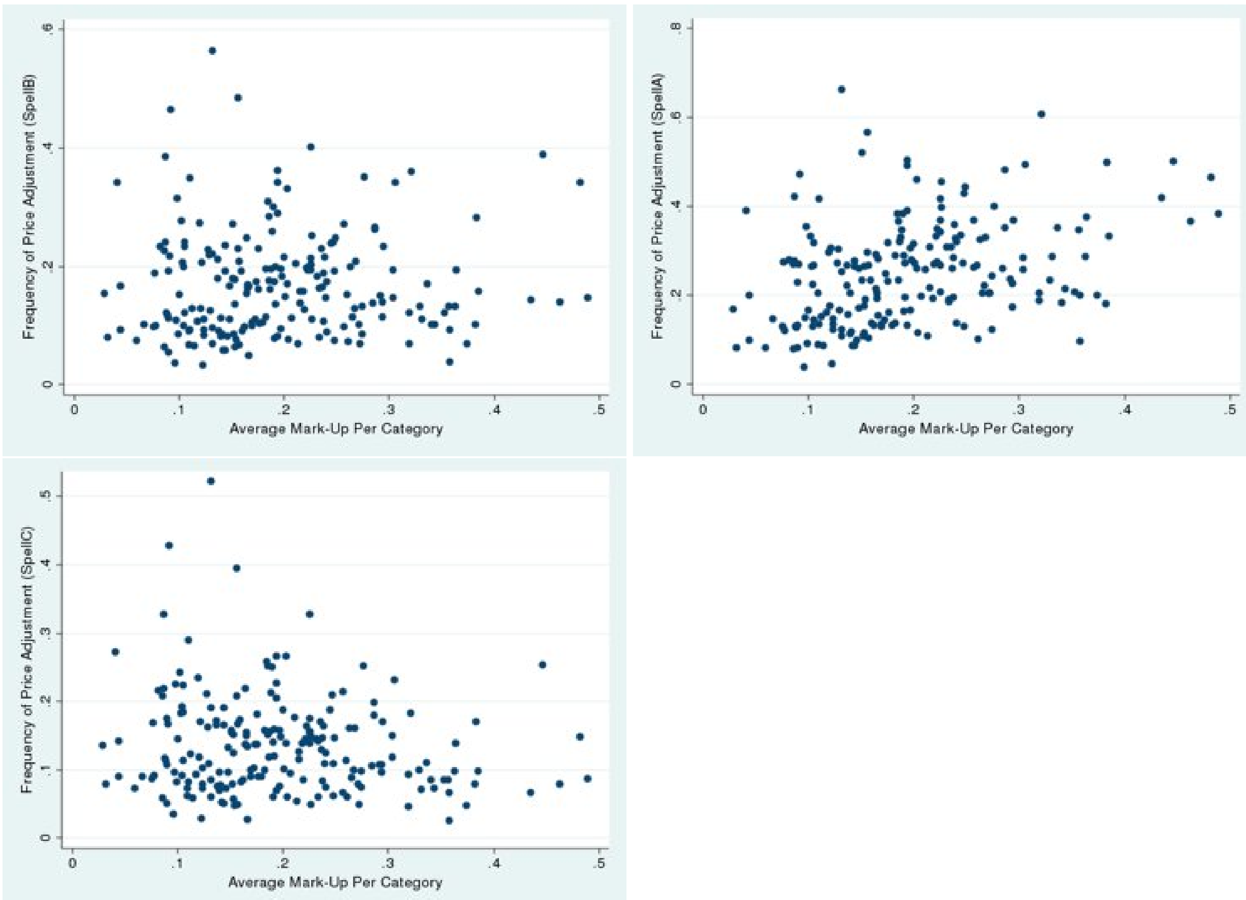


Figure 2.13: Generating Price Movement from Calvo Pricing

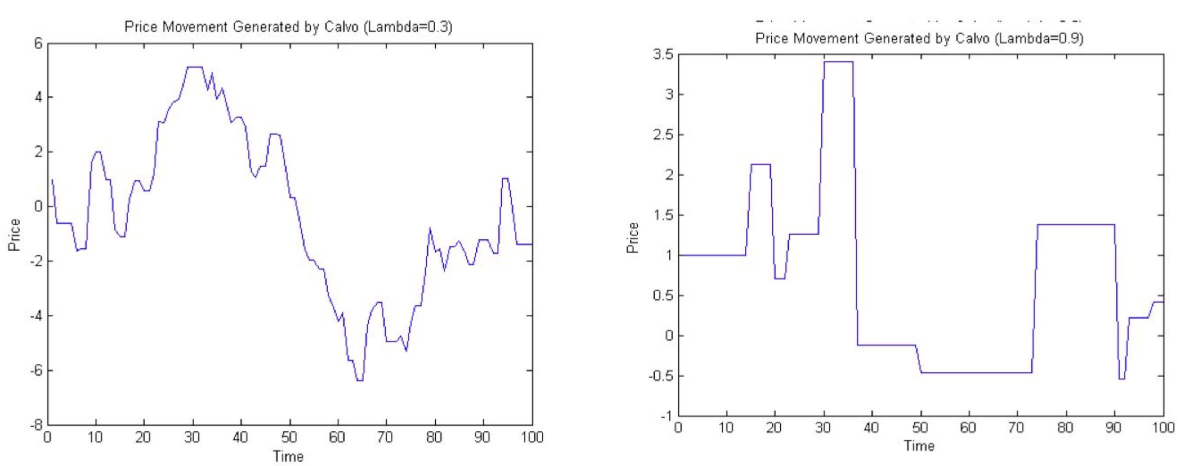


Figure 2.14: Price-cost comovement (Calvo Pricing)

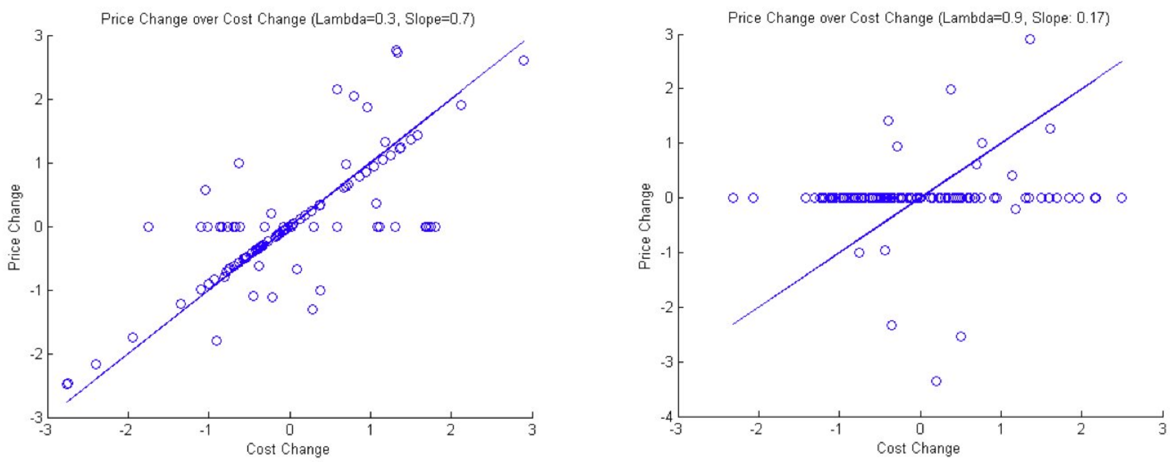
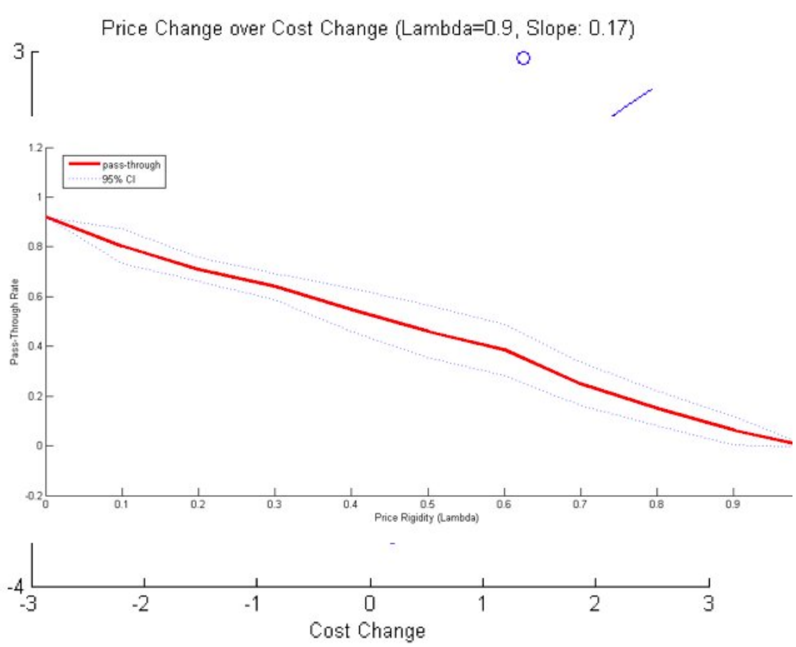


Figure 2.15: Relation between pass-through rates and price rigidity (Calvo Pricing)



Chapter 3

Vertical Structure and Retail Pricing Facts: Private Label vs. National Brands

3.1 Introduction

A number of recent empirical studies have used retail price data to document various aspects of pricing behavior, such as the frequency, size and timing of price changes and the extent of cost pass-through.[1] Price dynamics in retail markets play a crucial role as the final stage for transmission of monetary and real shocks, as retail prices allocate quantities and determine aggregate inflation rates. A consistent finding across empirical studies of large, multi-product data sets is the substantial heterogeneity in pricing behavior across products. In many theoretical models, this heterogeneity can amplify the aggregate transmission of shocks, underscoring the importance of understanding the source and nature of the heterogeneity.[2] The degree of vertical integration between an upstream and a downstream firm is a potentially important source of pricing heterogeneity. While vertical structure has been the subject of a growing trade literature that highlights substantial implications for pricing,[3] its relevance in a domestic retail setting is less understood.

In this paper, we document retail pricing facts for private label goods versus national

[1] Lach and Tsiddon (1996), Nakamura (2008), Nakamura and Steinsson (2008), Berck et al. (2009), Gopinath et al. (2011), Kehoe and Midrigan (2008), Kehoe and Midrigan (2010) and Eichenbaum et al. (2011). See Klenow and Malin (2011) for a survey.

[2] Bils and Klenow (2004), Carvalho and Schwartzman (2008), and Nakamura and Steinsson (2010).

[3] Bernard et al. (2006), Hellerstein and Villas-Boas (2010), Neiman (2010), and Neiman (2011).

brands using data from a large American grocery retailer. The growth of private label brands has been an important and ongoing trend in the retail sector over the past two decades, a parallel development to the growth of intra-firm transactions in international (and intra-national) trade of intermediate goods. Hoch et al. (2000) document that in the United States, private label market share grew an average of 1.12% per yea in the food and beverage sector between 1987 and 1994. More recent data show an increase in the market share of private label goods in this sector from around 15% in 2005 to 17.5% in 2009 (see Figure 3.1).

Our data contain weekly retail prices, wholesale prices, and quantities for 250 U.S. stores between January 2004 and June 2007. We focus on a subset of over 8,500 products in 10 product categories. These data have been used in several previous studies of pricing behavior (Eichenbaum et al. (2011), Gopinath et al. (2011), Burstein and Jaimovich (2009)) but we are the first to use them to analyze differences in retail and wholesale pricing behavior for goods with different degrees of vertical integration. We distinguish private label goods from national brands. Private label goods, in general, are products that are marketed and/or branded by a different party than the manufacturer. In this paper, we use a narrower definition of private label goods that specifically refers to brands that are managed and/or manufactured by the retailer directly. National brands, on the other hand, are owned, produced, marketed, and managed by an independent manufacturer. Private label goods are analogous to intra-firm traded goods and national brands are analogous to arm's length traded goods in the trade literature because the market power of the downstream party is reduced.

We find clear differences in pricing behavior across vertical structures for multiple product categories that can account for a significant amount of pricing heterogeneity. Private label prices change more frequently due to temporary sales, are more responsive to cost shocks, and exhibit greater synchronization. We contrast our findings with those from the trade literature and discuss them in the context of two models. First, we use a prototypical "supply" model - an extension of Gopinath and Itskhoki's (2011) menu cost model with variable markups that features potentially asymmetric cost adjustment across integrated and arm's length vertical relationships. Second, we consider a "demand" model - an extension of Chevalier and Kashyap's (2011) inter-temporal price discrimination model in which pricing behavior is driven by consumer heterogeneity and asymmetric consumer valuations for brands. We conclude that the differences in retail pricing behavior we observe for national and private label brands are likely due to a combination of the types of forces featured in both models, i.e. asymmetry in both supply and demand characteristics.

We find that private label goods exhibit roughly similar regular price durations, shorter wholesale price durations, and much shorter sales price durations - private label sales prices change 30 to 35% more frequently than national brand sales prices. Our findings on price duration broadly confirm the results from the trade literature that intra-firm prices exhibit shorter duration of price spells than their arm's length counterparts. Our findings, however, depart from these studies in one key respect. The richness of our data allows us to compare three different prices - the actual retail price, the list retail price (which is non-allocative), and the wholesale price paid by the retailer. The effect of vertical structure is different for each of the three types of prices, but the pattern is broadly consistent across different product categories. While the higher wholesale price change frequency we observe for private label goods is consistent with a model where the national brands differ only in terms of wholesale double-marginalization and menu costs, this model is inconsistent with the retail price durations we observe. A supply model would typically not predict the similar duration of regular prices (given the differences in wholesale price durations) nor the much shorter sale price durations for private label goods (well beyond the difference implied by the wholesale price durations). However, the shorter duration of private label sales prices is entirely consistent with our "demand" model where the cheaper, lower quality private label goods have more frequent sales aimed at the most price-sensitive consumers.

We use reduced-form pass-through regressions to analyze the responsiveness of price to cost shocks for private label and national brands. We depart from the large literature that uses exchange rates as exogenous shocks by instead examining the pass-through of commodity prices to domestic wholesale and retail prices. Using these plausibly exogenous shocks, we find that private label brand retail and wholesale prices have greater pass-through coefficients. The retail pass-through is greater when using actual sales prices instead of regular list prices, indicating that sales depth and frequency play a potentially important role in retail pass-through. We also document larger retail price pass-through of idiosyncratic changes in wholesale prices for private label brands. This suggests that lower pass-through of national brands is not entirely due to the presence of intermediaries with variable markups that buffer the retail firm from raw material cost shocks. Rather, different final demand elasticities may also play an important role in generating lower pass-through for national brands.

Synchronization, or the timing of price changes across stores and products, has important implications for aggregate price rigidity as lack of synchronization can amplify the effects of monetary non-neutrality in state-dependent and time-dependent pricing. Using the Fisher and Konieczny (2000) measure of synchronization, we find that price changes are much more synchronized within the set of private label brands than within the set of national brands. This fact is at odds with models where strategic complementarities generate greater synchronization among arm's length producers (Neiman (2011)) and with BLS import data that features greater synchronization for arm's length than intra-firm transactions (Neiman (2011)). For both types of goods we find that sales prices are more synchronized than list price changes within the sets of national and private label brands. We also explore synchronization between different vertical structures. One of the predictions of our demand model is that a multi-product retailer may often choose to synchronize sales on private label and national brands. We find only mixed support for this prediction in the data.

Finally, we find that the size of regular price changes is larger for private label brands but the size of price changes due to temporary sales is larger for national brands. Regular price changes are not large, and there are many small changes less than 5%. Greater regular price changes for private labels are generally consistent with our supply side model. Sales price changes are large, and the average discount is greater for national brands. Our demand model implies that larger sales discounts on national brands may be a feature of inter-temporal price discrimination by retailers.

Our paper has a similar focus to the trade literature that examines the effects of vertical structure on pricing behavior but differs in several respects. First, our data has several advantages in that we observe allocative retail prices along with quantity data and we can clearly distinguish between private label and national brand goods. In the BLS import micro-data, there is a concern that the quoted intra-firm prices are not allocative and may reflect transfer pricing motives. Criteria used to classify arm's length versus intra-firm transactions are also self-identified and not based on a technical definition or specific ownership threshold. Second, our focus on retail data means that we observe prices and price changes at a much higher frequency, allowing temporary sales to play a major role in price adjustment through both an intensive margin (size) and extensive margin (frequency) of sales. It also means that a single-firm (the retailer) sets all of the final prices, changing the nature of the strategic interaction in price-setting across products. Finally our focus on retail emphasizes the important role of demand-side factors related to consumer and product heterogeneity. This emphasis is typically absent in the trade literature on vertical structure, which assumes that intra-firm and arm's length transactions involve identical products and consumers and all differences come from differential price-setting power and markups. In our data and in retail more generally, private label goods tend to be viewed as cheaper and lower quality substitutes for national brands. The types of consumers that private label goods attract then determine the success of private labels within a category, whether they enter particular categories or not, and how prices are set conditional on entry.

The main limitation of our empirical findings is that we only observe the pricing behavior of a single retail chain. There is growing evidence that heterogeneity in pricing behavior across retailers is at least as important as heterogeneity across products/manufacturers at the aggregate level (Nakamura (2008)). Another limitation is that we do not observe differences in vertical integration at the manufacturing level. While the private label goods in our sample are easily identified and are more vertically integrated from the retailer's perspective in terms of marketing, packaging, and quality assurance (and in some cases manufacturing), not all goods are manufactured directly by the retailer. Finally, the short time horizon of our data set does not allow us to analyze the endogeneity of vertical structure with respect to technological change or shifts in consumer demand. However, our findings have implications for the dynamics of aggregate pass-through and price stickiness over the business cycle as well as cross-country pricing differences that we discuss at the end of the paper.

Our paper is related to three different literatures. As discussed above, our paper provides the national, retail-level complement to international trade studies that examine the impact of vertical structure on pricing (Bernard et al. (2006), Neiman (2010), Neiman (2011), Hellerstein and Villas-Boas (2010)) or that use menu cost models with variable markups to understand heterogeneity in pricing across products (Gopinath and Itskhoki (2011)). The paper is also related to a large and growing literature documenting retail pricing facts of interest to macroeconomics using BLS data (Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008)) and scanner data (Lach and Tsiddon (1996), Nakamura (2008), Villas-Boas (2007), Berck et al. (2008), Eichenbaum et al. (2011), Gopinath et al. (2011), Burstein and Jaimovich (2009), Kehoe and Midrigan (2008)). Our main difference from this literature is our specific focus on the role of vertical structure through the comparison of private label and national brand pricing behavior. Finally, our paper is related to the literature on the economic reasons for frequent temporary sales at the retail level, which include inventory management, loss-aversion and price-discrimination (Varian (1980), Pesendorfer (2002), Guimaraes and Sheedy (2011), Heidhues and Koszegi (2010), Chevalier and Kashyap (2011)). We analyze the price-discrimination motive as a determinant of sale frequency in the absence of demand or supply shocks.[4] Our contribution to this literature is to highlight the potential of impact of vertical structure - through the asymmetry it introduces in consumer valuations and marginal costs for private label and national brands - on the *differences* in sale frequency that we observe empirically.

Our paper proceeds as follows. Section 2 discusses the dataset, the basic characteristics of private label and national brand products, and our imputation procedures for missing data. Section 3 presents our empirical findings on duration, pass-through, synchronization and size of price changes for the two types of products. Section 4 analyzes a simple supply-side and a demand-side model and compares their implications with our results. Section 5 concludes.

[4]Kehoe and Midrigan (2008) and Eichenbaum et al. (2011) consider recurring sales but motivate them with a combination of supply/demand shocks and non-standard menu costs.

3.2 Data

3.2.1 Retailer data set

Our dataset covers 250 stores in 19 U.S. states operated by a single retail chain that sells both national brands and a series of private label (store) brands. This chain is one of the leading food and drug retailers in the U.S. and operates directly or through subsidiaries a total of 1,400 stores in the United States.[5] The data set contains information for 125,048 universal product codes (UPCs) classified into over 200 unique product categories sold between January 2004 and June 2007 (178 weeks). Most of the products are in the food and beverages categories, housekeeping supplies, books and magazines, and personal care products. This level of disaggregation allows for a very precise identification of products. For instance, in our data, a 25 ounce Perrier Mineral Water with a Lemon Twist and a 25 ounce Perrier Mineral Water with a Lime Twist are two separate items in the soft beverages product group. We focus on ten product categories containing 8,725 total UPCs - these categories represent a wide range of product attributes and feature a range of (non-zero) private label revenue shares. The ten categories we analyze are carbonated soft drinks, potato chips, cold cereal, cooking oil, sugar (and substitutes), coffee, all family juices, packaged pasta (dry), bathroom tissues and laundry detergent.

The four key pieces of information we use from the data are the retail list price, the wholesale list price, the retail price net of sales and coupons, and the wholesale price net of manufacturer rebates and promotions. 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. This means that our sale price is a linear combination of actual sales price and regular price, weighted by the number of items purchased at each price level.[6] Because the sales price is closer to the price actually paid by most customers, it is the appropriate "allocative" price for analysis, although fluctuations between list and sales prices help us identify periods of

[5] The data sharing agreement between this retailer and the research community is managed through the SIEPR-Giannini data center (http://are.berkeley.edu/SGDC/).

[6] To get a rough idea of measurement error, we examine cases where the size of discount is less than 5% (or 10%) of regular price. These observations are more likely to be the result of measurement error, in that we do not expect to observe sales of one or two percent. Conditional on an observed difference between gross and net revenue, 2% of our observations have an implied sale price less than 5% below the regular price, while 6% have an implied sale price less than 10% below the regular price.

temporary sales as distinct from the more permanent price changes associated with a change in the retail list price.

The retailer also reports a wholesale list price. The retailer requires 30 days notice in advance of changes in this price by vendors, implying that the wholesale list price is unlikely to respond to immediate, unforeseeable demand conditions. Our understanding is that the wholesale list price is allocative in most cases with the exception of promotional allowances. Promotional allowances are vehicles through which manufacturers incentivize the retailer to perform certain actions in return for certain rewards. The performance criteria may include selling a specified number of units, advertising in-store, on-line and through flyers, better placement on the shelves, shelving new products, or offering a price discount. Importantly, the retailer reserves the right to determine actual retail prices - comments on retail prices, including with regard to promotional allowances, are deemed informational and not binding. Thus the manufacturer may offer a per unit discount to the retailer in exchange for a retail price reduction but the retailer maintains the power to set its prices. Furthermore, some of the promotional allowances take the form of free goods or flat fees, which are therefore not reflected in changes in the marginal cost of goods to the retailer. Our data allow us to calculate a wholesale price net of manufacturer promotional allowances by subtracting the adjusted gross-profit per item (adjusted for manufacturer rebates) from the net revenues (net of promotions, coupons and rebates) and dividing by item quantity. [7]

In this paper we focus primarily on the wholesale list price as the store's relevant marginal cost. This is primarily because we lack information on the nature of the performance criteria and allowances for each item/period, which prevents us from identifying allowances aimed at retail price reductions (which we are interested in) from those that may result in higher unmeasured costs by the retailer (such as advertising or better shelf-placement). We are thus unable to used promotional allowances and performance criteria to calculate the economically relevant marginal cost to the retailer. However, our results concerning costs are largely unchanged when we examine the wholesale "sales" or "net" price measure - duration is slightly shorter but the differences are much smaller than those we document for regular list price versus sales price.

We supplement the data on wholesale prices with data on commodity prices. Commodity prices, like exchange rates, are arguably exogenous sources of cost variation that we can use to examine cost pass-through into both wholesale prices and retail

[7]Specifically, "adjusted gross profits" is defined as net revenues minus wholesale price plus "total allowances." The documentation provided by the retailer defines "total allowances" as "the sum of shipping allowances, scan allowances, direct-store-delivery case bill back allowances, header flat allowances, late flat allowances, and new item allowances, *minus* the sum of buying allowances, freight allowances, overseas freight, and distress and other allowances. It is important to note that this price measure does not include local costs (such as labor, rent, advertising, and utilities) at the store level.

prices. We collected weekly prices of raw materials (i.e. sugar, wheat, flour, coffee and rice) from Food and Agricultural Organizations of the United Nations. [8]

3.2.2 Private Label vs. National Brand products

Our main contribution in this paper is to document the different pricing behavior of private label versus national brand goods. A private label good is one that is marketed/branded by a different party than the manufacturer. Store brands are a subset of private label brands that are marketed/branded exclusively by the retailer that sells them, which is the case for the products in our data set. In some cases store brands are also manufactured in plants owned by the retailer - overall about 20% of our retailer's private label goods are produced in plants owned by the retailer.[9] Of the ten product categories we examine only soft drinks are manufactured directly by the retailer.[10]

Private label goods and store brands have been of great interest to marketing researchers for the last two decades due to dramatic growth in market share. Private label sales now exceed $48 billion, making up over 15% of supermarket sales, and over 44% of consumers regularly purchase private lable brands (Raju et al. (1995)). Private label goods as a group have higher unit market share than the top national brands in 77 out of 250 categories (Quelch and Harding (2004)). Private labels in grocery retailing are typically viewed as lower price and lower quality substitutes for national brand goods - while this perception has changed somewhat in recent years with additions of higher-quality and organic private label goods, it is still generally the case that private label brands are the cheapest among comparable goods sold within any retail chain. The cheaper but lower quality aspect of private label goods may explain why the Great Recession of 2008 saw a significant increase in the market share of private labels in grocery retail (see Figure 3.1). The growth of private labels in general has been very uneven across product categories, with market shares varying from over 50% (milk, frozen plain vegetables, sugar to name a few) to less than 10% (coffee, carbonated beverages, chips and snacks and cookies to name a few) (Hoch and Banerji (1993)). The marketing literature has mainly focused on the advantages and implementation issues involved with private label goods from a *manufacturer or retailer perspective*, such as

[8] http://www.fao.org/es/esc/prices

[9] Just as some store-brands may not be "private label brands" in the sense that the retailer owns the manufacturing plant and is thus fully vertically-integrated, some third-party private label manufacturers also market some of the goods produced in their plants. For example, Cott of Canada specializes in producing private label soft drinks while Friesland-Campina of the Netherlands produces dairy products that are sold under private labels and marketed and sold directly by the manufacturer.

[10] In future work, we plan to expand the sample to focus on the potential differences between private labels whose plants are owned by the retailer and those that are not.

the technological and managerial requirements of private label brands, the characteristics of categories that predict private label success, and the impacts of private label growth on national brand advertising and promotional strategies. Some studies also examine the *consumer* perspective - Batra and Sinha (2000) focus on the role of consumer search and uncertainty about quality as a determinant of the relative success of private label goods across categories.

From the retailer's perspective, private label goods represent an intermediate step towards vertical integration on the spectrum between arm's length transactions with national brand manufacturers and ownership of manufacturing plants. With private label brands the retailer typically controls the packaging, marketing, quality assurance and product development aspects of the good. A significant advantage from the retailer's point of view is that by controlling the branding and marketing of the product, they significantly reduce the market power of the manufacturer, lessening the degree of double-marginalization along the supply chain. In cases where profits get divided through a bargaining process between manufacturers and retailers, controlling the branding and marketing for the good and building brand equity in their store brands will also typically increase retailer's profit share as it increases their outside option (which is to switch manufacturers). Consistent with these observations and the findings of the marketing literature, we find significantly lower wholesale prices and higher gross margins for private label goods relative to national brands, though the relative profitability will be lower than the relative gross margins given that the retailer incurs some costs that are traditionally paid by national brand manufacturers.[11]

3.2.3 Imputation

Because our data is based on recorded transactions, there are missing values when an item is not purchased in a particular store/week. Although a missing value need not imply a price adjustment, failure to correct for missing values could bias our measurement of price duration and sale frequency if missing values are correlated with price changes. Our measures of pass-through and synchronization could also be affected. As Eichenbaum et al. (2011) note in their description of the data set, measurement error arises in the weekly sale price measure due to the fact that some items are purchased at the regular price by consumers not using coupons, rebates and loyalty cards. As in their paper, our estimates of the frequency of weekly price changes should be interpreted as an upper bound.

We adopt three different procedures to deal with missing values that are now standard in the literature (see Nakamura and Steinsson (2008) and Kehoe and Midrigan (2008)).

[11]Our data usage agreement with the retailer prevents us from reporting markup levels.

They are described in detail in Table 3.1. The first procedure, referred to as spellA, takes the data set as is, implying that spells end when there is a missing value. The second procedure, 'spellB,' 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 are 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 third procedure, 'spellC,' 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 $2 + 3 + 1 = 6$. Although we have no basis to accept one of these imputation procedures over the others, we focus on the spellB and spellC measures. Ignoring the missing values can induce serious measurement error - for example, under spellA magazines exhibit the highest price frequency (shortest price spells) but when we graph the price path, it is clear that the prices almost never change. The spellA method makes frequency measures overly sensitive to non-purchase occasions.

Table 3.2 reports the mean and median of price durations using our three imputation procedures. Depending on our measure of price spells, the regular price changes every 3 weeks to 3 months, while the sales price changes on average every two weeks to five weeks. Using SpellA results in the highest frequency of price changes (shortest duration), but even the highest duration we observe for sales prices (i.e. using the SpellC procedure yielding a frequency of 0.21/duration of about 5 weeks) is significantly shorter than the duration reported in Nakamura and Steinsson (2008) when they include sales in the BLS data (4-5 months). Our SpellC measure of sales price duration is comparable to Kehoe and Midrigan (2008) who report sales price durations of 3 weeks using a grocery store data set, but our SpellA and SpellB measures have even shorter durations. Regular price spells are significantly shorter than the findings using BLS data (Bils and Klenow (2004) (4.3 months), 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).

We also use a sales filter to censor periods when the change in sales price is below a specified threshold. These filters are used later when we measure the depth of sales (change in sales price conditional on a transition from non-sale to sale), frequency of sales and share of goods on sale. Because our measured sales prices are linear combinations of regular prices and actual sales prices (for reasons discussed earlier) we cannot accurately measure the sales prices. Some of the sales price changes we observe may reflect weekly variation in the share of consumers that do not take advantage of the sales through loyalty cards. We use 5%, 10% and 20% thresholds to provide a lower bound on the frequency of price changes inclusive of sales. Obviously these filters will necessarily reduce the frequency we measure but they potentially offer a more robust indicator of sales behavior. Table 3.3 reports the frequencies of sales using different sales filters.

3.3 Facts about pricing

We begin by summarizing the raw data for the categories that we analyze subsequently.

Table 3.4 presents the number of UPCs in each of our ten categories, the number that are private label brands, the revenue share of the private label brands, and a measure of the elasticity of substitution within the category we calculate directly using the Feenstra (1994) methodology (see appendix **??** for details). The importance of private labels (as measured by revenue share) varies significantly across categories, from over 30% for cooking oil and sugar products to under 10% for cereal, potato chips and laundry detergent. The correlation between revenue share of private label products and the elasticity of substitution is 0.4, suggesting that private labels have an easier time competing in product categories that are relatively undifferentiated/homogeneous (high price elasticity). We also observe a negative correlation between the elasticity of substitution for the category and the median percentage markup, ranging from -0.27 for national brands to -0.44 for private labels, with similar correlations when calculating median retail margin inclusive of sales.[12]

3.3.1 Price Duration, Sales Frequency and Vertical Structure

We begin by analyzing the duration/frequency of price changes in our data. We find that regular prices are about equally sticky under different vertical structures, but the median and average durations for sales price and wholesale prices are about 20 to 30 percent shorter for private label goods. These differences are not driven by a single category but hold within most of our ten categories.

Table 3.5 presents the distribution of frequencies for regular, sales, and wholesale price adjustment by national and private label brands. For example, the average frequency of regular price adjustment for private label is 0.07, which means that every week, there is 7% chance that a private label good changes its regular price. In other words, it takes about 14.1 weeks for a price change to occur. On average, the frequency of regular price adjustment tends to be similar for both types of vertical structures, with national brands showing slightly higher values for each percentile. This is in contrast

[12] We calculate a median percentage margin across all store/week/UPC observations within a product category. We cannot report markup levels.

with the frequency of sales and wholesale price changes that are are clearly higher value for private labels across the distribution.

Tables 3.6, 3.7 and 3.8 report category-level frequency of price and cost adjustments in different vertical structures. Category-level frequency is calculated as an expenditure weighted average given by $Freq_{cat,type} = \frac{1}{N_{type}} \sum (Freq_{i,type}) \cdot \omega_{i,type}$ where $\omega_{i,type}$ is the aggregate (across stores and weeks) expenditure share of UPC i with respect to expenditures in the category/vertical structure. We do find a great variation in frequency of price adjustments across category. For instance, frequency of private label goods regular price ranges from 0.033 (sugar) to 0.125 (potato chips), implying the average duration to range from 8 weeks to about 30 weeks. The question of interest is how much variation can be explained by differences types of vertical structure. Table 3.9 reports R-square and adjusted R-square from fixed-effect regressions using vertical structure and category-specific fixed-effects independently and together. We observe that category-fixed effect explains a large variation of this heterogeneity of price duration and R-square and adjusted R-square improve significantly by controlling for vertical structure additionally. For instance, vertical structure alone explains about 0.36% of the variation in frequency of price adjustments, while category-level variation explains 3.4 to 3.7%. Taking both factors together, R-square increases to 5 to 5.5%. The same patterns can be found for regular price and wholesale price as well.

A parametric test of category mean frequencies confirms that sales prices and wholesale prices change significantly more frequently for private label goods, consistent with the raw (as opposed to by category) differences we observed in Table 3.5. On the other hand we find some evidence of greater mean frequency of regular price change for national brands, though the medians are very similar. There is substantial heterogeneity in the frequency of price adjustment across categories. The category mean durations range from 7 to 10 months for regular price, 7 to 13 months for wholesale prices, but only 2 to 4 weeks for sales prices. Figure **??** shows scatter plots that compare the category mean frequencies of regular, sales, and wholesale price changes for both types of brands.

Table 3.10 reports the results of pooled regressions that regresses the log or level of duration (inverse of frequency) on a dummy for private label goods. We also add category-level fixed effects to control for heterogeneity across categories. Each observation is the average duration for a UPC averaged across stores using the "spellC" imputation for missing observations. For the log sales price, the coefficient -0.295 on the private label dummy indicates that these goods have a 29% shorter duration than national brands. The coefficient of -3.31 on the private label dummy for the level sales price regression indicates that private label goods have a sales price duration that is three weeks shorter than for national brands.

3.3.2 Hazard Rates and Vertical Structure

Hazard functions provide useful information for evaluating the relevance of state-dependent and time-dependent pricing models that is not captured by the unconditional frequency of price adjustment. Different macro pricing models generate differently shaped hazard functions. In the Calvo model, where the ability to change prices in a period is completely random, hazard functions are flat. State-dependent pricing models typically imply an upward sloping hazard function but the slope can vary depending on the composition of permanent and transitory shocks.

We follow the general definition of a hazard function in macroeconomics as the probability of price change at a specific time as a function of the length of time since the previous price change, denoted by t. More formally, the hazard function is defined as $\lambda(t) = P(T = t|T \geq t)$, where T is a random variable denoting the duration of a price spell.

We estimate hazard functions non-parametrically. First, we construct cumulative distribution function of probability of a price change at each week for a specific good across stores. Then, we calculate unweighted average frequency of price changes conditional on reaching time t for different vertical structures.

Figure 3.3 plots the hazard functions for each variables. The shape of hazard functions is similar for regular price and wholesale price in that there is little evidence for either increasing or decreasing hazard rates. This stands in stark contrast to the shape of the sales price hazard function. We find that (1) for sales price, both national and private label brands exhibit downward-sloping hazard functions with periodic spikes and (2) the private label brands have much more pronounced spikes, confirming the greater use of temporary sales for private labels brands. Hazard functions with several spikes are not uncommon for grocery store items. [13] Our findings are consistent with Nakamura and Steinsson (2008) in several aspects: hazard functions of regular price show less dramatic decrease in the first several weeks than those of sales prices and that for some categories, the hazard functions are interrupted by spikes. When adding vertical structure into hazard function, we find more pronounced decrease in hazard rates in the first several weeks for private label sales prices than national brands and more pronounced regular spikes. The downward-sloping feature of hazard functions may be due to a mixture of different (or flat) hazard functions. To investigate possible source of heterogeneity, we carry out hazard function analysis for each category and each vertical structure. We find that for each category, sales price hazard rates are downward-sloping for most of the categories. [14]

[13] see Fougere et al. (2004) and Nakamura and Steinsson (2008).

[14] See Figure 3.4 for example.

3.3.3 Pass-Through Rates and Vertical Structure

We use reduced-form pass-through regressions to examine the response of prices to costs. Two sets of cost measures are used: (1) raw material prices for selected categories that represent "common" category-level cost shocks and (2) wholesale prices reported in the data set that represent "idiosyncratic" product-level cost shocks. We find (1) pass-through rates are incomplete and (2) private label goods show higher pass-through rates than national brands for both types of cost shocks. While our measures are not directly comparable to previous studies that use exchange-rate as cost shocks, our findings are consistent with Neiman (2010) and Hellerstein and Villas-Boas (2010), who find that more vertically-integrated firms feature higher pass-through rates.

The typical approach to estimating pass-through rates uses either (a) arguably exogenous cost shocks, like exchange rates, that are unrelated to consumer demand and most other macro variables or (b) policy changes or changes in market structure that affect specific markets (Villas-Boas (2007)). Commodity price shocks are plausibly exogenous with respect to consumer and other variables in the same way as exchange rates. For the raw material cost pass-through rates, we specifically focus on the following six categories, whose costs of raw materials (sugar, rice, wheat, coffee) are easily available at the weekly level - carbonated soft drinks, sugar, coffee, rice, cold cereal, syrup. These goods also feature relatively high shares of value-added from raw material prices than other manufactured goods. This is in similar spirit with many recent studies that use data from supermarkets or home scanners combined with commodity prices to examine patterns of pass-through from common raw material cost shocks to retail prices (see Leibtag et al. (2007), Nakamura (2008), Kim and Cotterill (2008), Rojas et al. (2008), and Berck et al. (2009)).

We adopt four different reduced form regressions to estimate pass-through rates for each UPC-store combination which we first average across stores, and then average within a category and vertical structure to get the average price responsiveness to cost changes. Each pass-through rates are generated at UPC level at a specific store. The category-level pass-through rates, $\beta_c^{k,j}$ for each vertical structure is calculated as $\beta_c^{k,l} = \frac{1}{N_c^k}\sum_{i\in c}\beta_i^{k,l}$, where N_c^k is the number of UPC in a category c in vertical structure, k.

The first approach, which we call the *instantaneous pass-through ($\beta_{i,inst}$)*, is defined as follows:

$$\triangle p_{i,t} = \alpha_i + \beta_{i,inst}\Delta c_{i,t} + \varepsilon_{i,t} \tag{3.1}$$

where $\triangle p_{i,t}$ is the log price change for good i (in a particular store) at time t. Change in log cost, $\triangle c_{i,t}$, is defined similarly.

Our second approach is a pooled regression including lags that we call *long run pass-through(β_{LRPT})*. The long-run pass-through rate is the sum of the coefficients of either 4 lags (corresponding to one month, the median sales frequency under SpellC) or 12 weeks (one quarter). The LRPT rates are estimated using the following regression:

$$\triangle p_{i,t} = \alpha_i + \sum_{j=0}^{t} \beta_{ji} \Delta c_{i,t-j} + \varepsilon_{i,t} \tag{3.2}$$

where LRPT1 and LRPT2 are defined as:

$$LRPT1_i \equiv \sum_{j}^{4} \beta_{ji}, LRPT2_i \equiv \sum_{j}^{12} \beta_{ji} \tag{3.3}$$

We also run one specification for wholesale prices only. The reason for this is that over long horizons there is limited inter-temporal variation in the commodity prices, but we can use variation across stores in wholesale prices which usually differ across different regions. Our first approach estimates the pass-through we observe over the entire life of the item we observe in our data. That is, we take the earliest and lastest observations for a UPC-store combination and calculate the difference between these two observations for retail prices and wholesale prices. Because some of the items in our sample do not change price over the entire sample period, the cumulative price change for some observations is zero. Formally, *life-time pass-through ($\beta_{i,life}$)* is estimated using the following regression:

$$\Delta^T p_i = \alpha_i + \beta_{i,life} \Delta^T c_i + \varepsilon_i \tag{3.4}$$

where T is the time between the first and last observations for an item-store in the data set. Unlike the previous regressions which were run separately for each UPC-store combination, the observations (i) for this regression are stores and there is no time dimension.

Our first set of results concern pass-through of raw material prices to retail prices for the selected categories. Table 3.11 presents the results for regular list price pass-through rates and Table 3.12 presents the results for sales price pass-through rates. We find that pass-through rates using list prices are generally smaller than those using sales prices, which provides evidence that sales frequency and depth are potentially important dimensions of price adjustment by retailers to marginal cost shocks. We also find that private label brands show much greater pass-through of raw material costs than national brands using either retail price measure. Note that relatively low raw material pass-through is not surprising since a significant part of the cost of any retail good comes from non-material inputs, including the land, labor, and capital used in the manufacturing and retail process and the distribution costs.

Figure **??** contrasts the movements of raw material prices for two categories, sugar and coffee, with retail and wholesale price indices. We normalize all prices to 100 in the first week of our sample (the first week of 2004). We use Laspeyres indices in which the weekly price change for each UPC-store observation is weighted by its category expenditure share for a given vertical structure (aggregating across all stores and UPCs in the category in the week). Table 3.15 reports the overall price movement over our sample period, taking the difference between the first and last observation of each series. The "difference" measures the percentage growth of prices over 178 weeks, and "responsiveness" refers to the ratio of the percentage price change for a price index relative to the raw material price index. This is analogous to the life-time pass-through rates using wholesale prices as regressors, except there is no variation in raw material prices across stores. From Figure **??**, we observe that the volatility and the change in raw material prices is much more dramatic than for retail prices. Nevertheless, we find that private label goods prices are more responsive to the raw material price changes. For instance, in Table 3.15, we see that the price of sugar rose by 66% over 178 weeks from the first week of 2004. In comparison, the index of regular price for private label goods rose 29%, while the index of regular price for national brands rose 17.6% during the same period. We see a similar pattern for sales and wholesale prices.

Our second set of results use wholesale price variable as independent variables. Table 3.13 and Table 3.14 report the results. While the estimated pass-through rates vary across categories, we find evidence that category-level pass-through rates are greater for the private label brands than the national brands at both short (instantaneous pass-through in the first column) and very long (life-time in the last column) horizons. For some horizons and categories, pass-through from wholesale to retail sales prices (table 3.14) is much larger for private label than for national brands. For example, at long-horizons private label goods have double the pass-through for pasta and sugar and almost 50% higher pass-through for soft drinks.

3.3.4 Size of price changes and Vertical Structure

An additional aspect of pricing has been analyzed in the macroeconomics literature is the size of price changes. Using BLS micro data, Klenow and Kryvtsov (2008) found that the median price change is large in absolute size, but that there are also many small changes. Dotsey et al. (1999) and Golosov and Lucas (2007) explore the implications of the size of price changes for various pricing models - for example, the presence of many small price changes is inconsistent with the standard menu cost model.

We denote our measure of the size of regular price change as

$$\Delta p^r_{i,t} \equiv p^r_{i,t} - p^r_{i,t-1} \tag{3.5}$$

where $p^r_{i,t}$ is the log regular (r) price of UPC-store i at time t (for a particular store). We also define the depth of sales as follows:

$$\Delta p^s_{i,t} \equiv p^r_{i,t} - p^s_{i,t} \tag{3.6}$$

where the depth of sales is the deviation of the log sales (s) price ($p^s_{i,t}$) from the regular price at time t. We weight non-zero price changes by expenditure shares, $\omega_{i,c,t-1}$, which is the expenditure share of a UPC-store i at time t with respect to total expenditures of all goods whose prices changed in category c at time t. Thus our measure is period by period base-weighted price index that only includes goods whose price changed between t-1 and t. The mean price change for a given category c, $\overline{\Delta p^k_c}$ is defined as follows:

$$\overline{\Delta p^k_c} = \frac{\sum_{i\in c}\sum_t \omega^k_{i,c,t-1}\Delta p^k_{it}}{\sum_{i\in c}\sum_t \omega^k_{i,c,t-1}} \tag{3.7}$$

where the superscript k is r for regular price and s for sales price.

The sample mean size of price change, $\overline{\Delta p^k}$, is similarly defined as follows:

$$\overline{\Delta p^k} = \frac{\sum_i \omega_{i,t-1}\Delta p^k_{i,t}}{\sum_i\sum_t \omega_{i,t-1}} \tag{3.8}$$

Table 3.16 summarizes the size of regular and sales price changes for different vertical structures. The absolute size of regular price change is significantly greater for the private label brands. This holds when comparing positive and negative price changes separately. However, the size of temporary sales discounts is larger for national brands.

For instance, using the first sales filter (thereby throwing out sales price changes below 5% that may reflect changes in the share of consumers taking advantage of loyalty cards), national brands show on average 29% temporary price cuts, while private label goods show on average 27% temporary price cuts. The median sales discount results in a price decrease between 24% to 32% of the regular (list) price. The magnitudes of regular price changes are smaller than those of sales price changes, regardless of the vertical structures.

While there is a statistically significant difference in the mean regular price changes, the distributions of these price changes are strikingly similar. Most of the regular price changes are concentrated around +/- 5%. Private label brands show slightly higher fraction of larger price changes in +/- 20 to 50%. Figure **??** shows the distribution of regular price changes for national brands and private labels. Table 3.17 reports the smaller regular price changes less than 5%, 2.5% and 1%, respectively. For example, for private label goods, 60% of total non-zero price changes are less than 5% in absolute value. Distributions of smaller price changes look similar for both vertical structures, with slightly higher fraction of price changes less than 5% is observed in private label goods.

3.3.5 Synchronization and Vertical Structure

We next turn to the timing of price changes. The synchronization of price change is an important determinant of the size and persistence of business cycles and also reveals the presence of strategic complementarities that are absent in time-dependent pricing models like the Calvo and Taylor models. Blanchard (1983) provides a theoretical result that even under fully flexible prices, monetary non-neutrality can arise due to price inertia when there is a layer of the supply chain that does not coordinate the timing of the price changes. The degree to which firms coordinate the timing of price changes may also depend on the substitutability of goods. Bhaskar (2002) shows that if firms are allowed to choose the timing of price changes, the firms that produce more similar goods will show greater coordination of timing in price changes than firms that produce less similar goods. Olivei and Tenreyo (2007) documents there is a substantial "lumping" or uneven staggering of wage contracts during certain periods of the year, leading to different effects of monetary shocks at these times.

Empirical evidence on synchronization is mixed. Lach and Tsiddon (1996) use monthly food price data from Israeli stores to conclude that the timing of price changes is highly synchronized both within and across stores. Midrigan (2006) demonstrates that prices in narrowly defined product categories within a store tend to be synchronized. However, some other studies suggest that price changes are not synchronized across price-setters. Using price data of 10 Euro area countries, Dhyne et al. (2005) documents that the timing of price changes is not synchronized even within a country. Furthermore, using a Belgian micro-level data set, Dhyne and Konieczny (2007) finds that price changes are more staggered than synchronized.

Using import data set for both price increases and decreases, Neiman (2010) concludes that related party prices are less synchronized than arm's length transaction prices - a one standard deviation increase in the share of competitors with the same vertical structure that are raising (decreasing) prices raises the probability of an arm's length price increase (decrease) by 33 (59) percent, compared to 23 (49) for related parties.

We adopt the Fisher and Konieczny (2000) measure of synchronization of price changes that has an intuitive interpretation. Let $q^k_{c,t}$ be the proportion of goods that change the price at time t within a category (c) for vertical structure k, while $\overline{q^k_c}$ is the mean of $q^k_{c,t}$ across all the time periods in our sample. The Fisher-Konieczny(FK) measure is defined as:

$$FK_{c,k} = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}(q^k_{c,t} - \overline{q^k_c})^2}{\overline{q^k_c}(1-\overline{q^k_c})}} = \sqrt{\frac{s^2_{q^k_{c,t}}}{\overline{q^k_c}(1-\overline{q^k_c})}} \tag{3.9}$$

The FK measure is the standard deviation, over time, of the fraction of goods in a category with a price change, normalized to lie between zero and one. In the case of perfect synchronization where every good changes price or no good changes price in each period, FK equals one. When the fraction of goods with a price change in each period is constant and equal to the mean, FK equals zero. In our ten product categories, FK ranges between 0.11 and 0.36. Figure 3.7 plots the behavior of $q^k_{c,t}$ over the entire sample period for two goods, coffee (which has the highest FK) and all family juices (which has the lowest FK).

Table 3.18 reports category-specific FK measures. We observe two clear patterns for synchronization: (1) regular price synchronization is lower than sales price synchronization, and (2) private label goods show greater synchronization for both regular price and sales price, but particularly for sales price changes.

While our results are in stark contrast to Neiman (2010) and Neiman (2011) it is important to take note of the different environment. Empirically, Neiman (2010) is based on data where each arm's length and each intra-firm transaction is typically independent - while there may be multiple buyers or sellers within the intra-firm and arm's length classification, it is not obvious that the large multi-product firms play a greater or lesser role for either bin. In our data, there is only a single buyer - the retailer. This potentially changes the incentives for synchronization in retail prices and can change the synchronization of wholesale prices as well. For example, the theoretical model in Neiman (2011) features intra-firm prices that are more insulated from competition and more responsive to idiosyncratic cost shocks, leading to lower price synchronization than across arm's length price-setters who take into account strategic complementarities. From the point of view of a grocery retailer, price changes for either type of good do affect demand and pricing power for other goods but these effects are internalized. private label goods may compete vigorously with each other and national brands as they are usually placed next to each other on store shelves. Even with competition from other retailers, private label goods may not be as insulated from competition with each other and national brands as is the case for import transactions.

Our demand model suggests that the timing of sales may be synchronized within or across categories for strategic reasons, but these motives can be very different than the ones featured in the trade literature.

Table 3.19 documents synchronization in sales across vertical structures. We first calculate the share of goods that are on sale for private label and national brand goods for each category. Over the data period, we find that average proportion of goods on sales is greater for private labels for most of the categories. For instance, according to Table 3.19, private label cold cereals go on sale about 38%, while national brands cereals go on sale about 33% during 178 weeks. We calculate the correlation over time in the fraction of goods on sale in a category across vertical structures, i.e. $cor(q_{c,t}^{PL}, q_{c,t}^{NB})$. A positive correlation indicates that periods with higher than average sales for private labels are also periods with higher than average sales for national brands. A positive correlation thus indicates that the retailer views sales on national brand and private label brands as complements leading to synchronized sales, while a negative correlation indicates that the retailer views them as substitutes, leading to staggered sales. A zero correlation is consistent with zero variability in sales for either type of good or no systematic relationship. We find mixed evidence here - several categories have a significant positive correlation in sales frequency, several have a significant negative correlation, and others are zero.[15] The absence of a systematic pattern of synchronization of sales across private label and national brands suggests that the retailer does not view these two types of goods as substitutes or complements in general, but may adopt different strategies for different product categories.

3.4 Interpreting the differences in price dynamics between national and private label brands

In this section we analyze two simple models that shed light on the mechanisms behind the differences in pricing behavior we observe for private label and national brand goods in the previous section. Our goal is not so much to provide a quantitative account of our findings but rather to highlight the qualitative predictions of two classes of model and contrast them with our findings. The first model ("supply-side") introduces vertical structure into a stripped-down version of the Gopinath and Itskhoki (2011) model, which combines menu costs with variable markup elasticities to generate a correlation across goods between frequency and pass-through. We assume similar demand parameters for the two types of vertical structure and focus on the impact of

[15]Note: One factor that could lead to coordination in sales across the two types of goods is seasonality, as explored in Chevalier et al. (2003).

an intermediary firm on pricing behavior through double-marginalization. The second model introduces asymmetry in consumer valuations and marginal costs for two different goods, building on the Chevalier and Kashyap (2011) model that combines heterogeneous consumer valuations and storable demand to generate recurring sales as a means of inter-temporal price discrimination by the retailer. We emphasize the interaction between consumer heterogeneity and the heterogeneity in characteristics of private label brands (lower quality, lower cost) and focus on the implications for sales frequency.

After describing the models and their predictions, we use them to interpret our findings from the previous section and conclude that while both models capture important aspects of the data, neither is sufficient on its own. We conclude with a discussion of the macroeconomic implications of our findings.

3.4.1 Supply-Side Explanations: A Model of Price Duration and Pass-through with Vertical Structures

One of the main differences between private label and national brands is the nature of the supply-chain. By taking on many of the activities usually carried out by manufacturers and buying an unbranded product (or manufacturing it directly), the retailer removes market power from the manufacturer. This will typically result in lower markups by the manufacturer over marginal cost (and potentially zero markups when the retailer owns the manufacturer), which in a variable markup environment can affect the transmission of shocks from downstream to upstream firms because markups act like a buffer. This aspect of vertical integration is the one that is usually emphasized in the literature. For example Neiman (2011) analyzes a model with state-dependent pricing and incomplete pass-through due to menu costs, where the variable elasticity of demand that leads to incomplete pass-through is generated by strategic competition between arm's length intermediate goods firms. In the intra-firm case, there is no markup and there is also no markup variability.

In this section we present a simple static model of price-setting with variable markups and menu costs adapted from Gopinath and Itskhoki (2011) to analyze the effect of vertical structure on pass-through and frequency of price changes. Their model combines a variable demand elasticity that generates incomplete pass-through (using the Kimball consumption aggregator) with menu costs. We build on their model to analyze two distinct supply-chains - one in which a wholesale and retail firm are vertically integrated, and one in which they engage in arm's length transactions. In our model we emphasize the role of double-marginalization - the extra layer of markup imposed by the wholesaler on the retail firm's inputs in the arm's length case - and assume that neither the retailer nor the wholesale intermediary perform any additional services or add any value to the product. We will return to the role of other input costs later.

We begin with the vertically integrated case: a single firm with a menu cost of changing prices that faces a variable marginal cost (e.g. raw material price determined on commodity markets). The retailer has a menu cost and variable demand elasticity. Then, we introduce vertical structures by adding a wholesaler (manufacturer) that acts as an intermediary, buying the basic input at marginal cost and selling it to the retailer with a markup. In this scenario, the strategic interaction between the wholesaler (upstream firm) and the retailer (downstream firm) is as follows:

1. The wholesaler observes realized cost shocks and demand conditions and also the anticipated reaction of the retailer.
2. The wholesaler decides to change its price or not. The wholesaler incurs a fixed adjustment cost when changing the price. If she decides to change the price, the new price satisfies the wholesaler's first-order condition.
3. The retailer observes the wholesale price set by the wholesaler and decides whether or not to change its (retail) price, also upon observing the demand conditions. The retailer also faces a fixed cost of adjustment if it chooses to change the retail price.

Importantly, we assume that the retailer faces the same demand conditions in the two cases we consider, except through the effect of double-marginalization on the input cost. Figure 3.8 represents the timeline of the price setting in each vertical structure scenario.

For clarity of notation, we denote the ex-ante price level, p_0^k and the desired price level, p_1^k, where $k \in r, w$ with r representing a retail variable and w representing a wholesale variable. We also use *int* to denote the vertically integrated case and *arms* to denote the arm's length case. Each firm's profit is denoted Π^k.

Vertically Integrated Case

The retail firm faces a residual demand schedule given by $Q = \varphi(p^r|\sigma, \epsilon)$ where p^r is the retail price that the consumers pay and $\sigma > 1$ and $\epsilon \geq 0$ are the two demand parameters.

The price elasticity of demand is denoted by

$$\tilde{\sigma} \equiv \tilde{\sigma}(p^r|\sigma, \epsilon) = -\frac{\partial ln\varphi(p^r|\sigma, \epsilon)}{\partial lnp^r} \tag{3.10}$$

and the *super-elasticity* of demand, or the elasticity of the elasticity, as

$$\tilde{\epsilon} \equiv \tilde{\epsilon}(p^r|\sigma,\epsilon) = \frac{\partial ln\tilde{\sigma}(p^r|\sigma,\epsilon)}{\partial lnp^r} \tag{3.11}$$

An assumed super-elasticity of demand grater than zero is what generates incomplete pass-through in this model - in response to a cost increase, the firm will reduce its markup, buffering the consumers form the full effect of the cost increase. The case of $\epsilon = 0$ corresponds to CES demand with constant markups. We impose the following normalization on the demand parameters: when the price of the firm is unity (P=1), the elasticity and super-elasticity of demand are given by σ and ϵ respectively. We normalize demand $\varphi(1|\sigma,\epsilon) = 1$, which simplifies things later when we approximate the solution around $p = 1$.

The firm faces a marginal cost $MC(e) = (1+e)c$, where we assume that e is a symmetric shock with mean $E(e) = 0$ and standard deviation by σ_e. We normalize the marginal cost so that $MC = c = \frac{\sigma-1}{\sigma}$ when there is no cost shock - under this normalization, the optimal flexible price for the firm when $e = 0$ is equal to 1, since the marginal cost is equal to the inverse of the markup.

The profit of this firm is given by

$$\Pi^r = (p^r - MC(e))\varphi(p^r|\sigma,\epsilon) \tag{3.12}$$

The *desired retail price level* of the firm, denoted by p_1^r satisfies

$$p_1^r \equiv argmax_p \Pi^r(p^r|\sigma,\epsilon) \tag{3.13}$$

For a given cost shock e the desired flexible price maximizes profits so that

$$p_1^r = c(1+e) - \varphi(p_1^r)(\frac{\partial\varphi(p_1^r|\sigma,\epsilon)}{\partial p_1^r})^{-1} = \frac{\tilde{\sigma}(p_1^r)}{\tilde{\sigma}(p_1^r)-1}c(1+e) \tag{3.14}$$

and the corresponding maximized profit is $\Pi^r(p_1^r, e)$.

To analyze frequency as well as pass-through, we assume that the firm incurs a menu cost κ^r when changing its price. The firm's profit with no price adjustment is $\Pi^r(p_0^r, e)$ while the profit with adjustment is $\Pi^r(p_1^r, e)$. A profit-maximizing firm will then reset the price in response to a cost shock if the profit loss from non-adjustment exceeds the menu cost:

$$L^r(e) \equiv \Pi^r(p_1^r, e) - \Pi^r(p_0^r, e) \geq \kappa^r \tag{3.15}$$

The solution to this problem is worked out in Gopinath and Itskhoki (2011) and results in $p_0^r \approx 1$ so that the ex-ante price is set as if the anticipated cost shock is zero ($e = 0$).

As derived in Gopinath and Itskhoki (2011), the pass-through of cost shocks is given by

$$\Psi_e^r = \frac{1}{1 + \frac{\epsilon}{\sigma - 1}} \tag{3.16}$$

Note that this is directly related to the markup elasticity given by $\frac{\tilde{\epsilon}(p^r)}{\tilde{\sigma}(p^r)-1}$.

The loss from not adjusting $L^r(e)$ is approximated as

$$L^r(e) \approx \frac{1}{2}(\sigma - 1)\Psi_e^r e^2 \tag{3.17}$$

In this static framework, the frequency of price adjustment can be interpreted as the probability of resetting price given the distribution of cost shocks e. Define the set of shocks that do not lead the profit-maximizing retailer to adjust its price by:

$$\triangle \equiv \{e : L^r(e) \leq \kappa^r\} \tag{3.18}$$

The frequency of price adjustment, Φ^r, is then defined as

$$\Phi^r \equiv 1 - Pr(e \in \triangle, L^r(e) > \kappa^r) \tag{3.19}$$

Combined with the loss function, this implies

$$\Phi^r \approx Pr\left\{ |X^r| > \sqrt{\frac{2\kappa^r}{(\sigma - 1)\Psi_e \sigma_e^2}} \right\} \tag{3.20}$$

where $X^r \equiv (\sigma_e^2)^{-1/2} e$ is a standardized random variable with zero mean and unit variance and σ_e^2 is the variance of the cost shock e.

The above model implies that higher super-elasticities, ϵ, reduce both frequency of price adjustment and pass-through. The demand elasticity itself (σ) is positively related to frequency of price change and pass-through. Higher menu costs (κ^r) and smaller shocks (lower σ_e) lower frequency with no effect on measured pass-through.

Arm's length case

We now turn to a scenario with an identical retailer but with a wholesale (manufacturing) intermediary that faces its own residual demand curve and thus sets prices with a markup over marginal cost. The wholesaler thus takes the marginal cost e facing the retailer in the last problem, but adds a markup without adding any additional value or services, charging p^w to the retailer. The retailer takes p^w as given.

Similar to the first case, we assume that the wholesaler faces demand curve $\varphi(p^w|\sigma_w, \epsilon_w)$ with elasticity of demand, $\tilde{\sigma_w}(p_r^w|\sigma_w, \epsilon_w)$ and super-elasticity of demand, $\tilde{\epsilon_w}(p_r^w|\sigma_w, \epsilon_w)$ defined as above. This set-up assumes that the wholesaler sell to many retailers such that they face a smooth, continuously differentiable demand function.[16]

The wholesaler maximizes $\Pi^w = (p^w - MC)\varphi(p^r(p^w))$. He has a fixed cost of adjusting prices, κ^w.

The *desired wholesaler price level*, denoted by (p_1^w), follows the following pricing equation derived from the first order conditions for profit maximization:

$$p_1^w = (1+e)c - \varphi(p^w)(\frac{\partial\varphi(p^w)}{\partial p^w})^{-1} = \frac{\tilde{\sigma_w}(p_r^w|\sigma_w, \epsilon_w)}{\tilde{\sigma_w}(p_r^w|\sigma_w, \epsilon_w) - 1}(1+e)c \tag{3.21}$$

In this case, the wholesaler's problem is identical in the retailer's problem in the previous case (except the demand parameters may differ). The normal price charged by the wholesaler will be $p_0^w = \frac{\sigma_w}{\sigma_w - 1}c(1+e)$. Similar to the pricing decision the retailer has to make, the wholesaler decides to adjust its price when:

$$L^w(e) \equiv \Pi^w(p_1^w, e) - \Pi^w(p_0^w, e) \geq \kappa^w \tag{3.22}$$

where $\Pi^w(p_1^w, e)$ is the profit associated with price adjustment, and $\Pi^w(p_0^w, e)$, the profit associated with price no-adjustment.

The wholesaler will have a loss from not adjusting of $L^w(e) \approx \frac{1}{2}(\sigma_m - 1)\Psi_w^r e^2$. The *(desired) pass-through* is:

$$\Psi_w = \frac{1}{1 + \frac{\epsilon_w}{\sigma_w - 1}} \tag{3.23}$$

The *probability of price adjustment* is given by:

$$\Phi^w \approx Pr\left\{|X^w| > \sqrt{\frac{2\kappa}{(\sigma_w - 1)\Psi_e^w \sigma_e^2}}\right\} \tag{3.24}$$

[16]We do not consider the case where the wholesaler must take into account the retailer's menu cost and region of non-adjustment, as this greatly complicates the analysis. In such a setting the wholesaler faces a highly-kinked demand curve since changes in wholesaler price below some threshold, i.e. $\{p_w : L^r(p_w) < \kappa^r\}$, produce no change in retail prices and hence no change in volume.

where $X^w \equiv (\sigma_e^2)^{-1/2} e$ is a standardized random variable with zero mean and unit variance and σ_e^2 is the variance of the cost shock e.

We now contrast the pricing implications or the vertically integrated and arm's length cases. We first note that any raw material cost shock e that results in a price-adjustment by the wholesaler results in a smaller percentage change in p^w due to incomplete pass-through. The wholesaler, faced with a positive shock to costs that results in a wholesale price change, will decrease the wholesale markup to offset some of the effect of the shock on p^w.

Proposition 1: The desired pass-through in the arm's length case is smaller than the desired pass-through in the vertically integrated case ($\Psi_{int} \geq \Psi_{arms}$) assuming similar retail elasticities.

Proof: The desired pass-through rate for the vertically integrated firm is given by: $\Psi_{int} = \frac{1}{1+\frac{\epsilon_r}{\sigma_r - 1}}$. For the arm's length firm this is given by $\Psi_{arms} = \frac{1}{1+\frac{\epsilon_w}{\sigma_w - 1}} \frac{1}{1+\frac{\epsilon_r}{\sigma_r - 1}}$. The proposition follows trivially from the observation that $\frac{1}{1+\frac{\epsilon_r}{\sigma_r - 1}}$ is less than one.

This also means that *conditional on retail price-adjustment* (which implies that the wholesaler also adjusted prices), the observed pass-through of the e shock should be greater for the vertically integrated firm.

The caveat in the proposition highlights the subtle role of demand parameters in the model. Recall that the key force determining pass-through in the model is the markup elasticity given by $\frac{\tilde{\epsilon}(p^r)}{\tilde{\sigma}(p^r)-1}$. In the proposition we assume that the retail price of the two goods is identical ex-ante, which would only be the case if $c^{arms} < c^{int}$ since there is an extra layer of markups in the arm's length case. If $c^{arms} = c^{int}$ then the retail price of the arm's length good is higher ($p^{r,arms} > p^{r,int}$). For many commonly used demand functions with a positive super-elasticity, such as the Kimball aggregator used in Klenow and Willis (2006) and Gopinath and Itskhoki (2011), the super-elasticity itself is a decreasing function of p^r - i.e. a negative super-super-elasticity.[17] When retail price increases, the elasticity of demand increases which generates a fall in the markup and incomplete pass-through. However, the pass-through coefficient itself is

[17] There may be demand functions with positive super-elasticities and positive super-super-elasticities though we have not encountered any in the literature. The Kimball demand system features a demand function given by $C_j = \psi(D \frac{P_j}{P} \frac{C}{\Omega})$ where P_j is the price of variety j, $D \equiv \int_\Omega \Upsilon' \left(\frac{|\Omega| C_j}{C} \right) \frac{C_j}{C} dj$, P is the sectoral price index defined implicitly by $PC = \int_\Omega P_j C_j dj$, and Ω is the set of varieties (with measure $|\Omega|$). $\psi \equiv (\Upsilon\prime)^{-1} = \left[1 - \epsilon \ln \left(\frac{\sigma x_j}{\sigma - 1} \right) \right]$, where $x_j \equiv D \frac{P_j}{P}$. This demand set-up gives rise to $\tilde{\sigma}(x_j) = \frac{\sigma}{1-\epsilon \ln(\frac{\sigma x_j}{\sigma-1})}$ and $\tilde{\epsilon}(x_j) = \frac{\epsilon}{1-\epsilon \ln(\frac{\sigma x_j}{\sigma-1})}$. Combining these we have a markup elasticity $\frac{\tilde{\epsilon}(p^r)}{\tilde{\sigma}(p^r)-1} = \frac{\epsilon}{\sigma - 1 + \ln(\frac{\sigma x_j}{\sigma-1})}$ which is clearly decreasing in x_j and hence in P_j, the firm's own price.

decreasing in the markup and hence increasing in the retail price. Because this effect goes in the opposite direction of the incomplete pass-through at the wholesale level, the overall effect of vertical structure on desired pass-through in this model is theoretically ambiguous. Empirically, it may well be the case that demand for the arm's length and vertically-integrated goods are different to begin with; whether or not this is the case, when wholesale prices are observed one can directly test whether this demand effect dominates by testing the null hypothesis that pass-through of wholesale prices to retail prices is higher for arm's length firms. If this is not the case then the higher pass-through of primitive cost shocks into retail prices is unambiguously higher for the vertically integrated retailer.

The presence of a wholesale menu cost adds an additional source of incomplete pass-through of e shocks to the arm's length case. If the wholesaler faces a menu cost, any shock e such that $e \in (e : L^w(e) \leq \kappa^w)$ results in a wholesale price change of zero. This leads to zero change in retail prices and hence zero measured pass-through of e into p^r. Wholesale menu costs in this case effectively censor the distribution of shocks faced by the retailer. Whether this censorship matters in practice depends on the magnitudes of the menu costs for the retailer and the wholesaler - if the retail menu cost is high relative to the wholesale menu cost ($\kappa^r >> \kappa^w$) then the wholesale menu cost will have little effect on observed raw material cost pass-through. The opposite case where wholesale menu cost is high relative to retail menu cost would imply that all small shocks to raw material costs will be censored by menu costs in the arm's length case. This censoring mechanism is also at work in retail prices but affects both cases similarly.

Proposition 2: With wholesale menu cost κ_w, the measured pass-through is unambiguously smaller for the arm's length case than the vertically integrated case assuming similar retail elasticities.

Proof: With wholesale menu costs there is a region of cost shocks where pass-through is zero, given by e is $e \in (e : L^w(e) \leq \kappa^w)$. The measured pass-through into wholesale prices is then then a weighted average of this zero pass-through and the desired wholesale pass-through, given by: $\Psi_w^{observed} = Pr\left\{|X^w| < \sqrt{\frac{2\kappa}{(\sigma_w - 1)\Psi_e^w \sigma_e^2}}\right\}(0) + Pr\left\{|X^w| > \sqrt{\frac{2\kappa}{(\sigma_w - 1)\Psi_e^w \sigma_e^2}}\right\}(\Psi_w)$. Note that this is less than one. At the retail level, some small changes are also censored but the region of censorship is identical for the two cases, and since p^w is always smaller than e due to incomplete pass-through, menu cost related censorship and incomplete pass-through at the wholesale level leads to even more weight on this zero region, further decreasing the measured pass-through in the arm's length case.

Turning now to frequency of price adjustment, it is obvious that given any non-zero menu cost κ_w the frequency of wholesale price change is lower in the arm's length case than the vertically integrated case, where changes in raw material costs are reflected one for one in the internal "price" passed from the wholesale/manufacturing division to the retail division. What are the implications for the frequency of retail price changes? Recall that in this static model the frequency is equivalent to the probability of adjusting retail prices, given by $\Phi \approx Pr\left\{|X| > \sqrt{\frac{2\kappa^r}{(\sigma_r-1)\Psi_e^{int}\sigma_e^2}}\right\}$. For the arm's length retailer this formula is $\Phi \approx Pr\left\{|X| > \sqrt{\frac{2\kappa^r}{(\sigma_r-1)\Psi_e^r\sigma_{pw}^2}}\right\}$.

Proposition 3: The frequency of retail price adjustments of the arm's length firms is smaller than that of vertically integrated firms assuming similar retail elasticities.

Proof: The combination of incomplete pass-through (due to markups) and a region of non-adjustment/censorship (due to wholesale menu costs) will result in $\sigma_{p^w}^2 < \sigma_e^2$. The frequency of retail price changes will be lower for the arm's length retailer than for the vertically integrated retailer. The only exception is if (as discussed above) the retail elasticities are sufficiently different that $\Psi_e^r > \Psi_e^{int}$ and this effect outweighs the effect coming from the lower variance of cost shocks to the arm's length retailer.

In addition to predictions about pass-through and frequency differences between arm's length and vertically integrated firms, the model also has implications for the size of price changes. Unconditionally, wholesale price changes are smaller in the arm's length case due to lower pass-through of the underlying cost shocks (e) and to a region of non-adjustment due to menu costs. Conditional on observing a wholesale price change, these two effects go in opposite directions, censoring out small changes in e but also shrinking larger changes in e. The effect is ambiguous and depends on the relative importance of menu costs and incomplete pass-through. At the retail level, the vertically integrated firm experiences significantly larger marginal cost shocks conditional on the wholesale price adjusting but may have small changes in e censored by the wholesale menu costs. If retail menu costs are large relative to wholesale menu costs, then this the small censored shocks to e would have no effect on retail prices anyway. In this case, the size of observed retail price changes will be larger in the vertically integrated case because all of the price changes that exceed the cutoff (given by retail menu costs) are amplified relative to the arm's length case in which the distribution of underlying cost shocks gets compressed by the incomplete pass-through of the wholesale intermediary. We can write the condition for larger average (absolute) price changes for the vertically integrated retailer as:

$$E[|p_1^{int}| \mid L^{int}(e) > \kappa^r] \geq E[|p_1^r| \mid L^r(p_w) > \kappa^r, L^w(e) > \kappa^w] \tag{3.25}$$

In our data we find that, conditional on a retail price change, the regular price changes are larger for the private label/vertically integrated products but the sale price changes are larger for the national brand/arm's length products. If we believe that sales price changes only reflect cost shocks rather than price discrimination or other forces, then our findings are consistent with a relatively large wholesaler menu cost that censors many small price changes and produces a larger average price change for the national brands.

3.4.2 Asymmetric model of sales

As discussed briefly in the previous section, differences in demand elasticities may play a role in generating different pricing behavior for private label and national brand goods. These goods are not identical, and the conventional wisdom is that compared to national brands, private label brands feature lower quality but also lower prices (due to lower marginal costs, not necessarily lower markups). The role of heterogeneity in consumers and products is particularly important in retail, and there is a long literature examining how this may impact pricing. In this subsection we consider a model that captures a central feature of retail - the occurrence of frequent, temporary sales. The price discrimination model of sales goes back to Varian (1980) and has been analyzed more recently by Guimaraes and Sheedy (2011) to examine whether the types of sales generated by consumer heterogeneity can have macroeconomic implications. Our model draws heavily on the framework in Chevalier and Kashyap (2011), who consider a retailer facing heterogeneous consumers with storable demand. The retailer may use inter-temporal price discrimination - through temporary sales - to extract maximum surplus from the different types of consumers. Our model departs by introducing asymmetry in products as well. Chevalier and Kashyap (2011) focus on symmetric products, which will never go on sale simultaneously and that have a similar value to the bargain-hunting, price-sensitive consumer that drives sales frequency. We attempt to capture the fact that national brand and private label products have asymmetric characteristics.

For simplicity we limit the analysis to two brands which we label national brand (N) and private label (P). Based on the industry conventional wisdom, evidence from our data set, and the presumption that national brands cost more due to the extra layer of markups from manufacturer sets a markup over marginal cost, we assume that the retailer's marginal cost for the N brand is greater than for the P brand, or $c_N > c_P$. Our other central assumption is that consumers always have an equal or greater valuation for the national brand than the private label brand, due to advertising, quality, or familiarity (we abstract from dynamic sales motives such as consumer learning or habit formation). Sales occur in the model for the same reason as in Chevalier and

Kashyap (2011) - consumers have heterogeneous valuations and have demand that will accumulate over time if unsatisfied, leading retailers in some cases to adopt inter-temporal price discrimination through periodic sales that trade off larger per unit margins for larger volume.

Consider first a model with only two types of consumers, a high-type with valuation V_N for the national brand and V_P for the private label brand, and a low-type with identical valuation V_P for the two brand (these correspond to a national brand loyal and a bargain-hunting consumer in Chevalier and Kashyap (2011)). There is one unit of new consumer demand every period and the high-type consumers make up a fraction α. If consumers of either type do not make a purchase in a given period, the unsatisfied demand of that type carries over to the next period multiplied by factor ρ (with $0 < \rho < 1$).

In this particular set-up, there are no periodic sales. If $V_N - c_N > V_P - c_P > 0$ the retailer will sell N to the high-type and P to the low-type, setting $P_N = V_N$ to maximize profits from the high-type and setting $P_P = V_P$ to get some profits from the low-type.[18] In the other case where $V_N - c_N < V_P - c_P$ the retailer only sells brand P to both sets of consumers, charging $P_P = V_P$ (and $P_N > V_N$).

Suppose instead that the high-type has the same valuation for the national brand but has a higher valuation for the private label brand than the low-type, given by $V_P + \delta$ ($\delta > 0$). There are two broad cases and several distinct scenarios within each case:

1. $V_P + \delta - c_P > V_N - c_N$: in this case there is no incentive to ever sell the N brand. The retailer will either set $P_P = V_P$ in every period and sell P to both types, or may alternate between periods of selling P to the high-type only (with $P_P = V_P + \delta$) and to both types (with $P_P = V_P$).
2. $V_N - c_N > V_P + \delta - c_P$: in this case the retailer will either (a)sell brand P to both types in every period ($P_P = V_P$), (b)sell N to high-types and P to low-types every period ($P_N = V_N - \delta$, $P_P = V_P$), (c)only sell N to high-types every period ($P_N = V_N$,$P_P > V_P + \delta$), and (d)alternate over time between scenario (c) and periods of either (a) or (b).

There are thus three distinct scenarios that involve periodic sales. The first involves only sales of the P brand. The other two involve alternating between periods of high per-unit consumer surplus on the N brand and periods in which the retailer gives up some of the surplus on the N brand by selling the P brand to the low-type, which forces the retailer to either give up some surplus on the N brand (equal to δ) or have the high-type consumers switch over to the lower margin P good as well. Assuming that

[18]For simplicity we assume that consumers prefer the higher valuation brand when their consumer surplus is equal, but the retailer could just lower the price by one cent.

the retailer cannot withhold the P brand, this means that either the P brand goes on sale periodically and all consumers switch over, or both the P and N brands go on sale simultaneously.[19]

Figure 3.9 graphs the prices over time that maximize retailer profits for several parameterizations of the model listed in Table 3.20. Retailers may opt to sell only the N or P brands, sell both every period, or offer periodic sales on the P brand or on both brands simultaneously. There is no scenario with sales on N brands only as long as the marginal cost of the N brands exceed that of the P brand. The main insight from this model, which we extend more formally in the next subsection, is that since sales are driven by the tradeoff between surplus extraction and the extra volume generated by pent-up demand, the sales frequency of the lower valuation brands to which the low-valuation consumer is indifferent is always equal to or greater than the sales frequency of the national brand. A secondary insight is that the retailer often has an incentive to synchronize sales of the two brands if the margins on the N brands are high enough.

Finally, pass-through of marginal cost shocks can take different forms in this model. Cost shocks only have an effect in this model if they change the relative per-unit profits of the two brands. As in Chevalier and Kashyap (2011)), small cost shocks in this model only affect the frequency or existence of sales and never change the regular or sales prices for the two brands, which depend only on the valuation parameters (V_N, V_P, δ). If we are in a scenario in which N is sold in normal periods and P (and possibly N) are sold on sale periodically, an increase in relative costs for the N brand would leads to higher sale frequency. Large cost shocks in this model could also lead to a switch between a regime with periodic sales and one without. Consistent with our empirical findings, the sales price (which when averaged over time depends on the frequency of sales) is what responds to cost shocks rather than the non-sales price.[20]

We can easily extend the model to more consumer and brand types allowing for a more flexible pattern of sales. Suppose we still have the two previous types of consumers - a high-type with valuations V_N and $V_P + \delta$ for brands N and P respectively, and a low-type with valuations V_P for both. We restrict attention to equilibria in which both brands are sold, $\delta > 0$ and $V_N - c_N > V_P - c_P$. The effect of introducing a third con-

[19] In the case where only the P brand goes on sale, the retailer is always indifferent between charging $P_N = V_N - \delta$ and selling N to the high-type, or not putting the N brand on sale and allowing the high-type to switch over to the P brand.

[20] This is at odds with the finding by Eichenbaum et al. (2011) that changes in reference (regular) costs are fully passed-through into reference (regular) prices and retail markups are fairly stable, though any model with incomplete pass-through would have this feature. One way to rationalize this finding would be allowing cost shocks to be correlated with consumer willingness to pay, perhaps because the cost shocks are correlated with generalized inflation or cost shocks for other consumer goods that increase the nominal valuation for the brand in question. In some cases, we could observe full pass-through of costs to prices with no change in sales frequency.

sumer depends on their valuations (V_N^3 and V_P^3) but there are several general properties.

Proposition 4: The highest valuation consumer makes a purchase in every period as the retailer always sells to them.

Proof: The retailer can always sell one of the brands to the consumer with the highest margin by charging them their valuation, and this consumer will always make a purchase if the price is set below their valuation. The only reason a retailer does not sell to a consumer is to charge a higher price to a consumer with a higher valuation to achieve a higher margin. Since this cannot occur for the consumer with the highest valuation, it follows that they will make a purchase in every period.

Proposition 5: Any scenario in which P is the only brand sold in regular periods requires that the third consumer have valuations for P and N that satisfy (1)$V_P^3 - c_P > V_N^3 - c_N$, (2)$V_P^3 > V_H$, and (3)$V_N - c_N > V_P + \delta - c_P$.

Proof: The first condition ensures that it is more profitable to sell the P brand than the N brand to the third consumer during regular periods, the second is required for the retailer to not sell N to the high-type during these regular periods, and the third is required for it to be profitable to sell N on sale to the high-type (ensuring that both brands are sold at some point). These three conditions are necessary but not sufficient to have an equilibrium with regular period purchasing of P and periodic purchasing of N.

Proposition 5: If the lowest valuation by any of the three consumer types is equal for the two brands and both N and P brands are sold in regular (non-sale) periods then the sales frequency for P brands is always greater than or equal to the sales frequency for N brands.

Proof: If both brands are sold in regular periods there are two possibilities. One is that the lowest valuation type is buying P in regular periods, implying that all types are purchasing in regular periods, leading to no reason for sales. If the lowest valuation type is not buying P in regular periods, then one of the other types is buying P in regular periods, implying that the only reason to have a sale is to get the lowest valuation type to make a purchase; there is never any reason to sell N rather than P to the lowest valuation type (because the margin is always lower due to higher marginal cost). Note that this applies whether the low-type (with V_P for both brands) or the third-type (with V_N^3 and V_P^3) is the lowest valuation type.

Note that the last two propositions indicate that for a large range of parameters we are more likely to observe purchases of the N good during regular periods and purchases of the P good while on sale. If lower valuation consumer types tend to be more indifferent between the two brands, the lower marginal cost of the P brand leads the retailer to prefer selling them the P brand. Sales in this model are aimed at the lowest valuation consumers, which suggests that they may also be concentrated among the lowest valuation P brands. The impact of consumer heterogeneity on sales frequency can be non-monotonic in this model - periodic sales on the P good aimed at low valuation types may be increasing in the share of low valuation types up to a point, but eventually the periodicity of sales falls to one and an "every day low price" strategy dominates.[21]

In general this type of model tends towards synchronization of sales of the two brands as selling to lower valuation consumers typically requires giving higher valuation consumers some surplus, and it often makes sense to do this for the N brand. However the three consumer model can generate staggered sales of the N and P brands. With only two asymmetric brands N and P, the model is silent regarding synchronization within symmetric brands - the analysis in Chevalier and Kashyap (2011) suggests that there is no incentive to synchronize sales on symmetric brands when the low valuation consumers are indifferent because the retailer only needs to lower the price of one brand to attract them and can keep the price of the other brand high. However, if some lower valuation consumers have brand preferences within the symmetric N or P sets, there could be a motive for synchronization of price changes by the retailer within the N and P brands.

3.4.3 Discussion of Results

We begin by summarizing our empirical findings and comparing them with the predictions of our models and the theoretical and empirical work by Neiman (2010) and Neiman (2011) that is closest to ours. Table 3.21 presents the results of this comparison.

The first row highlights our somewhat surprising finding that the "regular" or retail list price change frequency is similar across both types of goods. This is at odds

[21] It is possible to have purchases of the P brand only during regular periods and/or to have sales periods during which only the N brand has its price lowered. It is also possible to observe sales of multiple-depth for a given brand (e.g. some periods a small discount, other periods a large discount). Thus while the model does suggest that frequent sales might be a more common feature of P brands, once we move beyond the two consumer case there is no automatic result that sales frequency is greater for the P brands.

with previous findings from the trade literature and the predictions of our supply model, which predicts higher price change frequency for the private label goods when the demand elasticities are similar. While it is theoretically possible that the retail markup elasticity with respect to wholesale prices is higher for private label brands (generating lower pass-through), due either to lower retail prices for private label goods or differences in product characteristics, empirically we find that it is lower - pass-through from wholesale to retail appears to be higher for private label goods. Under these conditions the supply model always predicts greater price change frequency for private label goods, which we do not observe for the regular price changes. The demand model can potentially match our finding since regular price changes only occur when consumer valuations change at different frequencies for the two goods or when cost shocks are large enough to cause a transition between sales and no-sales equilibria; these forces may well be absent from our data.

The second row points out that we do observe higher sales price change frequency for private label goods. Since this is the allocative price, we could interpret this finding as consistent with Neiman (2010) and Neiman (2011) and the supply model. However, we stress that these frequently recurring sales are not a feature of models that link frequency to cost shifters and pass-through - they usually occur in the absence of observed shocks to wholesale or raw material prices and they involve transitions between two particular price points.[22] Consistent with our demand model, we believe that these sales are more likely to reflect a price discrimination motive by the retailer for asymmetric goods. While different distributions of random demand shocks for the two types of brands could potentially explain the occurrence and frequency of sales, we find the type of systematic demand shock caused by consumer search and storable demand more compelling. Because the private label brands tend to be cheaper and consumed by more price-sensitive consumers, the retailer is more likely to use targeted sales to sell to these consumers while still extracting maximum surplus from the higher valuation consumers during non-sale periods.

Both models can potentially explain the higher pass-through of raw material cost shocks to retail prices (row 4). Given our findings on pass-through from wholesale to retail (row 5), the supply model predicts lower pass-through for national brands due to double-marginalization and markup adjustment. This effect would be further augmented if the raw material cost share was lower for national brands, which seems

[22] The reversion to pre-sale prices is thus unlikely to be explained by a model with shocks to the demand elasticity that might otherwise explain retail price changes uncorrelated with changes in costs. Papers that attempt to match this fact typically assume some type of dual menu cost that makes temporary price changes cheaper (Kehoe and Midrigan (2008)) or some costless technology for switching between two prices combined with a menu cost for changing those two prices (Eichenbaum et al. (2011)). As Chevalier and Kashyap (2011) point out, a key difference of price-discrimination models is that they lead to periodic sales with no change in either the supply or demand environment.

plausible. However, we stress that the pass-through we observe is generally higher for the sales price than the regular list price. If the frequency and depth of temporary sales is an important mechanism for retail pass-through, as appears to be the case, this is also suggests that the demand side mechanism of price discrimination is playing a role. While the demand model provides an important part of the mechanism for pass-through, it does not have unambiguous predictions for differential pass-through of private label and national brands.

In terms of synchronization, our results are the opposite of the empirical findings of Neiman (2010) and theoretical predictions of Neiman (2011). This may be due to the particular feature of our data set - multiple products are sold by the same retailer with power to set retail prices for all the brands. In Neiman (2011), lower synchronization for the vertically integrated goods occurs because pricing is more inward-looking and dependent on own idiosyncratic costs rather than the idiosyncratic costs of competitors. Since the retailer internalizes much of the competition between brands, this effect is less important. The demand model suggests instead that the retailer may choose to synchronize sales for these two types of brand due to their asymmetric characteristics and different targeted audiences. A model with more than two goods could potentially feature differential synchronization within the national brand and private label brand categories coming from the price discrimination motive as well.

Finally, we find that regular price changes are larger for private label brands but sales are deeper for national brands. Larger regular price changes for private label brands are generally consistent with the greater pass-through of raw material prices that we observe, but as we note above this may not be the case when the wholesale menu cost is sufficiently large for the national brand goods that many small price changes are effectively "censored" from the retailer's point of view. Conditional on observing a price change the average size of price changes may then be larger. The supply model does not have any predictions for sales depth as frequently alternating sale/non-sale periods are not a feature of the model. The demand model does not make unambiguous predictions about the size of regular price changes as these depend on size of changes in consumer valuation, but it can easily explain the greater sales depth of national brands.

In summary, our empirical findings are consistent with particular aspects of our two models but neither model can match all of our findings in isolation. Our most surprising finding is the greater pass-through of wholesale prices to retail prices for private label goods. This finding is inconsistent with both the differences in retail elasticities that would arise due to price differences (e.g. the negative super-super-elasticity of Kimball preferences) and the potentially greater share of non-material inputs in the cost of selling private label products due to the additional costs incurred by the retailer relative to national brands. It indicates an important role for demand heterogeneity across private label and national brands in generating different pricing behavior.

Before we conclude this section, we turn to a potentially important issue that was neglected thus far - the role of intermediaries and arm's length manufacturers in adding value to products through intangibles like insurance, quality assurance, distribution and advertising and promotion. When analyzing vertical structure, the industrial organization and trade literature typically assume that all of these activities are carried out by the manufacturer/intermediary/arm's length exporting party regardless of the vertical structure, so the goods transacted are identical in every respect. Differences in prices and pricing behavior are then attributed entirely to the effects of market power. However, in reality this may not always be the case. The lower price for an intra-firm transaction may reflect the displacement of some necessary firm activities from the downstream to the upstream division, with real economic costs imposed on the upstream division that do not show up in the unit price of the good. The greater pass-through for an intra-firm transaction may reflect the higher material cost share relative to an arm's length producer that adds significant intangible value to the product. This issue is particularly important in the context of private label and national brands, where the key distinction of private label brands is that the retailer takes over some or all of the intangible processes - particularly quality assurance, product development, packaging, and advertising - that are typically carried out by the manufacturers of national brands.[23]

Consider first the pass-through of common raw material prices to wholesale prices. If national brand manufacturers add significant value to the product through various intangible marketing inputs, this will effectively lower the raw material share of costs relative to the private label brand goods and lower the degree of raw material pass-through. This effect operates independently of market power - the prediction of the supply model analyzed above that an arm's length manufacturer may lower its markup in response to a cost shock. Thus in the case of pass-through from raw material to wholesale prices, the effect of marketing intangibles is to augment the variable markup mechanism. The lower pass-through of commodity prices into wholesale prices for sugar and coffee national brands in our data may be the result of either or both of these forces.

Next, consider pass-through of wholesale prices into retail prices. Here one expects

[23] We stress that the value added we have in mind here is distinct from the local non-traded costs that are frequently cited in the trade and international pricing literature as a reason for international price differentials or incomplete pass-through. All of our goods include a substantial amount of local non-traded costs (land, labor, capital, and energy used by the retailer) and distribution costs, but these factors are independent of the difference between private label and national brand goods and the role of vertical structure. On the other hand, the costs we have in mind are costs that must be paid ultimately but that may be transferred from the manufacturer to the retailer as a result of vertical integration.

the additional intangible marketing inputs that add value to play a bigger role for the private label brands - after all, the defining characteristic of private label brands is that these tasks, which are normally carried out by the manufacturer of national brands, are carried out by the retailer directly. If this is the case, we would expect the wedge between wholesale and retail prices to include both a markup component and a significant marketing intangibles cost component for private label brands, effectively lowering the wholesale price share for these goods. This would be expected to lower pass-through from wholesale prices to retail prices for private label brands relative to national brands. In our data, we observe the opposite - pass-through from idiosyncratic wholesale prices into retail prices is *higher* for private label brands. This suggests that these intangible costs may not play much of a role for private label brands, and further reinforces our conclusion above that product/demand heterogeneity plays an important role along the wholesale-retail pricing margin.

Overall, we find it plausible that the intangible marketing costs are greater for national brands than private label brands when we add together these costs along the entire supply chain. However, it is less obvious that the intangible cost *share* is greater for national brands, as many national brands may use greater quantity and quality of raw materials, and it is the share that matters for our pass-through regressions. Thus our result that pass-through from raw material to final retail prices is lower for national brands may be due to two supply side forces - both the double-marginalization effect and a lower material cost share - in addition to the role of product/demand heterogeneity. We are not aware of any studies that have explicitly quantified the relative importance of market power and markups versus intangible value added towards price transmission in the context of pricing across vertical structures, but hope to explore this issue in future research.[24]

3.4.4 Macroeconomic implications

Our findings suggest that there is a clear difference between pricing in different types of vertical structure. The strategic interaction of different price setting practices is important for macroeconomists. Haltiwanger and Waldman (1985) and Coibion and Gorodnichenko (2011) show that in a hybrid model with heterogeneous agents (e.g. heterogeneous in information processing abilities), strategic complementarities deter-

[24] Some researchers have attempted to quantify the role of "local non-traded costs" in this context by imposing more structure on the problem. The literature typically estimates demand elasticities which it uses to calculate implied markups, with residual price differences being attributed to these "local non-traded costs." See Goldberg and Hellerstein (2011) for an example in the beer industry. To the best of our knowledge this framework has not been applied to study vertical structure and the contribution of markups and other costs at different stages of the supply-chain.

mine real effects of monetary policy. We provide some evidence on strategic interaction between private label and national brands (i.e. the synchronization of sales), but we have only begun to explore this aspect and its potential implications for monetary policy. Even without strategic interaction, though, the large differences in pricing behavior we find for national and private label brands imply that there are potentially important implications for aggregate price rigidity and pass-through. The transmission of monetary, exchange rate, and real shocks within and across national borders depend critically on these aspects of pricing behavior as they determine the quantity of goods produced, traded, and consumed by households.

In the two models above, we discussed two main sources of heterogeneity in micro pricing behavior across private label and national brands. On the demand side, the price-sensitivity, willingness to substitute, and demand for quality by consumers, and heterogeneity in these attributes across consumers, can all directly affect the frequency of price adjustment and retail pass-through of cost shocks. These factors can affect price rigidity and pass-through regardless of vertical structure, but are also likely to affect the market share of cheaper private label goods and more expensive national brands. On the supply side, menu costs faced by firms and the presence of variable markups at various stages of the supply chain can buffer consumers from cost shocks, also affecting frequency and pass-through. These factis can affect price rigidity holding demand factors constant, and the market share of private label brands may evolve independent of demand factors if technological or managerial advances incentivize retailers to introduce new or promote established private label products. In our analysis we simply took vertical structure as given, but the market share of private label goods varies across categories and is likely to respond to both supply and demand factors. A natural question, then, is how the market share of private label goods varies across categories, across countries and over time, and what this could imply for aggregate pricing behavior.

In terms of heterogeneity across product categories, we find suggestive evidence that product categories with higher demand elasticities feature a larger revenue share of vertically-integrated private label brands. This is consistent with a model in which retailers face some (potentially fixed) cost to introducing and selling private label goods that must be balanced by profit gains. These profit gains will be larger in categories in which private labels can achieve significant volume conditional on entry. These categories tend to be the cases in which consumers are more price-sensitive and indifferent between the national brands and the (perceived to lower quality) private label brands. To take a concrete example from our data, sugar products in our data have the highest demand elasticity and the highest private label revenue share (over 40%) of all of our categories (see table 3.4). Private labels also do well in other relatively homogeneous categories like cooking oil. The high demand elasticity for sugar may generate higher sales frequency and pass-through for sugar products directly - many models imply a positive link between product differentiation and pricing power. Furthermore, high demand elasticity may also contribute to the large market share of private label goods, which will lead to greater sales frequency and pass-through, holding demand characteristics fixed (e.g. because pass-through from commodity to wholesale prices is greater). To the extent that consumer demand characteristics drive the heterogeneity in pass-through and price change frequency across product categories, the endogenous market share of private label goods will therefore augment and amplify this heterogeneity through the supply effects of vertical structure.

While cross-sectional heterogeneity matters for aggregate price rigidity and pass-through, an equally important issue is how the evolution of private label goods market share responds to broader macroeconomic forces. While we plan to explore the impact of these factors empirically and quantitatively in future work - the cyclicality of private label market share, the role of technological and managerial innovation, and differences across countries/jurisdictions in legal and regulatory environments that may limit private good market share - the time-series and cross-sectional dimension of our data does not allow us to do this. However we can briefly discuss some testable hypotheses about the macro 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. It is difficult to attribute the broad time-series and cross-country differences in the market share of private label goods to differences in consumer tastes, since income differences over time and across countries would tend to imply a smaller role for the lower quality, generic private label goods in the richer countries. 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. It 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 in higher cost pass-through and more frequent retail (and wholesale) price changes. There is a large trade literature documenting the decline in exchange pass-through for U.S. imports in the last few decades (Frankel et al. (2005)), a fact that is inconsistent with the rise in intra-firm transactions and the higher pass-through observed for intra-firm transactions (Neiman (2010)). We are not aware of any studies documenting the contribution of private label goods to the evolution of retail pass-through over the long-run or to cross-country differences.

Second, the short-run dynamics of private label market share may affect aggregate price rigidity and pass-through at business cycle frequencies. Here we emphasize the role of demand side factors, as the cheaper, lower quality nature of private label goods could contribute to a counter-cyclical market share. We conjecture that the rapid rise in private label market share during the Great Recession of 2008 is due in large part to demand side factors. When incomes decrease or unemployment increases (raising search costs), the share of price-sensitive, bargain-hunting consumers increases which may naturally lead to a rising market share of the private label goods. Coibion et al. (2011) have found evidence for cyclical behavior of sales prices in that sales are more active during bad state of the economy in terms of frequency, depth and share of goods on sales. Our findings suggest that private label goods may benefit from this active use of sales. Furthermore, Gicheva et al. (2010) show that negative shocks to disposable income lead to substitution towards cheaper brands and goods that are on sale. If consumer demand generates a counter-cyclical market share of private label goods, this will (a) make cost pass-through more counter-cyclical and (b) make aggregate price rigidity more counter-cyclical, relative to what would occur in the absence of this margin of adjustment. The endogenous, demand-driven market share of private label goods may therefore diminish the effectiveness of monetary (or exchange rate) policy designed to stimulate the economy during downturns. However, it will also increase the effectiveness of policy during business cycle peaks, and this asymmetry has potentially important consequences for the design and implementation of stabilization policy.

Third, the inflationary aspect of commodity price pass-through into retail prices has received a lot of 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 lack of any meaningful relationship between commodity price movements and core inflation since 1980s in the United States (for instance, Evans (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)). 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.[25] An obvious explanation for the greater inflationary pressure from commodity prices in developing countries is that the share of household expenditures 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,

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

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. Our findings also suggest that commodity price pass-through may be more counter-cyclical than otherwise due to the private label margin. 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 my incentivize firms to implement more frequent and deeper sales.[26] Given our finding that sales prices, not list prices, are more responsive to raw material prices, we conclude that inflationary pressure arising from raw material price hikes cannot be neglected.

3.5 Conclusion

We have documented significant differences in pricing behavior between private label and national brands across many different product categories. We find that private label brands change prices more frequently, exhibit greater cost pass-through, and have more synchronized price changes than national brands. The first two findings are broadly consistent with the existing empirical literature exploring the implications of vertical structure for pricing dynamics (Bernard et al. (2006), Hellerstein and Villas-Boas (2010), Neiman (2010)) but our data allow us to shed additional light on the mechanisms at play. For example, we show that the greater frequency of price change for private label goods mainly takes the form of the frequency of temporary sales discounts rather than changes in the regular (reset) prices, and that the greater cost pass-through occurs at both the commodity price to wholesale price and the wholesale price to retail price margins. Our third finding on price synchronization is the opposite of Neiman (2010) - we find that prices are more synchronized for the vertically integrated goods than the arm's length goods, a finding that we attribute to different environment facing a multi-product retailer that largely internalizes the strategic complementarities in price-setting.

We then use simple adaptations of the variable markup menu cost model in Gopinath and Itskhoki (2011) and the heterogeneous consumer inter-temporal price discrimination model in Chevalier and Kashyap (2011) to emphasize the distinct roles of supply and demand heterogeneity in generating the pricing differences we observe and highlight areas where our findings confirm or contradict model predictions. We argue that the supply model can explain many of our facts but fails to explain the differential use of frequent, temporary sales across vertical structures and also fails to explain the

[26]see Coibion et al. (2011).

greater pass-through from wholesale prices to retail prices observed in our data set. The demand model can address these facts but does not capture the important role for wholesale prices that we observe in the data - wholesale prices appear to absorb some of the raw material cost shocks for the national brands, consistent with the supply model, and may also contribute to the lower frequency of price changes for the national brands. We conclude that in the retail sector at least, one cannot examine vertical structure in isolation from heterogeneity in product and consumer characteristics. Our findings imply that studies using other sources of data - e.g. BLS import data - need to take care when attributing differences in price behavior to vertical structure alone. Just as Nakamura and Steinsson (2008) raise the question "Is price change just a price change?" we must in turn ask "Is a good just a good?" The impact of vertical structure on pricing behavior is of greatest interest when there are issues of market power, but these are precisely greatest where products are differentiated, raising the issue of whether the physical or intangible aspects of the good are truly identical when comparing intra-firm and arm's length transactions. Our retail data set is unique in providing allocative prices at multiple steps of the supply chain (retail and wholesale) and allowing us to easily identify transactions where the manufacturer has more or less market power (national brands versus private label brands), but it also emphasizes the fact that vertical structure is not random, exogenous, or orthogonal to product characteristics. Our findings have numerous implications for macroeconomic adjustment, given that long-run technological/regulatory changes and business-cycle frequency demand effects will influence private label market shares which in turn affect the aggregate behavior of prices. In future work we hope to more fully explore the causes and consequences of differences in private label market share, quantifying the contribution of retail vertical structure to aggregate price rigidity and transmission of monetary, exchange rate and commodity price shocks. In particular we plan to model the interaction of the supply and demand forces in a general equilibrium model with endogenous market shares of vertically integrated firms. Another issue we hope to explore is the relative role of markup adjustment versus intangible costs/value added in generating incomplete pass-through when there are differences in vertical structure and intermediation along the supply-chain. Finally, we abstract from the role of bargaining and long-term contracts in price-setting but believe that these factors may play an important role in generating pricing differences across vertical structures and in incentivizing retailers to adopt private label goods.

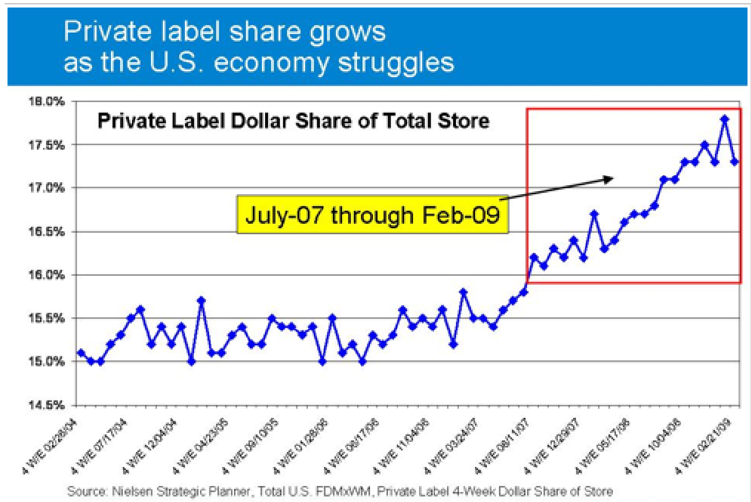


Figure 3.1: Share of private label goods over the years

Source: AC Nielsen Strategic Planner

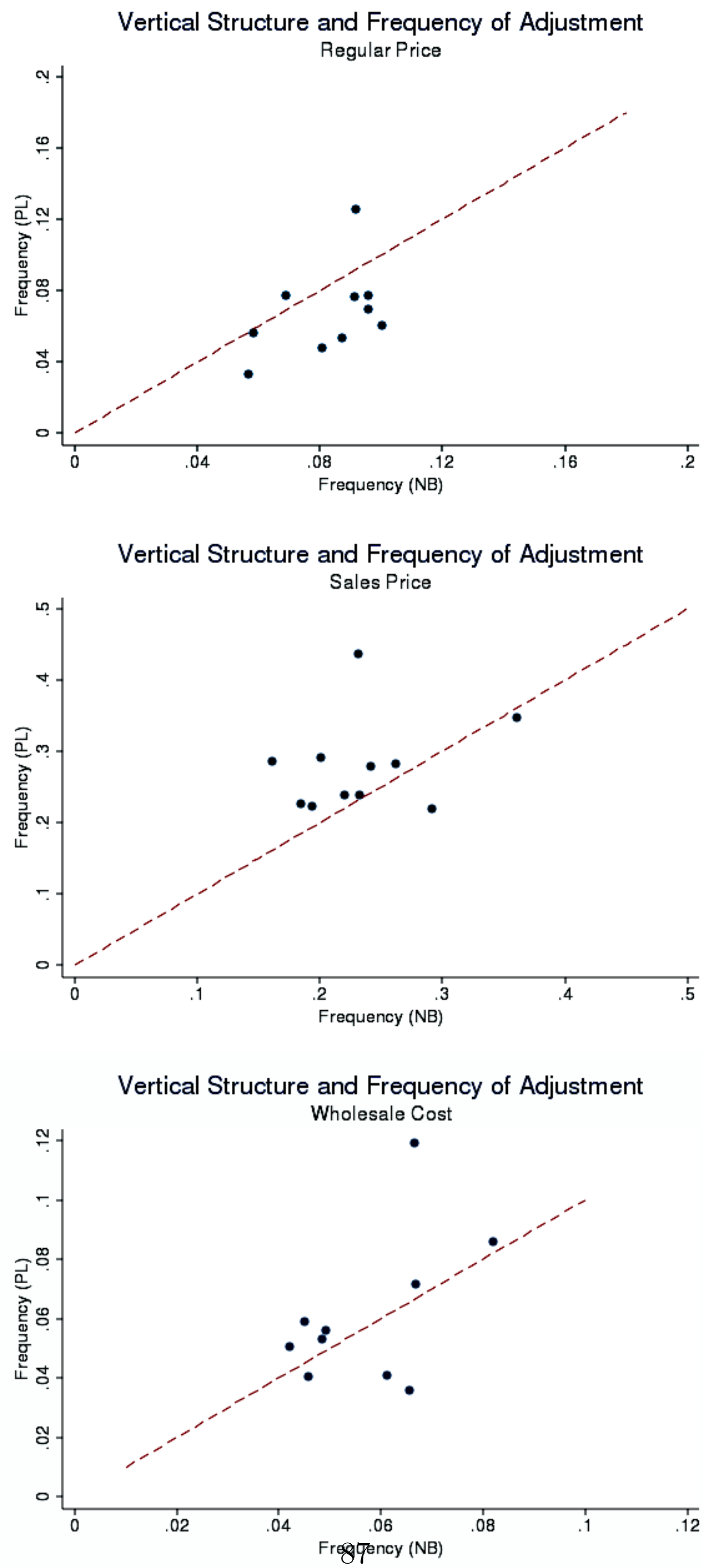


Figure 3.2: Scatter Plots: Private Labels and National Brands

Note: These figures show the scatter plots of the category-level mean frequencies of regular, sales and wholesale prices for each vertical structure (see tables 3.6, 3.7 and 3.8). $Freq_{cat,type} = \frac{1}{N_{type}} \sum (Freq_{i,type}) \cdot$

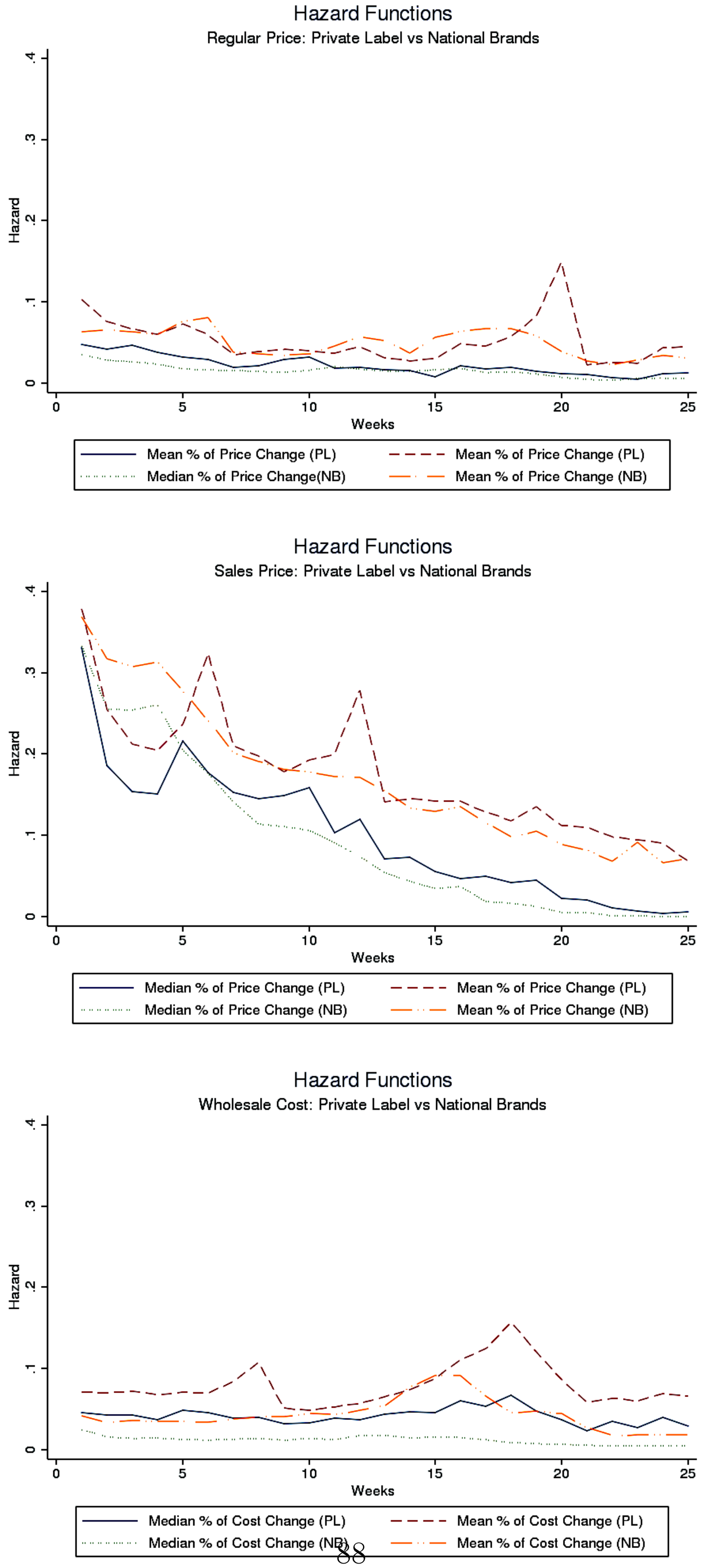


Figure 3.3: Hazard Functions and Vertical Structure

Note: The above figures represent the hazard functions for different vertical structures. The shape of hazard functions for regular prices and wholesale prices is similar: no evidence for decreasing or increasing

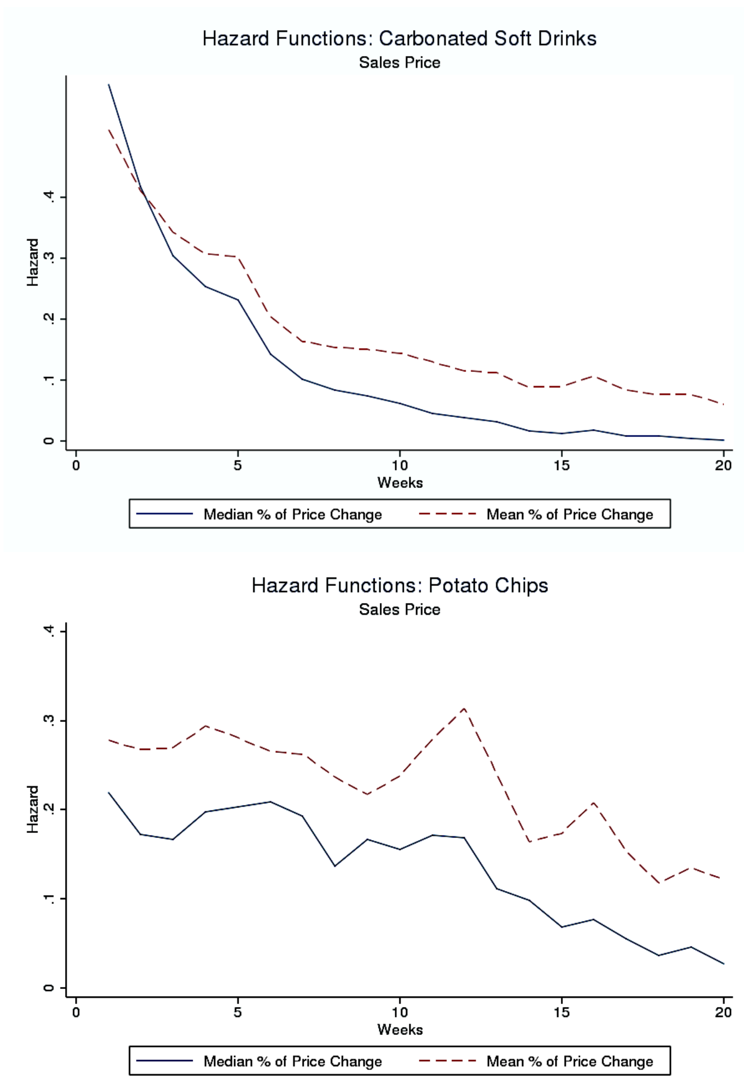


Figure 3.4: Hazard Functions Examples

Note: The above figures represent the hazard functions of sales prices for selected categories.

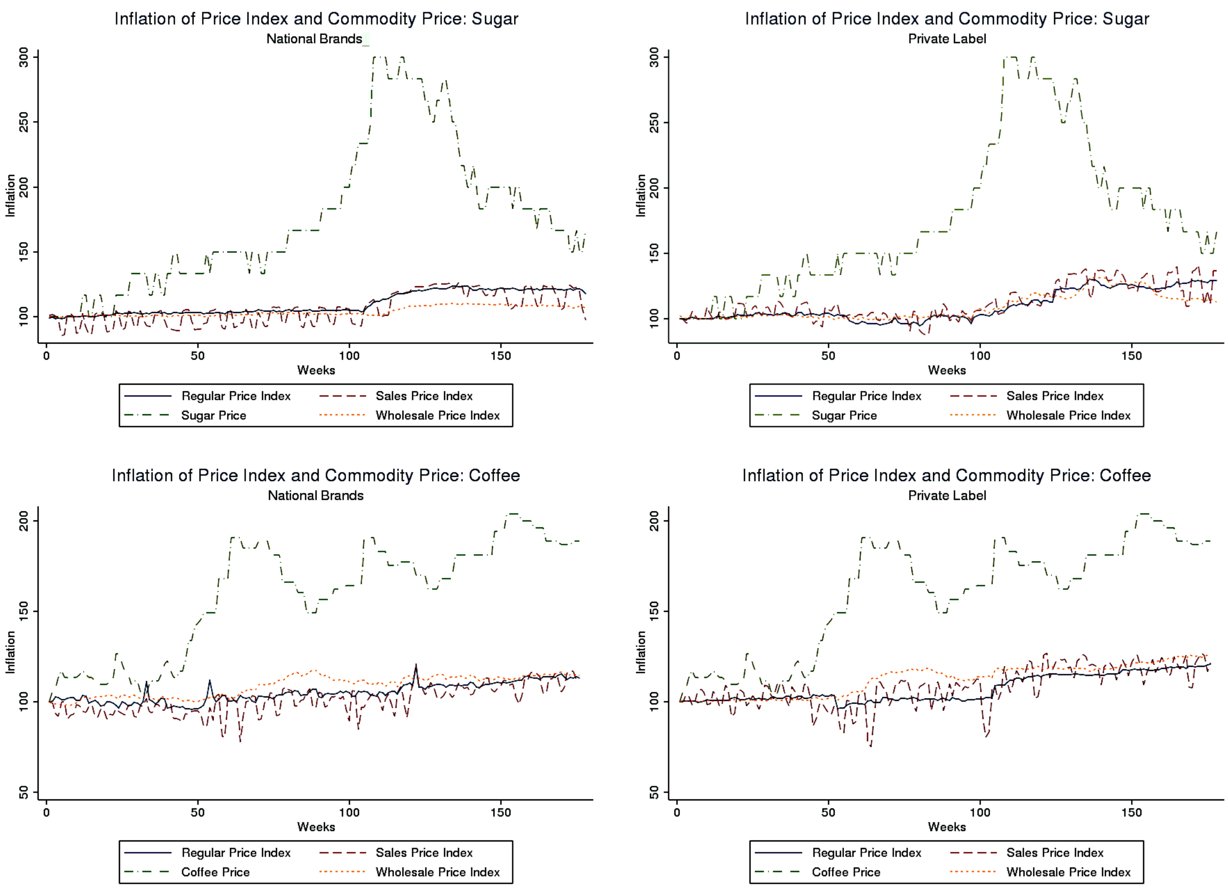


Figure 3.5: Inflation of Price Indices and Commodity Prices

Note: The raw material prices are collected from Food and Agricultural Organization of the United Nations (www.fao.org/es/esc/prices/). Weekly price indices are constructed as weighting weekly price (upc-store combination) by expenditure share of the weekly revenue of the good in comparison to the total weekly revenue of the category. The first observations of price indices and raw material prices, or base week, are normalized to 100.

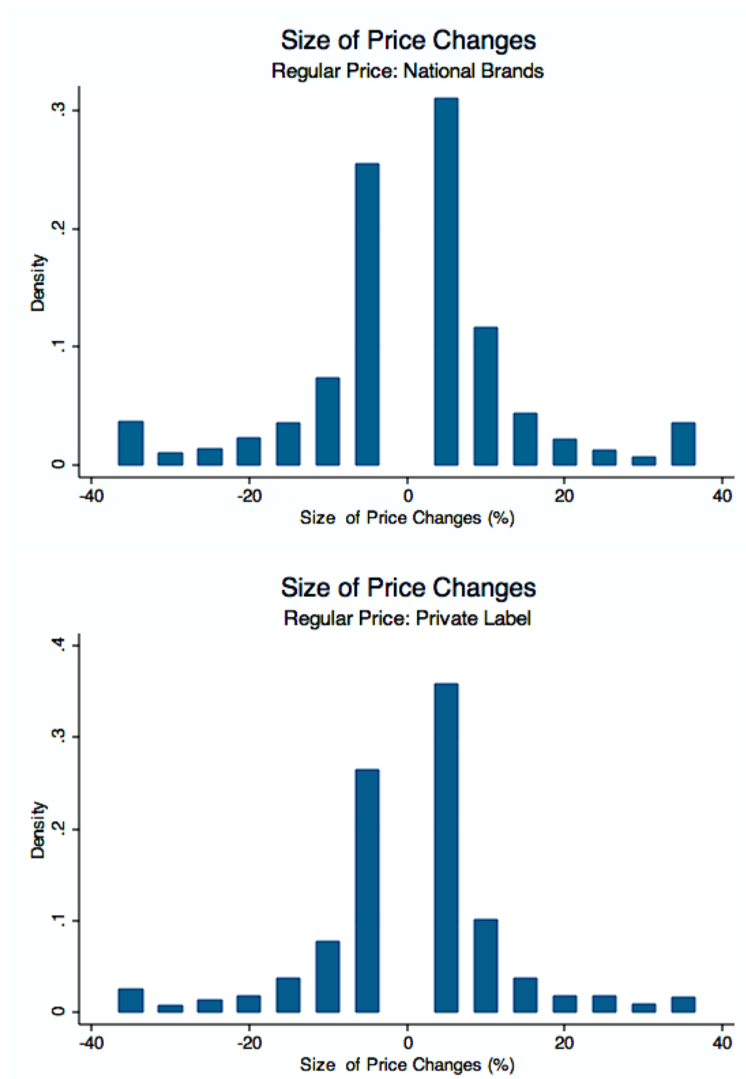
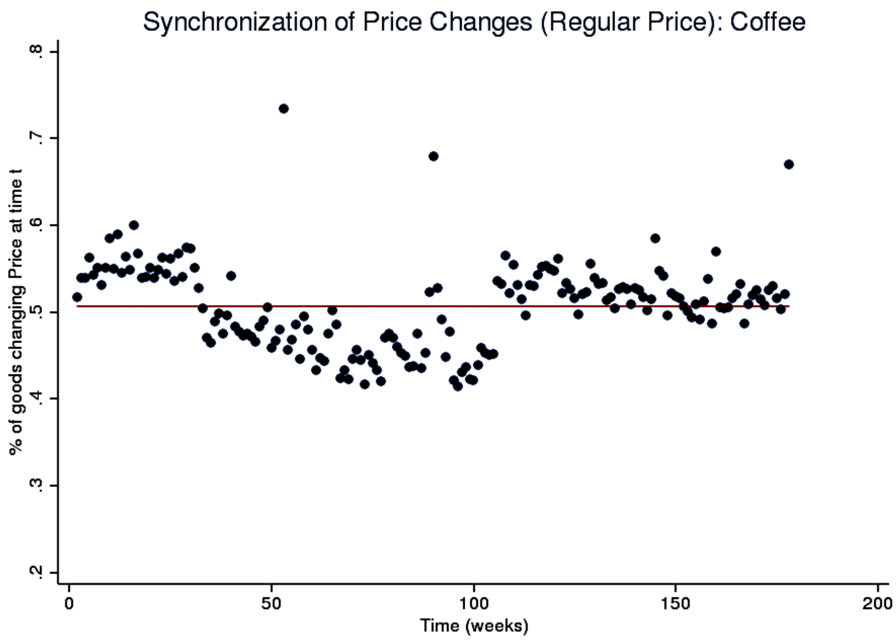


Figure 3.6: Distribution of Regular Price Changes

Note: Non-zero size of price changes is in %. Regular price changes are weighted by the expenditure share $\omega_{i,t-1}$. Price changes less than 5% comprise of about 60% of non-zero price changes.



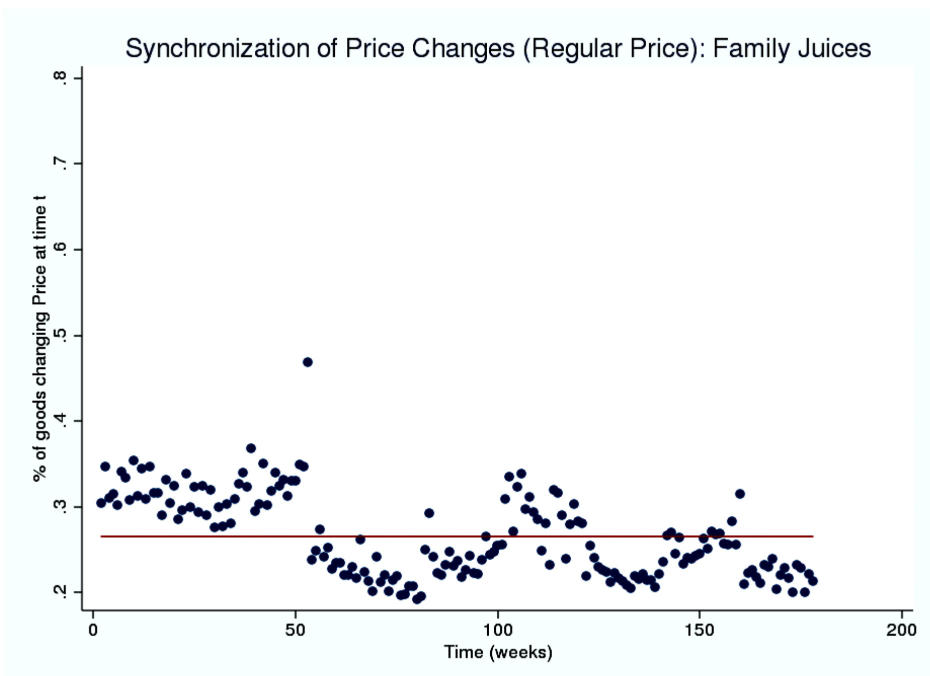
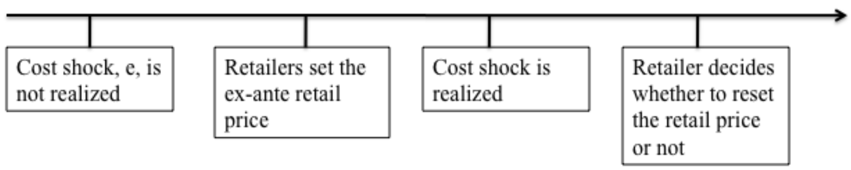
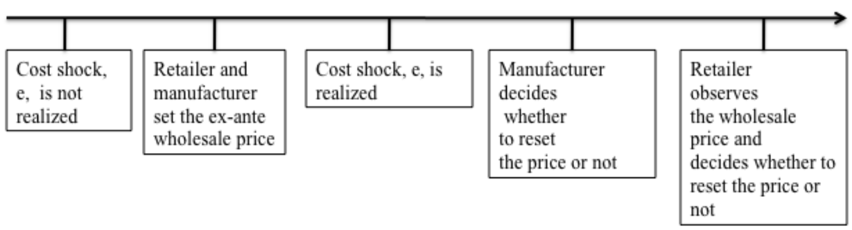


Figure 3.7: Changes in Proportion of Goods with Regular Price Changes Over Time

Note: Coffee category shows highest regular price FK with mean 0.36. All family juices category shows the lowest regular price FK with mean 0.11. The red lines in each graph represents $\overline{q_c}$, the sample mean of $q_{c,t}$ over time.



Timing of the price setting: Intra-firm Case



Timing of the price setting: Arm's Length Case

Figure 3.8: Price Setting Timeline

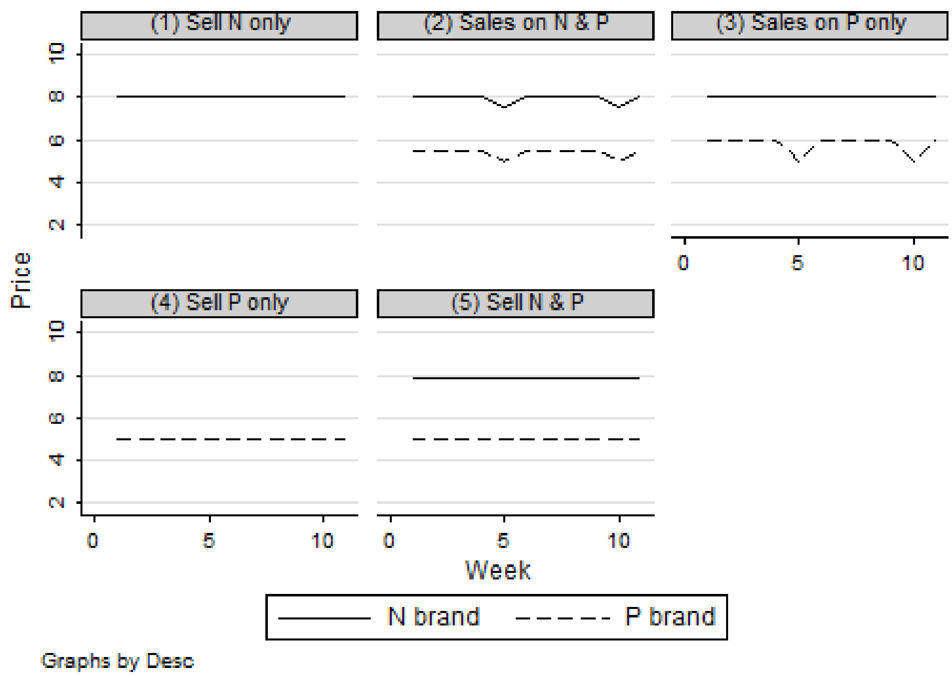


Figure 3.9: Simulation of Private Label (P) and National Brand (N) price paths from asymmetric sales model

Table 3.1: Treatment of Missing Values

	•	•	•	X	X	•	•	•
Time	1	2	3	4	5	6	7	8
Price	2	1	1			1	1.5	1.4
SpellA	1	2	2			3	4	5
SpellB	1	2	2			2	3	4
SpellC	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. SpellA takes the data set as it is, taking the observation after the missing value (t=6) as a beginning of a new spell. SpellB 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. SpellC is similar to SpellB, but differs in that SpellC takes the missing values as part of the spell. Naturally, prices seem to be stickier using SpellC than SpellB, and using SpellA results in the shortest measured price duration.

Table 3.2: Frequency of price changes (weeks)

Spell Type	Regular price		Sales price	
	Mean	SD	Mean	SD
A	0.3	0.25	0.49	0.25
B	0.13	0.17	0.34	0.25
C	0.08	0.12	0.24	0.21

Note: The frequency of each variable is the inverse of duration. For instance, the regular price frequency under SpellA is 0.3. Every week, a price change occurs with 30% probability.

Table 3.3: Frequency of price changes (weeks): Sales Filters

Sales Filter	Mean	SD
no sales filter	0.24	0.21
sales greater than 5 %	0.16	0.37
sales greater than 10%	0.14	0.35
sales greater than 20%	0.09	0.29

Note: We adopt 3 different sales filters based on the size of sales price changes. Sales price is compared to the previous sales price. If the absolute price change is greater than thresholds, 5%, 10% and 20%, we consider those observations as "sales."

Table 3.4: Product categories and private labels (PL)

Product Category	UPCs	PL UPCs	Rev. share of PL UPCs	Median σ
Carbonated Soft Drinks	1692	184	10.70%	5.7
Potato Chips	321	20	2.30%	4
Cold Cereal	836	187	9.00%	4.7
Cooking Oil	194	38	31.50%	4.7
Sugar (and substitutes)	96	12	40.40%	6.5
Coffee	1632	186	17.10%	5.9
All Family Juices	521	98	20.50%	5.3
Pasta Packaged (Dry)	1120	136	20.90%	3.7
Bathroom Tissues	197	33	23.00%	5.1
Laundry Detergent	388	44	6.20%	5.3

Note: The statistics recorded are across all U.S. stores in our sample for all 178 weeks. σ refers to the median CES demand elasticity across brands in a category calculated at the store-category level using the estimator from Feenstra (1994) (see **??**). We report the median σ across all stores in our sample.

Table 3.5: Price distribution of Frequency of Adjustment - Regular Price, Sales Price and Wholesale price

	Regular Price		Sales Price		Wholesale price	
	PL	NB	PL	NB	PL	NB
10%	0.05	0.06	0.22	0.19	0.016	0.011
25%	0.05	0.07	0.23	0.19	0.028	0.016
Mean	0.07	0.08	0.28	0.23	0.069	0.055
Median	0.08	0.09	0.28	0.23	0.049	0.027
75%	0.08	0.09	0.29	0.26	0.081	0.054
90%	0.08	0.1	0.35	0.29	0.134	0.099
SD	0.02	0.02	0.06	0.06	0.079	0.105

Note: We measure frequency as the unconditional probability that a good changes its price in a given week. We calculate the mean frequency across stores first, and then report different statistics from the distribution across goods. We use the "spellC" treatment (described in section 2) at the store-level to deal with missing observations.

Table 3.6: Frequency of Price Adjustment and Vertical Structure - Regular Price (Weeks)

Category	Type	25%	Median	75%	Mean	t-statistics
Carbonated Soft Drinks	PL	0.028	0.045	0.077	0.077	1.73
	NB	0.029	0.05	0.11	0.096	(0.003)
Potato Chips	PL	0.037	0.086	0.186	0.125	0.87
	NB	0.016	0.033	0.086	0.092	(0.0094)
Cold Cereal	PL	0.026	0.038	0.071	0.077	1.31
	NB	0.031	0.049	0.092	0.091	(0.004)
Cooking Oils	PL	0.023	0.04	0.067	0.061	1.87
	NB	0.039	0.067	0.11	0.1	(0.0086)
Sugar	PL	0.026	0.03	0.039	0.033	1.42
	NB	0.029	0.033	0.059	0.056	(0.005)
Coffee	PL	0.042	0.071	0.099	0.077	0.986
	NB	0.019	0.031	0.072	0.069	(0.0026)
Family Juices	PL	0.021	0.027	0.052	0.048	3.16***
	NB	0.028	0.051	0.099	0.081	(0.004)
Dry Pasta	PL	0.022	0.041	0.073	0.051	3.66***
	NB	0.031	0.056	0.099	0.087	(0.003)
Detergent	PL	0.022	0.041	0.061	0.07	1.02
	NB	0.031	0.059	0.096	0.096	(0.009)
Bathroom Tissues	PL	0.022	0.031	0.058	0.056	0.22
	NB	0.016	0.04	0.076	0.058	(0.0032)
All	PL	0.026	0.043	0.076	0.069	2.98***
	NB	0.025	0.045	0.089	0.081	(0.001)

Note: The values are calculated using spellC. t-statistics reported are for testing $H_0 : \overline{\mu_{NB}} = \overline{\mu_{PL}}$, where $\overline{\mu_{NB}}$ is the average frequency of national brands, and $\overline{\mu_{PL}}$ is the average frequency of private labels. Standard errors are recorded in parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.7: Frequency of Price Adjustment and Vertical Structure - Sales Prices (Weeks)

Category	Type	25%	Median	75%	Mean	t-statistics
Carbonated Soft Drinks	PL	0.124	0.187	0.319	0.219	3.51***
	NB	0.051	0.213	0.481	0.291	(0.006)
Potato Chips	PL	0.281	0.355	0.405	0.348	0.1702
	NB	0.071	0.257	0.659	0.361	(0.0174)
Cold Cereal	PL	0.169	0.236	0.338	0.279	2.36***
	NB	0.099	0.178	0.325	0.241	(0.007)
Cooking Oils	PL	0.071	0.163	0.344	0.226	1.25
	NB	0.065	0.117	0.25	0.184	(0.013)
Sugar	PL	0.03	0.285	0.419	0.287	2.27**
	NB	0.038	0.109	0.196	0.161	(0.0184)
Coffee	PL	0.146	0.237	0.284	0.226	1.8983
	NB	0.046	0.141	0.28	0.194	(0.0047)
Family Juices	PL	0.128	0.198	0.325	0.24	1.02
	NB	0.086	0.177	0.314	0.22	(0.0074)
Dry Pasta	PL	0.201	0.413	0.692	0.437	10.68***
	NB	0.064	0.161	0.368	0.231	(0.0066)
Detergent	PL	0.138	0.278	0.404	0.283	0.534
	NB	0.1	0.21	0.365	0.261	(0.0147)
Bathroom Tissues	PL	0.093	0.179	0.413	0.239	0.21
	NB	0.086	0.196	0.345	0.233	(0.01)
All	PL	0.143	0.236	0.361	0.275	5.56***
	NB	0.059	0.162	0.351	0.233	(0.0023)

Note: The values are calculated using spellC. t-statistics reported are for testing $H_0 : \overline{\mu_{NB}} = \overline{\mu_{PL}}$, where $\overline{\mu_{NB}}$ is the average frequency of national brands, and $\overline{\mu_{PL}}$ is the average frequency of private labels. Standard errors are recorded in parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.8: Frequency of Price Adjustment and Vertical Structure -Wholesale price (Weeks)

Category	Type	25%	Median	75%	Mean	t-statistics
Carbonated Soft Drinks	PL	0.047	0.093	0.145	0.119	5.09***
	NB	0.016	0.026	0.056	0.067	(0.003)
Potato Chips	PL	0.015	0.021	0.075	0.041	0.6475
	NB	0.0189	0.028	0.043	0.061	(0.008)
Cold Cereal	PL	0.029	0.0466	0.0733	0.0717	0.4672
	NB	0.019	0.0326	0.059	0.066	(0.005)
Cooking Oils	PL	0.0499	0.064	0.104	0.085	0.22
	NB	0.029	0.058	0.095	0.082	(0.007)
Sugar	PL	0.053	0.058	0.068	0.058	0.94
	NB	0.017	0.025	0.046	0.045	(0.005)
Coffee	PL	0.028	0.049	0.081	0.052	3.87***
	NB	0.016	0.027	0.054	0.042	(0.001)
Family Juices	PL	0.029	0.039	0.062	0.053	0.53
	NB	0.017	0.024	0.051	0.048	(0.004)
Dry Pasta	PL	0.028	0.049	0.081	0.056	3.88***
	NB	0.016	0.027	0.054	0.049	(0.001)
Detergent	PL	0.014	0.018	0.036	0.036	1.71*
	NB	0.022	0.033	0.067	0.065	(0.006)
Bathroom Tissues	PL	0.013	0.024	0.034	0.04	0.56
	NB	0.014	0.026	0.051	0.046	(0.003)
All	PL	0.028	0.049	0.081	0.069	3.86***
	NB	0.016	0.027	0.054	0.055	(0.0011)

Note: The values are calculated using spellC. t-statistics reported are for testing $H_0 : \overline{\mu_{NB}} = \overline{\mu_{PL}}$, where $\overline{\mu_{NB}}$ is the average frequency of national brands, and $\overline{\mu_{PL}}$ is the average frequency of private labels. Standard errors are recorded in parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.9: Price variation and Vertical Structure

	V-S	Category	R^2	Adjusted R^2
Regular Price	Yes	No	0.001	0.0009
	No	Yes	0.01	0.0073
	Yes	Yes	0.0137	0.0096
Sales Price	Yes	No	0.0036	0.0035
	No	Yes	0.0375	0.0347
	Yes	Yes	0.0545	0.0506
Wholesale Price	Yes	No	0.0018	0.0016
	No	Yes	0.0128	0.0101
	Yes	Yes	0.0181	0.014

Note: The table reports the R^2 and adjusted R^2 regressing frequency of price adjustment with vertical structure and category fixed-effects. In the second column, V-S stands for "vertical structure."

Table 3.10: Pooled Regression : Private Label vs. National Brands

Regular Price				
	Logs	Levels	Logs	Levels
PL	-0.02**	-0.021	0.03***	-0.002
	(0.0059)	(0.016)	(0.034)	(0.0158)
Category FE	N	N	Y	Y
N	7461	7461	7461	7461
Sales Price				
	Logs	Levels	Logs	Levels
PL	-0.3*	-2.06***	-0.35***	-3.46***
	(0.26)	(0.93)	(0.083)	(0.502)
Category FE	N	N	Y	Y
N	7443	7443	7443	7443

Note: The table reports the results from pooled regressions of private label goods durations over those of national brands. Standard errors are recorded in parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level. The results suggest that for regular price, the national brands show 5% (in logs) longer price duration than private label goods. on average, national brand sales price spells are about 30% longer (logs), and about 3 to 4 weeks longer than private label goods.

Table 3.11: Pass-through rates and Vertical Structures: Regular Price and Commodity Prices

		Inst.			LRPT1			LRPT2		
Product Category	Raw Material	NB	PL	t-stat	NB	PL	t-stat	NB	PL	t-stat
Coffee	Coffee	0.06	0.11	4.07***	0.03	0.08	3.28***	0.08	0.28	4.53***
		(0.04)	(0.06)	(0.04)	(0.07)	(0.11)	(0.03)	(0.04)	(0.06)	(0.01)
Sugar	Sugar	0.027	0.139	3.17***	0.066	0.077	3.24***	0.09	0.12	3.24***
		(0.02)	(0.02)	(0.07)	(0.02)	(0.04)	(0.04)	(0.04)	(0.06)	(0.02)
Cereal	Wheat	0.035	0.096	3.28***	0.005	0.003	1.79*	0.01	0.034	4.39***
		(0.04)	(0.06)	(0.06)	(0.07)	(0.06)	(0.05)	(0.01)	(0.03)	(0.02)
Syrup	Sugar	0.004	0.005	0.078	0.006	0.011	2.12***	0.01	0.02	1.8*
		(0.02)	(0.02)	(0.06)	(0.08)	(0.13)	(0.06)	(0.03)	(0.04)	(0.03)
Salt	Salt	0.136	0.278	3.51***	0.042	0.027	5.39***	0.02	0.03	1.1*
		(0.06)	(0.02)	(0.06)	(0.08)	(0.13)	(0.01)	(0.07)	(0.11)	(0.06)
Rice	Rice	0.005	0.003	0.68	0.018	0.04	3.08***	0.04	0.05	1.08*
		(0.04)	(0.06)	(0.03)	(0.08)	(0.09)	(0.02)	(0.07)	(0.07)	(0.1))
Soft Drinks	Sugar	0.004	0.014	3.15***	0.015	0.029	4.06***	0.016	0.031	3.87***
		(0.03)	(0.04)	(0.04)	(0.14)	(0.18)	(0.03)	(0.03)	(0.04)	(0.11)

Note: The table reports category-level pass-through rates using different definitions of pass-through. The first block reports instantaneous pass-through rates, the second block reports long-run pass-through rates using lags up to 4 weeks (LRPT1) and the third block reports long-run pass-through rates using lags up to 8 weeks (LRPT2). Parametric mean-comparison test is used to compare the mean pass-through rates of each category. T-statistics are reported and pooled standard errors are reported in the parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.12: Pass-through rates and Vertical Structures: Sales Price and Commodity Prices

Product Category	Raw Material	Inst. NB	Inst. PL	Inst. t-stat	LRPT1 NB	LRPT1 PL	LRPT1 t-stat	LRPT2 NB	LRPT2 PL	LRPT2 t-stat
Coffee	Coffee	0.19	0.21	2.49***	0.22	0.42	4.18***	0.21	0.38	4.25***
		(0.03)	(0.04)	(0.03)	(0.04)	(0.07)	(0.03)	(0.03)	(0.04)	(0.02)
Sugar	Sugar	0.03	0.13	3.59***	0.25	0.48	4.17***	0.29	0.18	3.24***
		(0.05)	(0.06)	(0.14)	(0.04)	(0.07)	(0.04)	(0.05)	(0.06)	(0.07)
Cereal	Wheat	0.24	0.27	1.32	0.28	0.31	3.28***	0.4	0.22	2.34***
		(0.01)	(0.02)	(0.15)	(0.07)	(0.06)	(0.05)	(0.01)	(0.02)	(0.09)
Syrup	Sugar	0.24	0.38	5.24***	0.2	0.27	3.24***	0.42	0.33	2.12***
		(0.08)	(0.07)	(0.08)	(0.03)	(0.06)	(0.07)	(0.03)	(0.04)	(0.04)
Salt	Salt	0.08	0.11	1.97	0.19	0.24	2.17***	0.16	0.38	5.39***
		(0.06)	(0.07)	(0.09)	(0.03)	(0.06)	(0.15)	(0.08)	(0.07)	(0.05)
Rice	Rice	0.22	0.42	4.18***	0.16	0.29	2.68***	0.17	0.29	3.08***
		(0.01)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.06)	(0.07)	(0.09)
Soft Drinks	Sugar	0.28	0.31	1.35	0.21	0.31	3.15***	0.13	0.29	4.06***
		(0.05)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.03)	(0.01)

Note: The table reports category-level pass-through rates using different definitions of pass-through. The first block reports instantaneous pass-through rates, the second block reports long-run pass-through rates using lags up to 4 weeks (LRPT1), and the third block reports long-run pass-through rates using lags up to 8 weeks (LRPT2). Parametric mean-comparison test is used to compare the mean pass-through rates of each category. T-statistics are reported and pooled standard errors are reported in the parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.13: Pass-through rates and Vertical Structures: Regular Price and Wholesale price

Product Category	Inst.			LRPT1			LRPT2			Life-time		
	NB	PL	t-stat	NB	PL	t-stat	NB	PL	t-stat	NB	PL	t-stat
Carbonated Soft Drink	0.19	0.41	4.18***	0.26	0.4	4.25***	0.016	0.031	3.87***	0.017	0.021	1.35
	(0.04)	(0.07)	(0.03)	(0.07)	(0.11)	(0.03)	(0.03)	(0.04)	(0.11)	(0.03)	(0.04)	(0.01)
Potato Chips	0.31	0.45	3.17***	0.124	0.23	3.24***	0.02	0.03	1.1*	0.012	0.031	2.45***
	(0.04)	(0.07)	(0.04)	(0.02)	(0.04)	(0.04)	(0.07)	(0.11)	(0.06)	(0.08)	(0.09)	(0.03)
Cold Cereal	0.026	0.04	4.25***	0.06	0.109	1.79*	0.04	0.05	1.08*	0.1	0.04	4.28***
	(0.07)	(0.11)	(0.03)	(0.07)	(0.06)	(0.05)	(0.07)	(0.07)	(0.1)	(0.06)	(0.03)	(0.01)
Cooking Oils	0.066	0.077	3.24***	0.28	0.31	1.35	0.08	0.28	4.53***	0.01	0.04	1.38
	(0.02)	(0.04)	(0.04)	(0.05)	(0.06)	(0.02)	(0.04)	(0.06)	(0.01)	(0.04)	(0.08)	(0.05)
Sugar	0.005	0.003	1.79*	0.19	0.21	2.49***	0.09	0.12	3.24***	0.09	0.12	2.14***
	(0.07)	(0.06)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.06)	(0.02)	(0.14)	(0.18)	(0.02)
Coffee	0.006	0.011	2.12***	0.03	0.13	3.59***	0.01	0.034	4.39***	0.01	0.03	1.68**
	(0.08)	(0.13)	(0.06)	(0.05)	(0.06)	(0.14)	(0.01)	(0.03)	(0.02)	(0.04)	(0.05)	(0.08)
Family Juices	0.042	0.027	5.39***	0.24	0.27	1.32	0.11	0.15	2.49***	0.017	0.021	1.35
	(0.08)	(0.13)	(0.01)	(0.01)	(0.02)	(0.15)	(0.07)	(0.06)	(0.04)	(0.03)	(0.04)	(0.01)
Dry Pasta	0.018	0.04	3.08***	0.27	0.39	5.24***	0.02	0.03	2.18***	0.012	0.031	2.45***
	(0.08)	(0.09)	(0.02)	(0.08)	(0.07)	(0.08)	(0.07)	(0.06)	(0.02)	(0.08)	(0.09)	(0.03)
Detergent	0.015	0.029	4.06***	0.06	0.12	1.97	0.03	0.07	3.19***	0.09	0.1	1.2
	(0.14)	(0.18)	(0.03)	(0.06)	(0.07)	(0.09)	(0.04)	(0.17)	(0.08)	(0.09)	(0.1)	(0.34)
Bathroom Tissues	0.004	0.014	3.15***	0.22	0.42	4.18***	0.02	0.03	3.87***	0.05	0.08	1.25
	(0.03)	(0.04)	(0.04)	(0.01)	(0.03)	(0.06)	(0.03)	(0.04)	(0.11)	(0.04)	(0.05)	(0.08)

Note: The table reports category-level pass-through rates using different definitions of pass-through. The first block reports instantaneous pass-through rates, the second block reports long-run pass-through rates using lags up to 4 weeks (LRPT1) and the third block reports long-run pass-through rates using lags up to 8 weeks (LRPT2). Parametric mean-comparison test is used to compare the mean pass-through rates of each category. T-statistics are reported and pooled standard errors are reported in the parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.14: Pass-through rates and Vertical Structures: Sales Price and wholesale price

Product Category	Inst.			LRPT1			LRPT2			Life-time		
	NB	PL	t-stat	NB	PL	t-stat	NB	PL	t-stat	NB	PL	t-stat
Carbonated Soft Drink	0.088	0.411	3.227***	0.0455	1.24	5.91***	0.347	0.363	3.42***	0.24	0.32	2.68***
	(0.066)	(0.156)	(0.0328)	(0.555)	(0.154)	(0.067)	(0.019)	(0.08)	(0.03)	(0.03)	(0.02)	(0.08)
Potato Chips	0.049	0.246	2.82***	0.099	0.1747	1.45**	0.28	0.298	3.22***	0.55	0.61	3.37***
	(0.048)	(0.058)	(0.018)	(0.208)	(0.277)	(0.096)	(0.032)	(0.02)	(0.07)	(0.002)	(0.003)	(0.17)
Cold Cereal	0.041	0.059	1.23	0.08	0.2773	1.635***	0.526	0.723	3.29***	0.37	0.4	1.75
	(0.107)	(0.161)	(0.034)	(0.765)	(0.257)	(0.132)	(0.01)	(0.09)	(0.07)	(0.009)	(0.008)	(0.01)
Cooking Oils	0.090	0.015	1.3	0.062	0.231	0.13	0.131	0.26	3.2***	0.01	0.2	2.97***
	(0.074)	(0.045)	(0.03)	(0.107)	(0.134)	(0.143)	(0.05)	(0.03)	(0.04)	(0.02)	(0.05)	(0.08)
Sugar	0.013	0.073	0.23	0.034	0.12	1.372***	0.11	0.12	1.68	0.13	0.34	3.14***
	(0.124)	(0.030)	(0.098)	(0.063)	(0.209)	(0.144)	(0.02)	(0.02)	(0.02)	(0.018)	(0.019)	(0.02)
Coffee	0.09	0.131	2.87***	0.192	0.213	0.123	0.163	0.3	2.53***	0.23	0.28	1.38
	(0.085)	(0.062)	(0.0321)	(0.154)	(0.198)	(0.053)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)	(0.04)
Family Juices	0.06	0.124	0.2297	0.384	0.62	1.984**	0.202	0.222	1.64	0.24	0.32	2.11**
	(0.104)	(0.067)	(0.0557)	(0.518)	(0.42)	(0.206)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.09)
Dry Pasta	0.055	0.073	0.164	0.069	0.055	1.91**	0.39	0.47	2.68***	0.4	0.74	2.97***
	(0.138)	(0.228)	(0.04)	(0.778)	(0.533)	(0.114)	(0.001)	(0.003)	(0.08)	(0.01)	(0.004)	(0.08)
Detergent	0.054	0.031	1.25	0.03	0.088	1.485**	0.48	0.57	2.12**	0.28	0.31	1.23
	(0.039)	(0.015)	(0.024)	(0.072)	(0.12)	(0.062)	(0.01)	(0.01)	(0.17)	(0.03)	(0.04)	(0.02)
Bathroom Tissues	0.019	0.03	0.79	0.051	0.144	0.892	0.13	0.28	4.32***	0.28	0.34	1.89
	(0.031)	(0.030)	(0.018)	(0.058)	(0.082)	(0.035)	(0.04)	(0.05)	(0.01)	(0.11)	(0.08)	(0.04)

Note: The table reports category-level pass-through rates using different definitions of pass-through. The first block reports instantaneous pass-through rates, the second block reports long-run pass-through rates using lags up to 4 weeks (LRPT1), and the third block reports long-run pass-through rates using lags up to 8 weeks (LRPT2). Parametric mean-comparison test is used to compare the mean pass-through rates of each category. T-statistics are reported and pooled standard errors are reported in the parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.15: Prices and Commodity Price Movements

Week	Commodity Price	Regular Price		Sales Price		Wholesale Price	
	Sugar	PL	NB	PL	NB	PL	NB
First Week	100	100	100	100	100	100	100
Last Week	166	129.30	117.63	136.8	97.21	112.43	106.32
Difference	66	29.30	17.63	36.8	-2.79	12.43	6.32
Responsiveness		0.44	0.27	0.56	-0.04	0.19	0.10
	Coffee	PL	NB	PL	NB	PL	NB
First Week	100	100	100	100	100	100	100
Last Week	188.67	120.56	113.13	121.36	111.18	125.77	114.61
Difference	88.67	20.56	13.13	21.36	11.18	25.77	14.61
Responsiveness		0.23	0.15	0.24	0.13	0.29	0.16

Note: Table reports the normalized prices and raw material prices (coffee and sugar) of the first (2004:1) and the last week (2007: 21) in log terms, first week observation is normalized to 100. The unit for raw material prices is dollar per pound. "Difference" is the price change in percentage term over this time horizon. "Responsiveness" is calculated by dividing growth rate of prices, or "differences" of prices, by growth rate of raw material price, or "difference" of raw material prices.

Table 3.16: Vertical Structure and Size of Price Changes

	NB			PL			
Sample	Mean	Median	SD	Mean	Median	SD	t-statistics
$\|dp^r\|$	0.076	0.03	0.141	0.092	0.04	0.156	56.2***
							(0.0001)
dp^r_+	0.07	0.031	0.124	0.09	0.04	0.149	54.3***
							(0.0002)
dp^r_-	-0.09	-0.034	0.159	-0.098	-0.04	0.164	25.02***
							(0.0002)
$dp^{s,non}$	0.293	0.259	0.194	0.265	0.223	0.175	7.678***
							(0.0006)
$dp_{s,1}$	0.299	0.294	0.134	0.261	0.24	0.131	8.392***
							(0.0002)
$dp_{s,2}$	0.311	0.317	0.126	0.275	0.267	0.126	8.321***
							(0.0003)
$dp_{s,3}$	0.399	0.315	0.133	0.275	0.261	0.139	5.321***
							(0.0001)

Note:Table reports the size of non-zero price changes in different vertical structures. $|dp_r|$ is the absolute size of regular price change, dp^r_+ is the positive regular price change, and dp^r_- is the negative regular price change. $dp^{s,non}$ is the size of sales conditional on the occurrence of sales. $dp_{s,k}$ is the size of sales price changes using the sales filter k. Sales filter 1, 2 and 3 keep observations when percentage of temporary price cuts are greater than 5%, 10% and 20%, respectively. T-statistics reported are for testing $H_0 : dp_{NB} = dp_{PL}$. Standard errors are recorded in parentheses. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.17: Small Regular Price Changes

	$\|dp^r\| < 5\%$	$\|dp^r\| < 2.5\%$	$\|dp^r\| < 1\%$
PL	0.62	0.41	0.15
NB	0.57	0.38	0.16

Note: The fraction of goods with absolute regular price change less than 5%, 2.5% and 1% is reported.

Table 3.18: Category FK

	Regular Price			Sales Price		
	All	PL	NB	All	PL	NB
Carbonated Soft Drinks	0.128	0.137	0.120	0.306	0.321	0.165
Potato Chips	0.281	0.322	0.240	0.561	0.828	0.198
Cold Cereal	0.158	0.133	0.137	0.272	0.345	0.142
Cooking Oils	0.184	0.184	0.154	0.395	0.480	0.296
Sugar	0.169	0.133	0.158	0.353	0.386	0.211
Coffee	0.365	0.125	0.204	0.370	0.460	0.224
Family Juices	0.119	0.120	0.116	0.340	0.402	0.429
Dry Pasta	0.157	0.167	0.143	0.352	0.386	0.358
Detergent	0.155	0.136	0.171	0.322	0.378	0.288
Bathroom Tissues	0.188	0.208	0.144	0.374	0.471	0.272

Note: This table shows category-level FK for each vertical structure. For all categories, FKs for sales prices are higher than those for regular prices. Also, private label goods generally show higher FK than national brands counterparts.

Table 3.19: Correlation of Timing of Sales: Cross-Vertical Structure

Category	Goods on Sales (%) PL	Goods on Sale (%) NB	Correlation
Carbonated soft drinks	0.4	0.51	0.335***
Potato Chips	0.52	0.53	-0.138
Cold Cereal	0.38	0.33	0.1138
Cooking Oils	0.22	0.16	-0.38***
Sugar	0.2	0.11	0.274***
Coffee	0.36	0.3	-0.122
Family Juices	0.39	0.38	-0.325***
Dry Pasta	0.36	0.29	-0.06
Detergent	0.37	0.25	-0.07
Bathroom Tissues	0.44	0.31	-0.02

Note: This table reports the share of goods on sales in each category for private labels and national labels. This is the average of sales flags over the entire data period, where sales flags is an indicator function, $I(p_{i,t}^{r,k} = p_{i,t}^{s,k})$. Here, $p_{i,t}^{r,k}$ is the regular price of item i at time t (for a particular store) in vertical structure k and $p_{i,t}^{s,k}$ is the sales price with similar definitions for superscripts and subscripts. Also, this table also reports the correlations of proportion of goods on sales in each vertical structure, $q_{c,t}^{PL}$, $q_{c,t}^{NB}$. $q_{c,t}^{PL}$ represents the proportion of private label goods on sales in category c at time t and $q_{c,t}^{NB}$ is similarly defined measure for national brands. *** implies 1% significance level, ** implies 5% significance level, * implies 10% significance level.

Table 3.20: Simulation of asymmetric model of sales

Parameter	(1) Sell N	(2) Sales on N&P	(3) Sales on P	(4) Sell P	(5) Sell N&P
V_N	8	8	8	7	8
V_P	5	5	5	5	5
C_N	4	4	4	4	4
C_P	2	2	2	2	2
ρ	0.5	0.8	0.8	0.8	0.8
α	0.95	0.95	0.9	0.4	0.8
δ	0.5	0.5	1	0.5	0.1
Sale freq.	0	0.2	0.2	0	0

Note: Figure 3.9 presents the price paths from these simulations. N denotes national brand and P private label brand. In scenario (1) the retailer only sells N to H (high-type). In scenario (2) the retailer sells N to H in regular periods and then sells N to H and P to L (low-type) *on sale* periodically. In scenario (3) the retailer sells N to H in regular periods and then sells P to H and L *on sale* periodically. In scenario (4) the retailer sells P to both H and L. In scenario (5) the retailer sells N to H and P to L.

Table 3.21: Pricing facts for private label vs. national brands

PL vs. NB	Data	Neiman (2010,2011)	Supply model match	Demand model match
Regular price change frequency	Same	Higher	No[1]	Yes
Sale price change frequency	Higher	?	No	Yes
Wholesale price change frequency	Higher	Higher	Yes	N/A
Raw material pass-through to retail price	Higher	Higher	Yes[1,2]	Yes
Wholesale pass-through to retail price	Higher	Same	No	Yes
Synchronization within PL/NB category	Higher	Lower	N/A	Yes
Synchronization across PL/NB category	?	?	N/A	Yes
Average absolute size of regular price change	Higher	?	Yes[3]	Yes
Average absolute size of sale price change	Smaller	?	N/A	Yes

Notes: (1)Result could be overturned with different retail prices
(2)Result could be overturned with different "marketing" inputs
(3)Result could be overturned if $\kappa^w >> \kappa^r$

Chapter 4

The Cyclicality of Effective Prices

4.1 Introduction

Explaining the apparent non-neutrality of money has led macroeconomists to study a variety of frictions, such as nominal and real wage rigidities or information rigidities. But the most commonly emphasized potential source of monetary non-neutrality remains sticky prices as epitomized by Woodford (2003). In part, this likely reflects the ubiquitousness of sticky prices in daily life. For example, Starbucks has raised its brewed coffee prices only once per year since the 2007-2009 recession began, despite the fact that the spot price of (Robusta) coffee bean rose 50% between February of 2007 and February of 2008, then fell 33% from February of 2008 to February 2010, before again rising 50% by February 2011. [1] This annual frequency of updating prices is not uncommon, and the notion that many prices change only infrequently has been well-documented in the literature. [2]

More recent work, on the other hand, has noted that the average durations of price spells are sensitive to the treatment of sales. If one counts the latter as price changes, then average price durations become relatively short and call into question whether price rigidities are strong enough to generate the significant monetary non-neutralities documented in Christiano et al. (1999) and Romer and Romer (2003) among others. Indeed, Chevalier and Kashyap (2011) argue that models with sales will imply results close to monetary neutrality because firms will use sales to adjust prices rapidly to economic conditions. Others have argued that the short-durations associated with sales cannot offset the effects of monetary policy shocks, and therefore regular price changes are the relevant metric for assessing predictions about monetary neutrality

[1] See "Starbucks to Raise Prices" in the January 4th, 2012 edition of the Wall Street Journal.

[2] See eg. Bils and Klenow (2002) and Nakamura and Steinsson (2008)

(e.g., Eichenbaum et al. (2011), Kehoe and Midrigan (2008)).
Using a unique panel dataset of prices at the UPC level across different stores in 50 U.S. metropolitan areas from 2001 to 2007, we build on this literature by studying the cyclicality of sales and regular price changes. Specifically, we consider how the frequency and size of both kinds of price changes vary with local unemployment rates. This presents a novel way to assess the importance of sales for macroeconomics: if sales are systematically used to lower prices when unemployment rates rise, then this would suggest that price rigidities are unlikely to be an important source of monetary non-neutralities. Instead, we document that the frequency and size of sales, as well as the share of goods bought on sale, decline when unemployment rates rise, i.e. these types of price changes become less prevalent precisely when their use could unravel the predictions of standard New Keynesian models.
Because the properties of regular price changes are largely invariant to economic conditions, we also find that higher unemployment rates are, if anything, associated with rising rather than falling prices of individual goods. This finding is similar in spirit, albeit based on micro-level data, to the work of Gali and Gertler (1999), Williams (2006), Roberts (2006) and others documenting the lack of a strong negative relationship between inflation and unemployment in U.S. macroeconomic data. However, because this dataset includes information on quantities of each kind of good purchased at each store, we also document that the average prices paid by consumers in each market decline (or rise more slowly) when local unemployment rates increase. Hence, there appears to be a sharp discrepancy between the cyclical behavior of posted prices and those actually paid by consumers, even at the level of the individual product.
We argue that both the counter-intuitive cyclical behavior of sales prices and the discrepancy between the cyclical changes in posted and paid prices can be accounted for by consumers switching across stores in response to economic conditions. Intuitively, a deterioration in local economic conditions should lead some price-sensitive consumers to reallocate some of their consumption expenditures toward lower-price retailers, thereby lowering the average price paid for any given good. At the same time, this store-switching behavior on the part of price-sensitive consumers should reduce the incentive of high-price stores to try and attract these price-sensitive consumers through sales, which could account for the counter-intuitive cyclical behavior of sales prices that we identify. In addition, these two effects should reinforce each other. To the extent that high-price stores reduce the frequency and size of sales, then this should induce additional store-switching behavior on the part of price-sensitive consumers, which in turn should again reduce the incentive of high-price stores to do sales, etc. We document three pieces of evidence consistent with this mechanism. First, because we have data for a variety of identical goods sold across different stores within a given geographic area, we can quantify the extent to which some stores are systematically more expensive than others. Higher-priced stores pursue more frequent, albeit

slightly smaller, sales on average than less expensive stores and sell a larger fraction of goods on sale. In addition, using these pricing ranks of stores, we show that high price stores do indeed experience larger declines in both the frequency and size of sales than lower-price stores when local unemployment rates rise. The share of goods bought on sale also declines by significantly more in expensive retail stores than in less expensive outlets. This differential response of sales across high-price and low-price retailers is consistent with the mechanisms described above.

Second, we exploit a detailed panel dataset tracking individual households expenditures at the UPC level and show that households do indeed reallocate their consumption expenditures toward lower price retailers when local economic conditions deteriorate. Specifically, we construct a household-specific time-varying expenditure-weighted measure of the price rank of stores at which households do their shopping. These measures decline significantly when local unemployment rates rise, pointing to consumers switching their expenditures toward lower-price stores on average. Furthermore, this pattern is more pronounced for those households in the middle of the income distribution than for those at the top (who more consistently shop at higher-priced retailers) or at the bottom (who more consistently shop at lower-price retailers) of the income distribution.

Third, we decompose the change in average prices paid by consumers into those components due only to variation in the prices of individual goods at a given store, variation in the expenditure shares associated with different stores, and the covariance between them. By assessing the sensitivity of each of these components of inflation to local unemployment rates, we can then quantify the relative importance of each channel in accounting for the overall sensitivity of average prices paid by consumers to the unemployment rate. The results indicate that most of this sensitivity reflects changing expenditure weights, while the individual price changes and the covariance term display little cyclical sensitivity.

Jointly, these results point to significant store-switching on the part of households in the face of changing economic conditions. To what extent does this matter for macroeconomists? The most obvious implication is with respect to the measurement of inflation. But whereas previous work has primarily emphasized long-run biases in inflation measures such as the CPI due to households substituting across goods, our results point toward cyclical mismeasurement even over a fixed basket of goods. And while the goods in our dataset cover only about 15% of the CPI basket, store-switching and its implications could readily apply to over 35% of the CPI basket because many other categories of goods would be subject to similar reallocation opportunities. Furthermore, we document that the substitution bias of the CPI, stemming from consumers switching toward lower price goods in response to relative price changes, also exhibits a pronounced cyclical pattern.

We illustrate this cyclical mismeasurement in several ways. One approach is to plot the aggregate average prices of goods in both high-price and low-price retailers which exhibit very similar time series patterns. When we also plot the average price paid by consumers across all retailers, this measure tracks the low-price level closely in the early 2000s, when the unemployment rate was high, but gradually approaches the high-price level by the end of 2007, as the unemployment rate fell over the course of this period. This suggests that the overall inflation rate in the mid-2000s was underestimated as consumers increasingly purchased the same goods at higher-priced retailers. A second approach is to assess statistically whether the aggregate differences between average prices paid by consumers across all retailers relative to average prices within either high-price or low-price retailers vary in a systematic manner with aggregate unemployment rates. We find robust evidence that these price differentials are indeed correlated with unemployment rates, supporting the notion that these cyclical biases obtain even when we aggregate across all goods, stores, and geographic areas.

Another implication of the cyclical mismeasurement of inflation relates to the implied slope of the Phillips curve. If consumers reallocate their expenditures toward lower-price retailers when unemployment rises, then this suggests that the Phillips curve is steeper than would be estimated using available inflation measures. We show that this result obtains in our data when we create two measures of aggregate inflation over all the goods in our sample: effective price inflation (which incorporates store-switching) and inflation in posted prices (similar to the CPI construction of inflation). The latter exhibits only a weak negative correlation with unemployment, consistent with the results of much of the Phillips curve literature in which estimates of the slope of the Phillips curve are typically small and often not statistically different than zero. However, the correlation between effective price inflation and unemployment is more negative, and statistically significant at conventional levels. This confirms that, at least for the goods covered in our dataset, the Phillips curve is significantly steeper than what one would otherwise find using unadjusted measures of inflation. As a result, the reallocation of consumer expenditures across retailers has immediate practical implications not just for the measurement of inflation but also for the implementation and design of monetary policy.

4.2 Data Description

We use a very extensive data set assembled by Symphony IRI, a marketing and market research agency, and discussed in more detail in Bronnenberg et al. (2008). This data set contains weekly scanner price and quantity data covering a panel of stores in 50 metropolitan areas and 31 product categories from January 2001 and December 2007. In addition, the data includes a panel of households in two of the metropolitan areas in which households provided detailed information on their characteristics and purchases.

This household dimension can be linked to the store-level information of the data-set. The metropolitan areas are typically defined at the Metropolitan Statistical Area (MSA) level, while four of them offer a greater coverage than a city, i.e. West Texas/New Mexico, South Carolina, and Mississippi. Two of the metropolitan areas are smaller than typical (Eau Claire, WI and Pittsfield, MA) but are the areas in which the household panel data was constructed. Within each metropolitan area, the data includes price and quantity data from a panel of stores, defined either as Drug Stores or Grocery Stores. Grocery stores vastly outnumber Drug stores within each metropolitan area. For example, data from San Francisco in 2005 covers 44 Grocery stores and 14 Drug stores. Each outlet has an identifier which is constant over time so one can track the prices and revenues at each retailer over time. However, retailers (or chains of retailers) are deliberately not identified by name.

For each retail outlet, weekly data are available at the UPC (unique product code) level. Goods are classified into 31 general product categories (e.g., Beer, Coffee, Deodorant) as well as more refined categories. Brand information is included (e.g., Budweiser, Heineken,Coors) but all private-label UPCs have the same brand identification so that the identity of the retailer cannot be recovered from the labeling information. Detailed information about each good is included, such as whether a product is low-fat, as is information about the volume of the product (e.g., 6-packs vs. 12-packs, volume per container). Unfortunately, no data on costs is available.

Retailers report the total dollar value of weekly sales (TR) for each UPC code, as well as total units sold (TQ). The combination of the two yields the average retail price during that week which is computed as follows:

$$P_{msctj} = \frac{TR_{msctj}}{TQ_{msctj}} \tag{4.1}$$

where m, s, c, t, and j index markets, stores, product categories, time, and UPC. This retail price includes retail features, displays and retailer coupons, but does not incorporate manufacturer coupons. In addition, retailers flag goods on sale. Thus, the dataset identifies the average price of a good paid by consumers during the course of the week, as well as whether this price is identified as a sales price. Because we are interested in differentiating between regular price changes and those due to sales, we adopt the following conventions. First, any change in prices between two periods when neither period has a sales flag is defined as a regular price change if it exceeds 1% in value. Second, when a sales flag is listed and the price after the sale expires is the same as prior to the sale, we assume no change in regular prices in intermittent periods. Third, in addition to the sales flag provided in the data set, we apply an additional filter similar to the filter in Nakamura and Steinsson (2008). Specifically, we consider a good on sale if a price reduction is followed by a price increase of the same magnitude within four weeks. [3]

Table 4.1 presents baseline statistics about the monthly frequency and size (in log-percentage terms) of both sales price changes and regular price changes across goods and for each of the main categories. We also present data on the average share of goods bought on sale. The frequency of sales and regular price changes is computed at the individual UPC level in a given month, then averaged across all UPC labels within a category in a given city and month, and finally averaged across time and cities. To aggregate across the individual UPCs within each product category, we use several weighting schemes: i) equal weights; ii) expenditure shares for a given city and year (city specific); iii) expenditure shares for a given year (common). [4]

The average size of sales is approximately 25% across all goods. While less than 20% of goods are on sale in any given month, more than 30% of all goods purchased are done so when goods are on sale. Frozen dinners and frozen pizzas are the goods which are proportionally most bought on sale, while cigarettes are the least frequently bought on sale (Appendix Table 4.1). It is also the case that frozen dinners and pizzas are among the goods which are most frequently on sale while cigarettes are only rarely on sale. Cigarettes and beer are the goods for which sales, when they do occur, tend to be smallest while frozen dinners and pizzas are, again, at the other extreme. Panel A of Figure 4.1 documents that there is a strong positive correlation between the frequency and size of sales across categories, while Panel C illustrates the fact that categories of goods with a higher frequency of sales also have a larger fraction of goods bought on sale.

Rows (4) through (9) in Table 4.1 focus on the properties of regular price changes. Across all goods, increases in regular prices are more frequent than price decreases. The average size of price changes is 3.5%. The average frequency of regular price changes is 5% per month, so that the average duration between regular price changes is approximately 20 months. This is higher than that found by Nakamura and Steinsson (2008) and others focusing on regular price changes. This difference reflects our treatment of missing observations as experiencing no change in regular prices. [5] Panel B of Figure 4.1 illustrates that, in contrast to sales, categories of goods with more frequent regular price changes tend to have smaller price changes.

Figure 4.1 also examines whether there is any systematic link between the properties of regular price changes and sales across categories. Panel D, for example, shows that there is little link between the frequencies of sales and regular price changes across cat-

[3] Results are similar when we do not use this filter because the vast majority of sales are picked by the flag provided in the dataset.

[4] City-specific and common weights are computed for each year separately. See Appendix for more details on how weights are constructed.

[5] As documented in Appendix, alternative treatments of missing observations lead to lower average price durations.

egories, while Panel E documents instead a positive relationship between the average size of sales (in percentage terms) and the average change in regular prices across categories. Finally, Panel F illustrates a weak positive relationship between the frequency of sales and the average size of regular price changes across categories.

4.3 The Cyclicality of Effective, Regular an Sales Price Changes

4.3.1 The Cyclicality of Posted Prices

While there is now a long literature studying pricing at the microeconomic level, little work has been done on the cyclical properties of pricing behavior. To assess how the properties of price changes vary with economic conditions, we adopt the following baseline empirical specification"

$$Y_{mct} = \beta UR_{mct} + \lambda_t + \theta_{(m,c)} + error \tag{4.2}$$

where m, c, and t index markets (e.g., Atlanta, Detroit), the category of the good (e.g., beer, yogurt), calendar time (i.e., month); Y_{mct} is a variable of interest (e.g., frequency of sales); $UR_m ct$ is the seasonally-adjusted unemployment rate; $\theta_{(m,c)}$ denotes the fixed effect for each market and category of good while λ_t denotes time fixed effects. Because the unemployment rate at the metropolitan level is only available at the monthly frequency, we estimate specification (1) at the monthly frequency as well. Since the error term in specification (1) is likely to be serially and cross-sectionally correlated, we use the Driscoll and Kraay (1998) method to construct standard errors. [6]

As dependent variables, we first focus on the same properties of price changes as in Table 4.1: the average frequency and size of sales, the frequency and size of regular price changes, the frequency and size of either positive or negative regular price changes, as well as the share of goods purchased on sale. In each case, we use the average of these measures across all of the goods within each of the 31 categories. We measure each at the monthly frequency to be consistent with the frequency of the unemployment data. To aggregate across UPC codes to the category level, we use equal, city-specific and common weights which are defined above.

The first column of Table 4.2 documents results from estimating specification (1) at

[6] Driscoll-Kraay standard errors tend to be conservative. Appendix Table 3 presents alternative estimates of standard errors.

the category level using a simple average across all UPC products within a category, excluding all fixed effects in specification (1). The results indicate that a higher unemployment rate is associated with more frequent sales and a larger share of goods on sales. However, it is unclear whether this larger role played by sales reflects the fact that sales become more prevalent within a market when i) the unemployment rises (i.e. business cycle effects), ii) regions with higher unemployment rates on average also experience more frequent sales for other reasons (i.e. systematically more depressed areas like Detroit have on average more frequent sales), or iii) there is a comovement of trends in unemployment and properties of sales. As a result, columns (2) and (3) present equivalent results controlling for geographic/category specific effects and time fixed effects to address ii) and iii). Introducing geographic/category level fixed effects eliminates much of the positive effect of unemployment on sales found in the previous specification, leaving little evidence of cyclical sensitivity of pricing behavior to economic conditions. However, this lack of sensitivity to economic conditions could also reflect macroeconomic shocks (or other omitted variables) which induce variation in both unemployment rates and the dependent variables and thus lead to potentially spurious correlations. As a result, our preferred specification includes both geographic/category fixed effects and time fixed effects. As illustrated in column (3), controlling for time fixed effects alters the results: higher unemployment rates within an area become associated with significantly less frequent sales and those sales which do occur are smaller in size (the positive coefficient points to smaller sales since these are measured as negative values). Concurrently, the share of goods bought on sale declines with increases in the rate of unemployment. Hence, these results indicate that once one controls for aggregate conditions, a worsening in local economic conditions reduces the size, frequency, and relative importance of sales.

In addition, column (3) documents the cyclicality of regular price changes. These results also point to a reduced frequency in regular price changes. This reduced frequency of price changes obtains for both price increases and price decreases, although the results are only marginally statistically significant for the former. However, when we measure category averages using expenditure weights, either city-specific (column (4)) or common across cities (column (5)), cyclical changes in the frequency of regular price changes are no longer significantly different from zero. Furthermore, we find little evidence that the size of regular price changes varies with local economic conditions, regardless of the category aggregation method. The cyclicality of sales behavior, on the other hand, is very robust to the aggregation method. The frequency and average size of sales, as well as the share of goods bought on sale, are robustly lower when local unemployment rates are higher. Finally, we assess the sensitivity of overall inflation in individual goods (or inflation of posted prices), aggregated at the category level, to local economic conditions. To do so, we first construct weekly inflation rates for each UPC good, which are then cumulated into monthly inflation rates for each good, and them cumulated into annual inflation rate as is done by the BLS. We denote the resulting inflation with π^{post}_{mct}. Category level inflation is a weighted average of UPC/store-level inflation rates, where again weights are defined as either equal weights across UPC/store combinations, constant UPC/store city-level expenditure weights, or constant UPC/store expenditure weights across all metropolitan areas. Regardless of the weighting procedure, Table 4.2 documents little systematic evidence of a correlation between inflation in prices of goods and local unemployment rates.

4.3.2 The Cyclicality of Prices Paid

While the previous section documents that the prices of individual goods within a store tend to be higher on average when unemployment rates rise, this need not imply that consumers pay higher prices for goods when economic conditions deteriorate. First, consumers could purchase more goods on sale. Second, consumers could substitute toward cheaper varieties of similar goods even if those goods are not on sale. Third, consumers could reallocate their consumption expenditures to stores in which average prices are lower. Each of these channels could lead to lower effective prices paid by consumers when unemployment rises even if the posted prices are themselves rising.
To assess each of these channels, we exploit the fact that the IRI Symphony data includes not just prices but quantities sold as well. For example, we can infer whether consumers switch more of their expenditures toward goods on sales when local conditions worsen by estimating (1) using our category-measure of the share of goods bought on sale. The results in columns (3)-(5) in Table (2) suggest that, regardless of how we aggregate across UPCs, the share of goods bought on sale declines when the unemployment rises. We will explore substitution across varieties in Section V. In this section we focus on the cyclical behavior of changes in the effective prices of individual goods paid by consumers taking into account the possibility that they switch across stores. Thus, like the CPI, we focus on the measurement of a fixed basket of goods but allow for substitution of purchases of individual goods across retailers. Importantly, previous research could not explore this channel because transaction data were available only in one retail chain or did not include data on quantities purchased whereas our data set contains information on quantities purchased at different retail outlets. Specifically, we first construct the quantity-weighted average effective price of a specific good j in category c across stores in geographic area m as

$$\bar{P}^{eff}_{mcjt} = \frac{(\sum_{(s \in m)} TR_{msctj})}{(\sum_{(s \in m)} TQ_{msctj})} \tag{4.3}$$

This measure can change because individual prices change or because consumers reallocate their consumption of the good across stores. For each good j in category c and market m, we then compute the inflation rate

$$\pi^{eff}_{mcjt} = log(\frac{(\bar{P}^{eff}_{mcj,t}}{\bar{P}^{eff}_{(mcj,t-12)}})) \tag{4.4}$$

Then, using weights ω_{mctj} for UPCs, we aggregate across all goods j within a category c to get the average category-level inflation rate across stores

$$\pi^{eff}_{mct} = \sum_{(j \in c)} \omega_{mctj} \pi^{eff}_{mctj} \tag{4.5}$$

which we refer to as the across-store effective inflation rate. Similar to the aggregation above, we consider the use of equal weights, city-specific weights, and common weights across UPCs within each product category.
The last row in Table 4.2 presents results examining the cyclical properties of the average effective inflation rate across stores. The key finding is that higher unemployment is associated with lower inflation once one accounts for households switching their purchases across stores, in contrast to what we observe with inflation measured at the level of a fixed store/good combination. This result suggests one possible explanation for why sales appear to behave procyclically: weakened economic conditions lead some consumers to switch to lower-priced retailers. Because these consumers are likely to have a higher price-elasticity of demand, this would tend to lower the incentive for high-priced retailers to engage in sales designed primarily to attract this class of agents. An alternative explanation is that, as economic conditions worsen and incomes decline, the incentive of high-priced retailers to engage in sales to attract lower-income consumers declines (since these consumers tend to bear a disproportionate share of income losses), thereby leading these consumers to switch toward lower-price retailers. In the next section, we provide more detailed evidence on household store-switching.

4.4 Household Store-Switching

To assess whether consumers do indeed reallocate their expenditures across retailers as their incomes change, we pursue three complimentary approaches. The first establishes that the procyclicality of sales is particularly pronounced for high-price retailers. The second employs the household panel in the data and documents that households do indeed reallocate their consumption expenditures toward lower-price retailers when local economic conditions are more dire. The third decomposes changes in effective inflation rates into subcomponents and documents that its sensitivity to unemployment rates is driven by the reallocation of expenditures across stores rather than changes in the prices of individual goods within stores.

4.4.1 Cross-sectional variation in the sensitivity of pricing to business conditions

To quantify expenditure switching across retailers, we construct a time-varying ranking of stores relative prices as follows. First, for each UPC-level good j in category c and market m, we rank each store s in a given market and period t by the price charged for that good. The resulting rank R_{mcstj} is such that R = 1 when a store has the lowest price, R = 2 for the second lowest price, and so on. Second, we compute the average rank for a store across the set of UPC products Ω. We consider several versions of Ω because different stores sell different goods: includes all UPCs that are sold in every store in a given market (Ω_{max}); Ω includes UPCs sold in 90% of stores in a market (Ω_{90}); Ω includes UPCs sold in 75% of stores (Ω_{75}). The average rank of a store for a given Ω is $R_{(mst,\Omega)} = \sum_c \sum_{(j\in\Omega)} \omega_{mcstj} R_{mcstj}$ where ω is a weight (equal, city-specific, or common). Finally, we normalize the ranking of stores in each market to be between 0 and 1, where 0 is the lowest-price and 1 is the highest-price store. A stores price ranking tends to be highly persistent over time, with an autocorrelation parameter of 0.80 at the annual frequency.
persistent over time, with an autocorrelation parameter of 0.80 at the annual frequency.
Figure 4.2 presents illustrative scatter plots of the relationship between expenditure-weighted store rankings and the average price setting decisions of each store across all categories of goods. More expensive stores tend to have more frequent sales than less expensive stores, but the average size of sales is larger in cheaper stores. Panel B documents that the share of goods bought on sale is significantly higher in more expensive stores than in cheaper stores. Panels D and E present the unconditional correlations between a stores rank and the properties of its regular price changes: more expensive stores tend to change prices less frequently and by smaller increments on average than less expensive stores.

To consider the extent to which the cyclicality of price changes varies depending on the relative price rank of the store, we perform the analysis at the store-level using the following empirical specification

$$Y_{mst,\Omega} = q_{sm} + a_1 UR_{mt} + a_2 UR_{mt} \times \bar{R}_{mst,\Omega} + \lambda_t + error \tag{4.6}$$

where $Y_{mst,\Omega}$ is a price moment considered for store s in market m at time t for the set of goods in Ω. The aggregation of the price measures across goods is done via expenditure shares of each UPC product across all stores. q_{sm} is a store-level fixed effect and λ_t captures a common trend component.

In Table 4.3, we present results using the three different definitions of Ω applied to the size and frequency of sales, the share of goods bought on sale, and the size and frequency of regular price changes. The results are consistent with the notion that a stores price rank has significant effects on the cyclicality of price changes. The effects are most pronounced for the behavior of sales. More expensive stores (those with a higher rank) exhibit much more pronounced declines in the frequency and size (in absolute value) of sales. This is accompanied by a significant decline in the share of goods bought on sale in more expensive stores. These results hold for all definitions of Ω and are therefore consistent with the notion that higher unemployment leads to store-switching by price-sensitive consumers and a reduction in the incentive of higher-price stores to offer discounts and sales to attract them.

The results in Table 4.3 also document that higher-price stores reduce the frequency but increase the absolute size of regular price changes in periods of higher unemployment.

4.4.2 Households'choices of shopping outlets as a function of business conditions

We also consider an alternative and more direct approach to quantifying the extent of consumers reallocation of their expenditures across stores. The household panel data developed by IRI Symphony tracks about between 5,000 and 10,000 households in Eau Claire, WI and Pittsfield, MA from 2001 to 2007. About 2,000 households are continuously present between 2001 and 2007. During this time, households expenditures on each UPC product were tracked, including the location of each purchase. Hence, these detailed data allow us to directly measure the extent of the store-switching phenomenon at the level of individual households in light of changing economic conditions.

To do so, we first construct a household-specific time-varying measure of the pricing rank of the stores in which each household does its shopping. Specifically, for each household h at month t in market m (either Eau Claire, WI or Pittsfield, MA) we construct an average rank defined as

$$\tilde{R}_{hmt} = \sum_{s \in m} \psi_{mhst} \bar{R}_{mst,\Omega} \tag{4.7}$$

where $\bar{R}_{mst,\Omega}$ is the average price rank of store s in market m at time t across the set of goods $\Omega asdefinedbeforeand\psi_{mhst}$ denotes the share of the households expenditures spent at store s in market m and month t. These measures therefore provide one way to quantify the extent to which each household is allocating their expenditures across retailers of different average price levels.

To assess whether individual households reallocate their expenditures across stores as local economic conditions change, we estimate the following specification across households in the two markets

$$\tilde{R}_{hmt} = q_{hm} + a_1 UR_{mt} + a_2 t + error \tag{4.8}$$

where q_{hm} is a household-specific fixed effect and t is a linear time trend. Because store price ranks can vary with the set of UPCs used in their construction, we produce these results for each of the definitions of Ω considered before. The results are qualitatively similar regardless of the choice for \$$\Omega$ or weights used to construct each households average expenditure-rank: the coefficient on unemployment is negative and statistically significantly different from zero at standard levels. Thus, higher local unemployment rates are associated with households substituting more of their expenditures towards lower-price retailers. In addition, the estimated magnitudes are relatively large: a 1% point increase in the local unemployment rate is associated with a decrease in the average rank at which households shop of between 0.04 and 0.14 depending on the specific measures used.

The household data also includes detailed characteristics of each household for that year, such as age of the head of household, income, and the number of household members. As a result, we can also investigate which types of households are most likely to engage in store-switching behavior. Specifically, we focus on the relationship between households income and store-switching via the following empirical specification:

$$\tilde{R}_{hmt} = q_h + a_1 UR_{mt} + a_2 UR_{mt} * lnY_{hmt} + a_3 UR_{m,t} * (lnY_{hmt})^2 + a_4 lnY_{hmt} + a_5 t + error \tag{4.9}$$

where Y_{hmt} is the log of household hs annual income in market m at time t. The results are presented in Table 4.4 for different measures of Ω and using both equal and expenditure-share weighting of different goods. In each case, the coefficients on unemployment and the linear interaction term are negative, while the quadratic income interaction coefficient is consistently estimated to be positive. This suggests that expenditure-switching occurs primarily towards in the middle of the income distribution. This seems intuitive: most low-income households are likely to shop in less expensive stores most of the time, while high-income households are more likely to consistently shop in the most expensive stores. Hence, sales by high-price stores are likely to be designed to attract the middle of the income distribution, and it is these consumers whose switching behavior is most significant over the course of the business cycle.

4.4.3 Decomposing the Sensitivity of Effective Inflation Rates to Unemployment

We documented in Table 4.2 that when the local unemployment rate rises, the effective inflation rate declines even though sales become less frequent and smaller in magnitude. To quantify the importance of store-switching in accounting for this phenomenon, we first note that changes in effective prices can be decomposed into components reflecting changing prices, changing expenditure weights, and a covariance term:

$$\begin{aligned}\bar{P}_{jcmt} - \bar{P}_{jcm,t-12} &= \sum_{s\in m} P_{jscmt} * w_{jscmt} - \sum_{s\in m} P_{jscm,t-12} * w_{jscm,t-12} \\ &= \sum_{s\in m}(P_{jscmt} - P_{jscm,t-12}) * w_{jscm,t-12} + \sum_{s\in m} P_{jscm,t-12} * (w_{jscmt} - w_{jscm,t-12}) \\ &+ \sum_{s\in m}(P_{jscmt} - P_{jscm,t-12}) * (w_{jscmt} - w_{jscm,t-12})\end{aligned} \tag{4.10}$$

where $\bar{P}_{jcmt}= \sum_{s\in m} P_{jscmt} * w_{jscmt}$ is the effective price of UPC i in category c in market m at time t and $w_{jscmt}=Q_{jscmt}/\sum_{r\in m}Q_{jrcmt}$ is the share of quantity of UPC j in category c in market m in store s at time t in total quantity sold of UPC j in category c in market m at time t. The first term $\sum_{s\in m} (P_{jscmt}\text{-}P_{jscm,t-12}) * w_{jscm,t-12}$ measures the direct contribution of changing prices while holding expenditure weights across stores constant at their t-12 level. The second component, $\sum_{s\in m} P_{jscm,t-12} * (w_{jscmt}\text{-}w_{jscm,t-12})$, measures the contribution of store-switching via changes in the weight (i.e. allocation of purchases across stores). The final component $\sum_{s\in m} (P_{jscmt}\text{-}P_{jscm,t-12}) * (w_{jscmt}\text{-}w_{jscm,t-12})$ measures the covariance between changes in stores prices and changes in stores shares.

To implement this decomposition in a manner that clearly identifies the reallocation of household expenditures between more and less expensive stores, we create two groups of stores within each metropolitan area: cheap (ranked below the 50% percentile) and expensive (ranked above the 50% percentile). With the effective inflation rate for UPC j in store c in market m at time t defined as π_{icmt}=($\bar{P}_{jcmt}$-$\bar{P}_{jcm,t-12}$)/$\bar{P}_{jcm,t-12}$, we can then rewrite the decomposition as

$$\pi_{jcmt}^{eff} = T_{1,jcmt} + T_{2,jcmt} + T_{3,jcmt} \tag{4.11}$$

where

$T_{1,jcmt}$≡((P_{jcmt}^{cheap}-$P_{jscm,t-12}^{cheap}$) $*$ $w_{jcm,t-12}^{cheap}$+($P_{jcmt}^{expensive}$-$P_{jscm,t-12}^{expensive}$) $*$ $w_{jcm,t-12}^{expensive}$)/$\bar{P}_{icmt}$,

$T_{2,jcmt}$≡ ((P_{jcmt}^{cheap}-$P_{jscm,t-12}^{cheap)}$) $*$ (w_{jcmt}^{cheap}-$w_{jcm,t-12}^{cheap}$)+($P_{jcmt}^{expensive}$-$P_{jscm,t-12}^{expensive}$) $*$ ($w_{jcmt}^{expensive}$-$w_{jcm,t-12}^{expensive}$))/$\bar{P}_{icmt}$,

$T_{3,jcmt}$≡ ($P_{jscm,t-12}^{cheap}$ $*$ (w_{jcmt}^{cheap}-$w_{jcm,t-12}^{cheap}$)+$P_{jscm,t-12}^{expensive}$ $*$ ($w_{jcmt}^{expensive}$-$w_{jcm,t-12}^{expensive}$))/$\bar{P}_{jcmt}$.

and P_{jcmt}^{cheap} is the effective price of good j in market m in category c in time t in cheap stores, w_{jcmt}^{cheap} is the quantity share of good i in market m in category c in time t bought in cheap stores, $\bar{P}_{jcmt}$ the effective price of good i in market m in category c in time t in all stores. We aggregate $T_{x,jcmt}$ across goods using equal weights or using expenditure shares. In constructing the store rankings, we again consider subsets of the UPC goods which are those sold in all stores, at least 90% of stores, or at least 75% of stores in a given city m and time t.

We can then apply the following econometric specification

$$T_{x,cmt} = q_{cm} + a_1 UR_{mt} + \lambda_t + error \tag{4.12}$$

where x,c,m,t index inflation component, categories, markets (cities), and time (months), q_{cm} is city/category fixed effect, λ_t is the month fixed effect, UR is the unemployment rate in market m. This test can help determine whether the sensitivity of effective inflation to local unemployment rates is driven by the sensitivity of price changes, expenditure reallocation across stores, or the covariance between the two. Because we use a different subsets of UPCs than those used in the baseline results, we also present estimates for the effective inflation rate ($T_{4,cmt} \equiv T_{1,cmt}$+$T_{2,cmt}$+$T_{3,cmt}$= $\bar{\pi}_{cmt}^{eff}$) for comparison with the results in Table **??**.

Table 4.5 presents the estimated coefficients on unemployment for different weighting methods and subsets of UPC goods. The first notable finding is that the estimated coefficients on unemployment when looking only at price changes (T_1) are small and generally not statistically significant. This confirms the finding of Table 4.2 that, overall, the prices of individual goods in a store are not particularly sensitive to the unemployment rate. At the same time, the estimated coefficients when using the change in expenditure weights across stores (T_2) are negative and statistically significant. Furthermore, they are approximately of the same magnitude as the coefficients when using the overall effective inflation rate (T_4), so that most of the sensitivity of the effective inflation rate to unemployment is indeed driven by the changing weights across stores from consumers expenditure reallocations. Consistent with this, we find little evidence of a relationship between local unemployment rates and the covariance term (T_3). Thus, these results illustrate that the sensitivity of effective inflation is indeed driven almost exclusively by retail-switching on the part of consumers rather than price changes on the part of retailers.

4.5 Cross-Good Substitution

While we have so far limited our attention to expenditure-switching across stores by households for a given UPC product, the literature on price measurement has long emphasized another margin of substitution, namely across goods. Our primary motivation for focusing on switching across stores for a given good is that, as in the construction of the CPI, it is helpful to consider the cost of a fixed basket of goods for welfare purposes. The substitution bias long emphasized in the literature, in which CPI inflation will be overstated because it ignores the possibility of consumers switching to substitute goods when relative prices change, instead involves a change in the composition of the basket which will have implications for welfare. Nonetheless, we also consider this additional margin here for two reasons. First, the substitution bias has primarily been considered as a source of a long-run bias in inflation measurements, while the cyclical properties of this margin have been ignored. Second, comparing the degree of store-switching to the amount of across-goods substitution provides one metric to assess how large the quantitative importance of store-switching for the measurement of inflation.

To quantify the degree of substitution across goods, we first construct the quantity-weighted average effective price across all goods j within category c in store s and geographic area m as

$$\bar{P}^{eq}_{mcts} = \frac{\sum_{j\in c} TR_{msctj}}{\sum_{j\in c} TQ_{msctj} * EQ_j} \tag{4.13}$$

where EQ_j is the quantity equivalent of good j. Hence, in calculating $\bar{P}^{eq}_{mcts}$, all prices are converted into quantity-equivalent measures so that e.g. the price of a 6-pack of beer is comparable to a 12-pack. $\bar{P}^{eq}_{mcts}$ can change because individual prices change or because consumers reallocate their consumption of goods within a given category. For category c, store s and market m, we compute the inflation rate $\bar{\pi}^{eq}_{mcts}$=log$(\bar{P}^{eq}_{mcts}/\bar{P}^{eq}_{mcs,t-12})$. Then, using weights ω_{mcst} for UPCs, we aggregate across all stores in market m to get the average category-level inflation rate

$$\bar{\pi}^{eq}_{mct} = \sum_{s\in m} \omega_{msctj} \pi^{eq}_{mcts} \tag{4.14}$$

which we refer to as the within-category effective inflation rate. Similar to the aggregation above, we consider the use of equal weights or expenditure-weights to aggregate across stores.

Because some categories include much more heterogeneity in goods than others, we consider two classification schemes for measuring the substitution of goods within categories. The first (and broadest) includes all UPCs within a category. The second allows substitution only within subcategories which approximately correspond to adding another digit to the level of disaggregation. For example, we use all types of milk when we calculate $\bar{P}^{eq}_{mcts}$ for the first classification. In contrast, the second classification considers separately such subcategories as whole milk, skimmed milk, 2% milk, etc. Inflation rates for subcategories are aggregated to the category level using equal or expenditure-based weights.

The sensitivity of these inflation rates to local unemployment is then assessed using

$$\bar{\pi}^{eq}_{mct} = \beta UR_{mt} + \lambda_t + \theta_{(m,c)} + error \tag{4.15}$$

which is equivalent to the specification used to measure the sensitivity of effective across-store inflation rates to economic conditions. The results, presented in Table 4.6, point to a statistically significantly negative relationship between unemployment rates and cross-good inflation rates. Thus, as in our baseline results, this indicates that there is significant substitution of expenditures by households in response to changing local economic conditions, but along a different margin, namely substituting across different goods within a category. Not surprisingly, the effect is stronger when we allow include a larger set of goods within each category. Importantly, the quantitative magnitudes are of the same order as those identified for across-store substitution.

4.6 Aggregate Effects of Store-Switching

To what extent should macroeconomists care about store-switching behavior? In this section, we discuss some of the potential implications of our findings for the measurement of inflation, understanding the behavior of inflation during the Great Recession, and interpreting estimates of the slope of the Phillips Curve.

The most obvious implication of households expenditure reallocation across stores is for the measurement of inflation. Standard estimates of inflation, such as the CPI, do not incorporate the fact that consumption expenditures may be reallocated across stores for a given good and therefore that the effective price paid by consumers for a given item may change even in the absence of a change in the listed prices of the good in retail stores. But as documented in the previous sections, this reallocation of consumer expenditures across stores follows cyclical patterns, which suggests that there will be a cyclical component to mismeasurement of prices and inflation in measures which do not adequately reflect this reallocation effect. For example, Table 4.2 documented that inflation in individual goods prices appears to be insensitive to local economic conditions, but that inflation rates over prices of individual goods actually paid by consumers across stores tend to fall when unemployment rates rise.

To illustrate this at a more aggregate level, we first construct measures of the average price of a good sold at high-price stores and an equivalent measure at low-price stores. We then aggregate these across all categories and metropolitan areas (we use expenditure shares) to construct an aggregate price index for high-price retailers and an aggregate price index for low-price retailers. These price levels, along with the aggregate unemployment rate, are plotted in Panel A of Figure 4.3. Both price measures are falling in 2001 and 2002 as the aggregate unemployment rate rises and rising in subsequent periods as the aggregate unemployment rate falls. The correlation between the two series is high . Panel B plots the difference between the two series. While there is a decline in 2001 as the unemployment rate rises, there appears to be little systematic link in the price differential between high-price and low-price retailers with the aggregate unemployment rate, with the gap between the two hovering around 6% for much of the sample.

In addition, we construct a measure of the effective price level across stores and metropolitan areas. This measure is also plotted in Panel A of Figure 4.3. The cyclical effects of store-switching are apparent. As the unemployment rate rises in 2001, the effective price level approaches the average level in cheaper stores. But as the unemployment rate declines during the mid-2000s, the effective price gradually moves away from the average price in less expensive stores and closer to that of higher-price stores. This suggests that the effective inflation rate was lower than the measured inflation rate in 2001 and 2002, as consumers switched toward lower-price stores, but systematically higher in the mid-2000s as consumers reallocated their expenditures toward higher price stores.

Panel B of Figure 4.3 also plots the differences between the average price levels at high-price stores and low-price stores with respect to the effective price level. Both gaps seem to exhibit some correlation with the aggregate unemployment rate, particularly the difference between the effective price level and the price level at cheap stores which mirrors the path of the unemployment. Table 8 investigates these time series correlations more systematically, again allowing for using different sets of UPCs and aggregations in constructing store ranks as well as different weights for aggregating prices across stores and metropolitan areas. The results point to statistically significant correlations in most cases: the gap between the expensive-store price level and the effective price level rises when the unemployment rate is higher while the gap between the cheap-store and effective price levels shrink, again consistent with the reallocation of consumption expenditures in response to economic conditions.

A related implication of store-switching behavior is with respect to the slope of the Phillips Curve. To the extent that consumers reallocate their expenditures toward less-expensive stores when unemployment is high, as documented in previous sections, and to the extent that this effect is not captured by standard inflation measurements, then estimates of the relationship between inflation and unemployment will tend to be biased downward, i.e the estimates of the slope of the Phillips curve will be too low. Figure 4.4 illustrates this by plotting a scatter for 2001 to 2007 of aggregate unemployment rates versus two measures of aggregate inflation: posted price inflation $\tilde{\pi}_t^{post}$ and effective price inflation $\tilde{\pi}_t^{eff}$. In each case, the inflation measures are constructed as weighted (by expenditure shares) averages of $\bar{\pi}_{mct}^{post}$ and $\bar{\pi}_{mct}^{eff}$ across metropolitan areas and categories. With inflation of posted prices, there is little visible evidence of a negative relationship between inflation and unemployment, and estimates of the slope are only marginally different from zero. With effective price inflation on the other hand, there is a clearly visible negative relationship between inflation and unemployment. Point estimates of the slope are negative and statistically significant, and point to a

Phillips Curve which is approximately twice as steep as what it would appear to be when using inflation of posted prices.

Because the slope of the Phillips Curve is a crucial component of New Keynesian macroeconomic models, the cyclical mismeasurement of inflation and its implications for the slope of the Phillips curve have nontrivial consequences. For example, the slope of the Phillips curve is of immediate practical significance for monetary policy, as is the correct measurement of inflation. Underestimating the slope of the Phillips curve would imply very large estimates of the sacrifice ratio and perhaps lead to an unwillingness to pursue disinflationary policies when they might, in fact, be warranted.

Furthermore, the cyclical mismeasurement of the Phillips curve could help explain why the Phillips curve relationship often appears to be so weak in macroeconomic data.

One limitation of our data is that it includes only a small component of goods purchased by consumers, representing approximately 15% of the weight in the U.S. Consumer Price Index. However, store-switching is likely to apply to a number of other categories of goods as well. For example, apparel, household furnishings, motor fuel, most categories of recreation goods, and some components of transportation, communication and other goods would readily be subject to store-switching effects. As a result, this cyclical mismeasurement could apply to over 35% of the basket of goods in the CPI, leading to substantial mismeasurement of aggregate inflation over the course of the business cycle.

Table 4.1: Descriptive Statistics

Dependent Variable	E qual weights	W	eighted	
		City specific	Common	
Sales Frequency	mean	0.195	0.237	0.237
	s.d.	(0.079)	(0.108)	(0.107)
Sales size	mean	-0.251	-0.249	-0.252
	s.d.	(0.077)	(0.088)	(0.089)
Shares of goods bought on sales	mean	0.248	0.319	0.317
	s.d.	(0.100)	(0.146)	(0.142)
Regular Price				
Frequency				
All	mean	0.048	0.047	0.048
	s.d.	(0.031)	(0.036)	(0.038)
Positive	mean	0.032	0.031	0.031
	s.d.	(0.025)	(0.028)	(0.029)
Negative	mean	0.016	0.016	0.017
	s.d.	(0.012)	(0.015)	(0.015)
Size				
All	mean	0.035	0.034	0.035
	s.d.	(0.046)	(0.043)	(0.044)
Positive	mean	0.120	0.100	0.102
	s.d.	(0.053)	(0.055)	(0.057)
Negative	mean	-0.121	-0.089	-0.091
	s.d.	(0.084)	(0.069)	(0.071)

Table 4.2: Cyclical properties of selected moments of price changes

Dependent Variable		E	qual weights	W	eighted
	Pooled OLS	City-Category FE	City-Category-Month FE	City-Category-Month FE	City-Category-Month FE
	(1)	(2)	(3)	(4)	(5)
Sales Frequency	0.785***	0.327	-0.365***	-0.422***	-0.475***
	(0.235)	(0.550)	(0.120)	(0.153)	(0.141)
Sales size	0.245****	0.321**	0.256****	0.183	0.224*
	(0.086)	(0.145)	(0.120)	(0.137)	(0.128)
Shares of goods bought on sales	1.126***	0.512	-0.461***	-0.563***	-0.629***
	(0.237)	(0.587)	(0.133)	(0.171)	(0.161)
Regular prices					
Frequency					
All	0.083	-0.066	-0.100**	-0.097	-0.070
	(0.097)	(0.222)	(0.044)	(0.065)	(0.064)
Positive	0.015	-0.126	-0.053*	-0.58	-0.050
	(0.056)	(0.128)	(0.032)	(0.040)	(0.041)
Negative	0.067	0.060	-0.047***	-0.040	-0.020
	(0.042)	(0.097)	(0.019)	(0.029)	(0.028)
Size					
All	-0.122	-0.292	-0.095	-0.008	-0.005
	(0.098)	(0.196)	(0.062)	(0.053)	(0.052)
Positive	0.024	0.142***	-0.55*	-0.020	-0.027
	(0.046)	(0.0172)	(0.092)	(0.079)	(0.080)
Negative	0.051	-0.014	-0.04	-0.026	-0.023
	(0.092)	(0.216)	(0.129)	(0.101)	(0.101)
Inflation (Posted)	-0.044	0.155	0.000	-0.103	-0.118
	(0.054)	(0.134)	(0.1200)	(0.105)	(0.115)
Inflation (effective)	-0.424***	-0.926***	-0.206***	-0.292***	-0.266***
	(0.056)	(0.115)	(0.078)	(0.086)	(0.092)

Note: Number of observation is 127,224. Estimated specification is given by equation (1). Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

Table 4.3: Use expenditure shares as weights for aggregate rank of UPCs within a store

Dependent variable	U	PC rank sample: max		U	PC rank sample:90		U	PC rank sample 75	
	UR	UR, rank	obs	UR	UR, rank	obs	UR	UR,rank	obs
Sales Frequency	-0.517***	-0.454***	144,265	-0.515***	-0.480***	144.274	-0.474***	-0.559***	144,274
	(0.141)	(0.104)		(0.148)	(0.109)		(0.148)	(0.110)	
Sales size	0.154	-0.195**	143,379	0.139	-0.167*	143,281	0.147	-0.178*,143,381	
	(0.101)	(0.089)		(0.101)	(0.091)		(0.100)	(0.100)	
Share of goods bought on sales	-0.383***	-0.653***	144,265	-0.382***	-0.687***	144,274	-0.326***	-0.794***	144,274
	(0.144)	(0.133)		(0.159)	(0.153)		(0.163)	(0.156)	
Regular prices									
Frequency									
All	-0.056	-0.089***	144,265	-0.058	-0.087**	144,274	-0.048	-0.109***	144,274
	(0.071)	(0.038)		(0.073)	(0.041)		(0.072)	(0.043)	
Positive	-0.009	-0.042*	144,265	-0.013	-0.035	144,274	-0.008	-0.044	144,274
	(0.045)	(0.014)		(0.032)	(0.014)		(0.031)	(0.015)	
Size									
All	-0.096*	0.049***	143,550	-0.112**	0.092***	143,556	-0.125**	0.118***	143,556
	(0.053)	(0018)		(0.056)	(0.026)		(0.057)	(0.028)	
Positive	-0.224***	-0.011	143,329	-0.219***	-0.023	143,334	-0.218***	-0.024	143,334
	(0.086)	(0.021)		(0.086)	(0.027)		(0.087)	(0.029)	
Negative	0.327***	-0.090***	143,175	0.305***	-0.040	143,181	0.302***	-0.033	143,181
	(0.078)	(0.031)		(0.074)	(0.035)		(0.075)	(0.035)	
Inflation (effective)	-0.782	1.578***	141,078	-0.843*	1.837***	141,085	-0.859*	1.796***	141,085
	(0.483)	(0.232)		(0.480)	(0.290)		(0.487)	(0.308)	

Table 4.4: Rank of the store where households shop as a function of local unemployment rate and household's income

UPCs	Weights	UE_{ct}	UE_{ct}, lnY_{shct}	UE_{ct}, $(lnY_{shct})^2$
Max	Equal	-9.316***	-1.845***	0.169***
		(2.903)	(0.315)	(0.058)
	Weighted	-2.797	-1.856***	0.137***
		(2.528)	(0.315)	(0.056)
90	Equal	-7.196***	-1.070***	0.119***
		(1.745)	(0.334)	(0.048)
	Weighted	-1.709	-0.892***	0.085*
		(1.549)	(0.305)	(0.046)
75	Equal	-7.703***	-1.045***	0.121***
		(1.862)	(0.341)	(0.048)
	Weighted	-3.890***	-0.815***	0.101***
		(1.283)	(0.280)	(0.038)

Notes: The table reports estimates of specification (4). The dependent variable is the average rank of stores where a household shops in a given month. Each regression has 471,615 observations. Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

Table 4.5: Decomposition of inflation for effective prices

UPCs	T_1	T_2	T_3	T_4
Ranking of stores: equal weight to ranks				
Max	0.025	-0.242***	-0.218**	-0.435***
	(0.135)	(0.100)	(0.101)	(0.095)
90	0.147	-0.402**	-0.155*	-0.409***
	(0.212)	(0.185)	(0.092)	(0.129)
75	0.149	-0.454***	-0.062	
	(0.191)	(0.136)	(0.091)	(0.114)
Ranking of stores: weighted by expenditure share				
Max	-0.230*	-0.240***	0.136	-0.335***
	(0.136)	(0.100)	(0.104)	(0.099)
90	0.032	-0.360***	0.030	-0.297***
	(0.114)	(0.108)	(0.118)	(0.090)
75	0.015	-0.282***	-0.011	-0.278***
	(0.127)	(0.073)	(0.106)	(0.095)

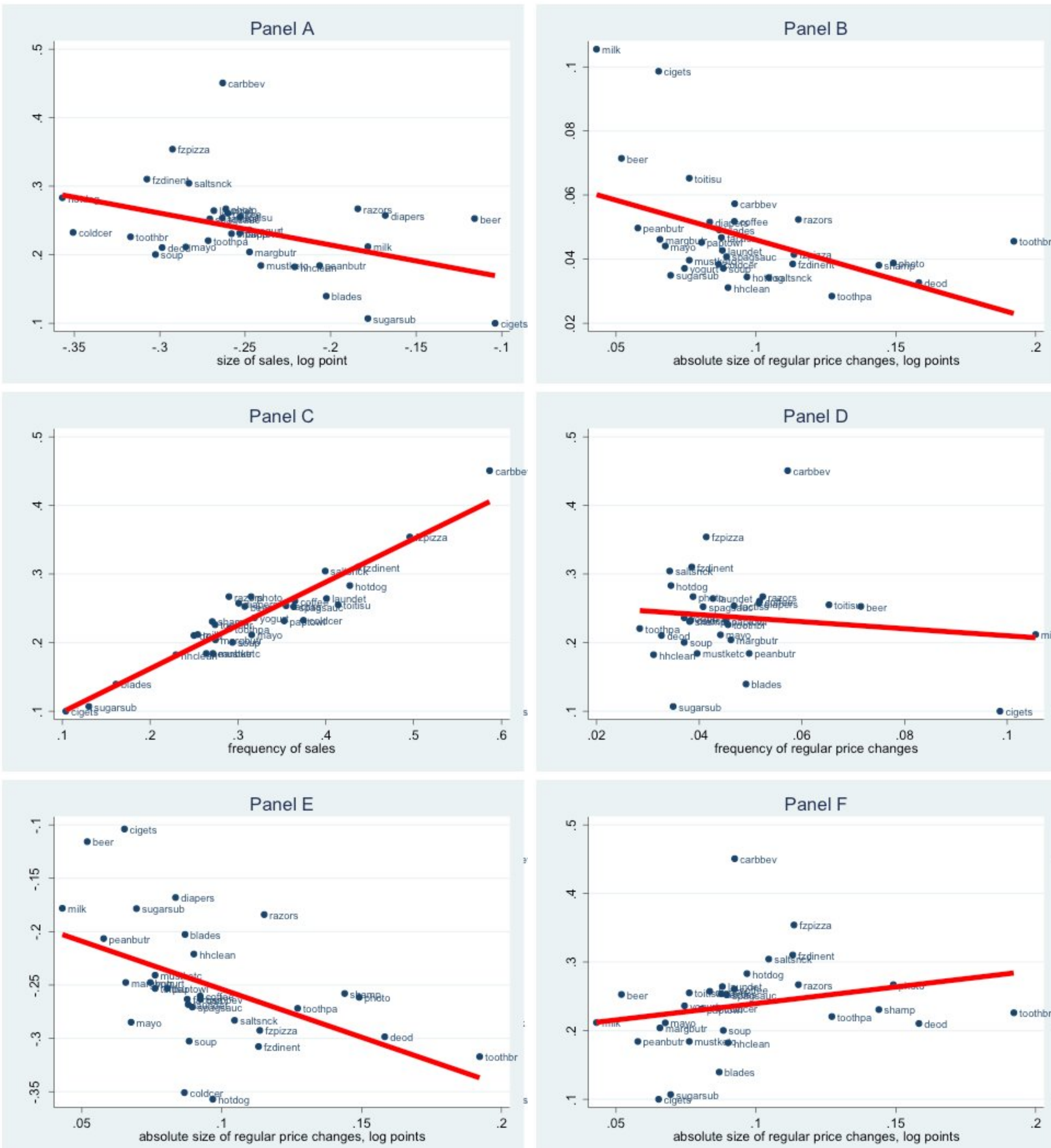
Notes:The table reports estimates of specification (5). Second row shows the dependent variable. Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

Table 4.6: Within category substitution

	Equal Weights	Sales Share
Substitution within broad categories	-0.495**	-0.598**
	(0.213)	(0.238)
Substitution within narrower categories	-0.385**	-0.416**
	(0.168)	(0.192)

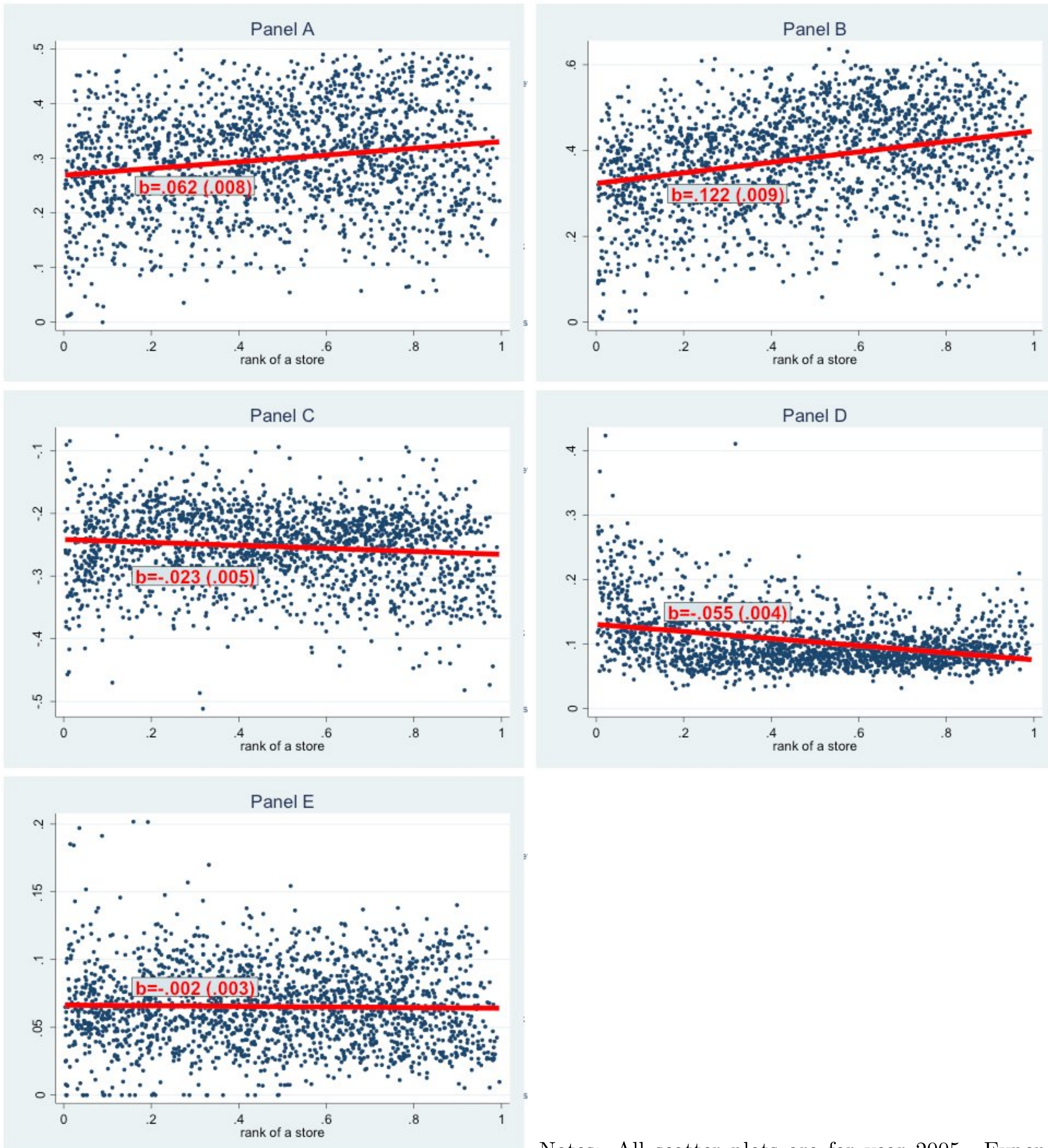
Notes: The table reports estimates of specification (6). Number of observations is 94,851. Driscoll and Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

Figure 4.1: Correlations between key months



Notes: figures report average (across time and goods) moments at the category level. Expenditure shares are used as weights to aggregate goods. Red line shows the best fit linear projection.

Figure 4.2: Correlations between store rank and key moments at the store level data



Notes: All scatter plots are for year 2005. Expenditure shares are used as weights to aggregate goods to the store level. Red line shows the best fit linear projection. The rank of the store is defined over the UPCs which are sold in 90% of stores in each market in any given month.

Figure 4.3: Aggregate dynamics of prices and price spreads for expensive and cheap stores

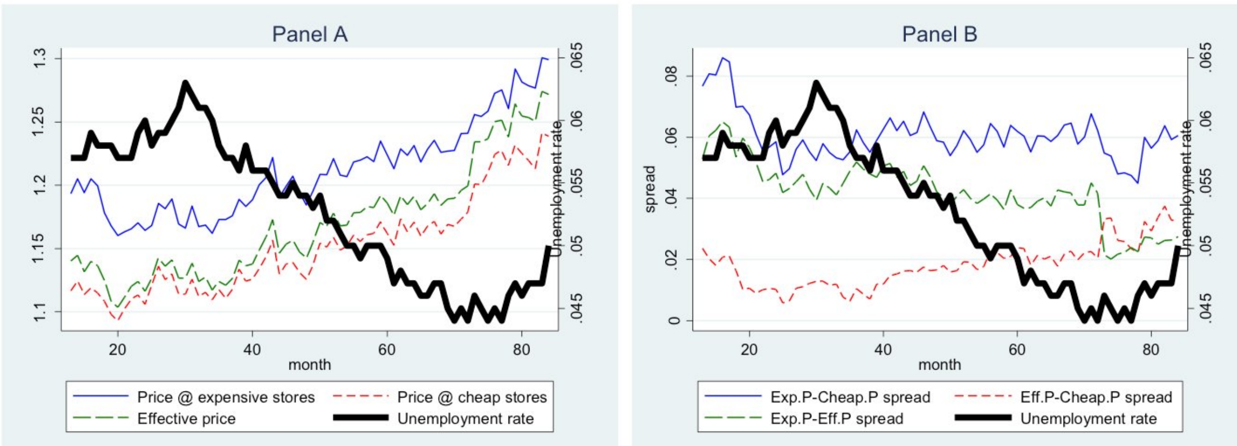
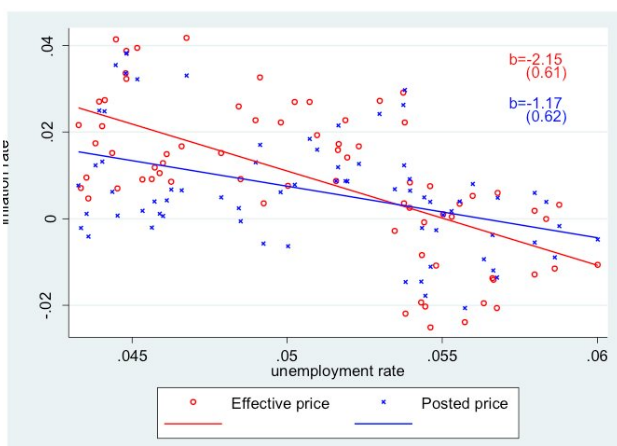


Figure 4.4: Correlation between unemployment rate and measures of inflation



Notes: The figure presents relationships between seasonally adjustment unemployment rate and two measures of inflation: posted price inflation π_t^{post} and effective price inflation $\pi?_t^{eff}$.

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