When Little Things Mean a Lot: On the Inefficiency of Item Pricing Laws

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8 October 2006

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JEL Codes: K20, L11, L81, E31

Key Words: Item Pricing Law, Cost of Item Pricing Law, Cost of Price Adjustment, Menu Cost, Retail Pricing

Last Revision: October 6, 2006

* We are grateful to the anonymous referee and to the editor, Sam Peltzman, for constructive comments and suggestions and to Joel Waldfogel, the discussant at the August 2003 NBER Law and Economic program meeting in Cambridge, MA, for thoughtful and constructive comments and criticism. We also thank the participants of the May 2005 Israeli Law and Economic Association Annual Conference at Haifa University, the August 2003 NBER Law and Economics Program Meeting in Cambridge, MA, and the June 2003 INFORMS-Marketing Science Conference in College Park, MD, as well as the seminar participants at Bar-Ilan University Economics Workshop, Bar-Ilan University Law School, Hebrew University, George Mason University, Tbilisi State University, Michigan State Legislature's House Committee of Commerce (the Michigan Item Pricing Law Subcommittee), and the Israeli Ministry of Industry, Trade, and Employment's Conferences on the Israeli Item Pricing Law, for helpful comments and discussions. We are thankful also to Yakov Amihud, Michael Beenstock, Robert Cooter, David Genesove, Daniel Kessler, Saul Lach, Daniel Rubinfeld, Rob Sauer, Eytan Sheshinski, and Kip Viscusi for useful conversations, suggestions and advice. Finally, we thank Jeff Sandgren and Bob Venable for helpful discussions and for answering our questions on numerous occasions, Mona Zeliger for helping with data collection, and Xiaogong Huang for helping with data analyses. All authors contributed equally. All errors are ours.

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Abstract

Item pricing laws (IPLs) require a price tag on every item sold by a retailer. We study IPLs and assess their efficiency by quantifying their costs and comparing them to previously documented benefits. On the cost side, we posit that IPLs should lead to higher prices because they increase the cost of pricing as well as the cost of price adjustment. We test this prediction using data collected from large supermarket chains in the Tri-State area of New York, New Jersey and Connecticut, which offer a unique setting because these states vary in their use of IPLs, but otherwise offer geographical proximity with each other and similar markets, supermarket chains, and socioeconomic environments. We find that IPL store prices are higher by about 20¢–25¢ or 8.0%–9.6% per item on average, in comparison to non-IPL stores. As a control, we use data from stores that are exempt from IPL requirements (because they use electronic shelf labels), and find that their prices fall between IPL and non-IPL store prices. To assess the efficiency of IPLs, we compare these costs to existing measures of the benefits of IPLs which are based on measurements of the frequency and the magnitude of pricing errors the IPLs are supposed to prevent. We find that the costs of IPLs are an order of magnitude higher than the upper bound of these estimate benefits.

"As Michigan's Attorney General, I want you to know that every time you open your wallet, my office will be there to protect your transactions. Our state law requires that most items on store shelves be clearly marked with a price tag. If those price tags don't match the price scanned at the register, the law gives you specific rights. Keep this card in your wallet or purse and refer to it whenever you have a question about your item pricing rights."

Mike Cox, Attorney General, *Item Pricing Wallet Card*, "Item Pricing Bill of Rights," August 28, 2002[1]

"Having been a retailer in Michigan since '47, we are well aware of the item pricing laws here and its expense. It takes 3 times or more to price and then stock shelves in our store… We also spend 50 hours a week, having someone scan each item making sure it agrees with the computer… this may have been one of the reasons Michigan has not seen tremendous growth in competition from those same national retailers. Our overhead is way out of line with the rest of the country."

Marv Imus, a Michigan Retailer, July 17, 2002[2]

"Chains in these [item pricing law] states don't make less money, yet we know their costs are higher, so it would follow that their prices must be higher, ceteris paribus… they try to avoid the cost by changing fewer prices, although this is only partially feasible, and much of the cost is unavoidable, as every item sold incurs the cost."

Bob Venable, Industry Expert[3]

I. Introduction

Item pricing laws (IPLs) require a price tag on every item sold by a retailer.[4] Currently, IPLs exist in nine US states, in Canada, in some European countries, and in Israel.[5] In the early 1970s, as retailers moved away from item pricing to using only shelf price labels and checkout scanners, states debated the merits of this transition and many considered IPLs. The debate continues today. For example, legislators in Michigan and in Israel are currently considering a revision of their IPLs.[6] The proposed new bill in Michigan would make item pricing optional if retailers use electronic shelf labels.[7] Similarly, a recent change in the IPL of Quebec, Canada, exempts retailers from the IPL if there are a minimum number of hand-held scanners in the store available for the use of consumers.[8]

The most commonly cited reason in support of IPLs is that without them the public would be unable to detect pricing mistakes. [9] Indeed, IPL requirements are often waived if retailers meet certain price accuracy criteria. For example, in Philadelphia, if overcharges exceed undercharges, then a store must item price until it passes four consecutive inspections.[10] In Schenectady, NY, retailers are exempted from IPL requirements if pricing errors do not exceed 2.3%.[11] Similarly, Massachusetts offers an IPL exemption if pricing accuracy is 98 percent.[12] Retailers in Connecticut, which has an IPL, are exempted from the IPL requirement if they install an electronic shelf label (ESL) system because with an ESL, shelf prices and cash register prices are identical. This suggests that pricing

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[1] Source: the Attorney General's Office, State of Michigan (www.michigan.gov/ag).
[2] Source: www.morningnewsbeat.com.
[3] Source: private correspondence with one of the co-authors.
[4] There are two other pricing laws: *shelf price laws* require a price tag on the shelf while *unit price laws* require the product price be provided per standard unit such as per oz, per liter, per gallon, etc. Both are in effect in most states and localities.
[5] In the US, IPLs exist in California, Connecticut, Illinois, Massachusetts, Michigan, New Hampshire, New York, North Dakota, and Rhode Island. In Appendix I, we provide a detailed description of the New York and Connecticut IPLs.
[6] In fact, this study was presented at both, the Michigan State's House Committee of Commerce and at the Israeli Ministry of Industry, Trade, and Employment's Committee Hearings. Both institutions are considering a revision of their local IPLs.
[7] Source: "Legislators to consider changes in item pricing law," *Holland Sentinel*, Jan. 27, 2003 (www.hollandsentinel.com).
[8] "Price Marking in Quebec: New Regulatory Rules," (www.opc.gouv.qc.ca/programmes/LettreAffPrice_Marking.pdf).
[9] According to Richard Gamber of the Michigan Consumer Federation: "They say we're behind the times. I say we're ahead of the times. Without a price tag on an item, a consumer is powerless to spot scanner errors" (Source: "The Battle Over item Pricing, Michigan Style," www.nacsonline.com, July 16, 2002). "We're opposed to any change in the IPL. It's a law that protects the consumers by allowing them to know when they are being charged the wrong price," says Ken Fletcher of the Michigan AFL-CIO (Source: "Legislators to consider changes in item pricing law," *Holland Sentinel*, January 27, 2003, www.hollandsentinel.com). Consider also the titles of typical articles on this topic: "UPC Scanner Pricing Systems: Are They Accurate?" (*Stores*, August 1994, RR10–RR11), "Don't Get Cheated by Supermarket" (*Money* 22, April 1993, p. 132–138.), "Is Precision Pricing Possible?" (*Progressive Grocer* 73(12), December 1994, 88–89), and "UPC Scanner Pricing Systems: Are They Accurate?" (*Journal of Marketing* 58, April 1994, 20–30). While suggestive, these articles all address the public's concern with pricing accuracy.
[10] Source: www.s-t.com/daily/08-97/08-24-97/f01bu217.htm.
[11] Source: "Smart Business: Item Pricing Laws."
[12] Source: "Retail Electronic Price Systems Exemptions," Section 329D, Amendment to Massachusetts Chapter 94, "Item Pricing Law," Outside Section 125 (www.mass.gov/eoaf/budget/fy04/print/outsec/p125.htm).

accuracy is a key concern for legislative and policy-making bodies.

Opponents of IPLs, however, argue that item pricing is inefficient and costly because of the excess labor needed to place new price tags on items when prices change.[13] Some have even suggested that the item pricing requirement and its costs may prevent new store openings.[14]

Although IPLs have been around for almost 30 years, there are no academic studies of their costs. This limits our ability to assess the efficiency of these laws through comparison of their costs and benefits. The goal of this study is to fill this gap in the literature. On the cost side, we assess the effect of IPLs on retail prices. We posit that IPLs lead to price increases because they increase the cost of pricing as well as the cost of price adjustment. This would be true even if the market is competitive because all stores operating under the IPL requirement are subject to the same cost increase.

To test this prediction, we collected retail price data at supermarkets facing IPLs and supermarkets not facing IPLs, with the restriction that all sampled stores be located in geographical proximity with each other, and operating in similar markets and socioeconomic areas. We also collected retail price data from supermarkets that face IPLs but are exempted from the item pricing requirement because they use ESL systems. ESL systems, albeit adding some overhead cost, are believed to save labor costs related to IPLs, allowing these data to be used as a control.[15]

The Tri-State area of New York, Connecticut and New Jersey offers a natural setting for studying the effects of IPLs because these states are geographically connected to each other, have similar markets and socioeconomic characteristics, have many of the same supermarket chains, and yet vary in their use of IPLs—New York has an IPL, New Jersey does not, and Connecticut has an IPL with an ESL exemption.

We collected two sets of price data, the first emphasizing the breadth in coverage *across products* while the other *across stores*. We find consistent evidence across products, product categories, stores, chains, states, and sampling periods, that the IPL store prices are higher than the non-IPL store prices by about 20¢–25¢ or 8.0%–9.6% per item, on average. In stores with ESL systems, and which are thereby exempt from IPLs, prices fall between the IPL and non-IPL store prices: they are lower than the IPL store prices by about 15¢ per item, but are higher than the non-IPL store prices by about 10¢ per item, on average. ESL systems allow the retailers to manage prices more efficiently but they are also costly. The finding that the ESL store prices fall in between the IPL and the non-IPL store prices, therefore, supports our interpretation of the cost effects of IPLs on prices.

To quantify the IPLs benefits, we focus on the size and the frequency of price mistakes that have been documented in the existing studies. We quantify the benefits of IPLs by conservatively assuming that IPLs prevent *all* price mistakes these studies have identified, and nonetheless find that the costs of IPLs are an order of magnitude higher than the benefits. We conclude, therefore, that the IPLs are inefficient: they seem to harm the consumers even though their primary goal is to protect them. This resembles previous studies on consumer protections laws, and laws regulating information provision, which have found that their costs exceed their benefits.[16] For example, Peltzman's (1972) study of the FDA found that increased regulation in the 1960s had limited benefit but large cost. We

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[13] For example, according to one retailer, "I have been in retail for over 15 years… The pressure that is put on the employees to price the items, and the time and labor invested to comply with the laws could be better used to provide the customer service the consumers complain they do not have." Source: an anonymous posting at www.michiganvotes.org, 12/10/2002.
[14] "…Aldi, a German company…, will not open stores in areas where grocers must place a price sticker on each article for sale. The company maintains that the labor costs for item pricing are too high to maintain profit margins" (Deborah Moore, *Albany Business Journal*, Albany, NY, July 13, 1998, www.albany.bizjournals.com.
[15] See Milyo and Waldfogel (1999).
[16] See, for example, Benham (1972), Beales, Craswell and Salop (1981), Gerstner and Hess (1990), and Rubin (1991).

find similar results for IPLs.

The paper is organized as follows. In section II we survey the literature. In section III, we discuss the effect of IPLs on retail prices. In section IV, we describe the data. The empirical findings are reported in section V. In section VI, we conduct a cost-benefit analysis of IPLs. In section VII, we discuss potential biases and other data measurement issues. Section VIII concludes.

II. Existing Literature on the Costs and Benefits of IPLs

Much of the literature on IPLs comes from the trade press as there are no academic studies of IPLs. Such articles typically focus on price accuracy surveys to assess the benefits of IPLs because of the belief that IPLs help the consumers notice price mistakes. One of the first such studies was conducted by *Money* magazine in 1993.[17] Prices of ten items were sampled in 27 stores and it was found that 30% of the stores overcharged, while 7% undercharged. In case of an overcharge, consumers were overcharged for one out of every ten items, on average.

Goodstein's (1994) study considered a sample of 30 items in three categories, sampled at 15 stores of three supermarket chains in California. He found that on regular items shoppers were undercharged 4.8 percent of the time and overcharged 3.6 percent of the time.

The most comprehensive studies to date on the subject were conducted by the FTC in 1996 and 1998.[18] In the 1996 study, the prices of 17,928 items were sampled in 294 department stores, drugstores, supermarkets, and other retail stores. In food stores, 1.92% of the mistakes were overcharges, and 1.55% undercharges. Total undercharges exceeded the overcharges by about $10.00. The average overcharge and undercharge were respectively $0.53 and $0.76, per item. The 1998 study sampled 107,096 items at 1,033 stores and found that one in every 30 items was mis-priced with 1/2 undercharges and 1/2 overcharges.[19] The 1998 study concluded that the error rates decreased since the 1996 survey. For example, at supermarket stores 1.36% of the mistakes were overcharges and 1.06% undercharges. Also, the average overcharge and undercharge per item were found to be $0.66 and $0.73 respectively.

Even less is known on the costs of IPLs. Weinstein (1991) estimates the cost of item pricing at $154,000 per store.[20] A similar figure was reported by *Giant*, a large US supermarket chain, which estimated "…its savings from the removal of item pricing at close to 1%" of its revenues.[21] Levy, et al. (1997) find that the average annual revenue of a supermarket is $15,052,716. Using this as a proxy for *Giant*'s revenues, a 1-percent saving translates to $150,527. According to J. Gillette, an executive of *Gillette's Food Market*, "…a full 6 percent of his labor costs go toward complying with the IPL."[22]

III. The Effect of Item Pricing Laws on Retail Prices: Theoretical Predictions

We posit that IPLs will affect retail prices for two reasons. First, IPLs increase the operating costs because every item must have a price tag. Second, IPLs increase the price adjustment cost (i.e., the menu cost) because if a product's price is changed, then the retailer has to change the price tag on every item of that product. Consider first the operating costs of item pricing. According to Levy, et al. (1998), the steps required for item pricing (beyond the steps undertaken for posting shelf price tags)

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[17] Vanessa O'Connell, "Don't Get Cheated By Supermarket Scanners," *Money* 22 (April 1993), 132–138.
[18] The 1996 study was conducted by the FTC, the NIST, and the states of FL, MA, MI, TN, WI, and VT (The FTC, 1996).
[19] The 1998 study was conducted by states and localities in 37 jurisdictions (The FTC, 1998).
[20] Source: A Cornell University study commissioned by the NY State Food Merchants Association (Weinstein, 1991).
[21] Source: "Farewell to Item Pricing? What 'Scanning' Means for Supermarket Shoppers," *Consumers Research Magazine* 64, October 1981, p. 12.
[22] Source: "Opponents Check Out Views on Item-Price Law," March 11, 1999 (www.rny.com).

take between 2.2–5.5 seconds per item. This figure does not include item pricing verification, which is done after every item-pricing session. Thus, item pricing an individual item might take only few seconds, but given the large number of items a large US supermarket carries, these figures add up.[23]

The effect of IPLs on the cost of price adjustment is subtler. Clearly IPLs increase the costs of price adjustment by forcing firms to replace the price tag on every item when a product price is changed. Levy, et al. (1997, 1998) study the impact of IPLs on the cost of price adjustment at five large US supermarket chains, one of which operates under IPLs. Their findings, which are reported in Table 1, indicate that the menu cost in the IPL chain is $1.33, in contrast to $0.52 in the other four chains. Thus, the menu cost at the IPL chain is more than 2½ times the menu costs at the other four chains.[24] Moreover, at the IPL chain, the average weekly frequency of price changes is only 1,578, in contrast to 3,916 at the other four chains.[25] Thus, the IPL chain changes its prices only 40 percent as frequently as the other four chains, on average. Further, an IPL clause at the state where the specific IPL chain is located, gives the retailers an exemption from item pricing requirement on 400 products (see Table 2). As the figures in Table 2 indicate, at the specific IPL chain, for the products that are exempted from the item pricing requirement, the weekly price change frequency is 21 percent, which is three times higher than the weekly price change frequency of the rest of the products.

The existing evidence, therefore, suggests that IPLs increase the cost of price adjustment, leading to less frequent price changes.[26] In total, however, it is not obvious whether the *total* costs of price adjustment will go up or down. Price changes are more costly, but done less frequently. According to Table 1, the *total* costs of price adjustment are similar at the IPL and non-IPL stores. Therefore, if IPLs merely create larger menu costs, this will not necessarily imply higher retail prices; it may simply mean that retailers use pricing less often as a marketing tool in their activities.[27]

We, however, argue that IPLs do more to costs of price adjustment than just making them larger. IPLs actually change the nature of the price adjustment costs. That is because IPLs make the price adjustment costs depend on the volume of the products sold.[28] For example, if a firm has 4 units on the shelf, it only incurs IPL costs for 4 prices. But if the firm is planning to sell 4,000 units, then its menu costs will be the cost of changing the price tags on all 4,000 units.[29]

Thus, the cost of item pricing and the menu cost, both depend on the sales volume. Therefore, both are variable costs. As a result, IPLs make the retail pricing and price adjustment more expensive, giving incentives to retailers to raise prices. Even if the supermarket industry is competitive, prices will increase, because all stores in a market will be subject to the same cost increase. Thus, we predict that the prices will be higher at IPL stores in comparison to non-IPL stores.

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[23] We should note, however, that some products are exempted from item pricing requirements. Despite these exemptions, supermarket chains still need to attach individual price stickers to hundreds of thousands of items on a regular basis.

[24] Recall the complaint of Marv Imus, that "… it takes 3 times or more to price [every item] …" (see footnote 2).

[25] A recent report indicates that some retailers change price even more often. For example, Home Depot *each day* changes the prices of about 13,000 different products ("Smart Business: Item Pricing Laws").

[26] Thus, many price changes are not made under IPLs because of the costs of changing individual item price tags. This is costly for the sellers. But it may be harmful for consumers as well. For example, if a more competitive environment leads to more frequent price changes, then this evidence suggests that the IPLs deny consumers some of the benefits of competition.

[27] Levy, et al (1997, p. 810) exclude from their menu cost estimates a sum of $44,168, which the IPL store in their sample spends on putting price tags on new items as they are brought to shelves, because it measures the cost of pricing rather than the cost of price changes. The total annual menu cost they report was about $106,000.00–$109,000, per store. This along with the item pricing cost of $44,168.00, yields annual IPL cost of about $150,168.00–$153,168, in the range of the figures reported in trade publications.

[28] The traditional menu cost is a fixed cost of changing a price (Mankiw, 1985). The larger this cost, the less frequently a firm will change its prices. Alternatively, these menu costs are sometimes treated as convex (Rotemberg, 1982; Cecchetti, 1985), i.e., the cost changes with the size of the price change: the bigger the price change the larger the cost of adjustment.

[29] Pricing mistakes also depend on the quantity sold: the greater the sales volume, the more mistakes are likely to occur (Levy, et al., 1998).

We also have data from two IPL chains in Connecticut that are exempted from the IPL because they use ESL systems which allow retailers to display prices and change them from a central computer via a wireless communication system. An ESL system consists of a PC, local wireless communication network, electronic labels (small LCD screens), rails, and a laser printer. The system obtains information from the store scanner database, and broadcasts it to the shelf labels. The laser printer produces the paper shelf tags and signs. The system continuously monitors the ESLs to ensure that they are present and that they display the correct information.

ESL systems yield 100% accuracy because the cash register prices are identical to the prices displayed on the ESLs as both are linked to the same database. Since 1993, therefore, the State of Connecticut exempts stores from IPLs if they install an ESL system. According to Zbaracki, et al. (2002), ESL systems are costly to purchase (fixed cost) and maintain (variable cost). First, the system price is $125,000–$185,000 in 2001 dollars, per store. The exact price depends on the options included. Second, the installation cost is $9,000–$12,000, per store. Third, training the employees to use the system entails additional cost. Fourth, the costs of converting to an ESL system include time-loss incurred by the stores and its customers. Further, the system software and hardware require continuous upgrade as the IT systems evolve. Also, ESL systems often break down, requiring maintenance. Finally, the labels require battery replacement. Also, if the labels disappear or break down because of tampering, then they need to be replaced.[30] The ESL systems, thus have both fixed and variable cost components.

We anticipate, therefore, that because of the higher costs, the retailers that use ESL systems will have higher prices in comparison to non-IPL stores.[31] Moreover, the fixed cost component of the ESL system increases the retailers' average cost, which could be passed through on to consumers. This is because the retailers face capital constraints, as well as alternative investment opportunities, such as opening new stores or expanding existing stores, which may yield higher net present value.[32]

Thus, the ESL stores prices will be higher in comparison to the non-IPL store prices—because of the high cost of ESL systems, but lower in comparison to IPL stores because ESL systems reduce the cost of item pricing and price adjustment. We test these predictions by comparing the ESL store prices with the IPL and non-IPL store prices. Such a comparison might reveal also the extent of cost saving ESL systems offer. We should note that some of the IPL-stores and *all three* ESL stores operate in Connecticut, and thus some of these comparisons are not subject to *cross-state* variation.

IV. Data Collection Methodology

To test the above prediction, we wanted to use price data from food stores at localities with and without IPLs that are similar demographically and socio-economically, geographically close to each other, and have similar supermarket chains in size, type, etc. New York, New Jersey, and

[30] A label costs about $5.50 ("New Study: Pricing Law Prevents Innovation, Savings," *Michigan Retailer*, July/Aug., 2002).
[31] Indeed, according to Grace Nome, the President of Conn. Food Assoc., "These systems are fairly expensive to maintain and they often break down. These are additional [variable] costs the retailer has to bear" (source: February 23, 2004 telephone interview with one of the coauthors). A reader may suspect that a representative of the supermarket industry might be biased. However, we have received a similar assessment from Ted Phyllis, the Foods and Standards Division Supervisor at the State of Conn.: "… ESL systems maintenance cost could be substantial. For example, if the ESLs run on batteries, they may fail until battery replacement" (source: March 8, 2004 telephone interview with one of the coauthors).
[32] A payback period of two years is the minimum necessary in the retail food industry (Levy, et al., 1998). According to Ted Phyllis, the Foods and Standards Division Supervisor at the State of Conn., however, "… it may take between 3–7 years…to pay off the cost of the system" (Source: March 8, 2004 telephone interview with one of the coauthors). To ensure timely payback, therefore, the stores that install the systems might pass some of the fixed costs of the system onto consumers. According to Grace Nome, the President of Conn. Food Association, "The system itself is very expensive and as a result small retailers could not afford it…only large retailers have adopted it and the smaller ones stick to the traditional item pricing…" (Source: March 8, 2004 telephone interview with one of the coauthors).

Connecticut (the Tri-State area) met these criteria and had other advantages as well. NY and CT have IPLs while NJ does not. In addition, CT exempts retailers from IPL if they install an ESL system.

The suburban towns of NY City in northern NJ, Westchester County in NY, and southern CT, are remarkably similar in density, socioeconomic profile, and demographics. Moreover, they are geographically close to each other. A drive from northern NJ to southern CT can take as little as half an hour. The towns have quality public schools, quiet roads with nicely sized houses, and downtown areas with a mix of small businesses, and branches of national businesses like Starbucks. These similarities make the Tri-State area a natural place to conduct our study. We collected data from these suburbs in NY, NJ, and CT. In Chart 1 we present a small map of the Tri-State area.[33]

Choice of Stores for Data Set I

We used two criteria for selecting the supermarket chains. The first was that the chain has stores located in the suburban areas of NY, NJ, and/or CT. The second criterion was that the chain uses Everyday Low Price Strategy (EDLP). In contrast to High/Low (HL) pricing strategy chains, the EDLP chains offer better data for our purpose because they change their prices less frequently.[34]

We sampled price data from three types of stores in the Tri-State area: (i) stores that are subject to IPLs (denoted as "IPL-Stores;", these stores are located either in NY or CT); (ii) stores that are not subject to IPLs (denoted as "No-IPL Stores;" these stores are located in NJ); and (iii) stores that are subject to IPLs but are exempted from it because they use ESL systems (denoted as "ESL-Stores"; these stores are located in CT).

Data Set I was sampled at four stores that belong to two supermarket chains, Stop & Shop and Food Emporium. Both are large chains prevalent in the Tri-State area, and both have stores of similar sizes that sell thousands of products of a similar variety. In addition, both use the EDLP pricing strategy. We collected price data at three Stop & Shop stores and one Food Emporium (see Table 3). One Stop & Shop store is located in Tarrytown, NY, which has an IPL; another in Clifton, NJ, which does not have an IPL; and the third in Stamford, CT, which is under an IPL but has an ESL-exemption. The Food Emporium store is located in Greenwich, CT, which has an IPL.[35]

We established two criteria for choosing products. First, they had to be subject to IPLs (if the store was under an IPL). Second, they had to be brand name products because their quality does not vary across stores. To make the data collection practically feasible, we limited our analysis to 15 randomly selected products in 11 randomly selected categories. These are listed in Table 4.

We visited each store 4 times (with one month between the visits) on the same time and day and recorded the shelf prices manually. The schedule was as follows: Saturday mornings, Stop & Shop in Clifton, NJ; between 1:00–2:00pm on Saturdays, Stop & Shop in Tarrytown, NY; Sunday mornings, Food Emporium in Greenwich, CT; and at noon, Stop & Shop in Stamford, CT. We collected the data during January 2001–April 2001. The trips took place on January 14–15, 2001, February 11–12, 2001, March 11–12, 2001, and April 8–9, 2001. If the store was subject to an IPL, then we recorded the individual sticker price. Thus our prices do not reflect any manufacturer or newspaper coupon discount, or any other kind of promotional offer. The price collection process for data set I yielded 2,640 price observations (4 stores×4 visits×11categories×15 products), which

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[33] A senior manager of an ESL system manufacturer has also suggested to us (in a personal email communication) that "… CT and NY provide some of the better 'neighboring counties' scenarios" for studying the effect of IPLs on retail prices.

[34] HL and EDLP refer to the general pricing strategy of the retailer. EDLP store prices are low and thus, they offer less sales or discounts. HL store prices are high but they offer more frequent discounts through sales and promotions.

[35] For details on the supermarket chains and the stores sampled, their locations, and the surrounding areas, see Appendix II.

include 660 observations from the ESL store.

Data Collection Process for Data Set II

The analysis of data set I revealed that for each of 11 product categories, the IPL store prices were higher than the non-IPL store prices. Further, the pattern was consistent across the 4 visits, with a stable price gap of about \$0.20–\$0.25 per product on average between the two types of stores. The second data set aimed to check the robustness of these findings across a larger sample of stores. We, therefore, added 16 new stores to our sample. For cost-effectiveness, however, we reduced the number of categories to two (condiments and household products). For data set II, therefore, we sampled the prices of 30 products at 20 stores that belong to seven chains.[36] 12 of the stores are IPL stores (10 in NY and 2 in CT), 5 No-IPL stores (all in NJ), and 3 are IPL stores with ESL exemptions (all in CT). Note that all stores of a chain in a given state are only of one type. For example, in CT there are no ESL and non-ESL stores that belong to the same chain. Table 3 lists these stores and their location.

In total, data set II contains 600 observations (20 stores×1 visit×2 categories×15products), which include 90 observations from ESL stores. In the two data sets combined, we have a total of 3,240 weekly price observations.

V. The Effect of Item Pricing Laws on Retail Prices: Empirical Findings

We begin by comparing the prices across IPL, no-IPL, and ESL regimes in the two data sets, starting with an aggregate level comparison and moving to finer comparisons by controlling for state- and store-level factors which might affect the prices. We follow by presenting the estimates of the average price differences and their statistical significance using linear regression analysis.

In Table 5, we report average prices in data set I. According to the figures in column (1) of the table, the IPL store prices exceed the non-IPL store prices in each category, with an average of 25.1¢. As well, the ESL store price exceeds the non-IPL store prices by 10.1¢, on average. In column (2), we exclude Food Emporium to control for a possible *cross-chain* variation, and find that the IPL store prices exceed the non-IPL store prices in each category, with an average of 20.2¢. In column (3), we conduct a within-state comparison to control for a possible *cross-state* variation and find that the IPL store prices exceed the ESL store prices in all but two categories, with an average of 20¢. These results hold for the vast majority of the individual products as well. For example, for 148 of the 165 individual products sampled (i.e. 90%), IPL store prices exceed the non-IPL store prices, as indicated by Figure 1. For 128 of the 165 (i.e. 78%) individual products, the average ESL store price exceeds the average non-IPL store price. Finally, for 140 of the 165 (i.e. 85%) individual products, the average price at IPL stores exceeds the average price at the ESL stores. Thus the ESL store prices fall between the IPL and non-IPL store prices.

In Table 6, we report average prices in data set II. In column (1), we compare the prices at 12 IPL and 5 non-IPL stores, and find that the IPL store prices exceed the non-IPL store prices with an average of 24.5¢. In columns (2)–(5), we conduct the IPL/no-IPL comparison within the same chain

[36] We limit the second data collection to 30 products following the practice of many IPL jurisdictions in conducting price accuracy audits. For example, in MA, the pricing accuracy compliance is determined based on a sample of 25 product prices ("Retail Electronic Price Systems Exemptions," Section 329D, Amendment to MA Chapter 94, "Item Pricing Law," Outside Section 125, www.mass.gov/eoaf/budget/fy04/print/outsec/p125.htm). In CA, it is based on the prices of 30 products (CA

and thus control for a possible *cross-chain* variation. As before, the IPL store prices exceed the non-IPL store prices in all cases. In columns (6), (7), and (8), we compare the IPL and the ESL store prices. In column (6), where we control for a possible *cross-state* variation, we find that that within the state of CT, the IPL store prices exceed the ESL store prices by 16.6¢, on average. In column (7), we conduct a finer comparison by focusing on stores that are located *in the same district* of the state of CT, and find a price difference of 28.5¢, on average. Finally, in column (8) we make an even finer comparison as the two stores (S16 and S18) are located *at the same intersection*. Here we find that the IPL store prices exceed the ESL store prices by 27.1¢.

Overall, when we compare all three types of chains, with the exception of Shop Rite, we find that ESL store prices fall in between the IPL and no-IPL store prices. As before, these findings hold for individual products as well. For example, in data set II, the average IPL store price is higher than non-IPL store price for all 30 products sampled (i.e., 100%), as indicated by Figure 2. Similarly, for 29 of the 30 products (i.e., 97%) the IPL store prices exceed the ESL stores prices. Finally, for 20 of the 30 individual products (i.e., 67%), the ESL store prices exceeds the non-IPL store prices.

We thus observe three sets of prices: non-IPL store prices, ESL store prices, and IPL store prices. Let the cost at non-IPL stores be the baseline. Then at stores in IPL jurisdictions that do not adopt ESL, the cost is about \$0.25 above the baseline, while at stores that adopt ESL, the cost is \$0.10 above the baseline. This set of observations is exactly what we would predict if IPLs increase costs and ESL systems can serve as a method of reducing but no entirely eliminating these costs.

Next, we estimate the econometric model,

$$(1) \qquad P_i = \alpha + \beta_1 IPL_i + \beta_2 \left(IPL \times ESL\right)_i + \varepsilon_i ,$$

where P_i is the i^{th} observation of the price, IPL_i is a dummy variable attaining the value 1 if the observation comes from an IPL store (including stores with an ESL exemption), and 0 otherwise, ESL_i is a dummy variable attaining the value 1 if the observation comes from an ESL store, and 0 otherwise, and $\varepsilon_i \sim N(0,\sigma^2)$ is an iid error term. The coefficients β_1 and β_2 capture the effect of the IPL on prices. If the IPL store prices are higher than non-IPL store prices, then we will expect that $\beta_1 > 0$. Similarly, within an IPL regime, if the ESL store prices are lower than non-ESL store prices, then we will expect $\beta_2 < 0$.

The error terms in (1) are uncorrelated across observations. Also, the specification in (1) cannot capture the unobserved variation in prices that might result from differences between stores or product categories.[37] To specify a model that can account for such variation, recall that in data set I, we had a small sample of stores and a large sample of product categories. The main purpose of this sampling procedure was to look for generalizability across product categories. We, therefore, model

Dept. of Food and Agriculture, Division of Measurement Standards, DMS Notice QC-02-5, October 16, 2002, "Statewide Automated Check-stand Scanner Survey," Attachment B, Inspection Procedure).

[37] The state may also be a source of unobserved heterogeneity. However, we are not able to control for state level variation because of the nature of the data: the state variable is perfectly correlated with the *IPL* variable. For example, all NY observations are IPL and all NJ observations are non-IPL, leading to singularity problems in estimating the β coefficients.

the store and product factors as having a fixed and random effect, respectively.

Accordingly, we modify (1) as follows (dropping the subscript *i* for simplicity):

$$P = \alpha + \theta_k CHAIN_k + \gamma_j CATEGORY_j + \beta_1 IPL + \beta_2 (IPL \times ESL) + u_j + \varepsilon \quad (2)$$

where $CHAIN_k$ is a dummy variable attaining value 1 if the observation comes from chain *k*, and 0 otherwise, $CATEGORY_j$ is a dummy variable attaining value 1 if the observation comes from category *j*, and 0 otherwise, θ_k and γ_j are the respective coefficients, and u_j is the random effect associated with $CATEGORY_j$.[38] In (2), the error terms are assumed to be distributed normally with mean zero, constant variance, and uncorrelated. That is, $E(\varepsilon_i) = E(u_j) = 0$, $E(\varepsilon_i^2) = \sigma_\varepsilon^2$, $E(u_j^2) = \sigma_u^2$, $E(\varepsilon_i u_j) = 0 \; \forall j$, and $E(\varepsilon_k \varepsilon_l) = E(u_k u_l) = 0 \; \forall k \neq l$.

Estimation results are reported in Table 7, Regression (2). The coefficients for *IPL* and *IPL*×*ESL* variables are both significant at 1%. The point-estimate of the coefficient on the *IPL* dummy variable is 0.203, significant at the 1% level. This figure suggests that the IPL store prices exceed the No-IPL store prices by 20¢ on average. The point-estimate of the coefficient on the interaction variable $IPL \times ESL$ is –0.101, also significant at 1% level. Thus, within an IPL regime, ESL store prices are lower than non-ESL store prices by 10¢ on average.

The error covariance structure in (2) has two limitations. First, it does not take into account the fact that data set I contains four repeated observations. Although they are a month apart, their sequential nature may still lead them to be serially correlated. Second, the assumption of constant variance, $E(u_j^2) = \sigma_u^2$, might not hold because different categories might be subject to different market conditions. In a further refinement of (2), therefore, we control for the repeated nature of the data by assuming an AR(1) error structure, $E(\varepsilon_i^2) = \sigma_\varepsilon^2$ and $E(\varepsilon_i \, \varepsilon_{t+n}) = \rho^n \sigma_\varepsilon^2$. In addition, we relax the assumption of constant variance by assuming that $E(u_j^2) = \sigma_{uj}^2$.

The results are reported in Table 7, Regression (2, modified). The coefficient estimates for both *IPL* and *IPL*×*ESL* variables are both significant at 1%, and their numerical values are similar to Regression (2): the IPL store prices are 21¢ higher than the non-IPL store prices, on average. Within the IPL regime, ESL store prices are 11¢ lower than non-ESL store prices, on average. Thus, the IPL store prices are highest, followed by the ESL store prices, and then Non-IPL store prices.

In data set II, we sample only two categories, condiments and households, but 16 additional stores. The reason for this design was to check the generalizability of our results across stores. We, therefore, include a fixed effect for product categories and a random effect for the store chains.[39]

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[38] Note that "chain" variable is perfectly correlated with the *IPL* variable. For example, all Stop & Shop (NJ) observations are non-IPL. This leads to the same singularity problems associated with the state variable as mentioned footnote 38.

[39] We considered the random effects of the two chains, Stop & Shop and Shop Rite. That is because these are the only chains that span all the experimental conditions—IPL, non-IPL, and ESL. We, however, have decided to exclude Shop Rite from the regression because it seems to be an outlier. As Appendix 2 suggests, Shop Rite is a cooperative rather than a regular supermarket chain and thus, it might be using different pricing rules. Indeed, according to Table 6, Shop Rite is the only chain in which ESL store prices exceed the IPL store prices. We club the rest of the stores under "other."

Thus, the regression model is given by

$$(3) \qquad P = \alpha + \theta_k CHAIN_k + \gamma_j CATEGORY_j + \beta_1 IPL + \beta_2 \left(IPL \times ESL\right) + v_k + \varepsilon \ ,$$

where, v_k is the random effect of $CHAIN_k$. In accounting for the chains' effects, note that Stop & Shop and Shop Rite are the only chains that span all the experimental conditions—IPL, ESL and non-IPL. We proceed by controlling for these two chains and clubbing the rest of the stores in a single category "other." We assume that the error terms satisfy the conditions $E(\varepsilon) = E(v_k) = 0$, $E(\varepsilon^2) = \sigma_\varepsilon^2$, $E(v_k^2) = \sigma_v^2$, $E(\varepsilon\ v_k) = 0\ \forall k$, and $E(\varepsilon_k \varepsilon_l) = E(v_k v_l) = 0\ \forall k \neq l$.

Similar to data set I, we run the above regression under the assumption of homoskedastic errors, i.e., $E(v_k^2) = \sigma_v^2$, as well as heteroskedastic errors, i.e., $E(v_k^2) = \sigma_{vk}^2$, and they are reported in the two columns of Table 8, respectively.[40] The coefficient estimates for the *IPL* variable are 0.230 and 0.227, respectively, both significant at the 7% level, suggesting that in data set II, IPL store prices are about 23¢ higher than the non-IPL store prices, on average.[41] Within the IPL regime, the ESL store prices are 6.2¢–6.4¢ lower than the non-ESL store prices, on average.[42] These estimates, however, are not statistically significant.[43] We conclude, therefore, that IPL stores do indeed charge higher prices than non-IPL stores—the average price difference per item being about \$0.20–\$0.25.[44]

Is a 20¢–25¢ difference big? As an absolute measure, it seems small. Consider, however, the fact the average price in our sample of non-IPL stores is \$2.50–\$2.71 in the two data sets. Then, the percentage price difference between the two types of stores is about 8.0%–10.0%, which seems substantial.[45] To appreciate this magnitude further, consider the following. In 2002, food represented 14% of total Personal Consumption Expenditures (Council of Economic Advisers, 2003).[46] If we take

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[40] We assume heteroskedasticity for the chain effects. Stores vary their pricing and promotion policies which could lead to store specific variances. No autocorrelation correction was needed here because in data set II we only sampled once. Thus, data set II constitutes a true cross-section.

[41] We did not find any significant difference in the log-likelihood figures of the two models, suggesting that the two models have similar explanatory powers. Indeed the coefficient estimates are identical within two decimal places.

[42] We have also estimated a regression model for the state of Connecticut alone. The goal of this analysis was to see whether the price differences between the ESL and the non-ESL stores within Connecticut are due to the store-level unobserved factors. Using variety of zip-code, city, and county-level socio-economic variables as proxies for these factors, we conclude that the inclusion of these possible explanatory factors leave the estimation results we report here essentially unchanged. The results of these analyses are not reported here to save space. They, however, are included in the referee appendix, which is available from the corresponding authors upon request.

[43] To understand the reason for this and to explore these results further, we ran the same regressions without the store effect dummies, and find that IPL coefficient estimate and significance remains unchanged. The estimated coefficient on the interaction variable *IPL*×*ESL* also remains around 6¢–7¢, but it is statistically significant. This suggests that the statistical insignificance of the above coefficients is likely due to the store effects, which might be a reflection of more fundamental differences between the IPL stores that choose to adopt ESL systems and the stores that do not. Therefore, the store variables pick up all the price differences between the ESL and non-ESL stores. This finding is consistent with the results of pair wise comparisons (available from the corresponding author upon request) starting with an aggregate level comparison and moving to finer comparisons by controlling for state- and store-level factors. In that analysis we found that when the analysis focused on store-level comparisons, the price differences between the ESL stores on the one hand and IPL and no-IPL stores on the other hand, indeed, were not statistically significant.

[44] We also ran a fixed effects model for both datasets. Under the specifications we have, the magnitude of the coefficients should not change, and they did not. However, for data set I, the mixed effects model resulted in a significantly better fit based on the log likelihood ratio test, $\chi^2(1) = 8680.002$, $p < 0.0001$. For data set II, based on the same test, there was no significant difference between the two models, $\chi^2(1) = 0.296$, $p = 0.586$.

[45] We would obtain a similar estimate if we used an average price based on a larger sample. For example, the average price in large US supermarket chains during 2001 was about \$2.08, yielding a price difference of about 12 percent.

[46] Note that grocery sales include non-food items such as household and health and beauty products.

14% as an approximation for households' grocery expenditures, then IPLs appear to reduce the real incomes of residents of states with such laws by 1.12%–1.40%, which is a nontrivial amount.

VI. Costs-Benefit Analysis of the Item Pricing Laws

Having estimated the costs of IPLs in terms of the price increases they seem to cause, we next compare them to the primary benefit IPLs are supposed to offer: help consumers notice price mistakes. To assess the benefits of the IPLs, we rely on previously documented price accuracy surveys. We consider two surveys. The first is the 1993 survey of the *Money* magazine, and the second is the 1998 "Price Check II" of the FTC. We choose these two because they reported the *highest* and the lowest amounts of overcharges per item, respectively. By choosing these two extremes, we can try to provide a range for the IPL benefit by bounding it from above and below.[47]

In the *Money* magazine survey, 30% of the stores overcharged and 7% undercharged. At the stores that overcharged, 10% of the sample reported an average overcharge of \$0.069. According to our cost calculations, IPL stores charge \$0.25 more per item, on average. Assuming that the item pricing protects the consumers from *ever being overcharged*, IPLs give them a benefit of \$0.069, while it costs them \$0.20–\$0.25, per item. Thus, the cost of IPL exceeds its benefit by a factor of 3, and that is a conservative estimate. If we factor in the undercharges, then the net loss is even higher.

In "Price Check II," 1.36% of the items checked in food stores were overcharges and 1.06% undercharges. The average overcharge was \$0.66 and the average undercharge \$0.73, per item. Thus, in a sample of 100 items, 1.36 items are overcharged, on average. At \$0.66 per overcharge, that is a total overcharge of \$0.90 per 100 items, or \$0.009 per item, which represents the maximum benefit consumers can gain from item pricing, assuming that the IPL prevents all price overcharges. Comparing it to the cost of IPL, \$0.20–\$0.25, the cost of the IPL exceeds its benefit by a factor of up to 27. Again, if we factor in the 1.06% undercharges, then the IPL's benefit is wiped out completely. This would eliminate the ability to garner any benefits from item pricing altogether.[48]

If we conservatively assume that consumers dislike any price mistake, *even if it is in their favor*, then total benefit of the IPL would be 0.009 + 0.0077 = 0.017 (where 0.0077 is obtained by multiplying 1.06 by 0.73). *Money* magazine study does not report average undercharge. However, if we assume that average undercharge equals the average overcharge, and we again conservatively assume that the shoppers are 100 percent honest and thus correct the cashier even if the pricing error in their favor, then the expected benefit of the IPL will double to about 0.138. The cost of the IPL in this case will still be twice as much as the benefit.

We infer that the costs of the IPLs are an order of magnitude higher than the upper bound of the estimated benefits. Moreover, all consumers in localities with IPLs pay the costs of the laws in the form of higher prices, but only a few will ever reap the benefits. If item pricing protects consumers from overcharges, and stores overcharge between 1–2 percent of the time, then that means that a vast majority of the consumers are not overcharged. They, therefore, do not benefit from item pricing, but they still have to pay the higher prices caused by the IPLs. Further, the consumers are not equally sensitive to price mistakes, especially if the mistakes are small.[49]

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[47] We should note, however, that the FTC's "Price Check II" study is the most relevant for our case because it was conducted in 1998 while the other studies date further back. Moreover, Price Check II is broadest as it relies on the biggest sample in terms of the size as well as the breadth of its coverage.

[48] Three of the four studies discussed above, showed that on average, undercharges exceeded overcharges in total value.

[49] See, for example, Reis (2006), Sims (2003), Bergen, et al. (2006), and Levy, et al. (2006).

VII. Potential Biases and Other Data Measurement Issues

Despite our best efforts to collect data at supermarkets located in areas as homogeneous as possible, there might still be differences between the localities covered in terms of property taxes, land rents, labor costs (e.g., minimum wages), average household income, etc. If these differences are systematic and substantial, the estimated price differences may not be entirely due to the IPLs, and in that case our measure of IPL costs may be biased upward. For example, NY and NJ have Federal minimum wages ($5.15/hour), while CT's minimum wage is higher ($6.90/hour).[50] Similarly, there may be differences in wholesale prices despite the Robinson-Patman Act.

To address these concerns, we have conducted several additional analyses in order to try and account for some of these unobserved factors, which might be driving our results. For this we have gathered zip-code level, city level, and county level data on several socio-economic variables including population, population density, number of households, median household income, median family income, per capita income, percentage of families below the poverty line, and percentage of population below the poverty line. Inclusion of these variables in the regressions do not change the key coefficient estimates, and thus leave our main findings unchanged.[51]

More importantly, the fact that our findings are robust across numerous types of comparisons is reassuring that these kinds of biases, if present, are unlikely to be severe. For example, recall that we have conducted price comparisons not only *across states* with IPLs and without IPLs, but also *across chains* within a state, *across chains* within a county/district/locality, *across stores* within a chain, and *across product categories*. Thus, if for example, property tax rates vary across states or across counties, then the comparison of prices sampled from the stores within the same county (comparing prices at CT-IPL and CT-ESL stores) is not affected by that. Further, the corroborating evidence we offer, relying on the existing studies of IPLs' effect on price adjustment costs, as well as the evidence we offer based on the comparison of the ESL store price change data with the IPL and non-IPL store price change data, all support our findings. We recognize, however, that because of the absence of time variation in legal variables, we cannot completely rule out the possibility that "NY is just a more expensive place to do business than NJ." Similarly, the adoption of an ESL technology is endogenous, and therefore we cannot rule out the possibility that "ESL investment is more profitable in high-volume (or low-cost or price-sensitive) markets."

In our analysis, we have only focused on the IPL's primary costs and benefits. For example, on the benefit side, we focused only on prevention of pricing overcharges.[52] People, however, have cited other benefits of the law. For example, they have argued that without item pricing, price comparison would be difficult making it easier for stores to raise prices. In addition, it has been argued, shelf price labels are often difficult to read, and misplaced items make shopping harder because of the difficulty of identifying their price.

However, the IPLs do not necessarily yield all these benefits. For example, the suggestion that without IPLs price comparison would be difficult may not be valid in light of the findings of Dickson

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[50] It also depends on whether or not these workers are unionized. These biases, however, may not be important because the supermarket workers handling pricing tasks are not minimum wage workers. As well, from econometric estimation point of view, inclusion of minimum wage data in our regressions would not be useful because minimum wages do not vary within states, leaving just three state-level observations to work with. That would lead to similar identification problems as the inclusion of state fixed effects, as discussed in footnotes 38 and 39.

[51] The results of these analyses are not reported here to save space. They, however, are included in the referee appendix, which is available from the corresponding authors upon request.

[52] IPL supporters are not necessarily representing all consumers. According to *Washington Post*, "… out of 60 shoppers questioned, a majority of 3 to 1 favored elimination of item prices as long as prices stayed lower. Only 1/6 of the people surveyed preferred individual item pricing even if prices were not lowered." Source: "Farewell to Item Pricing?" p. 11.

and Sawyer (1986) who report that item-pricing does not necessarily lead to a better price recall. Also, "search consumers" will not necessarily benefit from IPLs. For them, unit price information, such as price per oz or price per liter, is more valuable. Moreover, search consumers often focus on "sales" items, which are exempted from many IPLs (e.g., in Massachusetts). Therefore, the marginal benefit of reduced search cost that IPLs offer these "price sensitive" consumers may not be large.

Similarly, the argument that retailers will have incentive to take advantage of their customers by frequent overcharging if there is no IPL is unlikely to be valid, at least not universally. This is because the stores also have powerful incentives not to overcharge. Consider the following report: "When Payless Drug Store and Eagle Hardware & Garden in Seattle were criminally cited recently because scanner prices didn't match shelf prices, the story made the front page of the *Seattle Times*. The fines facing the stores were minimal, ranging from $20 to $200, but the damage from a public relations standpoint was considerable" Hennessy (1994, p. 88). Thus, as Goodstein (1994) notes, while undercharging means a small loss of profit for the retailer, overcharging means increased consumer mistrust and legal pressure for redress.[53]

Our measure of IPLs' costs may also be biased downward. This is because on the cost side, we have only focused on the primary costs of the IPLs ignoring various secondary costs. For example, state and local governments spend substantial amount of resources monitoring the retailers' compliance with the IPL requirements. For instance, in Massachusetts the annual cost of monitoring pricing accuracy exceeds $600,000, which includes the cost of 18 scanner accuracy enforcing agents.[54] Similarly, the State of Michigan conducts annual price check surveys.[55] In addition, resources go towards prosecuting violators of the IPLs.[56, 57] Moreover, as we saw, IPLs form barriers to frequent price changes. If a more competitive environment leads to more frequent price changes, the IPLs may be denying the consumers some of the benefits of competition. From a practical point of view, however, it is unclear how one could measure these secondary costs and benefits and, therefore, how their exclusion may have biased our findings.

Another possible difficulty may be data limitations. We have 3,240 weekly price observations. Some might consider this a small sample in comparison to say, scanner data used by Peltzman (2000), Barsky, et al. (2003), Chevalier, et al. (2003), or Ray, et al. (2006). We should emphasize, however, an important difference between the two types of data. Unlike scanner data, our data were collected manually. Considering that, our sample is actually larger than the samples used in other studies. For example, Goodstein's (1994) manually sampled data contain only 450 observations. Bergen, et al. (1996) manually sampled 446 price observations. Warner and Barsky (1995) also use hand-collected price data of a similar size. Thus, our sample size, over 3,000 observations, is at least seven times bigger than the samples of these studies.

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[53] There is a large event study literature which finds that small regulatory events such as punishments (for example, Federal Trade Commission orders) can lead to large stock market losses. See, for example, Peltzman (1981) who studies Federal Trade Commission advertising regulations, Peltzman and Jarrell (1985) who study the effect of product recalls, Rubin, Murphy, and Jarrell (1988), who study Consumer Product Safety Commission recalls, and Mathios and Plummer (1989) who study advertising regulation by the Federal Trade Commission. In all cases, value losses have been estimated to be much greater than direct costs to firms. These findings are typically interpreted as a loss in reputation that resulted from lying to consumers.

[54] Source: www.state.ma.us/standards/aboutus.htm.

[55] "Few Scanner Errors in State's Pricing Survey," by D. Durbin of the AP, December 4, 2002, *Detroit Free Press*.

[56] For example, according to the Nov-Dec 2000 issue of *Iowa Oil Spout*, Wal-Mart and OfficeMax were sued by Michigan's Attorney General, for not affixing individual price tags. Under the settlement, Wal-Mart has agreed to pay $250,000 and OfficeMax $125,000 in civil penalties.

[57] According to the January 22, 2004 report, a $7.35 million settlement has been reached in the class action lawsuit filed regarding Wal-Mart's failure to comply with Massachusetts' IPL. Source: http://www.bigclassaction.com/settlements/consumer.html.

These possible shortcomings notwithstanding, we believe, that as a first approximation, our analysis and the resulting figures are reasonable, assuming that we have correctly identified the primary costs and benefits of the law. As a comparison, we are aware of one study, conducted by Arthur D. Little, which tried to measure the cost of a government regulatory rule of a type similar to the IPL. The study, which is cited by Viscusi, (1993, p. 57), analyzed labeling costs associated with state-specific labels such as the California Proposition 65 Warnings for Carcinogens. According to Viscusi, for a 50¢ product the total extra cost of these state-specific warning labels was 5.4¢ per unit, which translates to 5.4/50 = 10.8 percent, a figure that is remarkably similar to our findings.[58]

VIII. Conclusion

IPLs seem to impose costs on all supermarkets and buyers in the localities that have adopted these laws. Only 9 US states have an IPL. An economist's explanation for why we do not see a more widespread use of IPLs would be that if people wanted item pricing, then the market would offer it without the need of the law. Nevertheless, studying the IPLs' costs, and comparing them to the benefits is important for identifying and quantifying their effects on various market participants. This paper makes four specific contributions. First, we demonstrate that IPLs will lead to higher prices. Second, we test this prediction using transaction price data gathered from IPL and non-IPL stores. Third, we quantify the impact of IPLs on retail prices. And fourth, using existing evidence on the accuracy of retail prices, we conduct a cost-benefit analysis of IPLs. We find that IPL stores prices are higher than no-IPL store prices by an average of 20¢–25¢ or 8.0%–9.6%, per item. We find that these costs are an order of magnitude larger than the existing documented measures of the benefits of IPLs. This is true even if we compare our estimated costs to the largest estimates of these benefits.

We conclude, therefore, that the IPLs may be inefficient, not only from the perspective of retailers, but also from the perspective of consumers. IPLs seem to harm the consumers, even though the primary reason given by proponents for creating these laws is to protect them. Our findings suggest that the inefficiencies caused by IPLs should be more carefully considered in the public policy debates on these laws. This is particularly important now, as several US counties and states, and other countries (e.g., Canada and Israel) are in the midst of discussing the revision of the existing IPLs.

Future work could consider a wider selection of products, including those exempted from IPLs. Comparing the prices of exempted products across IPL and non-IPL stores may reveal whether the price gaps between the two types of stores hold for the exempted products as well.[59] Future work could also consider price promotions between IPL and non-IPL stores. One implication of the costs of IPLs is that they should lead to fewer weekly promotional sales. Similarly, these IPL costs also suggest that high volume products should have fewer price changes. This suggests that gathering more data focused on price changes, rather than price levels, could help us better understand the implications of IPLs for retail pricing. There are other interesting questions that arise in the context of these laws that can be studied. For example, it may be useful to explore theoretical implications of endogenous price adjustment costs where the costs vary with the quantity sold.

[58] We are grateful to Kip Viscusi for bringing this study to our attention.
[59] However, as the referee has noted, the exempted product prices might be influenced by the existence of the IPLs because of the changes in he capital/labor ratio it would necessitate. For example, if the store's pricing policy involves some form of cross-subsidization, then that would make the results of such a comparison hard to interpret.

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Appendix I. Item Pricing Laws in New York and Connecticut

A) New York's Item Pricing Law

New York's IPL is defined in Section 214-i of Article 17 of the Agriculture and Markets Chapter in the New York State Consolidated Laws. The law begins by stating that although scanning technology is efficient and might make it economically advantageous for supermarkets to remove price markings on individual items, the legislature finds "that price constitutes an indispensable ingredient to a consumer's right to all reasonable information in order to make an informed purchase choice." The law finds that item pricing is necessary to protect consumers while electronic universal product code check out systems are further developed. It goes on to require that any store that sells food at retail has to clearly label each consumer commodity it sells with its selling price. Certain goods, like milk, eggs, produce, and single packs of gum, are excluded from the item-pricing requirement. In addition, if the store has fewer than three employees or grosses less than three million dollars in revenue annually, then it is exempt from the law. The law also says that a store cannot charge a price for an item that is higher than any item, shelf, sale, or advertised price of the item.

Next, the law details violations, penalties, and enforcement. Enforcement is left to municipal consumer affairs offices or to the municipal directors of weights and measures. If a store is inspected, then a sample of no less than fifty of the commodities subject to the law in a store are to be checked. For the first four violations, each penalty will be $50; $100 for each of the next twelve violations; and $150 for each subsequent violation, but the maximum penalty for the first inspection of the year can be no more than $5,000. However, if in subsequent inspections in a twelve-month period more violations are found, then the penalties will be doubled and there will be no maximum penalty. Failure to have a clearly readable price on three identical items of the same commodity is considered a violation. The law also allows the enforcement agent to compare the item, shelf, sale, or advertised price of an item with the price that is displayed in the computer at check out. In the case of overcharges, penalties ranging from $50 to $300 will be levied depending on the number of violations, and there is no maximum penalty. In subsequent inspections in a twelve-month period, the fines will double for violations. An inspector also has the authority to issue a "stop-removal order," which would prohibit the store from selling particular items until it can correct the violations it has with those items.[60]

B) Connecticut's Item Pricing Law

Connecticut's IPL is similar to New York's, although it is less detailed. Section 21a-79 of the General Statutes of Connecticut defines the state's IPL. Currently, there is a bill being considered in the Connecticut General Assembly that would update its IPL. A consumer commodity is defined by Connecticut as "any food, drug, device, cosmetic or other article, product or commodity of any other kind or class, except drugs sold only by prescription, which is customarily produced for sale to retail sales agencies or instrumentalities for consumption by individuals, or use by individuals for purposes of personal care or in the performance of service ordinarily rendered in or around the household, and which usually is consumed or expended in the course of such consumption or use."[61]

Connecticut's IPL states that any establishment that utilizes universal product coding in totaling a retail customer's purchases of consumer commodities, shall mark each consumer commodity with its retail price. It has the same product exceptions as New York's law, but also adds to its list of exceptions

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[60] New York State Consolidated Laws, "Item Pricing," Agriculture and Markets Chapter, Article 17, Section 214-I, Bill SO3847 (2001).

[61] Connecticut General Assembly, "Unit Pricing Statutes and Regulations," General Statutes of Connecticut, Section 21a-73.

alcoholic beverages and carbonated soft drinks. It goes on to state that the item pricing requirements will not apply if the Commissioner of Consumer Protection allows a store to use an electronic pricing system.

Connecticut's penalty for price accuracy errors is not as severe as New York's. It states that if an item is advertised as being on sale, then each item does not need to be remarked at the new price, but a sign indicating the sale price needs to be put adjacent to the items. If at the checkout counter a consumer is overcharged for the item on sale, then it will be given to the consumer for free.

The Commissioner of Consumer Protection is given the authority to enforce Connecticut's IPL. Penalties for violations of the law can be a warning citation, a civil penalty, or a fine. For the first offense, the civil penalty can be no more than $100 and the fine no more than $200, and there is no minimum specified. For subsequent offenses, the civil penalty can be no more than $500 and the fine no more than $1000, and there is no minimum specified. There are also no maximum amounts of penalties and fines specified.[62]

Connecticut's IPL does not have strict penalties for price accuracy errors in stores, while New York's IPL does. Connecticut's law also does not exempt certain businesses that gross under a certain amount in sales, like New York's law does. Connecticut's law simply says that any establishment that uses universal product coding is subject to the IPL. New York gives enforcement authority to municipalities, while Connecticut gives enforcement authority to a central state office. Penalties specified in both laws are severe for violations, but only New York specifically allows the enforcing agent to put an immediate stop on the sale of goods. New York's law details a structured penalty scheme, while Connecticut's law gives the enforcement agent more discretion.

Perhaps the most significant difference between the IPLs in each state though is that Connecticut has the electronic pricing system exception while New York does not. In fact, Connecticut is a unique state regarding IPLs. In 1992, the Connecticut legislature exempted stores from its IPL if the stores installed electronic pricing systems. The idea is that electronic pricing systems eliminate errors. Electronic labels that appear beneath goods on shelves are connected to the central computer of the supermarket. So when the price of an item is changed in the central computer, the new price is automatically displayed in the electronic label beneath that item. Besides saving thousands of labor hours and label and printing costs each year, supermarkets that use this system reduce the chances of human and scanning price errors that cause consumer mistrust and fines levied by the state. Supermarkets all over the country are increasingly using electronic pricing systems as the technology improves and its costs go down. However, in Connecticut especially, supermarkets are installing this technology to be exempt from IPLs which otherwise increase their annual costs by thousands of dollars.

[62] Connecticut General Assembly, "An Act Requiring the Display of Prices on Retail Items," General Statutes of Connecticut, Section 21a-79, Committee Bill No. 5135 (2001).

Appendix II. Information on the Supermarket Chains and the Stores Sampled

A) Supermarket Chains Sampled

Stop & Shop – In 1996, Stop & Shop became a wholly owned subsidiary of Royal Ahold NV, the fourth largest food retailer in the world. Headquartered in the Netherlands, Royal Ahold NV has supermarket companies in the United States, Europe, Latin America and Asia. Worldwide, the company employs more than 300,000 people and owns 4,000 stores with annual sales of approximately $35 billion. Today, Stop & Shop is a multibillion-dollar corporation and the largest food retailer in New England, operating two hundred and seventy-four supermarkets in five states: Connecticut, Massachusetts, New Jersey, New York, and Rhode Island. Stop & Shop employs 41,000 associates in its network of stores, distribution centers, manufacturing plants, and offices, which stretch across more than 180 communities.[63]

Food Emporium – With forty-two stores in Manhattan and upscale neighborhoods in Westchester, Long Island, Northern New Jersey, and Connecticut, Food Emporium is a preeminent supermarket in the Tri-State area. Food Emporium's parent company is The Great Atlantic & Pacific Tea Company, or A&P for short. The Great Atlantic & Pacific Tea Company, based in Montvale, New Jersey, operates combination food and drug stores, conventional supermarkets, and limited assortment food stores in sixteen U.S. states, the District of Columbia, and Ontario, Canada, under the A&P, Waldbaum's, Super Foodmart, Food Emporium, Super Fresh, Farmer Jack, Kohl's, Sav-A-Center, Dominion, Ultra Mart, and Food Basics trade names. By February 26, 2000, the Company operated 750 stores and served 65 franchised stores.[64]

C-Town – C-Town supermarkets are independently owned and operated. Since the chain's founding in 1975, it has grown to a group of almost 200 supermarkets doing business in a 5 state region encompassing New York, New Jersey, Connecticut, Massachusetts, and Pennsylvania. C-Town now ranks as the fifth largest food retailer in the metropolitan New York area. C-Town Supermarkets are supplied by Krasdale Foods. Founded in 1908, Krasdale Foods has become a leading distributor of name brand and store brand grocery products in the region.[65]

Pathmark – Pathmark supermarket chain was established in 1968. The company is known for pioneering the "super center" concept. Pathmark was also the first supermarket company in the Northeast to operate its stores 24 hours each day, 7 days a week. It was also among the first to adopt electronic scanning cash registers at the checkout. As of April 2003, Pathmark operates 144 supermarkets in the New York-New Jersey and Philadelphia metropolitan areas, employing over 27,000 associates. The company has stores that are located in both urban and suburban marketplaces. Since September 2000, Pathmark is a publicly traded company (PTMK, on the NASDAQ).[66]

Shop Rite – Shop Rite supermarket chain was born in 1946 as a cooperative of seven independent grocers under the name Wakefern Food Corporation. In 1951 the name Shop Rite was adopted. By the end of their first ten years in business, there were more than 70 Shop Rite Members with an annual sales volume of $100 million. In the late 1960's, Shop Rite lost nearly half of its wholesale volume when its largest Member, Pathmark, withdrew from the cooperative. Since then, Shop Rite has grown into the largest retailer-owned cooperative in the United States and the largest employer in New Jersey. The cooperative

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[63] Stop & Shop, About Us, http://www.stopandshop.com.
[64] The Great Atlantic and Pacific Tea Company, "Our Company," http://www.aptea.com.
[65] Source: www.ctownsupermarkets.com/Menu5/Default.htm.
[66] Source: www.pathmark.com, or www.restorationplaza.org/jv/rsc/rsc.html.

is comprised of 43 members who individually own and operate 190 Shop Rite stores in New Jersey, New York, Connecticut, Pennsylvania and Delaware.[67]

A&P – Founded in 1859, The Great Atlantic & Pacific Tea Company Inc (or A&P) A&P operates 465 stores in 10 US states (Connecticut, New York, New Jersey, Pennsylvania, Delaware, Maryland, Louisiana, Mississippi, Michigan, and Ohio) and the District of Columbia, and 180 stores in Ontario, Canada, under 11 retail banners, which include conventional supermarkets, food and drug combination stores, and discount food stores (under the names A&P US, A&P, Waldbaum's, A&P Super Foodmart, Food Emporium, Super Fresh, Farmer Jack, Sav-A-Center, Food Basics, A&P Canada, Dominion, Ultra Food & Drug, and The Barn Markets). A&P employs 78,000 associates and has annual sales volume of about $11 billion. The Company's shares are traded on the NYSE (under GAP). The Company also distributes private label product lines sold exclusively throughout its U S and Canadian banners.[68]

Shaws – Founded in 1860 in Portland, Maine, Shaw's supermarket chain operates 200 stores in Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, and Vermont, with annual sales of over $4.4 billion, and about 30,000 employees. The chain serves about 4 million customers each week. In 1987, the chain was purchased by J. Sainsbury, which is England's largest supermarket chain operator.[69]

B) Stores Sampled

(S1) Stop & Shop in Tarrytown, NY – Tarrytown and the surrounding Hudson Valley river towns in southern Westchester County are quiet upper class suburbs of New York City. See Chart 1. The Stop & Shop in Tarrytown is located right on the border between Tarrytown and Irvington (another small upper class town). There are also lower income parts of Tarrytown, and residents from these areas may shop at the Stop & Shop along with residents from the higher income areas of Tarrytown and Irvington.

(S2) C Town in Ossining, NY – Located in a solo building in a small commercial area of a residential suburban community in northeastern Westchester County. The store is of a relatively small size for a large chain. Ossining, while suburban, has lower income neighborhoods that are more predominant than in an area like Tarrytown, NY.

(S3) A&P in White Plains, NY – Located in a strip mall in a heavy commercial area of the small city of White Plains. The store is large. While many of the residents of White Plains are of lower income, we suspect that due to this store's location near higher end suburban communities, shoppers may come from these areas as well. White Plains is an urban city similar in size and look to Buckhead (Atlanta), but not as fancy.

(S4) Path Mark in Hartsdale, NY – Located in a strip mall in a heavy commercial area off of a busy main road that goes through southern Westchester. The store is of an average size. Hartsdale is a suburban, middle-income town that is near high income and low-income communities.

(S5) A&P in Scarsdale, NY – Located in a solo building on the same main road that the Path Mark in Hartsdale is on, but much farther down. The store is of an average size and is in a very commercial area. Scarsdale is a very high-income community, one of the highest, in Westchester County. Scarsdale is also large, and this store is not very near to all of the higher income areas of Scarsdale. It is close to Yonkers,

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[67] Source: www.shoprite.com/home/srframeset.htm.
[68] Source: www.aptea.com/company.asp.
[69] Source: www.shaws.com.

NY, and we suspect that the shoppers are a mix of a few high income, mostly middle income, and a few lower income people.

(S6) Path Mark in Yonkers, NY – Located in a part of a strip mall in a heavily commercial area just off of the same main road that the last 2 stores are on, but much farther down. The store is of an average size. Yonkers is relatively large and has a mix of middle and low-income neighborhoods, in an urban environment. This store is near both of these types of neighborhoods, and we suspect it gets an equal number of shoppers from both.

(S7) Food Emporium in Hastings, NY – Located in a large solo building in a small and light commercial area of a small residential and suburban town in the southern part of Westchester. Hastings is a high income, small town on the Hudson River, with many quiet suburban areas, and while close to Yonkers, Hastings is a good distance away from lower income neighborhoods.

(S8) Shop Rite in Monsey, NY – Located in a strip mall in a medium commercial area that is right in the middle of many suburban areas. Monsey is in Rockland County, which is on the other side of the Hudson River from Westchester County. Monsey, which is mostly middle income, has a mix of communities from blue-collar workers to retired senior citizens to an African American neighborhood to an ultra-orthodox Hassidic Jewish community. This supermarket seemed to be the largest one and the main one in the area, so we suspect its shoppers come form all of these areas.

(S9) Food Emporium in New York City – Located in the Upper East Side (Sutton Place) – This is one of the most expensive places to live in the entire world (Sutton Place). Many of the apartment buildings here have apartments worth as much as tens of millions of dollars. Many celebrities who live in NYC on the Upper East Side are known to frequent this store. It is located on 1st Avenue right underneath the 59th Street Bridge, and is large in size (it is the biggest supermarket in NYC that we have ever seen, and just might be the biggest in size). Needless to say, most of the shoppers are rich New Yorkers.

(S10) Food Emporium in Armonk, NY – Located in a small solo store in a small commercial area. Armonk is a small, affluent, suburban town in northwestern Westchester right near the Connecticut border. Not near any low-income areas.

(S11) A&P in Montvale, NJ – Located in a medium sized solo building off of a main road in a residential and suburban area. This is middle to high-income town. It is right near the New York border (Rockland County) in northeastern New Jersey in Bergen County. Bergen County is one of the most high-end counties in New Jersey, if not the highest end, and is the closest county to NYC.

(S12) Shop Rite in Rochelle Park, NJ – Located in a small building in a mixed commercial and residential suburban town. It is part of a strip mall. The area seems to be more middle income and with smaller homes than many of the other areas of Bergen County.

(S13) A&P in Pompton Lakes, NJ – Located in a very large, solo building. It is located off of two main roads/highways, but is in a very suburban and residential area. Pompton Lakes is in the central part of northern New Jersey, which is Passaic County, and is not close to NYC. The area seems to be higher than middle income, but lower than high income. While suburban, the area is more spread out than the tighter suburban areas of southern Westchester County, NY.

(S14) Path Mark in Montclair, NJ – Located in a medium sized building in an underground commercial mall. Montclair is an urban neighborhood that is almost entirely lower income. In fact the area resembles an inner-city ghetto. There is graffiti on all of the buildings and many burned and abandoned buildings around. Montclair is in Essex County, NJ. The store itself seemed to be in need of repair and had chipped paint and an unsightly ceiling with low hanging pipes. We don't think any of the shoppers here are of high income, with maybe a few being middle income, and most being low income.

(S15) Stop & Shop in Clifton, NJ – Clifton is a small suburban city of New York City that is surrounded by many high-income towns. It is located in southern Passaic County, New Jersey, right near the border of Bergen County, New Jersey. Bergen County, like Westchester County in New York, has many upper class towns and cities that are less than twenty miles from New York City. Due to the location of the Stop & Shop in Clifton, New Jersey, customers of the store most likely reside in these surrounding suburbs of Passaic County and Bergen County.

(S16) Food Emporium in Greenwich, CT – Greenwich location is perhaps the most upper class and prestigious location of all Food Emporium locations. Greenwich is located in southwestern Connecticut and is approximately the same distance out of New York City as Tarrytown. It has many areas of extreme wealth, where rich families have lived for generations. In fact, the Food Emporium in Greenwich is settled snuggly in between a Porsche and a Ferrari dealership with a Rolls Royce and a Mercedes dealership directly across the street.

(S17) Shaws in New Canaan, CT – This store is very small for a supermarket (the smallest we went to). Shaws is also the smallest chain of all the chains we went to, having the fewest number of stores and being exclusively in CT. This store is in a small, quaint commercial area. It is actually a very pretty store in a quiet shaded location. New Canaan is a very high income and small and quiet suburban town, and is around 10 miles north of Stamford.

(S18) Stop & Shop in Greenwich, CT – This store is literally right across the street from the Food Emporium listed above (less than 100 feet away). It is a medium size store, which is bigger than the Food Emporium (medium to small sized). It is newly renovated (earlier it was Grand Union station) and has an ESL system.

(S19) Stop & Shop in Stamford, CT – Stamford, Connecticut is another small suburban city of New York City that is surrounded by high-income towns and neighborhoods. It is located in the southwestern part of Connecticut and is a short drive from the New York State border. Of all the towns, Stamford is the farthest from New York City, but only by four to five miles. The Stop & Shop in Stamford is part of a mall complex that most likely draws its customers in from the surrounding high-income neighborhoods. However, there are a few lower income areas of Stamford that might also be a part of the store's customer base. The Stop & Shop in Stamford is only four to five miles southwest of the Food Emporium in Greenwich.

(S20) Shop Rite in Norwalk, CT – Norwalk is about 10 miles northeast of Stamford (15 miles northeast of Greenwich) and is very similar to Stamford. Norwalk is a higher income suburban town with some heavy commercial areas, which is where this store is located. The store is off of a main road, and it is humongous in size. It is almost as big as a football stadium and is even bigger than the Stamford Stop & Shop, which is also very large. It is directly across the street from an equally humongous Stop & Shop (that we did not go into). This area is like "gigantic supermarket/store alley." All the stores, not just the supermarkets, are very big. The store has an ESL system and many aisles.

Chart 1: The Tri-State Area of New York, New Jersey and Connecticut

Note:

Clifton, NJ, is in the bottom left, Tarrytown, NY, is in the top middle, and Greenwich, CT, in the top right (Scale: 1 inch=13.5 Km).

Table 1. The Effect of Menu Costs on the Weekly Frequency of Price Changes[a]

	Chain A	Chain B	Chain C	Chain D	Average of A–D[b]	Chain E IPL
Total Annual Menu Cost Per Store	$105,311	$112,635	$91,416	$114,188	$105,887	$109,036
Number of Price Changes Per Store Per Week	4,278	4,316	3,846	3,223	3,916	1,578
% of the Products for Which Prices Change in an Average Week[c]	0.17	0.17	0.15	0.13	0.16	0.06
Menu Cost Per Price Change[d]	$0.47	$0.50	$0.46	$0.68	$0.52	$1.33

[a] Source: Levy, et al. (1997, Table I, p. 797, and Table IV, p. 812).
[b] Chains A–D are regular (i.e., no-IPL) chains unlike Chain E which is an IPL (Item Price Law) chain.
[c] The proportion of products for which prices change on an average week is the ratio of number of price changes per store per week to 25,000. The latter is the average number of products carried per store each week.
[d] Menu cost (MC) per price change is computed as (Total annual MC/52)/(No. of price changes/week).

Table 2. Weekly Frequency of Price Changes at the IPL Chain (E),
Panel (a): Products Subject to the IPL, Panel (b): Products Exempted from the IPL[a]

	Products Subject to the IPL (a)			Products Exempted from the IPL[b] (b)		
Product Category	No. of Items in the Category	No. of Price Changes	% of Price Changes	No. of Items in the Category	No. of Price Changes	% of Price Changes
Grocery	8,500	631	0.074	256	43	0.170
Frozen Food	1,000	218	0.220	117	26	0.220
Dairy	500	147	0.300	27	14	0.520
Other Products[c]	15,000	582	0.038	–	–	–
Total	**25,000**	**1,578**	**0.063**	**400**	**83**	**0.210**

[a] Unpublished data. Source: An ESL study, cited by Levy, et al. (1997, 1998).
[b] An IPL clause at the state where Chain E is located, gives the retailers an exemption from item pricing requirements on 400 products.
[c] These include the categories of general merchandise, health and beauty products, etc.

Table 3. Stores Sampled in Data Sets I and II

Stores Sampled in Data Set I (Four Visits)	Stores Sampled in Data Set II (One Visit)
IPL	**IPL**
NEW YORK:	NEW YORK:
S1: Stop & Shop, Tarrytown, NY	S1. Stop & Shop, Tarrytown, NY S2. C Town, Ossining, NY S3. A&P, White Plains, NY S4. Path Mark, Hartsdale, NY S5. A&P Scarsdale, NY S6. Path Mark, Yonkers, NY S7. Food Emporium, Hastings, NY S8. Shop Rite, Monsey, NY S9. Food Emporium, NYC, NY S10. Food Emporium, Armonk, NY
CONNECTICUT:	CONNECTICUT:
S16. Food Emporium, Greenwich, CT	S16. Food Emporium, Greenwich, CT S17. Shaws, New Canaan, CT
ESL	**ESL**
CONNECTICUT:	CONNECTICUT:
S19: Stop & Shop, Stamford, CT	S18. Stop & Shop, Greenwich, CT S19. Stop & Shop, Stamford, CT S20. Shop Rite, Norwalk, CT
NO-IPL	**NO-IPL**
NEW JERSEY:	NEW JERSEY:
S15: Stop & Shop, Clifton, NJ	S11. A&P, Montvale, NJ S12. Shop Rite, Rochelle Park., NJ S13. A&P, Pompton Lakes, NJ S14. Path Mark, Montclair, NJ S15. Stop & Shop, Clifton, NJ

Notation:

IPL = Item Pricing Law stores

NO-IPL = Non Item Pricing Law stores

ESL = Electronic Shelf Label stores

Table 4. Categories and Products Sampled in Data Set I

Category and products in the category	Index	Category and products in the category	Index
Beverages		**Breakfast/Cereals**	
Coca Cola Classic – 2L bottle	B1	Kellog's Apple Jacks – 15oz	BF1
Diet Sprite – 2L bottle	B2	Kellog's Corn Pops – 15oz	BF2
Vintage Seltzer Water – 2L bottle	B3	Kellog's Special K – 12oz	BF3
Pepsi Cola – 12/12oz cans	B4	GM Cheerios – 15oz	BF4
Barq's Root Beer 12/12oz cans	B5	GM Cocao Puffs – 13.75oz	BF5
Dr. Brown's Cream Soda 6/12oz cans	B6	GM Lucky Charms –20oz	BF6
Poland Spring – 1 gallon container	B7	Post Raisin Bran – 20oz	BF7
Evian – 1L bottle	B8	Post Fruity Pebbles – 13oz	BF8
Lemon Lime Gatorade – 64oz bottle	B9	Nature Valley Granola Oats 'N Honey – 8.9oz	BF9
Arizona Iced Tea (boxed drinks) – 3/12oz	B10	Kellog's Nutri Grain Blueberry Bars – 8 bars	BF10
Fruit Punch Capri Sun – 10/6.75oz	B11	Kellog's Variety Pack – 10/1.5oz	BF11
V8 Vegetable Juice – 46 oz can	B12	Kellog's Pop Tarts Frosted Strawberry – 14.7oz	BF12
V8 Splash Tropical Blend – 64oz bottle	B13	Nestle Quick Drink Mix – 15oz can	BF13
Juicy Juice Fruit Punch – 46oz can	B14	Aunt Jemima Original Pancake Mix – 2lb box	BF14
Tropican Twisters Tropical Fruit – 1.75L bottle	B15	Aunt Jemima Pancake Syrup – 24oz bottle	BF15
Frozen Foods		**Dairy and Juices**	
Swanson Turkey (white meat) – 11.75oz	FRZ1	Farmland S.R. 1% Plus Lowfat Milk – ½ gallon	DR1
Swanson Salisbury Steak – 13oz	FRZ2	Lactaid 100 Fat Free Milk Lactose Free – 1 quart	DR2
Weight Watchers Smart Ones Basil Chicken – 9.5oz	FRZ3	Nesquick Chocolate Milk – 64oz	DR3
Weight Watchers Smart Ones Mac & Cheese – 10oz	FRZ4	Dannon Light Yogurt Cherry Vanilla – 8oz container	DR4
Healthy Choice Medly's Roast Turkey Breast – 8.5oz	FRZ5	Dannon Rasberry – 8oz container	DR5
Haagen Dazs Vanilla Ice Cream – 1 pint	FRZ6	Breakstone's Fat Free Cottage Cheese – 16oz	DR6
Stouffers Lean Cuisine Swedish Meatballs – 10oz	FRZ7	Land O' Lakes Salted Whipped Light Butter – 8oz	DR7
Stouffers Hearty Portions Salisbury Steak – 16oz	FRZ8	Kraft Fat Free American Cheese Singles – 16 slices	DR8
Green Giant Frozen Niblers Corn on the Cob – 4 ears	FRZ9	Philadelphia Cream Cheese – 8oz	DR9
Ego Blueberry Waffles – 16 count – 19.8oz	FRZ10	Nestle Carnation Coffemate – 16oz	DR10
Lender's Plain Bagels – 6 count	FRZ11	Breakstone's Fat Free Sour Creem – 16oz	DR11
Original Tombstone Supreme – 22.85oz	FRZ12	Tropicana Pure Premium Homestyle OJ – 64oz	DR12
Celentano Manicotti – 14oz bag	FRZ13	Welch's Fruit Cocktail White Grape Peach – 64oz	DR13
Ore Ida Golden Twirls – 28oz	FRZ14	Dole 100% Pineapple Juice – 64oz	DR14
Bird's Eye Mixed Vegetables – 10oz	FRZ15	Tropicana Pure Premium Grovestand OJ – 96oz	DR15
Condiments, Sauces & Spreads		**Soup/Canned Foods**	
Grey Poupon Dijon Mustard - 8oz jar	C1	Campbell's Chicken Noodle Soup - 10.75oz	SP1
Hellmann's Mayonnaise - 32oz jar	C2	Progresso Chicken & Wild Rice - 19oz	SP2
Heinz Ketchup - 24oz squeeze bottle	C3	Progresso Minestrone Soup - 19oz	SP3
Skippy Creamy Peanut Butter - 18oz	C4	Campbell's Cream of Broccoli - 10.75oz	SP4
Smucker's Concord Grape Jelly - 12oz Jar	C5	Campbell's Family Size Tomato Soup - 18.7oz	SP5
Kraft Thousand Island Dressing Free - 8oz	C6	Progresso New England Clam Chowder - 19oz	SP6
Wish Bone Fat Free Ranch Dressing - 8oz	C7	Campbell's Vegetarian Vegetable - 10.75oz	SP7
Domino Granulated Sugar - 2lb box	C8	Goya Black Beans - 15.5oz can	SP8
Equal Sugar Substitute - 50 count	C9	Ortega Thick & Chunky Medium Salsa - 16oz	SP9
Jello Cherry - 3oz box	C10	Dole Sliced Pineapple - 20oz can	SP10
Heinz Distilled White Vinegar - 32oz	C11	Del Monte Pear Halves - 29oz can	SP11
Pam Lemon Fat Free Cooking Spray - 6oz can	C12	Bumbe Bee Solid White Tuna in Water - 6oz can	SP12
A1 Steak Sauce Bold & Spicy - 10oz jar	C13	Starkist Chunk Light Tuna in Oil - 6oz can	SP13
Heinz Barbecue Sauce - 18oz bottle	C14	Chef Boyardee Beef Ravioli - 15oz can	SP14
Kraft Shake 'n Bake Classic Italian - 5.75 oz	C15	Mott's Homestyle Chunky Apple Sauce - 23 oz jar	SP15

Table 4 (Cont.). Categories and Products Sampled in Data Set I

Category and products in the category	Index	Category and products in the category	Index
Baby Products & Foods		**Health & Beauty Aides**	
Huggies Pull Ups for Boys 32 - 40lb's - 26 count	BBY1	Crest Multi Care Fresh Mint Toothpaste - 6.2oz tube	HLT1
Huggies Natural Care Scented Wipes - 80 count	BBY2	Scope Peppermint - 33oz	HLT2
Pampers Diapers Newborn to 10lb - 48 count	BBY3	Right Guard Sport Deodorant Gel Cool Scent - 3oz	HLT3
Luvs Diapers Ultra Leakguards #3 - 72 count	BBY4	Sudafed Max Nasal Decongestant - 24 tablets	HLT4
Beechnut Stage 2 Apples & Bananas - 4oz	BBY5	Halls Cough Drops Black Cherry - 25 count	HLT5
Earth's Best Organic Apples - 4oz	BBY6	Tylenol Extra Strength Gelcaps - 100 count	HLT6
Gerber 100% Apple Juice - 32oz bottle	BBY7	Johnson & Johnson Band Aids - 60 count	HLT7
Gerber Stage 1 Pears - 2.5oz	BBY8	Pepto Bismol - 12oz	HLT8
Enfamil Lactofree Infant Formula - 13oz can	BBY9	Bausch & Lomb Saline Solution - 12oz	HLT9
Johnson & Johnson Baby Shampoo - 15oz	BBY10	Oxi Max Cleansing Pads - 55 count	HLT10
Johnson & Johnson Baby Powder - 15oz	BBY11	Thermasilk Moisturizing Shampoo - 13oz	HLT11
Gerber Cereal for Baby Rice with Banana - 8oz	BBY12	Head & Shoulders Dandruff Shampoo Normal - 15.2oz	HLT12
Beechnut Cereal for Baby Oatmeal - 8oz	BBY13	Barbasol Original Shaving Cream - 11oz can	HLT13
Gerber Graduates Veggie Crackers - 4oz	BBY14	Dial Liquid Antibacterial Soap Refill - 15oz bottle	HLT14
Beechnut Table Time Mac & Cheese - 6oz	BBY15	Lever Soap 2000 - 2/4.5oz bars	HLT15
Candy & Snacks		**Paper Products, Bags & Pet Supplies**	
Planter's Mixed Nuts - 11.5oz can	CND1	Brawny Towels Thirsty Roll - 3 rolls	PAP1
Sun Maid Raisins - 9oz	CND2	Kleenex Cold Care Ultra - 70 count	PAP2
Sunsweet Pitted Prunes - 24oz	CND3	Vanity Fair 2 Ply Napkins - 100 count	PAP3
Hershey's Kisses Milk Chocolate - 8oz bag	CND4	Charmin Big Squeeze - 9 rolls	PAP4
Trident Original Sugarless Gum - 8/5 stick packs	CND5	Hefty Cinch Sak Trash Bags - 20 bags	PAP5
Rold Gold Pretzels Fat Free - 15oz	CND6	Glad Tall Kitchen Bags Quick Tie - 15 bags	PAP6
Wise B.B.Q. Potato Chips - 5.5oz	CND7	Ziploc Sandwich Bags - 100 bags	PAP7
Chips Ahoy Chocolate Chip Cookies - 12oz bag	CND8	Reynolds Wrap Aluminum Foil - 50 sq. feet	PAP8
Oreo Cookies - 1lb bag	CND9	Ziploc 1 Gallon Freezer Bags - 30 bags	PAP9
Pepperidge Farm Milanos - 6oz bag	CND10	Dixie Flatware Spoons - 50 count	PAP10
Pepperidge Farm Goldfish Cheddar - 6oz bag	CND11	Dixie Printed Bathroom Cups - 100/5oz	PAP11
Wheat Thins Original - 10oz box	CND12	Purina Dog Chow - 4.4lb bag	PAP12
Nabisco Ritz Bits Sandwich Crackers - 10.5oz box	CND13	Milk Bone Small - 24oz box	PAP13
Quaker Chocolate Chip Granola Bars - 10 bars	CND14	Purina Cat Chow - 56oz box	PAP14
Orville Redenbacher's Light Popcorn - 3/3.5oz bags	CND15	Fresh Step Cat Litter Scoop - 7lb bag	PAP15
Households			
Tide Ultra Liquid Detergent - 50oz	H1		
Downy Fabric Softener Mtn. Spring - 40 count	H2		
Clorox Liquid Bleach - 1 quart	H3		
Palmolive Original Dishwashing Liquid - 28oz bottle	H4		
Glade Rainshower - 9oz	H5		
Drano Build Up Remover - 32oz	H6		
Tilex Mildew Stain Remover - 32oz spray	H7		
Clorox Cleanup with Bleach - 32oz	H8		
Brillo Steel Wool Soap Pads - 18 count	H9		
Lysol Disinfectant Original - 12oz spray	H10		
Pledge Clean and Dust - 12.5oz spray	H11		
Fantastic All Purpose - 22oz	H12		
Windex Glass Cleaner - 26oz	H13		
Mr. Clean and Top Job with Ammonia - 40oz	H14		
Old English Lemon Polish - 12.5oz spray	H15		

Table 5. Average Prices in Data Set 1
All Categories (Top Panel) and Individual Categories (Lower Panel)

Category	**IPL**: Stop & Shop, NY-S1 Food Emporium, CT-S16 **NOIPL**: Stop & Shop, NJ-S15 **ESL**: Stop & Shop, CT-S19	**IPL**: Stop & Shop, NY-S1 **NOIPL**: Stop & Shop, NJ-S15 **ESL**: Stop & Shop, CT-S19	**IPL**: Food Emporium, CT-S16 **ESL**: Stop & Shop, CT-S19
	Aggregate Comparison (1)	**Control for Chain** (2)	**Control for State** (3)
All Categories			
IPL	2.965 (0.056)	2.916 (0.083)	3.015 (0.075)
NOIPL	2.714 (0.080)	2.714 (0.080)	
ESL	2.815 (0.079)	2.815 (0.079)	2.815 (0.079)
Individual Categories			
Beverage			
IPL	2.431 (0.092)	2.388 (0.119)	2.474 (0.142)
NOIPL	2.133 (0.131)	2.133 (0.131)	
ESL	2.310 (0.125)	2.310 (0.125)	2.310 (0.125)
Breakfast			
IPL	3.389 (0.068)	3.375 (0.100)	3.403 (0.093)
NOIPL	3.078 (0.099)	3.078 (0.099)	
ESL	3.040 (0.084)	3.040 (0.084)	3.040 (0.084)
Frozen			
IPL	2.916 (0.086)	2.860 (0.117)	2.971 (0.125)
NOIPL	2.842 (0.117)	2.842 (0.117)	
ESL	2.763 (0.119)	2.763 (0.119)	2.763 (0.119)
Dairy			
IPL	2.593 (0.100)	2.524 (0.140)	2.662 (0.144)
NOIPL	2.492 (0.147)	2.492 (0.147)	
ESL	2.440 (0.144)	2.440 (0.144)	2.440 (0.144)
Condiments			
IPL	2.304 (0.089)	2.213 (0.122)	2.396 (0.130)
NOIPL	2.045 (0.119)	2.045 (0.119)	
ESL	2.180 (0.116)	2.180 (0.116)	2.180 (0.116)
Soup			
IPL	1.497 (0.051)	1.470 (0.074)	1.524 (0.070)
NOIPL	1.255 (0.068)	1.255 (0.068)	
ESL	1.381 (0.069)	1.381 (0.069)	1.381 (0.069)
Baby			
IPL	4.373 (0.470)	4.552 (0.725)	4.194 (0.604)
NOIPL	4.283 (0.700)	4.283 (0.700)	
ESL	4.454 (0.683)	4.454 (0.683)	4.454 (0.683)
Health			
IPL	3.854 (0.185)	3.778 (0.260)	3.930 (0.265)
NOIPL	3.422 (0.253)	3.422 (0.253)	
ESL	3.772 (0.249)	3.772 (0.249)	3.772 (0.249)
Candy			
IPL	2.736 (0.081)	2.578 (0.097)	2.895 (0.127)
NOIPL	2.474 (0.099)	2.474 (0.099)	
ESL	2.546 (0.100)	2.546 (0.100)	2.546 (0.100)
Paper			
IPL	3.355 (0.122)	3.227 (0.164)	3.483 (0.182)
NOIPL	3.058 (0.151)	3.058 (0.151)	
ESL	3.125 (0.163)	3.125 (0.163)	3.125 (0.163)
Households			
IPL	3.172 (0.093)	3.115 (0.133)	3.228 (0.129)
NOIPL	2.770 (0.116)	2.770 (0.116)	
ESL	2.954 (0.119)	2.954 (0.119)	2.954 (0.119)

Table 6. Average Prices in Data Set 2, All Categories (Top Panel) and Individual Categories (Lower Panel)

Category	**IPL**: All 12 Stores **NOIPL**: All 5 Stores **ESL**: All 3 Stores	**IPL**: A&P, S3+S5 **NOIPL**: A&P, S11+S13	**IPL**: Shop Rite, NY, S8 **NOIPL**: Shop Rite, NJ, S12 **ESL**: Shop Rite, CT, S20	**IPL**: Path Mark, NY, S4+S6 **NOIPL**: Path Mark, NJ, S14	**IPL**: Stop & Shop, NY, S1 **NOIPL**: Stop & Shop, NJ, S15 **ESL**: Stop & Shop, CT, S18+S19	**IPL**: Food Emporium, CT, S16 Shaws, CT, S17 **ESL**: Stop & Shop, CT, S18+S19 Shop Rite, CT, S20	**IPL**: Food Emporium, CT, S16 **ESL**: Stop & Shop, CT, S18+S19	**IPL**: Food Emporium, CT, S16 **ESL**: Stop & Shop, CT, S18
	Aggregate Comparison **(1)**	**Control for Chain: A&P** **(2)**	**Control for Chain: Shop Rite** **(3)**	**Control for Chain: Path Mark** **(4)**	**Control for Chain: Stop & Shop** **(5)**	**Control for State** **(6)**	**Control for State and District** **(7)**	**Control for State, District, and Locality** **(8)**
<u>All Categories</u>								
IPL	2.745 (0.058)	2.724 (0.140)	2.451 (0.198)	2.651 (0.135)	2.602 (0.180)	2.744 (0.135)	2.844 (0.199)	2.844 (0.199)
NOIPL	2.500 (0.084)	2.532 (0.135)	2.438 (0.193)	2.585 (0.187)	2.414 (0.181)			
ESL	2.578 (0.104)		2.616 (0.194)		2.559 (0.123)	2.578 (0.104)	2.559 (0.123)	2.573 (0.177)
<u>Individual Categories</u>								
Condiments								
IPL	2.300 (0.075)	2.227 (0.172)	1.979 (0.254)	2.219 (0.176)	2.189 (0.221)	2.360 (0.185)	2.418 (0.266)	2.418 (0.266)
NOIPL	2.028 (0.105)	2.048 (0.160)	1.973 (0.255)	2.094 (0.249)	1.978 (0.234)			
ESL	2.155 (0.135)		2.169 (0.264)		2.149 (0.156)	2.155 (0.135)	2.149 (0.156)	2.169 (0.225)
Households								
IPL	3.190 (0.076)	3.221 (0.183)	2.923 (0.256)	3.083 (0.174)	3.017 (0.247)	3.129 (0.172)	3.270 (0.258)	3.270 (0.258)
NOIPL	2.973 (0.106)	3.017 (0.180)	2.903 (0.243)	3.077 (0.219)	2.850 (0.232)			
ESL	3.001 (0.132)		3.063 (0.238)		2.970 (0.160)	3.001 (0.132)	2.970 (0.160)	2.977 (0.237)

Table 7. Regression Results for Data Set I

	Regression (2)[a]			Regression (2, Modified)[b]		
Variable[c]	Estimate	*t*	Sig.	Estimate	*t*	Sig.
Intercept	1.256	2.520	0.013	1.262	8.903	0.000
[Chain = Food Emporium]	0.098	5.954	0.000	0.091	3.271	0.001
[Category = Baby]	2.963	4.204	0.000	2.966	2.124	0.052
[Category = Beverage]	0.919	1.304	0.194	0.923	3.126	0.005
[Category = Breakfast]	1.817	2.578	0.011	1.801	7.836	0.000
[Category = Candy]	1.216	1.725	0.087	1.208	4.756	0.000
[Category = Condiments]	0.801	1.137	0.257	0.793	2.779	0.011
[Category = Dairy]	1.122	1.592	0.113	1.128	3.473	0.002
[Category = Frozen]	1.452	2.060	0.041	1.449	5.191	0.000
[Category = Health]	2.318	3.289	0.001	2.322	4.304	0.001
[Category = Household]	1.609	2.283	0.024	1.601	5.779	0.000
[Category = Paper]	1.816	2.576	0.011	1.815	5.029	0.000
IPL	**0.203**	**12.281**	**0.000**	**0.208**	**7.469**	**0.000**
IPL×ESL	**–0.101**	**–6.150**	**0.000**	**–0.111**	**–3.993**	**0.000**

[a] Dependent Variable: price.
[b] This is the same as Regression (2) except that here were allow an autocorrelated and heteroskedastic error structure.
[c] The "Soup" Category and the "Stop & Shop" Chain dummy variables are excluded from the regression because of their redundancy.

Table 8. Regression Results for Data Set II

	Regression (3)[a]			Regression (3, Modified)[b]		
Variable[c]	Estimate	*t*	Sig.	Estimate	*t*	Sig.
Intercept	3.003	26.454	0.000	3.005	25.467	0.000
[Chain = Stop & Shop]	–0.163	–1.075	0.302	–0.164	–1.162	0.247
[Category = Condiments]	–0.892	–10.419	0.000	–0.892	–10.438	0.000
IPL	**0.230**	**1.966**	**0.071**	**0.227**	**1.874**	**0.076**
IPL×ESL	**–0.064**	**–0.313**	**0.759**	**–0.062**	**–0.336**	**0.737**

[a] Dependent Variable: price.
[b] This is the same as Regression (3) except that here we allow heteroskedastic error structure.
[c] The "Chain = Other" dummy and the Household category dummy variables are excluded from the regressions because of their redundancy.

Figure 1: Average Product Prices at IPL, ESL, and No-IPL Stores, Data Set I

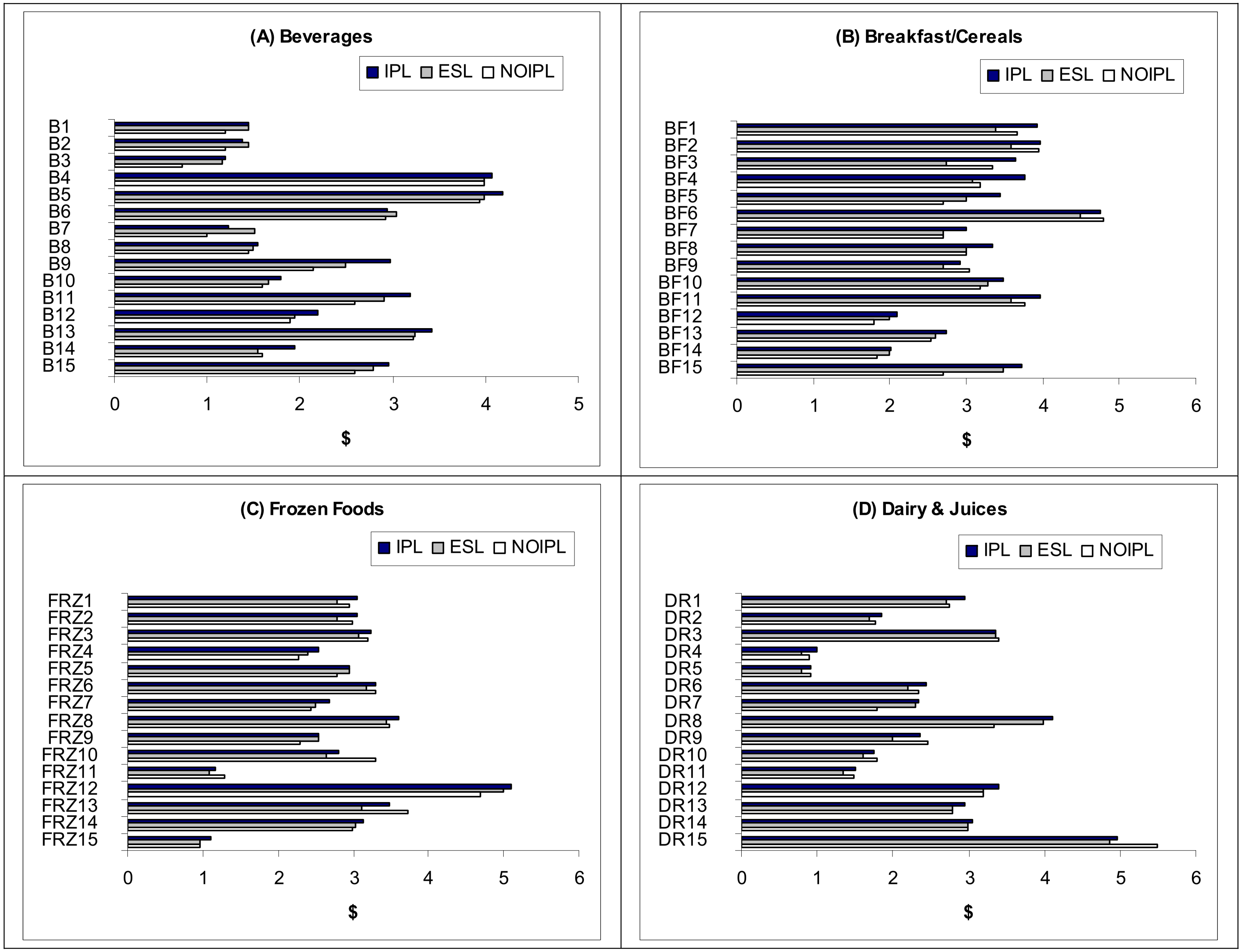


Figure 1: Average Product Prices at IPL, ESL, and No-IPL Stores, Data Set I (Cont.)

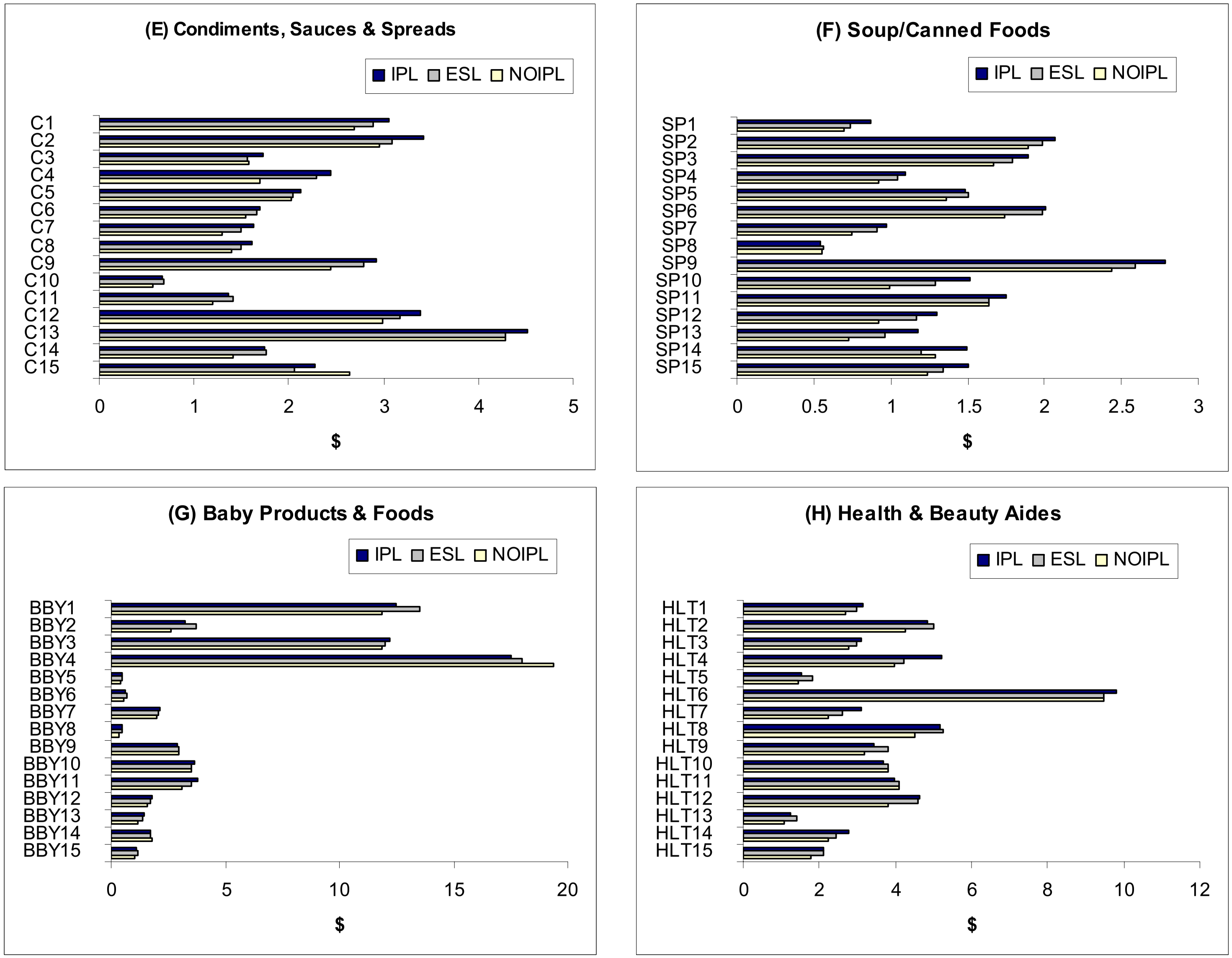
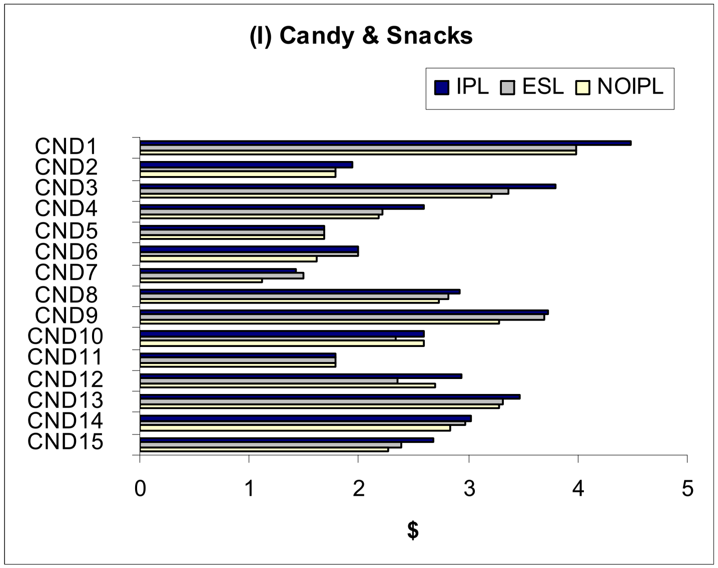
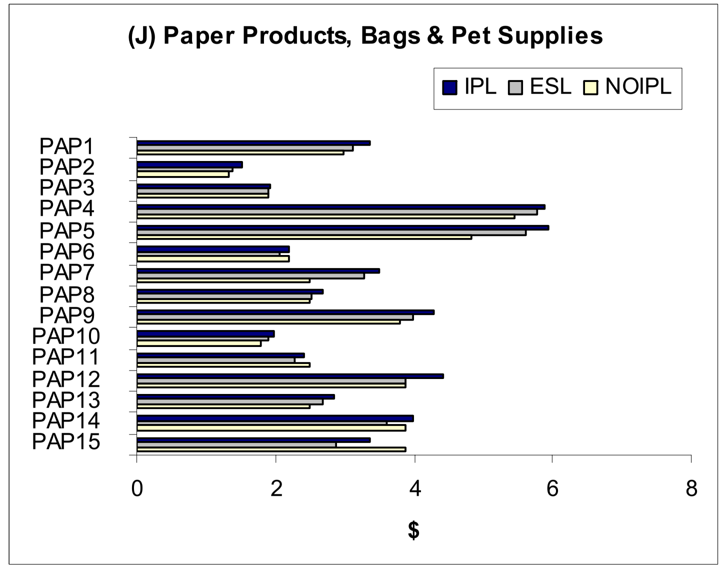


Figure 1: Average Product Prices at IPL, ESL, and No-IPL Stores, Data Set I (Cont.)





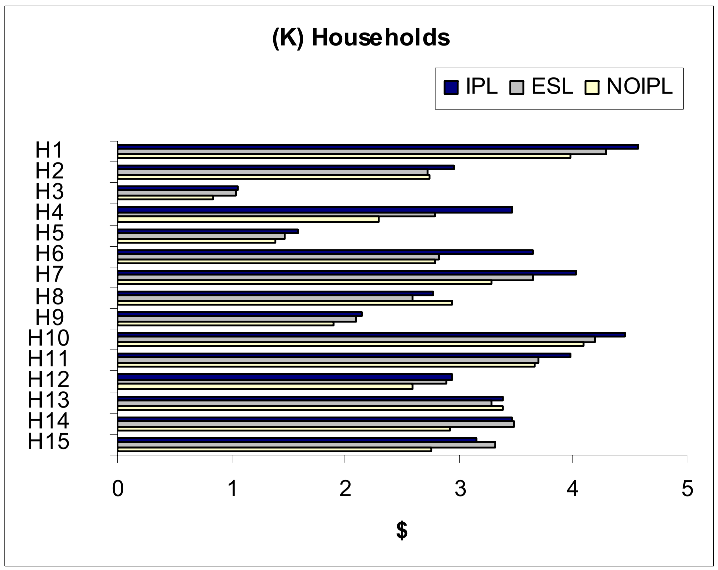


Figure 2: Average Product Prices at IPL, ESL, and No-IPL Stores, Data Set II