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

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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 costs of pricing and 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. We find that IPL store prices are higher by about 20¢–25¢ per item on average. As a control, we use data from stores that use electronic shelf labels and find that their prices fall between IPL and no-IPL store prices. We compare the costs of IPLs to existing measures of the benefits and find that the costs are an order of magnitude higher than the upper bound of the estimated benefits.

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> 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, 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 three 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. . . . [T]his 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, Michigan retailer)[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. . . . [T]hey 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]

1. Introduction

Item-pricing laws (IPLs) require a price tag on every item sold by a retailer.[4] Currently, IPLs exist in nine U.S. 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 Israel are currently considering a revision

[1] State of Michigan, Office of the Attorney General (http://www.michigan.gov/ag); available from the authors upon request.

[2] *Morning News Beat* (July 17, 2002, Internet edition); available from the authors upon request.

[3] Robert J. Venable, senior consultant, Robert W. Baird and Company, e-mail correspondence with Daniel Levy and Mark Bergen, April 30, 1996.

[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 to be provided per standard unit (such as per ounce, liter, or gallon). Both are in effect in most states and localities.

[5] In the United States, item-pricing laws (IPLs) exist in California, Connecticut, Illinois, Massachusetts, Michigan, New Hampshire, New York, North Dakota, and Rhode Island. In Appendix A, we provide detailed descriptions of the New York and Connecticut IPLs.

of their IPLs.[6] The proposed new bill in Michigan would make item pricing optional if retailers use electronic shelf labels (*Holland Sentinel* 2003). Similarly, a recent change in the IPL of Quebec exempts retailers from the IPL if there are a minimum number of handheld scanners in the store available for the use of consumers.[7]

The most commonly cited reason in support of IPLs is that without them the public would be unable to detect pricing mistakes.[8] 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 (Beck 1997). In Schenectady, New York, retailers are exempted from IPL requirements if pricing errors do not exceed 2.3 percent.[9] Similarly, Massachusetts offers an IPL exemption if pricing accuracy is 98 percent (Mass. Gen. Laws Ann., ch. 94, outside sec. 25, amending sec. 329D [2004]). 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 system, shelf prices and cash register prices are identical. This suggests that pricing 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.[10] Some have even suggested that the item-pricing requirement and its costs may prevent new store openings.[11]

[6] In fact, this study was presented at both the Michigan State House Commerce Committee and the Israeli Ministry of Industry, Trade, and Employment's committee hearings. Both institutions are considering a revision of their local IPLs.

[7] Quebec, Price Marking in Quebec: New Regulatory Rules (available from the authors upon request).

[8] 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" (National Association of Convenience Stores, The Battle over Item Pricing, Michigan Style [July 16, 2002]; available from the authors upon request). "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 (*Holland Sentinel* 2003, p. 7). Consider also the titles of typical articles on this topic: "UPC Scanner Pricing Systems: Are They Accurate? A Summary of a 1994 *Journal of Marketing* Article by Ronald C. Goodstein" (*Stores*1994), "Don't Get Cheated by Supermarket Scanners" (O'Connell 1993), "Is Precision Pricing Possible?" (Hennessy 1994), and "UPC Scanner Pricing Systems: Are They Accurate?" (Goodstein 1994). While suggestive, these articles all address the public's concern with pricing accuracy. See also Blattberg and Neslin (1989), Garry (1991), Lattin and Ortmeyer (1991), Weinstein (1992), Hoch and Banerji (1993), and Hoch, Drèze, and Purk (1994).

[9] Virtual Advisor Interactive, Smart Business: Item Pricing Laws (http://www.va-interactive.com/inbusiness/documents/LG/SB_LEG1.DOC).

[10] 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" (anonymous posting, December 10, 2002, Mackinac Center for Public Policy, Michigan Votes [http://www.michiganvotes.org].

[11] "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" (Moore 1998, p. 2).

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 costs of pricing and price adjustment. This is 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 subject to IPLs and supermarkets not subject to IPLs, with the restriction that all sampled stores be located in geographical proximity to each other and operate in similar markets and socioeconomic areas. We also collected retail price data from supermarkets that are subject to IPLs but are exempted from the item-pricing requirement because they use ESL systems, which, albeit adding some overhead cost, are believed to save labor costs related to IPLs, which allows these data to be used as a control (see Stigler 1961; Milyo and Waldfogel 1999; Jin and Leslie 2003; Müller et al. 2006, 2007).

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, 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 and the other across stores. We find consistent evidence across products, product categories, stores, chains, states, and sampling periods that IPL store prices are higher than no-IPL store prices by about 20¢–25¢, or 8.0–9.6 percent per item on average. In stores with ESL systems, which are thereby exempt from IPLs, prices fall between the IPL and no-IPL store prices: they are lower than IPL store prices by about 15¢ per item but are higher than no-IPL store prices by about 10¢ per item on average. Electronic shelf label systems allow retailers to manage prices more efficiently, but they are also costly. The finding that the ESL store prices fall between IPL and no-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 frequency of price mistakes that have been documented in existing studies. We conservatively assume that IPLs prevent all the price mistakes that those 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 consumers even though their primary goal is to protect them. This resembles previous studies on consumer protection laws and laws regulating information provision, which have found that their costs exceed their benefits (for example, Benham 1972; Beales, Craswell, and Salop 1981; Gerstner and Hess 1990; Rubin 1991). For example, Peltzman's (1973) study of the Food and Drug

Administration found that increased regulation in the 1960s had limited benefit but large cost. We find similar results for IPLs.

The paper is organized as follows. In Section 2, we survey the literature. In Section 3, we discuss the effect of IPLs on retail prices. In Section 4, we describe the data. The empirical findings are reported in Section 5. In Section 6, we conduct a cost-benefit analysis of IPLs. In Section 7, we discuss potential biases and other data measurement issues. Section 8 concludes.

2. Existing Literature on the Costs and Benefits of Item-Pricing Laws

Much of the literature on IPLs comes from the trade press, as there are no academic studies of IPLs. Such articles typically focus on surveys of price accuracy to assess the benefits of IPLs because of the belief that IPLs help consumers notice price mistakes. One of the first such studies was conducted by *Money* magazine (O'Connell 1993, pp. 132–38). Prices of 10 items were sampled in 27 stores, and it was found that 30 percent of the stores overcharged, while 7 percent undercharged. In case of an overcharge, consumers were overcharged for one out of every 10 items, on average.

Goodstein (1994) 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 Federal Trade Commission (FTC) in 1996 and 1998.[12] 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 percent of the mistakes were overcharges and 1.55 percent undercharges. Total undercharges exceeded overcharges by about $10.00. The average overcharge and undercharge were, respectively, $.53 and $.76 per item. The 1998 study sampled 107,096 items at 1,033 stores and found that one in every 30 items was mispriced, with half undercharges and half overcharges.[13] The 1998 study concluded that error rates had decreased since the 1996 survey. For example, at supermarkets 1.36 percent of the mistakes were overcharges and 1.06 percent undercharges. The average overcharge and undercharge per item were found to be $.66 and $.73, respectively.

Even less is known about the costs of IPLs. In a Cornell University study commissioned by the New York State Food Merchants Association, Weinstein (1991) estimates the cost of item pricing to be $154,000 per store. A similar figure was reported by Giant, a large U.S. supermarket chain, which estimated "its savings from the removal of item pricing at close to 1%" of its revenues

[12] The 1996 study was conducted by the Federal Trade Commission (FTC), the National Institute of Standards and Technology, and the states of Florida, Massachusetts, Michigan, Tennessee, Wisconsin, and Vermont (Federal Trade Commission 1996).

[13] The 1998 study was conducted by states and localities in 37 jurisdictions (Federal Trade Commission 1998).

(*Consumer Research* 1981, p. 12). 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" (*Rome Sentinel News* 1999, p. 5).

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

We posit that IPLs affect retail prices for two reasons. First, IPLs increase operating costs because every item must have a price tag. Second, IPLs increase the price adjustment cost (that is, 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) take between 2.2 and 5.5 seconds per item. This figure does not include pricing verification, which is done after every item-pricing session. Thus, pricing an individual item might take only few seconds, but given the large number of items a large U.S. supermarket carries, these figures add up.[14]

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, forthcoming), Levy, Dutta and Bergen (2002), Levy and Young (2004), Dutta et al. (1999), and Dutta, Bergen, and Levy (2002) study the impact of IPLs on the cost of price adjustment at five large U.S. 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 $.52 in the other four chains. Thus, the menu cost at the IPL chain is more than $2\frac{1}{2}$ times the menu costs at the other four chains.[15] 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.[16] 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. As the figures in Table 2 indicate, for the products that are exempted from the item-pricing requirement, the weekly price change

[14] 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.

[15] Recall the complaint of Marv Imus, that "it takes 3 times or more to price [every item]" (*Morning News Beat* [July 17, 2002, Internet edition]; available from the authors upon request).

[16] 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 (Virtual Advisor Interactive, Smart Business: Item Pricing Laws [http://www.va-interactive.com/inbusiness/documents/LG/SB_LEG1.DOC]).

Table 1
Effect of Menu Costs (MCs) on the Weekly Frequency of Price Changes

	No IPL				Average of Chains	IPL:
Variable	Chain A	Chain B	Chain C	Chain D	A–D	Chain E
Total annual MC per store ($)	105,311	112,635	91,416	114,188	105,887	109,036
Price changes per store per week	4,278	4,316	3,846	3,223	3,916	1,578
Products with price change in an average week (%)	.17	.17	.15	.13	.16	.06
MC per price change ($)	.47	.50	.46	.68	.52	1.33

Source. Levy et al. (1997, tables I and IV).
Note. The proportion of products for which prices change in an average week is the ratio of number of price changes per store per week to 25,000, the average number of products carried per store each week. Menu cost per price change is computed as (total annual MC/52)/(number of price changes per week). IPL = item-pricing law.

frequency is 21 percent, which is three times higher than the frequency for the rest of the products.

The existing evidence, therefore, suggests that IPLs increase the cost of price adjustment, which leads to less frequent price changes.[17] 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 are done less frequently. According to Table 1, the total costs of price adjustment are similar at IPL and no-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.[18]

We, however, argue that IPLs do more to the costs of price adjustment than just making them larger. They actually change the nature of the price adjustment costs. That is because IPLs make price adjustment costs depend on the volume of the products sold.[19] For example, if a firm has four units on the shelf, it incurs

[17] 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 IPLs deny consumers some of the benefits of competition.

[18] 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 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–$109,000 per store. This, along with the item-pricing cost of $44,168, yields an annual IPL cost of about $150,168–$153,168, which is in the range of the figures reported in trade publications.

[19] 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 1987; Cecchetti 1986); that is, the cost changes with the size of the price change: the larger the price change, the larger the cost of adjustment.

Table 2
Weekly Frequency of Price Changes at Item-Pricing Law (IPL) Chain E

	Products Subject to IPL			Products Exempted from IPL		
Product Category	Items	Price Changes (*N*)	Price Changes (%)	Items	Price Changes (*N*)	Price Changes (%)
Grocery	8,500	631	.074	256	43	.170
Frozen food	1,000	218	.220	117	26	.220
Dairy	500	147	.300	27	14	.520
Other products	15,000	582	.038	. . .	. . .	. . .
Total	25,000	1,578	.063	400	83	.210

Source. Unpublished data from a study of electronic shelf labeling cited in Levy et al. (1997, 1998).
Note. An IPL clause in the state where chain E is located gives retailers an exemption from item-pricing requirements on 400 products. "Other products" include general merchandise, health, and beauty products, and so on.

IPL costs for only four 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.[20]

Thus, the cost of item pricing and the menu cost both depend on sales volume. Therefore, both are variable costs. As a result, IPLs make retail pricing and price adjustment more expensive, which gives 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 prices will be higher at IPL stores than at no-IPL stores.

We also have data from two IPL chains in Connecticut that are exempted from the IPL because they use ESL systems that allow retailers to display prices and change them from a central computer via a wireless communication system. An ESL system consists of a computer, 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.

Electronic shelf label systems yield 100 percent 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

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

time loss incurred by the stores and its customers. Further, the system software and hardware require continuous upgrade as the technology systems evolve. Also, ESL systems often break down, requiring maintenance. Finally, the labels require battery replacement. If the labels disappear or break down because of tampering, then they need to be replaced.[21] 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 than will no-IPL stores.[22] Moreover, the fixed-cost component of the ESL system increases retailers' average cost, which can be passed on to consumers. This is because retailers face capital constraints and have alternative investment opportunities, such as opening new stores or expanding existing stores, which may yield higher net present value.[23]

Thus, ESL stores' prices will be higher in comparison to those of no-IPL stores—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 ESL store prices with IPL and no-IPL store prices. Such a comparison might also reveal the extent of the 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.

4. 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 socioeconomically, are geographically close to each other, and have similar supermarket chains in size, type, and so on. New York, New Jersey, and Connecticut (the tri-state area) met these criteria and had other advantages as well. New York and Connecticut have IPLs, while New Jersey does not. In addition, Connecticut exempts retailers from IPLs if they install an ESL system.

The suburban towns of New York City in northern New Jersey, Westchester

[21] A label costs about $5.50 (Klay and Clarr 2002).

[22] Indeed, according to Grace Nome, president of Connecticut Food Association, "These systems are fairly expensive to maintain and they often break down. These are additional [variable] costs the retailer has to bear" (telephone interview with Daniel Levy, February 23, 2004). A reader may suspect that a representative of the supermarket industry might be biased. However, we received a similar assessment from Ted Phyllis, supervisor in the State of Connecticut's Foods and Standards Division: "ESL systems' maintenance cost could be substantial. For example, if the ESLs run on batteries, they may fail until battery replacement" (telephone interview with Daniel Levy, March 8, 2004).

[23] A payback period of 2 years is the minimum necessary in the retail food industry (Levy et al. 1998). According to Ted Phyllis, however, " It may take between 3–7 years . . . to pay off the cost of the system" (telephone interview with Daniel Levy, March 8, 2004). To ensure timely payback, therefore, stores that install the systems might pass some of the fixed costs of the system on to consumers. According to Grace Nome, "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" (telephone interview with Daniel Levy, March 8, 2004).

Figure 1. The tri-state area of New York, New Jersey, and Connecticut (1 inch = 13.5 km)

County in New York, and southern Connecticut are remarkably similar in density, socioeconomic profile, and demographics. Moreover, they are geographically close to each other. A drive from northern New Jersey to southern Connecticut 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 such as Starbucks. These similarities make the tri-state area a natural place to conduct our study. We collected data from these suburbs in New York, New Jersey, and Connecticut. In Figure 1 we present a small map of the area.[24]

Choice of Stores for Data Set 1

We used two criteria for selecting the supermarket chains. The first was that the chain has stores located in the suburban areas of New York, New Jersey, and/or Connecticut. The second criterion was that the chain uses an "everyday low price" (EDLP) strategy. In contrast to chains that use a high-low (HL) pricing

[24] A senior manager of an ESL system manufacturer has also suggested to us (Jeff Sandgren, consultant, ERS, e-mail coorrespondence with Daniel Levy and Mark Bergen, April 30, 1996) that "Connecticut and New York provide some of the better 'neighboring counties' scenarios" for studying the effect of IPLs on retail prices.

Table 3
Stores Sampled in Data Sets 1 and 2

Regime and Location	Data Set 1	Data Set 2
IPL:		
New York	S1: Stop & Shop, Tarrytown	S1. Stop & Shop, Tarrytown
		S2. C-Town, Ossining
		S3. A&P, White Plains
		S4. Path Mark, Hartsdale
		S5. A&P Scarsdale
		S6. Path Mark, Yonkers
		S7. Food Emporium, Hastings
		S8. Shop Rite, Monsey
		S9. Food Emporium, New York City
		S10. Food Emporium, Armonk
IPL:		
Connecticut	S16. Food Emporium, Greenwich	S16. Food Emporium, Greenwich
		S17. Shaw's, New Canaan
ESL:		
Connecticut	S19: Stop & Shop, Stamford	S18. Stop & Shop, Greenwich
		S19. Stop & Shop, Stamford
		S20. Shop Rite, Norwalk
No-IPL:		
New Jersey	S15: Stop & Shop, Clifton	S11. A&P, Montvale
		S12. Shop Rite, Rochelle Park
		S13. A&P, Pompton Lakes
		S14. Path Mark, Montclair
		S15. Stop & Shop, Clifton

Note. We visited each store in data set 1 four times; we visited each store in data set 2 once. IPL = item-pricing law; no-IPL = no item-pricing law; ESL = electronic shelf label.

strategy, EDLP chains offer better data for our purpose because they change their prices less frequently.[25]

We sampled price data from three types of stores in the tri-state area: (1) stores that are subject to IPLs (these stores are located either in New York or Connecticut), (2) stores that are not subject to IPLs (these stores are located in New Jersey), and (3) stores that are subject to IPLs but are exempted from them because they use ESL systems (these stores are located in Connecticut).

Data set 1 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 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, New York, which has an IPL; another in Clifton, New Jersey, which does not have an IPL; and the third in Stamford,

[25] "High-low" (HL) and "everyday low price" (EDLP) refer to general pricing strategies of the retailer. Average EDLP store prices are low, and thus these stores offer fewer promotions. Average HL store prices are high, but these stores offer more frequent discounts through sales and promotions.

Connecticut, which is under an IPL but has an ESL exemption. Food Emporium is located in Greenwich, Connecticut, which has an IPL.[26]

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 B1.

We visited each store four times (with 1 month between the visits) on the same time and day and recorded the shelf prices manually. 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 1 yielded 2,640 price observations (four stores × four visits × 11 categories × 15 products), which include 660 observations from the ESL store.

Data Collection Process for Data Set 2

The analysis of data set 1 revealed that for each of 11 product categories, the IPL store prices were higher than the no-IPL store prices. Further, the pattern was consistent across the four visits, with a stable price gap of about 20¢–25¢ per product on average between the two types of stores. We used the second data set 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 2, therefore, we sampled the prices of 30 products at 20 stores that belong to seven chains.[27] Twelve of the stores are subject to IPLs (10 in New York and two in Connecticut), five are not subject to IPLs (all in New Jersey), and three are IPL stores with ESL exemptions (all in Connecticut). Note that all stores of a chain in a given state are only of one type. For example, in Connecticut there is no chain that has stores with an ESL system and stores without an ESL system. (See Table 3 for the stores and their locations.)

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

5. 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

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

[27] We limit the second data collection to 30 products following the practice of many IPL jurisdictions in conducting price accuracy audits. For example, in Massachusetts, pricing accuracy compliance is determined on the basis of a sample of 25 product prices (Mass. Gen. Laws Ann., ch. 94, outside sec. 25, amending sec. 329D [2004]). In California, it is based on the prices of 30 products (State of California 2002).

finer comparisons by controlling for state- and store-level factors that might affect the prices. We follow by presenting estimates of the average price differences and their statistical significance using linear regression analysis.

In Table 4, we report the average prices in data set 1. According to the figures in column 1, the IPL store prices exceed the no-IPL store prices in each category by an average of 25.1¢. The ESL store price exceeds the no-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 no-IPL store prices in each category by an average of 20.2¢. In column 3, we conduct a within-state comparison to control for possible cross-state variation and find that the IPL store prices exceed the ESL store prices in all but two categories by 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 (90 percent), IPL store prices exceed the no-IPL store prices, as indicated by Figure 2. For 128 of the 165 individual products (78 percent), the average ESL store price exceeds the average no-IPL store price. Finally, for 140 of the 165 individual products (85 percent), the average price at IPL stores exceeds the average price at ESL stores. Thus, ESL store prices fall between the IPL and no-IPL store prices.

In Table 5, we report the average prices in data set 2. In column 1, we compare the prices at 12 IPL and five no-IPL stores and find that the IPL store prices exceed the no-IPL store prices by an average of 24.5¢. In columns 2–5, we conduct a comparison of IPL and no-IPL stores within the same chain and thus control for a possible cross-chain variation. As before, the IPL store prices exceed the no-IPL store prices in all cases. In columns 6, 7, and 8, we compare IPL and ESL store prices. In column 6, where we control for possible cross-state variation, we find that that, in the state of Connecticut, IPL store prices exceed 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 and find an average price difference of 28.5¢. 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 IPL store prices exceed 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 between the IPL and no-IPL store prices. As before, these findings hold for individual products as well. For example, in data set 2, the average IPL store price is higher than no-IPL store price for all 30 products sampled, as indicated by Figure 3. Similarly, for 29 of the 30 products (97 percent), the IPL store prices exceed the ESL stores prices. Finally, for 20 of the 30 individual products (67 percent), the ESL store prices exceed the no-IPL store prices.

We thus observe three sets of prices: no-IPL store prices, ESL store prices, and IPL store prices. Let the cost at no-IPL stores be the baseline. Then at stores in IPL jurisdictions that do not adopt ESL, the cost is about 25¢ above the baseline, while at stores that adopt ESL, the cost is 10¢ above the baseline. This

Table 4

Average Prices in Data Set 1

Category	Aggregate Comparison (1)	Chain Controls (2)	State Controls (3)
All:			
IPL	2.965 (.056)	2.916 (.083)	3.015 (.075)
No-IPL	2.714 (.080)	2.714 (.080)	
ESL	2.815 (.079)	2.815 (.079)	2.815 (.079)
Individual:			
Beverage:			
IPL	2.431 (.092)	2.388 (.119)	2.474 (.142)
No-IPL	2.133 (.131)	2.133 (.131)	
ESL	2.310 (.125)	2.310 (.125)	2.310 (.125)
Breakfast:			
IPL	3.389 (.068)	3.375 (.100)	3.403 (.093)
No-IPL	3.078 (.099)	3.078 (.099)	
ESL	3.040 (.084)	3.040 (.084)	3.040 (.084)
Frozen:			
IPL	2.916 (.086)	2.860 (.117)	2.971 (.125)
No-IPL	2.842 (.117)	2.842 (.117)	
ESL	2.763 (.119)	2.763 (.119)	2.763 (.119)
Dairy:			
IPL	2.593 (.100)	2.524 (.140)	2.662 (.144)
No-IPL	2.492 (.147)	2.492 (.147)	
ESL	2.440 (.144)	2.440 (.144)	2.440 (.144)
Condiments:			
IPL	2.304 (.089)	2.213 (.122)	2.396 (.130)
No-IPL	2.045 (.119)	2.045 (.119)	
ESL	2.180 (.116)	2.180 (.116)	2.180 (.116)
Soup:			
IPL	1.497 (.051)	1.470 (.074)	1.524 (.070)
No-IPL	1.255 (.068)	1.255 (.068)	
ESL	1.381 (.069)	1.381 (.069)	1.381 (.069)
Baby:			
IPL	4.373 (.470)	4.552 (.725)	4.194 (.604)
No-IPL	4.283 (.700)	4.283 (.700)	
ESL	4.454 (.683)	4.454 (.683)	4.454 (.683)
Health:			
IPL	3.854 (.185)	3.778 (.260)	3.930 (.265)
No-IPL	3.422 (.253)	3.422 (.253)	
ESL	3.772 (.249)	3.772 (.249)	3.772 (.249)
Candy:			
IPL	2.736 (.081)	2.578 (.097)	2.895 (.127)
No-IPL	2.474 (.099)	2.474 (.099)	
ESL	2.546 (.100)	2.546 (.100)	2.546 (.100)
Paper:			
IPL	3.355 (.122)	3.227 (.164)	3.483 (.182)
No-IPL	3.058 (.151)	3.058 (.151)	
ESL	3.125 (.163)	3.125 (.163)	3.125 (.163)
Household items:			
IPL	3.172 (.093)	3.115 (.133)	3.228 (.129)
No-IPL	2.770 (.116)	2.770 (.116)	
ESL	2.954 (.119)	2.954 (.119)	2.954 (.119)

Note. Stores in the aggregate comparison are as follows: IPL: S1 and S16, no-IPL: S15, ESL: S19. Stores with chain controls are as follows: IPL: S1, no-IPL: S15, ESL: S19. Stores with state controls are as follows: IPL: S16, ESL: S19.

Table 5

Average Prices in Data Set 2

Category	Aggregate Comparison (1)	Chain Controls A&P (2)	Shop Rite (3)	Path Mark (4)	Stop & Shop (5)	State Controls (6)	State and District Controls (7)	State, District, and Locality Controls (8)
All:								
IPL	2.745 (.058)	2.724 (.140)	2.451 (.198)	2.651 (.135)	2.602 (.180)	2.744 (.135)	2.844 (.199)	2.844 (.199)
No-IPL	2.500 (.084)	2.532 (.135)	2.438 (.193)	2.585 (.187)	2.414 (.181)			
ESL	2.578 (.104)		2.616 (.194)		2.559 (.123)	2.578 (.104)	2.559 (.123)	2.573 (.177)
Individual:								
Condiments:								
IPL	2.300 (.075)	2.227 (.172)	1.979 (.254)	2.219 (.176)	2.189 (.221)	2.360 (.185)	2.418 (.266)	2.418 (.266)
No-IPL	2.028 (.105)	2.048 (.160)	1.973 (.255)	2.094 (.249)	1.978 (.234)			
ESL	2.155 (.135)		2.169 (.264)		2.149 (.156)	2.155 (.135)	2.149 (.156)	2.169 (.225)
Household items:								
IPL	3.190 (.076)	3.221 (.183)	2.923 (.256)	3.083 (.174)	3.017 (.247)	3.129 (.172)	3.270 (.258)	3.270 (.258)
No-IPL	2.973 (.106)	3.017 (.180)	2.903 (.243)	3.077 (.219)	2.850 (.232)			
ESL	3.001 (.132)		3.063 (.238)		2.970 (.160)	3.001 (.132)	2.970 (.160)	2.977 (.237)

Note. Stores included the samples are as follows: column (1) IPL: all 12 stores, no-IPL: all five stores, ESL: all three stores; column (2), IPL: S3 and S5, no-IPL: S11 and S13; column (3) IPL: S8, no-IPL: S12, ESL: S20; column (4), IPL: S4 and S6, no-IPL: S14; column (5), IPL: S1, no-IPL: S15, ESL: S18 and S19; column (6): IPL: S16 and S17, ESL: S18, S19, and S20; column (7): IPL: S16, ESL: S18 and S19; column (8): IPL: S16, ESL: S18.

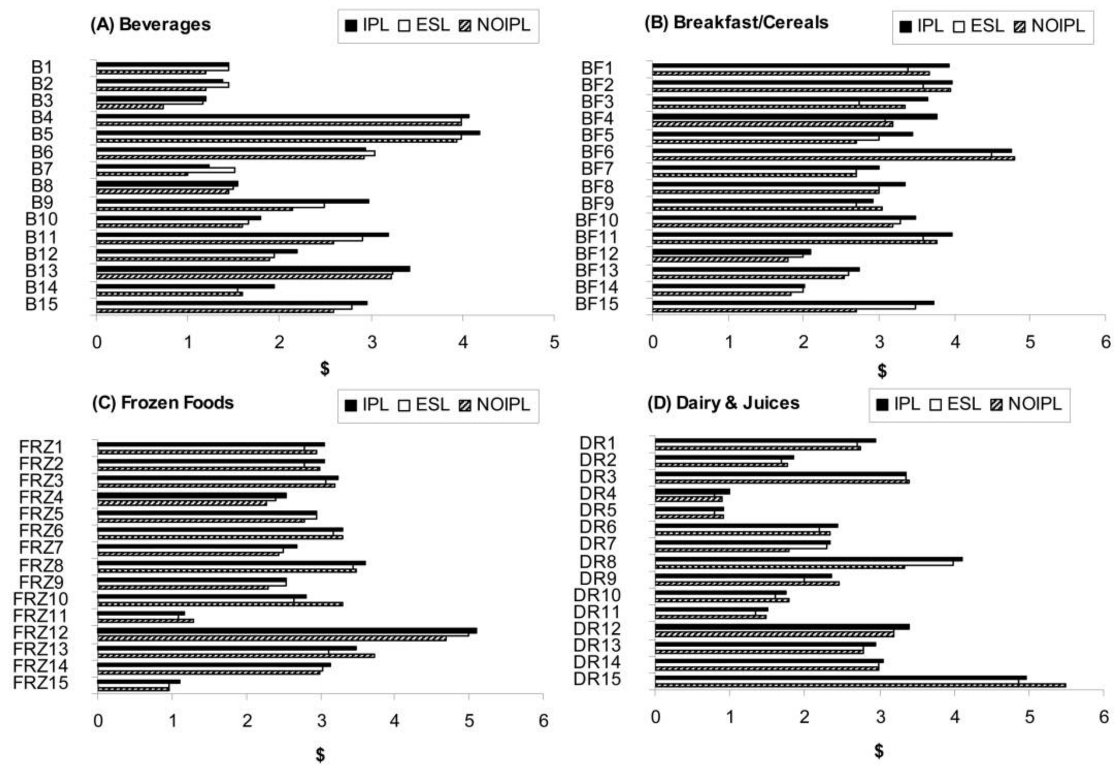

Figure 2. Average product prices at at stores with item-pricing laws (IPLs), electronic shelf labels (ESLs), and no item-pricing laws (no-IPLs), data set 1

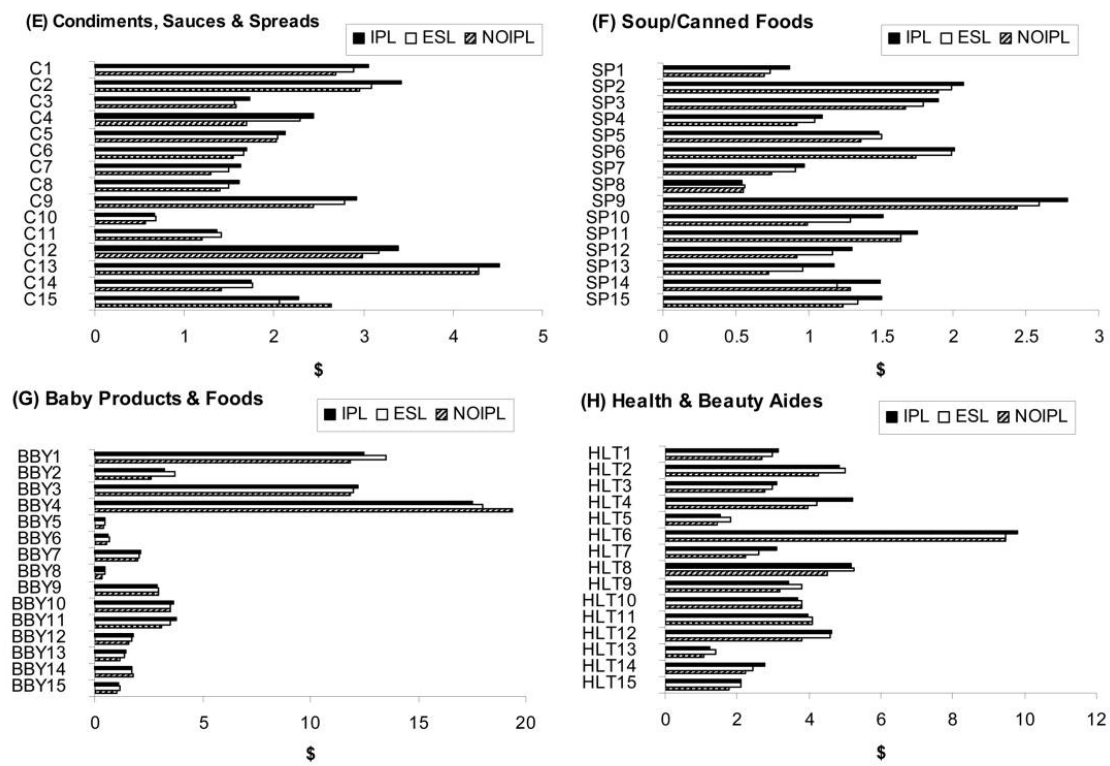

Figure 2. *Continued*

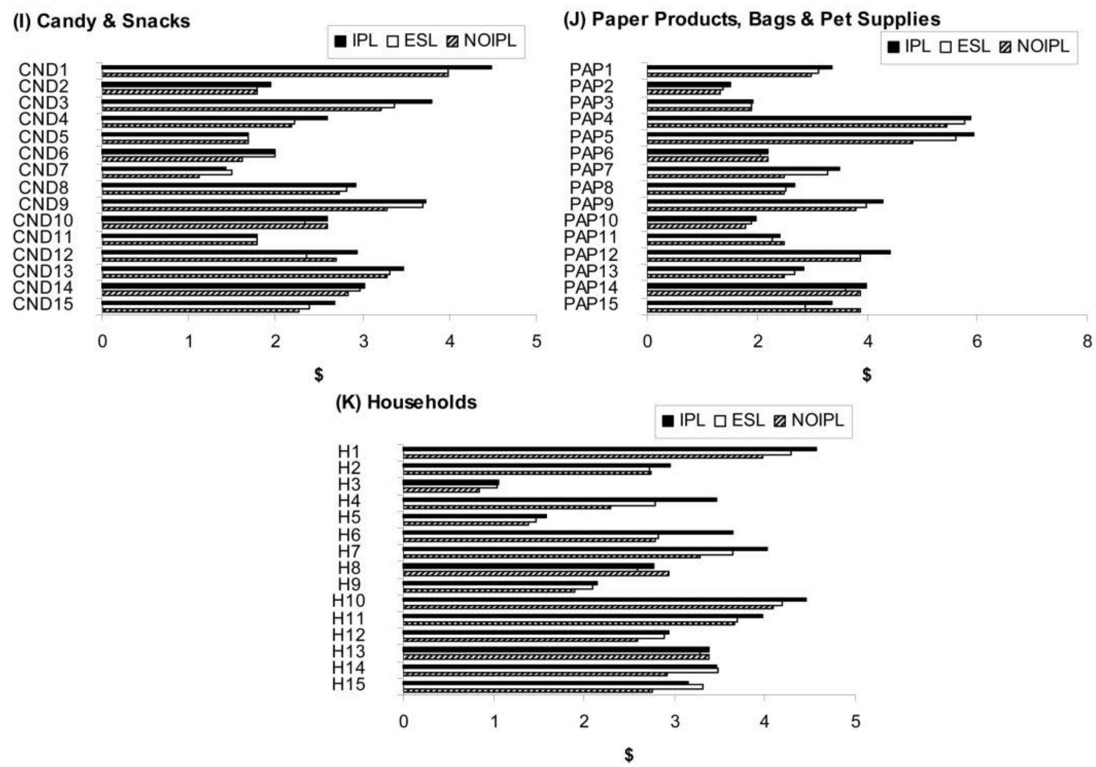

Figure 2. *Continued*

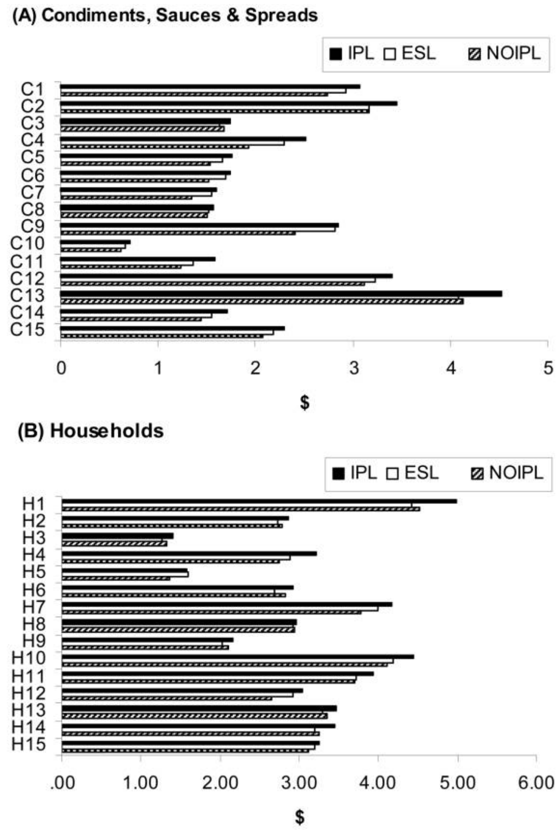

Figure 3. Average product prices at stores with item-pricing laws (IPLs), electronic shelf labels (ESLs), and no item-pricing laws (no-IPLs), data set 2.

set of observations is exactly what we would predict if IPLs increase costs and ESL systems can serve as a method of reducing but not entirely eliminating these costs.

Next, we estimate the econometric model,

$$P_i = \alpha + \beta_1 \mathrm{IPL}_i + \beta_2 (\mathrm{IPL} \times \mathrm{ESL})_i + \varepsilon_i, \tag{1}$$

where P_i is the ith observation of the price, IPL_i is a dummy variable attaining the value of one if the observation comes from an IPL store (including stores with an ESL exemption) and zero otherwise, ESL_i is a dummy variable attaining the value of one if the observation comes from an ESL store and zero otherwise, and $\varepsilon_i \sim N(0, \sigma^2)$ is an independent and identically distributed error term. The coefficients β_1 and β_2 capture the effect of the IPL on prices. If IPL store prices are higher than no-IPL store prices, then we will expect that $\beta_1 > 0$. Similarly, within an IPL regime, if ESL store prices are lower than no-ESL store prices, then we will expect $\beta_2 < 0$.

The error terms in equation (1) are uncorrelated across observations. Also, the specification in equation (1) cannot capture the unobserved variation in prices that might result from differences between stores or product categories.[28] To specify a model that can account for such variation, recall that in data set 1, 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 the store and product factors as having a fixed and a random effect, respectively.

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

$$P = \alpha + \theta_k \mathrm{CHAIN}_k + \gamma_j \mathrm{CATEGORY}_j + \beta_1 \mathrm{IPL} + \beta_2(\mathrm{IPL} \times \mathrm{ESL}) + u_j + \varepsilon, \quad (2)$$

where CHAIN_k is a dummy variable attaining value of one if the observation comes from chain k and zero otherwise, $\mathrm{CATEGORY}_j$ is a dummy variable attaining value of one if the observation comes from category j and zero otherwise, θ_k and γ_j are the respective coefficients, and u_j is the random effect associated with $\mathrm{CATEGORY}_j$.[29] In equation (2), the error terms are assumed to be distributed normally with mean zero and constant variance and to be 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 6, regression (2). The coefficients for the IPL and IPL × ESL variables are both significant at 1 percent. The point estimate of the coefficient on the IPL dummy variable is .203 and significant at the 1 percent level. This figure suggests that IPL store prices exceed the no-IPL store prices by 20¢ on average. The point estimate of the coefficient on the interaction variable IPL × ESL is −.101, also significant at the 1 percent level. Thus, within an IPL regime, ESL store prices are lower than no-ESL store prices by 10¢ on average.

The error covariance structure in equation (2) has two limitations. First, it does not take into account the fact that data set 1 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 equation (2), therefore, we control for the repeated nature of the data by assuming a first-order auto-

[28] 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 New York observations are IPL and all New Jersey observations are no-IPL, which leads to singularity problems in estimating the β coefficients.

[29] Note that CHAIN is perfectly correlated with the IPL variable. For example, all Stop & Shop (New Jersey) observations are no-IPL. This leads to the same singularity problems associated with the state variable.

Table 6
Regression Results for Data Set 1

	Regression (2)			Modified Regression (2)		
Variable	Estimate	t	Significance	Estimate	t	Significance
Intercept	1.256	2.520	.013	1.262	8.903	.000
Chain = Food Emporium	.098	5.954	.000	.091	3.271	.001
Category:						
Baby	2.963	4.204	.000	2.966	2.124	.052
Beverage	.919	1.304	.194	.923	3.126	.005
Breakfast	1.817	2.578	.011	1.801	7.836	.000
Candy	1.216	1.725	.087	1.208	4.756	.000
Condiments	.801	1.137	.257	.793	2.779	.011
Dairy	1.122	1.592	.113	1.128	3.473	.002
Frozen	1.452	2.060	.041	1.449	5.191	.000
Health	2.318	3.289	.001	2.322	4.304	.001
Household	1.609	2.283	.024	1.601	5.779	.000
Paper	1.816	2.576	.011	1.815	5.029	.000
IPL	.203	12.281	.000	.208	7.469	.000
IPL × ESL	−.101	−6.150	.000	−.111	−3.993	.000

Note. The dependent variable for regression (2) is price. The dependent variable for modified regression (2) is price, with an autocorrelated and heteroskedastic error structure. The soup category and the Stop & Shop chain dummy variables are excluded because of their redundancy.

regressive 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 6, modified regression (2). The coefficient estimates for both the IPL and IPL × ESL variables are significant at the 1 percent level, and their numerical values are similar to those for regression (2): the IPL store prices are 21¢ higher than the no-IPL store prices, on average. Within the IPL regime, ESL store prices are 11¢ lower than no-ESL store prices on average. Thus, IPL store prices are highest, followed by ESL store prices, and then no-IPL store prices.

In data set 2, we sample only two categories, condiments and household products, 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.[30] Thus, the regression model is given by

$$P = \alpha + \theta_k \mathrm{CHAIN}_k + \gamma_j \mathrm{CATEGORY}_j + \beta_1 \mathrm{IPL} + \beta_2(\mathrm{IPL} \times \mathrm{ESL}) + \nu_k + \varepsilon, \quad (3)$$

where ν_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

[30] We considered the random effects of the two chains, Stop & Shop and Shop Rite, because these are the only chains that span all the experimental conditions—IPL, no-IPL, and ESL. We, however, decided to exclude Shop Rite from the regression because it seems to be an outlier. As Appendix C suggests, Shop Rite is a cooperative rather than a regular supermarket chain, and thus it might use different pricing rules. Indeed, according to Table 5, Shop Rite is the only chain in which ESL store prices exceed the IPL store prices. We combine the rest of the stores under "other."

Table 7
Regression Results for Data Set 2

	Regression (3)			Modified Regression (3)		
Variable	Estimate	t	Significance	Estimate	t	Significance
Intercept	3.003	26.454	.000	3.005	25.467	.000
Chain = Stop & Shop	−.163	−1.075	.302	−.164	−1.162	.247
Category = condiments	−.892	−10.419	.000	−.892	−10.438	.000
IPL	.230	1.966	.071	.227	1.874	.076
IPL × ESL	−.064	−.313	.759	−.062	−.336	.737

Note. The dependent variable for regression (3) is price. The dependent variable for modified regression (3) is price, with heteroskedastic error structure. The chain = other and the household category dummy variables are excluded because of their redundancy.

experimental conditions—IPL, ESL, and no-IPL. We proceed by controlling for these two chains and combining the rest of the stores in a single category, "other." We assume that the error terms satisfy the conditions $E(\varepsilon) = E(\nu_k) = 0$, $E(\varepsilon^2) = \sigma_\varepsilon^2$, $E(\nu_k^2) = \sigma_\nu^2$, $E(\varepsilon\nu_k) = 0\ \forall k$, and $E(\varepsilon_k\varepsilon_l) = E(\nu_k\nu_l) = 0\ \forall k \neq l$.

As for data set 1, we run the above regression under the assumption of homoskedastic errors—$E(\nu_k^2) = \sigma_\nu^2$—as well as heteroskedastic errors—$E(\nu_k^2) = \sigma_{\nu k}^2$—and they are reported in Table 7.[31] The coefficient estimates for the IPL variable are .230 and .227, respectively, both significant at the 7 percent level, which suggests that in data set 2, IPL store prices are about 23¢ higher than no-IPL store prices, on average.[32] Within the IPL regime, ESL store prices are 6.2¢–6.4¢ lower than no-ESL store prices, on average.[33] These estimates, however, are not statistically significant.[34] We conclude, therefore, that IPL stores

[31] 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 2 we sampled only once. Thus, data set 2 constitutes a true cross section.

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

[33] We also estimated a regression model for the state of Connecticut alone to see if the price differences between ESL and no-ESL stores in Connecticut are due to store-level unobserved factors. Using variety of zip-code-level and city-level socioeconomic 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 available on request.

[34] To understand the reason for this and to explore these results further, we ran the same regressions without the store effect dummies and found that the IPL coefficient estimate and significance remain 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 store effects, which might be a reflection of more fundamental differences between IPL stores that choose to adopt ESL systems and those that do not. Therefore, the store variables pick up all the price differences between the ESL and no-ESL stores. This finding is consistent with the results of pairwise comparisons (available on 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 and the IPL and no-IPL stores, indeed, were not statistically significant.

do indeed charge higher prices than no-IPL stores—the average price difference per item being about 20¢–25¢.[35]

Is a 20¢–25¢ difference big? As an absolute measure, it seems small. Consider, however, the fact the average price in our sample of no-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 percent, which seems substantial.[36] To appreciate this magnitude further, consider the following. In 2002, food represented 14 percent of total personal consumption expenditures (Council of Economic Advisers 2003, table B17).[37] If we take 14 percent 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 percent, which is a nontrivial amount.

6. Costs-Benefit Analysis of 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: to 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 *Money* magazine (O'Connell 1993), and the second is the 1998 survey "Price Check II" (Federal Trade Commission 1998). 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.[38]

In the *Money* magazine survey (O'Connell 1993), 30 percent of the stores overcharged and 7 percent undercharged. At the stores that overcharged, 10 percent of the sample reported an average overcharge of $.069. According to our cost calculations, IPL stores charge $.25 more per item on average. Assuming that item pricing protects the consumers from ever being overcharged, IPLs give them a benefit of $.069, while it costs them $.20–$.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" (Federal Trade Commission 1998), 1.36 percent of the items checked in food stores were overcharges and 1.06 percent undercharges. The average overcharge was $.66 and the average undercharge $.73 per item.

[35] We also ran a fixed-effects model for both data sets. Under the specifications we have, the magnitude of the coefficients should not change, and they did not. However, for data set 1, the mixed-effects model resulted in a significantly better fit on the basis of the log likelihood ratio test ($\chi^2(1) = 8680.002$, $p < .0001$). For data set 2, on the basis of the same test, there was no significant difference between the two models ($\chi^2(1) = .296$, $p = .586$).

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

[37] Note that grocery sales include nonfood items such as household and health and beauty products.

[38] We should note, however, that Federal Trade Commission (1998) is the most relevant for our case because it was conducted in 1998, while the other studies are older. Moreover, the FTC study is broadest, as it relies on the largest sample in size and breadth of coverage.

Thus, in a sample of 100 items, an average of 1.36 items are overcharged. At \$.66 per overcharge, that is a total overcharge of \$.90 per 100 items, or \$.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 IPLs, \$.20–\$.25, the cost of an IPL exceeds its benefit by a factor of up to 27. Again, if we factor in the 1.06 percent undercharges, then the IPL's benefit is wiped out completely. This would eliminate the ability to garner any benefits from item pricing altogether.[39]

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 $.009 + .0077 = .017$ (where .0077 is obtained by multiplying 1.06 by .73). O'Connell (1993) does not report the average undercharge. However, if we assume that the 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 is in their favor, then the expected benefit of the IPL will double to about .138. The cost of the IPL in this case will still be twice as much as the benefit.

We infer that the costs of 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 IPLs. Further, consumers are not equally sensitive to price mistakes, especially if the mistakes are small (see, for example, Reis 2006; Sims 2003; Bergen et al. 2006). Indeed, some recent studies show that consumers might be inattentive to small price changes (see, for example, Ray et al. 2006; Chen et al. 2008; see also Sims 1998; Ball, Mankiw, and Reis 2003; Mankiw and Reis 2002; Zbaracki et al. 2004; Hall and Taylor 1997).

7. 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 among the localities covered in terms of property taxes, land rents, labor costs (for example, minimum wages), average household income, and so on. 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, New York and New Jersey have federal minimum wages (\$5.15 per

[39] Three of the four studies discussed above show that, on average, undercharges exceed overcharges in total value.

hour), while Connecticut's minimum wage is higher ($6.90 per hour).[40] Similarly, there may be differences in wholesale prices despite the Robinson-Patman Act (Anti-price Discrimination Act, 15 U.S.C. sec. 13 [1936]). It could be argued, therefore, that there are systematic differences (other than the IPL) between the IPL and no-IPL stores that could explain the differences in their price levels. Similarly, factors other than the presence of an IPL could explain the price differences between the exempt ESL and nonexempt ESL stores.

To address these concerns, we conducted several additional analyses in order to try to account for some of these unobserved factors, which might be driving our results.[41] We gathered zip-code-level, city-level, and county-level data on several socioeconomic variables including population, population density, number of households, median household income, median family income, per capita income, percentage of families living below the poverty line, and percentage of population living below the poverty line. We compared in detail the demographic characteristics of the IPL and no-IPL markets at all three levels of aggregation (county level, city level, and zip code level), and found no compelling evidence that the variation in price levels between the IPL and no-IPL stores can be explained by variation in their market characteristics. We draw similar conclusions from comparing the market-level characteristics of the ESL and no-ESL stores.[42]

More important, the fact that our findings are robust across numerous types of comparisons is reassurance that these kinds of biases, if present, are unlikely to be severe. For example, recall that we 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, or 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 stores within the same county (comparing prices at Connecticut IPL and Connecticut 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,

[40] 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. In addition, from an econometric estimation point of view, inclusion of minimum-wage data in our regressions is not useful because minimum wages do not vary within states, which leaves just three state-level observations to work with. That would lead to identification problems similar to the inclusion of state fixed effects.

[41] The results of these analyses are available on request.

[42] As an additional test of robustness, we reestimated the model in equation (3) by incorporating the new city-, county-, and zip-code-level variables in the estimated model. As in Section 5, we estimated these regression models with and without heteroskedastic error correction. We first estimated the model using the city-level variables because they may be better proxies for the trade area characteristics of the stores. We repeated the analyses using the zip-code-level and the county-level variables in these regressions. The results of these analyses (available on request) suggest that although the coefficient estimates of some of these sociodemographic variables are statistically significant, the variation in price level across the IPL, no-IPL, and ESL-exempt stores cannot be explained by them because the corresponding IPL and ESL coefficient estimates are robust to the inclusion of these variables. Thus, our overall findings remain unchanged.

as well as the evidence we offer based on the comparison of ESL store price change data with those for IPL and no-IPL stores, 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 New York is simply a more expensive place to do business than New Jersey. 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 focused only on IPLs' primary costs and benefits. For example, on the benefit side, we focused only on prevention of pricing overcharges.[43] People have, however, cited other benefits of the law. For example, they have argued that without item pricing, price comparison would be difficult, which makes 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 prices.

However, 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 and Sawyer (1986), who report that item pricing does not necessarily lead to a better price recall. Also, "search consumers" (consumers who conduct frequent price comparisons and search for the best price) will not necessarily benefit from IPLs. For them, unit price information, such as price per ounce or per liter, is more valuable. Moreover, search consumers often focus on sale items, which are exempted from many IPLs (for example, 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 an 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 stores 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.[44]

[43] Supporters of IPLs do not necessarily represent all consumers. According to the *Washington Post*, "[O]ut 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" (*Consumers' Research* 1981, p. 11).

[44] There is a large event study literature that 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

Our measure of IPLs' costs may also be biased downward. This is because, on the cost side, we have focused only on the primary costs of the IPLs and have ignored various secondary costs. For example, state and local governments spend substantial resources to monitor the retailers' compliance with 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.[45] Similarly, the state of Michigan conducts annual price check surveys (Durbin 2002). In addition, resources go toward prosecuting violators of IPLs.[46] Moreover, as we saw, IPLs form barriers to frequent price changes. If a more competitive environment leads to more frequent price changes, 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, Kashyap, and Rossi (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, and Warner and Barsky (1995) use hand-collected price data of a similar size. Our sample size, over 3,000 observations, is at least seven times larger than the samples of these studies.

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 IPLs. As a comparison, we are aware of one study, conducted by Arthur D. Little, a company that 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 California's Proposition 65 warnings regarding carcinogens. According to Viscusi, for a 50¢ product the total extra cost of these state-specific warning labels was 5.4¢ per unit, which

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advertising regulation by the Federal Trade Commission. In all cases, losses in value have been estimated to be much greater than direct costs to firms. These findings are typically interpreted as reflecting losses in reputation that result from lying to consumers.

[45] Commonwealth of Massachusetts, Office of Consumer Affairs and Business Regulation, About the Division of Standards (http://www.state.ma.us/standards/aboutus.htm).

[46] For example, according to *Iowa Oil Spout* (2000), Wal-Mart and OfficeMax were sued by Michigan's attorney general for not affixing individual price tags. Under the settlement, Wal-Mart agreed to pay $250,000 and OfficeMax $125,000 in civil penalties. A $7.35 million settlement was reached in the class action lawsuit filed regarding Wal-Mart's failure to comply with Massachusetts' IPL (LawyersandSettlements.com 2004).

translates to $5.4/50 = 10.8$ percent, a figure that is remarkably similar to our findings.[47]

8. Conclusion

Item-pricing laws seem to impose costs on all supermarkets and buyers in the localities that have adopted these laws. Only nine U.S. states have an IPL. An economist's explanation for why we do not see more widespread use of IPLs would be that if people wanted item pricing, then the market would offer it without needing the law. Nevertheless, studying 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 lead to higher prices. Second, we test this prediction using transaction price data gathered from IPL and no-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 store prices are higher than those of no-IPL stores by an average of 20¢–25¢, or 8.0–9.6 percent, per item. We find that these costs are an order of magnitude larger than 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 IPLs may be inefficient not only from the perspective of retailers but also from the perspective of consumers. Item-pricing laws seem to harm consumers, even though the primary reason given by proponents for creating IPLs is to protect consumers. 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 U.S. counties and states and other countries (for example, Canada and Israel) are in the midst of discussing revision of 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 no-IPL stores may reveal whether the price gaps between the two types of stores hold for exempted products as well.[48] In addition, we believe that it is worth considering the difference between exempt and nonexempt ESL stores using a larger data set sampled from a greater number of stores and for a greater number of products. Another interesting avenue for future research would be collecting data on store sizes (for example, square footage) in order to account for the possible store-level scale economies. The decision to invest in ESL technology might depend on store size and sales volume, which could be driving our findings. Future work could also consider price promotions of IPL and no-

[47] We are grateful to Kip Viscusi for bringing this study to our attention.

[48] However, as the referee noted, the exempted product prices might be influenced by the existence of IPLs because of the changes in the 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.

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. Gathering more data focused on price changes, rather than price levels, could help us better understand the implications of IPLs for retail pricing. Other interesting questions that arise in the context of these laws can be studied. For example, it may be useful to explore the theoretical implications of endogenous price adjustment costs where costs vary with the quantity sold.

Appendix A

Item-Pricing Laws in New York and Connecticut

A1. New York's Item-Pricing Law

New York's IPL is defined in N.Y. Agriculture and Markets Law, section 214-i (Consol. 2001). 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 asserts that item pricing is necessary to protect consumers while electronic universal product code checkout 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, such as milk, eggs, produce, and single packs of gum, are excluded from the item-pricing requirement. In addition, if a store has fewer than three employees or grosses less than $3 million 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 the municipal directors of weights and measures. If a store is inspected, then a sample of no less than 50 of the commodities subject to the law in a store are to be checked. Each penalty is $50 for the first four violations, $100 for each of the next 12 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 12-month period more violations are found, penalties are doubled and there is 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 displayed in the computer at checkout. In the case of overcharges, penalties ranging from $50 to $300 are levied depending on the number of violations, and there is no maximum penalty. In subsequent inspections in a 12-month period, the fines double for violations. An inspector also has the authority to issue a "stop-removal order," which prohibits the store from selling particular items until it can correct the violations with those items.

A2. Connecticut's Item-Pricing Law

Connecticut's IPL (Conn. Gen. Stat., secs. 21a–73) is similar to New York's, although it is less detailed. 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"(Conn. Gen. Stat., sec. 21b).

Connecticut's IPL states that any establishment that utilizes universal product coding in totaling a retail customer's purchases of consumer commodities must mark each consumer commodity with its retail price. It has the same product exceptions as New York's law, but adds to its list of exceptions alcoholic beverages and carbonated soft drinks. It further states that the item-pricing requirements do 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. The law states that if an item is advertised as being on sale, then each item does not need to be remarked with the new price but that a sign indicating the sale price must be put adjacent to the items. If a consumer is overcharged for the item on sale, then it must 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 $1,000, and there is no minimum specified. No maximum amounts of penalties and fines are specified.

A3. Comparison of New York and Connecticut Item-Pricing Laws

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 to 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 is that Connecticut has the electronic pricing system exception, while New York does not. In fact, Connecticut is a unique state with regard to 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. When the price of an item is changed in the central computer, the new price is automatically displayed on 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 cost decreases. However, in Connecticut especially, supermarkets are installing this technology to be exempt from IPLs that otherwise increase their annual costs by thousands of dollars.

Appendix B

Collection of Data Set 1

The schedule for data collection was as follows: Saturday mornings, Stop & Shop in Clifton, New Jersey; between 1:00 and 2:00 P.M. on Saturdays, Stop & Shop in Tarrytown, New York; Sunday mornings, Food Emporium in Greenwich, Connecticut; and at noon, Stop & Shop in Stamford, Connecticut. We collected the data during January–April 2001. The trips took place January 14–15, February 11–12, March 11–12, and April 8–9.

Table B1

Categories and Products Sampled in Data Set 1

Category and Product	Index
Beverages:	
Coca Cola Classic, 2-liter bottle	B1
Diet Sprite, 2-liter bottle	B2
Vintage Seltzer Water, 2-liter bottle	B3
Pepsi Cola, 12 12-ounce cans	B4
Barq's Root Beer 12 12-ounce cans	B5
Dr. Brown's Cream Soda 6 12-ounce cans	B6
Poland Spring, 1-gallon container	B7
Evian, 1-liter bottle	B8
Lemon Lime Gatorade, 64-ounce bottle	B9
Arizona Iced Tea, 3 12-ounce boxes	B10
Fruit Punch Capri Sun, 10 6.75-ounce boxes	B11
V8 Vegetable Juice, 46-ounce can	B12
V8 Splash Tropical Blend, 64-ounce bottle	B13
Juicy Juice Fruit Punch, 46-ounce can	B14

Table B1 (*Continued*)

Category and Product	Index
Tropican Twisters Tropical Fruit, 1.75-liter bottle	B15
Frozen foods:	
Swanson Turkey (white meat), 11.75 ounce	FRZ1
Swanson Salisbury Steak, 13 ounce	FRZ2
Weight Watchers Smart Ones Basil Chicken, 9.5 ounce	FRZ3
Weight Watchers Smart Ones Mac & Cheese, 10 ounce	FRZ4
Healthy Choice Medly's Roast Turkey Breast, 8.5 ounce	FRZ5
Haagen Dazs Vanilla Ice Cream, 1 pint	FRZ6
Stouffers Lean Cuisine Swedish Meatballs, 10 ounce	FRZ7
Stouffers Hearty Portions Salisbury Steak, 16 ounce	FRZ8
Green Giant Niblers Corn on the Cob, 4 ears	FRZ9
Ego Blueberry Waffles, 16 count, 19.8 ounce	FRZ10
Lender's Plain Bagels, 6 count	FRZ11
Original Tombstone Supreme, 22.85 ounce	FRZ12
Celentano Manicotti, 14-ounce bag	FRZ13
Ore Ida Golden Twirls, 28 ounce	FRZ14
Bird's Eye Mixed Vegetables, 10 ounce	FRZ15
Condiments, sauces, and spreads:	
Grey Poupon Dijon Mustard, 8-ounce jar	C1
Hellmann's Mayonnaise, 32-ounce jar	C2
Heinz Ketchup, 24-ounce squeeze bottle	C3
Skippy Creamy Peanut Butter, 18-ounce jar	C4
Smucker's Concord Grape Jelly, 12-ounce jar	C5
Kraft Thousand Island Dressing Free, 8-ounce bottle	C6
Wish Bone Fat Free Ranch Dressing, 8-ounce bottle	C7
Domino Granulated Sugar, 2-pound box	C8
Equal Sugar Substitute, 50 count	C9
Jello Cherry, 3-ounce box	C10
Heinz Distilled White Vinegar, 32-ounce bottle	C11
Pam Lemon Fat Free Cooking Spray, 6-ounce can	C12
A1 Steak Sauce Bold & Spicy, 10-ounce jar	C13
Heinz Barbecue Sauce, 18-ounce bottle	C14
Kraft Shake 'n Bake Classic Italian, 5.75 ounce	C15
Baby products and foods:	
Huggies Pull Ups for Boys 32–40 pounds, 26 count	BBY1
Huggies Natural Care Scented Wipes, 80 count	BBY2
Pampers Diapers, Newborn to 10 pound, 48 count	BBY3
Luvs Diapers Ultra Leakguards #3, 72 count	BBY4
Beechnut Stage 2 Apples & Bananas, 4-ounce jar	BBY5
Earth's Best Organic Apples, 4-ounce jar	BBY6
Gerber 100% Apple Juice, 32-ounce bottle	BBY7
Gerber Stage 1 Pears, 2.5-ounce jar	BBY8
Enfamil Lactofree Infant Formula, 13-ounce can	BBY9
Johnson & Johnson Baby Shampoo, 15-ounce bottle	BBY10
Johnson & Johnson Baby Powder, 15 ounce	BBY11
Gerber Cereal for Baby Rice with Banana, 8 ounce	BBY12
Beechnut Cereal for Baby Oatmeal, 8 ounce	BBY13
Gerber Graduates Veggie Crackers, 4 ounce	BBY14
Beechnut Table Time Mac & Cheese, 6 ounce	BBY15
Candy and snacks:	
Planter's Mixed Nuts, 11.5-ounce can	CND1
Sun Maid Raisins, 9-ounce box	CND2
Sunsweet Pitted Prunes, 24 ounce	CND3
Hershey's Kisses Milk Chocolate, 8-ounce bag	CND4
Trident Original Sugarless Gum, 8 5-stick packs	CND5

Table B1 (*Continued*)

Category and Product	Index
Rold Gold Pretzels Fat Free, 15-ounce bag	CND6
Wise B.B.Q. Potato Chips, 5.5-ounce bag	CND7
Chips Ahoy Chocolate Chip Cookies, 12-ounce bag	CND8
Oreo Cookies, 1-pound bag	CND9
Pepperidge Farm Milanos, 6-ounce bag	CND10
Pepperidge Farm Goldfish Cheddar, 6-ounce bag	CND11
Wheat Thins Original, 10-ounce box	CND12
Nabisco Ritz Bits Sandwich Crackers, 10.5-ounce box	CND13
Quaker Chocolate Chip Granola Bars, 10 bars	CND14
Orville Redenbacher's Light Popcorn, 3 3.5-ounce bags	CND15
Breakfast foods and cereals:	
Kellog's Apple Jacks, 15-ounce box	BF1
Kellog's Corn Pops, 15-ounce box	BF2
Kellog's Special K, 12-ounce box	BF3
General Mills Cheerios, 15-ounce box	BF4
General Mills Cocao Puffs, 13.75-ounce box	BF5
General Mills Lucky Charms 20-ounce box	BF6
Post Raisin Bran, 20-ounce box	BF7
Post Fruity Pebbles, 13-ounce box	BF8
Nature Valley Granola Oats 'N Honey, 8.9 ounce	BF9
Kellog's Nutri Grain Blueberry Bars, 8 bars	BF10
Kellog's Variety Pack, 10 1.5-ounce boxes	BF11
Kellog's Pop Tarts Frosted Strawberry, 14.7-ounce box	BF12
Nestle Quick Drink Mix, 15-ounce can	BF13
Aunt Jemima Original Pancake Mix, 2-pound box	BF14
Aunt Jemima Pancake Syrup, 24-ounce bottle	BF15
Dairy and juices:	
Farmland S.R. 1% Plus Lowfat Milk, 1/2 gallon	DR1
Lactaid 100 Fat Free Milk Lactose Free, 1 quart	DR2
Nesquick Chocolate Milk, 64 ounce	DR3
Dannon Light Yogurt Cherry Vanilla, 8-ounce container	DR4
Dannon Rasberry, 8-ounce container	DR5
Breakstone's Fat Free Cottage Cheese, 16 ounce	DR6
Land O' Lakes Salted Whipped Light Butter, 8 ounce	DR7
Kraft Fat Free American Cheese Singles, 16 slices	DR8
Philadelphia Cream Cheese, 8 ounce	DR9
Nestle Carnation Coffemate, 16 ounce	DR10
Breakstone's Fat Free Sour Cream, 16 ounce	DR11
Tropicana Pure Premium Homestyle OJ, 64 ounce	DR12
Welch's Fruit Cocktail White Grape Peach, 64 ounce	DR13
Dole 100% Pineapple Juice, 64 ounce	DR14
Tropicana Pure Premium Grovestand OJ, 96 ounce	DR15
Soup and canned foods:	
Campbell's Chicken Noodle Soup, 10.75 ounce	SP1
Progresso Chicken & Wild Rice, 19 ounce	SP2
Progresso Minestrone Soup, 19 ounce	SP3
Campbell's Cream of Broccoli, 10.75 ounce	SP4
Campbell's Family Size Tomato Soup, 18.7 ounce	SP5
Progresso New England Clam Chowder, 19 ounce	SP6
Campbell's Vegetarian Vegetable, 10.75 ounce	SP7
Goya Black Beans, 15.5 ounce can	SP8
Ortega Thick & Chunky Medium Salsa, 16 ounce	SP9
Dole Sliced Pineapple, 20-ounce can	SP10
Del Monte Pear Halves, 29-ounce can	SP11
Bumble Bee Solid White Tuna in Water, 6-ounce can	SP12

Table B1 (*Continued*)

Category and Product	Index
Starkist Chunk Light Tuna in Oil, 6-ounce can	SP13
Chef Boyardee Beef Ravioli, 15-ounce can	SP14
Mott's Homestyle Chunky Apple Sauce, 23-ounce jar	SP15
Health and beauty aids:	
Crest Multi Care Fresh Mint Toothpaste, 6.2-ounce tube	HLT1
Scope Peppermint, 33-ounce bottle	HLT2
Right Guard Sport Deodorant Gel Cool Scent, 3 ounce	HLT3
Sudafed Max Nasal Decongestant, 24 tablets	HLT4
Halls Cough Drops Black Cherry, 25 count	HLT5
Tylenol Extra Strength Gelcaps, 100 count	HLT6
Johnson & Johnson Band Aids, 60 count	HLT7
Pepto Bismol, 12 ounce	HLT8
Bausch & Lomb Saline Solution, 12-ounce bottle	HLT9
Oxi Max Cleansing Pads, 55 count	HLT10
Thermasilk Moisturizing Shampoo, 13-ounce bottle	HLT11
Head & Shoulders Dandruff Shampoo Normal, 15.2-ounce bottle	HLT12
Barbasol Original Shaving Cream, 11-ounce can	HLT13
Dial Liquid Antibacterial Soap Refill, 15-ounce bottle	HLT14
Lever Soap 2000, 2 4.5-ounce bars	HLT15
Paper products, bags, and pet supplies:	
Brawny Towels Thirsty Roll, 3 rolls	PAP1
Kleenex Cold Care Ultra, 70 count	PAP2
Vanity Fair 2 Ply Napkins, 100 count	PAP3
Charmin Big Squeeze, 9 rolls	PAP4
Hefty Cinch Sak Trash Bags, 20 bags	PAP5
Glad Tall Kitchen Bags Quick Tie, 15 bags	PAP6
Ziploc Sandwich Bags, 100 bags	PAP7
Reynolds Wrap Aluminum Foil, 50 sq. feet	PAP8
Ziploc 1 Gallon Freezer Bags, 30 bags	PAP9
Dixie Flatware Spoons, 50 count	PAP10
Dixie Printed Bathroom Cups, 100 5-ounce cups	PAP11
Purina Dog Chow, 4.4-pound bag	PAP12
Milk Bone Small, 24-ounce box	PAP13
Purina Cat Chow, 56-ounce box	PAP14
Fresh Step Cat Litter Scoop, 7-pound bag	PAP15
Household items:	
Tide Ultra Liquid Detergent, 50-ounce bottle	H1
Downy Fabric Softener Mtn. Spring, 40 count	H2
Clorox Liquid Bleach, 1-quart bottle	H3
Palmolive Original Dishwashing Liquid, 28-ounce bottle	H4
Glade Rainshower, 9 ounce	H5
Drano Build Up Remover, 32 ounce	H6
Tilex Mildew Stain Remover, 32-ounce spray	H7
Clorox Cleanup with Bleach, 32 ounce	H8
Brillo Steel Wool Soap Pads, 18 count	H9
Lysol Disinfectant Original, 12-ounce spray	H10
Pledge Clean and Dust, 12.5-ounce spray	H11
Fantastic All Purpose, 22 ounce	H12
Windex Glass Cleaner, 26 ounce	H13
Mr. Clean and Top Job with Ammonia, 40 ounce	H14
Old English Lemon Polish, 12.5-ounce spray	H15

Appendix C

Information on the Supermarket Chains and the Stores Sampled

C1. 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 multi-billion-dollar corporation and the largest food retailer in New England, operating 274 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.[49]

Food Emporium. With 42 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. 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 16 U.S. states, the District of Columbia, and Ontario under the trade names A&P, Waldbaum's, Super Foodmart, Food Emporium, Super Fresh, Farmer Jack, Kohl's, Sav-A-Center, Dominion, Ultra Mart, and Food Basics. By February 26, 2000, the company operated 750 stores and served 65 franchised stores.[50]

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 five-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.[51]

Pathmark. The Pathmark supermarket chain was established in 1968. The company is known for pioneering the "supercenter" concept. Pathmark was also the first supermarket company in the Northeast to operate its stores 24 hours a 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 super-

[49] Stop & Shop, About Stop & Shop: All the Ingredients (http://www.stopandshop.com/about).

[50] The Great Atlantic and Pacific Tea Co., A Family of Supermarkets (http://www.aptea.com/stores.asp).

[51] C-Town, Supermarkets for Savings (http://www.ctownsupermarkets.com).

markets in the New York–New Jersey and Philadelphia metropolitan areas and employs over 27,000 associates. The company has stores in both urban and suburban marketplaces. Since September 2000, Pathmark is a publicly traded company (PTMK, on the NASDAQ).[52]

Shop Rite. The 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 its first 10 years in business, there were more than 70 Shop Rite members, with an annual sales volume of $100 million. In the late 1960s, 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 is composed of 43 members who individually own and operate 190 Shop Rite stores in New Jersey, New York, Connecticut, Pennsylvania, and Delaware.[53]

A&P. Founded in 1859, the Great Atlantic & Pacific Tea Company (or A&P) operates 465 stores in 10 U.S. states (Connecticut, New York, New Jersey, Pennsylvania, Delaware, Maryland, Louisiana, Mississippi, Michigan, and Ohio) and the District of Columbia and 180 stores in Ontario 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 an 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.[54]

Shaw's. 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.[55]

C2. Stores Sampled

S1. Stop & Shop in Tarrytown, New York. Tarrytown and the surrounding Hudson Valley river towns in southern Westchester County are quiet upper-class suburbs of New York City (see Figure 1). The Stop & Shop in Tarrytown is located on the border between Tarrytown and Irvington (another small upper-

[52] Pathmark, Fresh for Less (http://www.pathmark.com). In March 2007, the Pathmark supermarket chain was purchased by A&P (*USA Today* 2007).

[53] Shop Rite, One Place. Your Place. (http://www.shoprite.com).

[54] The Great Atlantic and Pacific Tea Co., Our Company (http://www.aptea.com/company.asp).

[55] Shaw's, About Shaw's Supermarkets (http://www.shaws.com/pages/toolbar/aboutShaws.php).

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, New York. The store is located in a solo building in a small commercial area of a residential suburban community in northeastern Westchester County. It is a relatively small store for a large chain. Ossining, while suburban, has lower-income neighborhoods that are more predominant than in an area like Tarrytown.

S3. A&P in White Plains, New York. This large store is located in a strip mall in a heavily commercial area of the small city of White Plains. While many of the residents of White Plains are of lower income, we suspect that because of 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 upscale.

S4. Path Mark in Hartsdale, New York. This average-sized store is located in a strip mall in a heavily commercial area off a busy main road that goes through southern Westchester. Hartsdale is a middle-income suburban town that is near high-income and low-income communities.

S5. A&P in Scarsdale, New York. The store is of average size and is in a very commercial area. It is in a solo building on the same main road as the Path Mark in Hartsdale. 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 the higher-income areas of Scarsdale. It is close to Yonkers, New York, 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, New York. This average-sized store is located in a strip mall in a heavily commercial area just off the same main road as the Path Mark in Hartsdale and the A&P in Scarsdale. 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 that it serves an equal number of shoppers from both.

S7. Food Emporium in Hastings, New York. This store is located in a large solo building in a small light-commercial area of a small residential suburban town in the southern part of Westchester. Hastings is a high-income 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, New York. This store is located in a strip mall in a medium commercial area in the middle of many suburban areas. Monsey is in Rockland County, which is across the Hudson River from Westchester County. Monsey, whose residents are mostly middle income, has a mix of communities, from blue-collar workers to retired senior citizens to African-Americans to ultraorthodox Hassidic Jews. This supermarket seemed to be the largest, main one in the area, so we suspect its shoppers come from all of these communities.

S9. Food Emporium in New York City. This large store is located in the

Upper East Side (Sutton Place). Sutton Place is one of the most expensive places to live in the world. Many of the buildings here have apartments worth tens of millions of dollars. Many celebrities who live in New York City on the Upper East Side are known to frequent this store. It is located on 1st Avenue underneath the 59th Street bridge. It is the biggest supermarket in New York City that we have seen, and it may be the biggest in size. Most of the shoppers are wealthy New Yorkers.

S10. Food Emporium in Armonk, New York. This store is located in a small solo building in a small commercial area. Armonk is a small, affluent, suburban town in northwestern Westchester near the Connecticut border. It is not near any low-income areas.

S11. A&P in Montvale, New Jersey. This store is located in a medium-sized solo building off a main road in a residential suburban area. This is a middle- to high-income town near the New York border (Rockland County) in northeastern New Jersey in Bergen County. Bergen County is one of the wealthiest counties in New Jersey, if not the wealthiest, and is the closest county to New York City.

S12. Shop Rite in Rochelle Park, New Jersey. This store is located in a small building in a strip mall in a mixed commercial and residential suburban town. The area seems to have more middle income residents with smaller homes than do many of the other areas of Bergen County.

S13. A&P in Pompton Lakes, New Jersey. This store is located in a very large solo building. It is located off two main roads or 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 New York City. The area seems to be upper middle class. While suburban, the area is more spread out than the more congested suburban areas of southern Westchester County, New York.

S14. Path Mark in Montclair, New Jersey. This store is located in a medium-sized building in an underground commercial mall. Montclair is an urban neighborhood that is almost entirely lower income. There is graffiti on all of the buildings, and many of the buildings are burned and abandoned. Montclair is in Essex County, New Jersey. The store seemed to be in need of repair and had chipped paint and an unsightly ceiling with low hanging pipes. We do not think any of the shoppers here are of high income, with a few being middle income and most being low income.

S15. Stop & Shop in Clifton, New Jersey. Clifton is a small suburb of New York City that is surrounded by many high-income towns. It is located in southern Passaic County, New Jersey, 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 20 miles from New York City. Owing to the location of the Stop & Shop in Clifton, New Jersey, customers of the store most likely reside in these surrounding suburbs in Passaic County and Bergen County.

S16. Food Emporium in Greenwich, Connecticut. The 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 from New York City as is Tarrytown. It has many areas of extreme wealth, where rich families have lived for generations. The store is located between a Porsche and a Ferrari dealership, with Rolls Royce and Mercedes dealerships directly across the street.

S17. Shaw's in New Canaan, Connecticut. This store is very small for a supermarket (the smallest we visited). Shaw's is also the smallest chain we surveyed, with the fewest number of stores and locations exclusively in Connecticut. This store is in a small, quaint commercial area. It is a very pretty store in a quiet, shaded location. New Canaan is a very high income, small, quiet suburban town approximately 10 miles north of Stamford.

S18. Stop & Shop in Greenwich, Connecticut. This store is directly across the street from the Food Emporium (S16) (less than 100 feet away). It is a medium-sized store and is larger than the Food Emporium (which is medium to small in size). It is newly renovated (it was formerly Grand Union station) and has an ESL system.

S19. Stop & Shop in Stamford, Connecticut. Stamford is another small suburb of New York City that is surrounded by high-income towns and neighborhoods. It is 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 4–5 miles. The Stop & Shop is part of a mall complex that most likely draws its customers from the surrounding high-income neighborhoods. However, there are a few lower-income areas of Stamford that may also be a part of the store's customer base. The Stop & Shop in Stamford is only 4–5 miles southwest of the Food Emporium in Greenwich (S16).

S20. Shop Rite in Norwalk, Connecticut. Norwalk is about 10 miles northeast of Stamford (15 miles northeast of Greenwich) and is very similar to Stamford. It is a higher-income suburb with some heavy commercial areas, which is where this store is located. The store is off a main road, and it is extremely large. 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 enormous Stop & Shop (which we did not visit). This area contains a number of very large supermarkets. All of the stores, not just the supermarkets, are very big. The store has an ESL system and many aisles.

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