AN INVESTIGATION OF ASYMMETRIC PRICING “IN THE SMALL” IN THE RETAIL GROCERY SECTOR

AN INVESTIGATION OF ASYMMETRIC PRICING "IN THE SMALL" IN THE RETAIL GROCERY SECTOR

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Lay Abstract

This dissertation studies asymmetric pricing in the small (APIS), where small price increases outnumber small price decreases, the asymmetry disappearing for larger price changes; and the corresponding reversed phenomenon (APIS-R). There are only a few papers in the domain, and none explain their cross-sectional and longitudinal variations. Existing results are mostly based on a single retailer, limited products, short time span, and legacy datasets dating back to the 1980s and 1990s, leaving their current relevance unsettled. Recent papers also question if small price changes are measurement artifacts. This dissertation addresses these gaps by analyzing several large contemporary datasets. The research finds robust evidence of both APIS and APIS-R in the retail price spectrum, and provides explanations for their cross-sectional variation, across products and retailers, as well as longitudinal variations, across business cycles. The results indicate the pricing practices can be retailers' strategic responses to the cognitive tasks faced by consumers.

Abstract

This dissertation studies asymmetric pricing in the small (APIS), where small price increases outnumber small price decreases, the asymmetry disappearing for larger price changes; and the corresponding reversed phenomenon (APIS-R). Current evidence suggests retailers deploy these pricing practices despite menu costs and potential consumer concerns. There is also evidence that inflation is only a partial contributor to the phenomena. These point to possible strategic intent driving these retail pricing practices. However, there are only a few papers in the domain, and none specifically address the cross-sectional and longitudinal variations. Further, existing results are mostly based on a single retailer, limited products, short time span, and legacy datasets dating back to the 1980s and 1990s, leaving their current relevance unsettled. Recent papers also question if small price changes are measurement artifacts.

This dissertation addresses these gaps by analyzing several large contemporary datasets – a scanner dataset with more than 79 billion price observations and a matching consumer panel dataset with more than 50,000 participating panelists. Our key results imply the pricing practices can be retailers' strategic responses to the cognitive tasks faced by consumers.

Chapter 1 is a general introduction to the thesis. Chapter 2 sets up the fundamentals of the phenomena and reports robust evidence of APIS and APIS-R across the retail price spectrum. Chapter 3 examines the cross-sectional variations of the phenomena and finds that APIS and APIS-R are associated with product characteristics such as purchase frequency and category price level, as well as retail format such as HILO or EDLP. Chapter 4 explores the longitudinal variations and finds that business cycles are a major time-varying factor influencing retail practices of APIS and APIS-R. Chapter 5 concludes with reflections on the findings, implications for theory and practice, limitations, and suggestions for future studies.

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1. Introduction

The general phenomenon of small price changes is important for both marketing and economics for various reasons. For marketers, small price changes are often seen as a strategic choice with implications for profitability and competitive posturing. It is well known that customers do not always perceive prices changes and may ignore price changes either rationally or irrationally. Consumers' perception of reference prices is a function of prices they see (Thaler 1985, Mayhew and Winer 1992, Greenleaf 1995). In such cases, small price changes could become a meaningful lever for marketers. These pricing practices can have important implications for retailers because it presents an opportunity for them to turn their dynamic pricing capabilities into profit. Given the thin profit margin of an average grocery retailer, even small price changes in cents can significantly impact a retailer's bottom line when aggregated.

Small price changes are important for economics as well. In fact, macroeconomists have considered small price changes in the context of a general response to inflation, deflation, etc. They are tied to the issue of price rigidity and the associated monetary policy concerns. A convergence of sorts between these two disparate approaches is in the New-Keynesian line of research in economics and marketing that studies the micro level determinants of macro level price sluggishness in the economy. Yet, despite the significant business and policy implications associated with them, only a handful of research studies small price changes explicitly. Even these limited sets of studies have significant limitations that raise questions about the robustness and generalizability of the empirical findings.

Findings in existing papers also document significant variation in the asymmetry small price change patterns – both cross-sectional variation across products, as well as variation over time. Clearly, in order to benefit from these pricing practices, retailers need to address both their ability to implement small price changes, as well as their ability to identify the right asymmetry pattern and the right thresholds that differ across retailers, consumers, products, and time periods. Hence, it is important to understand the observed variations of the small price change patterns since they reveal the best practices of dynamic small pricing decisions in a market equilibrium. There are different explanations for such variation including both passive (e.g., inflation) as well as more active pricing practices (e.g., strategic intent on the part of the retailer). In fact, Chen et al. (2008) and Chakraborty et al. (2015) do provide possible explanations of the practice but do not address the variation found in the asymmetry patterns. In general, both APIS and APIS-R are explained by an underlying theme of consumer inattention, even if the explanations operate in slightly different ways.

The Rational Inattention (RI) theory (Chen et al. 2008, Ray et al. 2012) proposes that time and resource-constrained consumers might rationally ignore small price changes, which provides incentives for profit-maximizing retailers to make more frequent small price increases than decreases, thus leading to APIS. The strategic obfuscation (SO) logic (Chakraborty et al. 2015) suggests retailers strategically obfuscate their price spectrum for consumers, by mixing a few large price increases with numerous small but inconsequential price decreases ("penny drops") to maintain their competitive price image while aiming for higher margins, thus leading to APIS-R. These explanations notwithstanding, none of these papers address why certain categories exhibit APIS while others exhibit APIS-R, and what type of retailers prefer the strategic obfuscation incentives of APIS-R over the direct monetary utility of APIS. Similarly, there is no explanation why retailers deploy APIS and APIS-R differently during different time periods. The existing literature has found a link between the business cycle and consumer attention, shedding light on the longitudinal explanation of the phenomena from the rational inattention perspective. However, the impact of cyclical macro-level factors has been largely ignored by the dynamic pricing literature on small price changes.

Much of this gap is driven by the data limitations inherent in earlier papers – especially the limited number of retailers. Perhaps not surprisingly, both Chen et al. (2008) and Chakraborty et al. (2015) only report one type of asymmetry (i.e., either APIS or APIS-R). The significant variation of the APIS and APIS-R patterns present an opportunity to learn not just about how retailers should deploy their dynamic pricing practices, but also offer insights into the impact these pricing practices could have on the consumer's shopping experiences.

Hence, of particular interest to this dissertation is the relative prevalence of small price increases (penny rises) versus decreases (penny drops) in the retail price spectrum. In addition, it aims to explain the various patterns of small price changes across product categories, retailers, and time periods. Thus, using a large economy-wide aggregate price dataset, a matching consumer panel data, and an independent transaction price dataset, this dissertation re-examines the ripples (small changes) in grocery retail prices.

Our key research questions are – Do price increases outnumber price decreases in our retail price spectrum? How prevalent are APIS and APIS-R in the spectrum of current retail pricing practices? Are these mere artifacts of inflation and measurement problems? Specifically, what is the scale and scope of these phenomena after controlling for both inflation and some key measurement concerns raised in the literature? And finally, what are the explanations of these pricing patterns cross-sectionally and longitudinally? We contend that these are important questions for the literature and expect the answers will help researchers in marketing and economics focus further studies in the domain.

Hence, this dissertation focuses on the APIS/APIS-R phenomenon and attempt to discuss and address the previously mentioned gaps in three chapters. The next chapter (Chapter 2) documents the foundation of the APIS phenomenon. It estimates the degree to which the phenomenon is relevant to more recent times, checks whether the results are robust to different measurement challenges as well as offering new metrics for measurement. It measures the scale and nature of APIS and APIS-R in a large KNRS dataset comprising more than 79 billion weekly retail price observations over a 10-year period in a relatively recent time frame (2006–2015). The dataset covers a broad range of 527 product modules sold in 35,000 stores belonging to 161 retailers in the US. It also uses an independent transactions dataset to simulate the impact of price aggregation on the estimation of APIS and APIS-R. The third chapter explores the explanations of the variations of APIS across different products and retailers. It tests how consumer-preference-related product attributes and retailer strategies, such as their pricing positioning strategies, influence the existence and degree of the phenomenon. In addition to the KNRS data, a matching consumer panel dataset is used to measure the product attributes defined by consumer purchasing patterns. The fourth chapter focuses on the variations of APIS and APIS-R over the business cycle. It leverages the rational inattention (RI) explanation of the phenomenon: time-constrained consumers might rationally ignore small price changes, and they may be more (less) attentive to prices during economic downturns (booms). Hence, APIS and APIS-R should vary over the business cycle. It should diminish during recessions when unemployment is high and strengthen during expansions when unemployment is low. This study uses the same KNRS dataset and macroeconomic data (unemployment rate, recession, inflation, etc.) to test this prediction. Lastly, the fifth chapter concludes the findings from previous chapters, discusses the limitations of the studies, and provides directions for future research.

This dissertation aims at the following contributions. Firstly, it attempts to investigate if the evidence points to asymmetric price adjustments in the small being robust phenomena, which exist across different levels of aggregation – products, retailers, and time periods. It estimates and documents APIS in retail grocery, a key sector for the economy. This is important, for there are only a handful of papers (Ray et al., 2006; Chen et al. 2008) that document the APIS phenomenon. It also finds that APIS continues to be a part of the retail-pricing spectrum even after two decades of the data reported in the first study and even after major economy-wide technological changes that could reasonably be seen as affecting consumer decision making, and by implication, retail pricing practices. It will be only among a handful of studies that explore APIS, and perhaps the largest scale such effort in the grocery sector. Second, the phenomena are robust to important controls. It shows that the observed APIS and APIS-R findings are robust to several measurement concerns including potential measurement limitations and inflation – in particular, to unit value indices (UVIs) – pointed out as a key source of noise by Eichenbaum et al. (2014) and Campbell and Eden (2014). Third, it will also be the first significant evidence of APIS-R in a large-scale study. Chakravarty et al. (2015) is the only other paper that reports this. This extends the asymmetric pricing literature by expanding the documented spectrum of retail pricing practices. Fourth, it finds significant variation in the nature, scale, and measurements of the phenomena across different products and retailers. It is the first attempt to explain the cross-sectional variations of APIS and APIS-R patterns. In the process, we find robust evidence that both product level attributes and retailer characteristics (HILO or EDLP positioning) shape retailer's practices of APIS and APIS-R. Fifth, it provides the first evidence of APIS/APIS-R pricing practices in response to business cycles and contributes to furthering our understanding of how macroeconomic outcomes and micro level price setting are related to each other, a key tenet of New-Keynesian economics (Dutta, Bergen, and Ray, 2010). The findings are of interest to both economists interested in monetary policy, as well as retailers interested in effective dynamic pricing during recessions. Sixth, it contributes to the literature on small price changes by empirically documenting how rational inattention and strategic obfuscation incentives frame the retailer's dynamic pricing practices. And it is the first study to test whether the two theories, RI and SO, apply to a broader context with an economy-wide dataset. Last but not least, it contributes to marketing practice by documenting the best practices in the domain of managing small price changes – highlighting the factors that might be contributing to the success of APIS and APIS-R practices.

This dissertation is organized as follows. Followed by the introduction are the three chapters of the dissertation: Chapter 2 analyses a large retail price dataset for evidence of APIS and APIS-R and builds a foundation of the phenomena. Chapter 3 explores the explanations of the asymmetry variation across product categories and retailers. Chapter 4 investigates the variations longitudinally based on the RI theory. Chapter 5 concludes the findings and points to limitations and future research directions.[1]

[1] The empirical results in this thesis are the researcher's own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

2. Ripples in the Price Spectrum: Penny Rises and Penny Drops

2.1. INTRODUCTION

Marketers often see small price changes as a strategic tool with implications for profitability and competitive posturing. For economists, on the other hand, small price changes are key to the general response to inflation, deflation etc. Yet, despite the significant business and policy implications associated with them, only a handful of papers study small price changes, or ripples in the price spectrum, explicitly. Even these limited set of studies have significant limitations that raise questions about the robustness and generalizability of the empirical findings. Of particular interest to us is the relative prevalence of small price increases (penny rises) versus decreases (penny drops) in the retail price spectrum. Indeed, much of the empirical inferences in this domain of research are based on limited data – single retailer, limited product categories, short time span and legacy data dating back to the 1980s and 1990s. More recently, researchers have also raised concerns about whether the published findings in the literature are artifacts arising out of inherent measurement challenges for small price changes. Thus, in this paper, using a large economy-wide dataset, we re-examine the ripples (small changes) in grocery retail prices. Specifically, we document the phenomenon of asymmetric pricing in the small (APIS), where there are statistically more small price increases (penny rises) than small price decreases (penny drops), and where such asymmetry between positive and negative price changes tends to vanish for larger price changes. The corresponding reverse phenomenon where there are a statistically greater number of small price decreases than small price increases is asymmetric pricing in the small – reversed (APIS-R).

Our key research questions are – Do price increases outnumber price decreases in our retail price spectrum? How prevalent are APIS and APIS-R in the spectrum of current retail pricing practices? Are these mere artifacts of inflation and measurement problems? Specifically, what is the scale and scope of these phenomena after controlling for both inflation and some key measurement concerns raised in the literature? We contend that these are important questions for the literature and expect the answers will help researchers in marketing and economics focus further studies in the domain.

To address the research questions, we estimate APIS and APIS-R in a dataset comprising more than 79 billion weekly retail price observations over a relatively recent 10-year period (2006–2015). The data covers a broad range of 56 categories (product groups) and 527 sub-categories (product modules) sold in 35,000 stores belonging to 161 retailers in the US. We also use an independent transactions dataset to simulate the impact of price aggregation on the estimation of APIS and APIS-R.

Our study makes three main contributions. First, we estimate and document APIS in retail grocery, a key sector for the economy. This is important, for there are only a handful of papers (Ray et al., 2006; Chen et al. 2008) that document the APIS phenomenon. We also find that APIS continues to be a part of the retail-pricing spectrum even after two decades of the data reported in the first study and even after major economy-wide technological changes that could reasonably be seen as affecting consumer decision making, and by implication, retail pricing practices. Second, we document stable patterns of APIS-R. Chakravarty et al. (2015) is the only other paper that reports this. This extends the asymmetric pricing literature by expanding the documented spectrum of retail pricing practices. Third, we show that the observed APIS and APIS-R findings are robust to several measurement concerns – in particular, to unit value indices (UVIs) – pointed out as a key source of noise by Eichenbaum et al. (2014) and Campbell and Eden (2014). To the best of our knowledge, our research database of grocery retailers across the nation is the largest study of small price changes to date. Thus, our work also lends more generalizability to the documented phenomena. Our findings are robust across several bases of aggregation – increasingly granular categorization of products (module, group, and department), retailers, time, location, etc.

In the following section, we elaborate on the motivation behind this research, outlining the key theoretical perspectives of small price changes, and identifying the tensions arising out of conflicting results and propositions. We also describe the limitations of the data driving much of the published empirical results and the ensuing gaps in the literature that we seek to address. We follow in section 3, by discussing the trade-offs of using aggregated versus transactions data for our research, our approach to dealing with the challenges, and describing the new datasets used. Next, in section 4, we discuss measurement and estimation, followed, in section 5, by the findings, in section 6 discussions of the results and conclusions, in section 7.

2.2. MOTIVATION

2.2.1 The big role of Small Price Changes

The general phenomenon of small price changes is important for marketing for various reasons. Marketers, often consider small price changes as a strategic choice with implications for profitability and competitive posturing. It is well known that customers do not always perceive prices changes and may ignore price changes either rationally or irrationally. Consumers' perception of reference prices is a function of prices they see (Thaler 1985, Mayhew and Winer 1992, Greenleaf 1995). In such cases, small price changes could become a meaningful lever for marketers. Marketers could use price changes to modify the price spectrum to form customer reference prices. For example, small price changes may be used by retailers to strategically obfuscate their price spectrum while at the same time maintain their (competitive) price image (Chakravarty et al. 2015). Small price changes are important for economics as well. In fact, macroeconomists have considered small price changes in the context of a general response to inflation, deflation, etc. They are tied to the issue of price rigidity and the associated monetary policy concerns.

2.2.2 Multiplicity of perspectives and findings

Four main theoretical perspectives drive much of these studies of small price changes in marketing. The *price adjustment cost or "menu cost" (MC)* line of work focusses on the retailer's (in)ability to change prices on account of the associated costs (Barro 1972, Sheshinski and Weiss 1977, 1979, Mankiw 1985, Levy et al 1997, 1998; Dutta et al 1999). The *Rational Inattention (RI)* literature (e.g., Reis 2006a, b; Mankiw and Reis 2002, 2011; Ball et al 2005, Sims 2003, 2010) and *just-noticeable differences (JND)* literatures (Kalyanaram and Little 1994; Lichtenstein, Block, and Black 1988, Gupta and Cooper 1992, Fibich et al. 2007, Pauwels et al. 2007) focus on customer motivation and ability to process small price changes as a precursor to their consumption decisions. Studies in this literature argue that when price reductions are within certain thresholds, consumers do not react to them by changing their purchase behavior, and these thresholds may be asymmetric. An emerging fourth stream of research argues that small price adjustments are tactical in nature and are an essential part of the marketer's *strategic dynamic pricing efforts* (Ray et al. 2006, Ray et al. 2012, Wood et al. 2013, Chakravarty et al. 2015).

The multiple perspectives to interpret small price changes have generated a rich set of research insights for researchers, policy makers and marketers. However, the different perspectives used to study small price changes have conflicting predictions regarding their desirability and profitability for retailers. While the menu cost line of reasoning argues against the existence of any small price changes – increases or decreases, the RI and JND perspectives generally predict against the existence of small price decreases as part of retailer's pricing practice since these will not be profitable for the retailer. This prediction, of course, stand in contrast to the strategic obfuscation line of reasoning of Chakravarty et al. (2015) who argue for the existence of numerous small price decreases, counter to the proposition of Chen et al. (2008). Therefore, on the face of it, consensus weighs against observing systematic evidence of any type of small price changes, whether positive or negative. However, that is not the case. Existing empirical studies document a presence of frequent small price changes, both increases and decreases, in micro level transactions price data (e.g., Carlton 1986, Lach and Tsiddon 2007, Ray et al. 2006, Ray et al. 2012, Wood et al. 2013, Chakravarty et al. 2015). These conflicts certainly lead to questions about the robustness of previous findings. To this end, existing research has important limitations.

2.2.3 Data Limitations

Much of the limitations referred to above, have to do with data. Firstly, existing results are based largely on limited samples – in terms of both number of stores, as well as number of products. Further, much of the direct evidence are based on relatively old data collected in the late 1980s and early 1990s, before the advent of the internet and e-commerce (e.g., Carlton 1986, Lach and Tsiddon 2007, Ray et al. 2006; Chen et al. 2008). Overall, this limited nature of the data constrains the inferences we can draw about the generalizability and contemporary relevance of the findings. To add to this challenge, emerging research such as Eichenbaum et al. (2014) and Campbell & Eden (2014), have raised concerns about measurement of small price changes in aggregated data. They contend that much of our observations of small price changes might be artifacts of aggregation and other data handling practices when data collectors convert transaction level price data into aggregated scanner price data. Therefore, re-examining small price changes for generalizability as well as the impact of measurement artifacts is in order.

2.2.4 Relevance of APIS and APIS-R in the retail pricing spectrum

A core element of the domain of small price changes is the phenomena of asymmetric pricing in the small (APIS and APIS-R). These are important for the marketers in as much as they are strategically deployed dynamic pricing tactics by the retailer. Nevertheless, only a few papers directly study the phenomena, and even the findings of this small set can be contradictory. In fact, to the best of our knowledge, only Chen et al. (2008) and Chakraborty et al. (2015) specifically study APIS. While Chen et al. (2008) report robust evidence of APIS and none for APIS-R, Chakraborty et al. (2015) find robust evidence of APIS-R as well. This paucity of studies in the domain and heterogeneity in results, further amplify the limitations identified earlier. Therefore, how generalizable APIS and APIS-R are, in terms of their prevalence in the economy, and their current relevance as part of the retailer's spectrum of pricing practices are important research questions. Specifically, what is the scale and scope of these phenomena after controlling for some of the measurement concerns raised in the literature? We contend that these concerns are non-trivial for the literature, and we expect a more definitive answer to these questions will help researchers in marketing advance studies in this domain further.

2.3. DATA

Researchers studying retail pricing using secondary data generally have access to two types of datasets. True *transactions datasets* are generated at the retail point of sale. *Aggregate datasets* are compiled from multiple transactions – e.g., prices of all transactions in a day (week) can be aggregated to create a daily (weekly) average price for the product. While there are a limited number of small price change studies with *transactions data* (cf. Ray et al. 2012, Wood et al. 2013 and Chakraborty et al. 2015), most utilize *aggregated price data* (cf. Ray et al. 2006, Lach & Tsiddon 2007, Chen et al. 2008, Levy et al. 2020). Not surprisingly, both data types have their advantages and disadvantages for studying our research problem. We first discuss these trade-offs then discuss the research datasets.

2.3.1 Aggregate versus Transactions data for our study

(a) Data Availability: A key limitation for any empirical study can be availability of data. Aggregate price data are more widely available (as argued by Besanko et al. 2003, Nakamura & Steinsson 2013) than transactions data. These datasets are compiled by both government agencies (e.g., CPI indices computed by BLS) and private market research firms (e.g., scanner data collected by Nilsen or IRI). Most market research data are only available for a fee (e.g., Nielsen), but some are freely available (e.g., Dominick's scanner data). In contrast, transaction level price data are mostly privately owned by retailers and not widely shared due to privacy and competitive concerns. In rare cases, researchers can only get hands on transaction price data by cooperating with the retailers. Hence research with such data is mostly restricted to researchers who have access, often slowing down the process of widespread scientific exploration.

(b) Ecological Validity: Available aggregate level datasets tend to cover much larger number of retailers, much broader ranges of product categories, much longer time periods, and much wider geographic areas compared with typical transaction level data. For instance, the Nilsen scanner data consists of point-of-sale weekly aggregated price data for almost all product categories in retail grocery and covers around 35,000 retail stores across the US for a long time period since 2006. The wider scope of such datasets allows for conclusions with greater ecological validity and generalizability – considerations that can be important for policy making. In contrast, most transaction price data are firm specific, covering relatively limited number of stores and product categories, and shorter time spans (e.g., the transaction price data used by Wood et al. 2013, Eichenbaum et al. 2014, Chakraborty et al. 2015). The limited nature makes them less suitable for studying prevalence in practice. Scraped data from online retailers attempt to address part of this limitation (Cavallo & Rigobon 2016, Cavallo 2018). Even these are limited by the numbers of participating retailers, and inability to know exact transactions e.g., individual level discounts and promotions are not visible to the researcher.

(c) Noise: The process of aggregating prices can introduce measurement errors and noises, as argued by Eichenbaum et al. (2014), Campbell & Eden (2014) and Cavallo (2018). Spurious price changes may be generated when transaction level price data is aggregated over time or aggregated across different products within a category (discussed with more details in section 5.3). True transaction price data are mostly free of this concern since all price observations are collected from actual retail purchase transactions.

(d) Scope: Transaction datasets tend to record more micro level transactions parameters compared to aggregate datasets. For example, transactions data may have information about consumers, loyalty points, as well as consumer specific promotions and discounts. For studies that consider individual purchase decisions, these are important. However, for studies such as ours, that endeavour to establish retail practice, they are less so.

To summarize the trade-offs in using transaction versus aggregate data for our research – while aggregate data would be preferred from the perspective of (a) and (b) above, concerns with (c) – noise, would make transactions data preferred. The micro-level parameters discussed in (d) are largely not relevant for our study. Therefore, in this paper, we take a multi-pronged approach. First, we undertake a detailed analysis of a large, aggregated dataset to leverage (a) and (b). Second, we carefully check for any potential impact of the noise discussed in (c), by undertaking various measures to eliminate spurious price changes. Third, using an independent transaction dataset we simulate and calibrate the impact of any presumed aggregation problem.

2.3.2 Data Description

We use the Kilts-Nielsen Retail Scanner Dataset (KNRS), an aggregated dataset, as our main data for the analyses, supplemented by a separate transaction price dataset for an additional analysis. The KNRS data is a panel dataset of total sales (quantities and prices) at the UPC (barcode) level for around 35,000 geographically dispersed stores belonging to more than 160 retail chains (these numbers vary by year) across all US markets[2]. The data consists of *weekly* pricing, volume, and store-merchandising information aggregated from transactions recorded by the stores' point-of-sale systems from the year 2006 to 2015. The strength of this data is evident: it provides an economy-wide context in a contemporary setting, enabling the best generalizability possible.

The KNRS data organizes the product hierarchy into ten product departments, which are then further organized into 125 product groups followed by product modules and the individual SKUs or UPCs. For ease of referencing, we will sometimes refer to the groups as categories and the modules as sub-categories. The product hierarchy of our sample is organized into 9 randomly chosen product departments, which are then further organized into 56 randomly chosen product groups consisting of 527 product modules (sub-categories), comprising 4,311,648 UPCs. Figure 2.1 shows the hierarchy of the categorization. Alcohol and tobacco products are excluded because those products are heavily regulated in US. The selected 56 product groups with 527 modules (sub-categories) cover most of the categories studied in previous research, including most of the 27 categories covered by Chen et al. (2008). Our sample comprises of 161 retailers, belonging to 91 parent companies. This represents a majority of retailers recorded in the full database. The data sample, in total contains more than 79 billion weekly price observations. The details of group level observations are reported in Table 2.1.

As a robustness check of the claims against data aggregation, we also analyze an independent smaller transaction price data. This dataset consists of two stores in the North-

[2] The full dataset covers more than 50% of the total sales volume of US grocery and drug stores and more than 30% of all US mass merchandiser sales volume.

West Milan region of Italy. We discuss this later in the analyses.

Figure 2.1 Hierarchy of the Product Categorization in the KNRS Data

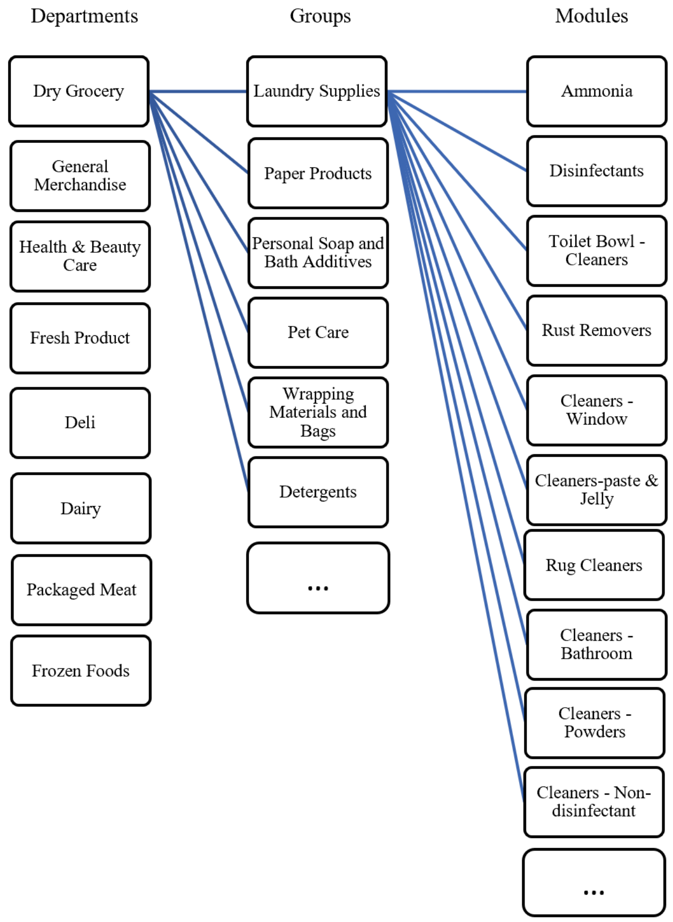


Table 2.1 Summary of Analyzed KNRS Data

Department Name	Group Name	No. of Modules	No. of UPCs	No. of Observations
Dry Grocery	Candy	14	289,747	5,907,425,280
	Gum	4	18,328	1,215,013,376
	Juice, Drinks - Canned, Bottled	18	107,917	3,592,290,560
	Pet Food	10	74,207	3,107,025,664
	Prepared Food-Ready-To-Serve	40	61,235	1,550,426,112
	Soup	5	42337	1882395136
	Baking Mixes	17	24596	781248704
	Breakfast Food	4	24107	1125582080
	Cereal	5	38266	1807372672
	Coffee	5	61510	1229685120
	Desserts, Gelatins, Syrup	12	20902	965305024
	Nuts	4	65059	1023383232
	Packaged Milk and Modifiers	6	17206	649159424
	Sugar, Sweeteners	5	9422	298786784
	Tea	8	61210	1257548928
	Bread and Baked Goods	14	299239	2605746688
	Cookies	2	102462	1891238912
	Crackers	10	30165	1107950976
	Snacks	18	213708	4488684544
	Soft Drinks-Non-Carbonated	9	59337	1618847360
Frozen Foods	Baked Goods-Frozen	12	18804	437997856
	Breakfast Foods-Frozen	2	14016	512820640
	Ice Cream, Novelties	4	91355	2096284544
	Juices, Drinks-Frozen	8	3441	157345696
	Pizza/Snacks/Hors Doeurves-Frzn	3	39026	944168256
	Prepared Foods-Frozen	23	96910	2701307648
	Unprep Meat/Poultry/Seafood-Frzn	15	39922	325982144
Dairy	Cheese	16	89513	1844350464
	Eggs	1	9941	94186312
	Milk	7	58193	746784320
	Snacks, Spreads, Dips-Dairy	4	32946	336883488
	Yogurt	2	36829	1207518976
Deli	Dressings/Salads/Prep Foods-Deli	16	128385	1779300864
Packaged Meat	Packaged Meats-Deli	12	105075	1786796416
	Fresh Meat	1	11147	122056672
Fresh Produce	Fresh Produce	25	121681	828927296
Non_Food Grocery	Detergents	6	34141	1644012160
	Household Cleaners	20	35886	1246793472
	Laundry Supplies	20	44919	1156176640
	Paper Products	11	178806	2523770112
	Personal Soap and Bath Additives	8	89812	1818637312
	Pet Care	9	143056	1081385344
	Wrapping Materials and Bags	13	28871	954846784
General Merchandise	Automotive	5	23392	291624032
	Batteries and Flashlights	2	39673	673595712
	Books and Magazines	1	13579	541083072
	Cookware	2	49007	348034592
	Glassware, Tableware	3	261232	925427968
	Kitchen Gadgets	8	264768	1246782592
	Toys & Sporting Goods	2	22885	25291164
Health & Beauty Care	Baby Needs	10	52799	680964096
	Hair Care	14	182990	3714681344
	Medications/Remedies/Health Aids	1	1879	89118656
	Oral Hygiene	12	50977	2499003648
	Skin Care Preparations	10	117057	1905587200
	Vitamins	9	157775	1907149312
Total #	56	527	4311648	79301793380

Note: to conserve space we do not include module level statistics, which are available from the authors upon request

2.4. MEASUREMENT AND ESTIMATIONS

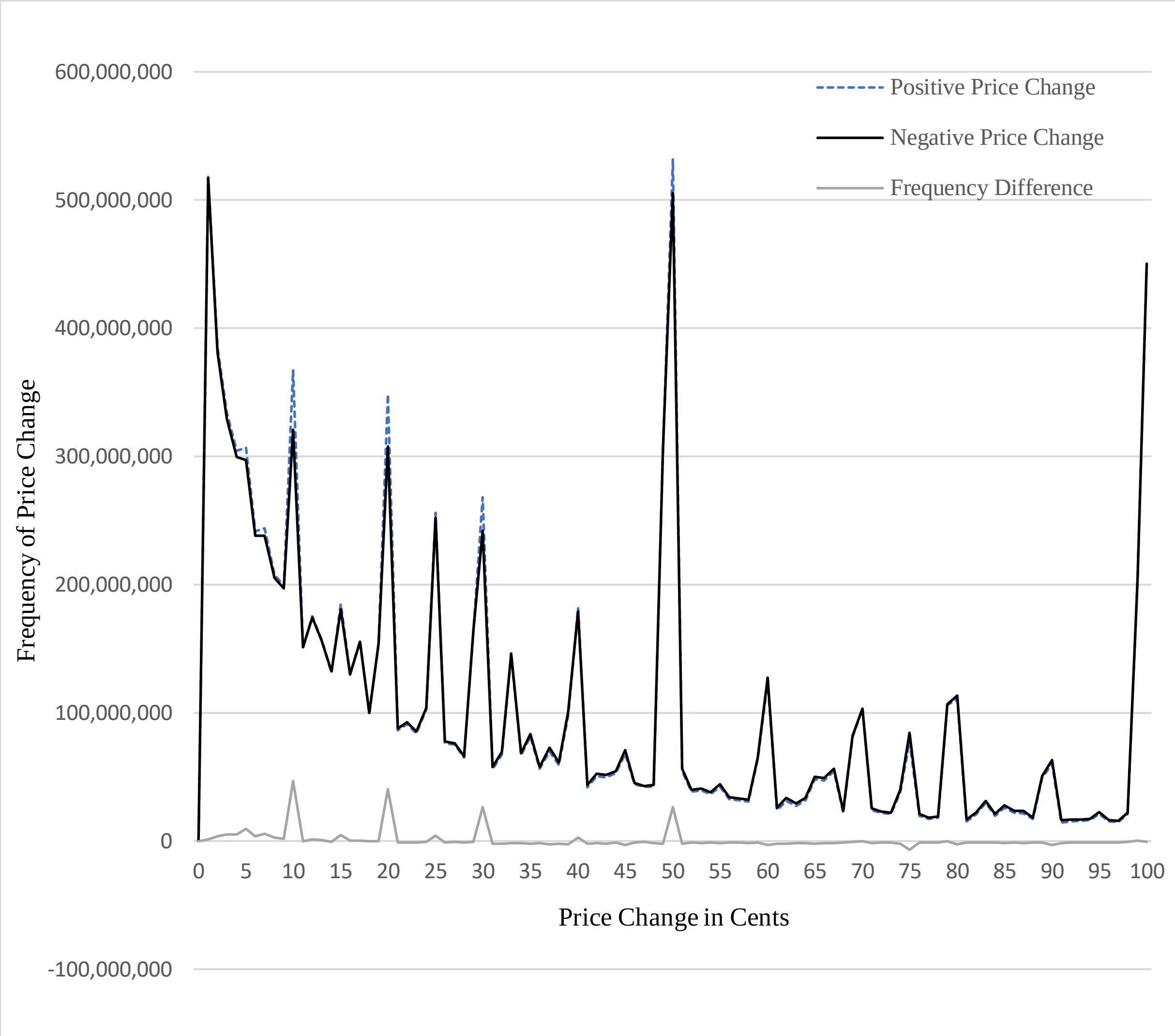
In this section, we look for evidence of, and estimate the nature and scale of APIS and APIS-R. For this we also need to identify what is "small" – i.e., the "asymmetry threshold." We estimate this threshold using the methods of Chen et al. (2008) and complement them with additional analyses and robustness checks to address measurement issues.

2.4.1 Asymmetric Pricing in-the-Small (APIS and APIS-R)

Following Chen et al. (2008), we analyze the frequency of both positive and negative price changes at different aggregation levels (e.g., category, retailer etc.). Product prices are measured by Unit Price in cents, which is calculated by dividing transaction price by Price Multiplier (see footnote 4). If a price is non-integer, we round it up to the next integer digit. Price changes are captured by calculating the unit price difference of a UPC between the current week and the previous week reported within a same store. The positive and negative price change frequencies are accumulated by each possible size of price change in cents: 1¢, 2¢, 3¢, etc., up to 1,000¢. For example, we calculate the number 5¢ price increases (and decreases) during the whole year (or the 10-year period) for all the UPCs in a certain product module.

In Figure 2.2, we plot the cross-category aggregated frequency of positive and negative price changes throughout the 10-year sample period in the KNRS data. This reveals the pattern of APIS – greater number of small price increases than decreases. This asymmetry exists for a range of up to about 10¢ of price-change. Beyond that range, the asymmetry disappears as the two lines start crisscrossing each other and the differences between positive and negative price change frequencies gradually converge to zero. Note also that the most frequent price change magnitudes are multiples of 10¢ – 10¢, 20¢, 30¢, 50¢, $1, $1.5, etc., which matches what Levy et al. (2011) find in their study of the 9-ending pricing phenomenon.

Figure.2.2 Aggregated Frequency of Price Changes in Cents (KNRS Data Full Sample)



2.4.2 Asymmetry Thresholds

We define the asymmetry threshold as the magnitude of price change below which asymmetric pricing is statistically supported. Following Chen et al. (2008), we compute the frequency distribution of the positive and negative price changes by the size of the change, starting with 1¢ and onwards. Then we identify the first point where the pricing asymmetry does not hold, i.e., the first point (from 1¢ price change to 1,000¢ price change) where we observe no statistical difference between the positive and negative price changes. We use a one-sample z-test of proportions to measure the statistical significance of the probability that the number of positive price changes equals the number of negative price changes – i.e., there is no asymmetry, at each price change magnitude. Rejection of this null hypothesis confirms the presence of asymmetry. The first point (from 1¢ price change to hundreds of cents price change in intervals of 1¢) where the null hypothesis of symmetric price change cannot be rejected, or the first point where the direction of asymmetry changes, is defined as the asymmetry threshold.

2.5. ANALYSES AND RESULTS

We first document the existence of APIS in the KNRS data as an overall average. Then we conduct three different analyses on the KNRS data controlling for various robustness concerns. In Analysis 1, we measure the APIS and APIS-R thresholds at different aggregation levels and for the low inflation or the deflation period sub-samples. In Analysis 2, we remove 1¢ price changes in order to eliminate any potential rounding bias. We then discuss the problem of spurious price changes raised by others such as Eichenbaum et al. (2014). We analyze a sub-sample where price change observations generated by price aggregation are partially removed in Analyses 3. We measure the asymmetry thresholds based on the sub-sample separately and compare them with the results in Analysis 1. If small price change asymmetry is still prominent after controlling for spurious price changes, it would be safe to say that APIS is a robust phenomenon in this dataset. We also analyze the separate two-store dataset to find evidence of APIS and APIS-R in a transaction level price data. And we simulate the effect of price aggregation on APIS and APIS-R, in an attempt to further test the robustness of our measurement with the aggregated price data. Finally, following Chen et al. (2008) we conduct several additional robustness checks on the KNRS data.

2.5.1 Analysis 1: Full Sample Asymmetric Thresholds

Analyzing the full sample of the KNRS data, we find that both APIS and APIS-R, systematically exists at different aggregation levels, with some variation in the thresholds across different categories. APIS is more prominent as the aggregation level goes up: the average threshold and the proportion of APIS increases significantly at the group and at the department levels compared with at the module level. Tables 2.2 and 2.3 report asymmetry thresholds at the product group and the department levels, respectively. Please see Table A2 in the Appendix for a summary of module level thresholds.

Overall, APIS patterns dominate at all aggregation levels. At the module level, 247 out of 527 (46.9%) modules exhibit APIS thresholds, whereas 164 modules (31.1%) exhibit APIS-R; the rest 116 (22%) have no asymmetry (i.e., the asymmetry threshold is 0). For most modules with APIS, the asymmetry thresholds fall in the range of positive 2¢ to 30¢, and in 10 modules (1.9%) the threshold is 1¢. The average thresholds are about 18.1¢ and 7.4¢ for APIS and APIS-R, respectively. The overall average asymmetry threshold is about 6.2¢. Figure 2.3 plots the distribution of asymmetry thresholds at the module level.

If we look at it at higher aggregation levels (groups and departments), APIS becomes more pronounced, but not so much APIS-R. At the group level, 31 product groups (55.4%) have an APIS threshold, and 22 groups (39.3%) have APIS-R thresholds (see Table 2.2). The overall average threshold is 13¢ at the group level, 6.8¢ higher than at the module level. Average APIS threshold is 27¢ at the group level, 8.9¢ higher than at the module level. Average APIS-R threshold is 4.7¢ at the group level, 2.7¢ higher than at the module level. The higher APIS thresholds are most pronounced at the department level where the average APIS threshold is 34.2¢ but four product departments have an average APIS-R threshold of 4.8¢ (see Table 2.3).

Table 2.2 Asymmetry Thresholds at Group Level in the KNRS Data

Department Name	Group Name	Analysis #1	Analysis #2	Analysis #3
DRY GROCERY	CANDY	-4	-4	-9
	GUM	0	-2	0
	JUICE, DRINKS - CANNED, BOTTLED	20	20	20
	PET FOOD	14	14	13
	PREPARED FOOD-READY-TO-SERVE	25	25	25
	SOUP	30	30	30
	BAKING MIXES	9	9	8
	BREAKFAST FOOD	-1	3	-1
	CEREAL	35	35	31
	COFFEE	0	10	-1
	DESSERTS, GELATINS, SYRUP	7	7	7
	NUTS	-2	0	-1
	PACKAGED MILK AND MODIFIERS	16	16	16
	SUGAR, SWEETENERS	21	21	22
	TEA	10	10	10
	BREAD AND BAKED GOODS	60	60	39
	COOKIES	-1	30	25
	CRACKERS	41	41	50
	SNACKS	35	35	14
	SOFT DRINKS-NON-CARBONATED	-1	12	-1
FROZEN FOODS	BAKED GOODS-FROZEN	21	21	14
	BREAKFAST FOODS-FROZEN	-1	16	-1
	ICE CREAM, NOVELTIES	30	30	13
	JUICES, DRINKS-FROZEN	24	24	23
	PIZZA/SNACKS/HORS DOEURVES-FRZN	0	8	-1
	PREPARED FOODS-FROZEN	25	25	23
	UNPREP MEAT/POULTRY/SEAFOOD-FRZN	78	78	77
DAIRY	CHEESE	32	32	14
	EGGS	34	34	34
	MILK	21	21	21
	SNACKS, SPREADS, DIPS-DAIRY	14	14	13
	YOGURT	5	5	5
DELI	DRESSINGS/SALADS/PREP FOODS-DELI	-1	21	-1
PACKAGED MEAT	PACKAGED MEATS-DELI	72	72	66
	FRESH MEAT	48	48	48
FRESH PRODUCE	FRESH PRODUCE	48	48	48
NON_FOOD GROCERY	DETERGENTS	1	-3	2
	HOUSEHOLD CLEANERS	1	-4	0
	LAUNDRY SUPPLIES	-1	2	-1
	PAPER PRODUCTS	-3	-3	-3
	PERSONAL SOAP AND BATH ADDITIVES	-4	-4	-5
	PET CARE	-4	-4	-4
	WRAPPING MATERIALS AND BAGS	26	26	28
GENERAL MERCHANDISE	AUTOMOTIVE	27	27	28
	BATTERIES AND FLASHLIGHTS	-5	-5	-5
	BOOKS AND MAGAZINES	-20	-20	-12
	COOKWARE	-9	-9	-9
	GLASSWARE, TABLEWARE	-9	-9	-9
	KITCHEN GADGETS	-9	-9	-9
	TOYS & SPORTING GOODS	-2	0	-2
HEALTH & BEAUTY CARE	BABY NEEDS	-6	-6	-6
	HAIR CARE	-9	-9	-6
	MEDICATIONS/REMEDIES/HEALTH AIDS	6	6	6
	ORAL HYGIENE	-5	-5	-4
	SKIN CARE PREPARATIONS	-4	-4	-4
	VITAMINS	-3	-3	-3
	Avg. APIS	27.0	25.3	24.9
	Avg. APIS-R	4.7	6.1	4.3
	APIS Count	31	37	31
	APIS-R Count	22	17	23

Note: a negative value in the field indicates an APIS-R.

The asymmetry also varies across retailers (chains). We find that 133 out of 161 retailers (82.6%) exhibit some form of asymmetry in the small: 93 exhibiting APIS and 40 APIS-R. Overall, the average APIS and APIS-R thresholds are 21.4¢ and 9.5¢, respectively. 59 retailers (36.6%) exhibit APIS thresholds of 10¢ or higher. In contrast, only five APIS-R thresholds exceed 10¢ and most APIS-R thresholds (22 out of the 40) are smaller than 5¢. Figure 2.4 plots the distribution of asymmetry thresholds using Retailer Code to identify the retail chains.

Table 2.3 Asymmetric Price Change Thresholds at Department Level for Inflation Analyses (KNRS Data)

Department Name	**Full Sample (Analysis #1)**	**Analysis #3**	**Low Inflation Sample (PPI)**	**Deflation Sample (PPI)**	**Inflation Sample (PPI)**
HEALTH & BEAUTY CARE	-6	-6	-2	-6	-5
DRY GROCERY	11	10	1	-1	13
FROZEN FOODS	30	26	11	11	21
DAIRY	10	8	7	10	10
DELI	-1	-1	-9	-1	-1
PACKAGED MEAT	72	66	21	50	38
FRESH PRODUCE	48	48	68	48	68
NON_FOOD GROCERY	-3	-3	-4	-3	3
GENERAL MERCHANDISE	-9	-9	-3	-9	-9
Avg. Threshold	**16.9**	**15.4**	**10.0**	**11.0**	**15.3**
Avg. APIS	**34.2**	**31.6**	**21.6**	**29.8**	**25.5**
Avg. APIS-R	**4.8**	**4.8**	**4.5**	**4.0**	**5.0**
APIS Count	**5**	**5**	**5**	**4**	**6**
APIS-R Count	**4**	**4**	**4**	**5**	**3**

Note: a negative value in the threshold field indicates an APIS-R threshold.

Figure 2.3 Asymmetry Thresholds Distribution at Module Level for Analyses 1, 2 and 3(KNRS Data)

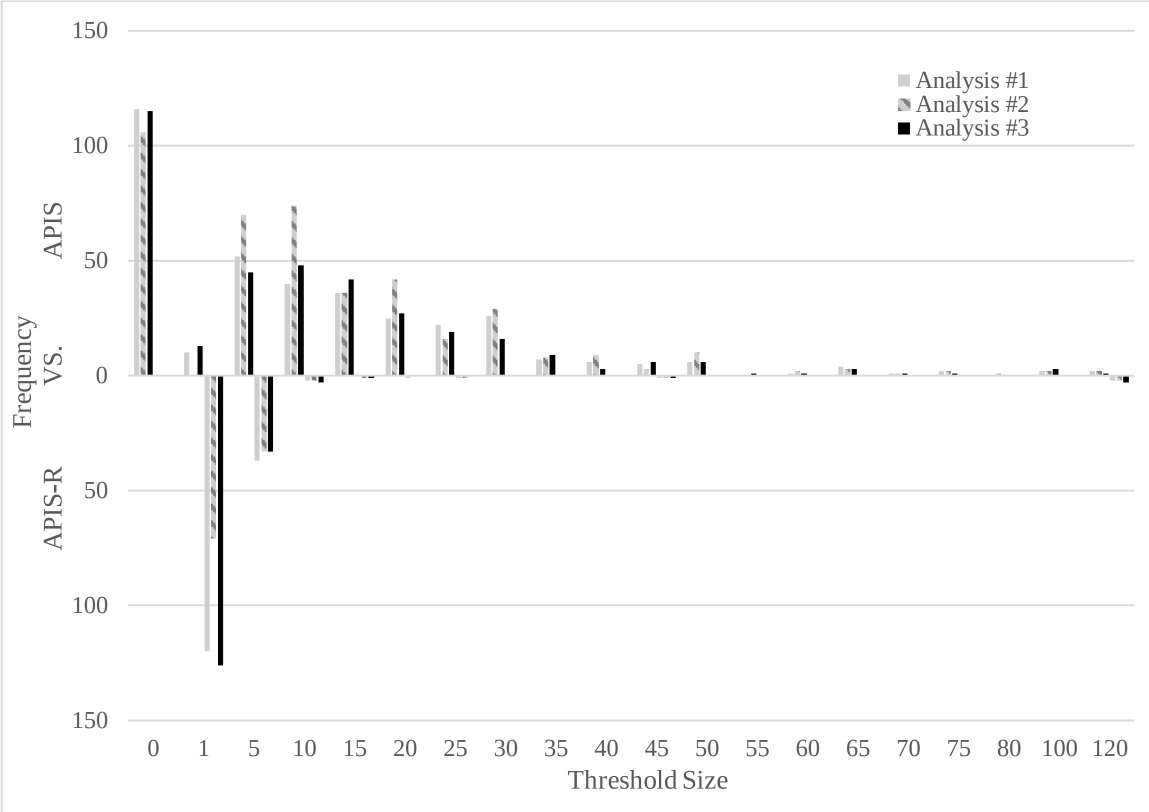
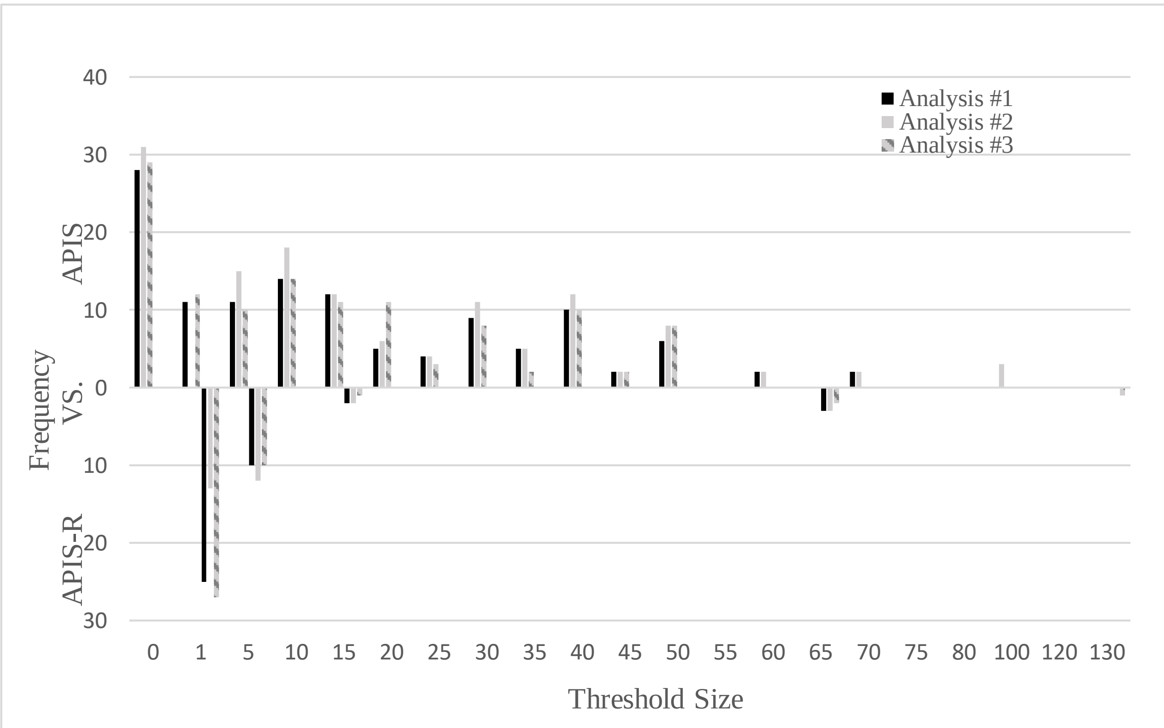


Figure 2.4 Asymmetry Thresholds Distribution at Retailer Level for Analysis 1, 2 and 3 (KNRS Data)



Controlling for Inflation

When examining the annual variation in the asymmetry thresholds, we find that the average threshold generally decreases over time from 2006 to 2015 as illustrated in Table 2.4. The United States was experiencing a moderate inflation in most of the sample years (except for 2009), with an annual rate of 3.85% to 0.12% (CPI Index). A trend of decreasing inflation rates is found throughout the sample period (see Table 2.4). In Chen et al. (2008), inflation is found to account for part of the asymmetry, because during inflation, more price increases than decreases are expected (Ball and Mankiw, 1994). Given our large sample size, we can control for inflation by applying the same method as in Chen et al. (2008).

Table 2.4 Asymmetric Price Change Thresholds at Yearly Level (KNRS Data)

Year	**Threshold**	**CPI Inflation Rate (%)**	**PPI Inflation Rate (%)**
2006	21	3.23	1.6
2007	21	2.85	7.85
2008	37	3.84	-4.31
2009	-4	-0.36	4.21
2010	-1	1.64	6.51
2011	30	3.16	5.32
2012	-1	2.07	0.85
2013	-9	1.46	0.25
2014	8	1.62	-2.48
2015	-2	0.12	-6.85
Avg.	**10.0**	**2.0**	**1.3**

Note: a negative value in the threshold field indicates an APIS-R threshold.

We conduct three analyses with three monthly sub-samples grouped by monthly inflation rates. The first sub-sample, which we define as the low-inflation period sample, only includes observations during which the monthly PPI inflation rate was positive but did not exceed 0.1% (only two months are identified as low-inflation period during the 2006–2015 period: August 2010 and June 2013). The second sub-sample is more conservative in which only months with non-positive inflation rate are included (the PPI inflation rate used is not seasonally adjusted). This sample, which covers 49 months with an average monthly inflation rate of about –1.06%, is defined as the deflation period sample. The third sample, which covers 47 months with an average monthly inflation rate of about 1.3%, is defined as the inflation period sample, where only months with PPI inflation rate higher 0.5% are kept. The analysis results at product department level are summarized in Table 2.3. See Table A3 in the Appendix for results at product group level.

We find that most of the module-level thresholds in the deflation sample are between 0 and 15¢. The average APIS threshold is about 11.8¢, 6.4¢ lower compared to the full sample, and an average APIS-R threshold is 4.4¢, which is 3¢ lower compared to the full sample. APIS is in 218 out of 527 modules. APIS-R become slightly more prominent, in 176 out of the 527 modules, but most thresholds are smaller than 5¢. At the product group level, the average APIS threshold is 19.7¢, which is 7.3¢ lower than the full sample result. The average APIS-R threshold is 3.2¢, 1.5¢ lower than the full sample result.

In the low-inflation sample, 27.7% of the modules exhibit APIS, with an average threshold of about 5.3¢. 26.8% of the modules exhibit APIS-R with an average threshold of 3.8¢. The average APIS threshold increases to 9.5¢, and the average APIS-R threshold increases to 4.1¢ at the group level.

Finally, we find that in the inflation sample, the proportion of modules with APIS increases to 52.2% (275 out of 527), while 26.9% (142 out of 527) of the modules still exhibits APIS-R. The module level average APIS threshold is 12.6¢, even smaller than 18.1¢ found in the full sample, and comparable with the deflation period sample. The average APIS-R threshold is 5.3¢, close to the deflation sample level. We find similar figures at the group level. The number of groups with APIS increases, but still there are 19 groups with APIS-R, and we see a decrease of APIS thresholds compared with the full sample.

In sum, the proportion of APIS thresholds decreases during the low-inflation and deflation periods, while the APIS-R thresholds are not influenced much. The proportion of APIS increases in the inflation sample, where fewer APIS-R are observed. At the product module level, the average APIS threshold in the full sample is 18.1¢. It decreases to 5.3¢ in the low-inflation sample, and to 11.8¢ in the deflation-period sample. However, the average APIS-R threshold is actually slightly higher in the inflation-period sample, than in the low-inflation and deflation samples.

At the group level, the overall average threshold also decreases during both the low inflation (from 13.1¢ to 3¢) and the deflation (to 6.9¢) periods. This indicates that inflation indeed plays a role in the formation of APIS as Chen et al. (2008) suggest. Specifically, during the low inflation and the deflation periods, APIS is not as significant as in the inflation period, and the proportion of APIS-R increases, vice versa in the inflation sample. However, under most circumstances both APIS and APIS-R thresholds systematically exist among a large portion of the products. Further, APIS categories always tend to have larger thresholds than APIS-R, even during deflation periods. We thus conclude that the asymmetry "in the small" still holds after ruling out the influence of inflation.

2.5.2 Analysis 2: Excluding 1¢ Price Changes to account for rounding

Recall that in calculating price changes, we had to round up non-integer price changes to the next integer, and thus all smaller-than-1¢ price changes appear as 1¢ changes. This may lead to an inaccurate measurement of some thresholds, because the asymmetry thresholds are identified by the first price-change where asymmetry is not statistically supported starting from 1¢. We indeed observe a large number of 1¢ price changes. We also find that a large portion of 1¢ APIS-R thresholds, which may be due to this noise – e.g., we find 54 1¢ APIS-R thresholds at the module level, comprising 10.2% of all the modules, and 32.9% of all APIS-R thresholds.

To check the impact of such rounding, we re-do all the estimations in Analysis 1 using the same samples but with all 1¢ price changes excluded. This results in removing about 1.03 billion price changes – about 1.3% of the erstwhile calculations. We find larger average thresholds and larger portion of APIS thresholds at almost all aggregation levels. At the module level, 58.8% of the thresholds are APIS compared to 46.9% in Analysis 1. The average thresholds are about 18.2¢ and 11¢ for APIS and APIS-R, respectively (see Table A2 in the Appendix). At the product group level, 17 groups exhibit APIS-R and 37 groups (66%) exhibit APIS, compared with 55.4% in Analysis 1. The overall average threshold is about 14.9¢, 1.8¢ higher than in Analysis 1. At the group level, the average APIS and APIS-R thresholds are 25.3¢ and 6.1¢, respectively (see Table 2.2). At the product department level, all categories remain the same except for Deli, the threshold of which changes from APIS-R 1¢ to APIS 21¢ (see Table 2.3).

To summarize, after excluding 1¢ price changes, we observe more APIS thresholds. Most 1¢ APIS-R thresholds turn into significant APIS thresholds, rather than APIS-R thresholds of other size, or no-asymmetry. This indicates that 1¢ price changes may contribute to the underestimation of asymmetry, especially APIS.

2.5.3 Assessing the Effects of Spurious Small Price Changes

The potential impact of aggregating from transactions data, on the estimation of small price changes has attracted some concern in recent times. Given their importance we address the concerns in two ways. First, we run our analyses attempting to control for much of the presumed artifacts. Second, we use an actual transactions dataset to compare the results before and after aggregation to establish the severity of the problem. We first discuss the nature of the concerns here followed by the analyses.

Eichenbaum et al. (2014) and Campbell and Eden (2014) argue that a large number of small price changes in some scanner data sets are due to measurement errors. Campbell and Eden (2014) note that technical errors and time aggregation (weekly prices computed by averaging daily prices) can potentially cause these measurement errors. Eichenbaum et al. (2014) argue that the two major sources of spurious small price changes in scanner data sets are unit value indices (UVIs), and bundle pricing. They use CPI and scanner data from multiple stores to show how UVI, i.e., the ratio of sales revenue from a product to the quantities sold in each transaction, affect the prevalence of small price changes (in the similar way as the 'time aggregation effect' suggested by Campbell and Eden). They note that if a single item is purchased for different prices within a week, e.g., some consumers get a discount while others don't, a spurious change would be induced in UVI-based pricing. They find that by removing problematic CPI items, the fraction of small price changes (which they define as prices changes smaller than 1%) in CPI dataset drops from 12.5% and 14% to 3.6% and 5%, for posted and regular prices respectively. They further test the extent of the existence of spurious price changes by using a dataset with actual transaction prices and compare the difference of price change distribution between UVI-based pricing and transaction prices. They find that by applying UVI method, the fraction of smaller-than-one price changes increased from 1.7% to 8.4%. In sum, three major sources of spurious price changes have been suggested in the existing literature: bundle pricing, UVIs price measurement method, and human or system errors.

Although these measurement issues are common in UVI-based scanner datasets, only a handful of papers attempt to address them. Cavallo (2018) address this by using alternative datasets that are immune to this issue. Gorodnichenko and Talavera (2017), discard smaller than 1¢ price changes because of their suspicion that these changes arise from measurement errors. Campbell and Eden (2014) replace fractional prices with the minimum price of the week reported in the matching individual purchase history dataset with transaction prices. For the remaining prices that have no matching transaction histories, they replace the fractional prices by either one of the two closest integer prices if they are a part of a decreasing or increasing sequence of prices. Alvarez et al. (2014) remove extreme price changes (smaller than 0.1% or larger than 120%) and smaller than 1¢ price changes from two scanner data sets (Dominick's and IRI scanner dataset). They find that the resulting distribution of price changes matches the distribution found in datasets that are immune to this type of errors.

We do notice that there are fractional price changes in the KNRS dataset, which may have influenced our threshold measurement, even after 1¢ price changes are removed. According to the data provider, our data set does use UVIs. The weekly price reported is a “volume-weighted average unit price,” i.e., the weekly price is a weighted average of true transaction prices. If a certain item is sold at different prices within a week the varying prices will be factored into the weighted average weekly price, resulting in a very small decrease (sometimes a non-integer decreases) from the regular price. Such situations can arise, e.g., when retailer discount or manufacturer coupons are not applied to all transactions of that week, or price discounts are given only to loyalty cardholders.

Another source of spurious price change is the use of bundle pricing (as pointed out by Eichenbaum et al. 2014). If a certain item is sold in a bundle as a promotion, the unit price may contain small fractions being divided by the price multiplier (number of units in one bundle), generating a non-integer small price change compared to the regular price.

Unfortunately, it is impossible to evaluate accurately to what extent our data is influenced by these types of price measurement problem, because we do not have the actual transaction prices for the KNRS data. On the other hand, it seems reasonable to expect the irregularly generated small price-changes would be random and symmetrically distributed. When an irregular or spurious small price decrease occurs due to a temporary price deduction (such as due to a coupon or a loyalty card use), a price increase would be expected after the promotion period.

We first test sub-samples of our KNRS data set by removing observations that may be generated by UVI price measurement methods. Then we use a separate transaction price dataset to simulate the impact of weekly aggregated prices on the estimated APIS/APIS-R thresholds.

2.5.4 Analysis 3: Bundle Pricing, Non-Integer Prices and Extreme Price Changes

We now drop all the observations that have a price multiplier greater than 1, and all the price changes due to the change of price-multiplier in the KNRS data. We also drop all fractional price changes. Our KNRS data set does consist of a large number of non-integer price changes, which we round up to the next integer when tabulating price change frequencies in Analysis 1. All the fractional prices should be a result of UVI price measurement methods since our price measurement unit is the cent. In addition, we exclude all extreme price changes (those that are smaller than 0.1% or larger than 120%), following Alvarez et al. (2014). Alvarez et al. (2014) exclude extreme price changes as well as smaller than 1¢ price changes, in their analyses of two scanner data sets (Dominick's and IRI scanner dataset). They find that the resulting distribution of price changes matches the distribution found in datasets which are immune to this kind of errors. We take their method further by not allowing for any fractional price changes.

In this subsample, we observe an average APIS threshold of 24.9¢ at the group level, 2.1¢ lower compared with the full sample, and an average APIS-R threshold of 4.3¢, 0.4¢ lower compared with the full sample. We find almost the same number of APIS thresholds and APIS-R thresholds compared with the full sample (31 APIS and 23 APIS-R, compared with 31 and 22 in the full sample). The number of the groups with no asymmetry drops slightly from 3 to 2, which means that more than 96% of the groups still exhibit asymmetry. At the department level, we still observe 6 APIS and 3 APIS-R out of the 9 departments, with an average APIS threshold of 25.5¢ and an average APIS-R threshold of 5¢.

Figure 2.3 shows the distribution of the asymmetry thresholds at the module level for Analysis 1, 2 and 3. By removing fractional price changes, extreme price changes and price changes due to bundle pricing, we observe about the same proportions of APIS and APIS-R with slightly lower average APIS threshold at different level of aggregation. This implies that spurious prices indeed influence the measurement of asymmetry thresholds to a small extent, but do not account for the majority of the pricing asymmetry we observe. Systematic pricing asymmetry "in the small" is still found in this subsample, even after taking measures to control for spurious price changes. Hence, we consider the asymmetry "in the small" regularity still holds in our KNRS data even if many small price-changes are the artifacts of various measurement errors, as our analyses suggest.

2.5.5 Simulating the impact of aggregation with transaction level price data

The price observations in our main dataset (the KNRS dataset) are volume weighted average price for the week. This price aggregation (or unit value indices (UVIs)) is argued as the main source of spurious price changes (Eichenbaum et al. 2014). To simulate this impact, we analyze a separate smaller transaction price data, consisting of two stores in the North-West Milan region of Italy (stores A and B). Both stores belong to one of the largest grocery chains in the country. Store A is a High-Low (HILO) type store and store B is a Every Day Low Price (EDLP) store. The data includes sales-receipts generated at the point of sale over about a one-year period starting July 2007 – around 2.6 million price observations for Store A and 3.4 million for Store B[3]. See Table A1 in the Appendix for some summary statistics.

We convert the transaction price observations in our two-store data into weekly weight average prices the same way KNRS dataset was handled. After conversion, we observe more frequent small price changes in Store B which is a EDLP type store. EDLP

[3] Data of Store A covers the period from July 2nd, 2007, to October 27, 2008, a total of 68 weeks. Data of Store B covers the period from July 16, 2007, to September 8th, 2008, a total of 59 weeks.

stores typically do not change price frequently. Many of price changes recorded are generated by coupon discounts, which is a main source of spurious price change during weekly price aggregation. On the other hand, we observe smaller amount of price changes after conversion in Store A, which is a HILO store (see price change frequency distribution of the two stores in Figure 2.5). This implies that the frequency (or proportion) of small price changes does not necessarily increase when prices are aggregated, as opposed to Eichenbaum's (2014) findings.

The price observations in the two-store data are reported at receipt level, i.e., each price observation represents the true price a customer paid in an actual transaction. There are discounts applied in certain transactions that may not apply for all transactions on the same item the same day (e.g., when a customer used a coupon). Hence, we may observe different transaction prices for a same item in the same day while the retailers only have one listing price for each item. To identify a daily price series, we define the median transaction price of an item in a day as the daily transaction price of the item. And we define the weekly aggregated price of an item in a store as the volume weighted average price of the week (total sales of an item divided by total quantity sold in the week). We drop items which are measured by weights scale since we are not able to calculate unit prices of these items. We then estimate the APIS/APIS-R of the daily transaction price sample and the weekly aggregated price sample separately. The results are summarized in Table 2.5 and Table 2.6.

We find that APIS and APIS-R exists in both samples before and after the conversion for both stores. For Store A, 3 out of the 19 product departments exhibit different asymmetry patterns at department level after conversion. For Store B, 2 out of the 6 departments exhibit different asymmetry patterns after prices are aggerated weekly[4]. We also notice that by price

[4] For Store B, there are 8 product departments with measurable unit price during the sample period. We only observe price changes in 6 out of the 8 departments.

aggregation, it can either underestimate or overestimate the APIS/APIS-R threshold in the few cases when the asymmetry patterns change. To further verify whether these differences are statistically significant we apply two sample mean T-Test of the asymmetry thresholds before and after conversion for both stores. The results at department level indicate no rejection of the null hypotheses that the means of the two samples are the same. We repeated the tests at department-year level, and still do not observe statistically different asymmetry patterns.

Thus, we observe that price aggregation does not systematically change the APIS or APIS-R patterns in our simulation. In particular, this aggregation may be underestimating the magnitude of asymmetry. Hence, we conclude that the APIS and APIS-R phenomenon cannot entirely be artifacts due to data handling such as price aggregations (UVIs). As such our estimated APIS and APIS-R patterns can be considered reasonably robust observations.

Table 2.5 Asymmetric Price Change Thresholds at Dept. Level for the Transaction Price Data

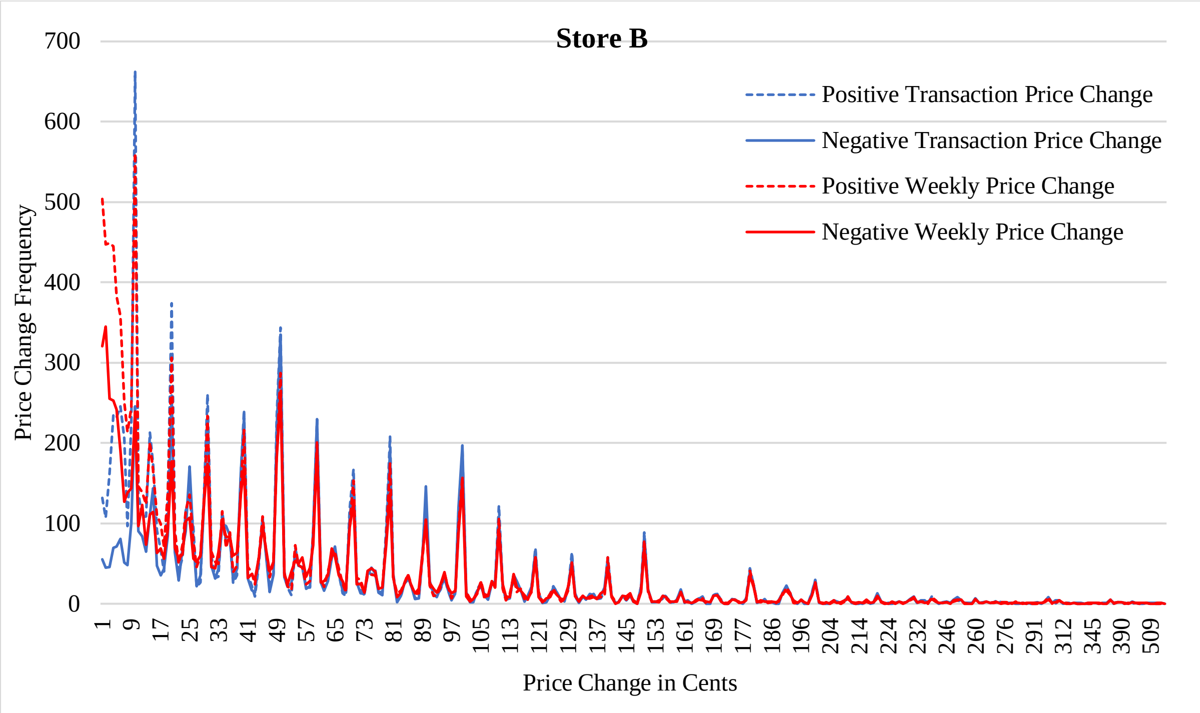
Dept. Name	**Store A**		**Store B**	
	Transaction Price	**Weekly Aggregate Price**	**Transaction Price**	**Weekly Aggregate Price**
Canned food	0	11	11	11
Canned products (not food)	0	6	0	1
Butcher's shop	0	0	0	2
Fruit and vegetables	0	0	0	0
Delicatessen	0	0	0	0
Dairy products	1	2	0	0
Bread	0	0		
Deep-frozen food	0	0		
Fishmonger's	0	0		
General store/ steward's office	0	0		
Affiliation	0	0		
Low level pharmacy/ Newspapers	0	0		
General store	0	0		
Textile/ household linen	0	0		
Housewares	0	0		
Toys	0	0		
Stationery store	0	0		

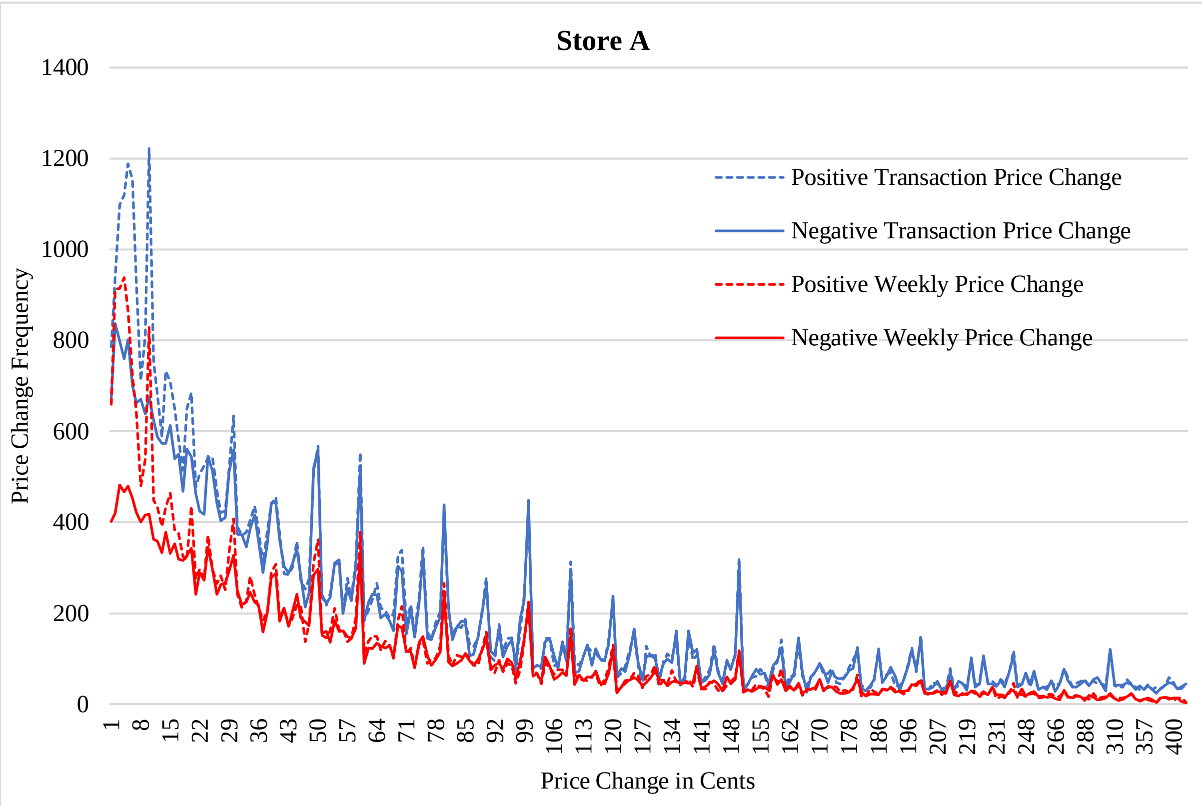
Underwear	7	7		
Support department	0	0		
Avg.	**0.4**	**1.4**	**1.8**	**2.3**

Table 2.6 Asymmetric Price Change Thresholds at Dept-Year Level for the Transaction Price Data

Dept. Name	**Year**	**Store A**		**Store B**	
		Transaction Price	**Weekly Aggregate Price**	**Transaction Price**	**Weekly Aggregate Price**
Canned food	2007	0	7	0	0
Canned products (not food)	2007	0	6	0	0
Butcher’s shop	2007	0	0	3	1
Fruit and vegetables	2007	0	0	0	0
Delicatessen	2007	0	0	0	1
Dairy products	2007	3	1	0	0
Bread	2007	0	0		
Deep-frozen food	2007	0	0		
Fishmonger’s	2007	0	0		
General store/ steward’s office	2007	0	0		
Low level pharmacy/ Newspapers	2007	0	0		
General store	2007	0	0		
Textile/ household linen	2007	0	0		
Housewares	2007	0	0		
Stationery store	2007	10	10		
Underwear	2007	0	0		
Support department	2007	0	0		
Canned food	2008	17	11	11	21
Canned products (not food)	2008	0	0	0	0
Butcher’s shop	2008	0	0	0	2
Fruit and vegetables	2008	1	0	0	0
Delicatessen	2008	0	0	0	-1
Dairy products	2008	0	0	0	0
Bread	2008	0	0		
Deep-frozen food	2008	0	0		
Fishmonger’s	2008	0	0		
General store/ steward’s office	2008	0	0		
Affiliation	2008	0	0		
General store	2008	0	0		
Textile/ household linen	2008	0	0		
Housewares	2008	0	0		
Toys	2008	0	0		
Stationery store	2008	0	0		
Underwear	2008	7	7		
Support department	2008	0	0		
Avg.		**1.1**	**1.2**	**1.2**	**2.0**

Figure 2.5 Transaction and Weekly Price Change Frequency Distribution (Two-Store Transaction Data)





2.5.6 Additional Robustness Tests

We conduct three additional tests to check the robustness of our results with the KNRS data. All tests confirm that asymmetry in-the-small is systematic and that inflation only partially explains the asymmetry.

Alternative Measures of Inflation

Since the earlier analyses used PPI inflation rates., we repeat them using inflation rates from CPI. The findings are similar. The average APIS threshold in the low inflation samples is 7.7¢ at the module level and 12¢ at the group level. The average APIS threshold for the deflation period is 13.2¢ at the module level, and 20.1¢ at the group level. During periods with a larger than 0.5% CPI inflation rates, the average group level threshold is still close to the results we obtained using the PPI inflation (see Table A4 in the Appendix for group level results).

Lagged Price Adjustment

We allow for lagged price adjustment and repeat the analysis with 4-, 8-, 12- and 16-week lags after the PPI-deflationary periods. The results show that the asymmetry still holds at different aggregation levels, averaging an APIS threshold of 9.2¢ at the module level and 12.5¢ at the group level when 4-week lag is applied. (See Table A5 in the Appendix).

First Year Sample versus Last Year Sample

Finally, to further control for the effects of inflation, we compare the asymmetry thresholds during the first year of our sample period with the ones during the last year at the module level. Since there is an upward inflation trend during 2006–2015, we are supposed to see stronger APIS in the last year if inflation is causing the asymmetry. The results indicate that in 247 of the 512 modules (the number of modules differs in each year), an APIS threshold is found in the first-year sample, but only 146 APIS thresholds (out of 524 modules) are identified in the last year. Most APIS thresholds are smaller in the last year compared with the first year (an average of 10.5¢ in the first year vs. 4.4¢ in the last year). We get similar results at the retailer level. Among the 93 retailers in the first year, for 56 (60.2%) of them we find APIS. That number drops to 42 (40.4% out of 104 retailers) in the last year. The average APIS threshold also decreases from 12.5¢ in the first year to 9.7¢ in the last year at retailer level.

2.5.7 Summary of the Results

Through our analyses, we find that APIS and APIS-R systematically exists and varies among a vast majority of the product categories and the retailers in both datasets. APIS is more prominent than APIS-R in most scenarios.

The findings are consistent throughout different robustness checks we conduct. In the first analysis, with our main dataset, we find 78% of the product modules exhibit asymmetry in the small. The average APIS and APIS-R thresholds are 18.1¢ and 7.4¢, respectively, at the module level. When examined at the retailer level, we find that APIS is the dominant pricing pattern for 57.8% of the retailers, while APIS-R dominates for about 24.8% of the retailers.

Both types of asymmetries still hold when we control for inflation. We find APIS-R becomes more prominent during deflation periods, while APIS is more prominent during higher inflation periods. However, APIS still accounts for a significant portion of the asymmetries even in the deflation periods (e.g., 41.3% of the modules in the deflation sample exhibit APIS). On the other hand, during months with a higher than 0.5% monthly inflation rate, we observe 26.9% of product modules exhibit APIS-R. This shows that while inflation plays a role in the formation of asymmetric pricing in the small, it is not the only factor; as otherwise, we would observe little or no APIS during deflation, or vice versa during inflation.

After controlling for noisy 1¢ price changes in Analysis 2, we observe that the proportion of the modules with APIS thresholds increases significantly (from 46.9% to

58.8%) and the average threshold of APIS-R goes up to 11¢ at the module level. This result implies that 1¢ price rounding artifacts do not likely lead to an underestimation of APIS with our threshold measurement method. This further validates the strong existence of asymmetry “in the small” in our dataset.

In Analysis 3, we still observe systematic asymmetries after taking measures to account for potential price measurement artifacts. The number of categories that exhibit APIS closely matches previous analyses. The average APIS threshold does decrease slightly for 2.1¢ at group level, while the average APIS-R threshold only decreases by 0.4¢ compared with the result for the full sample. In the additional analyses, we confirm the robustness of the findings in KNRS dataset by considering alternative measures of inflation, lagged price changes, and comparing thresholds in the first and the last years of the sample. We conclude that UVIs indeed influence the measurement accuracy of the asymmetric thresholds. Yet, while, our efforts cannot remove all spurious small price changes in our main data, our results suggest that the core observation of asymmetry in the small is robust.

In the analysis with the independent transaction level data, we do not observe statistically different APIS/APIS-R patterns after the transaction level prices converted into weekly aggregated prices. Hence, all results suggest that asymmetric price changes in the small is a robust phenomenon and exist across different types of price data – aggregated prices and transaction prices, and across different levels of aggregation – products, retailers, and time periods. Importantly, the finding is robust to various controls including potential measurement errors and the inflation level.

Table 2.7 Comparison of Asymmetry Threshold Results with Chen et al. (2008)

Product Categories		**Full Sample**		**Low Inflation Sample**		**Deflation Sample**	
Chen et al. 2008	**This paper**	**Chen et al. 2008**	**This paper**	**Chen et al. 2008**	**This paper**	**Chen et al. 2008**	**This paper**
Analgesics	Tooth & Gum Analgesics (module)	30	6	10	0	10	6
Bath soap	Soap- Bar (module)	6	-3	0	-8	0	-4
Bathroom tissues	TOILET TISSUE (module)	6	25	4	0	4	3
Bottled juices	JUICE, DRINKS - CANNED, BOTTLED (group)	12	20	15	-8	12	30
Canned soup	Soup- Canned (module)	12	30	12	9	10	11
Canned tuna		1		2		1	
Cereals	Cereal (group)	29	35	24	2	1	-1
Cheeses	Cheese (group)	9	32	9	2	9	12
Cookies	Cookies (group)	11	-1	11	-2	9	-1
Crackers	Crackers (group)	10	41	2	-1	4	13
Dish detergent	Automatic Dishwasher Compounds (module)	5	-2	4	0	6	-2
Fabric softeners	FABRIC SOFTENERS-LIQUID (module)	5	0	11	3	7	0
Front-end-candies	CANDY (group)	5	-4	5	1	5	-3
Frozen dinners	Dinners-Frozen (module)	2	-3	10	0	6	3
Frozen entrees	ENTREES - MEAT - 1 FOOD - FROZEN (module)	20	8	22	11	0	2
Frozen juices	Juices, Drinks-Frozen (group)	9	24	9	0	10	0
Grooming products	HAIR CARE (group)	20	-9	12	-2	12	1
Laundry detergents	Detergents (group)	16	1	13	-4	17	-4
Oatmeal		25		2		5	
Paper towels	Paper Towels (module)	2	11	2	1	2	-1
Refrigerated juices		15		9		6	
Shampoos	SHAMPOO-AEROSOL/ LIQUID/ LOTION/ POWDER (module)	0	-9	10	-1	10	1
Snack crackers	Crackers - Flavored Snack (module)	11	0	2	-2	2	2
Soaps	SOAP - BAR (module)	1	-3	1	-8	1	-4
Soft drinks	Soft Drinks-Non-Carbonated (group)	5	-1	3	4	5	-1
Tooth brushes		20		3		3	
Tooth pastes	ORAL HYGIENE (group)	18	-5	14	-8	6	-5
Avg. (all categories)		**11.3**	**9.0**	**8.2**	**-0.1**	**6.2**	**2.9**
Avg. (matching categories)		**11.3**	**9.5**	**8.3**	**0.1**	**5.5**	**1.3**
Avg. APIS		**11.7**	**21.2**	**8.5**	**4.1**	**6.5**	**7.6**
Avg. APIS-R		N/A	**-4.0**	N/A	**-4.4**	N/A	**-2.6**

For completeness, in Table 2.7 we compare our results of the KNRS data with the results reported by Chen et al. (2008). We find our average thresholds of the matching categories are close for the full sample (only a 2.4 cents difference). However, the average thresholds of low-inflation sample and deflation sample are significantly lower in our dataset. There are important differences between the two results. First, we are not able to have an exact match of categories. Second, the data comes from different periods. The sample period of our data was from a lower inflation rate period. The average monthly inflation rate in our dataset is -1.08% during deflation months and 0.07% during low inflation months, compared to -0.33% and 0.08% respectively, in the Dominick's data used by Chen et al. (2008). Also note that while there are no negative thresholds reported at category level in Chen et al. (2008), we observe a large proportion of APIS-R thresholds (which, of course, lower the average as negative numbers).

2.6. DISCUSSIONS

Four perspectives dominate studies of small price changes: the "menu cost" line of work, the rational inattention (RI) approach, the just-noticeable-difference (JND) literature, and the strategic intent argument. Nevertheless, the prescriptions of the theories do not always converge on the basic question of whether small price changes will even exist. For example, the RI and JND theories offer a rationale for the existence of small price increases; but they do not offer any predictions for small price decreases. The menu costs theory on the other hand, generally predict against small price changes per se. whether positive or negative. Together, they seem to rule out small price changes in general, certainly small price decreases (e.g., Dutta 1999, Ray et al. 2012, Levy et al. 2020, Gupta and Cooper 1992). The strategic obfuscation line of reasoning of Chakravarty et al. (2015), on the other hand, predicts small price decreases as a tactical behavior of profit seeking sellers.

Our results in this context are somewhat mixed. We find significant instances of small price changes in both directions, but we cannot sort between the different explanations. The robust evidence of APIS suggests RI and JND themed explanations for retail price setting. At the same time, however, robust evidence of a widespread practice of APIS-R suggests a strategic obfuscation themed reasoning could be driving the retail pricing behavior. This is not to say that menu costs do not play a big role in such price setting. Only that it is not evident from our current analyses. So, where does this leave us in terms of the importance of our findings? We believe we make four main research contributions.

2.6.1 Research Contributions

First, the ambiguities in the substantive predictions of small price changes create a secular need for more research into scale and scope of the phenomena. Indeed, current empirical evidence is quite limited. Not only have there been very few efforts in the domain, there have not been much large scale recent studies comprising multiple retailers and a large sample of products (cf. Carlton 1986, Lach and Tsiddon 2007, Ray et al. 2006, Chen et al. 2008, Wood et al. 2013). Even Chakravarty et al. (2015), whose research is among the very few contemporary studies that use a large dataset to study small price changes, are limited to a dataset with three retailers.

Conflicting empirical results compound the limitation of the paucity of work. To the best of our knowledge, only two papers specifically study asymmetric pricing in the small – Chen et al. (2008) and Chakravarty et al. (2015). Of these, while the former reports robust evidence of APIS and none for APIS-R, the latter finds robust evidence of APIS-R. Together, the ambiguity in substantive explanations, paucity of studies, limited nature of empirical analyses and conflicting results are a major limitation to further substantive research in the area of asymmetric pricing. To that end, our study offers the first large sample result of the scale and scope of the phenomena in the economy at large.

Second, small price changes can have a significant impact on the economy if they are widespread and endemic in the consumer facing price spectrum. Combined with the research gap discussed above, the need for a study like ours become imperative. Consider the following as a potential impact of small price changes: In our KNRS data, 17¢ is the average APIS threshold at the product module level after controlling for spurious price changes. Taking that as a metric for what is a "small" price change, we find the fraction of price changes that equal 17¢ or less is more than 10 percent (10.5%) in our sample. Specifically, there are 4,194,383,216 small price increases and 4,103,724,520 small price decreases equal or less than 17¢. The combined value of these ripples in the price spectrum exceeds $602 million.

Note that this is a conservative estimate of the impact on the economy, for it uses only a fraction of the whole Nielsen-Kilts data set. While this number may seem small compared to the total grocery segment sales ($648 Billion in the US in 2016 according to the USDA), its potential impact on retailers' bottom line is non-trivial. 17¢ is 0.49% of the average size of the US consumers' grocery basket, which is about $34.5 according to the Food Marketing Institute (2017). Given the average grocery retailer profit margin is only 1.7% before tax according to the Food Marketing Institute (2016), the potential impact of a 17¢ price change can be as high as 28% on retail profitability, assuming the extreme condition where retailers earn 17¢ more from each basket without demand change. Without question then, small price changes can have a big impact on both consumers and retailers. Thus, our results show that these ripples have significant implications for both economists and marketers in interpreting the retail price spectrum.

To the best of our knowledge, our research is the largest study of small price changes till date. Whereas earlier studies were limited to a single retailer database, we show that asymmetric pricing in the small is observed consistently across multiple retailers. We document the phenomena across a much larger sample of grocery products than was heretofore studied in the literature. We show that APIS is robust across several levels of aggregation – increasingly granular categorization of products – module, group and department.

Third, the advent of internet communication technologies (ICT) that we take for granted now (internet, mobile, etc.) creates a vastly different information spectrum, (compared to pre-ICT days), within which consumers make their decisions. With rational inattention indicated as a key contributor to small price changes, it is an open question if retailers have changed their pricing patterns to the presumed changes in how consumers make their purchase decisions. However, much of the published work in the domain use data from the pre-ICT days – late 1980s and early 1990s (Ray et al. 2006; Chen et al. 2008). Chakravarty et al. (2015) is one of the few studies that use a more contemporary dataset studying 370 products over 8 years (2003–2010). However, their dataset is limited to three retailers. To this end, we find that asymmetry in the small continues to be a part of the retail-pricing spectrum even after two decades since first reported, and even after major economy-wide technological changes that could reasonably be seen as affecting consumer decision making, and (by implication) the retail pricing practices. Hence, our findings suggest a certain level of immutability of the factors that drive the phenomena. Grocery retail is a significant sector of the economy and thus, our results are important from an economic policy perspective. Taken together, we believe our study moves the dial significantly to establishing the generalizability of the asymmetric pricing in the small phenomena.

Last but not the least, concerns about measurement of small price changes have become a key issue, posing a challenge to the veracity of the recorded phenomenon of APIS. For example, Eichenbaum et al. (2014) and Campbell and Eden (2014) contend that calculations of small price changes in traditional secondary research databases might be artifacts of aggregation and other data handling practices – in particular, concerns around unit value indices (UVIs). In this, we are among the first to acknowledge and partially address the sources of noise pointed out by Eichenbaum et al. (2014) and Campbell and Eden (2014). Our findings suggest that these criticisms are not without cause but that the finding of the asymmetric pricing in the small is quite robust even after we account for the noise.

2.6.2 Managerial and Policy Implications

With a potential net margin impact of the order of 28%, asymmetric pricing practices in the small present an opportunity for retailers to turn their dynamic pricing capabilities into profit. We observe significant variation in the practice of APIS and APIS-R across retailers, products, and periods. The idea that retailer price positioning strategies (e.g., HILO or EDLP) and product factors (e.g., average category price, share of consumer basket, purchase frequency) explain price dispersion in the market is quite common in marketing. For example, Researchers such as Bell and Lattin (1998), Fassnacht & El Husseini (2013), Lattin and Ortmeyer (1991) and Lal & Rao (1997) find that patrons of HILO and EDLP store exhibits different sensitivity to individual prices. Similarly, studies by Andreyeva et al. (2010), Long et al. (2015), Gordon et al. (2013) etc. reveal that consumer’s response to price change not only relates to consumer’s own characteristics (such as income, age, etc.), but also depends on the kind of categories they are shopping (such as a category’s share of basket, frequency of being purchased). These provide retailers opportunity to practice price discrimination between different types of shoppers according to its own price positioning strategy and product category attributes. However, mainly because the pricing patterns remained largely undocumented in marketing, the roles different factors play in explaining the variation in APIS and APIS-R remain unstudied (Chen et al. 2008, and Chakraborty et al. 2015 are notable exceptions). We need more research to explain the variations.

While both APIS and APIS-R seem to draw upon the same underlying notions of consumer inattention, there are marked differences in how they are argued to contribute to the retailer's bottom line. Chen et al.'s (2008) argument focuses on consumers saving on cognitive efforts and not changing their purchase patterns even if they see a price change. On the other hand, Chakraborty et al.'s (2015) argument hinges on consumers actually expending their cognitive efforts on processing small price changes (decreases), which allow the (large) price increases to go unnoticed. Clearly, in order to benefit from this, retailers need to develop their dynamic pricing capabilities. This needs to address both their ability to implement small price changes, as well as their ability to identify the thresholds that differ across retailers, consumers and products. At the same time, they need to acknowledge this pricing practice comes with inherent risks and develop their ability to respond to any consumer, competitive, or policy fall outs that might accrue, as we explain below.

An area of important concern for retailers should be the domain of public perceptions. While benefitting from consumer inattention might seem reasonable in terms of economic reasoning, note that it also is likely to trigger concerns around fairness of the practice. Kahneman, Knetsch and Thaler's (1986) dual entitlement theory predicts price changes discrepant with cost changes would affect consumers' fairness perception. This is one of the key reasons, in addition to competition, why retailers protect their cost information jealously, and why some retailers disguise their real price increases when practicing asymmetric price changes (Chakraborty et al. 2015, Anderson et al. 2017, Levy et al. 2020). Substantial damage in both image and actual sales performance can result otherwise (Malc et al. 2016). So, successful implementation of APIS or APIS-R cannot be completely neutral to developing appropriate capabilities for managing consumer and channel relations and marketing communication. Deploying a robust Customer Relationship Management (CRM) system would help retailers on this count.

The potential policy impact of this practice is still unclear. Certainly, if the fairness concerns identified above are true, the endemic nature of APIS and APIS-R calls for some policy analyses. However, on the face of it, it is not clear if these affect consumer welfares negatively. The key tenet of the rational inattention theory applied to APIS argues that consumers choose to ignore small price increases rationally (Lee et al. 2006, Lee et al. 2009, Chen et al. 2008, Levy et al. 2011, Ray, Wood & Messinger, 2012). So, the consumer essentially banks the cognitive savings to expend on other pursuits, and thus, APIS has no direct impact on consumer welfare. On the other hand, the obfuscation logic as applied to APIS-R argues that consumers spend their cognitive resources on small price decreases, depleting their cognitive resources to process the (large) price increases, and thus, APIS-R negatively affect consumer welfare. So, very counterintuitively, one may infer that in this case, price increases are welfare neutral, while price decreases may be welfare reducing. How should regulators approach this? Pricing regulations such as Item-Pricing Laws (IPL), introduced to monitor retailer's pricing behaviors have been shown to undermine consumer welfare (Bergen et al. 2008). Therefore, a more in-depth policy level analysis of the phenomena is in order.

2.7. CONCLUSIONS

Despite asymmetric pricing being a topic of a great importance to both marketers and economists, it is relatively under-studied. We estimate the scale and scope of both APIS and APIS-R, in a large dataset comprising over 79 billion weekly price observations over a relatively recent 10-year period (2006–2015). Our data covers 35,000 stores belonging to 161 retailers in the US and a broad range of 527 product modules sold in these stores. We believe ours is the largest study of small price changes till date, significantly contributing to our understanding of such ripples in the price spectrum at grocery retail. We conclude that the evidence points to both APIS and its reverse, APIS-R, being robust phenomena, observed across different levels of aggregation – products, retailers and in particular, time periods – in the context of the ICT era. We are the first to document stable patterns of APIS-R economy wide, with the notable exception of the more limited study by Chakraborty et al. (2015). Ours is also among the early papers to address potential measurement concerns associated with small price changes, offering greater robustness to our results, and building upon the work of Eichenbaum et al. (2014) and Campbell and Eden (2014). Our simulation of the effects of aggregation, with an independent dataset, suggests such aggregation does not drive the observations.

Despite our efforts, our work has certain limitations. We consider these as characteristic of research domains that are in their early stages, as the study of asymmetric pricing is. One limitation is in terms of the data itself. Certainly, our estimations of asymmetry thresholds would be crisper if we had access to large scale point of sale transaction prices. The computing challenges of dealing with such data would have been considered onerous even a decade back. However, continuing advances in computing and associated machine learning algorithms make working with such data more feasible now. The bottleneck continues to be access to such transactions data, per se. An associated challenge refining the measurement of the thresholds. While we control for several sources of noise, we call for more research, possibly using different data, modeling, and experimental approaches to address this. Future research should also develop a deeper understanding of these ripples in the price spectrum – the sources and drivers of variation in asymmetry thresholds. Our observations suggest there are consumer, product and retailer factors that can potentially explain some of the variation.

3. Strategic Intent in Small Price Changes: The Case of Asymmetric Pricing in the Small

3.1 INTRODUCTION

Price change frequencies are not symmetric in many retail settings[5]. A particular type of asymmetry is asymmetric pricing in the small (APIS) - where small price increases dominate small price decreases, and where such asymmetry disappears at the larger end of the price change spectrum (Chen et al. 2008, Ray et al. 2012, Chakraborty et al, 2015). The corresponding reverse phenomenon is called APIS-R, where small price decreases dominate small price increases. Findings in existing papers also document significant variation in the asymmetry patterns – both cross-sectional variation across products, as well as variation over time. There are different explanations for such variation including both passive (e.g., inflation) as well as more active pricing practices (e.g., strategic intent on the part of the retailer). However, the speculations notwithstanding, to the best of our knowledge, no paper exists that conduct a systematic investigation to document the strategic intent contributing to these pricing practices.

This lack of attention in the literature is surprising. On the one hand, the business logic of small price changes themselves is questionable. These may not contribute significantly to retail margins and on top, the retailer would incur menu costs, or the price adjustment costs in making these changes (Dutta, Bergen and Ray 2010; Ray et al. 2006). On the other hand, APIS and APIS-R practices present opportunities to turn the retailers' dynamic pricing capabilities into profit. Given that the average grocery retailer profit margin is only 1.7%

[5] See Cecchetti (2004), Baudry et al. (2004), Álvarez and Hernando (2004), Ray et al. (2006), Müller and Ray (2007), Lach and Tsiddon (2007), Chen et al. 2008, Dutta et al. (2010), Midrigan (2011), Ray et al (2012), and Alvarez et al. (2014).

before tax[6], even small price changes in cents can significantly impact a retailer's bottom line when aggregated across multiple products and stores. Clearly, in order to benefit from these pricing practices, retailers need to address both their ability to implement small price changes, as well as their ability to identify the right asymmetry patterns, and the extent to which they differ across retailers, consumers, products, and time periods. Hence, it is important to understand the observed variations of the APIS/APIS-R since they reveal the best practices of asymmetric pricing decisions in a market equilibrium.

Indeed, existing research results hint at possible roles of product characteristics (e.g., price level) and retailer pricing positioning strategies (e.g., HILO or EDLP). For example, consumer's attention to price changes have been traced to both product and retailer factors, in addition to consumer's own characteristics (e.g., Pauwels et al. 2007, Andreyeva et al. 2010, Gordon et al. 2013, Long et al. 2015, Shankar and Krishnamurthi 1996, Lal and Rao 1997, Ellickson and Misra 2008). However, this body of literature does not specifically study the retailers' APIS and APIS-R pricing practices. In fact, Chen et al. (2008) and Chakraborty et al. (2015) do provide possible explanations of the practice but do not address the variation found in the asymmetry patterns. In general, both APIS and APIS-R are explained by an underlying theme of consumer inattention, even if the explanations operate in slightly different ways.

The Rational Inattention (RI) theory (Chen et al. 2008, Ray et al. 2012) proposes that time and resource-constrained consumers might rationally ignore small price changes, which provides incentives for profit-maximizing retailers to make more frequent small price increases than decreases, thus leading to APIS. The strategic obfuscation (SO) logic (Chakraborty et al. 2015) suggests retailers strategically obfuscate their price spectrum by

[6] Source: Food Marketing Institute (2016)

mixing a few large price increases with numerous small but inconsequential price decreases ("penny drops") to maintain their competitive price image while aiming for higher margins, thus leading to APIS-R. These explanations notwithstanding, none of these papers address why certain categories exhibit APIS while others exhibit APIS-R, and what type of retailers prefer the strategic obfuscation incentives of APIS-R over the direct monetary utility of APIS. Much of this gap is driven by the data limitations inherent in earlier papers – especially the limited number of retailers. Perhaps not surprisingly, both Chen et al. (2008) and Chakraborty et al. (2015) only report one type of asymmetry (i.e., either APIS or APIS-R). The significant variation of the APIS and APIS-R patterns present an opportunity to learn not just about how retailers should deploy their dynamic pricing practices, but also offer insights into the impact these pricing practices could have on the consumer's shopping experiences.

This study attempts to answer these gaps by conducting a series of tests on a large scanner dataset which consists of almost 79 billion weekly prices from 2006 to 2015, covering 527 products, and about 35,000 stores across 161 retailers. We also measure consumer purchasing preferences across product categories by using a matching consumer panel dataset that reports purchases records of over 50,000 panelists in the US during the same periods. We find that APIS and APIS-R pricing are stronger among product categories with a smaller share of consumer basket, and that APIS-R is negatively associated with category purchase frequency and category price level. We also find that HILO type retailers are more likely to engage in both APIS and APIS-R relative to EDLP type retailers and that larger retailers are more likely to engage in these pricing practices.

We believe this study makes the following contributions. First, this study is the first attempt to explain the cross-sectional variations of APIS and APIS-R patterns. In the process, we find robust evidence that both product level attributes and retailer characteristics (HILO or

EDLP positioning) shape retailer's practices of APIS and APIS-R. Second, it contributes to the literature on small price changes by empirically documenting how rational inattention and strategic obfuscation incentives frame the retailer's dynamic pricing practices. It is the first study to test whether the two theories, RI and SO, apply to a broader context with an economy-wide dataset. Third, it complements the emerging literature in rational inattention by documenting how different retail strategies leverage consumer inattention across different categories. Last but not least, it contributes to marketing practice by documenting the best practices in the domain of managing small price changes – highlighting the factors that might be contributing to the success of APIS and APIS-R practices.

The rest of the paper is organized as follows. In section 2, it develops eight hypotheses involving a host of product and retailer characteristics and primarily drawing upon the predictions of RI and the strategic obfuscation perspectives. In section 3, we describe the data and measurement. In section 4, we discuss our empirical strategy, including the modeling and estimation methods. In section 5 we report our findings and assess the robustness of our results. In section 6 we discuss the implications of our results for the literature and practice. In section 7 we conclude with a brief discussion of limitations and future research.

3.2 BACKGROUND LITERATURE AND HYPOTHESES

Of particular interest to out purposes is variation in consumer attention across product categories and retailers (types). To this end, several paper in both marketing and economics document that consumer's attention to retail prices is not only related to consumer's own characteristics (income, age, etc.) but also directly associated with the characteristics of product categories (e.g., category price level) they are shopping and the types of stores (e.g., HILO, EDLP) they are shopping at. The literature on customer shopping behavior has documented evidence of how consumer's attention to price changes will vary when shopping in different categories. For instance, Andreyeva et al. (2010) find in a meta-analysis that consumers respond to price changes differently in different categories. They observe that categories such as food away from home, soft drinks, juice, and meat are most responsive to price changes, with a mean price elasticity of 0.7 to 0.8, whereas sugar, cheese, and fat/oil are some least price-sensitive categories. Long et al. (2015) find that customers are less likely to be inattentive to price changes for product categories on which they spend more. In a study on how price sensitivity changes with the macroeconomic environment, Gordon et al. (2013) reveal that a category's share of wallet positively correlates to consumer price sensitivity, especially when the economy is weaker. Chandon et al. (2000) and Pauwels et al. (2007) also pointed out that customers are more sensitive to price changes of expensive categories and brands.

Retail pricing strategy literature also investigates the customer outcome of retailer pricing strategy. Evidence has been found that patrons of retailers with different pricing positioning (e.g., HILO or EDLP) exhibit different levels of inattention to prices changes. For instance, Shankar and Krishnamurthi (1996) argue that a store's pricing strategy will attract a certain type of customer to that store. More price-conscious consumers will more likely choose an Every-Day-Low-Price (EDLP) store over a High-Low Pricing (HILO) store. In addition, the two types of shoppers have different levels of sensitivity to price promotions. They find evidence that shoppers of EDLP stores show a higher level of regular price elasticity, whereas the HILO price policy is associated with a lower level of regular price elasticity, but higher promotion price elasticity. That means, EDLP shoppers, although are more price-conscious in general, are less sensitive to promotions than HILO shoppers are. Consumer preference between HILO and EDLP is also influenced by family income situation. Ellickson and Misra (2008) found that consumers with lower income prefer EDLP, whereas consumers with higher income clearly prefer HILO. Bailey (2008) expected that higher-income consumers are less responsive to EDLP retailers because of lower price sensitivity. Bell et al. (1998) and Gauri et al. (2008) have similar findings that consumer income level influences their preferences toward store type.

A line of research directly related to consumer attention is the segmentation of customers into time-constrained shoppers, expected price-shoppers, and cherry pickers (Fassnacht & El Husseini, 2013). The time-constrained shoppers are consumers whose opportunity costs for shopping are relatively high (Popkowski Leszczyc et al. 2004). The expected price shoppers are those who want a reasonable price but do not want "to spent time monitoring day to day price changes during the retailer's deal interval" (Lattin and Ortmeyer 1991, p. 4). Cherry pickers are consumers who actively search for price promotions and are willing to make fast purchase decisions when a better price becomes available. Lal and Rao (1997) find that although time-constrained consumers are more attracted to EDLP stores and cherry pickers are more attracted to HILO stores, the opposite happens when service is included since HILO stores normally offer higher service levels. Popkowski Leszczyc et al. (2004) find that when both are time-constrained, service seekers prefer HILO stores, and price seekers are more attracted to EDLP stores.

Despite the abundance of studies on category level variations of consumer responsiveness (or inattention) to retail prices, there is little study investigating the implication of such variation to micro level category pricing strategies. On the other hand, although retail pricing literature looks into the consumer outcome of retail pricing strategies, little has been done to study how the varying consumer attention across retailer types would in turn shape a retailer's dynamic pricing practices, especially the pricing practices in the small price change spectrum. Some notable exceptions include the APIS-R study by Charkraborty et al. (2015) and Ray et al.'s (2012) study on multi-component systems pricing. Charkraborty et al. (2015) find that

APIS-R, as a price obfuscation strategy, is more prevalent in cheaper and less-frequently purchased products. Ray et al. (2012) reveal that in the systems market, a retailer's price-cutting strategy is contingent on the nature of the multi-component system products (tightly or loosely coupled). Even these studies have limitations in terms of the scale of context, e.g., number of retailers and number of categories studied. The scarcity of studies in this domain is not because of a lack of managerial interest, since it has been long recognized that these types of pricing practices are important for effective retail pricing (Rao, Bergen, and Davis, 2000). We contend that this is a substantial gap in the literature, and the gap must be filled to gain a more complete understanding of the dynamic retail pricing strategies in the small price change spectrum.

Hence, we attempt to address this gap by borrowing from both the RI theory (Chen et al. 2008, Ray et al., 2012) and the SO argument (Chakraborty et al., 2015) to explain the observed cross-sectional variations of the APIS and APIS-R phenomena. We develop our hypotheses based on these two themes. First, consumers are rationally inattentive – i.e., consumers may be inattentive to price changes when the costs of gathering information exceed the presumed benefit, thus creating a range of insensitivity. Second, small price changes can be effective tools for retail profitability. It happens when small price increases do not impact consumer purchase behavior, or when numerous small price decreases allow retailers to engage in strategic obfuscation. The former has significant implications for APIS when retailers profit from unnoticed small price increases without demand penalty. The latter is associated with APIS-R: numerous small price decreases can be part of a mechanism to strategically obfuscate infrequent large price increases that would otherwise be noted by consumers and discourage purchases. This obfuscation helps to increase the noise in consumers' estimation of their basket prices so that they overestimate their utility gains from the basket purchase in this store. (Chakraborty et al. 2015).

3.2.1 Hypotheses on product level variations and APIS/APIS-R

The RI theory (Chen et al. 2008, Ray et al., 2012) predicts that retailers are incentivized to engage in APIS where there is consumer inattention to small price increases and that the extent of APIS should vary with the amount of consumer attention. In situations where consumers are more attentive, they are more elastic to small price changes, we should see less APIS, while in situations where they are less attentive and inelastic to small price changes, we should see more APIS. This prediction provides an opportunity to explain the variations of APIS among product categories – consumers have different extents of attention/inattention when shopping in different categories, resulting in differences of asymmetry. Pricing decisions being more likely made at the store-category level rather than making a store-wide decision (Bolton & Shankar, 2003), it is reasonable to assume that there will be variation across different categories for a given retailer.

We argue that product category's price level, share of consumer basket, and consumer purchase frequency are the three most important product level attributes that may impact APIS and APIS-R practices. As discussed just earlier, several paper find that customers are more attentive to price changes for product categories with relatively higher prices, or with a higher share of customer basket (e.g., Chandon et al. 2000, Pauwels et al. 2007, Gordon et al. 2013, Long et al. 2015). Hence, one would expect to see fewer instances and degrees of APIS pricing practices among these categories, as retailers aim to leverage consumer inattention by raising prices by small amounts.

H1. APIS pricing practices are negatively associated with product category price level.

H2. APIS pricing practices are negatively associated with product category's share of consumer basket.

Of course, at issue here is whether our hypotheses above can sort between situations where price levels of two categories are close, but with different shares of consumer basket. We expect that the category which takes a larger share of basket would have a higher influence on consumer attention since that is the category consumers spend more on (see Long et al. 2015, P4).

Product level attributes should influence APIS-R practices differently, as the incentive for retailers to engage in APIS-R is different. The purpose of strategic obfuscation is to highlight small frequent penny drops and make the infrequent large price increases less salient. Small price drops in more expensive products will not really serve the purpose since consumers already are aware of their high prices by dint of greater attention. Further, frequent price drops in high-margin products will likely lead to downward creep in the consumer price expectations affecting the retailer's ability to protect their margins (Kalyanaraman & Winer, 1995). However, for cheaper products, which already contribute to a low-price image of the retailer, small penny drops serve to reinforce the lower prices and further legitimize the overall competitive-price image of the retailer (Chakraborty et al. 2015). So, relative to more expensive products, cheaper products will serve the purposes of strategic obfuscation better.

H3. APIS-R pricing practices are negatively associated with product category price level.

Very similar to the above logic, price drops in less frequently purchased products will also be more likely to contribute to the competitive-price image of the retailer, compared to more frequently purchased products. Obfuscation in more frequently purchased categories will be less effective since consumers are more attentive and have more knowledge about the prices of these products. For less frequently purchased products, retailers are more likely to be able to drive consumer attention from specific price points to the promotions, thereby making promotions salient. In addition, retailer's potential margin loss from frequent penny drops would be lower if they target less-frequently purchased products. Similar arguments have been made by Chakraborty et al. (2015). Hence, we expect to see more instances of APIS-R practices among product categories that are purchased less frequently.

H4. APIS-R pricing practices are negatively associated with consumer purchase frequency of a product category.

3.2.2 Hypotheses on retailer level variations and APIS/APIS-R

Another situation where consumer's attention to prices may differ is retailer pricing format (or positioning) heterogeneity. Patrons of retailers with different pricing positioning (e.g., HILO or EDLP) exhibits different shopping behaviors regarding prices changes (e.g., Shankar and Krishnamurthi 1996, Lal and Rao 1997, Ellickson and Misra 2008, Popkowski Leszczyc et al. 2004). EDLP shoppers, who are more price-conscious, tend to pay more attention to price changes, while HILO shoppers are more sensitive to retailer service level and are more promotion conscious. Following the predictions of the RI theory, we argue that HILO retailers appeal to people with lower attention to prices and therefore, would have a higher incentive to engage APIS. EDLP retailers, however, appeal to consumers who are more conscious of price changes, hence would have a lower incentive to engage in APIS.

Hypothesis 5. APIS pricing practices are positively associated with HILO pricing format relative to EDLP format.

Retailer pricing positioning strategy also influences APIS-R practices. According to the assumption of RI theory, the frequent small price decreases would make no sense when consumers are rationally inattentive to these small changes. Therefore, retailers who engage in APIS-R must heavily promote these price cuts in order to make the obfuscation work, which brings out the question that what type of retailers tend to maintain an image of frequent discounts while profiting from higher basket prices. We argue that the answer leans towards the HILO retailers – which are more attractive to consumers who are more promotion conscious (see our previous discussions). Charkraborty et al. (2015) also note that penny drops (APIS-R) are only one of many pricing patterns that is consistent with obfuscation which in itself is a flexible concept of retailers to deal with contingencies in price competition. Hence, while APIS-R is a reflection of obfuscation, the latter does not guarantee the prediction of APIS-R. Retailers which are engaging in price obfuscation (which tend to be HILO retailers) do not necessarily exhibit APIS-R, but there is a higher probability that they would do so in comparison with retailers of other pricing formats.

Hypothesis 6. APIS-R pricing practices are positively associated with HILO pricing format relative to EDLP format.

Lastly, a retailer's size can be a contributing factor that influences its APIS/APIS-R pricing practices. There are two distinct arguments. The first derived from a menu cost oriented logic and the other depending purely on scale effects on profit gains.

On menu costs, if retailers face fixed costs of changing prices, larger number of transactions will introduce economies of scale. Indeed, there are some suggestions in the literature that fixed components of menu cost can be a significant part of the total menu cost (*cf.*, Rotemberg 1983, Zbaracki et al., 2004, Stella 2014). Hence, larger retailers are more likely to benefit from the scale economies and thus, less held back from implementing APIS and APIS-R from a menu costs perspective. In addition, larger retailers are secularly more likely to be able to see the aggregated economic benefit from these pricing practices, simply because they have a larger the scale of operations. In combination, therefore, one would expect to see more instances of both APIS and APIS-R pricing practices among larger retailers.

Hypothesis 7. APIS pricing practices are positively associated with retailer's size.

Hypothesis 8. APIS-R pricing practices are positively associated with retailer's size.

3.3 DATA AND MEASUREMENT

3.3.1 Data description

The datasets we use come from two separate sources: the Kilts-Nielsen Retail Scanner Dataset (KNRS) as well as a Nielsen Consumer Panel Dataset. The KNRS dataset is a panel dataset of total sales (quantities and prices) at the UPC (barcode) level for around 35,000 geographically dispersed stores belonging to more than 160 retail chains (these numbers vary by year) across all US markets[7]. The data consists of *weekly* pricing, volume, and store-merchandising information aggregated from transactions recorded by the stores' point-of-sale systems and covers a ten-year period from 2006 to 2015. The strength of this dataset is evident: it allows us to measure APIS and APIS-R pattens in a contemporary setting and an economy-wide context, enabling the best generalizability possible.

The matching consumer panel dataset comprises a representative panel of 40,000 to 60,000 households (varies by year) across the USA, containing the records of shopping trips and purchases of these panelists from 2006 to 2015, with a total of 761,858,949 product purchases. It provides observations about the households, the products they buy, as well as when and where they make purchases. The panelists use in-home scanners to record all of their purchases, from any outlet. The product categories, retailers, and time periods in the consumer panel data match what is reported in the KNRS dataset. This data helps us capture product level attributes that can be measured by consumer shopping behaviors, such as

[7] The full dataset covers more than 50% of the total sales volume of US grocery and drug stores and more than 30% of all US mass merchandiser sales volume.

purchase frequency and share of the basket.

The product hierarchy of our data samples for this study is organized into 9 randomly chosen product departments, which are then further organized into 56 randomly chosen product groups consisting of 527 product modules (sub-categories), comprising 4,311,648 UPCs. Alcohol and tobacco products are excluded because those products are heavily regulated in the US. Our sample comprises 161 retailers, belonging to 91 parent companies[8]. This represents the majority of retailers recorded in the full KNRS database and the panel dataset. The KNRS data sample, in total contains more than 79 billion weekly price observations in total from the year 2006 to 2015

Table 3.1 Summary of Group Level Data

Department Name	Group Name	No. of Modules	No. of UPCs	No. of Observations
Dry Grocery	Candy	14	289,747	5,907,425,280
	Gum	4	18,328	1,215,013,376
	Juice, Drinks - Canned, Bottled	18	107,917	3,592,290,560
	Pet Food	10	74,207	3,107,025,664
	Prepared Food-Ready-To-Serve	40	61,235	1,550,426,112
	Soup	5	42337	1882395136
	Baking Mixes	17	24596	781248704
	Breakfast Food	4	24107	1125582080
	Cereal	5	38266	1807372672
	Coffee	5	61510	1229685120
	Desserts, Gelatins, Syrup	12	20902	965305024
	Nuts	4	65059	1023383232
	Packaged Milk and Modifiers	6	17206	649159424
	Sugar, Sweeteners	5	9422	298786784
	Tea	8	61210	1257548928
	Bread and Baked Goods	14	299239	2605746688
	Cookies	2	102462	1891238912
	Crackers	10	30165	1107950976
	Snacks	18	213708	4488684544
	Soft Drinks-Non-Carbonated	9	59337	1618847360
Frozen Foods	Baked Goods-Frozen	12	18804	437997856
	Breakfast Foods-Frozen	2	14016	512820640
	Ice Cream, Novelties	4	91355	2096284544
	Juices, Drinks-Frozen	8	3441	157345696
	Pizza/Snacks/Hors Doeurves-Frzn	3	39026	944168256
	Prepared Foods-Frozen	23	96910	2701307648
	Unprep Meat/Poultry/Seafood-Frzn	15	39922	325982144
Dairy	Cheese	16	89513	1844350464
	Eggs	1	9941	94186312
	Milk	7	58193	746784320
	Snacks, Spreads, Dips-Dairy	4	32946	336883488
	Yogurt	2	36829	1207518976
Deli	Dressings/Salads/Prep Foods-Deli	16	128385	1779300864
Packaged Meat	Packaged Meats-Deli	12	105075	1786796416
	Fresh Meat	1	11147	122056672

[8] Retailer banners are identified by 161 “Retailer Codes.” In addition, there are 91 “Parent Codes” reported in the dataset, some of which are the same as the banner level “Retailer Codes.” The rest of the “Parent Codes” are at parent company level. A parent company may own several retail banners.

Fresh Produce	Fresh Produce	25	121681	828927296
	Detergents	6	34141	1644012160
	Household Cleaners	20	35886	1246793472
	Laundry Supplies	20	44919	1156176640
Non_Food Grocery	Paper Products	11	178806	2523770112
	Personal Soap and Bath Additives	8	89812	1818637312
	Pet Care	9	143056	1081385344
	Wrapping Materials and Bags	13	28871	954846784
	Automotive	5	23392	291624032
	Batteries and Flashlights	2	39673	673595712
	Books and Magazines	1	13579	541083072
General Merchandise	Cookware	2	49007	348034592
	Glassware, Tableware	3	261232	925427968
	Kitchen Gadgets	8	264768	1246782592
	Toys & Sporting Goods	2	22885	25291164
	Baby Needs	10	52799	680964096
	Hair Care	14	182990	3714681344
Health & Beauty Care	Medications/Remedies/Health Aids	1	1879	89118656
	Oral Hygiene	12	50977	2499003648
	Skin Care Preparations	10	117057	1905587200
	Vitamins	9	157775	1907149312
Total #	56	527	4311648	79301793380

(See Table 3.1 for summary statistics of group level observations). We use the full purchase observations for all matching categories in the consumer panel dataset.

3.3.2 Dependent variables

In this study, we take a more robust approach to measure the APIS and APIS-R patterns based on the original method applied by Chen et al. (2008). To control for potential spurious price changes that might contribute to the variation of APIS and APIS-R (Eichenbaum et al., 2014; Campbell and Eden, 2014), we apply a series of noise elimination methods. We drop all the observations that have a price multiplier greater than 1 and all the price changes due to the change of price-multiplier in the KNRS data. We also drop all fractional price changes since all non-integer prices should be a result of price aggregation (note that our price measurement unit is the cent). In addition, we exclude all extreme price changes (those that are smaller than 0.1% or larger than 120%), following Alvarez et al. (2014).[9]

[9] In general, the noise elimination reduces potential error in identifying the existence of APIS or APIS-R. Without transaction level data, it is difficult to completely cure the presence of noise in estimating the thresholds.

We define asymmetry thresholds "as the last point at which the asymmetry is supported statistically" (Chen et al. 2008, p. 730). We compute the frequency distribution of the positive and negative price changes by the size of the change, starting with 0¢ and onwards, and identify the first point where no statistical difference between the positive and negative price changes is observed (via Z-test). APIS/APIS-R thresholds are estimated at both the two-dimensional panel (category-time and retailer-time) and three-dimensional (category-retailer-time) panel level as the unit of analysis in this research. That is because pricing decisions are made based on both product characteristics and retailer pricing positioning to maximize their gain (Ellickson & Misra, 2008; Fassnacht & El Husseini, 2013; Grewal et al., 2010). Multiple levels of analysis can provide us more insights into retailer's pricing practices. Our KNRS data consists of 56 product groups which can be broken down into 527 product modules. For this particular test, we choose group as the product level of analysis instead of module (the lowest tier of product categorization) to ensure each unit contains enough price movement for more accurate measurement of asymmetry.

We start by estimating the existence and scale of APIS and APIS-R as the dependent variables at group, retailer, and group-retailer combination levels respectively, creating three separate data samples. Two dummy variables *APIS* and *APIS-R* are created: coded 1 if a product group carried by a retailer exhibits said asymmetry in the small and coded 0 if symmetric. One categorical variable is created as well, coded -1, 0, and 1 for APIS-R, no asymmetry, and APIS respectively. In addition, *asymmetry threshold* is used directly as a dependent variable, representing the absolute extent of APIS or APIS-R. See Table 3.2 for a summary of dependent variables in the three samples.

Next, we measure the independent variables for the three samples, including the consumer inattention-related products attributes and the retailer attributes, using both the consumer panel dataset and the scanner dataset.

Table 3.2 Summary Statistics of Dependent Variables

				Asymmetry Threshold			
Level of Analysis	**Asym. Type**	**Obs.**	**Percent**	**Mean Threshold**	**Std. Dev. of Threshold**	**Min. Threshold**	**Max. Threshold**
Group	APIS-R	205	37.41	5.8	28.9	1	410
	APIS	289	52.74	14.70	15.6	1	82
	No Asymmetry	54	9.85	0	0	0	0
	Total	548	100				
Retailer	APIS-R	304	29.86	13.1	22.3	1	261
	APIS	559	54.91	16.00	15	1	81
	No Asymmetry	155	15.23	0	0	0	0
	Total	1,018	100				
Group-Retailer	APIS-R	11,517	2101.64	4.24	10.05	1	287
	APIS	15,622	2850.73	6.80	10.62	1	300
	No Asymmetry	28,155	5137.77	0	0	0	0
	Total	55,294	100				

3.3.3 Product Level Attributes

Among the three product level variables, *Average Category Price* is measured with the KNRS scanner data and the rest two are measured using the consumer panel data. All variables are measured at a yearly level to account for the possible change of shopping behavior of consumers during the 10-year period, in which online shopping evolved into maturity[10] (See Table 3.3 for the summary of product level independent variables)

Average Category Price. *Average Category Price* is captured by taking an average of prices reported in the scanner dataset for each category in a certain period. Given the

[10] There are missing observations in certain years for certain products in consumer panel data compared with the scanner data, which may be due to no purchase among the panelists. Those missing products are dropped in the final combined samples during estimation.

dynamic nature of price, the average item (SKU) prices are calculated first for each retailer in each period. Then we take the average of item prices for each category to get the average category prices.

Frequency of purchase. *Frequency of purchase* is measured as the average frequency of a category being purchased per consumer (panelist) in a year. A panelist's purchase frequency of a certain category is computed by the ratio of product purchase counts (of that category) over shopping trip counts in a given year. By averaging the purchase frequency of a product group across all panelists during the period, a measure of the average purchase frequency of the group is obtained.

Share of basket. *Share of basket* is the average ratio of the amount paid for a category over the basket price (i.e., the total amount paid for a certain category divided by the total amount paid for the whole basket) per consumer trip in a given year. The category share of basket for each shopping trip of each consumer in a given year is first calculated. Then we average the share of basket across consumers for each category. As such, it reflects the average proportion of consumer spending on a certain category relative to the whole basket in the consumer panel dataset.

Table 3.3 Description of Measurements and Variables

Variable/ Measurement Name	**Variable Description**
	Dependent Variables
Asymmetry	A multinomial (categorical) asymmetry indicator, where 1=APIS, 0=no asymmetry, -1=APIS-R
APIS-R	A binary (dummy) asymmetry indicator, where 1=APIS-R, 0=otherwise
APIS	A binary (dummy) asymmetry indicator, where 1=APIS, 0=otherwise
Threshold	Magnitude of APIS or APIS-R Threshold

	Product Attributes
Frequency of Purchase	The average frequency of a product being purchased per consumer (panelist) in a given year, computed by the ratio of category purchase counts over shopping trip counts in a given year.
Share of Basket	The average ratio of the amount paid for a category over the basket price per consumer trip in a given year.
Average Category Price	Average category price reported in the scanner dataset in a given year.
	Retailer Attributes
Average Product Price	The average ratio of the category price of a retailer divided by the average category price across all retailers
Average Depth of Price Cut	The average depth of price decreases of a retailer across a given year divided by average product prices
Price Variation	The ratio of the standard deviation of actual price over the mean actual price in a given year
HILO	A binomial (dummy) indicator, where 1=retailers with a HILO-like pricing positioning, 0=otherwise. It is obtained by cluster analysis of the three retailer attributes
	Control Variables
Number of Stores	Number of stores the retailer owns in the given year, a measurement of retailer size
Sales	Retailer total sales in a year, a measurement of retailer size
CPI	CPI inflation index (from NBER) is used to control for time-variant environmental factors.

3.3.4 Retailer Level Attributes.

The most popular pricing positioning strategies (also referred to as price format in the literature) available to retailers range from everyday low price (EDLP) to promotional pricing or high–low (HILO) strategies (Gauri et al., 2008). EDLP retailers tend to offer constantly lower average prices, whereas HILO retailers offer frequent discounts (Popkowski Leszczyc et al., 2004). Most prior pricing research emphasizes the EDLP and HILO strategy while a combination of the two (i.e., the Hybrid Pricing Strategy) also exists in between (e.g., Bell & Lattin, 1998; Ellickson & Misra, 2008; Gauri et al., 2008). In this research, we assume that the pricing positioning is a retailer banner (chain brand) level decision, rather than an individual store level decision. This assumption matches the practice that stores under the same banner (or brand) normally have the same pricing positioning. For consistency, we still use retailer as the name of the basic pricing positioning decision unit instead of banner[11].

The majority of published research takes retailer pricing positioning (EDLP, HILO, or Hybrid) as given information (e.g., Hoch et al., 1994; Shankar & Krishnamurthi, 1996; Ellickson & Misra, 2008; Gauri et al., 2008; DGauri, 2013). However, we do not have that information in our data. In order to identify the retailers' pricing positioning strategy, we need to cluster retailers into different groups (e.g., EDLP or HILO) according to their pricing patterns extracted from the price movement observations (see Bolton & Shankar, 2003; Shankar & Bolton, 2004). Bolton and Shankar (2003) categorize retailer's pricing positioning by measuring 4 dimensions of retailer pricing decisions and grouping retailers along these dimensions using K-means cluster analysis. We simplify this method according to our availability of data, using three retailer attributes as metrics to measure retailers' price movement patterns, and cluster retailers into groups (EDLP, HILO, or other formats). The three metrics are *Average Product Price, Price Variation, and Depth of Price Cut*.[12]

Average Product Price. *Average Product Price* is one of the most common metrics of retail pricing strategy. It is usually suggested that HILO retailers generally have higher average prices than their EDLP competitors (Hoch et al., 1994; Bell & Lattin, 1998; Popkowski Leszczyc et al., 2004; Rondán Cataluña et al., 2005; Tsiros & Hardesty, 2010). Naturally, the average prices of Hybrid positioning retailers lie in the middle. *Average*

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[11] As noted previously, the retailer codes in both the scanner dataset and the panel dataset are actually coded at banner level, making it easier for us to operationalize banner level positioning, also providing another reason to stick to *retailer* as the name of unit of analysis.

[12] Some researchers specifically use promotional price changes to measure retailer pricing strategy (e.g., Voss & Seiders, 2003; Bolton & Shankar, 2003). One can adopt sales filter to sperate regular and promotional price change when promotion indicator is not available (Kehoe & Midrigan, 2015; Nakamura & Steinsson, 2008). We do not consider this method here because what we have is not individual transaction data, thus a sales filter would introduce more noises into the already noisy price data.

Product Price is measured as the average ratio of the category price in a retailer divided by the average category price across all retailers [13].

Price Variation. *Price Variation* is made operational as the ratio of the standard deviation of actual price over the mean actual price in a given year (Bolton & Shankar, 2003; Shankar & Krishnamurthi, 1996). It represents the firm's pricing consistency and is often considered as one of the defining features of retailer pricing positioning (Bolton & Shankar, 2003; Ellickson & Misra, 2008; Voss & Seiders, 2003). It measures the extent to which a retailer follows a price position that can range from EDLP on one end to HILO on the other end of the continuum (Bolton & Shankar, 2003).

Average Depth of Price Cut. It is the average depth of price decreases across a given year (Shankar & Krishnamurthi, 1996). Average Depth of Price Cut is used as a proxy of the depth of discount which is widely considered as an indicator or measurement of retail pricing strategy (Bolton & Shankar, 2003; Shankar & Krishnamurthi, 1996). It is measured by the average magnitude of price drops standardised by average product prices for a retailer in a given year.

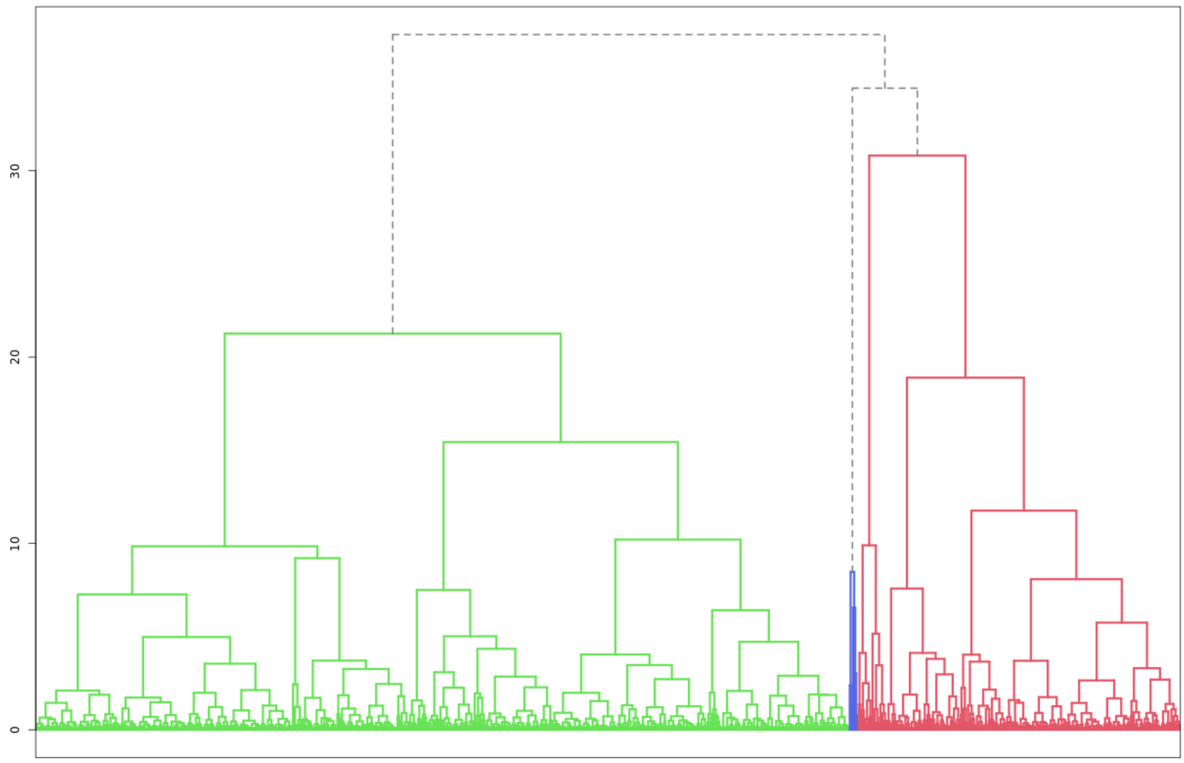
Deal frequency (or promotion frequency, discount frequency) is also considered as an important defining feature of retailer pricing positioning (Ellickson & Misra, 2008; Gauri et al., 2008; Hoch et al., 1994). We do not use this measurement for two reasons. First, some researchers argue that many EDLP retailers also engage in frequent price promotion (e.g., Hoch et al., 1994). Hence it may generate noisy results if we include deal frequency as one of the clustering measurements. Bolton and Shankar (2003) do not apply this measurement directly when clustering retailers, instead, they use it as one of the sub-measures to compute

[13] Similar to the *relative price* adopted in Bolton & Shankar's (2003) research.

deal intensity. Second, we do not have any information about promotions. We would have to use price change frequency as an alternative, which might introduce more noises.

HILO and ***EDLP.*** Following Bolton and Shankar (2003), we perform K-means cluster analysis based on the above 3 attributes (standardized) to classify the 161 retailers in our dataset. We consider the clustering result as an estimation of the firm's relative and yet discrete position in the continuum between extreme EDLP and extreme HILO strategies. Hence, we consider a 3-group cluster solution, where retailers are classified as EDLP, HILO, and other retailers. Hierarchical cluster analysis also suggesting a 3-cluster solution (see Figure 1 for the dendrogram of the clustering tree) [14]. To include possible longitudinal change of pricing positioning, the cluster analyses are performed at the retailer-year level. See Table 3.4 for a summary of average scores of each cluster.

Figure 3.1 Dendrogram for Cluster Analysis of Retailer Pricing Strategy Positioning



[14] The dendrogram represents the grouping process of observations into clusters. If two very distant groups are being merged, this will create a 'jump' in the dendrogram, indicating that it might be wise to stop the clustering process before. Our dendrogram shows that it is appropriate to stop at 3 clusters.

As indicated by Table 3.4, the average measurement values of cluster 1 exhibit characteristics of HILO retailers with the highest average price, highest price variation, and highest average price cut depth. Cluster 2 can be considered a collection of EDLP retailers since the mean scores of the three measures are all the lowest among the three clusters. Finally, retailers in cluster 3 can be considered outliers, since the size of this cluster is small (only 8 retailers) with extremely high average price and very low price-variations[15]. We drop this cluster in our sample. A new dummy variable *Hilo* is generated based on the clustering result, where 1 indicates HILO type of retailers and 0 indicates EDLP[16].

Table 3.4 Cluster Analysis Result (Retailer -Year Level)

Cluster Size	**Pricing Positioning**	**Pct. of All Retailers**	**Avg. Price (Price Ratio)**	**Avg. Depth of Price Cut (%)**	**Avg. Price Variation**
237	HILO	23.5%	1.02	0.26	0.09
785	EDLP	75.7%	0.98	0.18	0.06
8	Others (Premium Pricing)	0.78%	2.26	0.2	0.03

3.3.5 Other Variables.

Other than retailer pricing positioning, two control variables, *Number of Stores,* and *Retailer Sales* are included to test for retailer scale effects. We consider the two variables as proxies of retailer size: *Number of Stores* is measured by the total revenue contributed to a retailer by the categories in a given year, and *Retailer Sales* is measured by the number of stores a retailer owns during a given year. In addition, *CPI* inflation rates during the sample period is also included as a control variable to control for time-varying environmental

[15] They can be considered "premium pricing" type of retailers.
[16] The clustering result may not perfectly match the real world self-recognized (self-claimed) positioning of the retailers. Even the actual pricing practices may not match a retailer's self-claimed pricing positioning.

effects[17].

Therefore, the estimated retailer pricing positioning, *HILO* stays as a retailer level attribute. *Sales* and *number of stores* are still retailer level control variables. Category attributes of *Share of Basket, Frequency of Purchase,* and *Average Category Price* are measured at the product group level. And the asymmetry metrics, as dependent variables are measured at three levels: product, retailer, and product-retailer level. A summary of the definition of all variables and measurements can be found in Table 3.3.

3.4 EMPIRICAL STRATEGY

The previously discussed dependent and independent variables are measured and analyzed at three different levels: product category level (module level), retailer level, and category-retailer level (group-retailer level). Three samples are created accordingly at each level of measurement. A series of tests are performed on different samples to test the effects of both category and retailer level characteristics on APIS/APIS-R patterns. Firstly, we apply a Multinomial Probit model (MNP) to test the effects of category and retailer level attributes on the probability of the unit of analysis (group for a retailer, i.e., the combination of category and retailer) exhibiting APIS, APIS-R, or no asymmetry. Secondly, we apply a Panel Probit model to test the effect of these attributes on the probability of APIS and APIS-R separately. Lastly, their effects on the magnitude of APIS/APIS-R threshold are tested with a series of Fixed-Effects models. In addition, we apply an instrument-free approach to all models to control for the potential endogeneity of our categories level variables.

3.4.1 Endogeneity Concerns: Instrument-free Correction

[17] We do not use year dummies to control for time varying effects because we assume the category attributes and retailer positioning are also time varying. A combination of fixed-effect and time dummies would remove all variations in our regressions.

In the estimation of the effects of product level attributes, endogeneity problems may arise since the product attributes variables, *Frequency of Purchase, Share of Basket,* and *Average Category Price*, may be correlated with unobservables in the error term. APIS is a complicated phenomenon that can be dictated by many unknown factors. Many supply-side factors such as cost structure, cost shocks, and supply pricing are unobserved. Those omitted or unobserved factors may contribute to an overestimation of the direct effects of our explanatory variables. To address this concern, we need to control for the potential endogeneity of the category level attributes. The variable *HILO* is less of a concern in this case since retailer pricing positioning is a relatively stable and long-term corporate level decision that will not change frequently. *Number of Stores* is also a relatively stable firm characteristic, we consider it unlikely to be endogenous.

We apply an instrument-free approach using the Gaussian Copula method (Park & Gupta, 2012) to address the endogeneity issues. We implement it through a CF approach as suggested by Papies, et al. (2017). To control for the potential endogenous variables $X*$ in a matrix of independent variables X, an extra term p^* is added to the right-hand side of our model equations:

$$p^* = \emptyset^{-1}(H(X^*)) \quad (1)$$

where $H(X^*)$ is the empirical cumulative density function (CDF) of endogenous variables, and $\emptyset^{-1}$ is the inverse normal CDF (Papies, et al., 2017).

The identifying assumption in the model above is that endogenous variables should be non-normal, and the error term should be normal. While the latter condition is aligned with the assumption of our Multinomial Probit model, the first condition is not applicable to our retailer pricing positioning variable *HILO* since it is binomial. A Skewness/Kurtosis test for

Normality is done for *Share of Basket*, *Average Category Pric*e, and *Frequency of Purchase.* The result rejects the hypothesis that these three variables are normally distributed, hence they are suitable for this approach. We also test the distribution of the retailer level control variables (i.e., *Sales* and *Number of Stores*). The results show that they are both normally distributed, hence presumed inappropriate for this method.

We conduct the Hausman test for endogeneity by comparing the estimates before and after the copula CF method being applied. The test results at the product level can not reject the null hypothesis (that the differences in coefficients are not systematic), hence indicates a lack of endogeneity. Test results at the product-retailer level show rejection of the Null hypothesis (that the differences in coefficients are not systematic) with $p<0.001$, indicating the endogeneity of *Share of Basket*, *Average Category Pric*e, and *Frequency of Purchase.* Hence, the endogeneity-corrected estimates are only applied for product-retailer level tests.

3.4.2 Multinomial Probit (MNP) Models

We apply a Multinomial Probit (MNP) model to test the effect of category level attributes (e.g., *Average Price*, and *Share of Basket*) as well as retailer level attributes (e.g., *HILO*) on the probability of the unit of analysis (group for a retailer, i.e., the combination of category and retailer) exhibiting APIS, APIS-R or no asymmetry. The CF Copula terms are included in the model to control for the potential endogeneity of group attributes. Retailers make pricing decisions according to product characteristics and their own pricing positioning to maximize their gain (Ellickson & Misra, 2008; Fassnacht & El Husseini, 2013; Grewal et al., 2010). We consider the exhibition of certain asymmetry patterns as retailers' choices when maximizing profits through pricing decisions. It is similar to the assumption of a typical choice model that, when choosing, a rational consumer maximizes his/her utility function[18].

[18] Retailer's choices can be considered collective in the case of aggregated exhibition of APIS/APIS-R at category

Hence, we assume that the retailer's gain in this process is described by the function below:

$$\pi_{ni} = \theta_{ni} + \epsilon_{ni} \quad (2)$$

where π_{ni} is the linear function of maximized retailer gains on nth unit (i.e., category-retailer combo) on choosing i alternative (APIS, APIS-R or no asymmetry). θ is the observed component and ϵ is the unobserved component of the gain. The observed part of the function, $\theta_{ni} = X'_{ni}\beta$, in this case, is a vector of category and/or retailer attributes (regressors), and β is a vector of the m parameter to be estimated. The probability of a unit n exhibit alternative i over another alternative j is expressed as:

$$P_n(i) = \emptyset\left(X'_{ni}\beta + p^{*\prime}_{ni}\beta^*\right), \; i = 1, \ldots, N, \quad (3)$$

where $\emptyset$ is a normal CDF, X is a matrix of category and retailer attributes, p^*_{ni} is the CF Copula term, and β/β^* are vectors of the parameters to be estimated. Parameters of Equation (2) are estimated with the maximum-likelihood method in a reduced form[19]. Control variables (e.g., *firm size and inflation*) are also included as independent variables.

3.4.3 Panel Probit Models

In addition to the Multinomial Probit model, we apply a Panel Probit model to test the effect of category and retailer level attributes on the probability of APIS and APIS-R separately. Each of our data samples (group, retailer, and group-retailer combination level) is divided into three subsamples for estimation: the one with only APIS and APIS-R, the one with only APIS and no asymmetry, and the one with only APIS-R and no asymmetry. We want to test the effects of our independent variables on the probability of APIS against APIS-

level, or individually when analyzed at category-retailer combination level.

[19] We do not have information on alternative specific characteristics to estimate the function in the full form. We are yet to build the retailer gain structure of APIS-R.

R, as well as their probability relative to no asymmetry. Panel Probit model has the advantage to account for the time-invariant part of the subject-specific characteristics (fixed effects). It can be written as:

$$Y_{it} = \mathbf{1}(\beta X_{it} + p_{it}^{*}\beta^{*} + \alpha_i + \mu_{it} > 0), \quad i = 1, \dots., N, \ t = 1, \dots, T, \qquad (4)$$

where Y_{it} is a binary response variable, 1(*) is the usual indicator function, X_{it} is a vector of explanatory variables, including product level attributes, retailer level attributes, and control variables. p_{it}^{*} is the CF Copula term. β and β^{*}denote the vectors of parameters, and a_i is a vector of unobserved individual fixe effects.

3.4.4 Panel Fixed-Effects Models

Next, each of our data samples (group, retailer, and group-retailer combination level) are divided into two subsamples, the one with only APIS asymmetry and the one with only APIS-R asymmetry. The effects of category characteristics and retailer pricing positioning on the magnitude of APIS/APIS-R threshold is tested with a series of fixed-effects models, which can be written in the following unified form:

$$Y_{it} = X_{it}\beta + p_{it}^{*}\beta^{*} + \alpha_i + \mu_{it} \ , \ i = 1, \dots., N, \ t = 1, \dots, T, \qquad (5)$$

where Y is the absolute magnitude of the asymmetry threshold. X is a matrix of explanatory variables including control variables. p_{it}^{*} is the CF Copula term. β and $\beta^{*}$are the vectors of parameters to be estimated, α_i is the time-invariant individual fixed effect, and μ_{it} is the error term. Parameters are estimated separately on APIS sub-samples and APIS-R sub-samples. Hence equation (4) can be rewritten into two equations:

$$APIS_{it} = X_{it}^{1}\beta^{1} + p_{it}^{1*}\beta^{*1} + \alpha_i^{1} + \mu_{it}^{1} \ , \ i = 1, \dots., N, \ t = 1, \dots, T, \qquad (6)$$

$$APISR_{it} = X_{it}^{2}\beta^{2} + p_{it}^{2*}\beta^{*2} + \alpha_i^{2} + \mu_{it}^{2} \ , \ i = 1, \dots., N, \ t = 1, \dots, T, \qquad (7)$$

where equations (6) and (7) are the models to test the APIS sub-samples and APIS-R sub-samples respectively.

Heteroskedasticity. To ensure homoskedasticity, a modified Wald test (Greene 2000 p. 598) for heteroskedasticity is conducted on our three sample panels. The null hypothesis of homoskedasticity (or constant variance) is rejected (p<0.001) at all three samples, which means heteroskedasticity is detected in the panel. To control for this issue, we use alternative covariance matrix estimators developed by White (1980) when estimating our Fixed-Effect models to obtain robust standard errors[20] for the group and retailer level sample. For the group-retailer combined level sample, the heteroskedasticity issue can be solved in combination with the multi-way error dependence issue with a multi-way error clustering method.

Cross-Sectional Error Dependence. In our third sample (group-retailer level), the dependent variables are measured at three-dimensional levels: group, retailer, and time. Within each group or retailer, APIS and APIS-R patterns may be influenced by the characteristics of that particular group or retailer, creating a within-cluster dependence. This will produce biased or incorrect standard errors (clustered errors) since the i.i.d. assumption is violated. To correct cross-sectional error dependence in our panel models, we follow Cameron et al. (2011) to conduct a cluster-robust estimator with multi-way non-nested clustering of the standard error. This approach will take care of the heteroskedasticity issue as well. It is operationalized by a STATA program developed by Gu & Yoo (2019).

3.5. RESULTS

Our estimations are conducted at three levels of analysis separately: product level,

[20] It is operationalized in STATA by the option “robust”.

retailer level, and product-retailer combination level. As discussed in the previous section, APIS is a retailer-category combination level decision. We do not expect strong empirical supports to our hypotheses at the product and retailer level, since the APIS/APIS-R are measured aggregately in these two samples. Some cross-retailer and cross-product variations may be removed because of the aggregation. For instance, a retailer may implement varied pricing practices for different categories. However, when observed at the retailer level, the aggregated APIS/APIS-R measurement may be an average of diverse APIS and APIS patterns and end up shows no asymmetry at all. This is why we created the third sample, a three-dimensional panel that measures asymmetry at a category and retailer combination level.

Next, we report the results for all three samples for each model we estimated (see Table 3.5, Table 3.6, and Table 3.7 for details).

3.5.1 MNP Model Results

Product level. When tested with the MNP model at the product level, only *Share of Basket* and *Frequency of Purchase* shows significant effects. *Share of Basket* has a negative effect on the probability of choosing APIS-R relative to exhibiting no asymmetry (coefficient= -5.491, $p<0.05$), supporting *H2*.

Retailer level. At the retailer level, we do not observe any significant effect for the three retailer variables (*HILO, Number of Stores,* and *Sales*) in the MNP model estimates.

Table 3.5 Estimation Results at Product Level

	Multinomial Probit	Panel Probit	Panel Probit	Panel Probit	Fixed Effects	Fixed Effects
	Relative Prob.	Prob. APIS vs. APIS-R	Prob. APIS vs. Symmetry	Prob. APIS-R vs. Symmetry	APIS Threshold	APIS-R Threshold
	APIS-R					
Share of Basket	3.886	-7.829***	-2.885	2.142	-0.433	319.113
	(2.48)	(2.22)	(2.16)	(3.13)	(124.20)	(329.23)
Average Category Price	-0.081	0.102	-0.008	-0.034	3.095	-4.066
	(0.08)	(0.07)	(0.06)	(0.09)	(1.80)	(3.13)
Frequency of Purchase	1.82	1.984**	2.676**	2.46	(54.46)	(111.29)
	(1.21)	(0.67)	(0.83)	(1.30)	(28.71)	(124.64)
CPI	-0.059	.331***	.256***	-0.04	4.587***	-1.163
	(0.08)	(0.05)	(0.07)	(0.08)	(0.76)	(0.63)
Cons.	0.552	-0.003	0.528	0.376	3.46	-7.827
	(0.43)	(0.30)	(0.34)	(0.43)	(18.65)	(34.25)
	No Asymmetry					
	APIS					
Share of Basket	-5.491*					
	(2.75)					
Average Category Price	0.016					
	(0.08)					
Frequency of Purchase	4.053**					
	(1.23)					
CPI	.356***					
	(0.08)					
Cons.	0.656					
	(0.43)					
/lnsig2u		-1.682***	-14.255	-1.364*		
		(0.47)	(25.15)	(0.67)		
N	548	494	343	259	289	205
R-squared	.z	.z	.z	.z	0.192	0.008

Standard errors are in parentheses

*** p<.001, ** p<.01, * p<.05

Table 3.6 Estimation Results at Retailer Level

	Multinomial Probit	Panel Probit	Panel Probit	Panel Probit	Fixed Effects	Fixed Effects
	Relative Prob.	Prob. APIS vs. APIS-R	Prob. APIS vs. Symmetry	Prob. APIS-R vs. Symmetry	APIS Threshold	APIS-R Threshold
	APIS-R					
Hilo	0.022 (0.18)	-0.249 (0.15)	-0.293 (0.19)	-0.002 (0.19)	-1.668 (1.40)	6.497 (7.94)
Number of Stores	0 0.00	0 0.00	0 0.00	0 0.00	0 0.00	0 0.00
Sales	0 0.00	0 0.00	0 0.00	0 0.00	0*** 0.00	0 0.00
CPI	0 (0.05)	.21*** (0.04)	.182*** (0.05)	0.022 (0.06)	3.611*** (0.43)	-2.911** (1.05)
Cons.	0.113 (0.15)	0.208 (0.12)	.329* (0.14)	0.066 (0.14)	12.869*** (2.34)	-14.134 (15.55)
	No Asymmetry					
	APIS					
Hilo	-0.26 (0.17)					
Number of Stores	0 0.00					
Sales	0 0.00					
CPI	.218*** (0.05)					
Cons.	.411** (0.15)					
/lnsig2u		-.698** (0.27)	-0.562 (0.34)	-1.167* (0.52)		
N	1025	867	721	462	563	304
R-squared	.z	.z	.z	.z	0.199	0.093

Standard errors are in parentheses

*** p<.001, ** p<.01, * p<.05

Table 3.7 Estimation Results at Product-Retailer Level

	Multinomial Probit	Panel Probit	Panel Probit	Panel Probit	Fixed Effects	Fixed Effects
	Relative Prob.	Prob. APIS vs. APIS-R	Prob. APIS vs. Symmetry	Prob. APIS-R vs. Symmetry	APIS Threshold	APIS-R Threshold
	APIS-R					
Hilo	.239***	-.05*	.129***	.202***	-0.246	0.688
	(0.02)	(0.02)	(0.02)	(0.02)	(0.21)	(0.35)
Share of Basket	-1.304*	(1.04)	(0.75)	(1.27)	(18.67)	57.18
	(0.51)	(0.65)	(0.65)	(0.68)	(29.43)	(79.81)
Average Category Price	0.014	0.018	0.017	0	0.846	-1.418
	(0.02)	(0.02)	(0.02)	(0.02)	(0.44)	(1.14)
Frequency of Purchase	-1.467***	1.042***	-0.095	-1.009***	27.247*	36.632**
	(0.16)	(0.20)	(0.21)	(0.21)	(10.89)	(13.27)
Share of Basket (CF Copula Term)	.228***	-.14***	0.00	.212***	1.34	(1.32)
	(0.03)	(0.04)	(0.04)	(0.04)	(1.45)	(2.48)
Average Category Price (CF Copula Term)	-.145***	0.008	-.12***	-.124***	-1.116	1.059
	(0.03)	(0.04)	(0.03)	(0.04)	(0.94)	(1.33)
Frequency of Purchase (CF Copula Term)	.382***	-0.015	.28***	.279***	-5.051**	-4.441*
	(0.02)	(0.03)	(0.03)	(0.03)	(1.64)	(2.18)
Number of Stores	0	0	0	**0*** **	0	0
	0.00	0.00	0.00	0.00	0.00	0.00
Sales	0***	0***	0***	**0*** **	0	0
	0.00	0.00	0.00	0.00	0.00	0.00
CPI	-0.007	.108***	.102***	-.018**	1.096***	-.438**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.15)
Cons.	-.559***	-0.044	-.866***	-.573***	-0.677	-6.066
	(0.09)	(0.11)	(0.11)	(0.11)	(4.40)	(11.67)
	No Asymmetry					
	APIS					
Hilo	**.171*** **					
	(0.02)					
Share of Basket	**-2.026*** **					
	(0.50)					
Average Category Price	0.025					
	(0.02)					
Frequency of Purchase	-0.166					
	(0.15)					
Share of Basket (CF Copula Term)	.057*					
	(0.03)					
Average Category Price (CF Copula Term)	-.135***					
	(0.03)					
Frequency of Purchase (CF Copula Term)	.336***					
	(0.02)					
Number of Stores	0					

	0.00					
Sales	0*** 0.00					
CPI	.112*** (0.01)					
Cons.	-.68*** (0.08)					
/lnsig2u		-1.372*** (0.06)	-.581*** (0.04)	-.546*** (0.04)		
N	55465	27058	44085	39787	15678	11380
R-squared	.z	.z	.z	.z	0.037	0.009

Standard errors are in parentheses

*** p<.001, ** p<.01, * p<.05

Product-retailer combo level. At the product-retailer combination level, we find that *Share of Basket* exhibits significant negative effects on APIS probability relative to exhibiting no asymmetry (coefficient= -2.026, p<0.001), supporting *H2*. *Frequency of Purchase* exhibits a negative effect on APIS-R probability relative to no asymmetry (coefficient= -1.467, p<0.001), supporting *H4*. In addition, we find that *HILO* has a significant positive effect on APIS probability relative to no asymmetry (coefficient= .239, p<0.001), as well as a positive effect on APIS-R probability (coefficient= .171, p<0.001), supporting *H5* and *H6*. Lastly, *Sales* shows significant positive effects on both APIS and APIS-R probability relative to no asymmetry (P<0.001), supporting *H7* and *H8*. As a summary, by estimating the MNP models we find support for *H2*, *H4*, *H5*, *H6*, *H7*, and *H8*. (See all hypotheses testing results in Table 3.8)

3.5.2 Panel Probit Model Results

Product level and Retailer level. We don't find any support for our hypothesis from the Panel Probit estimates at the product level and at the retailer level. This is not unexpected as we discussed previously.

Product-retailer combo level. The Panel Probit estimates partially confirm what we find when estimating the MNP model at the product-retailer combo level. *Frequency of Purchase* shows a negative effect on APIS-R probability relative to no asymmetry (coefficient= -1.009, p<0.001), supporting *H4.* When testing with the APIS against the APIS-R subsample, we find that *Frequency of Purchase* has a significant positive effect on the probability of APIS relative to APIS-R (coefficient=1.04, p<0.001). That means product categories that are purchased more frequently tend to exhibit APIS. *HILO* again shows a significant positive effect on APIS probability relative to no asymmetry (coefficient= .129, p<0.001), as well as a positive effect on APIS-R probability (coefficient= .202, p<0.001), supporting *H5* and *H6*. We also find that *HILO* has a negative effect on the probability of APIS relative to APIS-R (p<0.05), suggesting HILO *HILO* retailers may tend to choose APIS-R more compared with EDLP retailers. The effects of retailer size (*Number of Stores* and *Sales*) are confirmed by the probit model as well. *Sales* shows a positive effect on both APIS and APIS-R probability relative to no asymmetry (p<0.001), supporting *H7* and *H8*. When comparing the APIS VS. APIS-R, *Sales* exhibits a positive effect on APIS probability (p<0.001), suggesting that larger retailers tend to engage in both APIS and APIS-R, but will more likely do APIS. In summary, the Panel Probit Model results support hypotheses *H4, H5, H6, H7,* and *H8*.

3.5.3 Panel Fixed-Effects Model Results

Product level and Retailer level. The estimates of the Fixed-Effects model at the product level are not significant. At the retailer level, we only find one support of our hypothesis. *Sales* shows a positive effect on APIS threshold (p<0.001), supporting *H7*.

Product-retailer combo level. When tested by the fixed-effect regressions, *Frequency of Purchase* shows a strong positive effect on APIS-R threshold (coefficient= 36.63, p<0.01). It indicates that when retailers are doing APIS-R they tend to implement larger thresholds for more frequently purchased products, i.e., larger price drops for these categories. This is consistent with our argument that it would be less effective when conducting APIS-R for more frequently purchased products. To make the obfuscation work in these categories, retailers would be forced to use larger price drops when implementing APIS-R, to drive home their low-price image.

We conclude that we find partial empirical evidence supporting seven out of our eight hypotheses. APIS and APIS-R pricing practices are found negatively associated with category's share of consumer basket. APIS-R is found negatively associated with category purchase frequency and category price level. We also find evidence in support of our predictions about the positive association between APIS/APIS-R and retail pricing positioning. And lastly, retailer size, measured by retailer sales and number of stores owned, is positively associated with both APIS and APIS-R. Between the two pricing practices, larger retailers are more likely to engage in APIS than APIS-R, as suggested by the Panel Probit model estimates. See Table 3.8 for a summary of all hypotheses testing result

3.5.4 Model Integrity Tests and Diagnostics

Firstly, tests for multicollinearity and autocorrelation are conducted. We use Wooldridge (2002) test for autocorrelation on our data. The null hypothesis (that there is no first-order autocorrelation) is not rejected, indicating no autocorrelation in the panels. Variance inflation factor (VIF) measurements also show little multicollinearity among regressors (VIF <5).

Secondly, the stationarity of the dependent variables is tested by the Levin-Lin-Chu (2002) unit-root test and the Harris-Tzavalis (1999) unit-root test. The null hypothesis is that all the panels contain a unit root. Both test results reject this null hypothesis, confirming the stationary of the panels.

In addition, we have controlled for the heteroskedasticity detected in our Fixed-effect models by a modified Wald test (Greene 2000 p. 598). We use alternative covariance matrix estimators developed by White (1980) to obtain robust standard errors.

As a summary, the panel in our regression analyses are free of multicollinearity and autocorrelation problem. The estimations are unbiased after we addressed the heteroskedasticity issue. We also controlled for the endogeneity of the product attributes variables through a CF Copula instrument-free approach. The inferences we draw from the estimated coefficients are robust.

3.6. DISCUSSIONS

Findings in existing studies have documented significant variation in the APIS and APIS-R patterns – both cross-sectional variation across products, as well as variation over time. There are different explanations for such variation including both passive (e.g., inflation) as well as more active pricing practices (e.g., strategic intent on the part of the retailer). However, to the best of our knowledge, no paper exists that conducts a systematic investigation to document the strategic intent contributing to these pricing practices.

Existing evidence also hints at possible roles of product characteristics (e.g., price level) and retailer pricing positioning strategies (e.g., HILO or EDLP) in terms of shopping behaviors. However, this body of literature does not specifically study the retailers' APIS and APIS-R pricing practices. In fact, Chen et al. (2008) and Chakraborty et al. (2015) do provide possible explanations of the practice but do not address the variation found in the asymmetry patterns. Much of this gap is driven by the data limitations inherent in earlier papers – especially the limited number of retailers. The significant variation of the APIS and APIS-R patterns present an opportunity to learn not just about how retailers should deploy their dynamic pricing practices, but also offer insights into the impact these pricing practices could have on the consumer's shopping experiences.

As a first attempt to address these gaps, we provide a systematic explanation of these variations, which are mostly supported by empirical evidence from analyzing a large-scale retail scanner dataset. We find that APIS is more frequent among product categories with a smaller share of consumer basket and that APIS-R is more evident among less frequently purchased categories and categories with lower prices because consumers are less attentive to price changes when shopping these categories. Although the share of basket is a similar measurement with product price level, it shows more significant influences on APIS and APIS-R patterns in our estimation, suggesting that share of basket is a more important product level decision factor than price. Our result also suggests that retailers tend to implement larger asymmetry thresholds (i.e., larger price drops) for more frequently purchased products when implementing APIS-R. This may be because APIS-R is relatively less effective in these categories, hence needs larger price drops to make it work.

We also find that HILO-type retailers are more likely to engage in both APIS and APIS-R, relative to EDLP type retailers, which makes sense since HILO retailers typically rely more on dynamic pricing schemes by definition. While both EDLP and HILO retailers will have an incentive to do APIS-R, what we observe in our sample indicates that relative to EDLP retailers, HILO retailers will be more likely to engage in APIS-R than APIS. In addition, we find evidence that firm size is closely related to the likelihood of a retailer to practice APIS or APIS-R pricing tactics. Larger retailers are more likely to exploit small price changes for profits, taking advantage of their economies of scale. Among retailers that are already doing either APIS or APIS-R, larger retailers are more likely to choose APIS over APIS-R. This matches the observation by Chakraborty et al, (2015) that retailers would have more incentive for APIS-R when they are facing more financial pressure. Larger retailers, with more resources and higher performances (measured by sales in our case), are less likely to choose APIS-R over APIS.

We believe this study makes the following contributions. First, this study is the first attempt to explain the cross-sectional variations of APIS and APIS-R patterns. In the process, we find robust evidence that both product level attributes and retailer characteristics (HILO or EDLP positioning) shape retailer's practices of APIS and APIS-R. Second, it contributes to the literature on small price changes by empirically documenting how rational inattention and strategic obfuscation incentives frame the retailer's dynamic pricing practices. It is the first study to test whether the two theories, RI and SO, apply to a broader context with an economy-wide dataset. Third, it complements the emerging literature in rational inattention by documenting how different retail strategies leverage consumer inattention across different categories. Last but not least, it contributes to marketing practice by documenting the best practices in the domain of managing small price changes – highlighting the factors, both at the product level and firm level, that might be contributing to the success of APIS and APIS-R practices.

3.7. CONCLUSION

Drawing upon RI theory and SO theory, we predict that it is less likely to see APIS at categories with higher prices and larger share of basket. We also predict that HILO stores are more likely to exhibit APIS and APIS-R since HILO store shoppers are less price-conscious relative to EDLP store shoppers. We test these predictions by conducting a series of analyses on the KNRS dataset and a consumer panel dataset, and we find substantial supports for our arguments. Although we do not find much evidence at the product level and retailer level, our predictions are mostly supported at the product-retailer combination level. We argue that

APIS and APIS-R pricing practices are retailer decisions at the category level, hence only when both product and retailer factors are taken into account can we find a significant association between product and retailer attributes and APIS/APIS-R patterns. Future research could build upon our work and move the literature further if the following limitations are addressed.

First, most of our evidence is found through the estimation of the MNP models and probit models because our theory is not developed enough for making strong predictions about asymmetry magnitude. The estimations of asymmetry thresholds would be crisper if we had access to large-scale point of sale transaction prices that are free of price measurement concerns. Even though we have controlled for spurious price changes, the measurement of asymmetry is still yet to be improved. Second, we do not have information about retailer pricing strategy positioning. We have to estimate retailer's positioning by conducting cluster analysis based on attributes measured from retailer price movement. It is difficult to achieve a highly accurate estimation based on limited information. Future research could potentially improve the results with the availability of actual retailer positioning or by using a more sophisticated clustering method. Last but not least, even though we conduct the Copula approach to control for endogeneity, we are not able to entirely solve the endogeneity issues on all variables. A field experiment would be ideal for future research to more reliable estimate the effects of firm and product factors on the APIS phenomenon.

Table 3.8 Hypotheses Testing Results

Hypotheses	Dependent Variable	Explanatory Variable	Predicted Sign	Product Level Support			Retailer Level Support			Product-Retailer Level Support		
				MNP	Panel Probit	Fixed-Effect	MNP	Panel Probit	Fixed-Effect	MNP	Panel Probit	Fixed-Effect
H.1	*APIS*	*Average Category Price*	–						√			
H.2	*APIS*	*Category Share of Basket*	–	√						√		
H.3	*APIS-R*	*Average Category Price*	–							√		
H.4	*APIS-R*	*Category Purchase Frequency*	–						√	√	√	
H.5	*APIS*	*HILO*	+							√	√	
H.6	*APIS-R*	*HILO*	+							√	√	
H.7	*APIS*	*Retailer Size*	+			√				√	√	
H.8	*APIS-R*	*Retailer Size*	+							√	√	

4. Asymmetric Price Adjustment in the Small and Business Cycles

4.1. INTRODUCTION

Economic booms and busts leave a long shadow on the public psyche and easily engage public attention in discussions of the ongoing or impending economic well-being of citizens. These business cycles impact the buying behavior of consumers as well as how firms engage with their customers. During recessions, for example, consumers tend to become more sensitive to the prices they pay. Any business practices, perceived as unfair, like price gouging tend to draw harsh public opprobrium, acting as a constraint on retail pricing practices. Yet, while there is a literature on how these business cycles impact customer attitudes and behavior, the literature on their impact on retailers' price-setting behaviors is thin. Generally speaking, one would expect any sustained macro-economic trends will affect aggregate outcomes on the supply and demand side (e.g., cost of supply, realized demand) and thus, aggregate price levels – the impact deemed significant only if, of noticeable magnitudes. There are fewer compelling reasons to expect these macro-level factors to affect more micro level price movements such as temporary price changes, especially of small magnitudes. Yet, retail pricing decisions are often nuanced, and many retailers engage in dynamic pricing practices comprising strategically implemented small price changes, to compete and maximize profit. It is unclear whether these practices will be affected by macroeconomic trends that accompany business cycles. In fact, the dynamic pricing literature on small price changes has largely ignored the impact of business cycles. In the context of grocery retail, this is an important gap. For example, in times of recession, when the very survival of the business is often in question, small price changes can have an outsize impact on retail profitability. Typically, grocery retailers work on thin margins and the marginal impact of small price changes can be quite big. This outsize impact of small price changes is magnified when these may be perceived as opportunistic by consumers.

In this paper, we investigate how business cycles affect asymmetric pricing behavior of retailers – where retailers are more likely to increase prices than decrease them – a practice that popular press discourse often flags as opportunistic profiteering by retailers. The particular retail pricing practices we investigate in this context are that of *asymmetric pricing in the small* or APIS - where small price increases dominate small price decreases, and the corresponding *reverse* phenomenon, APIS-R, where small price decreases dominate small price increases, with such asymmetry disappearing at the larger end of the price change spectrum (Ray et al. 2006, Chen et al. 2008, Ray et al. 2012, Chakraborty et al, 2015).

APIS and APIS-R practices have significant implications for retailers because they present opportunities for retailers to turn their dynamic pricing capabilities into profit. Although there are emerging explanations of these practices (see Ray et al. 2006, Chen et al. 2008 and Chakraborty et al. 2015), the literature explaining the variation of APIS and APIS-R across time, retailers, and products categories are still in its early stages. While the dominant explanation for APIS has been the Rational Inattention (RI) theory that leverages individual buyer behavior's impact on retail price setting, existing explanations do not apply to the entire spectrum of asymmetric pricing practices which include both APIS and APIS-R.

The RI theory (Chen et al. 2008, Ray et al. 2012) proposes that time and resource-constrained consumers might rationally ignore small price changes, which provides incentives for profit-maximizing retailers to make more frequent small price increases than decreases, thus leading to APIS. On the other hand, the strategic obfuscation logic (Chakraborty et al. 2015) explains APIS-R, suggesting that retailers strategically obfuscate their price spectrum by mixing a few large price increases with numerous small but inconsequential price decreases (“penny drops”) to maintain their competitive price image while aiming for higher margins. Notice that both explanations draw upon the basis of limited cognitive processing and inattention of consumers. The RI explanation for APIS leverages consumer inattention to *small* price changes. In a reversal of sorts, the strategic obfuscation logic leverages consumer inattention to *large* price changes. Clearly, in order to benefit from these pricing practices, retailers need to identify the right situational context to implement them. We build on the above explanations to argue that business cycles, reflected by unemployment rates and economic recessions, are major factors impacting consumer attention to prices, hence influencing retail practices of APIS and APIS-R over different time periods.

Our study uses part of the Kilts-Nielsen Retail Scanner (KNRS) dataset, a panel of weekly prices and sales at the SKU level for around 35,000 geographically dispersed stores belonging to more than 160 retail chains across all US markets[21]. The data covers a ten-year period from 2006 to 2015. In particular, the data covers a 19-month recession period, from December 2007 to June 2009, as defined by the National Bureau of Economic Research (NBER)[22], which allows us to investigate the possible effects of business cycles. We find distinct patterns of APIS and APIS-R pricing practices associated with unemployment and recessions, suggesting that retailers strategically deploy these pricing practices in response to fluctuating macroeconomic conditions. Our results would be the first evidence of such strategic pricing practices in response to business cycles and contribute to furthering our understanding of how macroeconomic outcomes and micro level price setting are related to each other, a key tenet of New-Keynesian economics (Dutta, Bergen, and Ray, 2010). Our

[21] The full dataset covers more than 50% of the total sales volume of US grocery and drug stores and more than 30% of all US mass merchandiser sales volume.

[22] National Bureau of Economic Research (NBER) define a recession as “the period between a peak of economic activity and its subsequent trough, or lowest point.” NBER keeps an updated records of business cycle, which can be found at https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

findings are of interest to both economists interested in monetary policy, as well as retailers interested in effective dynamic pricing during recessions.

The rest of the paper is structured as follows. In section 2, we discuss the relevant background literature leading to the testable hypotheses drawn from the RI and strategic obfuscation perspectives. In section 3, we describe the data. In section 4, we discuss our empirical strategy, including measurement and analyses. In section 5 we report our findings and assess the robustness of our results. In section 6 we discuss the implications of our results for the literature and practice. In section 7 we conclude with a brief discussion of limitations and future research.

4.2. BACKGROUND LITERATURE AND TESTABLE HYPOTHESES

The existing literature on the topic has found a link between the business cycle and consumer attention. Becker (1965) predicts theoretically that unemployed consumers would be more price-attentive and willing to spend more time shopping. Long et al. (2015) argue that during recessions, the opportunity cost of time is low for households, hence they can smooth unanticipated negative income shocks by spending more time on shopping. They find that the prices households pay are significantly lower when unemployment is high, and that households became more price attentive during the great recession. Nevo and Wong (2015) find that with higher unemployment rates, households devoted more time seeking better deals, shopped more frequently at discount stores, purchased more items on sale, and bought more private label products. Cha, et al. (2015), Aguiar et al. (2013) and McKenzie et al. (2011) document similar findings that consumers have more time shopping and are more sensitive to prices during the economic downturn when unemployment rates are high. Similarly, studies on consumer purchase behavior of private label products report that households tend to consume more private label products and less national brand products when employment rises (e.g., Dube et al. 2018, Quelch and Harding 1996, and Lamey et al. 2007). This further proves the linkage between the business cycle and consumer attention to prices, given the fact that the branded products are typically more expensive than private label products (Volpe 2011 and 2014, Dube et al. 2018). Studies of informational rigidities also documented observation that the extent of consumer attention varies over the business cycles. For example, Coibion and Gorodnichenko (2015) study the variability in information rigidity over the business cycle, and they find that individuals update and process information faster (hence are more attentive), during economic downturns than during economic booms.

Less studies have examined the pricing strategy of retailers over the business cycle, and these studies focus more on the firm strategy level of retailer's pricing practices, rather than the dynamics of small price changes. For instance, Little et al. (2011) compare firm performances between retailers with a differentiation strategy and those with a cost leadership strategy in the 2008-2009 recession period. Chou and Chen (2004) analyzed the success of retail pricing strategies during a recession in Taiwan. They find that a predatory pricing strategy leads to higher market performance if the retailer has abundant resources and operates in a market where consumers are price sensitive. Berezvai (2014) investigates the performance implication of retail strategy among 11 Hungarian food retail chains in the period from 2008 to 2012. They find that aggressive pricing strategies (i.e., low prices, but intensive price promotion) are the most successful and premium pricing is the least successful strategy. The only two studies, to the best of our knowledge, that specifically investigate small price change dynamics over the business cycle are conducted by Chakraborty et al, (2015) and Dixon, Seaton and Waterson (2014). Dixon, Seaton and Waterson (2014) work with scraped price data from three major UK supermarkets during the 2008-2010 recession. They find that the frequency of price changes increased substantially during the recession, and that small price-cut increased more significantly than price-rise during the crisis.

Chakraborty et al, (2015) documented a more significant APIS-R phenomenon during high inflation periods in a transaction dataset from three UK supermarkets.

As a summary, the available evidence points to consumers having more time and less income, thus giving greater attention to price changes during recession periods when unemployment rates are high, and vice versa during low unemployment periods. Yet, there is very little work examining how these impact retail pricing behavior. This is not due to a lack of managerial interest, for there is a strong recognition that effective retail pricing needs to incorporate these in their price-setting practices (Rao, Bergen, and Davis, 2000). So, this gap is an important one both for economists as well as for marketers. In a partial attempt to address this gap, we examine if unemployment and recessions are major time-varying factors that influence the retailer's pricing decisions regarding APIS and APIS-R. Interestingly, studies of APIS and APIS-R have found evidence that these practices may be related to inflation or deflation, but that inflationary tendencies cannot entirely explain the significant variations observed in APIS and APIS-R patterns (Chen et al. 2008; Ray et al. 2012; Chakraborty et al, 2015; Ling, Ray, and Levy 2021). So, our study will expand our understanding of the longitudinal influences on these practices.

Our hypotheses development builds on two key themes. First, consumers are rationally inattentive – i.e., when the cost of paying attention is higher than the presumed benefits, they will economize on attention and thus be rationally inattentive. Second, small price changes can be effective tools for retail profitability. The latter happens when small price increases do not impact consumer purchase behavior, or when numerous small price decreases allow retailers to engage consumer attention enough to reduce the salience of a few large price increases (Chakraborty et al. 2015).

Now, during economic downturns when the unemployment rate is high, it can be argued that consumers (a) may have more time at hand (lower opportunity costs of time), and relatedly, (b) perceive the cognitive costs of searching for information and prices to be low. These result in lowering the costs of paying attention to price changes, making consumers more likely to pay attention to price changes which they would have ignored earlier. The situations would be symmetrically reversed for low unemployment periods, when consumers will have less time at hand and face a greater demand on their time to process price information, making them less likely to pay attention to small price changes. It turns out these could have different implications for APIS or APIS-R.

During high unemployment periods, greater consumer propensity to pay attention, reduces the retailer's ability to benefit from small price increases, since consumers would be more likely to notice the price increases and reduce their purchases. Further, if asymmetric pricing is perceived as opportunistic during such economic downturns, it would likely also invite harsh public opprobrium, further driving consumers away from the retailer. Therefore, one would expect to see lesser instances and degrees of APIS pricing practices.

H1. Unemployment will be negatively associated with APIS pricing practices.

Relatedly, high unemployment also constrains consumer purchasing power, making them care more for the prices they pay. Consequently, retailers also have a greater incentive to convey a (low) price image which they can, with numerous small price decreases. This becomes even more important when the retailer faces cost pressures (e.g., during inflation) forcing them to either absorb the higher costs or protect retail margins by passing them on to the consumer. One way to protect margins would be to have one large price increase rather than spread out across multiple small increases. However, large price increases might convey a high price image inviting consumer flight. In such cases, multiple small price decreases might convey a low-price image and could reduce the salience of the occasional large price increase, in effect drawing lesser attention to large price increases. During low employment, the situation reverses, with consumers carrying greater purchasing power and relatively less caring about the prices they pay – thus, reversing retail pricing incentives as well. Therefore, one would expect to see higher instances and degree of APIS-R pricing practices during higher unemployment.

H2. Unemployment will be positively associated with APIS-R pricing practices.

4.3. DATA AND MEASUREMENT

4.3.1 Data Description

We use the Kilts-Nielsen Retail Scanner Dataset (KNRS), which is a panel dataset of total sales (quantities and prices) at the UPC (barcode) level for around 35,000 geographically dispersed stores belonging to more than 160 retail chains (these numbers vary by year) across all US markets[23]. The data consists of *weekly* pricing, volume, and store-merchandising information aggregated from transactions recorded by the stores' point-of-sale systems and covers a ten-year period from 2006 to 2015. The strength of this dataset is evident: it provides an economy wide context in a contemporary setting, enabling the best generalizability possible. In addition, the sample period of the dataset contains a 19-month recession period, from December 2007 to June 2009, as defined by the NBER, making it appropriate for testing the effects of business cycles.

The KNRS data organizes the product hierarchy into ten product departments, which are then further organized into 125 product groups followed by product modules and the individual SKUs or UPCs. For ease of referencing, we will sometimes refer to the groups as

[23] The full dataset covers more than 50% of the total sales volume of US grocery and drug stores and more than 30% of all US mass merchandiser sales volume.

categories and the modules as sub-categories. The product hierarchy of our sample for this study is organized into 9 randomly chosen product departments, which are then further organized into 56 randomly chosen product groups consisting of 527 product modules (sub-categories), comprising 4,311,648 UPCs. Alcohol and tobacco products are excluded because those products are heavily regulated in US. Our sample comprises of 161 retailers, belonging to 91 parent companies. This represents a majority of retailers recorded in the full database. The data sample, in total contains more than 79 billion weekly price observations. The details of group level observations are reported in Table 4.1.

In our 10-year sample, there is a 19-month recession period, from December 2007 to June 2009 (as defined by the NBER). We also have the US monthly unemployment data of the sample period, making it easy to define a matching 19-month low unemployment or high unemployment sample. However, the unemployment figures and the recession periods does not have an exact match. Unemployment lags behind the NBER recession by about 6 months. To cope with this lag, we create two different high unemployment samples. One is defined by the 19 NBER recession months (to capture high unemployment effect), and the other is defined directly by the 19 months with the highest unemployment rates during the full sample period. We also create a low unemployment sample, defined by the 19 months with the lowest unemployment rates.

Table 4.1 Analyzed KNRS Scanner Data

Department Name	Group Name	No. of Modules	No. of UPCs	No. of Observation
Dry Grocery	Candy	14	289,747	5,907,425,280
	Gum	4	18,328	1,215,013,376
	Juice, Drinks - Canned, Bottled	18	107,917	3,592,290,560
	Pet Food	10	74,207	3,107,025,664
	Prepared Food-Ready-To-Serve	40	61,235	1,550,426,112
	Soup	5	42337	1882395136
	Baking Mixes	17	24596	781248704
	Breakfast Food	4	24107	1125582080
	Cereal	5	38266	1807372672
	Coffee	5	61510	1229685120
	Desserts, Gelatins, Syrup	12	20902	965305024
	Nuts	4	65059	1023383232
	Packaged Milk and Modifiers	6	17206	649159424
	Sugar, Sweeteners	5	9422	298786784
	Tea	8	61210	1257548928
	Bread and Baked Goods	14	299239	2605746688
	Cookies	2	102462	1891238912
	Crackers	10	30165	1107950976
	Snacks	18	213708	4488684544
	Soft Drinks-Non-Carbonated	9	59337	1618847360
Frozen Foods	Baked Goods-Frozen	12	18804	437997856
	Breakfast Foods-Frozen	2	14016	512820640
	Ice Cream, Novelties	4	91355	2096284544
	Juices, Drinks-Frozen	8	3441	157345696
	Pizza/Snacks/Hors Doeurves-Frzn	3	39026	944168256
	Prepared Foods-Frozen	23	96910	2701307648
	Unprep Meat/Poultry/Seafood-Frzn	15	39922	325982144
Dairy	Cheese	16	89513	1844350464
	Eggs	1	9941	94186312
	Milk	7	58193	746784320
	Snacks, Spreads, Dips-Dairy	4	32946	336883488
	Yogurt	2	36829	1207518976
Deli	Dressings/Salads/Prep Foods-Deli	16	128385	1779300864
Packaged Meat	Packaged Meats-Deli	12	105075	1786796416
	Fresh Meat	1	11147	122056672
Fresh Produce	Fresh Produce	25	121681	828927296
Non_Food Grocery	Detergents	6	34141	1644012160
	Household Cleaners	20	35886	1246793472
	Laundry Supplies	20	44919	1156176640
	Paper Products	11	178806	2523770112
	Personal Soap and Bath Additives	8	89812	1818637312
	Pet Care	9	143056	1081385344
	Wrapping Materials and Bags	13	28871	954846784
General Merchandise	Automotive	5	23392	291624032
	Batteries and Flashlights	2	39673	673595712
	Books and Magazines	1	13579	541083072
	Cookware	2	49007	348034592
	Glassware, Tableware	3	261232	925427968
	Kitchen Gadgets	8	264768	1246782592
	Toys & Sporting Goods	2	22885	25291164
Health & Beauty Care	Baby Needs	10	52799	680964096
	Hair Care	14	182990	3714681344
	Medications/Remedies/Health Aids	1	1879	89118656
	Oral Hygiene	12	50977	2499003648
	Skin Care Preparations	10	117057	1905587200
	Vitamins	9	157775	1907149312
Total #	56	527	4311648	79301793380

Note: to conserve space we do not include module level statistics, which are available from the authors upon request

4.3.2 Measurement of APIS/APIS-R Threshold

We define the asymmetry threshold as the magnitude of price change below which asymmetric pricing is statistically supported (see Chen et al. 2008, Ling, Ray & Levy 2021). We compute the frequency distribution of the positive and negative price changes by the size of the change, starting with 1¢ and onwards. Then we identify the first point where the pricing asymmetry does not hold, i.e., the first point (from 1¢ price change to 1,000¢ price change) where we observe no statistical difference between the positive and negative price changes. We use a one-sample z-test of proportions to measure the statistical significance of the probability that the number of positive price changes equals the number of negative price changes – i.e., there is no asymmetry, at each price change magnitude. Rejection of this null hypothesis confirms the presence of asymmetry. The first point (from 1¢ price change to hundreds of cents price change in intervals of 1¢) where the null hypothesis of symmetric price change cannot be rejected, or the first point where the direction of asymmetry changes, is defined as the asymmetry threshold.

APIS/APIS-R thresholds are estimated at two-dimensional panels as the unit of analysis in this research (at both group-month level and retailer-month level). We use two types of dependent variables: the existence of asymmetry and the asymmetry thresholds. Two dummy variables *APIS* and *APIS-R* are created to measure the existence of asymmetry: coded 1 if the product or retailer exhibits said asymmetry in the small and coded 0 if otherwise. In addition, average group level and retailer level asymmetry thresholds are calculated to represent the absolute magnitude of APIS or APIS-R in a certain time period (by averaging thresholds of all groups/retailers in a certain period).

4.3.3 Measurement of Business Cycle

Business Cycle is a well-studied economic phenomenon. Mitchell (1927), the founder of the National Bureau of Economic Research (NBER), defines it as the alternation between periods of expansion and recession in the level of economic activity. Other definitions are similar, e.g., “ the periodic ups and downs in economic activity” (Christiano & Fitzgerald 1998), or “fluctuations in economic activity” (Morley & Piger 2009). NBER’s measurement of business cycle depends on some key economic level indicators, e.g., personal income, employment, and gross domestic product (GDP). Among these, the employment and personal income are the major indicators used by NBER for dating of business cycle[24]. Unemployment rate is also considered by the economics literature as one of the most important business cycle indicators (e.g., Moore 1961, Christiano & Fitzgerald 1998, Morley & Piger 2009). Hence, we use unemployment rate as the major measurement of business cycle in this study, and use NBER defined recession periods as another indicator. The data on the US monthly unemployment rates are included in our regressions as independent variables, as well as a recession dummy variable: 1 indicates the month being within the recession period, 0 otherwise. Two price indices measures: monthly PPI and CPI indices of the US are included as control variables. These are standard aggregate economic data from the US Bureau of Labor Statistics (NBER) database (see Table A1 in the Appendix for monthly series of these measurements). We combine the APIS threshold results obtained from the KNRS data with the NBER recession and price indices dates to apply the proposed tests.

4.4. EMPIRICAL METHODS

4.4.1 Descriptive Analyses

We conduct both descriptive analyses and regression analyses to test the effects of

[24] See “Business Cycle Dating” by National Bureau of Economic Research (https://www.nber.org/research/business-cycle-dating)

business cycle on consumer attention reflected by APIS threshold. We first compare the extent of asymmetry during the recession and expansion periods descriptively, as we have clearly defined business cycle periods in our data. The analyses are conducted by comparing the average group level asymmetry thresholds obtained using the NBER sample with the asymmetry thresholds obtained using lowest unemployment sample, as well as the comparison between highest unemployment sample with the lowest unemployment sample. Additionally, we compare average asymmetry thresholds and the corresponding inflation rates across these periods.

All analyses are conducted using 19-month windows for all samples, because the recession identified by the NBER during our sample period, was 19-month long. If unemployment rates indeed negatively impact APIS threshold, we expect to see lower APIS threshold (or a smaller number of APIS retailers and categories) during recession period and lowest employment periods, compared with thresholds in highest employment periods. The analyses results are summarized in the Table 1 and will be discussed in Section 5.

4.4.2 Regression Analyses

To isolate the effects of unemployment from other time varying factors (e.g., inflation) more robustly, we test the data by two sets of econometrics models: dynamic panel models and panel logit models. All models are estimated with fixed-effect at both group-month level and retailer-month level to control for time-invariant group-wise or retailer-wise fixed effects that influence asymmetry patterns. Two separate samples are created accordingly at each level of measurement.

We first take advantage of the panel structure of our prepared data and test the effects of business cycle on asymmetry thresholds with a dynamic panel fixed-effects model. We find from the descriptive analysis that the effect of recession lags behind the asymmetry patterns. Hence, we also use a dynamic specification to account for the possible lagged effects of the business cycle variables.

$$y_{it} = a_i + \beta_0 X_{it} + \sum_{m=1}^{q} x_{it-m}\beta_m + \varepsilon_{it}\,, \qquad i = 1, \dots, N,\ t = 1, \dots, T, \qquad (1)$$

where y_{it} is the group level month thresholds, X_{it} is a vector of explanatory variables, including *Recession* (dummy), *Unemployment Rate, PPI and CPI*. x_{it-m}denotes the lagged values of recession . β_m is a matrix of parameters to be estimated, ε_{it} is the error term, and q is the largest number of lags on *x*. a_i denotes the unobserved individual fixed effects. The maximum number of lags are determined by a combination of Akaike's Information Criterion (AIC) and Testing-Up method.

In addition, we use a panel probit model to test the effects of business cycle on the probability of a category (or a retailer) exhibiting asymmetry in the small (APIS, or APIS-R).

$$Y_{it} = \mathbf{1}\left(\beta_0 X_{it} + \sum_{m=1}^{q} x_{it-m}\beta_m + a_i + \mu_{it} > 0\right),\ i = 1, \dots, N,\ t = 1, \dots, T, \qquad (2)$$

where Y_{it} is a binary response variable, 1(*) is the usual indicator function, X_{it} is a vector of explanatory variables, including *Recession* (dummy), *Unemployment Rate, PPI and CPI*. The lagged value of recession is denoted by x_{it-m}. β denotes a vector of parameters, q donates the maximum length of lags on X, a_i is vector of unobserved individual fixed effects.

4.5. EMPIRICAL FINDINGS

4.5.1 Evidence Supporting Hypothesis 1.

As discussed in previous section, both the lowest and highest unemployment rates periods are defined as 19-month windows, because the NBER recession period was 19-month long during our sample period (see Table A6 for the series in the Appendix). The average unemployment rate of the lowest unemployment period was 4.6%, which occurred during

March 2006 to September 2007. The average unemployment rate of the highest unemployment period was 9.7%, which occurred from May 2009 to November 2010. According to the results in Table 2, the average monthly group level APIS threshold is 8.7 ¢ during the lowest unemployment period, and 5.7¢ during the highest unemployment period. The average APIS threshold is actually larger for the lowest unemployment periods than the average of all other periods (which is 8.1¢).

Across the 56 product groups, in 40 out of 56 possible comparisons (i.e., 71%) we find a stronger average asymmetry for the lowest unemployment period than for the highest unemployment period. In 30 out of the 56 cases (i.e., 54%), we find stronger average asymmetry for the lowest unemployment period than for the average of all other periods (see Table 1 for the group level asymmetry). Paired t-test also confirms this conclusion: for the 56 product categories, the average asymmetry is larger for the lowest unemployment period than for the highest unemployment period ($p < .01$ or better).

The relation between unemployment and asymmetry threshold is quite evident in Figure 1, which illustrate the series of average month thresholds across the whole sample period[25]. We observe a deep dive of asymmetry thresholds during high unemployment period. The NBER defined recession seems to have a lagged negative effect on asymmetry threshold, for a lag of about 8 to 10 months according to Figure 4.1. This may explain the close average threshold for the NBER recession period in comparison with the figure for the lowest unemployment period. Nonetheless, these finding empirically supports our first hypothesis that the unemployment rate negatively influences the asymmetry threshold.

[25] Figure 1 uses average thresholds calculated by considering APIS-R thresholds as negative values because of the reverse nature of APIS-R, to gain a unified view of the trend

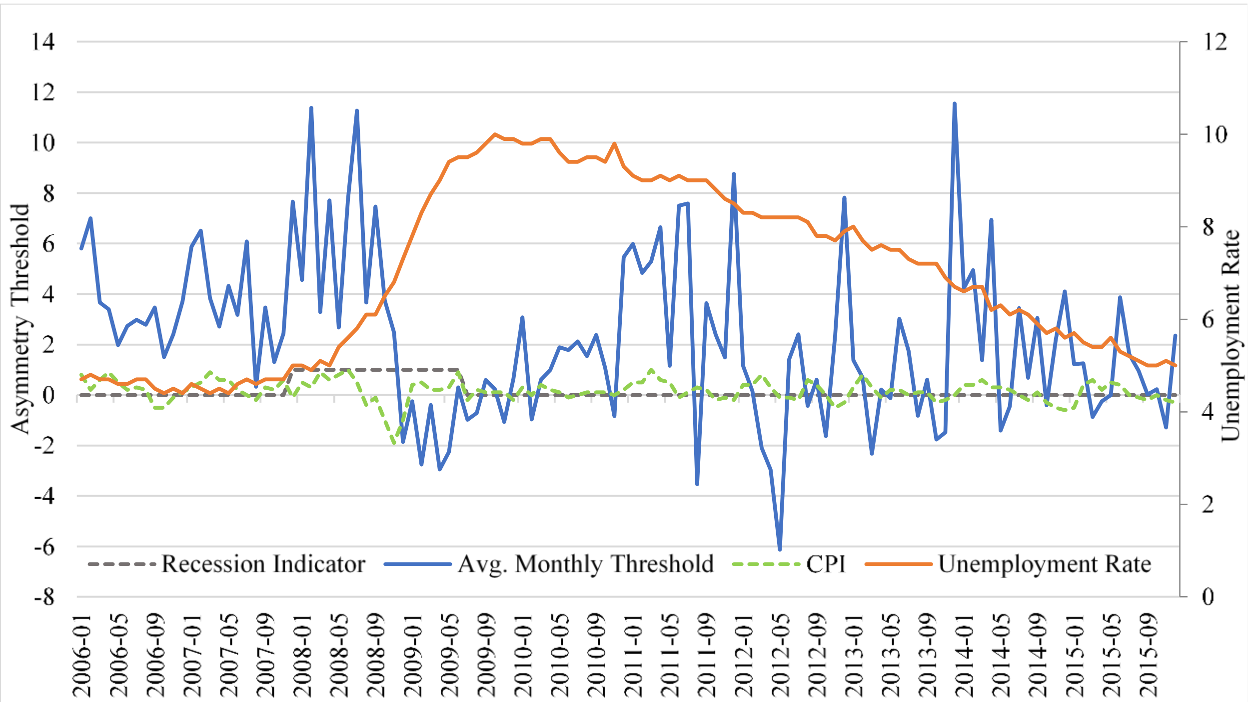
Table 4.2 Group level Avg. Monthly Threshold and Sample Size for Each Period

	Monthly Avg. Threshold				Sample Size (Number of Price Obs.)		
Group Name	**Full Sample**	**Highest u**	**Lowest u**	**NBER Recession**	**Highest u**	**Lowest u**	**NBER Recession**
CANDY	-4.4	-2.5	-0.6	-1.2	859,817,408	837,237,824	896,632,320
GUM	-0.2	-3.3	0.3	2.4	207,445,984	181,319,760	204,755,488
JUICE, DRINKS - CANNED, BOTTLED	5.6	3.5	8.1	4.1	505,527,840	479,555,712	502,440,096
PET FOOD	1.6	0.6	3.2	5.0	483,428,096	440,634,528	468,805,472
PREPARED FOOD-READY-TO-SERVE	4.7	0.8	4.1	6.6	249,944,240	239,026,208	253,794,880
SOUP	5.7	2.1	7.4	10.3	297,157,184	274,952,896	303,274,432
BAKING MIXES	1.2	-1.7	3.0	7.5	125,514,072	113,053,096	120,780,560
BREAKFAST FOOD	1.2	-1.2	0.9	2.9	174,045,216	155,143,760	169,686,176
CEREAL	2.7	-1.2	4.3	4.9	280,558,624	260,940,576	276,676,736
COFFEE	1.5	-0.3	4.6	2.6	177,780,480	151,631,680	171,430,512
DESSERTS, GELATINS, SYRUP	2.4	-0.5	6.8	4.3	152,171,984	153,627,232	156,700,880
NUTS	1.0	-1.4	1.6	1.5	159,800,096	139,705,376	155,654,320
PACKAGED MILK AND MODIFIERS	3.0	-3.3	8.1	1.6	101,487,616	85,874,496	95,017,088
SUGAR, SWEETENERS	6.9	6.2	8.4	15.2	48,410,664	41,752,200	45,562,244
TEA	1.7	0.3	3.3	2.6	194,856,752	161,765,296	186,517,968
BREAD AND BAKED GOODS	9.4	2.7	15.6	19.1	422,857,504	378,497,472	402,565,184
COOKIES	2.3	-1.9	3.2	3.7	282,145,376	293,699,776	292,751,808
CRACKERS	2.4	-0.3	3.6	4.7	177,022,848	166,138,400	178,945,360
SNACKS	4.6	-0.8	5.9	9.0	682,845,056	604,178,048	656,330,816
SOFT DRINKS-NON-CARBONATED	2.0	2.2	3.1	1.7	266,501,152	216,888,144	255,209,600
BAKED GOODS-FROZEN	4.8	2.9	7.4	9.3	69,675,560	69,239,336	73,605,808
BREAKFAST FOODS-FROZEN	0.8	-0.3	2.4	5.9	73,029,888	71,839,536	76,875,160
ICE CREAM, NOVELTIES	0.0	0.3	1.1	-0.9	336,143,712	297,925,536	314,354,688
JUICES, DRINKS-FROZEN	2.3	2.9	5.5	-1.9	26,753,666	27,979,608	27,264,024
PIZZA/SNACKS/HORS DOEURVES-FRZN	1.6	1.1	-0.6	3.2	145,487,648	133,137,704	145,346,976
PREPARED FOODS-FROZEN	1.5	0.5	0.3	6.5	426,967,200	389,616,000	416,111,424
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	0.9	-0.1	1.8	0.7	54,567,232	49,348,648	53,213,116
CHEESE	6.4	2.2	9.6	7.4	286,891,008	265,819,168	282,729,856
EGGS	9.8	9.5	10.6	3.7	14,507,543	12,945,817	14,240,498
MILK	4.8	7.2	15.1	-7.1	115,538,280	98,327,832	108,087,320
SNACKS, SPREADS, DIPS-DAIRY	1.4	1.6	3.8	-2.1	50,246,600	43,351,208	47,900,304
YOGURT	1.9	1.5	3.3	2.7	181,665,776	151,874,512	170,935,776
DRESSINGS/SALADS/PREP FOODS-DELI	2.8	0.3	6.8	5.3	291,547,392	246,774,048	281,901,696
PACKAGED MEATS-DELI	7.3	9.1	6.4	10.4	288,504,736	261,483,040	280,560,352
FRESH MEAT	6.9	5.6	6.0	8.8	17,474,000	13,497,543	15,976,689
FRESH PRODUCE	16.7	11.2	22.4	19.7	125,216,600	100,562,120	117,125,896
DETERGENTS	-0.4	0.4	-0.9	-1.4	257,270,176	232,552,320	252,557,808
HOUSEHOLD CLEANERS	2.3	-0.6	-1.6	4.9	196,387,024	186,944,000	195,366,784
LAUNDRY SUPPLIES	0.4	-1.7	-0.5	-0.2	183,361,712	182,735,984	187,335,568
PAPER PRODUCTS	0.7	-0.9	-2.1	4.5	393,869,920	369,017,088	390,851,840
PERSONAL SOAP AND BATH ADDITIVES	-0.5	-0.7	-0.5	-2.1	277,557,120	256,911,984	268,098,496
PET CARE	-0.1	-1.8	1.7	1.6	173,167,984	166,522,752	179,190,304
WRAPPING MATERIALS AND BAGS	4.3	3.9	1.8	4.1	155,275,184	147,064,272	154,000,320
AUTOMOTIVE	2.2	0.7	5.4	5.4	45,477,272	52,720,468	48,806,088
BATTERIES AND FLASHLIGHTS	-0.1	-1.8	1.7	-0.3	112,057,488	113,229,632	115,908,768

BOOKS AND MAGAZINES	-0.5	-1.5	-0.2	-0.8	93,807,328	122,707,408	107,642,464
COOKWARE	0.9	-1.6	3.7	2.3	54,751,108	52,157,368	56,171,880
GLASSWARE, TABLEWARE	-2.5	-5.5	-2.3	-1.8	141,442,752	148,260,768	152,967,504
KITCHEN GADGETS	-4.2	-9.4	-6.4	-6.6	198,516,336	198,014,160	199,182,544
TOYS & SPORTING GOODS	-0.1	-0.1	0.1	-0.6	2,487,988	7,369,555	7,559,495
BABY NEEDS	-0.2	-0.9	-1.9	0.9	112,002,784	119,879,896	118,591,776
HAIR CARE	-0.8	-1.1	-2.0	-1.5	586,099,136	600,029,184	599,973,824
MEDICATIONS/REMEDIES/HEALTH AIDS	0.3	0.2	0.8	0.3	14,784,702	14,254,848	15,008,505
ORAL HYGIENE	-0.3	-0.4	0.4	-1.1	394,412,832	394,390,208	398,341,056
SKIN CARE PREPARATIONS	-1.0	-1.2	-1.5	-1.5	297,859,072	307,407,360	310,131,168
VITAMINS	-0.7	-0.9	-0.9	1.1	285,637,952	235,190,752	267,839,008
Average	**2.2**	**0.5**	**3.4**	**3.3**	**220174301.8**	**205655431.1**	**218665834.3**
Median	**1.6**	**-0.2**	**3.1**	**2.7**	**179723128.0**	**163951848.0**	**179067832.0**

To further test our first hypothesis, we estimate the effects of monthly Unemployment Rate and Recession on the monthly APIS thresholds (see Table 3) with panel fixed effects (Model 1) and panel logit (Model 2) at both category (group) level and retailer level. CPI and PPI rates are included as control variables to control for inflation effects.

Figure 4.1 Avg. Monthly Asymmetry Threshold Across Products and Unemployment (06-15)



The estimation results show that Unemployment Rate has significant negative effects on both the APIS threshold and the probability of a group or retailer exhibiting APIS. When estimated with the group level sample, Unemployment Rate has a coefficient of -0.43 for the panel model and a coefficient of -0.87 for the panel probit model ($p<0.001$). At retailer level, we observe coefficient of -0.231 and -0.088 for the two models, with p-value smaller than 0.01 and 0.001 respectively. Hence, our first hypothesis is supported at both group level and retailer level (see Table 3 for a summary of estimation results). Recession dummies, as an alternative indicator of business cycle, are found positively influencing the APIS thresholds – the coefficients of Recession are positive and significant ($p< 0.001$) for the panel model at both retailer and group level. While apparently contradictory top our predictions, note that recession has a lagged effect on unemployment, as indicated in Figure 1. To determine the length of lags, we use a combination of AIC and Testing-Down method when estimating the models. At both group and retailer level, the optimum length of lags for Recession is 10 months for the panel fixed-effect model, and 8 months for the panel logit model. We find that recession has significant negative effects on APIS threshold (coefficient=-4.21, $p<0.01$) and the probability of APIS (coefficient=-0.854, $P<0.001$) when lagged by 10-month and 8-month respectively, similar to what we observe in descriptive analyses[26]. It further supports our prediction that unemployment negatively influences APIS. Overall, the estimation results are aligned with the findings in descriptive analyses, supporting Hypothesis 1.

[26] The lagged term of *Recession* would cause multicollinearity and influence the reliability of the coefficient of other variables. The lagged terms are included just to estimate the length and significance of the lagged effects of *Recession.*

Table 4.3 Estimation Results for APIS

	Group Level				Retailer Level			
	Model 1	Model 1 w/ Lags	Model 2	Model 2 w/ Lags	Model 1	Model 1 w/ Lags	Model 2	Model 2 w/ Lags
	APIS Threshold	APIS Threshold	Prob. APIS	Prob. APIS	APIS Threshold	APIS Threshold	Prob. APIS	Prob. APIS
Unemployment Rate	-.43***	0.043	-.087***	-0.033	-.231**	0.163	-.088***	-.052***
	(0.12)	(0.15)	(0.01)	(0.02)	(0.07)	(0.09)	(0.01)	(0.01)
CPI	-2.416**	-2.94**	-.236*	-.449***	-1.039	-2.289***	-.229**	-.354***
	(0.91)	(1.04)	(0.11)	(0.12)	(0.53)	(0.62)	(0.09)	(0.10)
PPI	.834**	.848*	.172***	.202***	.434*	.732***	.134***	.139***
	(0.29)	(0.33)	(0.04)	(0.04)	(0.17)	(0.20)	(0.03)	(0.03)
Recession	2.66***	5.843***	0.131	0.136	3.935***	5.17***	.183**	.382*
(Dummy)	(0.56)	(1.63)	(0.07)	(0.20)	(0.35)	(1.03)	(0.06)	(0.17)
L.recession		-3.625		0.275		-0.083		-0.045
		(2.26)		(0.28)		(1.35)		(0.24)
L2.recession		4.553*		-0.091		1.789		0.052
		(2.22)		(0.29)		(1.33)		(0.24)
L3.recession		-4.757*		-0.112		-1.967		-0.165
		(2.17)		(0.28)		(1.40)		(0.23)
L4.recession		4.528*		0.445		1.343		-0.149
		(2.21)		(0.29)		(1.40)		(0.23)
L5.recession		-4.564*		-0.318		-3.239*		0.199
		(2.29)		(0.29)		(1.35)		(0.23)
L6.recession		0.011		0.544		3.986**		.514*
		(2.26)		(0.29)		(1.36)		(0.24)
L7.recession		4.704*		-0.124		-1.803		-0.216
		(2.29)		(0.31)		(1.46)		(0.25)
L8.recession		-1.207		-.854***		0.307		-.63***
		(2.54)		(0.23)		(1.62)		(0.18)
L9.recession		-1.239				1.895		
		(2.30)				(1.58)		
L10.recession		-4.21**				-5.65***		
		(1.57)				(1.12)		
Cons.	11.858***	8.8***			9.424***	6.973***		
	(0.86)	(1.06)			(0.53)	(0.66)		
N	2979	2701	6720	6272	5252	4518	11715	10302
Pseudo R2	0.02	0.04	0.01	0.02	0.03	0.05	0.01	0.01

Standard errors are in parentheses
*** p<.001, ** p<.01, * p<.05

Table 4.4 Estimation Results for APIS-R

	Group Level				Retailer Level			
	Model 1	Model 1 w/ Lags	Model 2	Model 2 w/ Lags	Model 1	Model 1 w/ Lags	Model 2	Model 2 w Lags
	APIS-R Threshold	APIS-R Threshold	Prob. APIS-R	Prob. APIS-R	APIS-R Threshold	APIS-R Threshold	Prob. APIS-R	Prob. APIS-R
Unemployment Rate	.209**	.206*	.115***	.066***	0.218	0.009	.111***	.067***
	(0.08)	(0.09)	(0.01)	(0.02)	(0.13)	(0.16)	(0.01)	(0.02)
CPI	0.217	0.371	0.203	.381**	0.664	1.588	.335***	.526***
	(0.62)	(0.67)	(0.11)	(0.12)	(1.00)	(1.09)	(0.09)	(0.10)
PPI	-0.266	-0.334	-.152***	-.173***	-0.333	-0.447	-.145***	-.179***
	(0.21)	(0.22)	(0.04)	(0.04)	(0.32)	(0.35)	(0.03)	(0.03)
Recession (Dummy)	0.152	0.88	-0.013	-0.2	-1.673**	-1.993	-0.002	-0.048
	(0.41)	(1.15)	(0.07)	(0.21)	(0.65)	(1.78)	(0.06)	(0.18)
L.recession		-1.378		-0.201		-6.525*		-0.265
		(1.71)		(0.29)		(2.94)		(0.24)
L2.recession		0.575		0.298		6.455*		-0.244
		(1.72)		(0.29)		(2.97)		(0.25)
L3.recession		0.856		-0.014		0.035		0.36
		(1.63)		(0.29)		(2.53)		(0.25)
L4.recession		-2.267		-0.236		0.714		-0.1
		(1.62)		(0.29)		(2.75)		(0.24)
L5.recession		2.179		0.085		-6.055*		0.109
		(1.53)		(0.29)		(2.85)		(0.25)
L6.recession		-0.815		-0.264		6.091**		-.587*
		(1.13)		(0.30)		(2.03)		(0.25)
L7.recession				-0.055				.924***
				(0.31)				(0.19)
L8.recession				.767***				
				(0.23)				
Cons.	3.139***	3.163***			4.585***	5.969***		
	(0.61)	(0.68)			(0.99)	(1.15)		
N	2586	2489	6720	6272	3571	3352	11731	10511
Pseudo R2	.z	.z	0.01	0.01	.z	.z	0.01	0.01

Standard errors are in parentheses
*** p<.001, ** p<.01, * p<.05

4.5.2 Evidence Supporting Hypothesis 2.

To test our second hypothesis, we first compare the average monthly APIS-R threshold during different periods. We find that average APIS-R threshold is 3.8¢ during the lowest unemployment period, and 4.8¢ during the highest unemployment period. The average APIS threshold is lower during lowest unemployment periods than the average of all other periods. In 35 out of 56 product groups (i.e., 63%) we find smaller APIS-R threshold for the lowest unemployment period than for the highest unemployment period. In 36 out of the 56 cases (i.e., 64%), we find smaller APIS-R threshold for the lowest unemployment period than for the average of all other periods (see Table 2). This conclusion is again confirmed by paired T-Test.

The effects of unemployment on APIS-R threshold and probability of exhibiting APIS-R are further tested with our two econometrics models. Our hypothesis that the probability of a category or a retailer exhibits APIS-R is positively associated with Unemployment Rate are supported. Unemployment Rate has a significant negative effect on probability of a product group exhibiting APIS-R (coefficient=-0.209, $p<0.01$). We also find that Recession has significant lagged positive effect on probability of APIS-R, with an 8-month lag at group level (coefficient=0.767, $p<0.001$) and a 7-month lag at retailer level (coefficient=0.924, $p<0.001$). The association between Unemployment Rate and APIS-R Threshold is mixed. At group level, we see significant positive association between the two (coefficient=0.209, $p<0.01$), but Recession has no instant effect nor lagged effect. At retailer level, Unemployment Rate has no effect on APIS-R Threshold, but Recession has a lagged positive effect on with a lag of 6 months (coefficient=6.091, $p<0.01$). See Table 4 for a summary of estimation results on APIS-R.

Overall, most results support our hypothesis that APIS-R is stronger and more frequent when unemployment is high. The NBER recession periods have similar effects, with a lag of 6 to 8 months. The aggregate data's behavior is also consistent with our estimation results. Hence, we consider Hypothesis 2 is supported by our empirical evidence.

As a conclusion, both of our hypotheses are supported by the descriptive analyses and the regression analyses, at both group level and retailer level.

4.5.3 Model Integrity Tests and Diagnostics

We use Wooldridge (2002) test for autocorrelation on our data. The results indicate no autocorrelation in the panels. Variance inflation factor (VIF) measurements also show little multicollinearity among regressors with no lags (VIF <5). When lagged Recession terms are introduced, there would be significant correlations across regressors (VIF>20). However, the sign and significance of estimated coefficients of our variable of interest (unemployment rate) do not change much when lagged terms are added in the model. Moreover, we are more interested in the effects of lagged recession and the length of lags than the effect of unemployment rate when estimating the models with lag terms. Hence, multicollinearity should not be a concern in either our main models or the models with lags.

Secondly, the stationarity of the dependent variables is tested by the Levin-Lin-Chu (2002) unit-root test and the Harris-Tzavalis (1999) unit-root test. The null hypothesis is that all the panels contain a unit root. Both test results reject this null hypothesis ($p<0.05$), confirming the stationarity of the panels.

In addition, a modified Wald test (Greene 2000 p. 598) for groupwise heteroskedasticity is conducted on our fixed effect models. The null hypothesis is homoskedasticity (or constant variance), which is rejected ($p<0.05$). Heteroskedasticity is detected at both group level sample and retailer level sample. We use an alternative covariance matrix estimators developed by White (1980) to obtain robust standard errors[27]. The coefficients estimated by this approach are almost identical to the original results (See

[27] It is operationalized in STATA by the option “robust”.

Table 5 for estimates with robust standard errors).

In summary, the panel (and panel logit) fixed effects estimations in our regression analyses are robust. The inferences we draw from the estimated coefficients that unemployment positively impact APIS and negatively impact APIS-R still hold and our first two hypotheses are still supported.

4.5.4 Control for Spurious Price Changes

To rule out the possibility that the effects of business cycle are purely due to potential spurious price changes (Eichenbaum et al., 2014; Campbell and Eden, 2014), we apply the same noise elimination method used by Ling, Ray & Levy (2021)[28]. We drop all the observations that have a price multiplier greater than 1, and all the price changes due to the change of price-multiplier in the KNRS data. We also drop all fractional price changes since all non-integer prices should be a result of price aggregation (note that our price measurement unit is the cent). In addition, we exclude all extreme price changes (those that are smaller than 0.1% or larger than 120%), following Alvarez et al. (2014).

All analyses reported in previous section are conducted again with the samples where potential spurious price changes are controlled. See Table 6 for the estimates. The results are largely consistent with the full sample results. The only exception is that the coefficient for Unemployment Rate is no longer have significant for the APIS-R threshold. However, it is not clear if there is no impact on APIS-R because the relevant coefficients for the Probit models are significantly positive, suggesting evidence consistent with our predictions.

[28] We remove fractional price changes and price changes generated by bundling pricing and exclude extreme price changes (those that are smaller than 0.1% or larger than 120%) from the full sample (Campbell and Eden, 2014; Alvarez et al.,2014).

Table 4.5 A Comparison Between Original Estimates and Estimates with Robust Standard Errors

	Group Level				Retailer Level			
	Model 1	Model 1 w/ Robust S.E.	Model 1	Model 1 w/ Robust S.E.	Model 1	Model 1 w/ Robust S.E.	Model 1	Model 1 w/ Robust S.E.
	APIS Threshold	APIS Threshold	APIS-R Threshold	APIS-R Threshold	APIS Threshold	APIS Threshold	APIS-R Threshold	APIS-R Threshold
Unemployment Rate	-.43***	-.43**	.209**	.206*	-.231**	-.231*	0.218	0.218
	(0.12)	(0.15)	(0.08)	(0.09)	(0.07)	(0.09)	(0.13)	(0.13)
CPI	-2.416**	-2.416	0.217	0.276	-1.039	-1.039	0.664	0.664
	(0.91)	(1.57)	(0.62)	(0.79)	(0.53)	(0.78)	(1.00)	(0.85)
PPI	.834**	0.834	-0.266	-0.283	.434*	0.434	-0.333	-0.333
	(0.29)	(0.49)	(0.21)	(0.23)	(0.17)	(0.22)	(0.32)	(0.25)
Recession (Dummy)	2.66***	2.66***	0.152	0.129	3.935***	3.935***	-1.673**	-1.673**
	(0.56)	(0.72)	(0.41)	(0.41)	(0.35)	(0.67)	(0.65)	(0.64)
Cons.	11.858***	11.858***	3.139***	3.337***	9.424***	9.424***	4.585***	4.585***
	(0.86)	(1.11)	(0.61)	(0.92)	(0.53)	(0.68)	(0.99)	(0.97)
N	2979	2979	2586	2586	5252	5252	3571	3571
Pseudo R2	0.02	0.02	.z	.z	0.03	0.03	.z	0.00

Standard errors are in parentheses

*** p<.001, ** p<.01, * p<.05

Table 4.6 Estimation Results with Spurious Price Changes Controlled

	Group Level				Retailer Level			
	Model 1		Model 2		Model 1		Model 2	
	APIS Threshold	APIS-R Threshold	Prob. APIS	Prob. APIS-R	APIS Threshold	APIS-R Threshold	Prob. APIS	Prob. APIS-R
Unemployment Rate	-.278**	0.164	-.088***	.111***	-.199**	0.175	-.07***	.098***
	(0.10)	(0.10)	(0.01)	(0.01)	(0.06)	(0.11)	(0.01)	(0.01)
Recession (Dummy)	2.27***	-0.236	0.06	0.027	3.037***	-1.659**	.16**	0.026
	(0.51)	(0.48)	(0.07)	(0.07)	(0.31)	(0.55)	(0.06)	(0.06)
CPI	-2.362**	0.639	-.27*	0.189	-0.913	1.33	-.285***	.387***
	(0.81)	(0.75)	(0.11)	(0.11)	(0.48)	(0.87)	(0.09)	(0.09)
PPI	.709**	-0.459	.188***	-.154***	.385*	-.615*	.141***	-.132***
	(0.26)	(0.25)	(0.04)	(0.04)	(0.15)	(0.28)	(0.03)	(0.03)
Cons.	10.624***	3.942***			9.22***	4.879***		
	(0.76)	(0.72)			(0.46)	(0.85)		
N	3089	2679	6720	6720	5527	3857	11904	11845
Pseudo R2	.z	.z	0.01	0.01	.z	.z	0.01	0.01

Standard errors are in parentheses

*** p<.001, ** p<.01, * p<.05

4.5.5 Control for Endogeneity

The major regressors in our regression analyses, *Unemployment Rate* and *Recession*, are exogenous environmental factors. Hence the estimation of the effects of these two variables should be free of endogeneity issues. However, one may still argue that the effects of unemployment on asymmetry could be due to something unobserved which happens to correlate to *Unemployment Rate*. To test whether there is endogeneity, we need to have a model that controls for the possible endogeneity of *Unemployment Rate*. We apply the Gaussian Copula method (Park & Gupta, 2012) to control for endogeneity without the need of instruments. We implement this method through a CF approach as suggested by Papies, et al. (2017), by inserting a copula CF term z^* into the right-hand-side of the original equations, where z is the variable *Unemployment Rate*. Thus, our original models turn into:

$$y_{it} = a_i + \beta_0 X_{it} + \sum_{m=1}^{q} x_{it-m}\beta_m + z^* + \varepsilon_{it}\,, \quad i = 1, \ldots., N,\ t = 1, \ldots, T, \qquad (1b)$$

&

$$Y_{it} = \mathbf{1}\left(\beta_0 X_{it} + \sum_{m=1}^{q} x_{it-m}\beta_m + z^* + a_i + \mu_{it} > 0\right),\ i = 1, \ldots., N,\ t = 1, \ldots, T, \qquad (2b)$$

The copula CF term can be obtained by the function $z^* = \emptyset^{-1}(H(X))$, where *H(p)* is the empirical cumulative density function (CDF) of endogenous variables, and $\emptyset^{-1}$ is the inverse normal CDF.

Now we re-estimate our models with the extra copula term added. If the variable *Unemployment Rate* is indeed endogenous, this approach would be able to control for the endogeneity without using instruments. We conduct Hausman test for endogeneity by comparing the estimates before and after the copula CF method being applied. Test results on all models show no rejection of the Null hypothesis that the differences in coefficients are not systematic (p>0.1), hence indicate no endogeneity of *Unemployment Rate*.

4.5.6* Sample *Size.

There is no evidence that sample size significantly influences estimated APIS or APIS-R threshold. However, if the sample sizes differ in significant order of magnitude, we will observe larger threshold at higher level of analysis, e.g., product group level asymmetry is typically larger than most product module level asymmetry (*cf.* Chen et al. 2008; Ling, Ray & Levy 2021). To reduce the influence of sample size on asymmetry, all our analyses are conducted at a unified level of analysis, i.e., either at the group-month or the retailer-month level. When comparing asymmetry across periods, we are comparing monthly average thresholds across groups and retailers. Although different groups may still vary in terms of sample size, it is unlikely the reason that drives the asymmetry differences between the highest unemployment and lowest unemployment periods. Both the highest unemployment period and the recession period has a larger sample size than the lowest unemployment period (See Table 1 for sample size comparison). If sample size is driving the asymmetry difference between periods, we are supposed to see higher APIS thresholds during the highest unemployment period and in recession periods, which is not the case.

4.6. IMPLICATIONS AND CONTRIBUTIONS

This paper attempts to explain the longitudinal variations of APIS and APIS-R patterns across different product categories and retailers. This pricing practice has important implications for marketers because it presents an opportunity for retailers to turn their dynamic pricing capabilities into profit, and the profit gains from these small price changes can be significant when aggregated. Hence it is important for marketers to understand what macro level factors are driving consumer shopping behaviors that can be directly associated with the success of APIS and APIS-R practices. Built upon the Rational Inattention argument, we hypothesize that business cycles, reflected by unemployment rates and economic recessions, are a major time-varying factor impacting consumer attention to prices, hence influencing retail practices of APIS and APIS-R over different time periods. Our findings provide robust evidence in support of our hypotheses.

Extant marketing literature has found that consumer shopping and price attention behaviors change across business cycles, but little research has been done to investigate the implication and outcome of such change in terms of retailer pricing response. On the other hand, literature on asymmetric price changes and small price change spectrum has built up evidence of retail pricing patterns, but no study investigates the roles different factors play in explaining the variation in APIS and APIS-R. To the best of our knowledge, this study is the first attempt to address how the asymmetric price change in the small differs across the business cycle. We find that APIS is stronger and more frequent during economic booms when the unemployment rate is low, and APIS-R becomes stronger and more frequent during economic downturns when unemployment is high. This can be explained by the RI theory that consumers change their attention to prices over the business cycle, providing profit-seeking retailers incentives to adjust their pricing patterns. Our results hold even when we control for other possible explanations like inflation.

First, it contributes to the small price change literature and asymmetric pricing literature by being the first study to document the longitudinal variations of APIS and APIS-R patterns across the business cycle. And it is the first to find robust evidence that the business cycle is a major time-varying factor impacting consumer attention to prices, hence influencing retail practices of APIS and APIS-R over different time periods. Second, it contributes to the small price change literature by finding empirical evidence supporting the rational inattention and strategic obfuscation perspectives. We find that it is unemployment that impacts consumer's rational inattention, driving the retail price change patterns across the business cycle. It is the first study to empirically test whether RI and strategic obfuscation, apply to a much broader context with an economy-wide dataset. In addition, it contributes to marketing strategy literature by revealing how the business cycle impacts marketers' perspective towards small price changes, and how marketers leverage small price changes in response to business cycles. Last but not least, it contributes to marketing practitioners by helping them make the most relevant pricing decisions, with considerations of external environment factors such as economic recession, unemployment, and inflation.

4.7. CONCLUSIONS

We examine how business cycles affect the retail practices of asymmetric pricing in the small – APIS and APIS-R. Our theory draws upon two related perspectives – rational attention (RI) and strategic obfuscation. These predict unemployment should be negatively associated with APIS, but positively associated with APIS-R. We test these predictions on the KNRS dataset. Our predictions find strong supporting evidence in the differed average asymmetry thresholds across high unemployment and low unemployment periods, as well as in our dynamic panel and probit model estimations across both group and retailer levels. A series of additional analyses support the robustness of the results.

Like any study, ours has limitations. Our estimations of asymmetry thresholds would be crisper if we had access to point-of-sale transaction prices. Also, our measurement of asymmetry thresholds is data-driven and could benefit from a theoretically driven estimation. Further, there is only one business cycle in our sample period. A dataset with a longer duration that covers multiple business cycles would be better. We look forward to the release of the 2020 KNRS scanner dataset, which contains a major economic downturn caused by COVID-19. Yet, our results are very robust, and we hope this will encourage future researchers to address these limitations and contribute to this line of work.

5. CONCLUSION

Despite asymmetric pricing being a topic of great importance to both marketers and economists, it is relatively under-studied. This dissertation has attempted to address the gaps and limitations in existing marketing and economics literature on small price changes and asymmetric price adjustment. It rigorously documents the phenomenon of asymmetric price adjustment in the spectrum of small price changes and provides explanations of the varying patterns of APIS and APIS-R across product categories, retailers, and time periods. A combination of research methods (e.g., data mining, descriptive data analysis, econometric regressions, and unsupervised learning) are conducted to identify pricing patterns, product attributes, retailer format and to test our hypotheses. Terabytes-size datasets are analyzed leveraging high-performance computers, making it possible to test our findings in an extensive economy-wide context.

In Chapter 2, we address the key research questions: How prevalent are APIS and APIS-R in the spectrum of current retail pricing practices? Are these mere artifacts of inflation and measurement problems? We estimate APIS and APIS-R in a dataset comprising more than 79 billion weekly retail price observations over a relatively recent 10-year period (2006–2015). We conclude that the evidence points to both APIS and APIS-R, being robust phenomena, observed across different levels of aggregation – products, retailers, and in particular, time periods – in the context of the ICT era. APIS is found more prominent than APIS-R in most cases. This study is the first to document stable patterns of APIS-R economy-wide, with the only notable exception of the more limited study by Chakraborty et al. (2015). It is also among the early studies to address potential measurement concerns associated with small price changes, offering greater robustness to our results, and building upon the work of Eichenbaum et al. (2014) and Campbell and Eden (2014). The simulation of the effects of price aggregation, with an independent dataset, suggests such aggregation does not drive the observations.

Chapter 3 attempts to explain the cross-sectional variations of APIS and APIS-R we documented – the variations across product categories and retailers. Drawing upon the literature on how consumer attention to prices varies category-wise and retailer-wise, we predict that APIS and APIS-R patterns would change when category attributes and retailer's pricing positionings differ. Our predictions are mostly supported by our estimation of the KNRS dataset. We find that APIS and APIS-R pricing are stronger among product categories with a smaller share of consumer basket, and that APIS-R is negatively associated with category purchase frequency and category price level. These findings suggest that it will be more effective to deploy APIS and APIS-R practices for categories in which consumers pay less attention to price changes. We find that HILO type retailers are more likely to engage in both APIS and APIS-R relative to EDLP type retailers. This is not surprising since HILO retailers appeal to people with lower attention to prices but higher attention to promotions. We also learn that larger retailers are more likely to engage in these pricing practices because they can benefit from the economy of scale and significantly lower their menu costs which can be fixed costs.

Finally, in Chapter 4, we attempt to explain the longitudinal variations of APIS and APIS-R patterns across different product categories and retailers. We approach this longitudinal variation based on the Rational inattention (RI) theory and the Strategic Obfuscation (SO) perspective. The RI theory predicts that unemployment should be negatively associated with APIS and APIS thresholds, and it should positively associate with APIS-R and APIS-R threshold. This is because consumers are more attentive to both price changes and price promotions during an economic downturn when unemployment is high, making it inappropriate to deploy APIS but appropriate to deploy APIS-R. We test these predictions by conducting both descriptive analyses and regression analyses on the KNRS dataset. And our predictions are supported by analyzing the average asymmetry thresholds across high unemployment and low unemployment periods. These predictions are further supported by samples of APIS/APIS-R thresholds at both group level and retailer level, estimated by panel data models and panel logit models.

All the findings in Chapter 3 and Chapter 4 point to several key factors associated with retailers' decisions of deploying APIS and/or APIS-R: (1) consumer's attention to small price changes and their attention to promotions or deals; (2) retailer's price image; (3) retailer's size. This suggests that APIS and APIS-R are complicated decisions. While the last two only involve retailer level considerations, the first one should be evaluated with a combined consideration of product category characteristics, retailer's own positioning and the macro economic environment. Hence, these results contribute to marketing practice by documenting the best practices in the domain of managing small price changes – highlighting the combination of various factors that might be contributing to the success of small price change practices. The results would also be the first evidence of such strategic pricing practices in response to business cycles and contribute to furthering our understanding of how macroeconomic outcomes and micro level price setting are related to each other, a key tenet of New-Keynesian economics (Dutta, Bergen, and Ray, 2010). Thus, they also have important implications for macroeconomics and monetary policy.

While benefiting from customer inattention, a potential concern for retailers should be the public perception. These practices might seem reasonable in terms of economic value-maximizing, but they could also trigger concerns around the fairness of the practice. If not managed properly, substantial damage may happen in both image and actual sales performance (Malc et al. 2016). It would be difficult for retailers to successfully implement APIS or APIS-R without developing other capabilities, such as capabilities for managing consumer and channel relations and marketing communication.

There are still uncertainties in terms of the potential policy impact of these practices. The endemic nature of APIS and APIS-R definitely calls for some policy analyses if the fairness concerns identified above are true. However, it is still not clear if these actually damage consumer welfare. On one hand, the RI theory argues that consumers rationally choose to ignore small price increases (Lee et al. 2006, Lee et al. 2009, Chen et al. 2008, Levy et al. 2011, Ray, Wood & Messinger, 2012). In this case, APIS has no direct impact on consumer welfare, since the consumer essentially saves the cost of processing price changes to expend on other pursuits. On the other hand, APIS-R may negatively affect consumer's welfare. The obfuscation perspective argues that APIS-R creates noises in prices so that consumers would spend their cognitive resources on small price decreases, depleting their cognitive resources to process the (large) price increases, thus misestimating their basket prices. Hence it becomes tricky for regulators, since one may infer that price increases are welfare neutral while price decreases may be welfare reducing, which is very counterintuitive. Some pricing regulations have been shown to undermine consumer welfare, such as the Item-Pricing Laws (IPL) introduced to monitor retailer's pricing behaviors (Bergen et al. 2008). Therefore, it will be necessary to conduct a more in-depth policy level analysis of the phenomena.

Despite our efforts, as research domains that are in their early stages, our work has certain limitations. One limitation is in terms of the data itself. First, the estimations of asymmetry thresholds would be crisper if access to large-scale point of sale transaction prices is available. The continuing advances in computing and associated machine learning algorithms make working with such data more feasible now than a decade back. However, access to such transactions data continues to the bottleneck. An associated challenge is to refine the measurement of the thresholds. While we control for several sources of noise, we call for more research, possibly using different data, modeling, and experimental approaches to address this. further, we do not have information about retailer pricing strategy positioning. We have to estimate retailer's positioning by conducting cluster analysis based on attributes measured from retailer price movement. Future research could potentially improve the results with the availability of actual retailer positioning or when more sophisticated clustering methods become available. Future research could also investigate some additional product and retailer level attributes that may be associated with APIS and APIS-R practices, e.g., brand level factors such as national brand vs. private brand. Last but not least, even though we conduct the Copula approach to control for endogeneity, we are not able to entirely solve the endogeneity issues on all variables. A field experiment would be ideal for future research to more reliable estimate the effects of various factors on the APIS phenomenon.

Bibliography

Aguiar, M, Erik H, and Loukas K (2013). Time Use during the Great Recession. *American Economic Review* 103(5), 1664–1696.

Alvarez, F., Bihan, H. L., & Lippi, F. (2014). *Small and large price changes and the propagation of monetary shocks* (No. w20155). National Bureau of Economic Research.

Andreyeva, T., Long, M. W., & Brownell, K. D. (2010). The impact of food prices on consumption: A systematic review of research on the price elasticity of demand for food. *American Journal of Public Health,* 100(2), 216–222.

Ball, L., & Mankiw, N. G. (1994). Asymmetric price adjustment and economic fluctuations. *The Economic Journal*, *104*(423), 247-261.

Ball, L., Mankiw, N. G., & Reis, R. (2005). Monetary policy for inattentive economies. *Journal of Monetary Economics*, *52*(4), 703-725.

Barro, Robert J. (1972). A Theory of Monopolistic Price Adjustment. *Review of Economic Studies, 39 (1)*, 17–26.

Becker, Gary S. (1965). A Theory of the Allocation of Time. *Economic Journal* 75(299), 493–517.

Bell, D. R., & Lattin, J. M. (1998). Shopping Behavior and Consumer Preference for Store Price Format: Why “Large Basket” Shoppers Prefer EDLP. *Marketing Science*, 17(1), 66–88.

Bergen, M., Levy, D., Ray, S., Rubin, P. H., & Zeliger, B. (2008). When Little Things Mean a Lot: On the Inefficiency of Item-Pricing Laws. *The Journal of Law and Economics,* 51(2), 209-250.

Besanko, D., Dubé, J.-P., & Gupta, S. (2003). Competitive Price Discrimination Strategies in a Vertical Channel Using Aggregate Retail Data. *Management Science*, 49(9), 1121–1138.

Bitta, A. J. D., & Monroe, K. B. (1981). A multivariate analysis of the perception of value from retail price advertisements. ACR North American Advances.

Bolton, R. N., & Shankar, V. (2003). An empirically derived taxonomy of retailer pricing and promotion strategies. *Journal of Retailing*, *79*(4), 213–224.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2), 238-249.

Campbell, J. R., & Eden, B. (2014). Rigid prices: Evidence from us scanner data. *International Economic Review*, *55*(2), 423-442.

Carlton, D. (1986). The Rigidity of Prices. *American Economic Review*, *76*(4), 637-58.

Cavallo, A. (2018). Scraped data and sticky prices. *Review of Economics and Statistics*, *100*(1), 105-119.

Cavallo, A., & Rigobon, R. (2016). The Billion Prices Project: Using Online Prices for Measurement and Research. *Journal of Economic Perspectives*, 30(2), 151–178.

Cha, W, Pradeep C, and Sanjay D (2015). Food Purchases during the Great Recession. *Kilts Center for Marketing at Chicago Booth – Nielsen Dataset Paper Series 1-008*

Chakraborty, R., Dobson, P. W., Seaton, J. S., & Waterson, M. (2015). Pricing in inflationary times: The penny drops. *Journal of Monetary Economics*, *76*, 71-86.

Chen, H. A., Levy, D., Ray, S., & Bergen, M. (2008). Asymmetric price adjustment in the small. *Journal of Monetary Economics,* 55(4), 728-737.

Dubé, J, Günter J. H, and Peter R (2018), "Income and Wealth Effects on Private-Label Demand: Evidence from the Great Recession," *Marketing Science* 37(1), 22–53.

Dutta, S., Bergen, M., Levy, D., & Venable, R. (1999). Menu costs, posted prices, and multiproduct retailers. *Journal of Money, Credit, and Banking*, 683-703.

Dutta, S., Bergen, M. E., & Ray, S. (2017). Marketing in a World with Costs of Price Adjustment. *Review of Marketing Research* (pp. 168-187). Routledge.

Eichenbaum, M., Jaimovich, N., Rebelo, S., & Smith, J. (2014). How frequent are small price changes? *American Economic Journal: Macroeconomics*, *6*(2), 137-55.

Ellickson, P. B., & Misra, S. (2008). Supermarket Pricing Strategies. *Marketing Science, 27*(5), 811–828.

Fassnacht, M., & El Husseini, S. (2013). EDLP versus Hi–Lo pricing strategies in retailing—A state of the art article. *Journal of Business Economics*, 83(3), 259–289.

Fibich, G., Gavious, A., & Lowengart, O. (2007). Optimal price promotion in the presence of asymmetric reference-price effects. *Managerial and Decision Economics*, *28*(6), 569-577.

Gauri, Dinesh K. (2013). Benchmarking Retail Productivity Considering Retail Pricing and Format Strategy. *Journal of Retailing*, *89*(1), 1–14.

Gauri, Dinesh Kumar, Trivedi, M., & Grewal, D. (2008). Understanding the Determinants of Retail Strategy: An Empirical Analysis. *Journal of Retailing*, *84*(3), 256–267.

Gordon, B. R., Goldfarb, A., & Li, Y. (2013). Does price elasticity vary with economic growth? A cross-category analysis. *Journal of Marketing Research*, 50(1), 4-23.

Gorodnichenko, Y., & Talavera, O. (2017). Price setting in online markets: Basic facts, international comparisons, and cross-border integration. *American Economic Review*, *107*(1), 249-82.

Greene, W. H. (2000). *Econometric Analysis*, 4th ed., Prentice Hall, Upper Saddle River, N.J, 2000.

Grewal, D., Janakiraman, R., Kalyanam, K., Kannan, P. K., Ratchford, B., Song, R., & Tolerico, S. (2010). Strategic Online and Offline Retail Pricing: A Review and Research Agenda. *Journal of Interactive Marketing*, *24*(2), 138–154.

Gu, A., & Yoo, H. I. (2019). vcemway: A one-stop solution for robust inference with multiway clustering. *The Stata Journal*, 19(4), 900-912.

Gupta, S., & Cooper, L. G. (1992). The discounting of discounts and promotion thresholds. *Journal of Consumer Research*, *19*(3), 401-411.

Harris, R. D., & Tzavalis, E. (1999). Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of econometrics*, *91*(2), 201-226.

Hoch, S. J., Drèze, X., & Purk, M. E. (1994). EDLP, Hi-Lo, and Margin Arithmetic. *Journal of Marketing*, *58*(4), 16–27.

Kahneman, Daniel, Jack L. Knetsch, and Richard H. Thaler (1986). Fairness as a Constraint on Profit Seeking: Entitlements in the Market, *American Economic Review*, 76 (September), 728-41.

Kalwani, M. U., & Yim, C. K. (1992). Consumer price and promotion expectations: An experimental study. *Journal of Marketing Research*, *29*(1), 90-100.

Kalyanaram, G., & Little, J. D. (1994). An empirical analysis of latitude of price acceptance in consumer package goods. *Journal of Consumer Research*, *21*(3), 408-418.

Kalyanaram, G., & Winer, R. S. (1995). Empirical generalizations from reference price research. *Marketing science*, 14(3_supplement), G161-G169.

Kehoe, P., & Midrigan, V. (2015). Prices are sticky after all. *Journal of Monetary Economics*, *75*, 35–53.

Lach, S., & Tsiddon, D. (2007). Small price changes and menu costs. *Managerial and Decision Economics*, *28*(7), 649-656.

Lal R, Rao R (1997) Supermarket competition: the case of every day low pricing. *Marketing Science* 16(1):60–80

Lamey, L., B. Deleersnyder, M. G. Dekimpe, and J. B. Steenkamp (2012). The Effect of Business-Cycle Fluctuations on Private-Label Share: What Has Marketing Conduct Got to Do With It?. *Journal of Marketing* 76(1), 1–19.

Lattin JM, Ortmeyer G (1991). A theoretical rationale for everyday low pricing by grocery retailers. Research paper 1144, Stanford University, Stanford

Lawless, H. T., & Heymann, H. (1999). Measurement of sensory thresholds. In *Sensory Evaluation of Food* (pp. 173-207). Springer, Boston, MA.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of econometrics*, *108*(1), 1-24.

Levy, D, Lee, D., Chen, H.A., Kauffman, R., & Bergen, M. (2011). Price points and price rigidity. *Review of Economics and Statistics* 93 (4), 1417–1431.

Levy, D., Bergen, M., Dutta, S., & Venable, R. (1997). The magnitude of menu costs: direct evidence from large US supermarket chains. *The Quarterly Journal of Economics*, *112*(3), 791-824.

Levy, D., Dutta, S., Bergen, M., & Venable, R. (1998). Price adjustment at multiproduct retailers. *Managerial and Decision Economics*, *19*(2), 81-120.

Levy, D., Snir, A., Gotler, A., & Chen, H. (Allan). (2020). Not all price endings are created equal: Price points and asymmetric price rigidity. *Journal of Monetary Economics* (forthcoming).

Lichtenstein, D. R., Bloch, P. H., & Black, W. C. (1988). Correlates of price acceptability. *Journal of Consumer Research*, *15*(2), 243-252.

Long, Wen, Maria Luengo-Prado, and Bent Sørensen (2015). Heterogenous Consumer Shopping Behavior: Evidence from Retail Scanner data. *Manuscript, University of Houston.*

Malc, D., Mumel, D., & Pisnik, A. (2016). Exploring price fairness perceptions and their influence on consumer behavior. *Journal of Business Research*, 69(9), 3693–3697.

Mankiw, N. G. (1985). Small menu costs and large business cycles: A macroeconomic model of monopoly. *The Quarterly Journal of Economics*, *100*(2), 529-537.

Mankiw, N. G., & Reis, R. (2002). Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve. *The Quarterly Journal of Economics*, *117*(4), 1295-1328.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behaviour". In Frontiers in Econometrics, ed. P. Zarembka.(New York: Academic Press).

Mckenzie, D, Ernesto S, and Guillermo C (2011). Buying Less but Shopping More: The Use of Nonmarket Labor during a Crisis. *Economía* 11(2), 1–43.

Monroe, K. B. (1973). Buyers' subjective perceptions of price. *Journal of Marketing Research*, *10*(1), 70-80.

Nakamura, E., & Steinsson, J. (2008). Five Facts about Prices: A Reevaluation of Menu Cost Models [*]. *Quarterly Journal of Economics*, *123*(4), 1415–1464.

Nakamura, E., & Steinsson, J. (2013). Price Rigidity: Microeconomic Evidence and Macroeconomic Implications. *Annual Review of Economics*, 5(1), 133–163.

Neslin, S. A. (1995). The relationship between retail EDLP pricing and repeat purchasing. New York University, Leonard N. Stern School of Business.

Nevo, Aviv, and A. Wong (2015). The Elasticity of Substitution between Time and Market Goods: Evidence from the Great Recession. *NBER Working Paper No. 21318.*

Papies, D., Ebbes, P., & Van Heerde, H. J. (2017). Addressing endogeneity in marketing models. In Advanced methods for modeling markets (pp. 581-627). Springer, Cham.

Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science*, 31(4), 567-586.

Paul, P., Berlin, C., Maessen, M., & Valtonen, H. (2018). A comparison of regret-based and utility-based discrete choice modelling – an empirical illustration with hospital bed choice. *Applied Economics*, *50*(40), 4295–4305.

Pauwels, K., Srinivasan, S., & Franses, P. H. (2007). When do price thresholds matter in retail categories?. *Marketing Science*, 26(1), 83-100.

Popkowski Leszczyc, P. T. L., Sinha, A., & Sahgal, A. (2004). The effect of multi-purpose shopping on pricing and location strategy for grocery stores. *Journal of Retailing*, *80*(2), 85–99.

Quelch, J, and David H (1996). Brands versus Private Labels: Fighting to Win. *Harvard Business Review* 1, 99–109.

Ray, S., Chen, H. (Allan), Bergen, M. E., & Levy, D. (2006). Asymmetric Wholesale Pricing: Theory and Evidence. *Marketing Science*, *25*(2), 131–154.

Ray, S., Wood, C. A., & Messinger, P. R. (2012). Multicomponent systems pricing: Rational inattention and downward rigidities. *Journal of Marketing*, 76(5), 1-17.

Reis, R. (2006). Inattentive consumers. *Journal of Monetary Economics*, *53*(8), 1761-1800.

Rondán Cataluña, F. J., Sánchez Franco, M. J., & Villarejo Ramos, A. F. (2005). Are hypermarket prices different from discount store prices? *Journal of Product & Brand Management*, *14*(5), 330–337.

Rotemberg, J. J. (1983). Aggregate consequences of fixed costs of price adjustment. *The American Economic Review*, 73(3), 433-436.

Shankar, V., & Krishnamurthi, L. (1996). Relating price sensitivity to retailer promotional variables and pricing policy: an empirical analysis. *Journal of Retailing*, *72*(3), 249-272.

Shankar, Venkatesh, & Bolton, R. N. (2004). An Empirical Analysis of Determinants of Retailer Pricing Strategy. *Marketing Science*, *23*(1), 28–49.

Sheshinski, E., & Weiss, Y. (1977). Inflation and costs of price adjustment. *The Review of Economic Studies*, *44*(2), 287-303.

Sheshinski, E., & Weiss, Y. (1979). Demand for fixed factors, inflation and adjustment costs. *The Review of Economic Studies*, *46*(1), 31-45.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, *50*(3), 665-690.

Sims, C. A. (2006). Rational inattention: Beyond the linear-quadratic case. *American Economic Review*, *96*(2), 158-163.

Sims, C. A. (2010). Rational inattention and monetary economics. In *Handbook of Monetary Economics* (Vol. 3, pp. 155-181). Elsevier.

Stella, A. (2014). The Magnitude of Menu Costs: A Structural Estimation (No. 436). *Society for Economic Dynamics.*

Stella, A. (2014). The Magnitude of Menu Costs: A Structural Estimation (No. 436). *Society for Economic Dynamics*.

Tsiros, M., & Hardesty, D. M. (2010). Ending a Price Promotion: Retracting it in One Step or Phasing it out Gradually. *Journal of Marketing*, *74*(1), 49–64.

Volpe, R (2011). The Relationship between National Brand and Private Label Food Products: Prices, Promotions, Recessions, and Recoveries," *Economic Research Report* No. 129

Volpe, R (2014). National Brands, Private Label, and Food Price Inflation. *Journal of*

Agricultural and Applied Economics 46(4), 575–591.

Voss, G. B., & Seiders, K. (2003). Exploring the effect of retail sector and firm characteristics on retail price promotion strategy. *Journal of Retailing*, 79(1), 37-52.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, 48, 817–38.

Wood, C. A., Ray, S., & Messinger, P. (2013). Leaving the tier: An examination of asymmetry in pricing patterns in online high-tech shops. *Lecture Notes in Business Information Processing*, *155 LNBIP*, 63–73.

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. *MIT Press*, Cambridge, MA.

Zbaracki, M. J., Ritson, M., Levy, D., Dutta, S., & Bergen, M. (2004). Managerial and customer costs of price adjustment: direct evidence from industrial markets. *Review of Economics and Statistics*, 86(2), 514-533.

6. APPENDIX

Table A1. Summary Statistics of the Two-Store Transaction Price Data Analyzed

Retailer	Dept. Name	Avg. Price (in Cents)	Number of SKUs	Number of Observations
Store A	Canned food	153.9	4,725	615,107
	Canned products (not food)	226.2	2,124	172,032
	Butcher's shop	1016.4	62	39,613
	Fruit and vegetables	164.9	363	204,002
	Delicatessen	426.9	267	94,480
	Dairy products	183.2	1,329	307,362
	Bread	132.7	69	110,162
	Deep-frozen food	307.5	453	54,464
	Fishmonger's	450.2	10	97
	General store/ steward's office	249.0	407	7,195
	Affiliation	245.0	26	667
	Low level pharmacy/ Newspapers	190.9	2	155
	General store	186.3	18	1,214
	Textile/ household linen	295.8	61	692
	Housewares	190.2	49	1,207
	Toys	399.1	4	56
	Stationery store	246.6	27	594
	Underwear	244.2	25	306
	Support department	208.0	191	5,999
Store B	Canned food	184.3	6,435	852,131
	Canned products (not food)	180.2	915	270,785
	Butcher's shop	148.1	17	10,061
	Fruit and vegetables	286.0	26	2,574
	Delicatessen	161.0	177	85,629
	Dairy products	294.4	461	70,622
	Bread	202.7	22	1,330
	Fishmonger's	0.0	2	112
Total		**258.3**	**18,267**	**2,908,648**

Table A2. Asymmetric Price Change Thresholds Module Level Summary

Summary	Analysis #1	Analysis #2	Analysis #3	Low Inflation Sample (PPI)	Deflation Sample (PPI)	Inflation Sample (PPI)
N	527	527	527	521	527	527
Avg. Threshold	6.2	8.4	2.1	0.5	3.4	5.2
Avg. APIS Threshold	18.1	18.2	17.1	5.3	11.8	12.6
Avg. APIS-R Threshold	7.4	11.0	18.6	3.8	4.4	5.3
APIS Count	247	310	245	146	218	275
APIS-R Count	164	111	167	141	176	142

Note: more details about module level thresholds are available from authors upon request.

Table A3. Asymmetric Price Change Thresholds at Group Level

Group Name	**Analysis #1**	**Analysis #2**	**Analysis #3**	**Low Inflation Sample (PPI)**	**Deflation Sample (PPI)**	**Inflation Sample (PPI)**
CANDY	-4	-4	-9	1	-3	-9
GUM	0	-2	0	1	-2	-2
JUICE, DRINKS - CANNED, BOTTLED	20	20	20	-8	30	20
PET FOOD	14	14	13	6	-3	20
PREPARED FOOD-READY-TO-SERVE	25	25	25	-3	17	22
SOUP	30	30	30	14	0	30
BAKING MIXES	9	9	8	-3	-3	13
BREAKFAST FOOD	-1	3	-1	2	-1	-2
CEREAL	35	35	31	2	-1	24
COFFEE	0	10	-1	23	-1	10
DESSERTS, GELATINS, SYRUP	7	7	7	1	1	10
NUTS	-2	0	-1	-2	-2	1
PACKAGED MILK AND MODIFIERS	16	16	16	11	-1	18
SUGAR, SWEETENERS	21	21	22	-1	8	18
TEA	10	10	10	3	0	10
BREAD AND BAKED GOODS	60	60	39	-19	29	70
COOKIES	-1	30	25	-2	-1	13
CRACKERS	41	41	50	-1	13	50
SNACKS	35	35	14	-8	10	30
SOFT DRINKS-NON-CARBONATED	-1	12	-1	4	-1	-1
BAKED GOODS-FROZEN	21	21	14	2	11	21
BREAKFAST FOODS-FROZEN	-1	16	-1	1	-1	0
ICE CREAM, NOVELTIES	30	30	13	1	15	-1
JUICES, DRINKS-FROZEN	24	24	23	0	0	23
PIZZA/SNACKS/HORS DOEURVES-FRZN	0	8	-1	9	6	8
PREPARED FOODS-FROZEN	25	25	23	29	3	21
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	78	78	77	-2	58	1
CHEESE	32	32	14	2	13	32
EGGS	34	34	34	0	79	31
MILK	21	21	21	12	16	21
SNACKS, SPREADS, DIPS-DAIRY	14	14	13	14	-1	32
YOGURT	5	5	5	6	5	5
DRESSINGS/SALADS/PREP FOODS-DELI	-1	21	-1	-9	-1	-1
PACKAGED MEATS-DELI	72	72	66	21	50	38

FRESH MEAT	48	48	48	0	48	48
FRESH PRODUCE	48	48	48	68	48	68
DETERGENTS	1	-3	2	-4	-4	8
HOUSEHOLD CLEANERS	1	-4	0	-1	-2	1
LAUNDRY SUPPLIES	-1	2	-1	2	1	-1
PAPER PRODUCTS	-3	-3	-3	-4	-3	0
PERSONAL SOAP AND BATH ADDITIVES	-4	-4	-5	-5	-5	1
PET CARE	-4	-4	-4	-1	-4	-4
WRAPPING MATERIALS AND BAGS	26	26	28	-3	4	10
AUTOMOTIVE	27	27	28	18	-1	21
BATTERIES AND FLASHLIGHTS	-5	-5	-5	-2	-3	-2
BOOKS AND MAGAZINES	-20	-20	-12	0	-12	-19
COOKWARE	-9	-9	-9	0	-4	-3
GLASSWARE, TABLEWARE	-9	-9	-9	1	0	-9
KITCHEN GADGETS	-9	-9	-9	1	-9	-9
TOYS & SPORTING GOODS	-2	0	-2	0	0	-1
BABY NEEDS	-6	-6	-6	-1	1	-6
HAIR CARE	-9	-9	-6	-2	1	-9
MEDICATIONS/REMEDIES/HEALTH AIDS	6	6	6	0	6	1
ORAL HYGIENE	-5	-5	-4	-8	-5	-4
SKIN CARE PREPARATIONS	-4	-4	-4	2	-9	-3
VITAMINS	-3	-3	-3	-2	-3	-2
Avg. Threshold	**13.1**	**14.9**	**12.1**	**3.0**	**6.9**	**11.8**
Avg. APIS	**27.0**	**25.3**	**24.9**	**9.5**	**19.7**	**21.4**
Avg. APIS-R	**4.7**	**6.1**	**4.3**	**4.1**	**3.2**	**4.6**
APIS Count	**31**	**37**	**31**	**27**	**24**	**35**
APIS-R Count	**22**	**17**	**23**	**22**	**27**	**19**

Note: a negative value in the threshold field indicates an APIS-R threshold.

Table A4. Asymmetry Thresholds at Group Level for Alternative Inflation Measures

Group Name	**Full Sample**	**Low Inflation Sample (PPI)**	**Deflation Sample (PPI)**	**Inflation Sample (PPI)**	**Low Inflation Sample (CPI)**	**Deflation Sample (CPI)**	**Inflation Sample (CPI)**
CANDY	-4	1	-3	-9	-3	-3	-9
GUM	0	1	-2	-2	1	11	-2
JUICE, DRINKS - CANNED, BOTTLED	20	-8	30	20	10	0	18
PET FOOD	14	6	-3	20	-3	-3	27
PREPARED FOOD-READY-TO-SERVE	25	-3	17	22	-1	34	22
SOUP	30	14	0	30	6	0	30
BAKING MIXES	9	-3	-3	13	0	-3	13
BREAKFAST FOOD	-1	2	-1	-2	-2	13	1
CEREAL	35	2	-1	24	7	-1	3
COFFEE	0	23	-1	10	-1	-1	30
DESSERTS, GELATINS, SYRUP	7	1	1	10	1	2	28
NUTS	-2	-2	-2	1	-2	0	0
PACKAGED MILK AND MODIFIERS	16	11	-1	18	0	-9	30
SUGAR, SWEETENERS	21	-1	8	18	29	0	18
TEA	10	3	0	10	9	9	10
BREAD AND BAKED GOODS	60	-19	29	70	10	32	43
COOKIES	-1	-2	-1	13	-1	-1	27
CRACKERS	41	-1	13	50	0	9	50
SNACKS	35	-8	10	30	11	10	54
SOFT DRINKS-NON-CARBONATED	-1	4	-1	-1	5	-1	-6
BAKED GOODS-FROZEN	21	2	11	21	14	11	21
BREAKFAST FOODS-FROZEN	-1	1	-1	0	-2	-1	16
ICE CREAM, NOVELTIES	30	1	15	-1	5	15	0
JUICES, DRINKS-FROZEN	24	0	0	23	2	15	22
PIZZA/SNACKS/HORS DOEURVES-FRZN	0	9	6	8	3	-1	-1
PREPARED FOODS-FROZEN	25	29	3	21	10	8	13
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	78	-2	58	1	18	59	1
CHEESE	32	2	13	32	9	26	15
EGGS	34	0	79	31	35	39	0
MILK	21	12	16	21	21	26	16
SNACKS, SPREADS, DIPS-DAIRY	14	14	-1	32	-1	-1	38
YOGURT	5	6	5	5	5	5	6
DRESSINGS/SALADS/PREP FOODS-DELI	-1	-9	-1	-1	-2	0	0
PACKAGED MEATS-DELI	72	21	50	38	39	50	59

FRESH MEAT	48	0	48	48	39	48	48
FRESH PRODUCE	48	68	48	68	28	48	78
DETERGENTS	1	-4	-4	8	-1	-4	12
HOUSEHOLD CLEANERS	1	-1	-2	1	10	0	0
LAUNDRY SUPPLIES	-1	2	1	-1	-1	-4	10
PAPER PRODUCTS	-3	-4	-3	0	1	-3	3
PERSONAL SOAP AND BATH ADDITIVES	-4	-5	-5	1	-1	-5	1
PET CARE	-4	-1	-4	-4	-1	0	8
WRAPPING MATERIALS AND BAGS	26	-3	4	10	5	3	3
AUTOMOTIVE	27	18	-1	21	0	-1	20
BATTERIES AND FLASHLIGHTS	-5	-2	-3	-2	-7	1	-1
BOOKS AND MAGAZINES	-20	0	-12	-19	-7	-37	-14
COOKWARE	-9	0	-4	-3	1	-1	1
GLASSWARE, TABLEWARE	-9	1	0	-9	-9	0	-9
KITCHEN GADGETS	-9	1	-9	-9	-9	-9	-9
TOYS & SPORTING GOODS	-2	0	0	-1	0	2	-1
BABY NEEDS	-6	-1	1	-6	-1	-4	-3
HAIR CARE	-9	-2	1	-9	-4	-3	-5
MEDICATIONS/REMEDIES/HEALTH AIDS	6	0	6	1	0	6	1
ORAL HYGIENE	-5	-8	-5	-4	2	-5	-4
SKIN CARE PREPARATIONS	-4	2	-9	-3	-1	-9	-5
VITAMINS	-3	-2	-3	-2	-5	-3	1
Avg. Threshold	**13.1**	**3.0**	**6.9**	**11.8**	**4.8**	**6.6**	**13.0**
Avg. APIS	**27.0**	**9.5**	**19.7**	**21.4**	**12.0**	**20.1**	**21.0**
Avg. APIS-R	**4.7**	**4.1**	**3.2**	**4.6**	**3.0**	**4.7**	**5.3**
APIS Count	**31**	**27**	**24**	**35**	**28**	**24**	**38**
APIS-R Count	**22**	**22**	**27**	**19**	**22**	**24**	**13**

Note: a negative value in the threshold field indicates an APIS-R threshold.

Table A5. Asymmetric Price Change Thresholds at Group Level for Lagged Price Change

Group Name	**Full Sample**	**Deflation Sample (PPI)**	**4-week Lag Deflation Period (PPI)**	**8-week Lag Deflation Period (PPI)**	**12-week Lag Deflation Period (PPI)**	**16-week Lag Deflation Period (PPI)**
CANDY	-4	-3	-9	-9	-9	-9
GUM	0	-2	-4	1	1	0
JUICE, DRINKS - CANNED, BOTTLED	20	30	20	0	0	20
PET FOOD	14	-3	8	-5	-3	1
PREPARED FOOD-READY-TO-SERVE	25	17	16	17	-1	0
SOUP	30	0	19	33	6	30
BAKING MIXES	9	-3	5	0	-4	5
BREAKFAST FOOD	-1	-1	-1	-1	-1	-1
CEREAL	35	-1	11	3	6	0
COFFEE	0	-1	0	-1	-1	-1
DESSERTS, GELATINS, SYRUP	7	1	6	7	2	7
NUTS	-2	-2	-3	8	3	3
PACKAGED MILK AND MODIFIERS	16	-1	10	-1	-1	11
SUGAR, SWEETENERS	21	8	17	16	8	10
TEA	10	0	-1	-1	-1	11
BREAD AND BAKED GOODS	60	29	14	18	19	32
COOKIES	-1	-1	-1	-1	-1	-1
CRACKERS	41	13	2	6	5	-1
SNACKS	35	10	13	8	10	14
SOFT DRINKS-NON-CARBONATED	-1	-1	-1	-2	-1	-1
BAKED GOODS-FROZEN	21	11	11	13	12	11
BREAKFAST FOODS-FROZEN	-1	-1	-1	-1	-2	-1
ICE CREAM, NOVELTIES	30	15	0	-1	-1	9
JUICES, DRINKS-FROZEN	24	0	-1	22	19	32
PIZZA/SNACKS/HORS DOEURVES-FRZN	0	6	8	-1	-1	13
PREPARED FOODS-FROZEN	25	3	7	-1	-1	9
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	78	58	13	50	2	32
CHEESE	32	13	5	13	28	15
EGGS	34	79	31	48	48	49
MILK	21	16	10	12	24	21
SNACKS, SPREADS, DIPS-DAIRY	14	-1	0	0	-1	11
YOGURT	5	5	6	5	5	5

DRESSINGS/SALADS/PREP FOODS-DELI	-1	-1	-1	-1	-1	-1
PACKAGED MEATS-DELI	72	50	32	51	41	65
FRESH MEAT	48	48	48	49	48	48
FRESH PRODUCE	48	48	29	72	60	48
DETERGENTS	1	-4	3	2	-4	1
HOUSEHOLD CLEANERS	1	-2	-2	2	10	5
LAUNDRY SUPPLIES	-1	1	11	-2	-4	6
PAPER PRODUCTS	-3	-3	-5	-9	-4	-1
PERSONAL SOAP AND BATH ADDITIVES	-4	-5	-4	1	1	-7
PET CARE	-4	-4	0	-4	-3	1
WRAPPING MATERIALS AND BAGS	26	4	2	8	-1	10
AUTOMOTIVE	27	-1	11	21	0	21
BATTERIES AND FLASHLIGHTS	-5	-3	-2	1	-9	-9
BOOKS AND MAGAZINES	-20	-12	0	-12	-10	-9
COOKWARE	-9	-4	-20	-14	-9	-9
GLASSWARE, TABLEWARE	-9	0	1	-9	-9	0
KITCHEN GADGETS	-9	-9	-9	-9	-9	-9
TOYS & SPORTING GOODS	-2	0	-2	-1	2	2
BABY NEEDS	-6	1	1	-2	-6	1
HAIR CARE	-9	1	-3	-5	1	-9
MEDICATIONS/REMEDIES/HEALTH AIDS	6	6	6	7	4	8
ORAL HYGIENE	-5	-5	-6	-3	-7	-3
SKIN CARE PREPARATIONS	-4	-9	-3	-3	-1	-3
VITAMINS	-3	-3	-3	-1	-3	-3
Avg. Threshold	**13.1**	**6.9**	**5.3**	**7.0**	**4.6**	**8.7**
Avg. APIS	**27.0**	**19.7**	**12.5**	**18.3**	**15.2**	**16.7**
Avg. APIS-R	**4.7**	**3.2**	**3.9**	**3.8**	**3.6**	**4.3**
APIS Count	**31**	**24**	**30**	**27**	**24**	**34**
APIS-R Count	**22**	**27**	**21**	**26**	**30**	**18**

Note: a negative value in the threshold field indicates an APIS-R threshold.

Table A6. Avg. Asymmetry Threshold in Each Month from 2006 to 2015*

Month	Recession Indicator	Highest_u Indicator	Lowest_u Indicator	Avg. Monthly Threshold	Unemployment Rate	CPI Rate	PPI Rate
2006-01	0	0	0	5.8	4.7	0.8	0.8
2006-02	0	0	0	7.0	4.8	0.2	-1.5
2006-03	0	0	1	**3.7**	4.7	0.6	0.2
2006-04	0	0	1	**3.4**	4.7	0.9	1.3
2006-05	0	0	1	**2.0**	4.6	0.5	0.9
2006-06	0	0	1	**2.7**	4.6	0.2	0.2
2006-07	0	0	1	**3.0**	4.7	0.3	0.4
2006-08	0	0	1	**2.8**	4.7	0.2	0.7
2006-09	0	0	1	**3.5**	4.5	-0.5	-1.5
2006-10	0	0	1	**1.5**	4.4	-0.5	-1.9
2006-11	0	0	1	**2.4**	4.5	-0.1	1.5
2006-12	0	0	1	**3.7**	4.4	0.1	0.6
2007-01	0	0	1	**5.9**	4.6	0.3	-1
2007-02	0	0	1	**6.5**	4.5	0.5	1.7
2007-03	0	0	1	**3.8**	4.4	0.9	1.5
2007-04	0	0	1	**2.7**	4.5	0.6	1.2
2007-05	0	0	1	**4.3**	4.4	0.6	1.1
2007-06	0	0	1	**3.2**	4.6	0.2	0.3
2007-07	0	0	1	**6.1**	4.7	0	0.7
2007-08	0	0	1	**0.3**	4.6	-0.2	-1.5
2007-09	0	0	1	**3.5**	4.7	0.3	0.6
2007-10	0	0	0	1.3	4.7	0.2	0.7
2007-11	0	0	0	2.4	4.7	0.6	2.5
2007-12	1	0	0	7.7	5	-0.1	-0.2
2008-01	1	0	0	4.6	5	0.5	1.3
2008-02	1	0	0	11.4	4.9	0.3	0.9
2008-03	1	0	0	3.3	5.1	0.9	2.8
2008-04	1	0	0	7.7	5	0.6	1.6
2008-05	1	0	0	2.7	5.4	0.8	3
2008-06	1	0	0	7.8	5.6	1	2
2008-07	1	0	0	11.3	5.8	0.5	2.5
2008-08	1	0	0	3.7	6.1	-0.4	-3.2
2008-09	1	0	0	7.5	6.1	-0.1	-1.1
2008-10	1	0	0	3.8	6.5	-1	-5.3
2008-11	1	0	0	2.5	6.8	-1.9	-5.2
2008-12	1	0	0	-1.9	7.3	-1	-3.3
2009-01	1	0	0	-0.3	7.8	0.4	0.2
2009-02	1	0	0	-2.8	8.3	0.5	-1.1
2009-03	1	0	0	-0.4	8.7	0.2	-0.7
2009-04	1	0	0	-2.9	9	0.2	0.6
2009-05	1	1	0	**-2.3**	9.4	0.3	1
2009-06	1	1	0	**0.3**	9.5	0.9	1.9
2009-07	0	1	0	**-1.0**	9.5	-0.2	-0.9
2009-08	0	1	0	**-0.7**	9.6	0.2	1.4
2009-09	0	1	0	**0.6**	9.8	0.1	-0.5
2009-10	0	1	0	**0.2**	10	0.1	0.6
2009-11	0	1	0	**-1.1**	9.9	0.1	1.3
2009-12	0	1	0	**0.7**	9.9	-0.2	0.4
2010-01	0	1	0	**3.1**	9.8	0.3	2.1
2010-02	0	1	0	**-1.0**	9.8	0	-0.5
2010-03	0	1	0	**0.6**	9.9	0.4	1.3
2010-04	0	1	0	**1.0**	9.9	0.2	0.6
2010-05	0	1	0	**1.9**	9.6	0.1	0.2

2010-06	0	1	0	**1.8**	9.4	-0.1	-0.7
2010-07	0	1	0	**2.1**	9.4	0	0.3
2010-08	0	1	0	**1.5**	9.5	0.1	0.4
2010-09	0	1	0	**2.4**	9.5	0.1	0
2010-10	0	1	0	**1.1**	9.4	0.1	0.9
2010-11	0	1	0	**-0.8**	9.8	0	0.6
2010-12	0	0	0	5.5	9.3	0.2	1.1
2011-01	0	0	0	6.0	9.1	0.5	1.6
2011-02	0	0	0	4.8	9	0.5	1.6
2011-03	0	0	0	5.3	9	1	1.7
2011-04	0	0	0	6.6	9.1	0.6	2
2011-05	0	0	0	1.2	9	0.5	0.5
2011-06	0	0	0	7.5	9.1	-0.1	-0.1
2011-07	0	0	0	7.6	9	0.1	0.3
2011-08	0	0	0	-3.5	9	0.3	-0.7
2011-09	0	0	0	3.6	9	0.2	0.2
2011-10	0	0	0	2.4	8.8	-0.2	-1.3
2011-11	0	0	0	1.5	8.6	-0.1	0.1
2011-12	0	0	0	8.8	8.5	-0.2	-0.8
2012-01	0	0	0	1.1	8.3	0.4	0.5
2012-02	0	0	0	0.2	8.3	0.4	0.4
2012-03	0	0	0	-2.1	8.2	0.8	1.3
2012-04	0	0	0	-3.0	8.2	0.3	-0.2
2012-05	0	0	0	-6.1	8.2	-0.1	-0.9
2012-06	0	0	0	1.4	8.2	-0.1	-1
2012-07	0	0	0	2.4	8.2	-0.2	0.2
2012-08	0	0	0	-0.4	8.1	0.6	1.3
2012-09	0	0	0	0.6	7.8	0.4	0.8
2012-10	0	0	0	-1.6	7.8	0	-0.4
2012-11	0	0	0	2.4	7.7	-0.5	-0.8
2012-12	0	0	0	7.8	7.9	-0.3	-0.1
2013-01	0	0	0	1.4	8	0.3	0.5
2013-02	0	0	0	0.7	7.7	0.8	0.9
2013-03	0	0	0	-2.3	7.5	0.3	-0.1
2013-04	0	0	0	0.2	7.6	-0.1	-0.2
2013-05	0	0	0	-0.1	7.5	0.2	0.3
2013-06	0	0	0	3.0	7.5	0.2	0.1
2013-07	0	0	0	1.8	7.3	0	0
2013-08	0	0	0	-0.8	7.2	0.1	-0.1
2013-09	0	0	0	0.6	7.2	0.1	-0.1
2013-10	0	0	0	-1.8	7.2	-0.3	-0.7
2013-11	0	0	0	-1.5	6.9	-0.2	-0.6
2013-12	0	0	0	11.6	6.7	0	0.4
2014-01	0	0	0	4.2	6.6	0.4	0.9
2014-02	0	0	0	4.9	6.7	0.4	0.9
2014-03	0	0	0	1.4	6.7	0.6	0.6
2014-04	0	0	0	6.9	6.2	0.3	0.6
2014-05	0	0	0	-1.4	6.3	0.3	-0.1
2014-06	0	0	0	-0.4	6.1	0.2	0.1
2014-07	0	0	0	3.4	6.2	0	-0.1
2014-08	0	0	0	0.7	6.1	-0.2	-0.5
2014-09	0	0	0	3.1	5.9	0.1	-0.3
2014-10	0	0	0	-0.4	5.7	-0.3	-1.5
2014-11	0	0	0	2.2	5.8	-0.5	-1.2
2014-12	0	0	0	4.1	5.6	-0.6	-1.9
2015-01	0	0	0	1.2	5.7	-0.5	-2.5
2015-02	0	0	0	1.3	5.5	0.4	-0.5

2015-03	0	0	0	-0.9	5.4	0.6	0.2
2015-04	0	0	0	-0.3	5.4	0.2	-0.3
2015-05	0	0	0	0.0	5.6	0.5	1.3
2015-06	0	0	0	3.9	5.3	0.4	0.7
2015-07	0	0	0	1.6	5.2	0	-0.5
2015-08	0	0	0	1.0	5.1	-0.1	-1
2015-09	0	0	0	0.0	5	-0.2	-1.5
2015-10	0	0	0	0.2	5	0	-0.8
2015-11	0	0	0	-1.3	5.1	-0.2	-1
2015-12	0	0	0	2.4	5	-0.3	-1.2

* Grey background indicates NBER defined 19-month recession periods. Green font indicates the consecutive 19-month period with the lowest unemployment rates; red font indicates the consecutive 19-month period with highest unemployment rates;