Three Essays on Empirical Industrial Organization

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Introduction

This dissertation consists of three chapters in the field of empirical industrial organization, focusing on how firms and policymakers influence market outcomes. The first chapter examines retailer strategies to improve their bargaining power through private labels. The second chapter studies their efforts to increase profits through consumer inattention, while the third chapter explores the design of German subsidies for photovoltaic (PV) system adoption.

In the first chapter, I examine the role of private label products in reshaping retailer-supplier negotiations. By introducing private labels, retailers can gain bargaining power over producers, leveraging them as credible substitutes for national brands. Using a structural model to estimate wholesale costs and shelving fees, the study estimates how private labels impact these proxies for bargaining power. The findings suggest that private label entry reduces wholesale costs and increases shelving fees, thus showing that retailers improve their ability to extract favorable terms from producers. In total, I estimate a private label entry to improve retailer's variable profits by about 0.8% in a given quarter. Additionally, the study explores how these effects vary by retailer size, highlighting that smaller retailers may benefit more from private labels in negotiations.

In the second chapter, joint with Ian Meeker, we investigate consumer inattention to product downsizing, a pricing strategy where firms effectively raise unit prices by reducing package content. Because consumers tend to underuse size information, they may overlook such changes. The pepper industry provides a compelling setting to test consumer inattention to downsizing. We develop a novel method to assess inattention to package content changes and apply it to grocery scanner data. Our findings indicate that nearly all consumers fail to notice reductions in package size. With full information about size changes, consumers would shift toward packages with more content, reducing the market share of downsized products by 25%. This shift would lead to a welfare improvement of approximately 2.7%, despite consumers caring more about price over size.

In the third chapter, joint with Sebastian Rausch, we study Germany's photovoltaic (PV) subsidy program, one of the world's largest and most influential renewable energy policy. We estimate a dynamic model of new technology adoption, accounting for heterogeneity in residential ownership structures. Our analysis highlights the sub-optimality of the feed-in tariff structure, showing that investors—households or homeowners and landlords—heavily discount future benefits, leading to an inefficient use of government funds. High administrative costs associated with tenant electricity contracts strongly discourage landlords from investing in new energy technologies. Our analysis suggests that governments should prioritize upfront investment subsidies over feed-in tariffs to promote renewable energy adoption and reduce administrative costs in tenant electricity programs to unlock investments by landlords and expand solar energy access for tenants.

Chapter I

Private Labels as a bargaining tool in retailer-producer relationships

1 Introduction

Private label products have long been an integral feature of retail markets, originally offering consumers lower-cost alternatives to national brands. Over time, many retailers have introduced private labels that compete directly with premium national brands, potentially reshaping retailer-supplier relationships.[1] This paper examines how private labels influence the bargaining power of retailers. By providing an alternative to national brands, private labels may give retailers leverage, allowing them to negotiate better terms and secure more favorable contracts with suppliers. Since private labels can serve as a replacement threat to national brands, their similarity to these brands may enhance the credibility of this threat, another aspect explored in this work.

While earlier studies from the 2000s have explored the impact of private labels on bargaining power, they have generally relied on simpler models that do not fully capture the complexity of retailer-supplier negotiations. My paper builds on this body of work by adopting a more comprehensive framework to examine how private labels influence bargaining power. In this framework, I am able to estimate not only wholesale costs as a proxy of bargaining power but also shelving fees which function as lump-sum transfers from the producers to the retailers. By employing a more extensive framework of the bargaining process, this study offers a deeper understanding of the dynamics between retailers and suppliers, highlighting how private labels shape bargaining outcomes.

An additional contribution of this paper is its examination on how the impact of private labels varies across retailers of different sizes. While previous research has often treated retailers as a homogeneous group, this study recognizes that the bargaining power derived from private label products may differ depending on the retailer's size. Smaller retailers, in particular, may benefit more from the introduction of private labels, as national brand producers may want to improve the competitive position of smaller retailers to help curb the bargaining power of larger retailers.

This work builds upon the bargaining model developed by Hristakeva (2022b), which provides a framework to analyze vertical relations between producers and retailers. In her four-stage model, producers first make take-it-or-leave-it two-part tariff offers. These two-part tariffs consist of wholesale costs and a lump-sum transfer, which is often understood as a shelving fee or a similar payment to the retailer. In the second stage, retailers have the option to accept or reject these offers, and in turn, the retailer's product assortment

[1] See Ter Braak et al. (2013) and Geyskens (2018).

is determined. The third stage of the model comprises the price setting of the retailer, where retail price competition is modeled as a differentiated product Bertrand-Nash game. Finally, in the fourth stage, consumer demand is realized based on product characteristics, household characteristics, and other influencing factors. This framework enables the estimation of bargaining parameters between producers and retailers, which is essential to understand how private label products may influence bargaining power in retailer-supplier negotiations.

Using the bargaining outcomes derived from the structural model of Hristakeva (2022b), I then explore how the introduction of private labels influences the bargaining power between retailers and producers. To achieve this, I estimate a reduced-form model that controls for geographical, time, and product fixed effects, allowing me to focus on changes in bargaining power rather than its absolute level. To account for changes in market structure induced by product entry, I differentiate between the effects of private label entry and the entry of regular products. This distinction enables me to isolate the specific effects of private labels on bargaining outcomes without confounding them with the broader effects of market structure on bargaining. Ultimately, this approach allows for an empirical analysis of how private label products impact the terms of supplier contracts.

After estimating the model using Nielsen Retail Scanner and Nielsen Consumer Panel data from the US ice cream market, I find that the entry of private labels significantly influences the bargaining power between retailers and producers. Specifically, the introduction of private labels leads to a decrease in wholesale costs and an increase in lump-sum transfers, both of which indicate increased bargaining power for retailers. Smaller retailers, in particular, benefit more from the entry of private labels, with the effect on marginal costs being twice as large for small retailers compared to large retailers. On the other hand, a heterogeneous effect of private labels on bargaining power depending on product closeness to the national brand was not consistently observed. Nevertheless, the overall impact of private label entry is economically significant, with an average increase in variable retailer profits of approximately 0.7%, and an increase in lump-sum transfers translating into another 0.11% increase in variable retailer profits. These findings underscore the important role of private labels in strengthening retailer bargaining power, especially for smaller retailers, and offer valuable insights into the broader dynamics of vertical negotiations in differentiated product markets.

The paper is structured as follows. In Section 2, I review the relevant literature on private label brands, bargaining power, and product assortment decisions, highlighting key insights from previous research and identifying the gaps that my study aims to address. Section 3 introduces the dataset and provides an overview of the data sources used in the analysis. Section 4 outlines the relationship between private label entry and product assortment choices of the retailer. Moreover, it outlines a theoretical framework that underpins the empirical analysis, identifying multiple hypothesis between private label entry and bargaining power. Section 5 presents the structural model, which strongly builds on Hristakeva (2022b). Finally, Section 6 discusses the results of the structural model including the demand estimation results as well as the bargaining power results. In Section 7, I conclude the paper by dissecting the effect of private label entry on bargaining power, coming back to the hypotheses formulated in Section 4.

2 Literature Review

This paper draws on three key areas of research: private label brands, endogenous product and assortment choice, and vertical relations. The impact of private-label brands on bargaining has been a frequent subject of empirical investigation, often focusing on simple linear pricing rules, such as wholesale costs. Chintagunta et al. (2002) examined the introduction of private label brands, finding improved margins for retailers and increased bargaining power.[2] Bonfrer and Chintagunta (2004) reported mixed effects on retailer prices following the introduction of private labels, which appear to depend on the market power of national brands. Theoretical studies, such as Scott Morton and Zettelmeyer (2004), argue that retailers strongly value control over the positioning of private-label products. They show the incentives of retailers to position private-label products close to national competitors in order to gain bargaining power. In this paper, I integrate these insights to explore the return in bargaining power to positioning private labels close to national brands in product space.

The second stream of papers studies endogenous product-type choices and product assortment decisions in differentiated product markets. Draganska et al. (2009) shows the importance of incorporating strategic product assortment choices in the context of merger evaluation. In Hristakeva (2022b), observed product assortment choices are used to infer information about the bargaining parameters. Hristakeva (2022a) develops a model and shows empirical evidence that the gain in bargaining power through replacement threats in their prodcut assortment is less important for high-bargaining power retailers. Moreover, Eizenberg (2014) studies innovation in central processing units (CPUs) and evaluates its effects on the assortment of personal computer products of the producers. Regarding endogenous product type decisions, Seim (2006) modeled the choices firms make regarding their product types and the strategic positioning of these products in the competitive landscape. Fan and Yang (2020) estimate the effects of oligopolistic competition on the number and composition of smartphone offerings. This literature studies how market structure, demand, and firm costs affect equilibrium product availability. In this context, I show how intermediaries in a vertical market may choose to act as a producer to affect equilibrium outcomes through product assortment. Moreover, I want to study how their choices differ on the basis of their respective levels of bargaining power or size.

The third strand of literature on vertical relations investigates the effects of market structure on equilibrium outcomes. In recent years, the literature on vertical relations has been extended to consider product assortment decisions and how assortment decisions can

[2]See also Meza and Sudhir (2010).

impact choices at different levels of the supply chain. In particular, this has been studied in Ho and Lee (2017) and Ho and Lee (2019) in the context of the health care markets. There, insurers negotiate with hospitals over network inclusion in a Nash-in-Nash framework where the hospital network of an insurer can be viewed as their assortment. In their extension paper, they include the threat of replacement in their bargaining framework. This allows the insurer to threaten hospitals with their replacement and extends the outside option which was previously limited to the outcome of the disagreement. More recently, Hristakeva (2022b) has developed a framework to estimate the bargaining parameters between retailers and producers. In that setting, retailers have full control over the assortment and may use this control to improve their bargaining power. I will use her model to study the entry of private labels and its effect on bargaining power and assortment.

3 Data

My primary data sources comprise Nielsen Retail Scanner and Nielsen Consumer Panel data provided by the Kilts Center at the University of Chicago. The Retail Scanner data provides comprehensive point-of-sale data for around 35,000 stores in all 210 designated market areas (DMA) across the United States from 2006 to 2020. This information serves as the foundational data for estimating the model. The Consumer Panel tracks the purchases of roughly 50,000 households per year. The Consumer Panel is used to supplement the analysis and provide demographic information on the DMAs.

In addition to the Nielsen data, IPUMS data is also used, which provides integrated census and survey data from around the world, spanning time and space. This data includes detailed demographic information for each DMA-year combination, particularly on household income and age. For each DMA-year combination, there are, on average, around 10,000 households. From this sample, I will draw 500 households to approximate the population in the demand estimation.

The analysis is carried out at the product-retail chain-dma-quarter level. I focus on ice cream products that are sold in containers such as pints. Therefore, frozen novelties which are defined as a single-serve (i.e., less than 6 ounces) frozen dessert are excluded. Ice cream continues to enjoy significant popularity in the United States, with yearly consumption averaging around 12-13 pounds per person in recent years. It is worth mentioning that this consumption has experienced a minor decline of a few pounds over the past decades.[3]

The rest of the section is structured as follows. First, in order to run the analysis, I need a well-defined concept of retailers and brands in the data. Thus, I construct my sample following rules from DellaVigna and Gentzkow (2019a), Draganska et al. (2009) and Hristakeva (2022b) in reasonable cases. Finally, I discuss the product characteristics

[3]https://www.statista.com/statistics/183500/per-capita-consumption-of-ice-cream-in-the-us-since-2000/ , last accessed 18.07.2023

and the reasons for choosing ice cream to study my research question.

3.1 Retail Chains

I focus my main analysis on food and mass-merchandise stores that sell bullk ice cream from 2012 to 2018. Retail chains are defined following DellaVigna and Gentzkow (2019a). They use the combination of the *parent_code* and the *retailer_code* provided in the Nielsen data. The *retailer_code* indicates the retail chain, and the *parent_code* indicates the parent company that owns a chain. Sometimes, especially given the large sample, retailers are acquired by different companies or merge with other retailers. Therefore, there will be *retailer_codes* that have multiple *parent_codes*.

To establish a sample of retail chains that show a continuous presence in the market, I follow and adapt the criteria developed by DellaVigna and Gentzkow (2019a). First, I require retail chains to be present for at least 6 out of 8 years. Second, in cases where a *retailer_code* appears for stores with multiple *parent_codes*, I keep the stores with the combination present in the majority of stores and exclude cases, where the most common combination accounts for less than 80% of the stores. Lastly, I exclude chains in which 60% of their stores change either of the two codes in my sample.

3.2 National Brands

The Retail Scanner data carries information about the brand of each product. I identify the producer of each brand. This allows me to apply a rule which requires national brands to have at least 2% market share in at least 2% of the markets. This ensures that I study producers of interest and do not distort the analysis through tiny producers. I will still allow these small producers to act as replacement threats. As a consequence, however, I do not study the bargaining power between the retail chains with the small brands. This rule relaxes the restriction made by Draganska et al. (2009) who study assortment choices of retailers and require 5% market share in at least 5% of the markets. Finally,

Table 1: Sample Formation Rules

Sample Formation	Stores	Chains	DMAs	Products	Rev. in bn$/year
Full Sample	37,038	298	208	9,353	1.912
Drop unclassified prod.	36,957	298	208	7,105	1.592
Chain restriction 1: 6 yr.	22,165	79	207	6,360	1.411
Chain restriction 2: 80 %	22,106	67	207	6,350	1.404
Products: Price > 10 ct	22,106	67	207	6,347	1.350
Missing IPUMS data	19,608	67	138	6,246	1.247

DellaVigna and Gentzkow (2019a) report measurement errors as they find some prices to be below 10 cents. I also apply this rule to eliminate these measurement errors. Moreover, there are a couple of 300 OZ ice cream pints and other unreasonable large ice cream pint sizes. I exclude all ice cream pints containing more than a gallon of ice cream.

Table 1 describes the changes in the sample induced by these rules. The restrictions result in $19,608$ stores from 67 retail chains, $6,246$ products and covering \$1.247 billion yearly revenue on average from ice cream pint sales.

3.3 Product characteristics

As already outlined in the introduction of this section, I partly chose the product category for its horizontal and vertical differentiation. In the following, I first discuss the horizontal differentiation in the product category and afterwards the vertical differentiation.

3.3.1 Horizontal Differentiation

Ice Cream is extremely horizontally differentiated, offering more than 30 different distinct flavors and also many combinations of those. As most of them have tiny market shares, I aggregate them into the flavors shown in Table 2. It is not surprising that pints containing

Table 2: Market Shares by Flavor

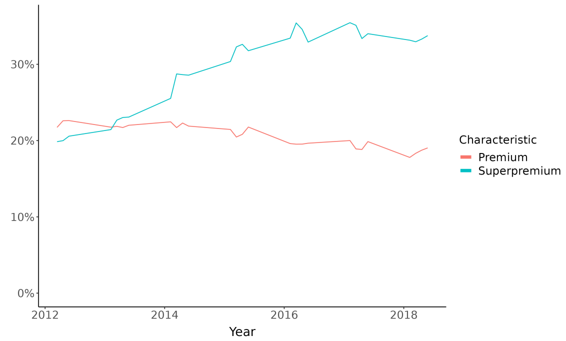
Flavor	Vanilla	Chocolate	Cookies	Mint	Fruit	Nuts	Others
Market Share	0.371	0.553	0.264	0.079	0.178	0.147	0.036

chocolate or vanilla are the most prevalent (55% and 37%, respectively). I allow ice cream pints to have multiple flavors. For example, Ben & Jerry's well-known Chocolate Fudge Brownie ice cream is classified as both chocolate- and cookie-flavored, as fudge is part of the cookie flavor according to my definition. Although it is possible to define the flavors in more specific categories, it is not feasible to consistently differentiate between the base flavor and the mix-in flavors for private labels in the Nielsen data. The approach was done by Sullivan (2017), who studied Haagen-Dazs and Ben & Jerry's in particular. While he was able to search for these products and manually define their base flavor, I am unable to do so for private labels due to the anonymity of the retailers.

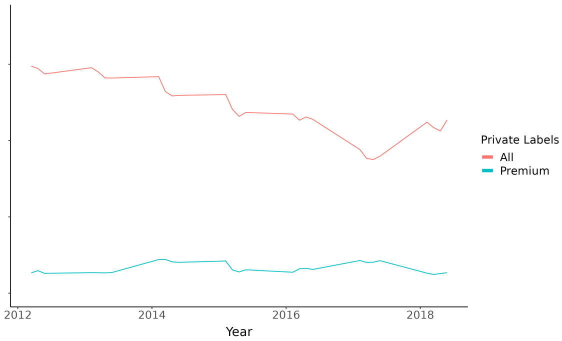
3.3.2 Vertical Differentiation

Ice cream products are generally classified into three qualities: regular, premium and superpremium. Drawing on a combination of information from the unique product code (UPC) description and looking up their UPC, I can differentiate between the three kinds. Figure 1a clearly shows the increase in popularity of superpremium ice cream brands, such as Haagen-Dasz and Ben & Jerries. The market share of superpremium ice cream brands has almost doubled throughout my sample, having increased from just below 20% to almost 35%. The market share of premium ice cream products, on the other hand, has remained relatively stable throughout my sample, dropping by about 2-4 percentage points. This provides clear evidence that this market is extremely vertically differentiated.

Figure 1: Market share of premium and private label products



(a) Premium Products



(b) Private Label Products

3.3.3 Private label products

Ice cream private labels account for approximately 20 to 30% of the market share, as shown in Figure 1b, which makes this product category particularly relevant for studying my research question. Notably, 10 to 25% of the private label offerings fall under the premium category. As a result, retailers are directly competing with established premium national brands, such as Haagen-Dazs, through their private label products. This competitive dynamic is significant for my research, as it highlights that retailers are not only challenging national brands in the low-end segment but also positioning themselves against premium competitors. As can be seen from Figure A1 in the Appendix, retailers continuously introduced private labels during my sample. Superpremium private labels were rarely added, we can mostly see introductions in 2017. It coincides with a drop in premium entrants. What remains to be explored is the extent to which private labels have been able to improve their bargaining power, especially in comparison to superpremium ice cream producers, during a period in which they have continuously grown their market share.

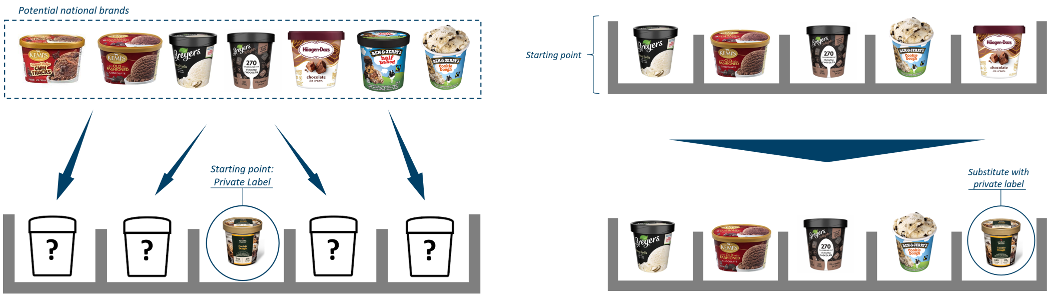
4 The Role of Private Label Entry in Assortment and Bargaining Power

In this section, I examine various theories on how retailers use private labels. First, I explore how retailers adjust their product assortment when introducing private labels. Next, I build on the model of Inderst and Shaffer (2019) to hypothesize how private labels can influence the bargaining power of producers, depending on the proximity of their national brands to the private labels in product space. Additionally, the model predicts how the impact of private labels on bargaining power may vary based on retailer size.

4.1 Private label entry and assortment formation choice

In the first part of the section, I discuss how the decision to introduce private labels interacts with retailers' choices in forming their product assortment. After presenting competing theories, I provide empirical evidence that supports one of these theories within this product category.

Figure 2: Competing theories of assortment choice response to private label introduction



(a) Private label as centerpiece (b) Private label added into assortment

In general, there are two ways to think about the interaction of private label entry with assortment formation. First, retailers could develop a private label product as the centerpiece of their assortment, structuring the category around it and selecting complementary products accordingly. This is illustrated in Figure 2a. In this case, the introduction of a private label brand would coincide with large changes in assortment. However, retailers could design their private label product with a specific placement strategy in mind—deciding which product to position it next to or which product to replace. In that case, the assortment should be similar before and after introduction, with the main difference that the private label product has been substituted into the assortment.[4]

In order to study this, I will first define the measure of cosine similarity to quantify the variation in the assortment of products. This measure can be constructed within and across markets or at the store level over time. Its interpretation depends on its construction, and it captures the fraction of overlapping products, e.g. within/across markets or within a store over time. Here, the measure is constructed to track the assortment changes of a given store over time. Let store s's assortment be described by a $N \times 1$ vector A_t where N denotes the number of products. $A_t(n)$ takes the value 1 if the product is offered in the store and 0 otherwise. The assortment similarity between store i in period t and period $t+1$ is measured as

$$similarity_{t,t+1^s} = \frac{A_t' A_{t+1}}{||A_t|| \cdot ||A_{t+1}||} \tag{1}$$

and is robust to the size of the assortment.

The measure captures how much the assortment of each store changes across two peri-

[4]Of course, it could have also been added to the assortment by increasing the assortment size. This is not considered now to keep the assortment size constant.

ods, which are defined as quarters here. To study how private label product introductions influence the changes in assortment over time, I regress the similarity measure on private label entry, subject to market fixed effects. The results are shown in Table 3.[5]

Table 3: Reduced-Form Evidence of Assortment continuity

	(1)	(2)
Entry	-0.03	-0.027
	(0)	(0)
Private label	-0.0005	-0.0009
	(0.27)	(0.018)
Private label x Entry	0.0005	0.0001
	(0.54)	(0.92)
Retail Chain FE	Y	Y
Year FE	N	Y
N	9,261,483	9,261,483

Notes: Based on scanner data from 2006 to 2020. The dependent variable is the cosine similarity measure computed within retail chains in a given DMA over time. The columns report p-values in parentheses. Retail chain - DMA - Product - Quarter level regression.

By the definition of the measurement, *Entry* should have a negative impact on the similarity measure. The insignificance of the coefficient related to *Private label x Entry* suggests that retail chains do not make substantial changes to their product assortment after introducing private labels. Therefore, it seems highly unlikely that, in this product category, retailers design the private label as the new centerpiece on their shelves and build the assortment around it. Instead, it seems more likely that retailers design a private label with the goal of integrating it into the current assortment. This approach allows retailers to consider the characteristics of their existing products and design their private label to complement the assortment.

This evidence justifies using reduced-form inference in Section 7. Since private label entry does not lead to large changes in the assortment, I can focus on studying how the bargaining power of existing products changes to address my hypotheses which will be discussed in the following section.

4.2 Hypotheses on the effects of private label entry

To demonstrate the varying importance of replacement threats for retailers of different sizes and to elaborate the role of substitutability of private labels, I use the model introduced by Inderst and Shaffer (2019). Their theoretical framework serves as a simplified version of the structural model outlined in Section 5, providing an initial platform for gaining insight into the model's mechanics.

[5]Note that these results look the same at the store-quarter level.

4.2.1 Model

The model features two downstream firms that are differentiated in terms of marginal cost. Firm 1 faces higher marginal cost and can therefore be considered as the *small retailer* as is common in the literature. Both downstream firms can either purchase the input from an incumbent supplier, who exhibits market power, or from a competitive fringe, who are willing to supply at cost. One can think of the competitive fringe as a private label supplier that does not directly participate in the market with its own brand, like a producer with a national brand would. The incumbent supplier derives its market power from a cost advantage over the private label supplier and on the degree of substitutability of the two products. The game is illustrated in Figure 3.

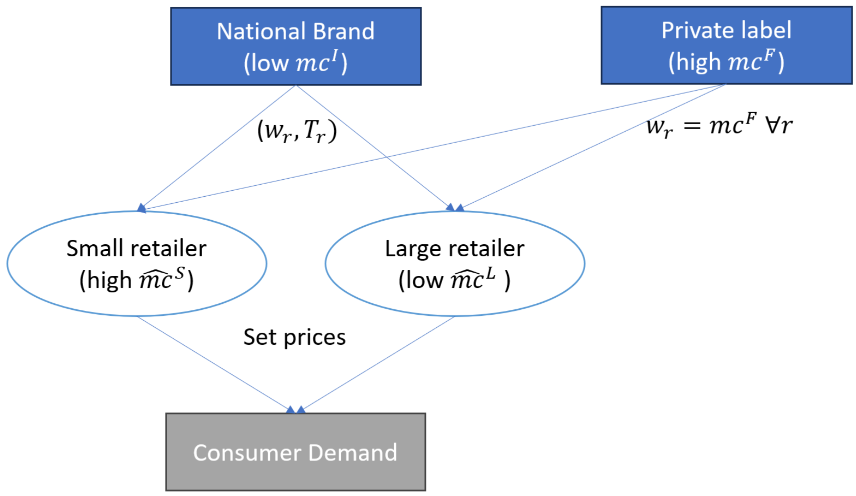


Figure 3: Model Setup

The demand is modeled as a linear demand

$$q_i(p_i, p_j) = \alpha - p_i + \gamma p_j$$

where $\gamma = \bar{\gamma}$ if $\{i, j\}$ sell the same product and $\gamma = \hat{\gamma}$ if they don't. The degree of substitutability therefore depends on the value of $\hat{\gamma}$, where the products are perfect substitutes whenever $\hat{\gamma} = \bar{\gamma}$ and are not substitutable at all whenever $\hat{\gamma} = 0$. The model features three stages. In the first stage, the incumbent makes observable take-it-or-leave-it two-part tariff offers.[6] In the second stage, the retailers accept or reject and purchase from the private label. In the third stage, the retailers set prices and the demand realizes.

4.2.2 Model Results

In the absence of a credible outside option in the baseline scenario, Inderst and Shaffer (2019) demonstrate that the incumbent aims to optimize the joint channel profit. Specifically, the incumbent strategically sets wholesale prices to elicit prices that maxi-

[6]Two-part tariff features a per-unit price and a lump sum fee.

mize channel profit and then captures all profits from the retailers through the transfer mechanism.

The game becomes more interesting when the outside options become credible. In this scenario, if the incumbent aims to retain both retailers as customers, it must make an offer that is weakly better than each retailer's outside option. Notably, the authors establish that given the cost advantage of the incumbent, it is in the incumbent's interest to serve both retailers in any equilibrium. With the participation constraints induced by the outside options of the retailers, the profit maximization of the incumbent can be rewritten as a function of channel profits and retailers' outside options

$$\max_{w} \Pi(w) = \Omega(\mathbf{k}(\mathbf{w})) - \sum_{i=1}^{2} \pi_i^R(\hat{\mathbf{k}}(\mathbf{w})), \tag{2}$$

where $\mathbf{k}$ denotes the vector of marginal costs and wholesale costs w whenever the retailers purchase from the incumbent. The vector $\hat{\mathbf{k}}$ indicates the parameters whenever they contract with the private label supplier. Thus, Ω denotes the channel profit under full supply of the incumbent and the last sum indicates the outside option profits of both retailers.

In the absence of a credible outside option, the latter term becomes zero, and the incumbent would adjust wholesale prices to maximize Ω. However, this is not the scenario under binding outside options. Altering w_i not only changes the channel profit but also influences the outside option of firm j, given the competition between retailers. As a result, the incumbent typically deviates from charging wholesale prices that maximize channel profit.

Finally, I discuss how the availability of more substitutable private labels affects the profits of the two differently sized retailers in this model. Increased substitutability between the private label and the incumbent's product clearly improves the outside options available to both retailers. Consequently, the wholesale costs proposed to both retailers by the incumbent decrease as the substitutability of the private label increases. However, as illustrated in Figure 4, it becomes apparent that the smaller retailer manages to obtain better wholesale cost offers from a closely substitutable private label compared to the larger retailer.

In summary, the model features the following results. In the absence of product competition ($\hat{\gamma} = 0$), there is no longer an effect of outside options which in turn allows the incumbent to direct sales to the more efficient retailer (i.e., the large retailer with lower marginal cost) to maximize channel profits. Through the transfer of the two-part tariff, the incumbent can then extract all channel profits. However, as $\hat{\gamma}$ increases, the incumbent must adjust wholesale prices to satisfy increasing participation constraints. The wholesale price of the small retailer is partly determined by its effect on the outside option of the large retailer. Therefore, the incumbent has the incentive to improve the competitiveness of the small retailer in order to decrease the profitability of the outside

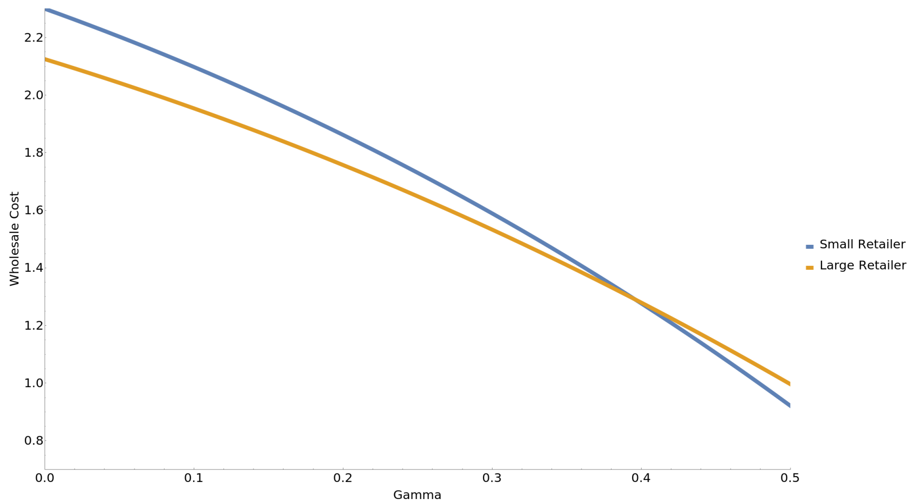


Figure 4: Product Substitutability and Wholesale Prices

option of the large retailer. This model demonstrates why smaller retailers may benefit more from the availability of close substitutes to the incumbent's product compared to larger retailers.

This model then motivates two questions. First, I expect private labels to improve retailer's bargaining power and for this effect to be more pronounced if the private label is close to the national brand in product space. Second, I expect this effect to be more pronounced for smaller retailers. After outlining the model and its results in Sections 5 and 6, I collect empirical evidence to answer these questions in Section 7.

5 Structural Model

The structural model follows Hristakeva (2022b), providing a framework for the vertical market and enabling the estimation of bargaining power between retailers and producers. In this model, bargaining occurs through take-it-or-leave-it offers made by the producer. However, I deviate from Hristakeva (2022b) by analyzing the market at the product level rather than the product line level. While I also compute replacements at the product line level, this approach allows me to capture more granular details about the flavors available within a product line. Consequently, I can better account for the substitutability between a new private-label product and an existing product line, which is necessary to understand the heterogeneous effects of private label entry on bargaining power depending on product similarity in Section 7.

The model facilitates the estimation of a two-part tariff between the producer and the retailer, comprising the wholesale cost w and lump-sum payments T. Changes in the two-part tariff then imply changes in bargaining power, and I use the two interchangeably for the remainder of the paper. The vertical market model is divided into four stages.

1. **Producer's Offers:** Producers make take-it-or-leave-it offers.

2. **Retailer Decisions:** Retailers decide to accept or reject offers, thereby determining their assortment.

3. **Price Setting:** Retailers set prices according to Bertrand-Nash competition.

4. **Consumer Choices:** Consumers make selections.

The model is solved backward. In the final stage, I estimate the demand model and learn substitution patterns from the data. In the third stage, I deduce the wholesale cost given the assumed price-setting behavior following a Bertrand-Nash assumption. Then, the first two stages allow me to identify the lump-sum payments. In a Nash bargaining framework with either one retailer or one producer, take-it-or-leave-it offers from the producer would suggest full bargaining power according to the Nash bargaining parameter. However, given the multilateral nature on both sides in this setting, this result does not hold.

Stage 4: Consumer choice

The consumer demand model follows the standard consumer choice model developed by Berry et al. (1995a). For each market and time period, consumers observe the complete set of products offered, A_{mt}, and select the product-retailer pair that maximizes consumer i's indirect utility from choosing product j at retailer r in market m at time t:

$$u_{ijrmt} = X_{jrmt}\beta_i - \alpha_i p_{jrmt} + F_m + F_q + \xi_{jrmt} + \varepsilon_{ijrmt}$$

Here, utility depends on observed product characteristics X_{jrt}, prices p_{jrmt}, and characteristics observed by the consumer but not by the researcher ξ_{jrmt}. Note that unlike Hristakeva (2022b), X_{jrt} contains product-specific characteristics such as flavor rather than only product line-specific ones[7]. F_m and F_q represent fixed effects for markets and quarters, respectively. Furthermore, product characteristics, in addition to price and flavors (as described in Section 3.3.1), include an indicator variable for premium and superpremium products. Consumer heterogeneity is introduced only through regional demographics, where I draw households from the empirical distribution of demographics. The idiosyncratic shocks ε_{ijrmt} are modeled as i.i.d. extreme value type I errors.

Demographics are an essential component of demand estimation in this product category. The ex-CEO of Dreyer's[8] discusses in an interview that they observed a huge difference in flavor preferences between neighborhoods. This would suggest that a model at the store level would be interesting to estimate. However, since the negotiations between the retailer and the producer are not at the store level but rather at the DMA level,

[7] Product-line specific characteristics here include premium and superpremium only.

[8] Dreyer's is one of the leading premium ice cream brands in the United States and served as the national distributor of Ben & Jerry's from 1987-1998. The University of California-Berkeley conducted an oral history of Dreyers, interviewing former executives after its acquisition by Nestle: http://www.lib.berkeley.edu/libraries/bancroftlibrary/oral-history-center/projects/dreyers. Thanks to Sullivan (2017) for the hint.

I aggregate across DMA codes. This still allows us to capture some of the geographical heterogeneity, and utilize the demographic information from IPUMS.

Implementing the differentiation instruments developed by Gandhi and Houde (2019b), I can calculate and identify predicted shares for each product-retailer pair in a market

$$s_{jr}(A, \theta_D, \xi, X, p) = \int \frac{\exp(X_{jr}\beta_i - \alpha_i p_{jr} + \xi_{jr})}{1 + \sum_{lk \in A} \exp(X_{lk}\beta_i - \alpha_i p_{lk} + \xi_{lk})} dF(\theta_D),$$

where the assortment A represents the collection of products offered by all retailers in the market and is determined in Stage 2.

Stage 3: Bertrand Nash Price competition between retailers

Lump-sum payments have no impact on marginal profits, but instead influence the selection of the product assortment. Therefore, given assortments, lump-sum payments become irrelevant for the price-setting analysis which depends on variable profits.

Given market assortments A and retailers' marginal costs and wholesale prices $(\mathbf{mc}^r, \mathbf{w})$, retailer r's variable profits $(\pi^r(A, \mathbf{mc}^r, \mathbf{w}))$ equal

$$\pi^r(A, \mathbf{mc}^r, \mathbf{w}) = \sum_{j \in A^r} (p_{jr} - mc^r_{jr} - w_{jr}) M s_{jr}(A, \mathbf{p}),$$

where I omit market m and time t subscripts for clarity.

Retailer profits depend not only on its own assortment and pricing but also on those of competing retailers. Under Bertrand-Nash competition, equilibrium prices satisfy the first-order conditions:

$$s_{jr}(A, p) + \sum_{k \in A^r} (p_{kr} - mc^r_{kr} - w_{kr}) \frac{\partial s_{kr}(A, p)}{\partial p_{jr}} = 0.$$

From these conditions, I can identify the total marginal cost $mc^r + w$ under the assumption of uniquely determined prices in a pure-strategy interior Bertrand-Nash equilibrium, following Nevo (2001). To unravel these two cost measures, further assumptions would be required about their specific structures (Berto Villas-Boas (2007)). In this work, my main focus is on the changes in wholesale costs induced by the introduction of private labels. There are essentially no reasons to expect that the marginal costs incurred by retail stores—such as those related to stocking shelves—would be affected by the introduction of private labels. These types of costs are largely invariant to whether a product is branded or private label. Consequently, there is little justification for modeling them separately, especially at the cost of introducing additional assumptions.

Stage 2: Retailers' product selection

Retailer r's expected profit from supplying A^r is given by:

$$\mathbb{E}_\xi[\Pi^r(A, mc^r, w, T)] = \mathbb{E}_\xi[\pi^r(A^r, mc^r, w)] + \sum_{j \in A^{r,-PL}} T_{jr} - C^r.$$

Here, π^r denotes the variable profits from Stage 3, T_{jr} is the lump-sum payment retailer r receives for offering product j, and C^r captures the fixed costs associated with supplying A^r in its store. Moreover, the retailer does not receive lump-sum transfers from the supply of private label brands. The expectation is taken over ξ, which represents product-specific demand shocks (unobserved quality) observed by consumers but not by the researcher.

Then, assuming risk-neutral retailers and their outside options of rejecting a product offer and supplying an alternative product, equilibrium conditions require that no retailer may increase its total profits by unilaterally altering its assortment. Formally,

$$\mathbb{E}_\xi[\pi^r(A, mc^r, w)] \geq \mathbb{E}_\xi[\pi^r(A', mc^{r'}, w')], \tag{3}$$

where A' denotes any counterfactual assortment in which retailer r deviates unilaterally from A, replacing any product with an alternative obtained from a wholesaler at fixed, non-negotiated prices.

Note that it is also possible to remain agnostic about the negotiation protocol. The take-it-or-leave-it assumption allows for a point identification of the lump sum payments as shown in Equation 4 below, enabling the study of the comovements of wholesale costs and lump sum payments. Without it, it is still possible to identify bounds for the lump sum payments.

Counterfactual assortments A' are constructed following Hristakeva (2022b), where the potential replacement products have contracts with lump-sum payments equal to 0, and the non-negotiated wholesale costs are assumed to be the highest wholesale costs observed in the retailer's market for that product. This contract mirrors the purchase from a wholesaler in the market who typically have a higher purchase price than a bilateral agreement. In addition, the retailer does not receive lump sum payments from the wholesaler. This conservative approach ensures that the alternative is constructed carefully, and it is likely that the profitability of the replacement threats is underestimated. For each replacement, it is necessary to compute the equilibrium prices in the market, which are implied by the Bertrand first-order condition from Stage 3. Morrow and Skerlos (2011a) reformulate the problem as a contraction, ensuring convergence, and I leverage their result to solve the fixed point problem quicker.

Furthermore, it is improbable that retailers negotiate over individual products. Hristakeva (2022b) estimates the entire model at the product line level, aggregating similar products of the same brand into a product line. However, as I am interested in studying how closely retailers' private-label products resemble national brands, I need to estimate demand at the product level instead of the product line level. Therefore, to compute product line-level replacement threats, I replace all products within a given product line with all products from an alternative product line. As the number of products within one product line may be different from that of another product line, I average the profits across products within each product line and compare the profitability of two product lines in this matter. This is an implicit assumption made in Hristakeva (2022b), as she disregards the number of products within a profit line.

With these assumptions in place and estimating take-it-or-leave-it offers, the replacement threats in Equation 3 boil down to the lump-sum payments T_{jr} below. Here, A^r denotes the original assortment and $A^r_{-j,l}$ denotes the altered assortment, where product j has been withdrawn and product l added.

$$T_{jr} = \max\{0, \max_{l \notin A^r}\{\mathbb{E}_\xi[\pi^r(A^r_{-j,l}, mc^r_{-j,l}, w^r_{-j,l})] - \mathbb{E}_\xi[\Pi^r(A, mc^r, w)]\}\} \qquad \forall j \in A^r \tag{4}$$

This expression then allows me to point identify the lump-sum payments for all products in the data.

Stage 1: Producer's choice problem

The producer's profits from supplying their own product are expressed as:

$$\mathbb{E}_\xi[\Pi_p(A, mc^p, w, T)] = \mathbb{E}_\xi[\pi_p(A, mc^p, w)] - \sum_{\{jr\} \in A_p} T_{jr}$$

The take-it-or-leave-it offers of producers aim to maximize their own profit subject to retailers' outside options which enter through the lump-sum payments. This optimization problem allows me to estimate producer markups. Moreover, by plugging in the expression for lump-sum payments and deriving the optimal wholesale cost offers of producers, it can be shown that multiproduct producers internalize the externality of the wholesale cost of one product on the outside option for its other products.

Binding retailer outside options serve as a means for retailers to extract rents from the producers. Given the competition at the retailer level, it is less logical for producers to transfer rents through wholesale costs. Instead, it is more efficient for them to utilize lump-sum payments.

6 Structural Model Results

I organize the discussion of the results in two steps. First, I discuss the results of the demand estimation. Second, I describe the estimates of the bargaining parameters, the wholesale price and the lump-sum transfer.

The demand estimation results are summarized in Table 4. To address price endogeneity, I use cost shifters representing key ice cream inputs, such as the Cream II and dry milk index. In addition, I construct differentiation instruments following Gandhi and

Houde (2019b), which capture the crowdedness of a product space and its impact on the price-setting power. For example, when a product faces many close competitors, its ability to post high prices diminishes, whereas limited competition strengthens its pricing power. These instruments also account for heterogeneity in product characteristics. Furthermore, to identify variation in consumer preferences for characteristics and prices driven by demographics, I interact product characteristics with demographic variables.

The logit specifications in columns 1 and 2 of Table 4 confirm the expected direction of bias in an OLS estimate of price. Since the price of a product responds to high demand, higher sales are associated with higher prices. As a result, when endogeneity is ignored, I expect the price coefficient to be biased toward zero, making it less negative. This expectation is confirmed in the results, as the price coefficient shifts from -3.036 to -6.817 when instrumenting for price.

Table 4: Demand Results

	Logit		Random Coefficient Model		
	OLS	IV	Means	HH Income	Age
Prices	-3.036	-6.817	-8.560	0.023	-0.090
	(0.104)	(2.838)	(0.0007)	(0.0002)	(0.0011)
Premium	-0.134	-0.253	2.428	-0.002	0.018
	(0.015)	(0.093)	(0.0014)	(0.0002)	(0.0017)
Superpremium	0.738	2.926	-1.978	0.010	-0.222
	(0.067)	(1.673)	(0.0001)	(0.0005)	(0.0018)
Vanilla	0.290	0.173	1.010	-0.017	0.054
	(0.008)	(0.089)	(0.0004)	(0.0006)	(0.0014)
Chocolate	0.048	0.013	0.529	0.022	-0.011
	(0.019)	(0.033)	(0.0003)	(0.0002)	(0.0008)
Cookies	0.038	-0.034	-0.682	0.004	0.033
	(0.013)	(0.060)	(0.0003)	(0.0003)	(0.0012)
Mint	0.018	-0.004	-9.800	0.012	-0.084
	(0.029)	(0.041)	(0.0003)	(0.0006)	(0.0012)
Fruit	-0.216	-0.237	1.202	-0.022	0.038
	(0.017)	(0.023)	(0.0005)	(0.0005)	(0.0011)
Nuts	0.010	0.042	0.343	0.009	-0.041
	(0.005)	(0.024)	(0.0002)	(0.0002)	(0.0017)
Fixed Effects	No	No	Market, #Quarter		
N	652182	652182	652182	652182	652182

Notes: Based on scanner data. The columns report standard errors in parentheses. Robust standard errors.

In my full model, I find that demand slopes downward with respect to price. The average own-price elasticity is estimated at -3.26, with only about 0.5% of estimates suggesting inelastic demand and none indicating positive elasticity. Compared to estimates in the literature, which range from -2 in Draganska et al. (2009) to -7 in Sullivan (2017), my results fall in the middle. Hristakeva (2022b), who studies the yogurt market—a category similar to the ice cream market—finds an own-price elasticities of around -4.

I also observe that wealthier and younger households are less sensitive to price (0.023, -0.09). Given standard deviations of approximately 57 for income and 17 for age, their relative significance is similar. It's intuitive that wealthier households are less price-sensitive. Moreover, when holding income constant, younger households are likely to exhibit lower price sensitivity. This seems reasonable as their expected lifetime income is higher than that of older households.

In terms of the two-part tariff, I find that the average marginal cost is approximately 39 cents, implying a markup of around 19 cents and a margin of roughly 39%. These estimates align with industry expectations, as a 30% markup is commonly considered standard in these markets. Ice cream frequently ranks among the top categories in terms of markup, as documented in NACS SOI reports[9]. Thus, it seems reasonable that I find a higher than average margin in this product category.

In Table 5, I examine marginal costs as a function of various characteristics of ice cream. The most striking result is that superpremium products have significantly higher marginal costs. This is largely due to the higher production costs, which come from their lower air content per fluid ounce and the use of higher-quality ingredients.

Table 5: Descriptive Statistics of Marginal Costs

	Marginal Cost		
Constant	0.2899		
	(0.0009)		
Premium	-0.0497	-0.0467	-0.0756
	(0.0008)	(0.0035)	(0.0034)
Superpremium	0.4507	0.4519	0.5449
	(0.0008)	(0.0061)	(0.0040)
Vanilla	0.0086	0.0100	0.0257
	(0.0007)	(0.0013)	(0.0008)
Chocolate	-0.0391	-0.0399	-0.0287
	(0.0007)	(0.0011)	(0.0010)
Cookies	-0.0083	-0.0103	0.0011
	(0.0007)	(0.0012)	(0.0007)
Mint	-0.0472	-0.0478	-0.0449
	(0.0012)	(0.0015)	(0.0007)
Fruit	0.0381	0.0376	0.0462
	(0.0009)	(0.0011)	(0.0006)
Nuts	-0.0177	-0.0188	-0.0220
	(0.0010)	(0.0009)	(0.0006)
Fixed Effects	None	Market	Market, Brand
S.E. Type	Robust	Clustered	Clustered
Observations	523,925	523,925	523,925

Notes: Standard errors in parentheses. Private label products not part of these descriptives. Analysis run at market-retailer-product level.

Premium ice creams do not exhibit higher marginal costs compared to the non-premium category. Given that premium and non-premium ice creams make up similar shares of the market and do not differ significantly in price, they do not stand out in terms of rarity or pricing. Additionally, the non-premium category includes light, vegan, and other specialty ice creams, some of which are considered high quality in other ways.

[9]See, for example, the NACS SOI reports, cited here: `https://www.nacsmagazine.com/Issues/September-2020/self-starter`, last accessed 03.03.2025.

Since these products often have higher input costs and are sold at premium prices, the cost difference between premium and non-premium ice creams remains small.

The estimated average lump-sum transfer per quarter-market-store-product line is \$324.49, compared to \$69.61 in Hristakeva (2022b)[10]. The larger average transfer is highly reasonable due to several factors. First, the ice cream market is about 24% larger than the yogurt market[11]. Second, my sample includes mass merchandisers, which typically generate higher revenue and, consequently, receive larger lump-sum transfers. Finally, and most importantly, the yogurt market is highly concentrated: two dominant producers—–Group Danone and General Mills—–account for 70% of total sales in the sample used by Hristakeva (2022b). The stronger bargaining power of these two firms likely resulted in lower lump-sum transfers. In contrast, the ice cream industry has a more fragmented market structure, giving retailers greater bargaining power, which translates into larger lump-sum transfers.

Table 6: Descriptive Statistics of Lump-Sum Transfers

	Lump-Sum Transfer		
Constant	3,726.1		
	(33.33)		
Premium	-149.2	-104.0	-170.4
	(39.94)	(15.11)	(15.69)
Superpremium	278.7	421.1	349.3
	(33.85)	(28.32)	(17.41)
No Stores	-19.21	-19.67	-19.88
	(0.23)	(1.89)	(1.83)
Staple	-647.6	-278.4	-197.8
	(30.73)	(20.91)	(27.76)
Fixed Effects	None	Market	Market, Brand
S.E. Type	Robust	Clustered	Clustered
Observations	75,860	75,860	75,860

Notes: Standard errors in parentheses. Private label products not part of these descriptives. Analysis run at market-retailer-product line level.

This represents approximately 24.4% of retailers' variable profits, which is reasonable compared to the 19.9% reported by Hristakeva (2022b), given the different competitive environments in the ice cream and yogurt markets. Additionally, 65% of the product lines in my sample show a profitable deviation, which aligns with the 55% observed in Hristakeva (2022b).

In Table 6, I report descriptive statistics for the lump-sum transfers. There is a strong argument that popular products should not need to offer lump-sum transfers to secure shelf space. This is reflected in the estimates, since staple products feature lower lump-sum

[10]In 2010 dollars, this corresponds to \$64.04; all values in this paper are represented in 2015 dollars.

[11]Revenue in the U.S. ice cream market is projected to reach \$15.01 billion in 2025: `https://www.statista.com/outlook/cmo/food/confectionery-snacks/confectionery/ice-cream/united-states`. Revenue in the U.S. yogurt market is expected to be \$12.16 billion in 2025: `https://www.statista.com/outlook/cmo/food/dairy-products-eggs/yogurt/united-states`. Both links last accessed on 04.03.2025.

transfers on average.[12] In contrast, superpremium products must offer larger lump-sum transfers, indicating that their producers have lower bargaining power. While there are well-known superpremium brands, such as Ben & Jerry's, many of these products are also made by local farmers or smaller ice cream shops, which typically have weaker bargaining power compared to larger producers.

7 Private label entry on bargaining power

In this section, I study the effects of private label entry on bargaining power, using estimates of marginal costs and lump-sum transfers as proxies for bargaining power. I primarily test three hypotheses, which I outlined in Section 4. First, I expect that private label entry enhances the bargaining power of any retailer. Second, I examine if private label entry increases bargaining power over producers whose products are close substitutes to the private label. Finally, I study if the effect of private label entry is more pronounced for smaller retailers, as discussed in Section 4.2.2.

A common challenge in studying entry is that entry itself alters market structure and, consequently, the competitive environment. Increased competition induces both retailers and producers to adjust their pricing strategies, complicating the task of isolating changes in wholesale costs. Several approaches have been proposed to address this issue. Meza and Sudhir (2010), for instance, examine the effects of private label entry by distinguishing between imitating and non-imitating private labels. They find that once changes in wholesale costs from non-imitating private labels are accounted for, the effects associated with imitating private labels are not confounded by changes in the competitive environment. In a similar vein, I account for the effects of general entry in my reduced-form analysis. Since there are many producers in this market, the increased competition should be similar regardless of the type of product introduced. Therefore, I can focus solely on the change in bargaining power induced by private label entry, after accounting for general entry effects.

I define a product as having entered when no prior sales are recorded in the DMA code. Therefore, the same product could have different entry points across two different DMA codes if it started selling in different quarters in each area. The Nielsen data makes it more challenging to study private labels, as retailers are anonymous. This means it is impossible to identify specific products or gather information through the universal product code (UPC). Instead, the analysis relies solely on the UPC to track product entries.

This creates a potential issue, as retailers may slightly alter a product or change its label, which would classify it as a private label entry according to my definition. In these cases, competition from the private label already exists for the national brand, but it is treated in subsequent reduced form analysis below as though there is new competition.

[12] Staple products are defined as those available in at least 60% of all retailers in a market.

This leads to an overestimation of private label entries and, consequently, an underestimation of the true impact of private label entries that actually introduce new competition.

Table 7 presents the summary statistics for private label entry. The number of private label entries at the DMA-retailer level ranges from 0 to 108, with the median being 3 and the mean 10, suggesting a right skew. The 90th percentile shows about 33 entries, which could be a symptom of the classification issue discussed earlier. While it is speculative, this might reflect cases where a private label product line was redesigned.

Table 7: Summary Statistics of Private Label Entry

	Mean	Min	p10	Median	p90	Max
Value	9.8	0	0	3	33	108

Wholesale costs are estimated at the market-retailer-product level as part of the total marginal costs, while lump-sum transfers are estimated at the market-retailer-product line level. Since there is no reason to believe that the marginal costs of retailers, excluding wholesale costs, vary with private label entry, I use total marginal costs as a proxy for wholesale costs. Given that bargaining outcomes vary across different levels of product definitions, I present two separate sets of regressions in Table 8. Private label entry is defined at the DMA-quarter-retailer level, but I do not include DMA-quarter fixed effects in these regressions, as they would absorb much of the variation in entry. Instead, I control for differences in geographical market structure by including fixed effects for the DMA codes. To account for variations in demand conditions, I include quarter fixed effects. Finally, to capture varying levels of bargaining power for each product or product line, I use product or product line fixed effects, depending on the regression level.

In addition to *Entry* and *Private label entry*, I include *Distance to closest entrant* and its interaction with *Private label entry* in columns 2 and 5. The *Distance to closest entrant* variable measures the distance in product space between a national brand and private label entrants. In cases with multiple private label entrants, it reflects the distance from the national brand to the most similar private label entrant. Furthermore, I approximate retailer size using the *Number of stores*, which is a regional proxy of retailer size. This aligns with the assumption that negotiations occur at the DMA level, where only the local size is relevant. To study the relevance of retailer size, I also interact it with *Private label entry* to estimate the differential impact of private label entry on bargaining outcomes.

I find evidence that private label entry enhances retailer bargaining power. Specifically, it leads to a significant reduction in marginal costs (column (1)) and an increase in lump-sum transfers (column (5)). These effects are robust across all specifications, except for column (8), where the sample lacks sufficient statistical power to identify the effect of entry and its interaction with Number of Stores. To better assess the economic magnitude of these effects, I compare the estimates in columns (1) and (5) in terms of standard deviations. A one standard deviation increase in private label entry reduces marginal costs by 0.01 standard deviations and increases lump-sum transfers by 0.04 standard

Table 8: Effects of Product Entry on Bargaining Power

Dependent Var.:	Marginal Cost				Lump-sum Transfer			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Entry	-0.000	-0.000	-0.000	-0.000	-18.50	-18.40	-4.21	-5.01
	(0.000)	(0.000)	(0.000)	(0.000)	(6.47)	(6.45)	(4.51)	(4.52)
Priv. label Entry	-0.001	-0.001	-0.001	-0.001	28.87	26.81	21.36	3.85
	(0.000)	(0.000)	(0.000)	(0.000)	(12.74)	(13.14)	(10.45)	(15.12)
Distance to closest entrant		-0.011				19.64		
		(0.010)				(242.2)		
Priv. label Entry x Dist		0.000				25.83		
		(0.001)				(34.56)		
Number of Stores (Stores)			-0.000	-0.000			-14.76	-15.50
			(0.000)	(0.000)			(5.06)	(5.50)
Priv. label Entry x Stores				0.00008				0.33
				(0.00003)				(0.26)
Fixed Effects	DMA code, Quarter, Product				DMA code, Quarter, Product line			
S.E. Type	Clustered				Clustered			
Observations	507,429				73,386			

Notes: Standard errors in parentheses. Private label products not part of these descriptives. Analysis run at market-retailer-product level.

deviations. This highlights the importance of tracking changes in lump-sum transfers resulting from private label entry, as the change in lump-sum transfers is four times larger than the change in wholesale costs. Although the changes in standard deviations are small, I demonstrate at the end of this section that their economic significance is substantial.

Another hypothesis outlined earlier in the paper is that the effect of private label entry on bargaining power is stronger for national brand products that are closer in product space. The underlying intuition is that when a private label serves as a strong substitute for a national brand, the national brand's outside option weakens, leading to a greater loss in bargaining power. However, I do not find evidence to support this hypothesis, as the effects are not significant for marginal costs (column (2)) or for lump-sum transfers (column (5)).

This effect has been documented in prior work, such as Meza and Sudhir (2010), who analyze data from a single retailer. They identify imitating private labels using internal retailer data and confirm imitation by examining individual product characteristics. In contrast, my study draws on market-wide data, which allows for broader generalizability. However, due to the anonymization of retailers in the Nielsen dataset, I am unable to map private label products to specific national brand counterparts. As a result, I cannot definitively determine whether a given private label product imitates a national brand. Instead, I rely on the closeness in product space, measured through characteristics such as premium, superpremium, and flavors. The difference in findings suggests that for a retailer to capture additional bargaining power, they must design their product to closely resemble the national brand they wish to imitate. Merely replicating the product in terms of characteristics is insufficient.

The final hypothesis outlined in Section 4 concerns how the impact of private label entry varies with retailer size. The theoretical model suggests that the more credible the threat of replacement via private labels, the stronger the incentive for producers to improve the competitive position of smaller retailers. This strategic support helps discipline the bargaining power of larger retailers by increasing the competitive pressure from their smaller competitors.

I find full support for this claim. While the negative effect of private label entry on marginal costs is significantly larger for smaller retailers (column (4)), there is no significant difference in lump-sum transfers (column (8)). Improving lump-sum transfers for smaller retailers does not enhance their competitive threat to larger retailers. Instead, producers reduce wholesale costs, which lowers the marginal costs for small retailers, leading to lower prices. This, in turn, may discipline larger retailers in their negotiations with producers, as their replacement threat becomes weaker. The heterogeneity of the effect is substantial, which can be illustrated by comparing the impact of an additional private label on small and large retailers. For instance, when defining small retailers as those in the 1st quartile of *number of stores* and large retailers as those in the 3rd quartile, one additional private label reduces marginal costs by 0.0012 for small retailers, compared to 0.0006 for large retailers, making the decrease twice as large for smaller retailers.

Finally, it is important to discuss the total impact of private label entry in terms of variable retailer profits. Ignoring potential changes in the price set by the retailer[13], I calculate the impact of a reduction in wholesale costs due to the entry of one private label product in a given market-retailer pair, compared to the change in lump-sum transfers. On average, one additional private label entry increases variable profits by about 0.7%, which translates to approximately $5,195.14. In comparison, the change in lump-sum transfers results in an average increase of $882.61, considering that there are on average 30 national product lines per retailer-market pair. This corresponds to a median profit change from lump-sum transfers of about 3.5%.[14] While the change in marginal costs leads to larger profit changes in nominal terms, the change in lump-sum transfers results in a larger relative change, making it a crucial factor to track when studying changes in bargaining power.

8 Conclusion

This work explores the role of private labels in influencing bargaining power between retailers and producers, with a focus on the U.S. ice cream market. To understand the dynamics of bargaining power, I estimate vertical contracts consisting of wholesale costs and a lump-sum transfer, often referred to as shelving fees or vendor assortment fees.

[13] It is possible to account for the change in prices that the retailer would set. Moreover, the replacement threats in this case would also change, implying a change in lump-sum transfers. As a proper account of the chain of reactions would require extending the structural model with an entry stage, I abstain from modelling only part of the reactions here.

[14] Due to the presence of several product lines with zero or near-zero lump-sums, leading to very high percentage changes in lump-sum transfer profits with entry, the mean is not a meaningful measure.

This extends previous literature on the role of private labels. I find that the profit margin of retailers is about 39%, consistent with findings from NACS' yearly retailing industry report.[15] Moreover, shelving fees account for approximately 24% of retailers' variable profits according to my estimates, underscoring the importance of tracking these fees to understand the impact of private label entry on bargaining power.

The findings show that the introduction of private labels plays a significant role in reshaping retailer-supplier negotiations. More specifically, private label entry leads to lower wholesale costs and higher shelving fees, indicating an increase of bargaining power for retailers. On average, the entry of an additional private label increases a retailer's variable profits by approximately 0.81% in a given quarter, emphasizing the economically significant role of private labels in the retail market.

During the sample period, the ice cream market experienced a process of premiumization, where higher-quality, more expensive products became more prominent. Intuitively, one might expect retailers to introduce premium private labels to gain a competitive edge in bargaining over the increasingly important superpremium national brands. However, the empirical evidence does not support this expectation, as private labels closely aligned with national brands in terms of product characteristics do not result in stronger bargaining power. Packaging and brand identity, which could potentially improve bargaining power, are not captured in the Nielsen data due to retailer anonymity. Future research could explore whether private labels imitating (super-)premium brands have been more successful in improving bargaining power over national (super-)premium brands.

Finally, this study provides both theoretical and empirical evidence that smaller retailers may benefit more from private label entry through improved bargaining power. One important caveat is that private labels are sometimes supplied by producers who also sell national brands in the same market. This dual role may alter the dynamics of bargaining, as producers negotiate over both their own brands and private label products with the same retailer. These complexities were not addressed in the current analysis and present a promising direction for future research.

[15] NACS (National Association of Convenience Stores) is a global trade association that supports convenience and fuel retailers by providing resources, networking, research, and advocacy to advance the industry.

Chapter II

Does Peter Piper Pick Pepper Inattentively? Consumer Inattention to Package Content

Joint with Ian Meeker

1 Introduction

Food manufacturers sometimes replace packaged goods with smaller versions, a practice known as product downsizing. Some manufacturers shrink their packaging to reflect the reduced content, but some do not. Examples of downsizing abound. In 2024, Tropicana reduced the amount in its orange juice bottles by 12 percent from 52 to 46 fluid ounces; Purina reduced the amount in its Kidney Function dog food by 26 percent from 34 to 25 pounds; and Kellogg's reduced the amount in boxes of Frosted Mini-Wheats by 11 percent from 18 to 16 ounces (Dworsky, 2024). As these examples show, product downsizing occurs across a wide range of products.

Downsizing is a way to increase unit prices (i.e. price per ounce), keeping package prices constant while reducing package content. Most firms do not advertise such size changes. To identify downsizing, consumers must correctly process the available sizes. Because many consumers use visual estimates in place of explicit size information, they may fail to notice the reduced content as firms downsize their products in a number of different, and often subtle, ways. If consumers are inattentive, downsizing represents a hidden price increase.

Rising grocery prices have brought renewed concern over the use of downsizing to shroud unit price increases. These concerns have prompted policy interest in and action against downsizing in the US and Europe. Since July 2024, France requires retailers to notify customers whenever a product is downsized (Adamson, 2024). In the US, recently proposed legislation would direct the Federal Trade Commission to establish downsizing as deceptive practice.[16]

In this paper, we examine whether consumers are in fact inattentive to downsizing and consider the welfare implications of inattention. We develop a novel method to recover inattention using a standard random-coefficient discrete choice framework. We apply this method to test whether consumers are inattentive to reductions in package content in the pepper industry. In the model, inattention results in consumers evaluating product utility according to the product's original net weight, causing the change in the net weight to enter utility as an additional product characteristic with a random coefficient. The distribution of this random coefficient characterizes the degree of inattention. Estimating

[16] Shrinkflation Prevention Act of 2024, S. 3819, 118th Cong. (2024) `https://www.congress.gov/bill/118th-congress/senate-bill/3819/text`

the extent of inattention thus amounts to estimating the distribution of the random coefficient, allowing us to estimate the model using standard, demand estimation techniques.

We consider a downsizing event in the pepper industry where McCormick, the industry's largest firm, shrank the content of eleven black pepper products, representing 33% of the market. This downsizing event provides an ideal opportunity to study inattention due to the wide range of available sizes. Consumer substitution between products with different net weights allows us to estimate how much consumers value net weight.

Intuitively, our model recovers inattention by comparing how market shares actually change after downsizing to how they should change given consumers' underlying preferences for net weight. When consumers are inattentive, they will not switch to other products after the downsizing and the share of the downsized products remain the same. However, when consumers are attentive, some will switch to other products after the downsizing and the share of the downsized products will decline. The difference between the observed market shares and the expected market shares after downsizing captures inattention. Because of the wide range of sizes, our paper is the first study to quantify inattention to downsizing. Existing variation is necessary to construct the expected trend.

Applying the model to retailer-level data from NielsenIQ, we find that almost all consumers fail to notice a change in the net weight. Inattention explains why consumers do not substitute away from the downsized product despite preferring more pepper to less. Overall, we find that consumers are far more sensitive to changes in package prices compared to changes in net weight even when fully attentive.

Motivated by ongoing policy debates, we consider two counterfactual scenarios. In the first scenario, we eliminate consumer inattention. This counterfactual assesses how policies aimed at increasing attention to downsizing, like a recent French law, may affect consumer welfare. The second counterfactual scenario examines the impact of a ban on downsizing.

Despite consumers being more sensitive to changes in package prices compared to changes in net weight, the removal of inattention has a large impact on consumer choices. The share of the downsized products falls by around 7.5 percentage points (or about 20-25 percent) relative to other pepper products. The changes in market shares translate to a 2.7 percent increase in consumer welfare.

Banning downsizing results in a smaller improvement in consumer welfare of 2.4 percent. In this case, the benefit from larger packages is outweighed by higher package prices. Banning downsizing is welfare-enhancing because it eliminates the inattention problem. If package content does not change, there is nothing for consumers to be inattentive to. Our results indicate that banning downsizing is only an effective policy tool if nudges are ineffective or if the rate at which consumer learn about downsizing is slow.

2 Literature

We add to a scarce literature on downsizing. Only two papers document the extent of downsizing among consumer packaged goods in the US. Looking at the period from 2010 to 2020, Janssen and Kasinger (2024) finds that downsizing occurred across a wide range of product categories from candy to pet care. Similarly, Rojas et al. (2024) finds that average package sizes have decreased in the last decade. Both papers highlight the role of manufacturers and retailers in the trend toward smaller sizes. In some cases, manufacturers are shrinking their products and in other cases, retailers are choosing to stock smaller products even when larger versions exist.

More papers examine how consumers respond to downsizing events in particular industries. Cakir and Balagtas (2014) and Yonezawa and Richards (2016), for instance, find that consumers are less sensitive to size than package price in the ice cream and cereal industries, respectively. Neither explore why consumers appear to undervalue package content. In a study of the Korean milk industry, Kim (2024) finds that consumers prefer downsizing to price increases and additionally, that this preference persists over time. He argues that the benefit-price ratio of a product is higher for downsizing relative to a price increase for fully rational consumers. Examining canned tuna, Harris-Lagoudakis et al. (2024) show that consumers in states requiring unit price disclosures are more responsive to downsizing and that consumers benefit from increased information about unit prices.

Looking across industries, Janssen and Kasinger (2024) find that consumers react more to increases in package price than decreases in package size. This differential is not present for upsizing, suggesting that firms may be obfuscating sizes decreases, but highlighting price increases.

Given consumers' insensitivity to size, several articles consider firm's decisions to use downsizing. Cakir (2022) shows that firms that use downsizing are able to achieve higher pass-through rates, implying that downsizing can be an effective strategy to increase profits. In contrast, Yonezawa and Richards (2016) find that price and size are strategic complements and that downsizing intensifies price competition, reducing the profits of the downsizing firm.

We explore whether inattention explains consumers' apparent preference for downsizing. Consumers frequently ignore explicit information on net weight and instead rely on visual cues (Lennard et al., 2001). Visual estimates can be inaccurate as they are subject to cognitive biases. For instance, consumers perceive tall, narrow objects to be larger than short, wide objects of the same volume (Krishna, 2006). Such perception biases grow when the packaging changes across multiple dimensions (Chandon and Ordabayeva, 2009). Particular packaging changes can result in consumers failing to notice even a 24% decrease in package size (Ordabayeva and Chandon, 2013).

Consumers' poor grasp of volumes translates to unit prices as well. Many consumers do not compare unit prices across different sizes of the same product and often pay a surcharge for larger quantities (Clerides and Courty, 2017). Consumers who do not compare unit prices within brands are unlikely to compare unit prices across brands. This suggests that downsizing can be an effective strategy to hide an increase in the unit price. Determining the level of inattention is important as it dictates the degree to which firms can engage in downsizing.

Consumers exhibit inattention and cognitive biases in a variety of settings. A large literature demonstrates that consumers do not pay close attention to shrouded attributes, like shipping costs (Brown et al., 2010) or sales taxes (Chetty et al., 2009). Consumers can also misperceive product attributes. Allcott (2013), for example, finds that consumers misjudge the value of fuel economy when choosing cars. In some cases, consumers give particular attributes too much consideration. For instance, many consumers place overemphasize the left-most digit and pay higher prices for cars whose mileage falls below 10,000 miles (Lacetera et al., 2012). If cognitive biases can influence major purchases, they should also impact minor ones.

Even if consumers are inattentive to changes in package content, exploiting inattention comes with risks. Consumers may feel deceived and react negatively toward the downsizing brand upon discovery of the size decrease. In lab experiments and surveys, consumers presented with downsized products expressed a lower willingness to buy the presented brand (Kachersky, 2011; Wilkins et al., 2016; Evangelidis, 2023). Evangelidis (2023) finds that participants are more likely to view downsizing as unfair compared to an equivalent price increase due to their beliefs that downsizing is deceptive. The possibility of a backlash may explain why many firms do not advertise their downsizing decisions.

A number of studies provide methods to identify and to recover inattention to product attributes. Abaluck and Compiani (2020) test for inattention using the cross derivatives of the choice probabilities. Their method is not applicable in our context because it assumes that consumers ignore the hidden attribute when searching. Brown and Jeon (2020) provide a method for recovering consumers' information processing strategies grounded in a rational inattention framework. For their method to be tractable, they place restrictions on the prior distribution of product utilities and hence the information processing strategy. In contrast, our model recovers the level of inattention without functional form assumptions, but unlike Brown and Jeon (2020), our model does not explain how consumers become inattentive.

Our model fits with other papers that estimate random coefficient choice models with discrete types (e.g. Doi, 2022; Greene and Hensher, 2013; Fox et al., 2011; Berry and Jia, 2010; Berry et al., 2006). One difference from these papers is that our types have a clear interpretation based on attention and inattention. Our model is closest to Greene and Hensher (2013) as it incorporates both discrete and continuously distributed random variables. However, unlike Greene and Hensher (2013), we estimate an aggregate demand model in the style of Berry et al. (1995b), rather than using maximum likelihood or the Expectation-Maximization algorithm.

3 Data

3.1 Summary

To analyze downsizing, we use the NielsenIQ Retail Scanner data and the NielsenIQ Consumer Panel data from the Kilts Center at the University of Chicago. The Retail Scanner data provides weekly point-of-sale data for around 35,000 stores in the United States and covers over 4 million consumer package goods. The Consumer Panel data provides a micro-level panel of consumer purchases, which tracks between 40,000 and 60,000 households. We use the Scanner data from 2014 to 2016 in the structural estimation and we use the individual-level purchase data to inform the modeling.

Pepper products encompass a wide variety of spices that add heat and flavor to food. The products range from true pepper, *Piper nigrum*, to botanically unrelated chilies like cayenne and include seasoning blends whose primary ingredient is pepper like lemon pepper. In the scanner data, we observe 1,468 unique pepper products, which we categorize into 22 different varieties. The two most popular varieties are black and white pepper, which account for 63.9 percent of sales. Other pepper popular categories include red pepper, cayenne pepper, and black pepper blended with some type of citrus. Many of the pepper categories are quite niche and have only a few products. We group these pepper categories into a single other category.

Pepper is staple seasoning with the majority of households purchasing it at least once in the five-year span from 2012 to 2016.[17] While most consumers will purchase pepper at some point, they do so infrequently. In any given year, only around 40% of consumers buy pepper. Many go over a year before purchasing pepper again. Long interpurchase times are due to pepper's high storability. As pepper products come from dried berries or chilies, they do not easily spoil, but instead lose their pungency over time (Feucht, 2019).

The different types of pepper in flavor and heat levels. However, pepper products of the same type are very similar in most respects as they come from the same plants. Products within the same variety differ slightly in terms of quality and taste which stem from differences in soil, climate, and processing method. For a given type of pepper product, the largest differences are in branding and packaging. From 2014 to 2016, there are 247 different brands in the scanner data.

Given the similarity between products, many consumers opt for cheaper store brands. Store brands capture around 40% of the market during this period. In contrast, the typical name brand is a small and regional with a market share that is less than 0.1%. Among name brands, McCormick stands out with its 40% market share. The brand's owner McCormick & Co. dominates the industry, owning three of the top five selling name brands in McCormick, 5th Season, and Spice Classics. Through its various brands and private labels, the company controls around 50% of the market. The next largest firm B&G Foods, the producer of the brands Tone's and Durkee, accounts for approximately

[17]Author's calculation based on a balanced panel from the NielsenIQ Consumer Panel data.

2.5% of the market and almost no other brands exceed more than 2% of the market.

In addition to the large number of brands, the industry features a wide array of product weights. In the consumer panel data, products range from 0.4-ounce bags to 32-ounce containers with many weights in between (Figure A2)[18]. Examining the histogram of weights purchased from 2014 to 2016 among the panelists, the most-frequently purchased sizes were two and four ounces, which correspond to the standard weights of small and medium tins of black pepper, respectively.

Most stores in the scanner data offer these two sizes of black pepper along with many others. The typical store offers 23 different sizes of pepper products at any given month (Figure A3), 14 of which are black pepper products. Some stores offer as many as 53 distinct sizes and others as few as a single size. Although most stores offer more than twelve sizes, a noticeable percentage of stores offer a limited variety, having fewer than four distinct sizes at a given point in time. Differences in the available sizes across stores force consumers to substitute to similarly sized products and directly reveals consumer substitution patterns, which in turn allows us to separate size preferences from inattention.

In addition to the scanner data, we have monthly data on spot prices for black and white pepper from the International Pepper Community. We use this data in the later structural estimation to construct instruments.

3.2 Estimation Sample

The sheer size of the data creates computational challenges during the structural estimation. The weekly store-level data has more than 40 million observations. To ease the computational burden, we aggregate the data from the store-level to the level of retailer and designated market area (DMA).[19] As DellaVigna and Gentzkow (2019b); Hitsch et al. (2021) show, prices and product offers are very similar within the same retailer. Aggregating to the DMA level preserves some of the geographic variation in the original data. We also aggregate from weekly data to monthly data. Given the infrequency of pepper purchases, we do not need to worry about consumers buying multiple products in a given month. After aggregating, we have 1,369 retailer-DMA combinations for a total 1,377,556 observations. For simplicity, we will refer to a retailer-DMA combination as a retailer in what follows.

In the estimation sample, the typical retailer offers 30 unique sizes of pepper products with most retailers offering between 22 and 52 different sizes. Figure A4 shows the number of unique sizes offered at a retailer in a given month. As with the store-level data, there are some retailers that offer a limited selection of sizes. While the aggregation process inflates the number of distinct sizes, the overall variation is similar to that of the store level.

[18] There are a few outliers of 80-ounce sales

[19] Following DellaVigna and Gentzkow (2019b) and others, we define a retailer as a combination of the fields *parent_code* and *retailer_code*.

In estimation sample, the mean price of a pepper product during this period was \$3.93. Most prices are between \$0.99 and \$7.99. This translates to an average unit price of \$0.84 per ounce. The vast majority of unit prices fall between \$0.01 and \$4.00.

4 Downsizing in the Pepper Industry

4.1 Background

Downsizing in the pepper market came in response to rising commodity costs. Figure A5 shows the wholesale price of pepper over time. From 2009 to 2014, wholesale black pepper prices were increasing due to growing demand in emerging markets. With prices trending upward, a poor harvest in 2014 caused wholesale prices to spike. Over the course of 2014, the wholesale price of black pepper increased by over 30%. Manufacturers responded to this sudden cost increase in different ways. Most chose to increase their product prices, while others like McCormick and Spice Classics reduced the content of select black pepper products. Except for one blend pepper product, these firms only adjusted their black pepper products.

Faced with higher wholesale prices, retailers responded by adjusting their product offerings, with some phasing out larger products for smaller ones. In addition, some retailers chose to downsize their store-brand black pepper products. A federal court noted that McCormick asked the private-labeled brands that it manufactures to reduce their fill levels and most agreed to the new smaller sizes for black pepper (in-, 2019).

McCormick downsized its black pepper products and store brands in February 2015. McCormick initially downsized its products by reducing the fill levels while keeping the packaging the same size. The company eventually adjusted its package sizes to reflect the reduced content in the middle of 2016 (in-, 2019).[20] This change is not observable in the data as it does not affect the product codes or descriptions. We do see some private-label brands that switch their packaging from glass to plastic after downsizing.

4.2 Identification of Downsized Products

Downsized products can have different Universal Product Codes (UPCs) than their original versions. To determine the downsized products present in the data, we examined the unit sales of every pepper product over time. As retailers sell out their existing product inventories and stock up on the new smaller version, sales of the original product should decrease and sales of the downsized version should increase. We therefore look for a pattern of declining sales for one product and increasing sales for another slightly smaller product with an identical description. For private-label products, we consider the total units sold across stores within the same retailer.

From comparing time series plots, we identified 30 downsized products, including 15 McCormick and 15 private-label products. Table B1 provides a complete list of the name

[20] See **(alias?)** (2015, p. 7) for a side-by-side comparison of downsized tins.

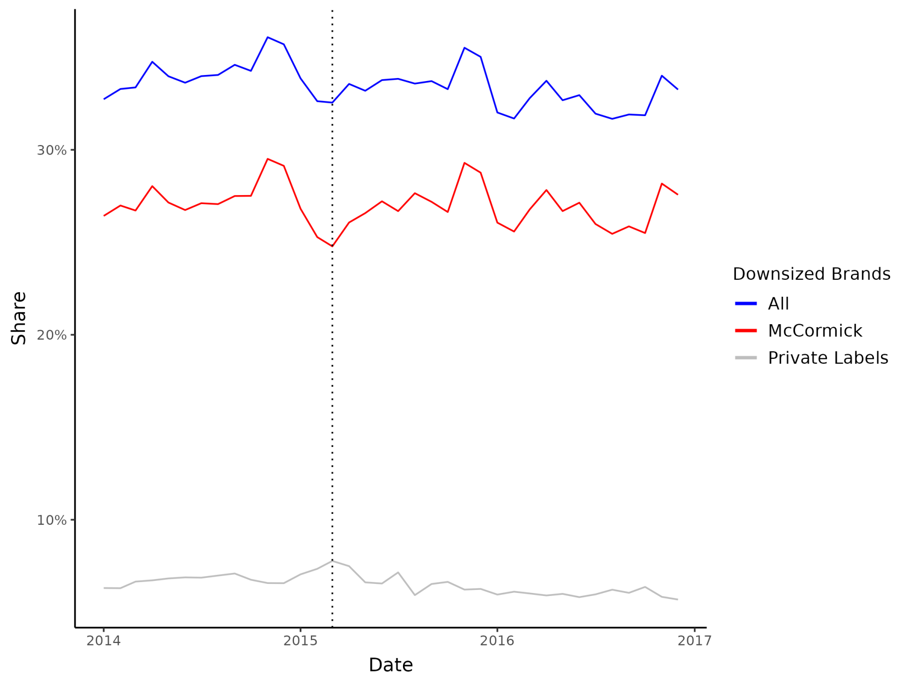
brand products in the estimation sample. Spice Classics and Spice Supreme are the only other name brands to engage in downsizing with each shrinking only a single product. The sales of these two products are negligible and as such, we ignore them and instead focus on downsizing by McCormick and private labels.

4.3 Market Shares and Prices

While the number of downsized products is small, these products account around 33.5 percent of all pepper sales in the data. McCormick's downsized products account for around 27 percent of sales and the downsized private-label products for around 7.5 percent.

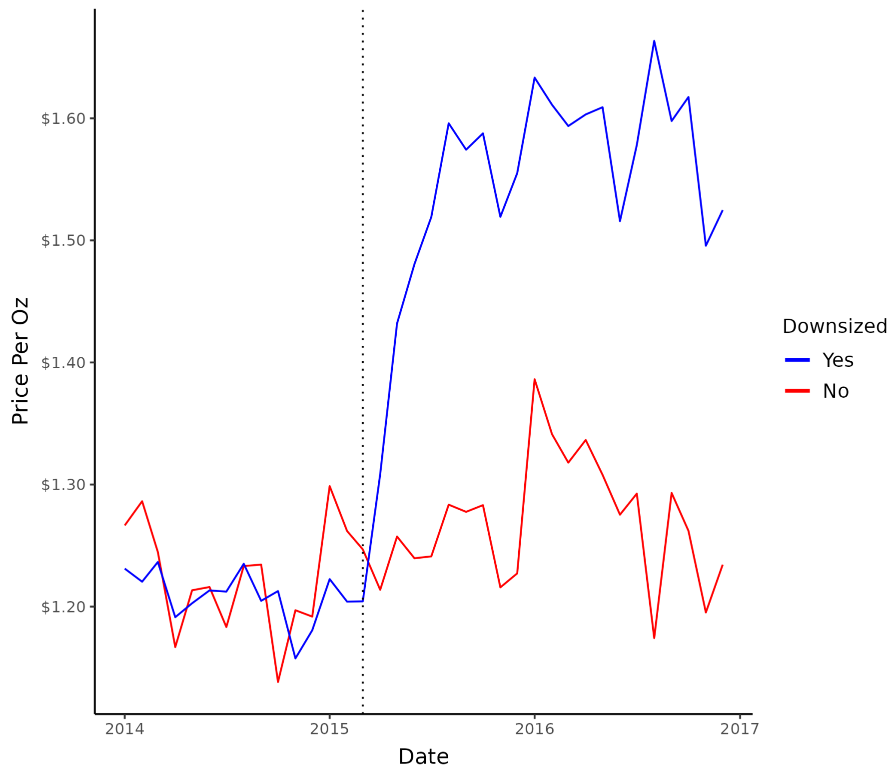
Figure 5 shows the share of the downsized products, separately by McCormick and private labels. The dashed line represents the date when McCormick started to ship its downsized products. The shares include the sales of both the original and downsized versions. Before downsizing, the share represents the original product. Just after downsizing, the shares represent a combination of downsized and original versions as retailers sell out their existing inventory of the original version and replace it with the new version. By the middle of 2016, the share mainly reflects shares of the downsized version.

Figure 5: Market shares of the downsized products



As the figure shows, the share of the downsized products is stable over time both for McCormick and the private-labels products. The stability of the shares is surprising given the unit price changes. Figure 6 shows the average price per ounce of the downsized products relative to the nondownsized products. From 2014 to 2017, the average unit price of the nondownsized products increased by \$0.10. In contrast, the average unit price of the downsized product increases by around \$0.35, more than three times the amount of the non-downsized products. Despite this large increase in relative unit prices, there was not a corresponding decline in the share of the downsized products.

Figure 6: Unit prices



There are several possible explanations for the observed trends in shares and unit prices. The first is brand loyalty. Consumers may have a strong attachment to the downsized products and as a result, do not substitute away from these products despite high unit prices. However, given that black pepper products are fairly homogeneous, strong brand attachment is irrational in some sense.

Another possibility is that fully rational consumers are more sensitive to package prices than package content. In his article on downsizing in the milk industry, Kim (2024) argues that consumers do not respond to content reductions because consumers receive more surplus from downsizing than an equivalent price change. Our structural model accounts this possibility.

We focus on a third possibility that consumers are inattentive. Consumers do not respond to downsizing because they do not notice it. Consumers underuse the available information on net weight and unit prices to their detriment.

None of the explanations for downsizing are mutually exclusive. For instance, consumers can be less sensitive to size changes and inattentive. In that case, consumers will substitute away from the downsized product by very much even if they were fully attentive.

5 Evidence of Inattention

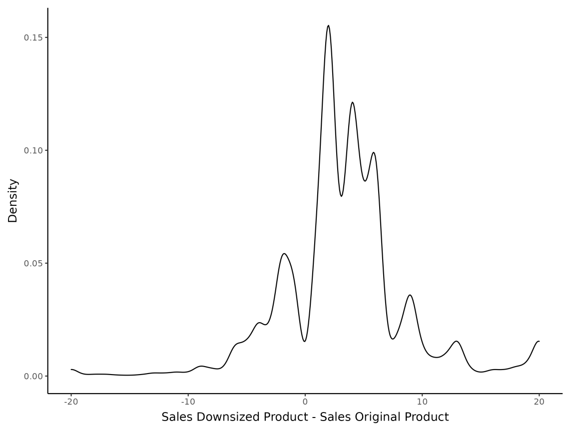
Sales at stores that sell both the original and downsized versions at the same time provide evidence of inattention. During the transition period from the old product to the new one, some stores start to stock the downsized version before selling out of the original, resulting in both versions appearing together and in some cases, side by side.[21].

In the data, we observe 2,558,006 store-weeks where consumers buy both the original and downsized versions of a product in the same week. This does not mean that the products appear together. Because stores report their units sold weekly, a store could sell out of the original product on Wednesday and start selling the new product on Thursday. Subsequently, both products would appear in the scanner data in the same week without being together on store shelves. To minimize this possibility, we restrict to store-weeks where the downsized product appears before the last week where the original product has positive units sold. This smaller sample consists of 374,848 store-weeks.

We further focus on McCormick's downsized products as McCormick did not initially change its packaging. McCormick's original and downsized products are identical except for the fill levels and the statement of net weight. In many cases, the original and the downsized products even have the same package price. Restricting to McCormick products leaves 107,752 store-weeks in the overlap sample.

Figure 7 shows a density plot of the difference in sales between the downsized and original products for pairs that have the same package price. The plot shows that the downsized product is more popular than the original. Consumers are choosing to pay a higher unit price for less pepper. Given that the products are identical expect for the fill level, it is hard to explain this difference without appealing to inattention.

Figure 7: Differences in sales of a downsized product pair



The difference in units is top/bottom coded at the values -20 and 20.

To extend this analysis to product pairs with different packaging prices, we regress the difference in the number of units sold of the downsized product and the original product

[21]For an example, see page 10 of the complaint in **(alias?)**.

on the difference in the package prices. If consumers are fully attentive, they should switch quickly to the original product as the downsized version becomes relatively pricier. Table 9 reports those results. In order to mitigate the impact of outliers on our regressions, winsorize 1% of both the difference in sold units and in prices of the extreme values. We report the winsorized results in specifications (3) and (4).

In many cases, the original and downsized products do not sell in the same week but are available.[22] As such, we do not observe both prices at the same time. We impute the missing prices in these cases and report the results in specifications (5) and (6).

Table 9: Difference in sold units between downsized products and their original counterparts

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.320		2.175		2.772	
	(0.026)		(0.029)		(0.012)	
Price Difference	-0.490	-0.462	-0.681	-0.786	-0.441	-0.412
	(0.053)	(0.056)	(0.035)	(0.231)	(0.028)	(0.029)
Num. Obs.	107,752	107,752	107,752	107,752	398,102	398,102
Product & Time FE	NO	YES	NO	YES	NO	YES
Winsorize	NO	NO	YES	YES	NO	NO
Imputed Prices	NO	NO	NO	NO	YES	YES

The negative coefficient on the price difference implies that consumers will switch to the original product as the downsized product is more expensive. However, if we consider the magnitude, we find that consumers are not responsive enough. Using the most conservative result of a coefficient of -0.786 in specification (4) implies that the downsized product needs to be at least 1.5 dollars more for a single consumer to switch from the downsized to the original. For context, pepper products cost around two dollars on average so 1.5 dollars is almost an additional unit. Consumers are simply not responsive enough to price differences and inattention may be part of the reason.

Overall, these descriptive results suggest that consumers fail to notice downsizing. Under equal prices, they choose the downsized product more often than the original version. Generally, they do not respond nearly enough to differences in the package price, preferring instead to buy the more expensive downsized product.

6 Product Choice under Inattention

6.1 Model

In period t, M_{kt} consumers visit retailer k looking to buy pepper.[23] Each consumer selects one product from the available pepper products J_{kt} or selects the no-purchase option 0.

[22] We observe sales of the original version in subsequent weeks.

[23] Note that k indicates a retailer-DMA combination.

Consumer i's *actual* utility from purchasing product j is:

$$U^a_{ijkt} = x_{jkt}\beta + \gamma_i z_{jkt} - \alpha_i p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \tag{5}$$

where x_{jkt} is a set of observable characteristics; p_{jkt} is the price; z_{jkt} is the current net weight; ξ_{jkt} is the unobserved product attributes; and ϵ_{jkt} is a random shock. The utility of the outside option is:

$$U^a_{i0kt} = 0 + \epsilon_{i0kt} \tag{6}$$

Some consumers may be inattentive and fail to notice changes in net weight. They may remember the old weight and simply assume that weight has not changed since their last purchase. Other consumers may evaluate product weights based on package sizes and mistakenly conclude that the downsized products have the same weight as rival products because they have the same package size.[24] Regardless why inattention occurs, inattentive consumers evaluate the product using its original product weight, whereas attentive consumer evaluate the product using its current product weight.

Consumers are either attentive or inattentive to downsizing. Let τ_i be an indicator for whether consumer i is attentive. An *inattentive* consumer evaluates the downsized product j using its original weight and *perceives* his utility from j as:

$$\begin{aligned} U^p_{ijkt} &= x_{jkt}\beta + \gamma_i z_{jk0} - \alpha_i p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \\ &= x_{jkt}\beta + \gamma_i z_{jkt} + \gamma_i\big(z_{jk0} - z_{jkt}\big) - \alpha_i p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \\ &= U^a_{ijtk} + \gamma_i \Delta_0 z_{jkt} \end{aligned} \tag{7}$$

where z_{jk0} is the original weight before downsizing and $\Delta_0 z_{jkt} = z_{jk0} - z_{jkt}$ is the change in the product weight. In our context, product weights change once or not at all. If the size changes in period t', $z_{jkt} = z_{jk0}$ for all periods $t < t'$. In contrast to actual utility, perceived utility depends both on the current and original weight. Inattention drives a wedge between the perceived and actual utility for downsized product j equal to $\gamma_i \Delta_0 z_{jkt}$.

For attentive consumers, actual and perceived utility are the same. We can write the perceived utility of any consumers as:

$$U^p_{ijkt} = U^a_{ijtk} + (1 - \tau_i)\gamma_i \Delta_0 z_{jkt} \tag{8}$$

where τ_i is an indicator for if the consumer is attentive. Because types are idiosyncratic and not observable, we can view τ_i as a random coefficient that follows a Bernoulli distribution where the probability of success η represents the probability of being attentive. In essence, inattention causes the change in the weight to enter perceived utility as an

[24] In this case, consumers misevaluate product size only when rival products occupy a large enough shelf space. As the shelf space devoted to a product is not observable in the NielsenIQ data, we cannot model inattention stemming from a reference size.

additional product characteristic with a random coefficient. We denote the cumulative distribution function of the random coefficients as $G(\tau_i, \gamma_i, \alpha_i)$ where $\tau|_{\gamma,\alpha} \sim$ Bernoulli(η).

Assuming that the random taste shock ϵ is drawn i.i.d. from a Type I extreme value distribution, the consumer i's share for product j at retailer k in period t conditional on the random coefficients is:

$$s_{ijkt}(\beta, \alpha_i, \tau_i, \gamma_i) = \frac{\exp\left\{x_{jkt}\beta - \alpha_i p_{jkt} + \xi_{jkt} + \gamma_i z_{jkt} + (1-\tau_i)\gamma_i \Delta_0 z_{jkt}\right\}}{1 + \sum_{l \in J_{kt}} \exp\left\{x_{lkt}\beta - \alpha_i p_{lkt} + \xi_{lkt} + \gamma_i z_{lkt} + (1-\tau_i)\gamma_i \Delta_0 z_{jkt}\right\}} \tag{9}$$

Integrating over the joint distribution of the random coefficients, the unconditional retailer share for j in period t is:

$$s_{jkt} = \int s_{ijkt}(\beta, \alpha_i, \tau_i, \gamma_i) dG(\tau, \alpha, \gamma) \tag{10}$$

and the expected demand for product j in period t at retailer k is then:

$$Q_{jkt} = s_{jkt} M_{kt} \tag{11}$$

The model ignores retailer choice. This abstraction is reasonable as consumers select a retailer based on a basket of products rather just than pepper (Thomassen et al., 2017). In the consumer panel data, every household purchases pepper with another product and as such, pepper prices are likely not an important determinant of retailer choice.

6.2 Generalization

We can extend the model with two types to accommodate more varied forms of inattention by assuming that consumers are attentive or inattentive to specific products. With L downsized products, there are 2^L combinations of downsized products to which a consumer can be inattentive. In this more general framework, we need an indicator τ_{ij} for whether consumer i is inattentive to downsized product j. In all of the equations, we would have τ_{ij} rather than τ_i.

Because a consumer's type is not observable, perceived utility has a latent structure. A latent class consists of a combination of downsized products for which a consumer is inattentive. With L products, there are 2^L latent classes. The joint distribution $G(\tau, \gamma, \alpha)$ dictates the probability of observing any one type and hence the latent structure. This more general model accommodates many types of inattention. For illustrative purposes, consider a set of 4 downsized products ordered from smallest to largest in terms of the absolute change in weight. Consumers that belong to the latent class $\{1, 2, 4\}$ do not notice the change in size of products 1, 2 and 4. Complete attention corresponds to the case where all consumers belong to the class, $\emptyset$. In contrast, complete inattention corresponds to the case where all consumers belong to the class $\{1, 2, 3, 4\}$. Another possibility is that consumers notice changes above a certain threshold (e.g. Han et al., 2001). In this case, consumers who notice small changes in size must notice larger ones.

Under threshold perception, consumers must fall into one of 5 classes $\{\emptyset, \{1\}, \{1,2\}, \{1,2,3\}, \{1,2,3,4\}\}$. As these examples show, different assumptions about the type of inattention place different restrictions on the possible classes. While the modeling structure is flexible enough to find any of these outcomes as well as others, it scales poorly with the number of products. With just 20 products, the number of latent classes is well over a million. For computational tractability, we focus on the model with two types.

6.3 Identification

There are two sources of variation that help pin down the inattention parameter. The first is retailers that offer the original and downsized versions of the product at the same time. The second is deviations in market shares from consumers' preferences for net weight.

As discussed previously, there are many retailers that offer both versions of the product at the same time. Differences in the market shares after accounting for other factors points to inattention.

We need to be cautious about using these period of overlap to identify inattention. Because we are aggregating the data to the monthly level, we may incorrectly conclude that the downsized and original products appear side-by-side. The original product may sell out in the first week of the month and then the downsized product is sold in the remaining three weeks. The market shares would imply that consumers favor the downsized product when side-by-side when in actuality the retailer never offered these products together.

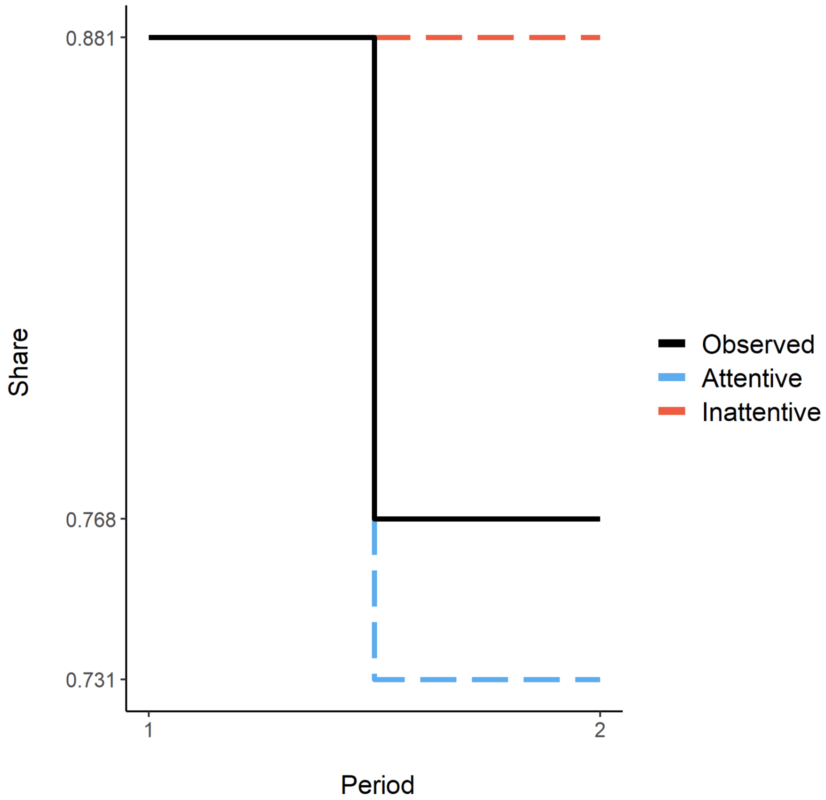
The second source of identifying is deviations in relative market shares from consumers' preferences for net weight. When a product's net weight decreases, its share should change in line with consumers' weight preferences when consumers are fully attentive. Inattention will dampen this response. Thus, a smaller than expected change in retailer shares or no change at all would indicate inattention.

If consumers are attentive, the difference in the shares of the original and downsized versions will reflect the difference in the weight all else equal. In contrast, if consumers are inattentive, there will be no difference in the shares. The degree of inattention therefore governs how closely the observed difference is to the expected difference.

The above logic applies not just to the original product, but to any product, including the outside option. As an illustrative example, consider a retailer that offers a single product over two periods $t = 1, 2$. In both periods, consumers can select the product or an outside option. The utility of the product is $u_{1t} = \gamma z_t + \epsilon_{1t}$ where z_t is the product's weight in period t and ϵ_{1t} is a random shock drawn from a Type I extreme value distribution and the utility of the outside option is $u_{0t} = 0 + \epsilon_{0t}$. Initially, the product's weight is 2 and its market share is $s_1 = \frac{e}{1+e} \approx 0.731$. The product's weight and market share imply a value of γ equal to $\frac{1}{2}$. Before period 2, the weight of product declines from 2 to 1.

Suppose that 20 percent of consumers are inattentive and fail to notice the change in downsizing. Figure 8 shows the observed change in market shares after downsizing (the black line), the change in market shares that would occur under complete attention (blue line), and the change in market shares that would occur on complete inattention (red line).

Figure 8: Market Shares



If consumers are fully attentive, the product's market share in period 2 will decrease in line with consumers' weight preferences to $s_2 = \frac{e^{0.5}}{1+e^{0.5}} \approx 0.622$ (the red line). However, if consumers are fully inattentive, they will evaluate the product's utility using the original weight $z_1 = 2$ and the product share would remain constant (the blue line). In reality, the observed product share (the black line) reflects a combination of attentive and inattentive consumers. The observed market share is $s_2 = \eta\frac{e^{0.5}}{1+e^{0.5}} + (1-\eta)\frac{e}{1+e}$ where η is 0.8, the fraction of attentive consumers.

The greater the fraction of attentive consumers the closer the observed trend is to the expected trend (a smaller vertical distance between the black and blue lines). Because of this, the difference between the observed change in the product's share and the expected change if consumers were attentive identifies the percentage of attentive consumers. The distance between the blue and black lines relative to the blue and red lines is 0.8, which is the faction of attentive consumers.

This comparison is possible only because the weight preferences γ are observable from the initial period and do not change over time. If γ is unknown or changes over time, we could not determine the product's share under complete attention.

This argument rests on weight preferences are time-invariant. If weight preferences change over time, a shift in weight preferences in favor of smaller amounts would also explain a smaller than expected decline after downsizing. The time-invariance of weight preferences is therefore a key identifying assumption for our estimation strategy.

6.4 Limitations

Our model has two main limitations. The first is that the model does not describe the frictions that lead to inattention. Consumers are either attentive or inattentive. This prevents us from considering how changes in information, like labels with unit prices, affect the degree of inattention. Other frameworks, like the rational inattention, would allow us to model the information acquisition process. This flexibility comes at the cost of clarity. A rational inattention model in the vein of Brown and Jeon (2020) requires specifying the functional form of the prior beliefs over product utility.

The model also abstracts away dynamics. Given pepper's long shelf life, consumers may make dynamic inventory decisions. For example, they may stockpile pepper products that are on sale. The consumer panel data suggests that stockpiling behavior is not of huge concern. Figure A6 shows the number of units purchased on any given shopping trip broken down by whether the product was on promotion. As the figure shows, the vast majority of consumers, over 84 percent, do not buy pepper on promotion. Moreover, when consumers buy pepper, they buy only a single unit. Very few consumers buy more than one unit even when the product is on promotion. In general, pepper products are rarely on promotion. All of this suggests that consumers buy pepper when they run out of it and modeling it as a static decision is reasonable.

7 Estimation Details

7.1 Market Size

Because the number of potential pepper customers M_{kt} is unobservable, we proxy for it using total sales in the seasoning product category. This product category includes pepper as well as various seasoning blends like Old Bay and spices like cinnamon. We assume that the number of potential pepper customers at a retailer is equal to the total sales of all such products at that retailer. We do not use the number of visitors to a retailer as many consumers never buy pepper.[25] Given this market size, the share of the outside option is between 60.5 and 97.1 percent and is 89.7 percent on average.

[25] About 20% of all panelists present from 2012-2016 have never bought pepper during this period.

7.2 Estimation Procedure

With the shares defined, we estimate our model of inattention following Berry et al. (1995b). In the inner loop, we find the unobservable demand shocks ξ_{jt} to equate the observed market shares with those predicted from the model. In the outer loop, we choose the model parameters to minimize sample versions of the unconditional moment restrictions $\mathbb{E}\left[\xi_{jt} z_{jt}\right]$ given instruments z_{jt}. For the instruments, we use a combination of exogenous product characteristics and the local differentiation instruments from Gandhi and Houde (2019a).

We allow random coefficients on price and net weight drawn from independent normals with means $\bar{\alpha}$ and $\bar{\gamma}$ and standard deviations σ^p and σ^w, respectively. The inattention parameter follows a Bernoulli distribution where a success indicates that a consumer is attentive. The probability of a success is η. Direct estimation of this probability can result in numerical problems due to the probability bounds. To avoid boundary issues, we recast the Bernoulli probability in terms of the logit so that we are estimating a continuous parameter. We define the probability of being attentive as:

$$\eta = \frac{e^{\zeta}}{1 + e^{\zeta}} \tag{12}$$

The random coefficient τ_i is a draw from this Bernoulli.

The inattention coefficient τ_i modifies the standard BLP estimation procedure slightly. Normally, one recovers mean utility with the BLP contraction and then recovers the fixed coefficients and the means of the random coefficients using an IV regression. However, with inattention, the random coefficient on net weight γ_i is multiplied by the inattention parameter τ_i. As a result, we need to search over the mean of the net weight distribution $\bar{\gamma}$ in the outer loop.

Following BLP, we rewrite the conditional shares in (9) in the following form:

$$s_{ijkt}(\beta, \alpha_i, \tau_i, \gamma_i) = \tau_i \frac{\exp\left\{\delta_{jt} + \mu_{ijt}\right\}}{1 + \sum_{l \in J_{kt}} \exp\left\{\delta_{kt} + \mu_{ikt}\right\}} + (1-\tau_i) \frac{\exp\left\{\delta_{jt} + \mu_{ijt}^{inattention}\right\}}{1 + \sum_{l \in J_{kt}} \exp\left\{\delta_{kt} + \mu_{ikt}^{inattention}\right\}} \tag{13}$$

where

$$\delta_{jkt} = x_{jkt}\beta - \bar{\alpha} p_{jkt} + \xi_{jkt} \tag{14}$$

and

$$\mu_{ijt} = \left(\bar{\gamma} + \sigma^w \nu_i^w\right) z_{jkt} + \sigma^p \cdot \nu_i^p \; p_{jkt} \tag{15}$$

$$\mu_{ijt}^{inattention} = \left(\bar{\gamma} + \sigma^w \nu_i^w\right) z_{jkt} + \sigma^p \cdot \nu_i^p \; p_{jkt} + \left(\bar{\gamma} + \sigma^w \nu_i^w\right) \Delta_0 z_{jkt} \tag{16}$$

with ν_i^w and ν_i^p being draws from standard normals.

We account for the Bernoulli parameter in closed form and do not have to integrate over its distribution. Following BLP, we can integrate over the normally distributed parameters to retrieve the estimated shares.

With this formulation, we can apply the standard BLP algorithm. We draw 100 randomized Halton draws from the distribution of the random coefficients. We simulate the shares and then use the BLP contraction mapping to recover δ. We then recover the parameters $(\beta, \bar{\alpha})$ using IV estimation. Finally, we find unobserved quality ξ as the residual and construct the sample moments to be minimized with two-step GMM.

To quantity the uncertainty around our estimates, we construct bootstrapped confidence intervals using 250 bootstrap replicates. When constructing the bootstrapped sample, we sample retailer-DMA combinations to preserve the structure of the data.

Finally, we also perform a Monte Carlo simulation to check the validity of our estimator. The simulation can be found in Appendix III. Using a specification similar to the one in our counterfactual analysis, we show that our procedure is able to correctly recover the true parameter values.

8 Empirical Results

8.1 Demand Estimates

Table 10 shows the point estimates and 95% confidence intervals from the BLP estimation. The different columns represent different specifications of the random coefficients. All of the specifications include the inattention term. Column (1) does not include random coefficients on price and net weight; column (2) includes a random coefficient on price, but not net weight; column (3) includes a random coefficient on net weight, but not price; and column (4) includes random coefficients on price and net weight.

All of the coefficients have the correct expected sign across all specifications. Consumers place a positive valuation on McCormick products. This is not surprising as McCormick is the industry leader and is the main brand of pepper in most stores.

Consumers also place a positive valuation on pepper products that contains whole peppercorns. Whole peppercorns stay fresher and more aromatic longer than pre-ground pepper. The grinding process releases some of the essential oils, making pre-ground pepper less fragrant. As a result, products with whole peppercorns are generally of higher quality.

All of the pepper categories have negative valuation relative to white pepper. Many categories like citrus, garlic, and red are less versatile and their use is more context dependent. These categories are not staple seasonings, unlike black or white pepper. Black pepper has a negative marginal utility relative to white pepper. White pepper comes from removing the outer husk of the peppercorn, giving white pepper its distinct flavor. Due to more processing, white pepper is more expensive, which accounts for its lower market share. The negative coefficient on black pepper indicates that white pepper is more popular after taking into account the difference in price.

As expected, the coefficient on price is negative; consumers prefer to pay lower prices. Specifications (2) and (4) include a normally distributed random coefficient on price. In both specifications, the standard deviations is positive and significantly different from

Table 10: BLP Results

	(1)	(2)	(3)	(4)
Means				
Price	-1.695	-1.933	-1.695	-1.933
	[-1.731; -1.666]	[-1.981; -1.863]	[-1.731; -1.663]	[-1.983; -1.778]
Net Weight	0.714	0.658	0.714	0.662
	[0.697; 0.729]	[0.630; 0.670]	[0.697; 0.731]	[0.597; 0.682]
McCormick	1.993	2.052	1.993	2.054
	[1.958; 2.029]	[2.014; 2.092]	[1.949; 2.028]	[2.005; 2.096]
Is Whole	0.157	0.061	0.157	0.058
	[0.132; 0.176]	[0.031; 0.078]	[0.137; 0.179]	[0.018; 0.098]
Black Pepper	-0.510	-0.417	-0.510	-0.403
	[-0.558; -0.471]	[-0.458; -0.360]	[-0.567; -0.455]	[-0.489; -0.337]
Blend Pepper	-0.195	-0.085	-0.195	-0.074
	[-0.227; -0.162]	[-0.109; -0.044]	[-0.227; -0.163]	[-0.150; -0.028]
Cayenne Pepper	-0.624	-0.596	-0.624	-0.586
	[-0.666; -0.588]	[-0.631; -0.546]	[-0.684; -0.583]	[-0.634; -0.532]
Citrus Pepper	-2.289	-2.207	-2.289	-2.194
	[-2.365; -2.226]	[-2.267; -2.113]	[-2.365; -2.208]	[-2.262; -2.100]
Garlic Pepper	-2.693	-2.650	-2.693	-2.642
	[-2.758; -2.626]	[-2.708; -2.582]	[-2.761; -2.622]	[-2.719; -2.569]
Red Pepper	-1.227	-1.161	-1.227	-1.247
	[-1.281; -1.185]	[-1.318; -1.205]	[-1.285; -1.169]	[-1.321; -1.198]
Other Pepper	-1.031	-1.017	-1.031	-1.047
	[-1.066; -0.992]	[-1.048; -0.987]	[-1.071; -0.994]	[-1.047; -0.980]
Random Coefficients				
Bernoulli: Attention	0.000	0.000	0.000	0.000
	[0.000;0.000]	[0.000; 0.000]	[0.000; 0.000]	[0.000; 0.000]
σ: Price		0.226		0.227
		[0.168; 0.243]		[0.098; 0.241]
σ: Net Weight			0.000	0.022
			[0.000; 0.000]	[-0.032; 0.045]

Notes: Bootstrapped 95% confidence intervals in brackets.

zero, indicating consumers are heterogeneous in their sensitivity to price.

The coefficient on net weight is positive, indicating that consumers prefer more pepper to less all else equal. Specifications (3) and (4) include a normally distributed random coefficient on net weight. In contrast to price, the standard deviation on net weight is not significant, suggesting that there is little variation in how consumers value package content. Because of this, we use the estimates from specification (2) where only price preferences are heterogeneous in the counterfactual exercises that follow.

Translating the price and net weight coefficients into elasticities, we find that the own-price elasticities are larger in magnitude than the net weight elasticities. Excluding the inattention term and making every consumer attentive, the average own-price elasticity is -6.58, whereas the own-net weight elasticity is 2.03. So, even if consumers were fully attentive, they would be more than three times more sensitive to a price increase than to a size decrease. As a result, downsizing can be an effective strategy even when consumers are attentive. This result is consistent with Kim (2024) who argues that attentive consumers respond less to downsizing than price increases. Differential sensitivity to size and price does not necessarily reflect inattention.

As described previously, the Bernoulli random coefficient represents the probability of being attentive. Across all specifications, this probability is essentially zero, indicating that consumers are completely inattentive and do not notice downsizing. This result holds across all specifications and is not sensitive to the inclusion of random coefficients on price or net weight. Our result suggests that consumers ignore or underutilize information on net weight.

One concern is that the estimated probability may depend on the functional form for how net weight enters utility. In the main specifications, we assume that net weight enters linearly. The functional form matters because it dictates the utility wedge from inattention. Appendix III shows the derivations of the wedge term under quadratic and log functional forms. As a robustness check, we estimate the model under two different functional form assumptions. We consider a quadratic in net weight and the log of net weight. Columns (1) and (2) of table 11 shows the BLP results under two alternative functional form assumptions.

Table 11: Robustness

	Functional Form		No Overlap	Overlap
	(1)	(2)	(3)	(4)
Means				
Price	-1.895	-1.993	-1.959	-1.683
	[-2.075;-1.857]	[-2.125;-1.703]	[-2.023; -1.907]	[-1.804;-1.582]
Net Weight	0.941		0.721	0.463
	[0.880; 0.981]		[0.703; 0.745]	[0.423; 0.508]
$(\text{Net Weight})^2$	-0.016			
	[-0.018;-0.012]			
log(Net Weight)		2.186		
		[2.153; 2.219]		
McCormick	1.439	1.134	2.111	1.876
	[1.414; 1.492]	[0.970; 1.201]	[2.071; 2.162]	[1.817;1.949]
Is Whole	0.253	0.345	0.185	-0.203
	[0.217; 0.284]	[0.314; 0.386]	[0.154; 0.212]	[-0.244;-0.155]
Black Pepper	-0.794	-0.866	-0.475	0.014
	[-0.851;-0.722]	[-0.905;-0.784]	[-0.543; -0.420]	[-0.084;0.101]
Pepper Blend	-0.298	-0.453	-0.286	0.340
	[-0.331;-0.256]	[-0.478;-0.417]	[-0.330; -0.238]	[0.281;0.388]
Cayenne Pepper	-0.245	-0.792	-0.657	-0.252
	[-1.000;-0.900]	[-0.829;-0.726]	[-0.717; -0.602]	[-0.326;-0.173]
Citrus Pepper	-2.500	-2.059	-2.541	-1.182
	[-2.575;-2.409]	[-2.123;-1.897]	[-2.638; -2.456]	[-1.354;-1.017]
Garlic Pepper	-2.659	-2.245	-2.223	-2.223
	[-2.725;-2.592]	[-2.303;-2.078]	[-2.750; -2.598]	[-2.374;-2.075]
Red Pepper	-1.294	-0.749	-1.386	-0.723
	[-1.344;-1.228]	[-0.809;-0.572]	[-1.456; -1.323]	[-0.808;-0.650]
Other Pepper	-1.115	-0.908	-1.165	-0.716
	[-1.145;-1.073]	[-0.936;-0.843]	[-1.219; -0.117]	[-0.760;-0.671]
Random Coefficients				
Bernoulli: Attention	0.000	0.000	0.000	0.000
	[0.000; 0.000]	[0.000; 0.000]	[0.000; 0.000]	[0.000; 0.000]
σ: Price	0.244	0.463	0.225	0.298
	[0.221; 0.430]	[0.383; 0.488]	[0.185; 0.259]	[0.254;0.364]

Notes: Bootstrapped 95% confidence intervals in brackets.

The functional form for net weight does not affect the main results. All of the non-size coefficients have the same sign and similar magnitude as our main specifications. Under both specifications, consumers prefer more pepper to less all else equal. Crucially, the probability of being inattentive is still zero.

Another possible concern is that the overlap between the original and downsized products may bias the probability of being attentive toward zero. Because we aggregate the scanner data to the retailer, DMA, and month level, the original and downsized product can appear in the same choice set despite never actually appearing together. For a given retailer and DMA, one store may stock the original product, while the others stock the downsized product. During the transition from the original product to the downsized product, the share of the original product will decrease as the share of the downsized product increases, potentially creating bias .

To test whether the overlap biases our results, we estimate our model on a sample that excludes the overlap and on a sample that is just the overlap. Columns (3) and (4) of table 11 shows the BLP results for the non-overlap and overlap samples. The probability of being attentive is zero in both the overlap and non-overlap samples, suggesting that the overlap does not create bias. Our main result is therefore robust to the functional form of net weight and the inclusion of the overlap between products.

9 Counterfactuals

In this section, we consider the welfare implications of consumer inattention to downsizing. Inattention can reduce welfare by distorting product choices. Erroneous product choices arise because consumers are maximizing perceived utility rather than actual utility. In the long run, consumers will learn about downsizing and adjust their choices accordingly. Nudges and notices can help consumers make more informed choices and combat inattention in the short run.

Reducing inattention does not address the direct welfare loss from smaller products. Consumers are still stuck with smaller products that yield less utility. Restricting firms from downsizing prevents both inattention-related issues and utility loss from small packages. However, without downsizing, firms will raise unit prices by increasing package prices. The increase in package prices may offset the gain from preserving larger sizes.

To examine these trade-offs, we conduct two counterfactual simulations. In the first counterfactual, we quantify the welfare loss due to inattention. We assume that firms still engage in downsizing, but that consumers are now attentive. The second counterfactual examines whether consumers would be better off if downsizing never occurred. These counterfactual scenarios provide guidance to policymakers about the benefits of improving attention to downsizing or banning downsizing entirely.

Removing inattention and banning downsizing affect equilibrium prices. In the first scenario, we solve for the new equilibrium using just the demand results by placing restrictions on the supply-side model. The second scenario requires us to estimate the supply side, as we need to account for how marginal costs change with net weight. After estimating supply, we set products to their original weights and adjust the firms' marginal costs accordingly. We describe the supply model before discussing the results of the counterfactuals.

9.1 Supply

We assume that manufacturers simultaneously set retail prices and retailers extract profits through slotting fees. To maximize their profits, manufacturers set the wholesale price equal to the retail price, so the retail margin is zero.

Because consumers choose retailers based on basket of goods, pepper prices are unlikely to impact consumers' choice of retailer. Consequently, retailers act as local monopolists when pricing pepper. Consequently, manufacturers can maximize their overall profits by maximizing their profits at each retailer in each DMA. A manufacturer m sets the retail price at a retailer-DMA k in time t to maximize its profits:

$$\pi_{kt}^{m} = \sum_{j \in J_{mkt}} \left[p_{jkt} - mc_{jkt}^{m} \right] s_{jkt}(p_{kt}) M_{kt} \tag{17}$$

where J_{mkt} is the set of products that m sells to retailer k at time t; M_{kt} is the market size; and mc^{m} is the marginal cost of the manufacturer.

The first-order conditions with respect p_{jkt} is:

$$s_{jkt} + \sum_{j \in J_{mkt}} \left[p_{jkt} - mc_{jkt}^{m} \right] \frac{\partial s_{jkt}}{\partial p_{jkt}} = 0 \tag{18}$$

Stacking the first-order conditions of all manufacturers and rearranging terms, the equilibrium prices satisfy:

$$p_{kt} + \Delta_{kt}^{-1} s_{kt}(p_{kt}) = mc_{kt}^{m} \tag{19}$$

where Δ_{kt} is a matrix with entry (r, s) equal to $\frac{\partial s_{mkt}}{\partial p_{nkt}}$ if manufacturer m sells products r and s to retailer k during period t and zero otherwise.

From the first conditions, we can estimate marginal costs from the demand-side results. To do this, we assume that the marginal cost of a product j is a linear function of its net weight z_{jkt}, other observable characteristics x_{jkt}, and an unobserved cost shock ω_{jkt} so that:

$$mc_{kt}^{m} = p_{kt} + \Delta_{kt}^{-1} s_{kt}(p_{kt}) = x_{jkt}\kappa_1 + z_{jkt}\kappa_2 + \omega_{jkt} \tag{20}$$

We estimate the marginal cost parameters using two-stage least squares. The marginal cost parameters allow us to adjust marginal costs in the case of a ban of downsizing when firms do not adjust net weights. We discuss the supply-side estimates in Appendix section III. Crucially, marginal costs increase with net weight, so firms that face lower costs. Restricting downsizing prevents firms from realizing some cost savings.

Our supply-side model is static while the decision to downsize is dynamic. Firms pay a sunk cost today to adjust their packaging, but accrue the benefits of that decision in the form of lower costs in the future. We think of our supply-side model as the outcome of a two-stage model along the lines of Wollmann (2018). In the first stage, firms decide their product offerings after observing a set of sunk costs. Given their product offerings, manufacturers set retail prices after realizing the demand and marginal cost shocks. Manufacturers weigh the expected profits of introducing the downsized products and changing their product offerings against the sunk costs of doing so. Manufacturers downsize when the expected returns is greater than a threshold value. So while dynamics play a role in the first stage, the second stage is ultimately a standard static supply model.

9.2 First Counterfactual: Removing Inattention

9.2.1 Equilibrium Prices and Quantities

In this counterfactual, we consider how market outcomes and consumer welfare change if consumers were attentive given the existing product offerings. By distorting product utilities, inattention affects demand and hence equilibrium prices and quantities.

The removal of inattention represents a quality decrease for the downsized products because newly attentive consumers now find these products less attractive than before. The decrease in demand for the downsized products should result in lower prices for the downsized products and higher prices for the nondownsized ones. If consumers are fully attentive, prices will adjust to some new level p^a_{kt}.

When consumers are fully attentive, product demand $s^a_{kt}(p^a_{kt})$ does not depend on the size change. In addition, the response matrix Δ^a_{mkt} now depends on the new demand with entry (n, o) equal to $\frac{\partial s^a_{nkt}}{\partial p_{okt}}$. Crucially, changing the level of inattention does not affect the marginal cost of the manufacturer. As a result, we have:

$$p^a_{kt} + \Delta^{-1}_{a,mkt} s^a_{mkt}(p^a_{mkt}) = p_{kt} + \Delta^{-1}_{kt} s_{kt}(p_{kt}) = mc^m_{kt} \tag{21}$$

This equation defines the counterfactual prices as an implicit function of the demand-side parameters.

We first find the marginal costs from the observed prices using the second equality in equation (21). To solve for the counterfactual prices, we follow Conlon and Gortmaker (2020) and Morrow and Skerlos (2011b) and rewrite the markup equation as a contraction mapping. We then simply iterate on the modified markup equation.

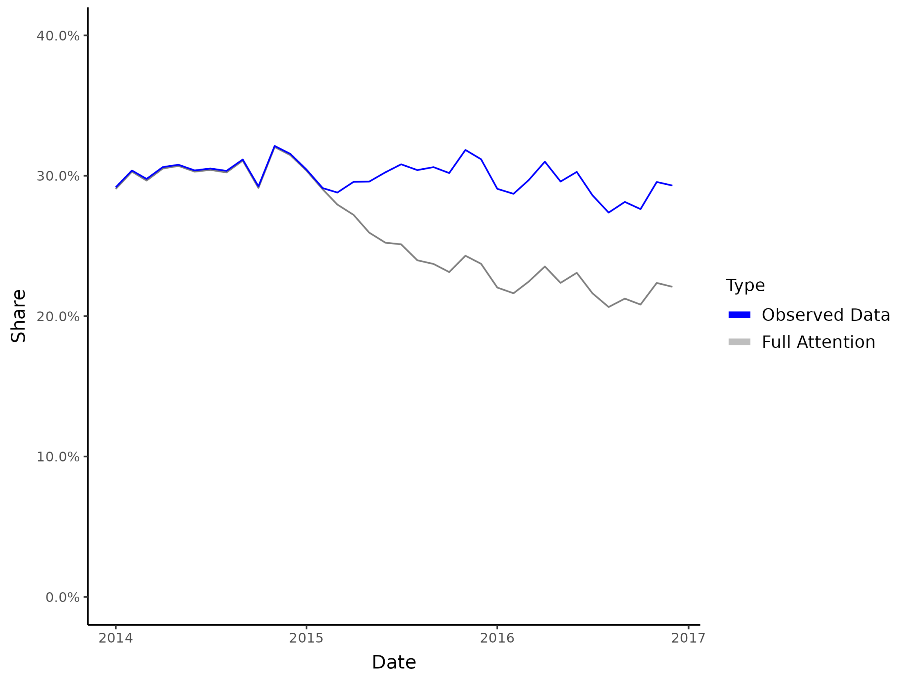
Figure A7 shows the difference between the observed prices and the counterfactual prices for all products, and Figure A8 shows the difference for the downsized products. In many cases, prices do not change because many retailers do not offer the downsized products.[26] In particular, prices of downsized products are affected the most. However, most of the price decreases are small and close to zero. Almost all of the price changes are less than \$0.05. The fact that prices do not change by much is not surprising given

[26]Moreover, the graph with all products also includes markets before any downsizing happened.

the restrictions of the supply-side model.

Figure 9 shows the equilibrium market shares when inattention is removed. We rescale the market shares so they are in terms of the inside goods. The blue line represents the observed share of the downsized products while the grey line represents the share of the downsized products under complete attention.

Figure 9: Market Shares



If consumers were attentive, the share of the downsized products would fall from approximately 30 percent to 22.5 percent points, or in other words by 25%.[27] This is a large decline in the market shares. While the downsized products lose 7.5 percentage points in market share, McCormick overall loses only about 3 percentage points. Consumers substituting away from the downsized McCormick products often switch to non-downsized McCormick products.

9.2.2 Consumer Welfare

Inattentive consumers buy a downsized product under the belief that it contains more pepper than it actually does. After purchasing, some of these consumers may experience discontent when they discover the smaller package content. Post-purchase discontent, however, does not necessarily imply welfare losses.

For inattention to reduce consumer welfare, inattention must alter the final choice that the consumers make or must allow firms to charge higher prices. By distorting product

[27] This estimate can be considered as an upper bound of the product switching behavior. In our analysis, consumers' product choice includes all products from a retailer in a designated market area (DMA). Therefore, the choice set is larger compared to the choice set in a single retailer store. A larger product choice set implicates more product switches amongst consumers.

utilities, some inattentive consumers choose a product that is not utility maximizing. Only inattentive consumers can experience this type of loss.

Inattention also affects the welfare of all consumers indirectly through prices. Under inattention, consumers pay more for the downsized products. So even attentive consumers are hurt because of the higher prices.

Consumers can choose the wrong product because they base their purchase decision on perceived utility rather than actual utility. For instance, an inattentive consumer at retailer k in period t chooses the product that maximizes perceived utility $j^* = \underset{1,\ldots,J_{kt}}{\arg\max}\ U^p_{ijkt}$ instead of the one that maximizes actual utility is $m^* = \underset{1,\ldots,J_{kt}}{\arg\max}\ U^a_{ijkt}$. This assumes that prices remain the same. If we remove inattention, the prices change which affects the choice. To assess the welfare loss from inattention, we need to examine the choice that maximizes actual utility under the new prices, $c^* = \underset{1,\ldots,J_{kt}}{\arg\max}\ U^a_{ijkt}(p^a_{kt})$ The consumer experiences a loss in utility of:

$$\mathcal{W} = U^a_{ic^*kt}(p^a_{kt}) - U^a_{ij^*kt} \tag{22}$$

Note that j^* and c^* depend on the random parameters and the taste shock ϵ_{ijkt}. Taking the expectation over these gives the average welfare loss from imperfect knowledge:

$$\Delta CS = \frac{\mathbb{E}\big[\mathcal{W}\big]}{\alpha} = \frac{\mathbb{E}\big[U^a_{ic^*kt}(p^a_{kt})\big]}{\alpha} - \frac{\mathbb{E}\big[U^a_{ij^*kt}\big]}{\alpha} \tag{23}$$

Given the logit-form, the welfare loss has the form:

$$\Delta CS = \int \Bigg[\log\Bigg(1 + \sum_{J_{kt}} \exp\big\{x_{jkt}\beta - \alpha_i p^a_{jkt} + \xi_{jkt} + \gamma z_{jkt}\big\}\Bigg) \tag{24}$$

$$- \log\Bigg(1 + \sum_{J_{kt}} \exp\big\{x_{jkt}\beta - \alpha_i p_{jkt} + \xi_{jkt} + \gamma z_{jkt} + (1-\tau_i)\gamma\big(z_{jk0} - z_{jkt}\big)\big\}\Bigg) \tag{25}$$

$$+ \sum_{J_{kt}} s_{jkt}(\alpha_i, \tau_i)\ (1-\tau_i)\gamma\big(z_{jk0} - z_{jkt}\big)\Bigg] \frac{1}{\alpha_i} dG(\alpha, \tau) \tag{26}$$

where the market shares correspond to consumers' observed choices under imperfect attention. Our formula for the welfare loss is close to that of Train (2015). The only difference is that we incorporate price changes due to the removal of imperfect knowledge, similar to Stivers (2019).

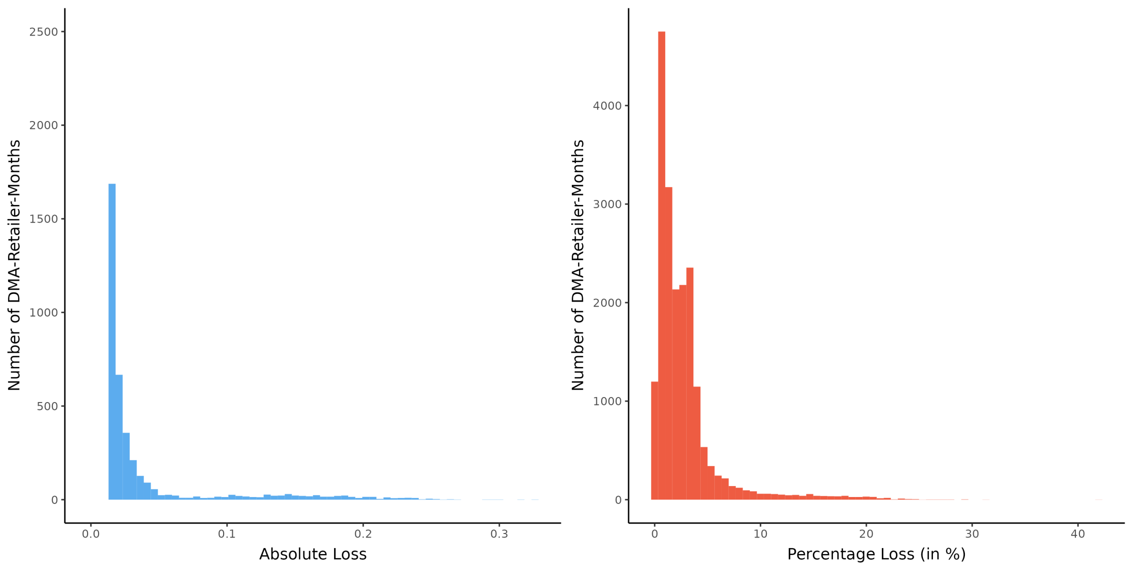
The first term is the standard log-sum formula based on actual utility evaluated at the counterfactual prices. The log-sum formula is the closed form for the expectation from making the choice. The second term is the log-sum formula based on perceived utility and the final term is the average difference between actual and perceived utility. The final term is really a summation over the downsized products as size does not change for the nondownsized products.

Consumers can only experience a loss in welfare at retailers who offer downsized products. If a retailer does not does not stock downsized products, consumers cannot mistakenly choose those products. In the estimation sample, there are 36,682 DMA-retailer-months. After McCormick starts downsizing products, around 90% of the markets feature downsized products. Thus, most consumers can experience a welfare loss from inattention.

Figure 10a shows the the histogram of the absolute welfare losses for retailers with downsized products. We find that inattention reduces consumer welfare by a small amount in absolute terms for most consumers. The welfare loss ranges from around \$0.00 to \$0.69, and the average loss is \$0.012. Clearly, there are markets where the harm is quite large.

Figure 10: Welfare Loss from Inattention

(a) Absolute Welfare Loss (b) Relative Welfare Loss



Note that these Images contain only markets featuring at least one downsized product.

As pepper is a relatively cheap product, relative welfare loss is easier to interpret. In Figure 10b, we compare the welfare loss to the share-weighted average price at a given retailer in a given month. On average, the loss from inattention represents approximately 2.7 percent of the product price on average. Moreover, for some markets, the welfare loss exceeds 20 percent. In practical terms, inattention has a significant effect on welfare both in absolute and relative terms. This result is not that surprising given the large changes in shares.

9.3 Second Counterfactual: Banning Downsizing

9.3.1 Equilibrium Prices and Quantities

We now consider how consumer welfare would change if manufacturers chose not to downsize, but instead simply raise prices. We can think of this counterfactual as representing a ban on downsizing. We assume that manufacturers keep their product offerings the same, but offer the original versions in place of the downsized versions.

The swap of the downsized version for the original one affects demand and supply. The greater net weights on some products will change consumers' utilities and therefore demand. However, because there is no downsizing, inattention does not affect demand as there is nothing for consumers to miss. The size change term simply does not matter since it is always zero.

The increase in the net weight increases the marginal costs of the affected products. Consequently, we need to use the supply-side results to adjust the marginal costs to reflect the original net weights. In the supply model, the marginal cost is a linear function of the net weight and the cost shock ω. We simply substitute in the original net weight to obtain the new marginal costs $mc^m_{kt}(z_{0kt})$.

The new equilibrium prices p'_{kt} satisfy:

$$p'_{kt} + \Delta^{-1}_{kt} s_{kt}(p'_{mkt}) = mc^m_{kt}(z_{0kt}) \tag{27}$$

In this counterfactual, prices change by a lot due to the large changes in marginal cost of the downsized products. Figure A10 shows the price changes of originally downsized products. The price of most downsized products increases by between \$0.20 and \$0.40 and some prices increase by more than \$0.80. The average price of a pepper product is around \$3.00 so these are fairly large changes. The large changes in price offset the increase in net weight so the market shares of the downsized products do not change much, as can be seen in Figure A11.

9.3.2 Consumer Welfare

The intuition on the computation of the consumer welfare largely remains the same. The welfare loss has the form:

$$\Delta CS = \int \Bigg[\log \Bigg(1 + \sum_{J_{kt}} \exp \big\{ x_{jkt}\beta - \alpha_i p^a_{jkt} + \xi_{jkt} + \gamma z_{jk0}) \big\} \Bigg) \tag{28}$$

$$- \log \Bigg(1 + \sum_{J_{kt}} \exp \big\{ x_{jkt}\beta - \alpha_i p_{jkt} + \xi_{jkt} + \gamma z_{jkt} + (1-\tau_i)\gamma \big(z_{jk0} - z_{jkt} \big\} \Bigg) \tag{29}$$

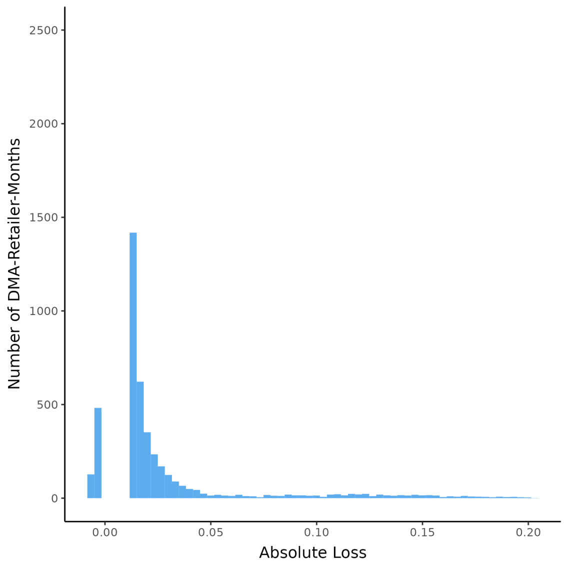
$$+ \sum_{J_{kt}} s_{jkt}(\alpha_i, \tau_i)\ (1-\tau_i)\gamma \big(z_{jk0} - z_{jkt} \big) \Bigg] \frac{1}{\alpha_i} dG(\alpha, \tau)$$

where the only difference is the use of the original product sizes z_{jk0}.

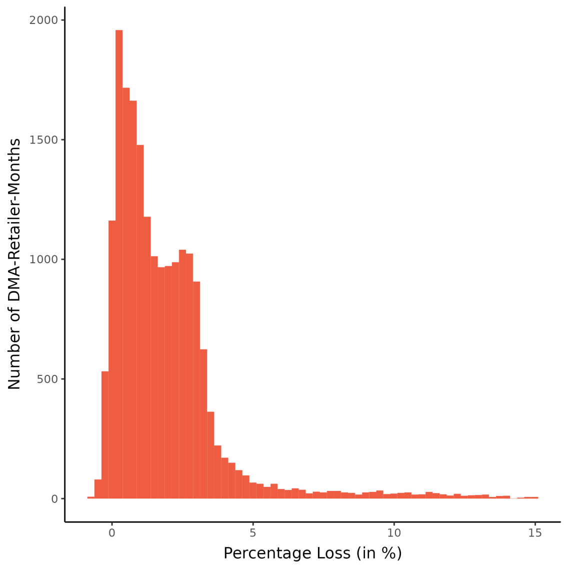
Figure 11a shows the the histogram of the absolute welfare losses for retailers selling downsized products. We find that inattention reduces consumer welfare by a small amount in absolute terms for most consumers. The welfare loss ranges from around \$0.00 to \$0.65, and the average loss is \$0.011. Again, there are markets where the harm is quite large.

Figure 11: Welfare Loss from Downsizing Practice

(a) Absolute Welfare Loss



(b) Relative Welfare Loss



The relative loss is on average about 2.3%. The welfare loss overall is similar to the welfare loss from inattention. The smaller loss means that the gain from banning downsizing is smaller. The smaller improvement in welfare is the result of the large increase in package prices. When prevented from downsizing, McCormick faces higher prices and as a result raises its package prices by a fair amount. As consumers are more sensitive to package prices than size changes, these price increases reduce their welfare by more than the size decreases. As a result, consumers are worse off from banning downsizing than simply just removing inattention.

There is a still a welfare improvement from banning downsizing. However, this welfare gain comes from removing issues related to inattention. Without changes in product content, there is nothing for consumers to be inattentive to. Banning downsizing is therefore only an effective policy solution if consumers learn about downsizing slowly or nudges are ineffective at increasing consumer awareness.

10 Conclusion

The practice of product downsizing occurs across a wide range of products and represents one strategy that firms use to increase unit prices. When consumers underuse size information or ignore unit prices, downsizing represents a hidden price increase. We utilize a downsizing event in the black pepper industry to determine whether consumers are inattentive to decreases in product size. The large amount of existing size variation in this industry allows us to recover the degree to which consumers are inattentive.

To study how consumers respond to downsizing, we build a demand model that incorporates inattention to size changes and apply it to scanner data. In the model, inattentive consumers misperceive the net weights of the downsized products and as a result, they evaluate them based on their original net weights. Because of this, the change in net weight enters utility as an additional product characteristic with a random coefficient, whose distribution we recover using standard demand estimation techniques.

We find that almost all consumers fail to notice the reduction in fill levels. Moreover, the estimated preferences' suggest that even if consumers were fully aware, they would be more responsive to price than to product size. Inattention simply makes downsizing more effective than it already is.

Inattention not only distorts product choices, its removal also has an impact on shares and consumer welfare. If consumers were fully attentive, the share of the downsized products would fall by 7.5 percentage points relative to the inside goods or by about 1.5 percentage points relative to the total market. These changes in shares translate into a 2.7% welfare loss in consumer welfare. Moreover, the downsizing practice overall induces a 2.3% welfare loss.

Our results suggest that statements of net weight do not prevent consumers from misperceiving product sizes. In fact, the vast majority of consumers appear to ignore such statements. Our results suggest that policies aimed at decreasing inattention to downsizing, like a French law requiring food retailers to notify consumers of downsizing (Rajbhandari and Adghirni, 2023) may benefit consumers. Our results further show that banning downsizing can be counterproductive. When unable to downsize, firms raise their package prices significantly, an outcome that consumers dislike more than smaller packages. If consumers learn about downsizing quickly, policy interventions may not be necessary.

Chapter III

How Effective Were Subsidies for Solar Energy in Germany

Joint with Sebastian Rausch

1 Introduction

Subsidies for new, low-carbon energy technologies are a widely used policy approach to bolster decarbonization—motivated by incomplete carbon pricing and positive externalities in knowledge creation and diffusion (Popp, 2002; Acemoglu et al., 2012; van Benthem et al., 2008; Bollinger and Gillingham, 2014). The German subsidy program is one of the largest renewable energy policies globally and is widely regarded as a forerunner in establishing and popularizing subsidies to promote the uptake of solar energy.[28] The subsidy is structured as a fixed production subsidy—the feed-in tariff—that guarantees the owner of the PV system a price for 20 years at which they can sell the produced electricity. Empirical and theoretical studies (Allcott and Greenstone, 2012; Busse et al., 2013; De Groote and Verboven, 2019; Langer and Lemoine, 2022) have documented that the undervaluation of future benefits from investments in new energy technologies can significantly hinder adoption and undermine the effectiveness of policies, particularly when subsidies target future consumption or output rather than upfront investment costs—as is the case with the German subsidy scheme.

This paper provides novel empirical estimates of the extent to which households discount future benefits from PV investments and employs counterfactual experiments to assess the cost-effectiveness of the German subsidy program, one of the world's largest renewable energy support policies. In doing so, we specifically consider the ownership structures of residential buildings in Germany from 2012 to 2021. The ownership structure is important because the self-consumption of the generated electricity is responsible for about half of the revenues earned from a PV system. Self-consumption is more profitable than feeding electricity into the grid since the feed-in tariff has consistently been several orders of magnitude lower than the retail electricity price for consumers.[29] Consequently, investment incentives differ significantly between homeowners and landlords.

To address this disparity, the German government introduced the tenant electricity

[28]Introduced in 2002, the German model inspired more than 50 countries worldwide to implement similar policy support schemes. Notably, countries such as Japan, China, and Ontario, Canada, have adopted especially large-scale versions. The program's design and outcomes have significantly shaped international renewable energy policy frameworks, demonstrating the potential of feed-in tariffs to drive widespread adoption of wind and solar energy technologies. Appendix III provides a breakdown of key countries that adopted FiT programs influenced by the German subsidy policy.

[29]The feed-in tariff varies based on the year of construction and system size, declining from 20 cents per kWh in 2012 to approximately 7 cents in 2021. The retail electricity price for consumers during this period was around 30 ct/kWh.

model, which allows landlords to sell PV-generated electricity directly to their tenants, thereby capturing the financial benefits of self-consumption. The German government subsidizes such contracts in addition to the regular feed-in tariff, but the high administrative burden associated with these contracts has impeded widespread adoption. Understanding landlords' investment incentives and evaluating the effectiveness of tenant electricity regulations are therefore essential for gaining a comprehensive perspective on PV adoption in Germany.[30]

We estimate a dynamic model of new technology adoption based on De Groote and Verboven (2019). To identify discount factors, we use the feed-in tariff and the tenant contract subsidy as an exogenous shifter that affects the future but not the present utility. In each period, households or landlords can choose to invest or postpone their investment. We estimate the model at both aggregate and state level, using comprehensive administrative data capturing all PV installations that received subsidies from the federal government between 2012 and 2021 and including information on whether the electricity generated is sold to tenants.

Our results suggest that the current feed-in tariff structure is suboptimal. Homeowner investors, or households, assign a value of only 67 cents to each euro of the total discounted future benefits from PV electricity production. Put differently, they apply an implicit real interest rate of 8.6% when assessing these future benefits—a rate significantly higher than the real market interest rate of 2–3% during the same period.[31] This undervaluation of future benefits is problematic from a public policy perspective: one-time upfront subsidies on the investment costs of a PV installation could have achieved the same level of adoption as continued production subsidies at 36% lower cost, translating to potential government savings of approximately 2.7 billion euros. In addition, as the German feed-in tariff was financed through a levy paid by all electricity consumers[32], the production subsidies not only resulted in unnecessarily high public costs but also shifted the subsidy burden onto consumers who did not directly benefit from the subsidy, as well as onto future households. Such distributional concerns could have been circumvented if upfront investment subsidies had been used instead of production subsidies.

Moreover, landlords are strongly discouraged from investing in PV systems in combination with tenant electricity contracts. We estimate that administrative costs associated

[30]The landlord-tenant problem is a classic principal-agent dilemma, where the agent (tenant) enjoys the benefits (here, the reduced future cost of electricity), while the principal (landlord) bears the initial investment costs. This has been shown to impede the adoption of new energy technologies (Gillingham et al., 2009; Borenstein, 2015). Recognizing this issue, several countries have adopted programs similar to Germany's tenant electricity model, aiming to enable landlords or housing associations to provide renewable energy directly to tenants or facilitate energy sharing through renewable energy communities. Some recent examples are listed in Appendix III.

[31]While we provide the first estimate for case of Germany, these results are in line with previous literature. De Groote and Verboven (2019) find for the Belgium program subsidizing PV installations between 2006-2012 that consumers are willing to pay only approximately 0.5 euro upfront for 1 euro of discounted benefits from future electricity production.

[32]The *Renewable Energy Surcharge* (*EEG-Umlage*) covered essentially the difference between the market price of electricity and the higher feed-in tariffs. It was paid by electricity consumers until 2022, when it was abolished and replaced with direct government funding from the federal budget.

with the tenant electricity program account for approximately 22.5% of the total revenue stream, significantly discouraging adoption. In an optimal scenario where landlords face the same incentives as homeowners, the number of potential PV adopters in Germany could more than double, given that 52% of households live in rental properties (Statista, 2025). In turn, this could decrease the necessary subsidies even further while keeping adoption constant, increasing cost-effectiveness.

This paper makes four contributions. First, we add to the empirical intertemporal choice literature, which examines how consumers value future payoffs. A significant portion of this research focuses on the adoption of new technologies that require upfront investment but generate long-term savings. One strand of this literature studies the energy efficiency gap which is the apparent under-adoption of energy-saving technologies despite financial benefits (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012; Hausman and Greenstone, 2015; Gerarden et al., 2017). We provide novel empirical estimates from one of the world's largest subsidy program to promote investment in new energy technologies. Moreover, much of the literature does not account for rapidly evolving technologies, such as PV systems, which have become significantly cheaper over time. We follow De Groote and Verboven (2019) by incorporating the timing of adoption as a key decision variable, rather than focusing solely on the investment decision. Given the government-set feed-in tariff schedule and the declining cost of PV panels over time, it would be too narrow to attribute every non-purchase decision to a dislike of future payoffs. Instead, some households may delay adoption in anticipation of better purchase conditions. By allowing consumers to postpone their purchase in our model, we can better capture these forward-looking decisions and assess the role of policy incentives more accurately.

Second, we contribute to the literature on PV system subsidies and adoption. Several studies, including Burr (2016), Feger et al. (2022), and De Groote and Verboven (2019), demonstrate the effectiveness of upfront subsidies in promoting PV system adoption. Although Burr (2016) and Feger et al. (2022) rely on specific assumptions about time discounting, we adopt the more flexible approach proposed by De Groote and Verboven (2019), in which the discount factor is identified through variation in initial investment costs and future payoffs. In addition, this approach requires minimal assumptions about the future investment opportunities of households. Our findings build on this body of work by estimating how discounting behavior influences adoption and how alternative subsidy structures could improve policy efficiency.

Third, we contribute to the extremely sparse literature on tenant electricity. Kühn et al. (2024) describe the landlord-tenant dilemma, where landlords have little incentive to invest in new technologies, and even when they do, the cost-benefit ratio for tenants is often unfavorable. To address this misalignment of incentives, the German government introduced the tenant electricity framework, which includes subsidies to encourage adoption. However, Moser et al. (2021) document limited tenant electricity uptake after the reform, with only 1% of available subsidies utilized. Their survey-based analysis identifies the restrictive legal framework as the primary barrier to adoption. To our knowledge, we provide the first empirical estimate of the implicit costs of administrative burdens in a tenant electricity framework, quantifying how regulatory complexity affects landlord participation. Our approach assumes that landlords' true discount factor is similar to that of homeowners.[33] By comparing estimated discount factors for homeowners and landlords, we infer the implicit costs of administrative barriers and evaluate how policy reforms could improve adoption rates.

Finally, we contribute by providing the first ex-post assessment of the cost-effectiveness of the German renewable energy subsidy program. Existing studies analyze effectiveness of the German feed-in tariffs in terms of their impacts on the adoption and deployment of renewable energy technologies (Hitaj and Löschel, 2019), reductions in CO_2 emissions (Frondel et al., 2010; Hitaj and Löschel, 2019), electricity price and employments effects Frondel et al. (2010), as well as the innovation effects related to new energy technologies Frondel et al. (2010); Böhringer et al. (2020).[34] Abrell et al. (2019) examine the optimal and second-best designs of renewable energy support policies in the presence of a carbon externality using ex-ante analysis and a structural model of the German electricity market. In contrast, we quantify the cost-effectiveness of the German subsidy program ex-post by conducting a econometrically-based counterfactual analysis.

This paper proceeds as follows. Section 2 provides industry background and describes the data used in our analysis. Section 3 outlines our dynamic adoption model, and Section 4 presents our empirical results and counterfactual simulations and discusses policy implications. Section 5 concludes. Appendixes contain additional results from sensitivity analyses and details on the policy context.

2 Industry and Policy Background

2.1 Data

CORE ENERGY MARKET DATA REGISTER.—Our primary dataset, the Core Energy Market Data Register (*Marktstammdatenregister*), provides comprehensive information on all registered PV systems in Germany. Since July 2017, registration has been legally mandated to maintain grid access and eligibility for subsidies.[35] For each installed system, we observe adoption date, location, capacity, ownership type, efficiency, feed-in type, and whether electricity is sold to tenants. We focus on PV systems owned by private house-

[33]If landlords discount the future less than homeowners—given their generally higher wealth—our approach would underestimate the negative impact of the restrictive legal framework on landlords' investment behavior.

[34]Winter and Schlesewsky (2019) conduct an empirical analysis of the distributional effects of the German feed-in tariff, examining how the costs and benefits of renewable energy subsidies are distributed across different income groups and regions.

[35]Owners of PV installations installed before this date were legally required to register retroactively to remain eligible for the subsidy. Consequently, our data captures all PV installations in Germany that received government subsidies during the sample period.

holds, with system sizes below 15 kW and without battery storage.[36] Systems exceeding 15 kW are typically larger than a standard residential rooftop and fall outside our analysis scope. Similar to De Groote and Verboven (2019), we analyze the data using seven capacity size categories (0-2 kW, 2-4 kW, ..., 12-15 kW) at a monthly frequency.

PV SYSTEM PRICE DATA.—We supplement this dataset with PV system price data from EUPD Research (2024). These prices include not only panel costs but also inverters, mounting structures, electrical equipment, and labor. We have system price data spanning 2012 to 2023 for systems under 100 kW. Additionally, we collect data on solar panel prices from PhotovoltaicXchange (2024), a retailer of solar modules. Their publicly available price index tracks panel prices from 2010 onwards and is published on a monthly basis.

ENERGY PRICES.—We also obtain consumer retail electricity prices from the German Federal Statistical Office (Statistisches Bundesamt, 2024) and crude oil prices from the Federal Reserve Economic Data (2024).We also collect basic electricity supply tariffs from the German Federal Statistical Office (Statistisches Bundesamt, 2024). These tariffs, set by municipal utilities (*Stadtwerke*), serve as a reference for pricing tenant electricity contracts.

SUBSIDIES (FEED-IN TARIFFS).—The primary form of subsidy for PV systems under 100 kW in Germany is provided through feed-in tariffs, as established by the German *Renewable Energy Sources Act* (EEG - *Gesetz für den Ausbau erneuerbarer Energien*) (Federal Ministry of Justice, 2023). These tariffs guarantee a fixed payment to the owners of the PV system for the electricity generated and fed into the grid. The German government sets the feed-in tariff to achieve its renewable energy adoption targets. By adjusting the tariff rate, the government influences the profitability of PV investments, ensuring that adoption aligns with policy goals. From the perspective of the investor, the feed-in tariff is determined on the date of commissioning of each PV system and is guaranteed for 20 years. Generally, the feed-in tariff is lower for larger systems, reflecting the higher installation cost per kW of smaller systems. In addition, the feed-in tariff for new systems decreases over time as installation costs, primarily due to cheaper panels, have also decreased. For our sample period 2012 to 2021, we use the archived remuneration rates for PV installations, including for full and partial feed-in as well as for tenant electricity, published by the Federal Network Agency (2024).[37]

[36]Battery installation and purchase costs are not included in the dataset.

[37]We lack comprehensive data on subsidy programs at the communal and state level. Overall, this limitation is not problematic. Failing to account for these programs likely leads to an underestimation of households' reluctance to invest in PV systems, suggesting that households may discount the future more than our estimates indicate. Therefore, our estimated cost savings from an upfront investment subsidy should be interpreted as a lower bound, indicating that the potential savings could be even greater. Subnational programs, which show relatively little variation over time, are controlled by our model with fixed effects at the state level.

2.2 Tenant Electricity

As PV investments gained momentum in 2012, discussions emerged in Germany about the challenges that prevent tenants from accessing solar-generated electricity. After years of debate, the government enacted the *Tenant Electricity Law (Mieterstromgesetz)* in 2017, creating a framework that allowed landlords or energy companies to sell self-generated solar electricity directly to tenants without using the public grid. To encourage adoption, the government provided subsidies ranging from 0 to 3 cents per kilowatt hour for electricity sold directly to tenants. However, the system involved significant bureaucratic hurdles for setup and proper integration with the grid. In addition, landlords were required to supply the entire electricity demand of their tenants, further complicating the implementation. Since it was impossible to cover the entire electricity demand of tenants with self-generated solar power, landlords were required to sign contracts with electricity providers to supply the remaining energy needed.

The law mandated that landlords charge the same price for both self-generated and grid-sourced electricity, leading to two key challenges. First, tenants had no incentive to shift their electricity usage to periods of peak solar production. Second, landlords faced increased uncertainty regarding electricity supply costs and the share of PV energy consumed on-site.

While the law aimed to address a significant gap in Germany's renewable energy landscape, its impact was hindered by complex regulations and bureaucratic barriers. Some of these restrictions were lifted in 2024, but they remained in effect during our sample period from 2017 to 2021 for tenant electricity.

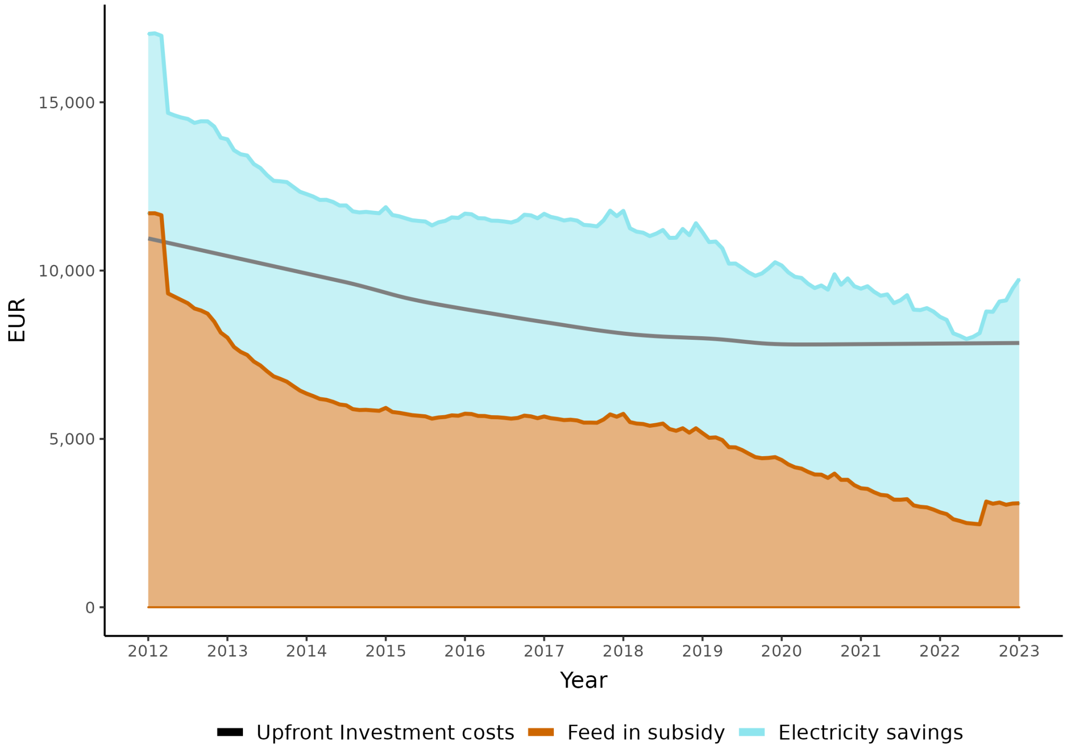
Tenant electricity contracts are not directly observable, which requires us to make assumptions about typical electricity prices. A survey conducted by the Center for Solar Energy and Hydrogen Research Baden-Württemberg as part of the government's evaluation found that, on average, tenant electricity prices amounted to 85% of the basic supply tariff (German Bundestag, 2019).

2.3 Evolution of Costs, Benefits and Adoption

To illustrate the financial assessment of a PV system purchase decision, we compare costs and benefits for 6kW partial feed-in systems across time. While the investment cost is incurred at the time of purchase, the benefits of a PV system are realized through its electricity production over its lifetime. The lifetime of PV systems is expected to be 20 years. To convert future benefits in present value terms, we use a real interest rate of 3 percent and convert all prices to 2015 prices.

One difficult question related to partial feed-in PV systems concerns the percentage of electricity that households consume at home. Weniger and Quaschning (2013) derive the own consumption as a function of the capacity of the PV system. They suggest in another paper that this model could be extended to include annual household electricity consumption for greater accuracy. However, since we do not have data on household size

Figure 12: **Present value of benefits and costs of a 6kW PV system in EUR 2012**



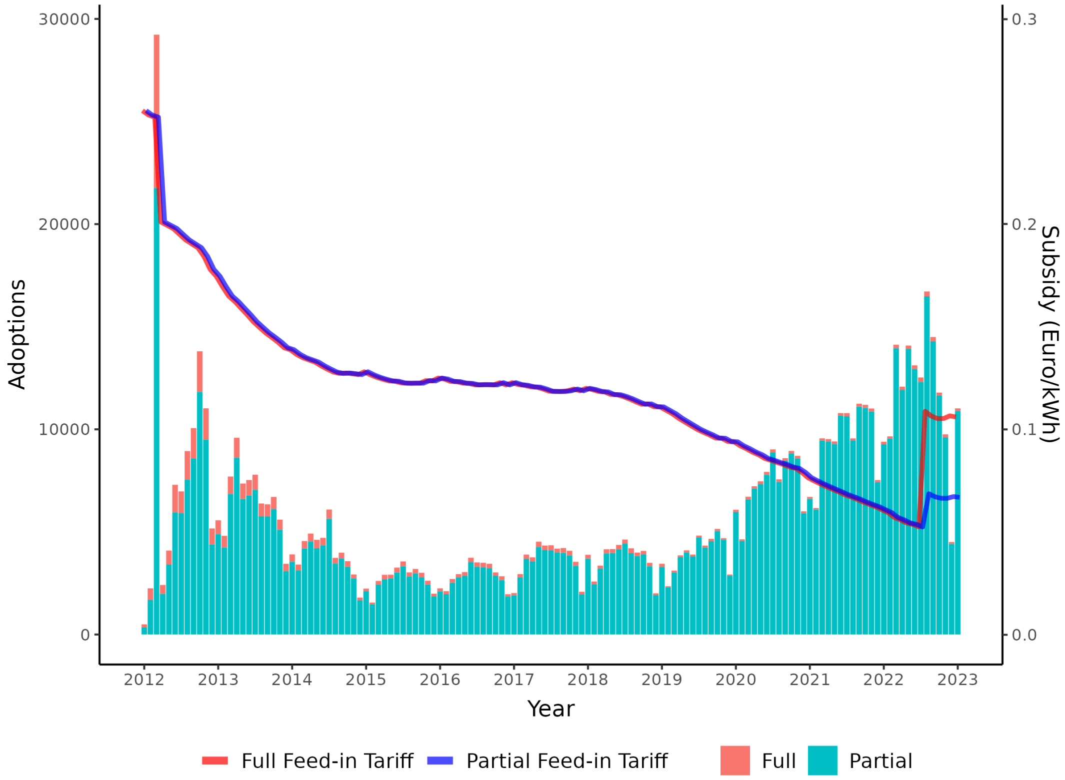
Notes: Areas shown refer to stacked values. Real interest rate used to calculate discounted benefits and costs = 3 percent. Upfront investment costs based on (approximation of) price index from EUPD Research (2024).

or electricity consumption, we will model the percentage of the own consumption solely as a function of the size of the PV system capacity. Based on their calculations, our model assumes own consumption rates of 50% for a 2 kW system, 25% for a 5 kW system and 17% for a 10 kW system. The benefits of own consumption depend on the consumer price of electricity, as PV electricity replaces purchased grid electricity. Using historical consumer electricity prices, we estimate a simple trend to account for the changes in electricity prices during the lifetime of the PV system.

Figure 12 summarizes the benefits and costs of a 6kW PV system with partial feed-in. We can see that the benefits outweigh the cost throughout the sample. In 2012, most of the benefits came through feed-in subsidies. This changed during the following decade despite own consumption using only 22% of the electricity produced for 6kW PV systems. Profitability was almost at 0% before the new governments took the higher priority on installations. Finally, the higher electricity prices induced by the war in Ukraine increase the net present value of its electricity savings.

Given the importance of benefits derived from electricity savings, it is not suprising that private households mostly build partial feed-in systems. Figure 13 provides compelling empirical evidence of a strong preference for partial feed-in systems. We can also see that there was a huge spike in adoptions in July 2012. Given the large drop in feed-in

Figure 13: **PV adoption numbers and feed-in rates over time**



Notes: The bars for "Full" and "Partial", referring to the left vertical axis, show the number of monthly adoptions under the full and partial feed-in model, respectively. The two solid lines, referring to the right vertical axis, show the average feed-in tariff (across different capacity sizes) for the two categories.

subsidies, it hints to the dynamic nature of the household adoption problem. Households decided to invest before the drop rather than after, thus shifting a lot of adoption just before the drop.

Figure 13 thus also makes the point that full feed-in PV systems are extremely unpopular among households. Although some systems were still installed toward the beginning of the sample period, the number of installed full feed-in systems had virtually dropped to zero by the end of the 2010s. Figure A12 in an appendix shows that full feed-in systems are largely unprofitable, even when discounted at the market interest rate. Considering that households may discount the future much higher than the market interest rate, it rationalizes the low adoption rates.

3 Model

In this section, we specify a dynamic adoption model that can be estimated with aggregate data. We closely follow De Groote and Verboven (2019) in model formulation and exposition. We first describe the adoption decision for homeowner and landlord investors which mainly differ in the conditional value of adoption. We then derive our estimating equation and describe our estimation strategy, including the choice of instruments.

3.1 The Adoption Decision

In a given period t, an investor i of type h may either choose not to adopt a PV system ($j = 0$) or choose to adopt one of the available PV alternatives ($j = 1, ..., J$) referring to the different available capacity sizes. Adopting one of the alternatives ($j \neq 0$) represents an irreversible, terminating decision, while not adopting ($j = 0$) gives the household the option of adopting in a later period. Investor types comprise homeowners and landlords ($h \in \{Homeowners, Landlords\}$). In each period, an investor experiences a random taste shock $\varepsilon_{i,j,t}$ which is assumed to follow a type I extreme value distribution. Let $\delta_{j,t}$ denote the conditional value of alternative j in period t, i.e. the expected discounted utility from choosing j at t before the realization of the random taste shock $\varepsilon_{i,j,t}$.[38]

We assume that in each period t investors choose the alternative j that maximizes their random utility, given by $\delta_{j,t} + \varepsilon_{i,j,t}$. This decision framework results in a choice probability or an aggregate market share for each alternative in each period. Before deriving these probabilities, we first describe the conditional value of (no) adoption, $\delta_{j,t}$.

CONDITIONAL VALUE OF ADOPTION.—The conditional value of adoption represents a terminating action and can therefore be expressed as the expected discounted utility of adoption:

$$\delta_{j,t} = x_{j,t}\,\gamma - \alpha\, p_{j,t} + \xi_{j,t}\,, \qquad j = 1, \ldots, J\,, \tag{30}$$

where $x_{j,t}$ is a dummy variable for the alternative j at period t, $p_{j,t} = p_{j,t}(\beta^h)$ is the price variable as a function of the monthly discount factor β^h, and $\xi_{j,t}$ is the unobserved quality of alternative j at period t. The price variable is the sum of the upfront investment price, $p_{j,t}^{INV}$ and the discounted future flow benefits from the fixed feed-in tariff, $p_{j,t}^{FIT}$, and electricity cost savings—in the case of homeowners—or revenues from selling electricity directly to tenants—in the case of landlords, $p_{j,t}^{ELE,h}$:

$$p_{j,t} = p_{j,t}(\beta^h) \equiv p_{j,t}^{INV} - \theta_j \frac{1-(\beta^F)^R}{1-\beta^F} p_{j,t}^{FIT} - (1-\theta_j)\frac{1-(\beta^E)^R}{1-\beta^E} p_{j,t}^{ELE,h}\,, \tag{31}$$

where β^F and β^E are monthly adjusted discount factors, specified as

$$\beta^F = (1-\lambda)(1-\pi)\beta^h \tag{32}$$

$$\beta^E = (1-\lambda)(1+\vartheta_h)\beta^h\,, \tag{33}$$

adjusting the monthly discount factor β^h for a depreciation parameter λ, the inflation rate

[38] Given the lack of household-level information in our data, the conditional value does not include a household-specific component. The drawback of this approach is the assumption that household heterogeneity is uncorrelated over time. In reality, it is likely that investors inclined to adopt today remain inclined to adopt in the future. Additionally, household preferences for PV systems with similar capacity sizes may be correlated. This correlation is plausible, as the physical constraints of a household's roof may limit the feasible PV system size. Both of these aspects stem from data limitations, which prevent a more nuanced modeling of household-specific adoption behavior.

π, and the trend in real electricity prices ϑ_h. $R = 240$ indicates the number of months over the fixed 20-year period (after installation) for which subsidies are guaranteed for investors under the German feed-in program.

λ reflects the efficiency loss due to physical degradation of solar panels which is assumed to be 1 percent (Audenaert et al., 2010). We assume a yearly inflation rate of 2 percent. Using data from (Statistisches Bundesamt, 2024) to estimate the trend in real electricity prices, both for the household price of electricity and basic supply tariffs (the latter being relevant for tenant electricity), we find evidence for almost no growth in both price variables in the period 2012-2021. Finally, θ_j represents the share of our own consumption and depends on the size of the PV system. As we do not observe the electricity consumption behavior of tenants, we assume that tenants consume electricity from the PV system the same way that homeowners would, implying that θ_j is assumed to be identical across both the homeowner and landlord investment decisions. We rely on estimates from Weniger and Quaschning (2013) to obtain θ_j.

The conditional value of adoption differs between homeowners and landlords with respect to discounted future benefits from electricity production that is not directly related to the feed-in tariff (i.e., the third term on the right-hand side of (31)). Homeowners take into account electricity cost savings which depend on the price of household electricity purchased from the grid. In contrast, landlords consider the income stream earned from selling electricity to tenants. The variables $p^{FIT}_{j,t}$ and $p^{ELE,h}_{j,t}$ are essentially prices per kW in period t, multiplied by the capacity size k_j of the alternative j and a factor that converts the PV capacity into monthly electricity production. Combining the adjusted monthly discount factors (β^F, β^E) with R months of income generated from the guaranteed feed-in tariff and R months of electricity savings converts the future monthly benefits into present value terms.

CONDITIONAL VALUE OF NO ADOPTION.—The conditional value of not adopting is identical for both homeowners and landlords and is determined by the flow utility in each period t, $u_{0,t}$, plus the option value of waiting:

$$\delta_{0,t} = u_{0,t} + \beta \mathbb{E}_t \bar{\Delta}_{t+1}\,, \tag{34}$$

where $\bar{\Delta}_{t+1}$ is the ex-ante value function, i.e. the continuation value from behaving optimally from period $t+1$ onward. Assuming a type I extreme value distribution for the random taste shocks $\varepsilon_{i,j,t}$, the ex-ante value function $\bar{\Delta}_{t+1}$ has the closed-form logsum expression,

$$\bar{\Delta}_{t+1} = \bar{\mu} + \ln \sum_{j=0}^{J} \exp(\delta_{j,t+1})\,, \tag{35}$$

where $\bar{\mu} \approx 0.577$ is the mean of the type I extreme value distribution (i.e., the Euler-Mascheroni constant).

RANDOM UTILITY MAXIMIZATION.—With random utility maximization, we obtain the following choice probabilities or the predicted market shares for each alternative $j = 0, \ldots, J$ at period t:

$$S_{j,t} = s_{j,t}(\delta_t) \equiv \frac{\exp(\delta_{j,t})}{\sum_{i=0}^{J} \exp(\delta_{i,t})} \,. \tag{36}$$

As in Berry (1994), we can equate the predicted market shares $s_{j,t}(\delta_t)$ to the observed market shares $S_{j,t}$ because of the inclusion of unobserved qualities $\xi_{j,t}$ for every product and period. The market shares of the alternative j are calculated using the number of adopters $q_{j,t}$ over the number of potential adopters in period t, N_t. Since adoption is a terminal action, the number of potential adopters decreases with time. As a starting point, we take the number of households in Germany (about 40 million) and multiply it by the number of home owners (42%).

3.2 Estimating Equation

We closely follow De Groote and Verboven (2019) to address the two main complications involved in solving the aggregate market share equation (36). First, the conditional value for not adopting $\delta_{0,t}$ involves the expected future value term $\mathbb{E}_t(\bar{\Delta}_{t+1})$, which is recursively defined by (35). This can be addressed by deriving an analytic expression for $E_t\bar{\Delta}_{t+1}$. Second, the conditional value for adopting $\delta_{j,t}$ contains the unobservable product quality term $\xi_{j,t}$, which enters nonlinearly into the aggregate market share equation. This can be addressed by inversion of the market share equation.

EXPECTED EX-ANTE VALUE FUNCTION.—The expectation operator in $E_t\bar{\Delta}_{t+1}$ integrates over uncertainty about the next period state variables, that is, $\omega_t = (u_{0,t+1}, \delta_{1,t+1}, \ldots, \delta_{J,t+1})$. Usually, an explicit stochastic process of state transitions is defined. De Groote and Verboven (2019) instead follow Scott (2014) and decompose $E_t\bar{\Delta}_{t+1}$ into the realized ex ante value function $\bar{\Delta}_{t+1}$ and a short run prediction error $\eta_t \equiv \bar{\Delta}_{t+1} - \mathbb{E}_t\bar{\Delta}_{t+1}$. They then write

$$\delta_{0,t} = u_{0,t} + \beta(\bar{\Delta}_{t+1} - \eta_t) \,, \tag{37}$$

which bears the advantage of having a flexible prediction and avoids arbitrary assumption on households belief about the evolution of states.

The ex ante value function $\bar{\Delta}_{t+1}$ recursively depends on the future value function. Hotz and Miller (1993) show how to write $\bar{\Delta}_{t+1}$ in terms of conditional choice probabilities (CCP). Taking any terminal action in our setting, that is, any adoption decision, we can rewrite the recursive future value functions as follows for $j = 1$: $s_{j,t+1} \equiv$

$\exp(\delta_{j,t+1})/\sum_{j=0}^{J}\exp(\delta_{j,t+1})$. Rewriting and taking logs, we get

$$\ln\sum_{j=0}^{J}\exp(\delta_{j,t+1}) = \delta_{j,t+1} - \ln s_{1,t+1}(\delta_{t+1})\,, \tag{38}$$

which yields the following expression after substituting it into (35)

$$\bar{\Delta}_{t+1} = \bar{\mu} + \delta_{1,t+1} - \ln s_{1,t+1}(\delta_{t+1})\,. \tag{39}$$

The ex ante value function is essentially equal to the utility of choosing option $j = 1$ plus the mean of the type I extreme value distribution (that is, being able to get another draw) plus the CCP correction term $-\ln s_{1,t+1}(\delta_{t+1}) \geq 0$. The last term adjusts for the fact that $j = 1$ may not be optimal and thus the expected utility is on average higher (unless $s_{1,t+1}(\delta_{t+1}) = 1$).

Substituting these insights into the decomposed value mean value of not adopting, we get

$$\begin{aligned}\delta_{0,t} &= u_{0,t} + \beta(\bar{\mu} + \delta_{1,t+1} - \ln s_{1,t+1}(\delta_{t+1}) - \eta_t) && (40)\\ &= \beta(\delta_{1,t+1} - \ln S_{1,t+1} - \eta_t)\,, && (41)\end{aligned}$$

where the second equality follows from normalizing $u_{0,t} + \beta\bar{\mu} = 0$ and from the fact that the CCP at the realized mean utilities is equal to the observed market share ($S_{1,t+1} = s_{1,t+1}(\delta_{t+1})$.

MARKET SHARE INVERSION.—De Groote and Verboven (2019) follow the approach of Berry (1994) to invert the market share equation. We can divide $S_{j,t}$ by $S_{0,t}$ in the market share equation (36) and take logs to obtain

$$\ln(S_{j,t}/S_{0,t}) = \delta_{j,t} - \delta_{0,t}, \quad j = 1, \ldots, J\,. \tag{42}$$

Substituting in our expressions for our conditional values from (30) and (34), we get

$$\ln(S_{j,t}/S_{0,t}) = (x_{j,t} - \beta x_{1,t+1})\gamma - \alpha(p_{j,t} - \beta p_{1,t+1}) + \beta\ln S_{1,t+1} + e_{j,t}\,, \tag{43}$$

where

$$e_{j,t} \equiv \xi_{j,t} - \beta(\xi_{1,t+1} - \eta_t) \tag{44}$$

is the econometric error term. De Groote and Verboven (2019) provide the following intuition for the case of $J = 1$. Then, the equation can be rewritten as

$$\ln(\frac{S_{j,t}/S_{1,t+1}^{\beta}}{S_{0,t}}) = (x_{1,t} - \beta x_{1,t+1})\gamma - \alpha(p_{1,t} - \beta p_{1,t+1}) + e_{1,t}\,, \tag{45}$$

which is essentially a regression for the change in the number of new adopters on the change in price and other characteristics, given β being close to 1. With forward-looking consumers, one may then expect a relatively low number of adopters this period if there is a significant price drop in the next period.

3.3 Estimation

Given the non-linearity of the unknown parameter β—i.e., its non-linear involvement in the price terms—in the estimating equation (43), we will require a non-linear estimator. The error term $e_{j,t}$ consists of the household prediction error and demand shocks. The household prediction error is, by construction, uncorrelated with variables at time t and therefore does not give rise to endogeneity terms. Instead, the demand shock may be correlated with the price variables. First, this may be due to an increased cost of building a PV system when demand is high. In addition, feed-in tariffs are financed through higher electricity prices, known as the German *Renewable Energy Sources Act* surcharge[39], making them a function of current demand shocks.

De Groote and Verboven (2019) deal with these issues by constructing an instrument vector $z_{j,t}$ that is uncorrelated with the error term, and estimate the model using Generalized Method of Moments with the following moment conditions:

$$\mathbb{E}(z_{j,t}e_{j,t}) = 0\,. \tag{46}$$

We construct the vector of instruments $z_{j,t}$ as follows. First, we use a module price index to proxy for PV modules. It is expected to correlate with the endogenous upfront investment price, and as a cost shifter it arguably does not directly influence demand. This instrument will help identify the price coefficient α. Secondly, we include contractually fixed future benefits from the feed-in subsidy, which varies over alternatives and time. Thus, it is a strong instrument to identify the discount factor β^h. To further strengthen the identification of β^h, we incorporate electricity and oil price instruments, as these affect future benefits by influencing savings from electricity consumption. Finally, we also add exogenous $x_{j,t}$ which in our case are alternative j fixed effects. A second source of identification comes from the dynamics of the model. For example, the feed-in tariff is greatly reduced in 2012, and people reacted by adopting just before the decline in subsidies—as evidenced by the large peak in 2012 in Figure 13. This decrease causes a change in the option value if households choose not to adopt, which in turn depends on the discount factor. We follow De Groote and Verboven (2019) and use an approximation to optimal instruments based on Chamberlain (1987) in the household models. They are difficult to implement in the landlord models due to the low number of adoptions, and thus we do not implement them in those contexts.

[39] This surcharge, known as the "EEG-Umlage" in German, is a levy imposed under the *Erneuerbare-Energien-Gesetz (EEG)* (Renewable Energy Sources Act) to help fund Germany's renewable energy transition.

Table 12: **Summary statistics**

Variable	Mean	SD	Min	Median	Max	N
Number of PV adoptions						
Partial Feed-in	703.75	807.13	5	477.50	5,142	840
Full Feed-in	51.99	123.71	0	22	1,691	840
Tenant Electricity	1.61	1.87	0	1	9	378
Subsidies (ct/kWh)						
Feed-in tariff below 10kW	12.33	3.74	6.23	12.16	25.53	840
Feed-in tariff below 30kW	11.91	3.60	6.05	11.83	25.53	840
Subsidy for tenant electricity	2.51	1.21	0	3.04	3.75	378
Price variable (in 2012)						
Investment price	11,274	5,774.05	2,835	10,941	31,672	840
Monthly feed-in revenue	74.23	50.20	5.58	69.57	295.80	840
Monthly electricity savings	39.91	10.45	24.13	38.36	63.58	840
Monthly electricity sales	39.33	10.27	24.37	37.50	62.85	378
Energy and module prices						
Electricity prices (ct/kWh)	29.23	0.86	26.93	29.51	30.42	840
Basic supply electricity prices (ct/kWh)	30.79	0.67	30.25	30.31	31.93	378
Oil prices ($/Barrel)	70.73	27.40	17.31	62.41	129.46	840
Module price (/Wpeak)	0.40	0.14	0.20	0.44	0.75	840

Notes: Both the household macro sample for partial and full feed-in have $N = 840$ observations, the landlord macro sample has $N = 378$ observations.

4 Results

We first describe the investment decisions of homeowners and landlords, with a focus on the extent to which future benefits from PV investments are undervalued. Next, we quantify the cost-effectiveness of the German solar energy subsidies by comparing the fiscal (budgetary) costs of the subsidy program to a counterfactual policy design for promoting PV installations. Finally, we assess the administrative costs associated with tenant electricity.

4.1 Main Findings: Undervaluation of Future Benefits

SUMMARY STATISTICS.—Table 12 provides summary statistics for the sample (January 2012–December 2021). We observe that the number of adoptions for full feed-in and tenant electricity PV systems is low, with partial feed-in systems accounting for the vast majority of adoptions targeted by the government. The feed-in tariffs are identical for both investor types—households and landlords. The investment price of a PV system has on average been 11,274, with a large standard deviation both because of falling prices over time and large differences depending on the capacity size. The government also subsidizes tenant electricity contracts to encourage landlords to adopt tenant electricity models. These subsidies appear effective, as the monthly electricity savings for households closely match the monthly electricity sales for landlords. However, despite identical investment

Table 13: **Empirical results for homeowners (national-level model, partial feed-in)**

	Dynamic		Static	
Price sensitivity in 10^3 Euro (α)	0.4742	(0.2421)	0.5452	(0.2133)
Monthly discount factor (β)	0.9931	(0.0018)	0.9900	(0.0020)
Annual implicit real interest rate in %	8.66	(2.40)	12.82	(2.72)
Alternative-specific constants (γ)				
Common constant	-11.7617	(4.9066)	-8.6638	(0.6485)
2kW	-2.9704	(0.3818)	-3.5503	(0.4119)
4kW	-1.1750	(0.2482)	-1.4760	(0.2638)
8kW	0.1383	(0.2452)	0.4407	(0.2623)
10kW	0.2876	(0.3404)	0.7967	(0.3391)
12kW	-3.2405	(0.5888)	-2.4291	(0.5947)
15kW	-2.4892	(0.8388)	-1.2296	(0.8477)
Number of observations	819		819	

Notes: "Dynamic" refers to estimation results obtained with the dynamic adoption model presented in Section 3. "Static" refers to results obtained from a static model, which assumes that investors cannot delay their investment. Consequently, the discount factor β influences only the NPV of future income streams, without affecting the timing of the investment decision. For all models, standard errors are clustered at the monthly level. Both models are estimated using GMM with the optimal weighting matrix obtained from a two-step estimation procedure. [a]Computed as $r = \beta^{-12} - 1$. Sample period from January 2012 until December 2021. Optimal instruments are approximated following the approach by Chamberlain (1987).

costs and feed-in revenues, landlords adopt an average of only 1.61 systems for tenant electricity. This strongly suggests the presence of substantial unobserved administrative costs.

HOMEOWNER INVESTMENT DECISIONS.—Table 13 shows the empirical results for homeowners using national-level data for Germany for the period January 2012 to December 2021. We provide estimates derived from a static and dynamic model. The static model simplifies the dynamic adoption model presented in Section 3 by setting $\beta = 0$ in (43), while keeping β in the price variables, as given by (31)-(33). Effectively, this implies that households cannot delay their investment but still consider the discounted future income stream of their investment.[40]

The investment price coefficient (α) is positive, which means that investors react positively to a drop in the investment prices of PV systems. The size of the price sensitivity is comparable to the estimates obtained in De Groote and Verboven (2019). We find that the price coefficients between the static and dynamic models are relatively similar. This difference is more pronounced in De Groote and Verboven (2019) as their data exhibit frequent bunching of PV investments. In contrast, our data display only a single instance of bunching, which occurs in 2012 (see Figure 13).

The estimated real discount factor (β) quantifies the relative valuation of future bene-

[40]Static models have frequently been applied in other contexts, such as in analyzing the trade-off between future fuel cost savings and higher upfront purchase prices. For example, Verboven (2002), Busse and Zettelmeyer (2013), and Allcott and Wozny (2014) employ static models in such settings. Including a static model in our analysis, as in De Groote and Verboven (2019), facilitates a direct comparison of estimated discount factors between studies, helping to contextualize our findings within the broader literature.

fits compared to the initial investment cost. The monthly discount factor for both models differ significantly from 1. The discount factor for the dynamic model is higher than for the static model. However, their confidence intervals overlap, making them non-statistically different. It is instructive to convert the monthly discount factor into an annual implicit real interest rate, calculated as $r = \beta^{-12} - 1$. We find that the implicit interest rate is 8.66% in the dynamic and 12.82% in the static model (with a standard error of 2.4% and 2.27%, respectively). The implicit interest rates are thus several order of magnitudes higher than comparable market interest rates during the sample period 2012-2021. For example, risk-free interest rate ranged between 0% and 1%, while medium-risk investments yielded around 2%. In addition, the government-owned German development bank KfW provided favorable loans for environmentally friendly investments, which further reduced the effective borrowing costs compared to market conditions. Despite these financing options, households appear to require a significant return premium to carry out investments into new PV technologies.

These estimates add to existing evidence that consumers significantly discount the future benefits of new technologies such as PV installations. An alternative, useful way to interpret these discount factors is to quantify consumers' willingness to pay for each euro of future discounted benefits. Given a future benefits period of $R = 240$ months, the present value of one euro in benefits is calculated as follows:

$$\Gamma(\beta) = \frac{1 - ((1-\lambda)\beta)^R}{1 - (1-\lambda)\beta} \,. \tag{47}$$

Using the empirical estimate for the discount factor from the dynamic model—$\Gamma(0.9931)$—and expressing the benefits relative to benefits obtained at a market discount factor of 3%—$\Gamma(1.03^{-1/12})$—yields: $\Gamma(0.9931)/\Gamma(1.03^{-1/12}) = 0.67$.[41] Thus, homeowner investors are willing to pay only 67 cents for every euro of total discounted future benefits from electricity production.[42] Notably, this means that the same level of German feed-in tariffs would have led to a faster adoption rate if German households placed a higher value on future energy savings—that is, if they were more forward-looking.

We also estimate the model at the state level, which allows us to account for heterogeneity in state-level regulation. Empirical results are shown Table B4 in an appendix. Although the price coefficient differs nominally, it is not statistically different. The discount factor and its standard error are virtually the same as in the main specification.

LANDLORD INVESTMENT DECISIONS.—Table 14 shows the empirical results for landlords obtained from the national-level model for the period July 2017 until December

[41] The comparable number obtained from the static model is 53 cents. We continue to rely on the estimate from the dynamic model as our preferred specification.

[42] This is comparable with De Groote and Verboven (2019) who find a slightly lower consumers' willingness to pay 50 cents. It also aligns with the discount rates reported in Allcott and Wozny (2014), where consumers valued future gasoline cost savings at just 76% of the upfront vehicle purchase price. Since market interest rates were higher during their sample period, our results suggest that households in our sample discount future income streams even more heavily than the consumers studied in Allcott and Wozny (2014).

Table 14: **Empirical results for landlords (national-level model, partial feed-in)**

	Dynamic		Static	
Price sensitivity in 10^3 Euro (α)	-0.0001	(0.0000)	-0.0001	(0.0000)
Monthly discount factor (β)	0.9893	(0.0026)	0.9897	(0.0010)
Annual implicit real interest rate (%)	13.78	(3.55)	13.23	(1.32)
Alternative-specific constants (γ)				
Common constant	-0.1716	(0.0415)	-16.0986	(0.0001)
2kW	-0.0831	(0.0001)	-0.0831	(0.0000)
4kW	-0.0415	(0.0001)	-0.0415	(0.0000)
8kW	0.0414	(0.0001)	0.0414	(0.0000)
10kW	0.0830	(0.0001)	0.0830	(0.0000)
12kW	0.1243	(0.0002)	0.1244	(0.0001)
15kW	0.1863	(0.0003)	0.1863	(0.0001)
Number of observations	378		378	

Notes: "Dynamic" refers to estimation results obtained with the dynamic adoption model presented in Section 3. "Static" refers to results obtained from a static model, which assumes that investors cannot delay their investment. Consequently, the discount factor β influences only the NPV of future income streams, without affecting the timing of the investment decision. Standard errors are not clustered at the monthly level given the small number of adoptions. Both models are estimated using GMM with the optimal weighting matrix obtained from a two-step estimation procedure. ^{a}Computed as $r = \beta^{-12} - 1$. Sample period from July 2017 until December 2021.

2021. Due to the limited number of tenant electricity model adoptions in this sample period, price sensitivity is difficult to identify. Additionally, compared to homeowner investment decisions, there is substantially less variation in investment prices.

The discount factor is highly similar between the dynamic and static models, corresponding to an annual implicit real interest rate of 13.72% and 13.16%, respectively. Using the estimates from the dynamic and static model in (47), we find that landlords are willing to pay 51 cents (52 cents) for each euro of total discounted future benefits from electricity production, respectively. First, this suggests that landlords also appear to require a significantly higher return premium to adopt new technologies such as PV installations. Second, the return premium for landlord investors is even higher than what is required by homeowner investors. We argue in Section 4.3, that a large chunk of this may be attributed to costs associated with bureaucracy around the regulation of tenant electricity.

4.2 Cost-Effectiveness of German PV Subsidies

Our analysis reveals that (homeowner) investors applied an implicit interest rate of approximately 8.6% when deciding to adopt PV installations, despite market interest rates being around 1–2% during the same period. This has an important policy implication: the same level of adoption could have been achieved at a lower budgetary cost by replacing the future production subsidies, providing an income stream over 20 years, with an equivalent upfront subsidy for PV investment costs (paid as a lump-sum subsidy at the time of installation).

To analyze this, we can use equation (31) to calculate the perceived net present value of feed-in tariff revenues over R months for a homeowner investor who adopts a PV system with capacity size j at time t:

$$NPV_{j,t}^{Perceived\ by\ homeowners} = \frac{1-[(1-\lambda)(1-\pi)\beta]^R}{1-(1-\lambda)(1-\pi)\beta} p_{j,t}^{FIT}(\beta)\,. \tag{48}$$

Using our estimate (from the dynamic model) from Table 13, $\beta = 0.9931$, yields the upfront subsidy the government would have needed to pay out to an homeowner investor to incentivize the same level of PV adoption. The net present value of the feed-in subsidy payments for the government, spread over the same number of months, is given by:

$$NPV_{j,t}^{Costs\ for\ government} = \frac{1-[(1-\lambda)(1-\pi)\hat{\beta}]^R}{1-(1-\lambda)(1-\pi)\hat{\beta}} p_{j,t}^{FIT}(\hat{\beta})\,, \tag{49}$$

where $\hat{\beta}$ denotes the monthly discount factor used by the government. The German government bond interest rate for a 20-year period was approximately 2.5% in 2012 (and 0.2% in 2021). To provide a conservative estimate, we use a discount rate of $r^{gov} = 2\%$. Hence, $\hat{\beta} = [1/(1+r^{gov}]^{(1/12)} = 0.9983$.

The government could have incentivized the same level of PV adoptions with capacity j at time t with paying the amount $NPV_{j,t}^{Perceived\ by\ homeowners}$ as an upfront subsidy, while saving the amount $NPV_{j,t}^{Costs\ for\ government} - NPV_{j,t}^{Perceived\ by\ investors}$. Summing over all adopters[43] and PV capacity sizes during our sample period from 2012 to 2021 provides the total budgetary savings, assuming the effective level of PV installations remains fixed:

$$\Psi = \underbrace{\sum_j \sum_t NPV_{j,t}^{Costs\ for\ government}}_{\substack{\text{Actual budgetary cost} \\ \text{of feed-in subsidies}}} - \underbrace{\sum_j \sum_t NPV_{j,t}^{Perceived\ by\ homeowners}}_{\substack{\text{Perceived value by investors} \\ \text{(=equivalent upfront lump-sum subsidy)}}}\,. \tag{50}$$

Put differently, Ψ measures the cost-effectiveness of the feed-in tariff program, i.e. foregone public spending resulting from the use of a sub-optimal subsidy design that fails to account for the undervaluation of future benefits from electricity production by investors. Based on the actual feed-in tariff rates and observed adoption rates, we estimate the actual budgetary cost over our sample period to be 7.5 billion euros. The perceived value of the feed-in subsidies by homeowner investors is estimated at 4.8 billion euros. Therefore, we estimate potential savings of $\Psi = 7.5 - 4.8 = 2.7$ billion euros (or 36% of the amount spent) for the German government, which could have been realized while achieving the same number of PV adoptions.

[43]Given the low number of PV adoptions by landlords, we only consider homeowner investments when the counterfactual savings obtained from an equivalent upfront investment subsidy.

4.3 Administrative Costs of Tenant Electricity

We do not explicitly model the bureaucratic requirements that would typically influence the adoption decisions of landlords as an administrative cost (in comparison to homeowners). Instead, by omitting these factors, they are incorporated into the error term, thereby affecting the estimated discount factor. With a fixed level of PV system adoption, underestimating these costs would lead to a higher estimated discount factor. If we assume that landlords and homeowners have the same discount factor but observe a lower estimated discount factor for landlords, the observed difference can be attributed to the additional costs associated with tenant electricity contracts. We argue that this discrepancy reflects the unobserved administrative costs involved in implementing tenant electricity.

We argue that it is reasonable to assume that the discount factor of homeowners provides a lower bound for the discount factor of landlords:

$$\beta^{Landlords} \geq \beta^{Homeowners} \tag{51}$$

as both groups have similar access to lending conditions and financial literacy. This similarity suggests that the discount factors of landlords are likely to be comparable to, or even higher than, those of homeowners. We compare landlords with homeowners because landlords in our sample do not have any other reasonable investment opportunities. We also considered two alternative approaches to modeling a landlord's investment decisions but found them less suitable. First, landlords could theoretically invest in full feed-in systems. However, given the data, these investments are almost never financially viable and would imply a discount factor greater than 1, meaning the investor would incur a loss (see Figure B5 and Table A12 in the appendix). Second, we cannot link ownership of multiple systems to a single individual, making it impossible to determine whether some investors in our sample are both homeowners with photovoltaic systems and landlords. As a result, using the homeowner's discount factor as a lower bound for landlords is, in our view, the most reasonable approach.

Assuming that (51) holds, we can estimate a lower bound for the administrative costs associated with tenant electricity. To do so, we compute the net present value of the benefits from PV investments in tenant electricity, discounting them at the household's discount factor, and compare this to the corresponding value discounted at the landlord's discount factor:

$$\Omega_{j,t} = NPV_{j,t}^{Tenant\ electricity}(\beta^{Landlords}) - NPV_{j,t}^{Tenant\ electricity}(\beta^{Homeowners}) \,. \tag{52}$$

To compute $NPV_{j,t}^{Tenant\ electricity}(\beta^{h})$, we need to account for both the revenue streams from feed-in electricity and from the electricity sales to the tenant

$$NPV_{j,t}^{Tenant\ electricity}(\beta^h) = \frac{1-[(1-\lambda)(1-\pi)\beta^h]^R}{1-(1-\lambda)(1-\pi)\beta^h} p_{j,t}^{FIT} + \frac{1-[(1-\lambda)(1+\vartheta)\beta^h]^R}{1-(1-\lambda)(1+\vartheta)\beta^h} p_{j,t}^{ELE,Landlords}.$$

We then use the estimated discount factor from the homeowner ($\beta^{Homeowners}$) and landlord investment decision ($\beta^{Landlords}$) as shown in Table 13 and Table 14, respectively, into (52).

We find that the implicit administrative costs for landlords account for an average of 22.5% of the total benefits of the PV system (95% CI: 21.4%–23.7%), corresponding to approximately 2,240 euros (95% CI: 2,121–2,358 euros). Given the low adoption rate of the tenant electricity program, this result is unsurprising. These findings suggest that administrative costs pose a significant barrier to landlord participation in the tenant electricity program. Policymakers took steps to reduce bureaucratic hurdles in 2021 and again in 2023, but it remains an open question how effective these reforms have been in cutting administrative costs and incentivizing adoption.[44] Here, we provide an estimate of the administrative costs for the period 2012-2021, highlighting the need for measures aimed at reducing these costs.

5 Conclusion

This paper examines the effectiveness of Germany's PV subsidy scheme, particularly in the context of residential ownership structures and the incentives faced by homeowners and landlords. Our analysis highlights the suboptimality of the feed-in tariff structure, showing that households heavily discount future benefits, leading to an inefficient use of government funds. By estimating a dynamic adoption model, we find that households value each euro of total discounted future benefits at only 67 cents, implying that a lump-sum subsidy paid on upfront investment cost could have achieved the same level of adoption at a 36% lower cost. Our estimates suggest that transitioning from the current feed-in tariff system to an upfront subsidy would have resulted in potential government savings of approximately 2.7 billion euros.

Furthermore, we analyze the investment decisions of landlords within the tenant electricity framework and identify significant barriers to adoption. Despite additional subsidies provided for landlord-tenant electricity contracts, the complexity of administrative regulations has deterred investment. We estimate that administrative costs account for approximately 22.5% of the total benefits of a PV system for landlords, amounting to an

[44] Amendments to the German *Tenant Electricity Law (Mieterstromgesetz)* aimed at reducing bureaucratic hurdles and promoting tenant electricity include increased tender volumes for solar projects, segmented tendering with higher compensation for installations on buildings to incentivize landlord participation, the promotion of solar on transport infrastructure, and the relaxation of distance regulations to enable more effective land use.

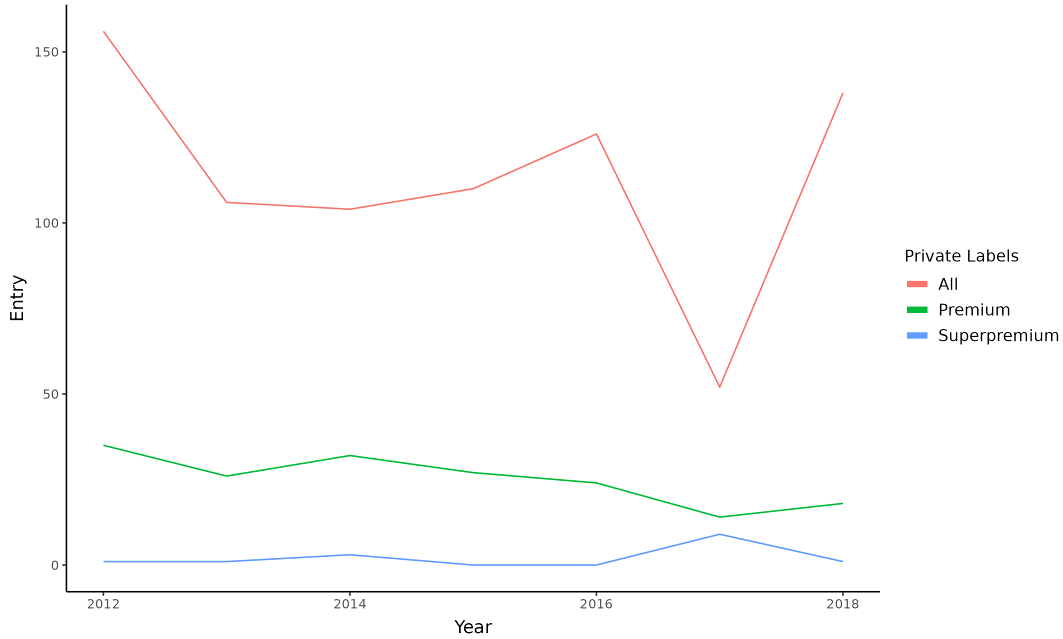
additional cost burden of roughly 2,240 euros per investment. These excessive costs have significantly hindered the success of tenant electricity programs, resulting in low adoption rates despite policy incentives. However, the importance of these programs should not be understated. Given the large number of tenants in Germany, the policy has the potential to increase the number of potential adopters in Germany by more than 100%. Since the German government has set an adoption target, facilitating greater landlord participation could have allowed for a reduction in subsidies while still achieving the desired expansion in PV adoption.

Our findings provide important policy implications. First, governments aiming to accelerate renewable energy adoption should prioritize upfront subsidies over long-term feed-in tariffs, ensuring that funds are utilized more effectively. Second, reducing bureaucratic hurdles in the tenant electricity framework is crucial to unlocking the investment potential of landlords and expanding solar energy access for tenants. Although recent regulatory reforms have sought to address these inefficiencies, further research is needed to assess their impact on adoption rates. Third, while many countries (not Germany), have transitioned to auction-based subsidies or other market-driven mechanisms to promote solar energy, the insights gained from a large-scale subsidy program like Germany's are likely to be valuable for designing cost-effective incentives in other public policy areas critical for decarbonization, particularly for the household adoption of electric vehicles and heat pumps.

Appendix

Chapter I Appendix

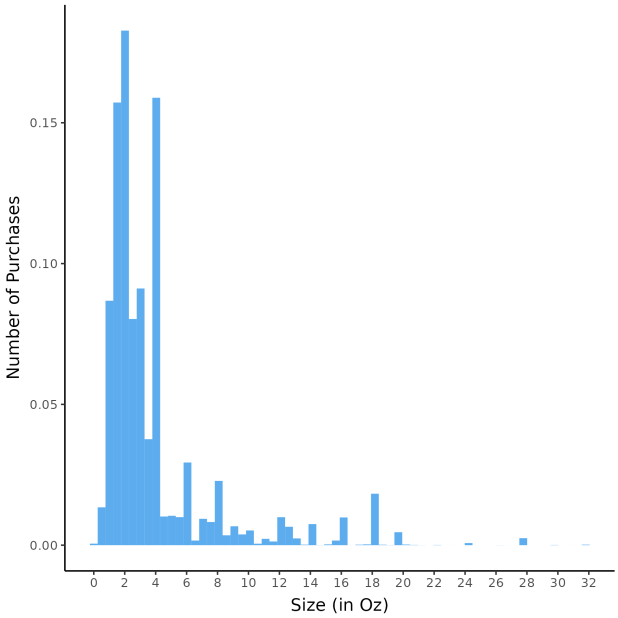
Figure A1: **Entry of private labels by quality**



Chapter II Appendix

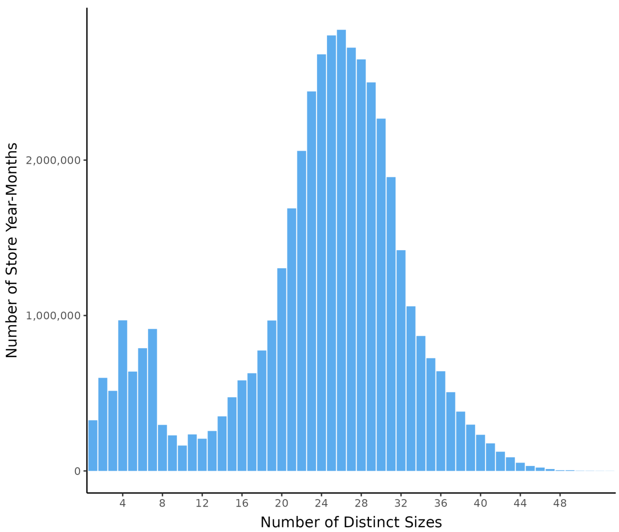
Figures and Tables

Figure A2: The Distribution of Sizes Purchased



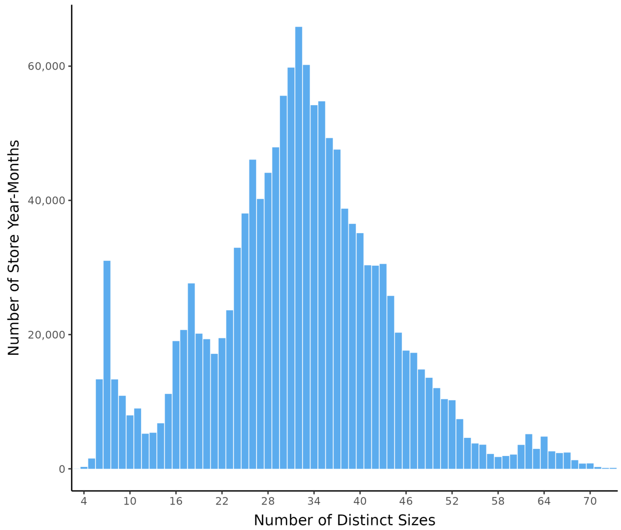
Based on household purchases from 2014 to 2016.

Figure A3: The Distribution of Distinct Sizes Offered
Store-Level Scanner Data



Based on the scanner data from 2014 to 2016.

Figure A4: The Distribution of Distinct Sizes Offered
Retailer-Dma Code Scanner Data



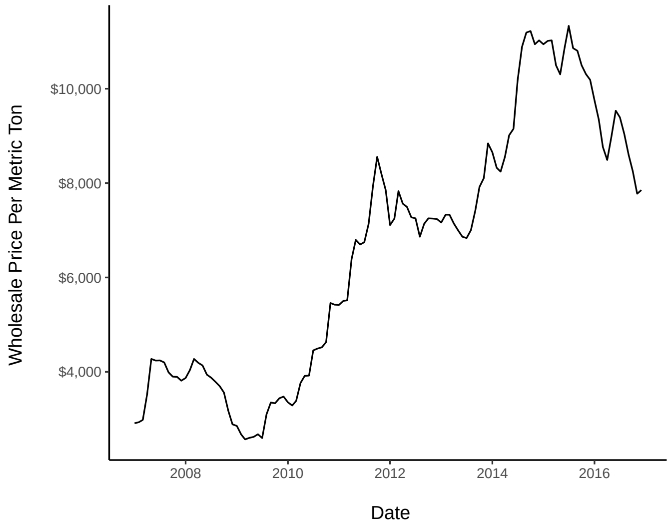
Based on the scanner data from 2014 to 2016.

Table B1: Downsized Products

	Product	Pepper Type	Original Size (Oz)	New Size (Oz)	Size Decrease (Oz)	
1.	McCormick Large Jar	Black	18	16	2	11%
2.	McCormick Large Jar	Black	8.75	7.75	1	11%
3.	McCormick Large Tin	Black	8	6	2	25%
4.	McCormick Medium Jar	Black	4.25	3.5	0.75	17%
5.	McCormick Medium Tin	Black	4	3	1	25%
6.	McCormick Medium Jar	Black	4	3.12	0.88	22%
7.	McCormick Medium Grinder	Black	3.1	2.5	0.6	19%
8.	Spice Supreme Medium Tin	Black	2.5	1.62	0.88	35%
9.	McCormick Medium Jar	Black	2.37	1.87	0.5	21%
10.	McCormick Small Tin	Black	2	1.5	0.5	25%
11.	Spice Classics Small Jar	Black	2	1.62	0.38	19%
12.	McCormick Small Jar	Red	1.75	1.37	0.38	22%
13.	McCormick Small Jar	Blend	1.62	1.25	0.37	23%
14.	McCormick Blend Small Jar	Black	1.62	1.25	0.37	23%
15.	McCormick Small Grinder	Black	1.24	1	0.24	19%

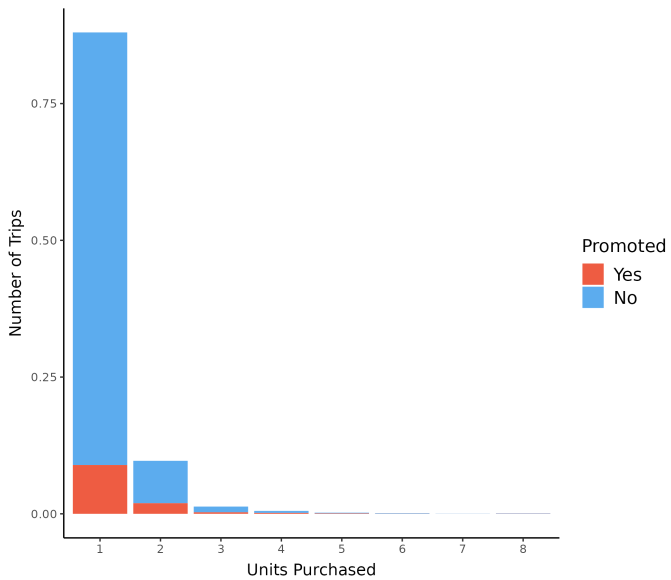
The list includes only name brand products. The products are ordered from largest to smallest size change.

Figure A5: Spot Price of Black Pepper in New York



Source: Pepper Statistical Yearbook 2018, International Pepper Community

Figure A6: The Distribution of Units Purchased per Shopping Trip



Only shopping trips with a pepper purchase are included. Based on household purchases from 2012 to 2016.

Figure A7: Counterfactual 1: Distribution of Changes in Prices (All Products)

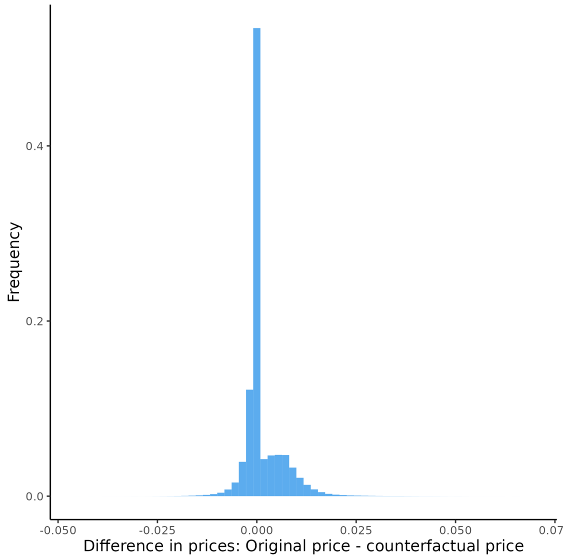


Figure A8: Counterfactual 1: Distribution of Changes in Prices (Downsized Products)

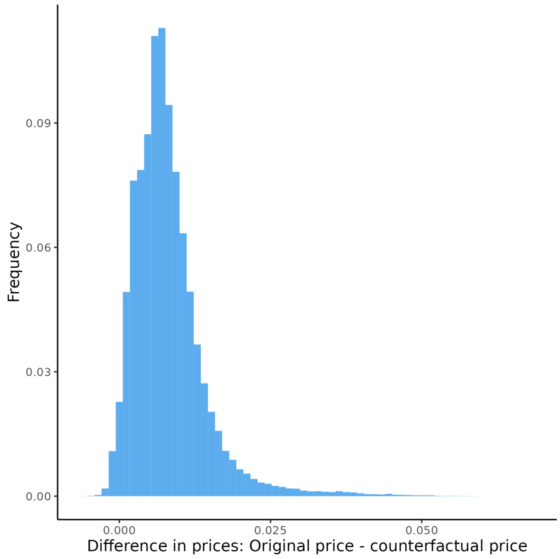
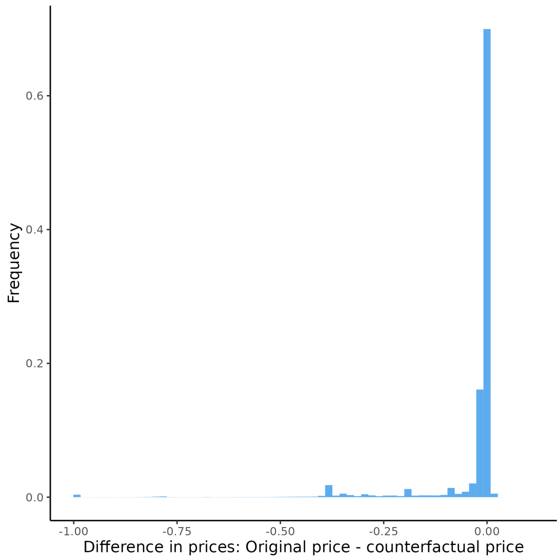


Figure A9: Counterfactual 2: Distribution of Changes in Prices (All Products)



The leftmost bin ”-1” contains all values lower than -1.

Figure A10: Counterfactual 2: Distribution of Changes in Prices (Downsized Products)

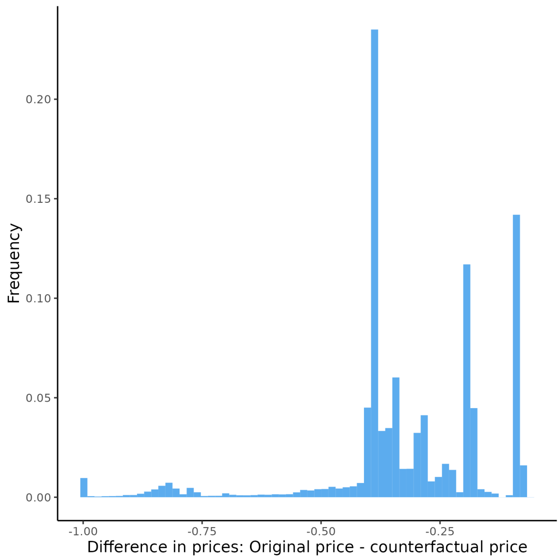
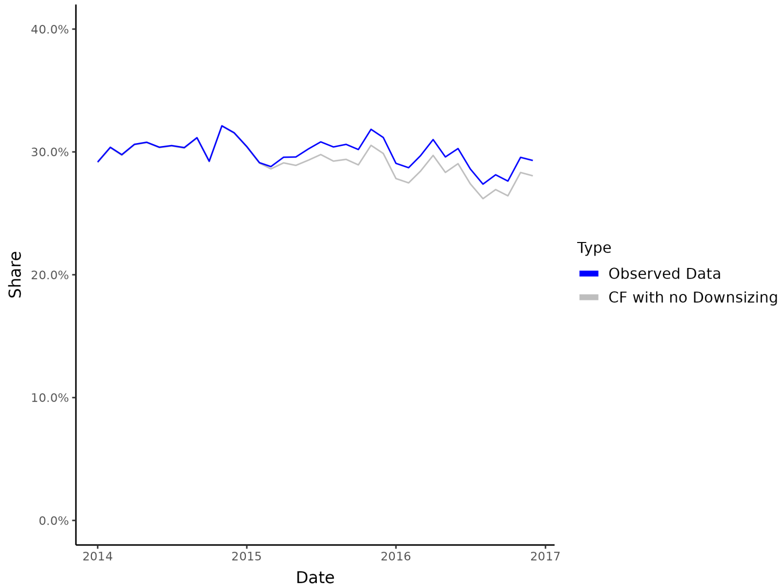


Figure A11: Counterfactual 2: Market shares



Monte Carlo Simulation

Data Generating Process We simulate $T = 100$ markets, each having $J = 50$ products. Consumers evaluate product j in market t based on an exogenous characteristic $X_{jt} \sim N(0, 1)$ and an unobserved characteristic $\xi_{jt} \sim N(0, 0.3^2)$. We draw product sizes Z_{jt} from a uniform distribution between 2 and 16. Consumer i's actual utility from consuming product j is:

$$U^a_{ijt} = \beta_0 + X_{jt}\beta_1 + Z_{jt}\gamma - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{53}$$

where $(\beta_0, \beta_1, \gamma) = (-5, 1, 1)$, $\alpha_i \sim N(-2, 0.5^2)$, and ϵ_{ijt} is distributed Type I extreme value.

To simulate downsizing, we randomly select 30 percent of the products and shrink the sizes of those products by 20 percent. We then randomly select which markets receive the downsized product. So like the real world, some markets have the original products and some have the downsized ones.

We assume that the probability of being inattentive and failing to notice the downsizing is $\eta = 0.3$. As in our main model, inattention causes consumers to misjudge the size of a product. An inattentive consumer i *perceives* the utility of downsized product j based on its original size Z_{j0} as:

$$U^p_{ijt} = \beta_0 + X_{jt}\beta_1 + Z_{j0}\gamma - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{54}$$

For the supply side, we assume marginal cost pricing with:

$$p_{jt} = mc_{jt} = 0.5X_{jt} + Z_{jt} + W_{jt} + \xi_{jt} + \varepsilon_{jt} \tag{55}$$

where $W_{jt} \sim N(0, 1)$ is an exogenous cost shifter, $\varepsilon_{jt} \sim N(0, 0.1^2)$ is a cost shock. The cost shifter W_{jt} serves as an instrument for price in the demand estimation.

Results We estimate the model using the BLP procedure described in section 7.2. The table below presents the results for 100 simulations. On average, we come close to the true values. Crucially, we accurately recover the inattention parameter. The confidence interval for $\hat{\eta}$ is fairly narrow and covers the true value of $\eta = 0.3$.

Table B2: Monte Carlo Results

	β_0	β_1	α	γ	σ_p	η
True Values	-5	1	-2	1	0.5	0.3
Estimate	-4.95	1.00	-2.05	0.99	0.53	0.29
	[-5.36;-4.39]	[0.98;1.02]	[-2.44;-1.68]	[0.98;1.01]	[0.3;0.75]	[0.24;0.34]

Inattention under Different Functional Form Assumptions

In this subsection, we derive the utility wedge due to inattention under different functional forms for how net weight enters utility.

As in modeling section, M_{kt} consumers visit retailer k looking to buy pepper in period t. Each consumer selects one product from the available pepper products J_{kt} or selects the no-purchase option 0. For now, we assume that consumers do not have heterogeneous tastes over net weight and price.

Quadratic Suppose that net weight enters utility as a quadratic. Consumer i's *actual* utility from purchasing product j is:

$$U^a_{ijkt} = x_{jkt}\beta + \gamma_1 z_{jkt} + \gamma_2 z^2_{ijt} - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \tag{56}$$

where x_{jkt} is a set of observable characteristics; p_{jkt} is the price; z_{jkt} is the current net weight; ξ_{jkt} is the unobserved product attributes; and ϵ_{jkt} is a random shock.

An *inattentive* consumer evaluates the downsized product j using its original weight and *perceives* his utility from j as:

$$\begin{aligned} U^p_{ijkt} &= x_{jkt}\beta + \gamma_1 z_{jk0} + \gamma_2 z^2_{jk0} - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \qquad (57)\\ &= x_{jkt}\beta + \gamma_1\big(z_{jkt} + z_{jk0} - z_{jkt}\big) + \gamma_2\big(z^2_{jkt} + z^2_{jk0} - z^2_{jkt}\big) - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt}\\ &= x_{jkt}\beta + \gamma_1 z_{jkt} + \gamma_2 z^2_{jkt} - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} + \gamma_1 \Delta_0 z_{jkt} + \gamma_2 (\Delta_0 z_{jkt})^2\\ &= U^a_{ijtk} + \gamma_1 \Delta_0 z_{jkt} + \gamma_2 \Delta_0 z^2_{jkt} \end{aligned}$$

where $\Delta_0 z_{jkt} = z_{jk0} - z_{jkt}$ is the change in the product weight and $\Delta_0 z^2_{jkt} = z^2_{jk0} - z^2_{jkt}$ is the change in the square of the product weight. The wedge term caused by inattention is therefore $\gamma_1 \Delta_0 z_{jkt} + \gamma_2 \Delta_0 z^2_{jkt}$. Because of inattention, the change in net weight and the change in the squared net weight enter perceived utility as additional characteristics.

Log Suppose instead that net weight enters utility as a log. Consumer i's *actual* utility from purchasing product j is now:

$$U^a_{ijkt} = x_{jkt}\beta + \gamma \log(z_{jkt}) - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \tag{58}$$

Consumers are either attentive or inattentive to downsizing. Let τ_i be an indicator for whether consumer i is attentive. An *inattentive* consumer evaluates the downsized product j using its original weight and *perceives* his utility from j as:

$$\begin{aligned} U^p_{ijkt} &= x_{jkt}\beta + \gamma \log(z_{jk0}) - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \qquad (59)\\ &= x_{jkt}\beta + \gamma \log(z_{jk0}) + \log(z_{jkt}) - \log(z_{jkt}) - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt}\\ &= x_{jkt}\beta + \gamma \log(z_{jkt}) - \alpha p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} + \gamma \log\left(\frac{z_{jk0}}{z_{jkt}}\right)\\ &= U^a_{ijtk} + \gamma \log\left(\frac{z_{jk0}}{z_{jkt}}\right) \end{aligned}$$

The utility wedge from inattention is therefore $\gamma \log\left(\frac{z_{jk0}}{z_{jkt}}\right)$.

Marginal Cost Results

The table below shows the supply-side results. The first three columns use a linear specification and the last three use a log-linear specifications. We also consider three different functional forms for net weight: linear, quadratic, and log.

Table B3: Marginal Cost Results

	(1) mc	(2) mc	(3) mc	(4) log(mc)	(5) log(mc)	(6) log(mc)
Constant	3.156	2.977	3.012	0.976	0.915	0.886
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Net Weight	0.336	0.426		0.097	0.132	
	(0.001)	(0.001)		(0.003)	(0.000)	
(Net Weight)^2		−0.005			−0.002	
		(0.000)			(0.000)	
log(Net Weight)			1.662			0.533
			(0.002)			(0.001)
Is Whole	0.380	0.426	0.568	0.032	0.047	0.109
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)
Black Pepper	−1.006	−1.093	−1.292	−0.294	−0.323	−0.422
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Blend Pepper	−0.426	−0.489	−0.752	−0.037	−0.059	−0.161
	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)
Cayenne Pepper	−1.238	−1.273	−1.385	−0.471	−0.483	−0.532
	(0.009)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)
Citrus Pepper	−2.018	−2.079	−2.289	−0.664	−0.685	−0.798
	(0.008)	(0.008)	(0.009)	(0.003)	(0.003)	(0.003)
Garlic Pepper	−1.505	−1.572	−1.774	−0.410	−0.433	−0.521
	(0.011)	(0.011)	(0.011)	(0.004)	(0.004)	(0.004)
Red Pepper	−1.458	−1.450	−1.372	−0.559	−0.557	−0.532
	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
Other Pepper	−0.430	−0.456	−0.389	−0.118	−0.127	−0.117
	(0.009)	(0.009)	(0.010)	(0.004)	(0.004)	(0.004)

Notes: Robust 95% confidence intervals in brackets.

The coefficients have the correct expected sign. Across all specifications, marginal cost increases with net weight. Using more of an input naturally increases the cost of a product.In addition, the coefficients for the various types of peppers are all negative, indicating that these types of pepper are more expensive than white pepper. As discussed previously, white pepper requires more processing since producers must first remove the outer skin of the pepper berries before drying.

Our results also indicate that whole spices have higher marginal costs. This may seem counterintuitive as whole spices require less processing. However, whole spices use different packaging. Most products with whole spices come in packages with built-in grinders, which adds to the cost. Whole spices also take up more volume, requiring larger packages for the same net weight.

Chapter III Appendix

State level Results

Table B4: **Empirical results for homeowners (state-level model, partial feed-in)**

	Dynamic		Static	
Price sensitivity in 10^3 Euro (α)	0.6943	(0.1826)	0.7843	(0.2132)
Monthly discount factor (β)	0.9941	(0.0014)	0.9912	(0.0014)
Annual implicit real interest rate in %	0.0732	(0.0181)	0.1118	(0.0190)
Alternative specific constants (γ)				
Common constant	-0.6943	(6.4912)	-6.6194	(0.9332)
2kW	-2.8312	(0.4445)	-3.6812	(0.4940)
4kW	-1.1308	(0.2753)	-1.5675	(0.3094)
8kW	0.0727	(0.2761)	0.5094	(0.3113)
10kW	-0.1520	(0.3986)	0.5992	(0.4178)
12kW	-3.9412	(0.6797)	-2.7474	(0.7170)
15kW	-3.2928	(0.9837)	-1.4388	(1.0409)
Region Dummies	Yes		Yes	
Number of observations	12,285		12,285	

Notes: "Dynamic" refers to estimation results obtained with the dynamic adoption model presented in Section 3. "Static" refers to results obtained from a static model, which assumes that investors cannot delay their investment. Consequently, the discount factor β influences only the NPV of future income streams, without affecting the timing of the investment decision. For all models, standard errors are clustered at the monthly level. Both models are estimated using GMM with the optimal weighting matrix obtained from a two-step estimation procedure. [a]Computed as $r = \beta^{-12} - 1$. Sample period from January 2012 until October 2021. Optimal Instruments are approximated using results from Chamberlain (1987).

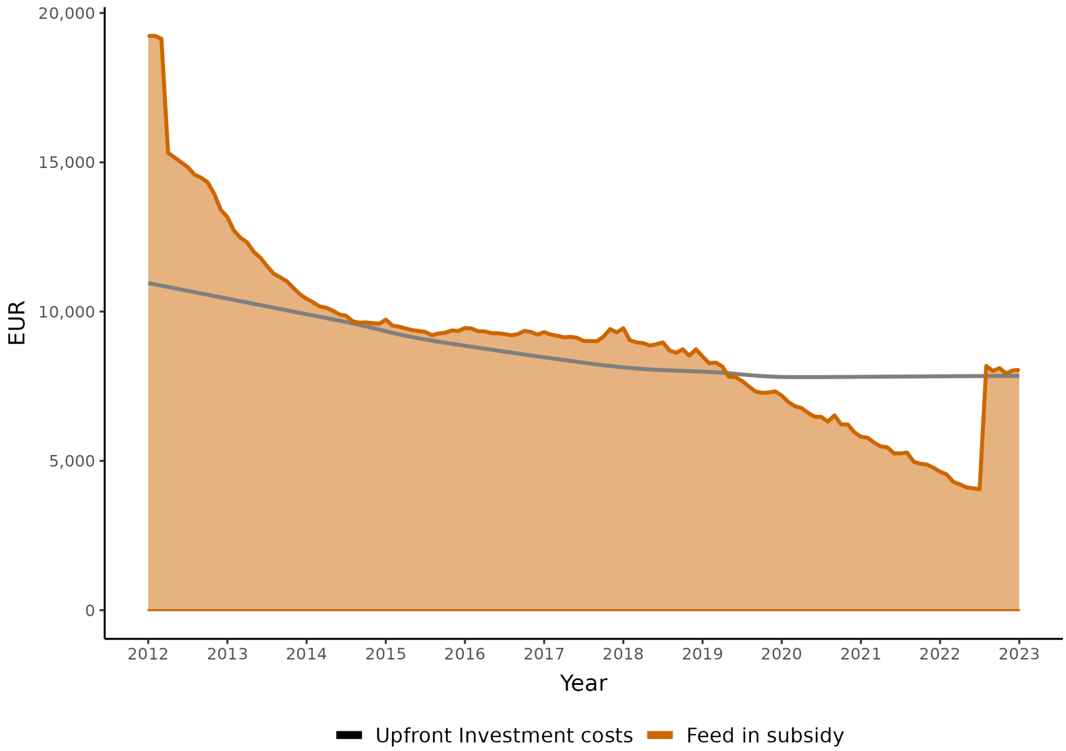
Results for Full Feed-in

Table B5: **Empirical results for homeowners (national-level model, full feed-in)**

	Dynamic		Static	
Price sensitivity in 10^3 Euro (α)	-0.0002	(0.0003)	-0.0001	(0.0003)
Monthly discount factor (β)	1.0005	(0.0096)	1.0078	(0.0404)
Annual implicit real interest rate in %	-0.0059	(0.1145)	-0.0889	(0.4379)
Alternative specific constants (γ)				
Common constant	0.0086	(0.1212)	-12.6262	(0.0021)
2kW	-0.0060	(0.0011)	-0.0062	(0.0011)
4kW	-0.0029	(0.0006)	-0.0031	(0.0004)
8kW	0.0029	(0.0006)	0.0031	(0.0012)
10kW	0.0061	(0.0007)	0.0062	(0.0015)
12kW	0.0091	(0.0012)	0.0093	(0.0022)
15kW	0.0136	(0.0019)	0.0139	(0.0033)
Number of observations	497		497	

Notes: "Dynamic" refers to estimation results obtained with the dynamic adoption model presented in Section 3. "Static" refers to results obtained from a static model, which assumes that investors cannot delay their investment. Consequently, the discount factor β influences only the NPV of future income streams, without affecting the timing of the investment decision. For all models, standard errors are clustered at the monthly level. Both models are estimated using GMM with the optimal weighting matrix obtained from a two-step estimation procedure. [a]Computed as $r = \beta^{-12} - 1$. Sample period from January 2012 until October 2021.

Figure A12: **Benefits and costs of a 6kW full feed-in PV system.**



Notes: Real interest rate used to calculate discounted benefits and costs = 3 percent. Upfront investment costs based on (approximation of) price index from EUPD Research (2024).

Countries which have adopted feed-in tariff programs following the German program

Germany's feed-in tariff (FiT) program directly influenced more than 50 countries worldwide. Below is a breakdown of some of the key countries that adopted FiT programs inspired by Germany:

Europe
1. Spain (2004): One of the earliest adopters, but its generous FiTs led to an unsustainable solar boom, forcing retroactive cuts.
2. Italy (2005): The Conto Energia program drove rapid solar growth but was later scaled back.
3. France (2006): Introduced high solar FiTs, later revised as costs fell.
4. United Kingdom (2010): Implemented a German-style FiT but later reduced incentives.
5. Portugal (2007): Established a FiT model that helped grow its renewable sector.
6. Greece (2006): Adopted high FiTs, leading to a solar boom.
7. Czech Republic (2005): Implemented generous FiTs, leading to a surge in solar installations.
8. Belgium (2006): Used FiTs alongside green certificates for solar incentives.
9. Austria (2002): Implemented FiTs to drive small-scale renewables.
10. Switzerland (2009): Launched a FiT program called KEV for renewables.
11. Hungary (2016): Launched a German-style FiT program called METÁR.
12. Poland (2016): Introduced FiTs for small-scale solar and wind projects.

13. Romania (2011): Initially used FiTs but later switched to a green certificate system.
14. Turkey (2010): Implemented FiTs to promote local solar manufacturing.

Asia-Pacific
15. Japan (2012): Introduced an aggressive FiT post-Fukushima, leading to a solar boom.
16. China (2011): Adopted FiTs for large-scale solar but later shifted toward auction-based subsidies.
17. South Korea (2006): Implemented FiTs but transitioned to a renewable portfolio standard.
18. Taiwan (2009): Modeled FiTs on Germany's system to boost solar adoption.
19. India (2010): Launched FiTs under the Jawaharlal Nehru National Solar Mission (JNNSM).
20. Thailand (2007): Introduced a FiT program known as the Adder Program.
21. Malaysia (2011): Adopted FiTs to accelerate solar deployment.
22. Australia (2008): State-based FiTs helped drive rooftop solar adoption.
23. Vietnam (2017): Introduced one of Asia's most successful FiT programs for solar growth.
24. Philippines (2012): Adopted FiTs for renewable energy.
25. Indonesia (2016): Launched a FiT system to encourage solar power.

North America
26. Canada (Ontario, 2009): Ontario's FiT program was one of the most ambitious outside Europe, inspired directly by Germany.
27. United States (California, Vermont, Hawaii) – Several states implemented FiTs, though the U.S. focused more on tax credits than nationwide FiTs.

Latin America
28. Brazil (2012): Established FiTs to promote solar energy.
29. Mexico (2013): Adopted a similar incentive mechanism.
30. Chile (2008): Implemented FiTs for small and medium renewable projects.

Middle East & Africa
31. South Africa (2009): Launched a FiT system but later transitioned to competitive auctions.
32. Israel (2008): Introduced FiTs for solar power.
33. Jordan (2012): Implemented a FiT program to promote renewables.

Countries which have implemented programs similar to Germany's tenant electricity model

Several countries have implemented programs similar to Germany's tenant electricity model, aiming to enable landlords or housing associations to provide renewable energy directly to tenants or to facilitate energy sharing through renewable energy communities:

California: The Solar on Multifamily Affordable Housing (SOMAH) program incentivizes the installation of solar energy systems on multifamily affordable housing units. It aims to deliver clean power and direct tenant benefits, reducing energy bills for low-income renters.

Belgium: The ASTER project equips social housing with free solar panels, allowing tenants to consume renewable energy at reduced rates. This initiative not only lowers energy bills but also addresses energy poverty by making clean energy accessible to low-income households.

Italy: Since 2020, Italy has facilitated energy sharing through renewable energy communities. Members connected to the same high-voltage substation can jointly operate renewable energy systems up to a capacity of one megawatt. An incentive system rewards decentralized consumption, providing a premium for shared energy generated and consumed by the community. The City of Magliano Alpi established Italy's first renewable energy community in December 2020, enabling citizens to become energy prosumers by producing energy from sustainable sources like rooftop solar and sharing it with neighboring buildings.

Austria: The Renewables Deployment Act facilitates the creation of energy communities, allowing citizens to participate actively in the energy transition. Members can consume, share, store, and sell their own renewable energy production, promoting autonomy over energy supply.

Spain: Collective self-consumption has been possible since 2015, with significant growth following the abolition of the "sun tax" in 2018. Renewable energy communities, defined in line with EU directives, allow local citizen participation in renewable projects, with various regional programs promoting these initiatives.

Portugal: The legal framework permits shared self-supply from renewable energy sources through the distribution grid. Generation systems and consumers must be connected to the same transformer station, and energy sharing is incentivized with reduced grid usage fees.

France: Energy sharing is facilitated through renewable energy communities, allowing shared self-supply via the distribution grid. In rural areas, a distance of up to 20 kilometers is permitted between generation systems and consumers, promoting decentralized renewable energy consumption. These initiatives demonstrate a growing global effort to integrate tenants into the renewable energy transition, ensuring that the benefits of clean energy reach a broader spectrum of society.

These initiatives demonstrate a growing global effort to integrate tenants into the renewable energy transition, ensuring that the incentives for and benefits from renewable energy investments can be shared among a broader group of market participants.

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Eidesstattliche Versicherung gemäß §8 Absatz 2 Buchstabe a) der Promotionsordnung der Universität Mannheim zur Erlangung des Doktorgrades der Volkswirtschaftslehre (Dr. rer. pol.)

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   Die eingereichten Dissertationsexemplare sowie der Datenträger gehen in das Eigentum der Universität über.

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