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Essays on Industrial Organization

by

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Committee in charge:

Associate Professor Benjamin Handel, Chair
Associate Professor Jonathan Kolstad
Associate Professor Benjamin Faber

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Abstract

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We study the question of whether women, on average, pay a price premium — a so-called "pink tax" — for the products they buy. A particular concern facing policy makers is whether such differences are a form of gender based price discrimination. Using scanner data, we find that averaged across the entire retail grocery consumption basket, women pay 4% more per unit for goods in the same product-by-location market as do men. This price differential is generated by a 15% higher average per unit price paid by women on explicitly gendered products, like personal care items, as well as a 3.8% higher average per unit price paid by women on ungendered products, like packaged food items. Higher prices paid by women could be the result of differences in demand elasticity, competitive structure, or sorting into goods with differing marginal costs. To disentangle these mechanisms, we estimate demand differences between men and women and structurally decompose price differences into markups and marginal costs. We find that women are, on average, more price elastic consumers than men, suggesting that as a consumer base women are not likely to be charged higher markups under price discrimination. Overall, we find that the pink tax is not sustained by higher markups charged to women, but by women sorting into goods with higher marginal costs and lower markups.

Medical provider price transparency is often touted as a key policy for efficiently lowering health care spending, which is nearly 20% of GDP. Despite its many proponents, the impact of price transparency is theoretically ambiguous: it could lower health care spending via increased consumer price shopping or improved insurer bargaining position but could instead raise health care prices via improved provider bargaining or either tacit or explicit provider collusion. We conduct a randomized-controlled trial to examine the impact of a state-wide medical charge transparency tool in outpatient provider markets in the state of New York. In the experiment, individual providers' billed charges (list prices) were released randomly at the procedure X geozip level. We use a comprehensive commercial claims database to

assess the impact of this intervention and find that the intervention causes a small increase in overall billed charges (+1%) but a relatively lower increase in the charges for procedures with many out-of-network claims (-2%). We find no evidence for quantity effects. We find larger charge increases for specific categories that are almost always insured and less elective in nature, e.g. MRI (+6%) and radiology (+3%) and charge decreases for categories that are less often insured and more elective in nature, e.g. psychology (-2%) and chiropractor (-3%) services. Taken together, these results are consistent with our intervention having a minimal effect on consumer price shopping but a meaningful effect driving increases in providers' charges, especially for less elective services that are almost always covered by insurance, potentially reflecting perverse price effects resulting from tacit collusion or reduced information asymmetries.

To Bella con Cejas Barnes Lopez

My canine coauthor who slept on the job all day, everyday. Who enforced daily breaks at 5pm to go play. Who never left my side when my code broke or my estimates didn't converge. Who measured my worth in my ability neck scritches and tummy rubs rather than my academic prowess. You are the goodest girl.

And to Emmanuel Lopez

Who loved and supported me through every moment of this PhD.

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Introduction

This dissertation studies how consumers interact with market structure to affect market outcomes. My dissertation research can be divided into two distinct categories: (1) understanding gender disparities in the consumption and production of retail packaged goods and (2) consumer decision making in healthcare and its implications for healthcare markets. While these categories are distinct in setting, the topics and mechanisms are closely related in the study of markets and demand within the sub-field of Industrial Organization. The first two chapters of my dissertation explore how consumers with heterogeneous preferences and demand can create systemic disparities in consumption across gender. The third chapter studies how reducing information asymmetries for both consumers and providers can effect prices and quantities.

All three chapters explore how demand and supply interact to create equilibrium allocations of products or services. This has long been a topic of interest and the focus of much economic research. My dissertation contributes to this ongoing research by studying systemic disparities within these equilibrium allocations and by considering full market responses to information treatments. The research focuses on the settings of consumer packaged goods, which are products purchased from grocery stores, and outpatient health care markets, which consist of all health care services that do not require admission to a hospital or an overnight stay. These settings encompass a large share of consumer spending and also reflect the markets that consumers most often operate in. The frequent purchases and detailed data available from consumer packaged goods markets make it an ideal setting for studying the nature of preferences and demand. Healthcare markets in the US are rife with information asymmetries that can distort markets. On the supply side, both settings offer significant variation in market competition, ranging from non-competitive or highly differentiated to highly competitive or homogeneous.

Chapter 1

Estimating the causal components of the Pink Tax using a Constant Elasticity of Substitution model of Demand

Authors: Kayleigh Barnes and Jakob Brounstein

"It costs a lot of money to look this cheap."
— Dolly Parton

1.1 Introduction

Is it more expensive to be a woman? Economic and societal forces have shaped preferences and product offerings to create disparities in the way men and women consume goods. The notion that there exists a price premium on women's consumer goods relative to those of men is colloquially referred to as the "pink tax". The concept has received considerable attention in popular media and has spurred recent legislation in New York and California. This public discourse on the pink tax often attributes it to gender based price discrimination, where goods that are marketed to women have higher markups resulting from less elastic demand or less competitive markets. Existing studies of the pink tax find mixed evidence of its scope and magnitude and either focus on a narrow set of goods or do not delve into its underlying economic mechanisms (Moshary, Tuchman, and Bhatia 2021; Guittar et al. 2022; NYCDCA 2015; Duesterhaus et al. 2011; Manzano-Antón, Martinez-Navarro, and Gavilan-Bouzas 2018). Moshary, Tuchman, and Bhatia (2021) evaluate the existence of the pink tax for personal care items and find no evidence of higher markups on women's products when controlling for proxies of marginal costs. Controlling for marginal costs restricts comparisons to between goods with the same inputs and tests for third degree price discrimination. However, this type of comparison abstracts away from men's and women's purchase decisions and does not capture the role of differential sorting by men and women.

This paper explores the existence and underlying mechanisms of the pink tax by describing consumption baskets for men and women, analyzing how they vary by quantity, price, and diversity of products consumed, and then decomposing observed price differences into markups and marginal costs. Our paper considers a broad definition of the pink tax[1], considering any channel through which women may face higher markups in the retail consumer packaged goods (CPG) space. This definition allows us to capture the role of differential sorting between men and women and second degree price discrimination, or versioning, in generating the pink tax. We find that, averaged across the entire grocery consumption basket, women pay 4% higher per unit prices than men do for products in the same product-by-location market. We find that this price difference is sustained not just by purchases of gendered products, like men's and women's razors, but also by differences in purchasing habits between men and women for food and household items. This finding could be driven by three economic mechanisms that determine pricing: (i) women could have less elastic demand than men, (ii) women could consume products with more market power or from less competitive markets than men, or (iii) women could consume products with higher marginal costs. Pricing disparities due to markups based on demand differences or competitive structure impact consumer surplus directly, potentially driving welfare differences by gender. Price differences based on underlying production costs across the consumption baskets, on the other hand, do not reduce consumer surplus and are not perceived as an issue for "fairness" (Kahneman, Knetsch, and Thaler 1986). Disentangling the mechanisms driving the observed price premium on women's products is, thus, important to inform economic understanding and policy alternatives.

To characterize the Pink Tax and, broadly, gender differences in consumption habits, we employ several data sets that contain detailed information on individuals and their purchases, store-level product offerings, and retail prices. The Nielsen Consumer Panel Survey features a 15-year rotating panel of households and the near-universe of their purchases at big box retailers and grocery stores. Importantly, the data includes rich household demographic information as well as highly detailed product and purchase characteristics—including deal/sale usage, prices paid/quantities consumed, and a hierarchy that aggregates products into tractable market definitions. By restricting the bulk of our analysis to single-member households, we are able to attribute each purchase made to a specific gender. We augment the Consumer Panel with the Nielsen Retailer Scanner data which contains store level data on prices and quantities sold in any given week.

[1] We identify three scenarios through which the pink tax may operate: 1) different prices for goods with the identical inputs: e.g. without changing anything else, by coloring a product pink, retailers and producers

We begin by establishing the existence of systematic gender differences in consumption and pricing along two margins: consumer behavior and the product space. To document consumer behavior, we describe consumption bundles for men and women, documenting differences in their unit price and composition. We find that women spend about 6% more than men do on retail CPG consumption and that their consumption bundles are larger and more diverse. The products that women purchase are on average 4% more expensive per unit than those purchased by men in the same product-by-location market. In the product space, we document a significant share of products that are exclusively bought by one gender, with the majority of these products gendered towards women. These products are particularly common in markets with explicit gender differentiation in marketing and product design, such as in beauty and personal care goods. We categorize products bought at least 90% of the time by one gender as "gendered" products, categorizing all other products as "ungendered". We then decompose the average 4% price premium paid by women into a contribution from differential sorting into ungendered products and from purchases of explicitly gendered products, finding that women pay an average of 3.9% higher prices on ungendered products relative to men and that women pay an average of 15% higher prices on gendered products relative to men. While gendered items have large price premiums, they make up a small share of actual purchases; the bulk of the price premium is being driven by women buying more expensive ungendered items than men.

We then turn our attention to understanding the demand and supply mechanisms that give rise to women paying higher prices. Profit maximizing firms set prices as a function of own-price elasticities, market shares, cross-price elasticities of products owned by the same parent company, and marginal costs. Less elastic own-price elasticities put upward pressure on prices as firms can raise prices without losing much of their consumer base. Higher prices paid by women could then be consistent with women being less elastic and firms price discriminating off of the gender composition of their consumer base. Alternatively, differences in competition and market structure can also contribute to higher markups if women's markets are more concentrated, meaning that their products have higher market shares, or if women's products are more likely to be owned by multi-product firms, as substitution to products with the same parent company puts upward pressure on prices. Both the demand elasticity and competition narratives would contribute to higher prices through women paying higher markups, which has potential welfare effects for women. Finally, women could face higher prices if the products that they prefer have higher marginal costs than the products that men prefer, that is, if women differentially sort into products with higher costs of production.

can charge a higher price. 2) different prices for goods with identical uses but non-identical inputs: i.e. the price difference between goods purchased by men or women is attributable to differences in the cost of production. 3) expense differences driven by goods that are almost exclusively purchased by a single gender: e.g. the purchase of makeup or feminine hygiene products. In some instances, the pink tax refers to the luxury, sales, or value added taxes statutorily placed on women's hygienic products. Our analysis focuses on the more general case of price differences between men's and women's consumer goods.

To assess these possibilities, we model demand and supply, attributing differences in pricing and product choice to markups and marginal costs. We begin by estimating demand elasticity differences between men and women across the entire retail grocery consumption basket. We develop a simple, tractable model assuming constant elasticity of substitution that allows us to estimate demand by gender in the aggregate population. We aggregate individual-level purchase data to the a gender-by-product module-by-location market level and we find that, on average, women consume products more elastically than do men. This finding is consistent with women being the consumer group that is charged lower markups rather than higher markups under price discrimination.

Our findings suggest that the pink tax is not a form of systemic price discrimination against women but that, if anything, women pay lower markups on average than men. Current legislation is largely focused on banning price differences for products that differ only in gender. Our paper suggests that these laws are likely to be ineffective at addressing price disparities between men and women, as the majority of our observed pink tax can be explained by men and women sorting into products that differ by more than just gender.[2] Our findings have important implications for other policy relevant issues, like potential disparities in the incidence of inflation between men and women. Finally, our findings motivate future research to study how men's and women's preference differences are formed as well as the role of preference differences in generating product differentiation through product entry and exit.

We proceed as follows: Section 2 discusses the background and history of the pink tax as well as relevant literature. Section 3 describes our data. Section 4 presents our descriptive analysis. Section 5 describes and estimates a constant elasticity of substitution demand model of men and women's consumption. Section 6 discusses the implications of our results and concludes.

1.2 Background and Literature Review

The term "The Pink Tax" was first coined in the 1990's in California, when concerns about gendered price discrimination of services, such as dry cleaning and in hair salons led to the explicit anti-price discrimination law, The Gender Tax Repeal Act. Soon after similar legislation was passed in New York City and Miami. A national version of The Gender Tax Repeal Act has been introduced federally several times since 2016 but has never been passed. More recently, there has been renewed policy interest in the Pink Tax, particularly in the setting of gendered price discrimination for consumer retail products. In 2020, the state of New York passed legislation that would outlaw gender differential pricing. In 2022,

[2]The state of New York has banned pricing on the basis of gender through bill S2679 which took effect in 2020. A similar bill, AB 1287, was signed into law in California by Governor Gavin Newsom on Sept. 27, 2022. The Pink Tax Repeal Act has been presented in Congress four times and aims to put national law in place similar to the New York and California policy.

California passed a similar law. The language surrounding these laws frames the Pink Tax as a price discrimination story with the underlying assumption that markups are higher for women's products.

However, in spite of its importance as a potential component of gender inequality and its wide presence in popular discussion, there are few studies that rigorously substantiate the Pink Tax. The New York law was based on evidence collected and presented in a New York Department of Consumer Affairs (NYC DCA) study in 2015. The NYC DCA compares products in thirty-five categories and five broader industries with "clear male and female versions" sold by New York City retailers, finding that women's products cost on average seven percent more than similar products for men. While it provides key preliminary suggestive evidence of a "pink tax", the NYC DCA analysis is largely incomplete: it consists of a highly limited number of goods that were gender-matched in a subjective manner; moreover, it only documents raw list price differences rather than actual prices paid. Recently, Moshary, Tuchman, and Bhatia (2021) assess the pink tax under the definition in the New York law, products that differ only in gender. They control for brands and ingredients as a proxy for marginal costs and find no evidence of a systemic pink tax. Other works similarly focus on health and beauty products, using in store surveys of products to descriptively document price premia of around 5% on women's goods. (Duesterhaus et al. 2011; Manzano-Antón, Martinez-Navarro, and Gavilan-Bouzas 2018; Manatis-Lornell et al. 2019) Taken together, list price differences suggest that women may be paying more than men for goods with similar uses, but Moshary, Tuchman, and Bhatia (2021)'s finding of no pink tax when matching on marginal costs suggests that women and men are sorting into products that differ by more than just gender. Our paper explicitly studies differences in the prices, markups and marginal costs of the entire range of retail goods that are bought by men and women, capturing this sorting component.

Within economics, there is relatively little work that focuses on gender disparities in the pricing of goods and services. The most-related work on gendered price discrimination focuses on bargaining contexts for wages or products. Most recently, Rousille (2021) attributes nearly 100% of gender pay inequality among tech industry workers to differences in wage-asks by interviewees, underscoring the potential role for differences in bargaining power to generate gender-inequality. Ayres and Siegelman (1995) provide evidence of race and gender discrimination in bargaining for new cars, finding that women and black men paid significantly higher markups for cars than white men. This setting has been further studied by Goldberg 1996 and Trégouët 2015, with Castillo et al. (2013) also documenting systematic differences in stages of taxi-price bargaining for men and women. Fitzpatrick 2017 finds evidence of gender price discrimination in the context of bargaining for anti-malarial drugs. While these studies provide evidence and precedence of price discrimination against women, they do not capture a mechanism by which price discrimination can occur of goods with simple take-it-or-leave-it list prices nor the role of differences in preferences across product offerings.

Because we investigate the pink tax across the retail consumption basket, we view this work as closely-related to research on inequality in consumption and product offerings. Jaravel 2019 finds that poorer households experience higher inflation and price indices, exacerbating income inequality in real terms. Though we do not directly calculate differences in inflation for men and women, our work on gender explores a new angle through which price index inequality may shape wealth inequality at large. Aguiar and Hurst 2005 use survey data to demonstrate that consumption remains relatively constant among individuals as they transition into retirement, simultaneously documenting differences in sources of consumption (e.g. restaurant dining, home-production, etc.) between men and women. Aguiar and Hurst 2007 also quantify objects such as the substitution elasticity between shopping and home production and and the willingness to engaging price shopping or to take advantage of deal; while not explicitly focused on gender distinctions, their findings on the price returns of time spent shopping have important implications for understanding the differences in prices paid by men and women.

The implications of the Pink Tax for gender equality are wide-reaching: taking into account differences in the cost of consumption prompts us to re-frame the widely-studied difference in wages between men and women as a *nominal* wage gap. Moretti (2013) has shown that population specific price indices have important implications for wage inequality in real terms. Estimates of the raw gender pay gap tend to around 20% today, decreasing to about 10% after including differences in qualifications (Blau and Kahn (2017)). The presence of an aggregate Pink Tax on women's consumption augments these inequalities by reducing women's purchasing power. Moreover, by accounting principles, the existence of a Pink Tax also highlights differences in overall consumption and savings between men and women. Women, facing on average higher prices for their respective consumption bundles face both lower real wages and potentially lower scope to accrue lifetime savings and consume.

Faber and Fally 2022 study how product offerings and firm sorting drive price index inequality across incomes. They find that larger, more productive firms endogenously sort into markets that cater to richer households and that this drives asymmetry in price indices across the income distribution. This study suggests that supply side factors may play an important role in differences in product offerings and marginal costs for men and women. Simultaneously, DellaVigna and Gentzkow 2019 find substantial price mis-optimization for retail chains, where stores typically implementing uniform prices throughout all US stores irrespective of local demand and cost factors—suggesting some limitations to how and to what extent firms engage in optimal price strategy. B. J. Bronnenberg et al. 2015 study how information and experience may drive inequality in product choice on the consumer side by looking at differences in choices made between experts (by profession) and non-experts in purchasing drugs and grocery items. They find that non-experts over pay for brand name products more than experts do. While expertise may not be a direct driver of differences in product choices between genders, this work highlights the potential for misinformation and incorrect product beliefs to affect choices and prices paid.

1.3 Data

We combine data on from two main sources and two supplemental sources to conduct our analysis. Our main analyses rely on the NielsenIQ data including the HomeScan Panel (HMS) and the Retailer Scanner Data (RMS). The HMS data contains purchase histories of for a rotating panel of households from 2004 to 2019. The RMS data contains anonymized purchases of products aggregated to the store-week level throughout 2007 to 2017. We supplement the NielsenIQ data with the Consumer Expenditure Survey public use micro data (CE PUMD) to document descriptive evidence of differences in consumption spending across the entire consumption basket. Lastly, we incorporate data from National Promotion Reports' PRICE-TRAK database (PromoData), which features data on wholesaler prices charged to retailers for certain products from 2008-2013. While we discuss these data in turn, see B. J. Bronnenberg et al. (2015) and Allcott, Lockwood, and Taubinsky (2019) for further discussion of the NielsenIQ data.

The entire HMS features data on the shopping trips and transactions of approximately 60k households per year. Households remain in the panel for on average 54 months, with approximately 200,000 distinct households rotating through the HMS in total. The data report on purchases made by households on the 20 million shopping trips from 2004 to 2019 made by the panelists. For each individual item purchase, we observe the transaction metadata such as date, store/retailer-info, and panelist identifier, as well as granular data on product and transaction details, including prices paid, amounts and units of quantities purchased, deal/sale usage, and detailed nests of product identifiers.

Our primary uses for the HMS data are to document differences in the purchasing behavior of men and women and understand how product markets differ for men and women. To confidently assign product purchases to consumer gender demographics, we restrict our consumer panel to single-individual households that log at least 12 shopping trips per year, which eliminates approximately 75% of the panelists in the HMS. This leaves us with a panel of 47,012 households which we use to study differences in consumer behavior. Summary statistics for the sample can be found in 1.1. Our final sample is skewed women, with about 70% of our panelists identifying as a woman. In terms of balance, the men in our sample tend to have higher income and be more educated, which we will control for in the analysis. The second component of our analysis focuses on how the product market space varies by gender. For this analysis, we restrict our data to products that we can confidently assign a gender to. We describe our methodology in detail in Section 3.2. The NielsenIQ data covers approximately 1.8 million products and we are able to confidently assign gender to 700,000 of them. However, these 700,000 products comprise 97% of the purchases made in our singles panel.

There is considerable discussion on the representativeness of the HMS panel. B. J. Bronnenberg et al. (2015) summarize this discussion that argues in favor of the representativeness of the panel of US consumers. While applying the included HMS projection weights render the sample much more representative of the US, the raw using-sample departs significantly from basic US demographics. Our sample skews significantly more female than male, by a ratio of 3:1, and the in-sample median age of 53 is significantly older than the US median age of 38. The panelist's income demographics appear slightly more representative, with the median single-individual household earning approximately \$37,000 USD per year and the median household, unconditional, reporting approximately \$55,000 USD.[3] Nonetheless, applying the projection weights yields demographics that much more closely align with those of US consumers.

Both components of the NielsenIQ data feature a highly detailed product hierarchy classification that organizes all goods into smaller nests with increasing degrees of specificity. Products in the NielsenIQ are identified with their Universal Product Code (UPC) which corresponds to a unique barcode. All UPCs fit into one of ten *departments* (the broadest category, e.g. "Health and Beauty" and "Dry Grocery"). From here, products in a department are allocated to *Product Groups*—of which there are 120 total—such as "Shaving Needs". Finally, UPCs in the same Product Group are assigned to *Product Modules*—the most granular grouping of multiple products—e.g. "Disposable Razors". The Nielsen data identifies over 1300 distinct product modules. Brand description represents an alternate grouping that features the brand name for a given set of UPCs, not strictly contained in any single Product Module or Group contained, such as "Venus", for the brand of razors. We consider Product Modules as constituting a self-contained goods market; for certain reduced-form analyses, we further divide product modules into Module-Unit groups (modules composed of goods all with the same counting units: e.g. the coffee product module contains bagged coffee measured in weight (ounces) and Keurig cup coffee measured as a count (number of K-cups).

The Consumer Expenditure Survey Public Use Microdata (CE PUMD) is publicly available from the Bureau of Labor Statistics and provides information on a household's expenditures and income. The CE PUMD is comprised of a quarterly interview survey of 6,000 households that tracks overall spending and large purchases and a diary survey of 3,000 households that tracks all purchases over a two week period. We utilize only the quarterly interview surveys to inform aggregate consumption basket price and composition differences. Similar to the Nielsen HMS data, we restrict our analysis to individuals that live alone which allows us to attribute spending to one gender. We use data from years 2010 to 2017 which comprise 67,950 person-quarter observations. Summary statistics are presented in Table A.1.4. Similarly to our HMS single household panel, our CE PUMD single household panel shows that women tend to be older and poorer than the men in the sample, but otherwise are roughly similar

[3]These figures represent the midpoint of the discrete income buckets used for the household income field

demographically. The CE PUMD interview survey contains quarterly spending info for several categories; we focus on the eight categories that comprise the vast majority of spending: food, housing, clothing, transportation, health, entertainment, personal care, and alcohol and cigarettes. Each category aggregates all of the spending made by the individual in the quarter before their interview. Thus the food category contains all spending related to food: groceries, restaurants, convenience stores, etc. The housing category includes both rental and mortgage spending, health includes health insurance, payments to health care providers and prescriptions, and personal care includes hygiene, well being and beauty spending.

1.4 Price Disparities Across the Consumption Bundle

We present evidence of gender differences in both consumer behavior and the product space. We begin by examining overall differences in consumption basket composition, finding significant differences in how men and women choose to allocate their income. We document that, within grocery and big box retail purchases, women spend more than men—both overall and per item—and that products primarily bought by women are priced higher than those bought equally by men and women or primarily by men. These consumer behavior differences and product space differences indicate that gender disparities in consumption are driven by both demand and supply side forces. Women spend more per item, and there exists a larger product space of goods marketed more exclusively toward women than toward men. In line with these findings, we demonstrate the existence of a women's price premium of approximately 4% on average.

Consumer Behavior by Gender

First, we document that women's consumption bundles are different from those of men in terms of composition. Using the CE PUMD we find that women and men do not have significant differences in total yearly spending, but how they choose to allocate their spending highlights important differences in preferences across all types of spending. Figure 1.1 plots women's yearly spending as a percentage of men's. Each bar plots the coefficient from a regression of log spending for a category on an indicator for the individual being a woman controlling for age, income and race. Women spend significantly more of their income on housing, clothing, health and personal care, while men spend relatively more on food, alcohol and cigarettes, and transportation. These findings roughly correspond with markets that are often discussed in discourse on the pink tax and gendered marketing more broadly. The focus of this paper is on differences in men and women's behavior and product space for retail markets like grocery and big box stores. These purchases largely fall under the categories of food, alcohol and cigarettes, and personal care but they do not map perfectly. A key descriptive result of our paper is that women spend more on retail purchases than do men; in the context of figure 1.1 this would imply that women spend more on food as groceries while men spend more on food out. Similar overall levels of spending with differing allocation patterns highlights the important role that preferences, substitution patterns and societal expectations play in evaluating the pink tax.

While figure 1.1 speaks to full consumption basket differences between men and women, we now turn our focus to retail spending consumption baskets and how they vary by gender. We find that women's retail consumption baskets are larger, more expensive, and filled with a greater number of unique UPCs. Figure 1.2 plots levels of female activity as a proportion of male activity for annual spending, unique product purchases, and overall product purchases. We find that women's yearly spending is greater than that of men by about 6%, their product diversity is greater than men's by about 27% and their consumption baskets are larger than men's in terms of items purchased by about 9%. This pattern is primarily driven by differences in behavior in consumption of Health and Beauty products, where women spend 51% more than men, consume 53% more unique products, and consume 49% more items. However, we observe similar results for all products after excluding Health and Beauty; such spending categories include are food grocery products, household products and alcohol. Among these products women spend about 2% more, have 25% greater product diversity and 7% more items than men.

Figure 1.2 compares men and women that otherwise look demographically similar in terms of location, age, race, income and education. Our panel of singles is weighted to be representative of all single men and women in the United States, and thus we can also make comparisons of how men and women's spending differs in the aggregate, by location, etc. Table 1.2 reports yearly spending differences between men and women subsequently adding in these demographic controls. Column (1) reports aggregate differences in spending between men and women, including only controls for year. We find small differences in yearly spending without demographic controls of about 1.6% higher yearly spending by women. Columns 2, 3, 4, 5, and 6 add in fixed effects for county of residence, income, age, race and education respectively. Column (2) compares yearly spending between men and women that live in the same county, finding 2.5% higher spending by women. We can interpret the increase in the magnitude of the coefficient across columns (1) and (2) as the contribution of geographic sorting of single men and single women to overall spending differences and is consistent with single women more often living in lower cost areas than do men. This interpretation continues as we move to columns (3) and (4) which add in controls for income and age which raise the spending gap to 4.4% and 6.2% respectively. Because single women tend to skew lower income and older in age than single men, we can see the attenuating effect that lower spending among older and poorer women has in the aggregate. Columns (4) and (5) add in controls for race and education; while racial composition differences between single men and single women do contribute to the spending gap somewhat, the magnitude of the change is much smaller than the contribution from geography, age and income. Controlling for education has no contribution that cannot be accounted for by geography or the other demographic variables. While yearly spending differences vary significantly across different comparisons of interest, the same analysis on the number of unique products consumed or total number of items purchased in a year shows little variation. These findings suggest that while there are many factors that contribute to yearly spending differences between men and women, gender differences in consumption basket size and composition are fairly constant.

Figure 1.2 and 1.2 document that women's consumption bundles differ from those of men in important ways, but does not fully inform the way through which a pink tax may take form. Aggregate spending differences can arise from differences in prices paid for similar goods or from differences in quantities purchased. As a clarifying example, consider consumption habits for shampoo. Women, on average, have longer hair than men which may lead them to buy more bottles of shampoo over the course of a year, we refer to this as driving up total spending on the extensive margin, that is, buying more product. It is also possible that women have preferences for higher priced shampoos, we refer to this as the intensive margin, where women are paying higher per unit prices. Figure 1.2 indicates that the "extensive" margin is an important contributor to overall differences in spending. While total items purchased captures the differences both in the intensity and variety of products purchased, information on unique products captures only this latter element, and could be driven by both greater taste for variety by women within shared-gender product spaces as well as a greater volume of products typically intended for exclusive consumption by women (e.g. feminine hygiene products, medication and beauty products).

Popular discussion of the pink tax is often focused on differences in prices paid between men and women, the intensive margin contribution to the overall spending gap. We compare per unit prices paid by men and women for products in the same market with the following specification:

$$log(P_{ijt}) = \phi_{t(j)} + \beta \mathbf{1}_{w(i)} + \gamma X_i + \epsilon_{ijt}$$

Where i denotes the individual, j denotes the product purchased and t denotes the market. Table 1.3 presents the results. Column (1) regresses log unit UPC price on a woman indicator and includes fixed effects for the interaction of product module, units the good is sold in and the year of purchase. Similar to Table 1.2, we can think of the 2.3% result as the raw difference in prices paid between single men and women, not accounting for other demographic factors or location and retail chain sorting. Column (2) runs the same specification but adds in controls for age, income, and race. The large increase in the coefficient, from 2.3% to 4.67% highlights the important role of demographic differences between single men and single women because older and lower income people tend to buy lower priced products. Columns (3) and (4) subsequently add in county and retailer fixed effects. We can think of Column (3) as the contribution of women sorting into more or less expensive locations, because the coefficient change is small, the contribution is minimal. Similarly, column (4) can be thought of as the contribution of sorting into more or less expensive retail chains, i.e. Whole Foods vs. Walmart. Controlling for the retail chain lowers our price premium estimate to 4.19%, suggesting that retail chain sorting plays a small but significant role. Finally, in Column (5) we add in fixed effects for month rather than year. The results indicate that women spend more than 4.02% more than do men per unit of goods in the same product market, bought in the same retail chain, county, and month. We consider this our preferred specification because it attempts to control, as much as possible, for all potential differences that could arise between the two groups other than gender.

We refer to this 4% finding as our observed pink tax on the intensive margin. This price premium could be driven by many different factors. First, it can be driven by women buying products that are made specifically for and marketed to women, this would be in line with how the pink tax is traditionally thought about. Alternatively, it could be driven by differences in preferences between men and women for products that are otherwise ungendered. That is, if women happen to like organic products or name brand products more than men then we would likely observe that women pay higher per unit prices than do men. Once we understand which types of products are contributing to our observed pink tax, we want to know whether these price premiums are being driven by markups or marginal costs. The underlying implication of popular discourse on the pink tax is that it is a price discrimination story: two products differ only in their color but the pink product is priced higher, because their costs of production must be the same the women's product faces a higher markup. This price discrimination story would require that women either consume products less elastically or the competitive structure of the market is such that the products women buy face higher markups. The alternative explanation is that the products that women buy have higher marginal costs of production. This would be consistent with women having preferences for higher "quality" goods.[4] The rest of the paper strives to understand what generates our 4% pink tax by analyzing how product markets vary for men and women and estimating differences in demand between men and women.

Table 1.4 estimates the same equation as Table 1.3 while including product level fixed effects instead of module level fixed effects:

$$log(P_{ijt}) = \phi_{jt} + \beta \mathbf{1}_{w(i)} + \gamma X_i + \epsilon_{ijt}$$

The interpretation of the coefficient becomes the difference in prices paid between men and women for the same exact product. Differences in prices paid for the same good can be attributed to differences in price shopping behavior, like coupon usage and sale shopping, consistent with being a more elastic consumer. We sequentially add in fixed effects in the same manner as Table 1.3, so the coefficients can be interpreted as a raw difference between men and women in column (1) and then iteratively making comparisons between demographics, location, retail chain and month. Just like Table 1.3 we find that demographic differences and differential sorting into retail chains and locations contribute to the price shopping gap. While we find that women, on average, buy more expensive products than

[4]We cannot directly attribute higher marginal costs to higher quality as quality is likely not fully innate but perceived by the individual.

do men, we find that they spend 0.8% less than men on the *same* product. Column (5) captures differences in prices paid for the same product by people that differ only in gender over a month, which we attribute to differences in price shopping behavior. Combining this with our result from Table 1.3 suggests that women are buying higher priced goods while also exhibiting behaviors associated with being more elastic consumers. Hendel and Nevo (2013) study promotional sales as a form of intertemporal price discrimination, our results would indicate that women are likely to comprise a larger share of the consumer base that benefits from this type of price discrimination.

Table 1.5 estimates the preferred specifications from tables 1.3 and 1.4, stratifying by department. We can see that our results hold generally across most departments with the exceptions being Alcohol and General Merchandise.[5] Among all other departments we find that women buy higher priced products relative to men while displaying acutely more price shopping behavior. Our findings are particularly strong for Health and Beauty products in Column (1), women buy products that cost on average 5.34% more than those bought by men, but when buying the same exact product women typically spend about 2.15% less than men do. Given the types of products focused on in the media when discussing the pink tax, one may expect that any results would be driven by Health and Beauty products where market segmentation by gender is particularly apparent. However, while our Health and Beauty results are relatively larger in magnitude, the pattern of our finding holds across all departments, including ones where the product space is less intuitively stratified by gender. This consistent pattern suggests that the pink tax is not just about goods marketed to men versus women but also about systematically different preferences for otherwise ungendered items.

Gender in the Product Space

We now shift our focus from consumer behavior to understanding how the the product space varies by gender. Media portrayal and public discussion depicts the pink tax as phenomenon associated with specifically gendered products. The generally suggested mechanism is that by creating products that are bought exclusively by one gender, firms can segment the market and price discriminate accordingly. Our descriptive evidence above has shown that women buy more expensive and larger consumption bundles and that the products they buy are more expensive relative to similar products bought by men. However, these observations could be driven by differences in purchase intensity of otherwise ungendered products. To fully characterize the pink tax, we document the existence of goods that are gendered, that is they are only ever bought by one gender, and decompose our observed pink tax of 4% into into its respective contributions from gendered products and differential purchasing of

[5]However, we identify these Nielsen departments as possibly underestimating consumption, as there are many purchases of these types of products made at stores not included in the Nielsen panel.

ungendered products.

First, we assign values of gender-stratification to each good. We begin by calculating a woman purchase share for each UPC in our data as the projection-weighted fraction of purchases by women. We define the observed time-invariant woman purchase share of UPC j as

$$\hat{w}_j = \frac{\sum_{i \in \mathcal{I}} Purchase_{ij} \mathbb{1}\{woman_i = 1\}}{\sum_{i \in \mathcal{I}} purchase_{ij}}$$

This fraction assigns $\hat{w}_j \in [0, 1]$ where 0 denotes a good that is only bought by men and 1 denotes a good that is exclusively bought by women.[6] We sometimes use $\hat{w}_j$ as a continuous measure, but for simplicity use it to categorize goods as either gendered or ungendered. We define explicitly gendered products as those that are purchased at least 90% of the time by a single gender. That means we assign goods with $\hat{w}_j \leq .1$ as men's products, and those with $\hat{w}_j \geq .9$ as women's products. For robustness, we repeat analyses with a cutoff of .25 and .75 and include them in the Appendix.

Approximately two-thirds of the UPCs purchased by Nielsen panelists are only ever observed to be purchased once, these UPCs would always be assigned to having an explicit gender of 0 or 1. To reduce measurement error, we only assign an observed women purchase share to products that are observed to be bought with enough frequency. In theory, each UPC in our data has a true woman purchase in the population, w_j, that we do not observe. We choose a cutoff number of unique observations, n_j^*, needed to assign a UPC gender such that we are 95% sure that the true woman purchase share lies within a ten percentile bin centered around the observed value. We observe a UPC's woman purchase share, $\hat{w}_j$, and the number of unique individuals that purchase it, n_j. Our observed values represent a draw from a binomial distribution.

$$P(w_j \notin [\hat{w}_j - .05, \hat{w}_j + .05]) = \int\limits_{x < \hat{w}_j - .05, x > \hat{w}_j + .05} \binom{n}{\lceil \hat{w}_j n \rceil} x^{\lceil \hat{w}_j n \rceil} (1-x)^{n - \lceil \hat{w}_j n \rceil} f(x) dx$$

Where $f(x)$ is the empirical pdf of woman purchase share and $\lceil \hat{w}_j n \rceil$ is the closest integer to generating woman purchase share. We calculate the threshold, n_j^*, such that the probability, $P(w_j \notin [\hat{w}_j - .05, \hat{w}_j + .05])$, is .05.

Figure A.1.1 displays the gender-composition of UPC by each Nielsen department. First, we find that the majority of UPCs are unassigned because their unique purchase count falls under the inclusion threshold. The median UPC in our sample is purchased by 4 unique individuals and 63% of UPCs are purchased by less than 8 individuals. In our sample, we

[6] The HMS sample features a woman-man gender-split of approximately 70-30. We scale purchases using the proprietary Nielsen projection weights, which yields a gender-composition of 53-47. This means that the average good will be skewed slightly towards women but accurately representative of the population.

observe 1.8 million UPCs across 155 million purchases. While we are only able to confidently assign UPC gender to 700,000 unique products, Figure 1.3 shows those we are able to assign gender to account for greater than 95% of all purchases made in the data by expense. Next, we consider goods assigned to women. We find that gendered products make up a small share of purchases, 3.6% for men and 4.6% for women. Within Health and Beauty products though, gendered products make up 20% of women's purchases and 10% of men's purchases.

We plot the distribution of woman purchase share for all products, Health and Beauty products, and all products excluding Health and Beauty in Figure 1.4. Panel 1.4a depicts the woman purchase share for all UPCs in our data after making our cutoff restriction. There is significant excess mass at the right tail of the distribution where goods are bought exclusively by women but virtually no excess mass at the left tail of the distribution where goods are bought exclusively by men. Importantly, re-weighting purchases to account for the differential gender-composition of the Nielsen panelist sample implies that this difference can be attributed to differences in consumption behaviors and preferences between men and women. Part of this difference may lead to a mechanical overstatement of gender stratification. For instance, if women purchase a greater number of unique products than do men, products will still be more frequently categorized as women's products, even after accounting for gender differential sample-composition. The general right skew of the UPC gender distribution indicates that even among goods that are not explicitly gendered, there are more goods that are bought more frequently by women. Panel 1.4b shows the distribution of female purchase share for Health and Beauty products, where we find that the distribution is extremely right skewed. There is a considerably large mass of goods that are purchased exclusively by women and very few that are purchased exclusively by men.

We now describe how prices vary along our measure of UPC gender. Figure 1.5 plots the coefficients from a regression of log unit price on ten-percentile-width bins of female purchase share and two bins for pure gender stratification at the tails, taking the 50th percentile bin as the reference point. Bin b contains goods with UPC gender $\hat{w}_j \in ((b-1)/10, b/10]$, save for the tail bins. This corresponds to estimating the following regression:

$$log(P_{jt}) = \phi_{t(j)} + \sum_{b \in \mathcal{B}} \beta_b \mathbf{1}_{d(j)=b} + \epsilon_{jt}$$

The regression contains fixed effects for the product module of the UPC, county and half-year of purchase: so the coefficients can be interpreted as averages across comparisons made of products in the same market and bought in the same location and time frame relative to products bought equally by men and women. We document significant price premiums of $\sim 10-40\%$ for goods purchased exclusively by either men or women relative to goods in the same market purchased by relatively equal shares of each.

We observe higher prices for women's products as compared to men's products. This difference ranges from just under 10% for non-health and beauty products to almost 20% for health and beauty products. This finding falls in line with popular depictions of the pink tax, which tend to focus on examples of price premiums for women's products relative to products that are explicitly gendered towards men. Less talked about in discourse on the pink tax is the potential for price premiums on gendered products in general which we find strong evidence of given the overall U shape of the graph. Beyond the tails of the graph, a striking pattern emerges, prices tend to monotonically increase in woman purchase share. That is, products that are bought more often, but not entirely, by men are priced lower than products that are bought more often by women. This monotonic increase in prices along woman purchase share suggests that our overall price premium of 4% from Table 1.3 is likely explained not just by explicitly gendered products (i.e. pink products and blue products) but also by differences in preferences for otherwise ungendered products. This finding is consistent with women having preferences for higher (perceived) quality items like, for example, organic products. This is supported by studies of differences in preferences for organic food between men and women. Ureña, Bernabéu, and Olmeda (2008) finds that women are more likely to buy and value organic food but that men are more willing to pay a higher price.

Using our definitions of product gender, we can decompose our overall 4% price premium into a contribution from differential sorting between men and women into ungendered products and their purchases of gendered products. We define gendered products as those that are bought at least 90% of the time by one gender. Because among these products it is mechanically unlikely that individuals buy a product of the other gender, we do not further divide products into men's and women's. We run the same regression specification as Table 1.3 column (5) but now include an indicator for whether a good is gendered and an interaction between the woman indactor and the product gender indicator:

$$log(P_{ijt}) = \phi_{t(j)} + \beta_1 \mathbf{1}_{w(i)} + \beta_2 \mathbf{1}_{g(j)} + \beta_3 \mathbf{1}_{w(i)} \cdot \mathbf{1}_{g(j)} + \gamma X_i + \epsilon_{ijt}$$

The results are presented in Table 1.6. β_1 captures the average difference in prices that women pay for ungendered products relative to men, β_2 captures the the differences in average prices that men pay for gendered products compared to the ungendered products they buy and β_3 captures the difference in average prices that women pay for gendered products relative to the ungendered products they buy. The average difference in prices that women pay for gendered products relative to gendered products bought by men is given by a linear combination of the coefficients, $\beta_1 + \beta_3 - \beta_2$. The coefficient on the woman consumer indicator in column (1) indicates that women pay a price premium of 3.83% on ungendered products relative to ungendered products bought by men. The coefficient on the gendered product indicator in column (1) shows that, across all departments, men pay lower prices on gendered products than they do ungendered products by about 1%, though the result is marginally significant. Finally, the coefficient on the interaction between the woman consumer indicator and the gendered product indicator in column (1) shows that women buying gendered products pay about 11.39% more relative to the ungendered products that they purchase. Overall, we find that women pay approximately 16.26% higher prices on gendered products than do men. While the magnitude of coefficient on women buying gendered products is large, it's contribution economically to the overall price premium is small. The 4% price premium from Table 1.3 is approximately the purchase weighted average of the 3.83% price premium that women pay on ungendered items and the 16.26% price premium they pay on gendered products. From Figure 1.3, we know that gendered products make up an overall small share of a consumption bundle. So while we find evidence of woman gendered products having significantly higher prices, the vast majority of our observed pink tax is being driven by differential sorting between men and women on ungendered products.

Columns (2) and (3) of Table 1.6 separately estimate the results for Health and Beauty and all other product categories. The results largely follow the same pattern as the aggregated estimation with a key deviation being prices of men's gendered products relative to men purchasing ungendered products. While in non-health and beauty products we find that man gendered products are priced lower, within health and beauty we find that men buying man gendered products spend about 3.63% more than similar products they buy that are ungendered. This finding lines up with Figure 1.5, man gendered items correspond to products in the 0 bucket and the 10 bucket in the graph (products bought up to 10% of the time by a woman). While we find upticks in prices for goods that are only ever bought by men in all departments, products that are bought between 0% of the time and 10% of the time (non-inclusive) by women are priced lower for non-health and beauty products. All in all, we take this as evidence that gender price premiums may exist for both men and women for health and beauty products, though premiums on women's products tend to be larger. This opens an avenue for potential price discrimination on gendered niche-ness rather than on a specific gender. However, across all departments, women pay higher prices than men regardless of if a product is gendered or not.

Together, our descriptive analysis of consumer behavior and the product space suggest that women and men make significantly different consumption choices from product markets that differ in composition. Women buy products that are more expensive and there exist significantly more products marketed to women than men. These two findings contribute to the observation that women's retail consumption baskets are more expensive, larger and more diverse than men's are. We find that women pay about 4% more than do men for products in the same market. However, this price premium is not driven solely by the existence of products that are only marketed to and bought by women but also by differential sorting into purchasing products that are otherwise ungendered. While these analyses document observable differences between the consumption habits of men and women, they do not speak to the mechanisms that give arise to them. We now turn our attention to estimating the demand side forces that could yield such a market equilibrium.

1.5 Men's and Women's Demand Elasticities

Following our descriptive analysis, we want to decompose the 4% price premium paid by women into markups and marginal costs. By formally estimating demand and imposing supply side competitive structure, we can back out markups and marginal costs from estimated price elasticities with a modified Lerner Rule of the form $\frac{P-MC}{P} = -\frac{1}{\varepsilon}$ where P is the price of a product, MC is the marginal cost of production and ε is the residual demand elasticity for the product incorporating cross price elasticities to other products owned by the firm. Because our descriptive results indicate that women pay higher prices across the entire consumption basket, we would like our demand analysis to speak to the entire retail consumption basket as well. However, as we broaden the set of markets that we focus on, we face a trade off between increasing the representativeness of our results and allowing for flexible substitution patterns and market structure. We strike a balance by employing two types of demand analysis: a constant elasticity of substitution model that is common in the trade literature (Faber and Fally 2019; Hottman, Redding, and Weinstein 2016) and a differentiated products model that is common in the industrial organization literature (Berry, Levinsohn, and Pakes 1995.

We use our constant elasticity of substitution (CES) model to estimate differences in price elasticities of demand between men and women using our panel of single individual households in the HMS. A benefit of this aggregated approach is that not only can we estimate elasticities for all markets in our sample, but that we can also attribute price responses to a specific gender. However, this comes at a cost of the data being relatively sparse. We have about 15,000 individuals in any given year of our sample but over one million UPCs that we observe to be purchased. This means that our estimates are largely based off of goods that are bought frequently, which tend to be ungendered products in food grocery markets. These products comprise the bulk of the consumption basket, but we won't have good identification on infrequent purchases. Because of this, our CES model captures the role of demand composition and sorting across ungendered products and the relative value of women and men as consumer bases to price discriminate against.

CES Model and Estimation

To estimate demand elasticity differences between men and women, we augment the constant elasticity of substitution (CES) model used in Faber and Fally (2019). This approach allows us to aggregate elasticities and make comparisons of the purchasing habits of men and women across a wide range of products. The model characterizes a representative consumer for each location and period, l, that varies in gender, g. The consumer allocates their income between retail goods, G, and consumption of the outside option:

$$U(g) = U(U_G(g), C(g))$$

We assume that the basket of goods that comprise the outside option, C, is consumed normally.

The model aggregates products in two tiers: the consumer allocates consumption across product modules with Cobb-Douglas elasticity and substitutes between goods with module-specific constant elasticity of substitution. We denote product modules with n and refer to a market, t as a product module within a location and time period. The consumer maximizes their utility subject to their budget constraint by choosing a vector of quantities, q, that represents their consumption bundle across all goods:

$$U_G(g,l) = \max_q \prod_{n \in \mathcal{N}_l} \left[\sum_{j' \in G_t} \left(q_j \varphi_j(g) \right)^{\frac{\sigma_t(g)-1}{\sigma_t(g)}} \right]^{\alpha_t(g) \frac{\sigma_t(g)}{\sigma_t(g)-1}} \tag{1.1}$$

$\mathcal{N}_l$ refers to the set of product modules that the representative consumer in location and time l consumes from, and j refers to a specific UPC (product) within a product module. Some studies that estimate demand elasticities with the Nielsen data study products at the brand-level, whereas we consider the UPC-level due to inconsistencies in the gender-marketing of products within brands. To illustrate, in the disposable razors market, all product brands produced by Gillette map to the gender of the product (e.g. Gillette Venus marketed toward women versus Gillette Fusion marketed toward men), but other razor brands like Bic do not always have brand names that map to one gender (e.g. Bic Plus razors have both female- and male-marketed UPCs under the same brand). φ_j refers to the perceived product quality of a product j in module n. σ_t represents the elasticity of substitution within a market, and α_t denotes the share of expenditures allocated to a market $n \in \mathcal{N}_l$[7]. σ_t is our main parameter of interest, as it captures differences in price responsiveness between men and women.

Specifying the upper tier as Cobb Douglas implies that comparisons of consumption amounts between products within the same module depend on their relative quality-adjusted prices:

$$\frac{b_{jt}(g)}{b_{kt}(g)} = \left(\frac{p_j/\varphi_j(g)}{p_k/\varphi_k(g)} \right)^{1-\sigma_t(g)}, \tag{1.2}$$

where $b_{jt}(g)$ is the budget share spent on product j in market t. From Equation (2), we derive our estimating equation:

$$\Delta log(b_{gjt}) = (1 - \sigma_t(g))\Delta log(\bar{P}_{gjt}) + \eta_{gt} + \varepsilon_{gjt}. \tag{1.3}$$

Where differences are taken from one time period to the next and η_{gt} captures the change in the price index. Though we derive this estimating equation from a CES demand model, it has the additional benefit of being interpreted in other useful ways. Deviating from constant

[7]We assume that $\sum_{n \in \mathcal{N}_l} \alpha_t(g) = 1$ for set of modules $\mathcal{N}_l$

elasticity of substitution, this estimating equation can be interpreted in a reduced form way as an average of heterogeneous price responses within a market. In our estimation we define markets, t, as a product module-county-half year or product module-county-retail chain-half year. This ensures that our estimated results are based off of true changes in behavior rather than changes in composition of out overall sample over time. We estimate our model at the half-year level because many product categories are prone to stockpiling, which in shorter time intervals would bias our demand estimates towards greater elasticity. To address auto-correlation in the error term, we cluster standard errors at the UPC-county level.

We face the standard issues of simultaneity in demand estimation where price changes may be correlated with demand shocks. To address this issue, we rely on two identifying assumptions typically employed in empirical works. First, we assume that local demand shocks are uncorrelated and idiosyncratic across localities while supply shocks are correlated across space and retailers Hausman (1999). Second, we assume that retail chains set prices at the national or regional level and that these prices are set independent of local demand shocks following evidence presented in DellaVigna and Gentzkow (2019). From these assumptions, we estimate $(1 - \sigma_t(g))$ using two instruments. The first are Hausman instruments, which we construct as national leave-out means in price changes at the county level, $\frac{1}{N-1}\sum_{c \neq c'} \Delta \log(P_{gjt})$. The second are instruments that follow DellaVigna and Gentzkow (2019) developed by Allcott, Lockwood, and Taubinsky (2019) which are constructed as national leave-out means of price changes at the county-retailer chain level, $\frac{1}{N-1}\sum_{r,c \neq r',c'} \Delta \log(P_{gjt})$. Much of the variation in the DellaVigna Gentzkow instrument is driven by variation in how often a product is placed on a promotional sale. The timing of these sales is driven by a bargaining process between the retailer and the manufacturer and typically only one manufacturer is put on promotional sale at a time. If competition among manufacturers is strong enough, then promotional sale decisions are largely independent of demand shocks as well.

Equation (3) estimates the elasticity of substitution across products within the same market but does not explicitly estimate the price elasticity of demand. We now derive overall price elasticities associated with our model in terms of the elasticity of substitution, σ_{gt}, and market share, $s_{jt}(g)$. Solving Equation (1) yields:

$$q_{jt}(g) = \left(P_t(g) \frac{\varphi_{jt}(g)}{p_{jt}} \right)^{\sigma_t(g)-1} \frac{\alpha_t(g) E(g)}{p_{jt}}$$

Where $P_t(g)$ is a price index, $P_t(g) = \left[\sum_{i \in G_t} p_{jt}^{(1-\sigma_t(g))} \varphi_{jt}(g)^{(\sigma_t(g)-1)} \right]^{\frac{1}{1-\sigma_t(g)}}$. From here we can directly derive the own-price elasticity of demand as:

$$\varepsilon_{jt}(g) = \sigma_t(g) - (\sigma_t(g) - 1) \cdot s_{jt}(g) \tag{1.4}$$

Where $s_{jt}(g)$ is the market share of product j in market t. Thus, we can calculate $\varepsilon_{jt}(g)$ as a function of known and estimated parameters. In the special case of monopolistic competition, all market shares are approximately zero and $\varepsilon_{ni}(z,g)$ collapses to the elasticity of substitution, $\sigma_n(z,g)$. To map elasticities to markups, we assume single product firms compete on prices and maximize firm profits given the demand that they face. Firms price their products in response to the sales weighted average demand elasticity that they face across the population:

$$\mu_{jt} = \frac{p_{jt} - c_{jt}}{p_{jt}} = \frac{\sum_g x_{jt}(g)}{\sum_g \varepsilon_{jt}(g) x_{jt}(g)}.$$

Where $x_{jt}(g)$ is the sales of product j to gender g in market t. Because we can only attribute purchases to a gender for single individuals, we are limited to extrapolating the results from our singles to the whole population.

CES Model Results

We begin by estimating differences in the elasticity of substitution, $\sigma_t(g)$, between men and women. Table 1.7 presents results of estimating Equation (3) and pooling the elasticities across all departments. The main coefficient of interest is $\sigma_m - \sigma_w$, the difference in elasticity of substitution between men and women. In column (1) We include a UPC-market fixed effect and estimate differences in demand elasticities between men and women for the same price change for the same product. If we assume that demand shocks affect men and women in the same way, this regression does not need to be instrumented since the endogenous portion is differenced out. We find that for the same UPC in the same market, women are about 4.45 percentage points (pp) more elastic than men. Column (1) restricts only to UPCs purchased by both men and women in the same market, columns (2-4) include a market level fixed effect and the results correspond to our full CES model, incorporating differing product choices between men and women. Column (2) includes a market fixed effect at the module, county, half year level and instruments with Hausman instruments only. We find that women are 11.6 pp more elastic than men. Columns (3) and (4) define markets at the module, county, retail chain, half year level. Column (3) Instruments for price with the DellaVigna Gentzkow instruments and finds similar results that women are 11 pp more elastic consumers than men. Finally, column (4) includes both instruments and finds that women are 6.9 pp more elastic consumers than men.

To test for robustness, we estimate the model letting the representative consumer vary in income or age in addition to gender and present the results in Appendix X. Overall, we find that the single individuals in our sample are relatively inelastic consumers, with estimates of men's elaticities of substitution around -.7 and women's elasticities of substitution of around -.8. In a similar analysis, Faber and Fally (2022) estimate σ for all households in the Nielsen data of around -2. When we run our specification on all households rather than our panel of single individuals we find similar levels of elasticity, indicating that our singles panel is significantly more inelastic than non-single households. Taken together, the results suggest that women substitute more elastically than men.

We now turn our focus to how elasticities of substitution vary across product departments and find that women are either more elastic than men are or are not significantly different than men in terms of elasticity. Table 1.8 presents elasticity of substitution results pooled to the department level. We present results defining markets at the retail chain, designated marketing area (DMA), half year level. DMAs are more aggregated geographic areas than counties but less aggregated than states. Using DMAs does not change our results in terms of magnitude but improves power by reducing the amount of sparsity in the data. We find that across almost all food products women are significantly more elastic consumers than are men, with $\sigma_m - \sigma_w \in [-0.15, -0.46]$. Among non-food retail products we find no significant differences in the elasticities of substitution between men and women and the magnitude of the coefficient for Health and Beauty products suggest the possibility that women are less elastic in that market space.[8] The vast majority of purchases that constitute the retail consumption basket in the Nielsen data are food purchases, so our finding that women are more elastic applies to the bulk of the consumption basket. However, the majority of gendered products exist in non-food purchases, particularly Health and Beauty products. We take this as evidence that women appear to be more elastic across markets with little explicit gendering, but we cannot refute that women are less elastic in markets with significant gendering.

So far we have estimated the elasticity of substitution, $\sigma_t(g)$, while actual price elasticities of demand are given by Equation (4) and are a function of the elasticity of substitution and market shares. This means that price elasticities of demand will range from $\sigma_t(g)$, under monopolistic competition where market shares are approximately 0, to 1, under monopoly where the market share of the single good is 1. Because we have found that women generally substitute more elastically than men, the only remaining channel for them to be less elastic consumers is through market competition being significantly less competitive in women's markets than in men's. From Figure 1.2 in the descriptive analysis, we know that women buy more unique products than do men by about 27%. This suggests that women's markets are more diverse than men's and are also likely more competitive.

In Figure 1.6 we show the histogram of log market shares for the men and women in our sample. The entire distribution of market shares for women is shifted to the left, indicating that their markets are more competitive. Further, market shares in our data are very small, on the order of 0.05% for the median UPC. This means that, in our setting, elasticities of substitution are close approximations of price elasticities of demand. On average, we can conclude that women are more price elastic consumers than men are. This finding is consis-

[8] We find that Health and Beauty and General merchandise products tend to be less elastic than other departments. The finding that Health and Beauty products are more inelastic than other types of products is consistent with the findings in Faber and Fally (2022) and our findings in Section 6.2. General Merchandise contains many products which can either be purchased or have substitutes sold at retailers not included in the Nielsen data and thus many of the purchase habits from this department cannot be considered complete. Examples include tools, automotive, household appliances, photographic supplies and stationary.

tent with women being less likely to be the consumer group to pay higher prices under price discrimination. Abstracting from the role of multiproduct firms, this finding is also consistent with products having relatively more women as their consumer base being associated with higher marginal costs.

1.6 Markups under CES Demand and Oligopolistic Competition

Our aggregated demand analysis rules out gender based price discrimination as the primary driver of our observed 5% price premium on products bought by women. Instead, it suggests that women sort into products that are higher marginal cost. Our demand analysis thus far has been focused on assessing differences in demand behavior between men and women, which required focusing on single individuals who are an incomplete portion of the market. Firm's pricing decisions will be based on the average price elasticity that they face, a large portion of which will be household purchases made by families. To close our study of aggregate demand for largely ungendered products, we compute price elasticities for all households in the Nielsen data and study how the elasticities of the products that women sort into compare to the products men sort into. Attributing household purchases to a specific gender is difficult; women often take the role of primary shopper in the household (Flagg et al. 2014) but men increasingly play a role in role in shopping and all decisions are likely some aggregation of the preferences of the shopper, their partner and (or) their children. From our analysis on single individuals we have ruled out that the price premiums paid by women are from systemic price discrimination from women being more inelastic consumers. Still, the demand behavior of non-single households along with differences in consumption basket composition between men and women could lead to women spending more of their income in markups than men. We calculate price elasticities of demand using our model for the entire population of consumers in the Nielsen data, and then compare the difference in price elasticity of demand for the average purchase made by women to the average purchase made by men.

The results are presented in Table 1.9. Column (1) aggregates across all product departments, while columns (2) and (3) separate Health and Beauty products from non-Health and Beauty Products respectively. Though we find that women are more elastic than are men for the same type of good, overall the goods that comprise a woman's consumption basket are slightly more inelastic than men's. Our results are significant but economically small. The average product in our sample has a price elasticity of about -2, the average difference in markups paid by women as opposed to men is then less than a half of a percent. This number is significantly smaller than the overall difference in spending between between men and women of 6% and the similar good price premium of 4%. Therefore, we can confidently say that the main driver of the observed price premium paid by women is due to marginal costs.

1.7 Discussion

Our paper documents retail spending differences between men and women and decomposes observed spending differences into demand and supply side mechanisms. Our work was motivated by the hypothesized "Pink Tax", the idea that women's products are priced higher due to price discrimination. Three economic mechanisms factor into firms' pricing decisions: price elasticity of demand, competitive structure, and marginal costs. We document price premiums paid by women but when we decompose these price premiums into their economic mechanisms we find they are primarily driven by differences in marginal costs. Our paper suggests that public discourse on the pink tax, which often cites cherry picked examples of price differences for gendered products, fails to capture differences in actual consumption choices between men and women that result from differential sorting. Our work also suggests that current legislation in New York City and proposed legislation in California, which place bans on price differences for products that differ only in gender, are likely to be ineffective as the majority of price disparities between men and women can be explained by sorting into products that likely differ in more than just gender.

We allow for a broad definition of the pink tax, considering any and all consumption differences that may lead to women's consumption bundles being more expensive or women paying more in markups. We show that women do buy higher priced products, paying an average price premium of 4% relative to similar goods that are bought buy men. We decompose this observed price premium into differential sorting between men and women into otherwise ungendered products and price premiums on explicitly gendered products. We document the existence of gendered products, products that are almost exclusively purchased by one gender, and show that there are significantly more women's products than men's products. We document that price disparities for gendered products are about 15%. However, purchases of gendered products make up a small fraction of the overall consumption bundle and we can attribute the majority of the 4% price premium paid by women to sorting in ungendered products. These descriptive findings provide a more nuanced view of the pink tax, or more broadly, gender differences in consumption habits and product markets.

We then analyze the demand behavior of men and women by estimating a CES demand model for men and women. This model allows us to pool results across product markets to look at average differences between men's and women's demand for consumer packaged goods. We find that women are significantly more elastic than men are across almost all product departments. Incorporating this result into the model implies that products that are disproportionately bought by women should have lower markups. This would then imply that higher prices on the products that women buy are driven by higher marginal costs. This result counters the general consensus on the pink tax, that it is a form of price discrimination. Our research highlights the importance of the role of preferences, demand behavior and competition when deciding whether pricing id “fair”.

Though our results go against common beliefs about the pink tax, they are supported by general gender norms in society around shopping. Women are typically socialized to handle household shopping, particularly for grocery and household items. This norm should, in turn, make women better shoppers than men and more likely to exhibit taste for quality and elastic demand as they have more experience than men. In this sense we believe our results are neither surprising nor at odds with public opinion.

In this paper, we have focused on a definition of the pink tax of higher prices placed on women’s products, but there are also discussions of actual taxes levied on women’s products or entire product markets that exist soley for women that fall under an umbrella term of “The Pink Tax”. The uniting undercurrent across these definitions is that these are things that increase the cost of living for women and make the cost of a standard consumption bundle for women higher. Our findings highlight the nuance of this, that gendered social norms create large preference differences between men and women that make welfare comparisons difficult. This paper is focused on consumer packaged goods, where women have higher societal pressure to shop and care about items than men. But our analysis using the consumer expenditure survey suggests that in other markets our findings may be flipped, like cars and transportation. Economics, as a field, is currently not well equipped to perform welfare analysis when preferences are malleable or changing, we need a fixed static point from which to measure changes or make comparisons. Despite our methods being ill-equipped, we still believe these factors are important to consider when discussing heterogeneous pricing or pricing related policy measures.

Figures and Tables

Table 1.1: Demographics of HMS panelists sample of single-member households

	Total	Women	Men	Difference
Income	44687	39514	50682	-11167.86**
	(37202.4)	(34048.25)	(39718.72)	(340.2182)
Age	53.47	53.21	53.77	-.556**
	(16.4528)	(17.223)	(15.5078)	(.1522)
High school	0.602	0.637	0.562	.074**
	(.4894)	(.481)	(.4961)	(.0045)
College	0.238	0.206	0.275	-.069**
	(.4258)	(.4044)	(.4464)	(.0039)
Post-grad	0.120	0.115	0.127	-.012**
	(.3255)	(.3187)	(.3332)	(.003)
White	0.785	0.767	0.805	-.038**
	(.4111)	(.4228)	(.3962)	(.0038)
Black	0.133	0.157	0.106	.051**
	(.3399)	(.3636)	(.308)	(.0031)
Asian	0.0250	0.0220	0.0270	-.005**
	(.155)	(.1479)	(.1627)	(.0014)
Hispanic	0.0660	0.0670	0.0650	0.00200
	(.2485)	(.2503)	(.2463)	(.0023)
No. households	47012	33628	13384	20244

This table displays demographic data of men and women constituting single-member households as well as their differences. These figures and their corresponding gender-differences were computed using the proprietary analytic household weights included in the Nielsen Consumer Panel Survey. Dollar amounts are expressed in USD 2016.
$*p < .05$, $**p < .01$

Table 1.2: Yearly spending differences between men and women

	(1)	(2)	(3)	(4)	(5)	(6)
Women	0.0162**	0.0248***	0.0444***	0.0616***	0.0677***	0.0677***
	(0.0080)	(0.0077)	(0.0076)	(0.0076)	(0.0075)	(0.0075)
Observations	216890	216743	216743	216742	216742	216742
Adjusted R^2	0.018	0.097	0.105	0.125	0.133	0.133
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes	Yes
Income FE	No	No	Yes	Yes	Yes	Yes
Age FE	No	No	No	Yes	Yes	Yes
Race FE	No	No	No	No	Yes	Yes
Education FE	No	No	No	No	No	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimates of the percent difference in yearly spending between men and women using the following regression: $\log y_{it} = \phi_t + \beta \cdot \mathbb{1}\{woman_i = 1\} + \Gamma X_i + \varepsilon_{i,t}$, where y_{it} is yearly spending. $\mathbb{1}\{woman_i = 1\}$ is an indicator for whether the individual is a woman, ϕ_t is a time fixed effect and X_i is a vector of demographic controls including income, county, age, race and education which we add in sequentially. Standard errors are clustered at the individual-level. Column 1 can be thought of as a raw gap between single men and single women, each subsequent column demonstrates the contribution of controlling for an additional demographic factor.

Table 1.3: Unit prices in same product module

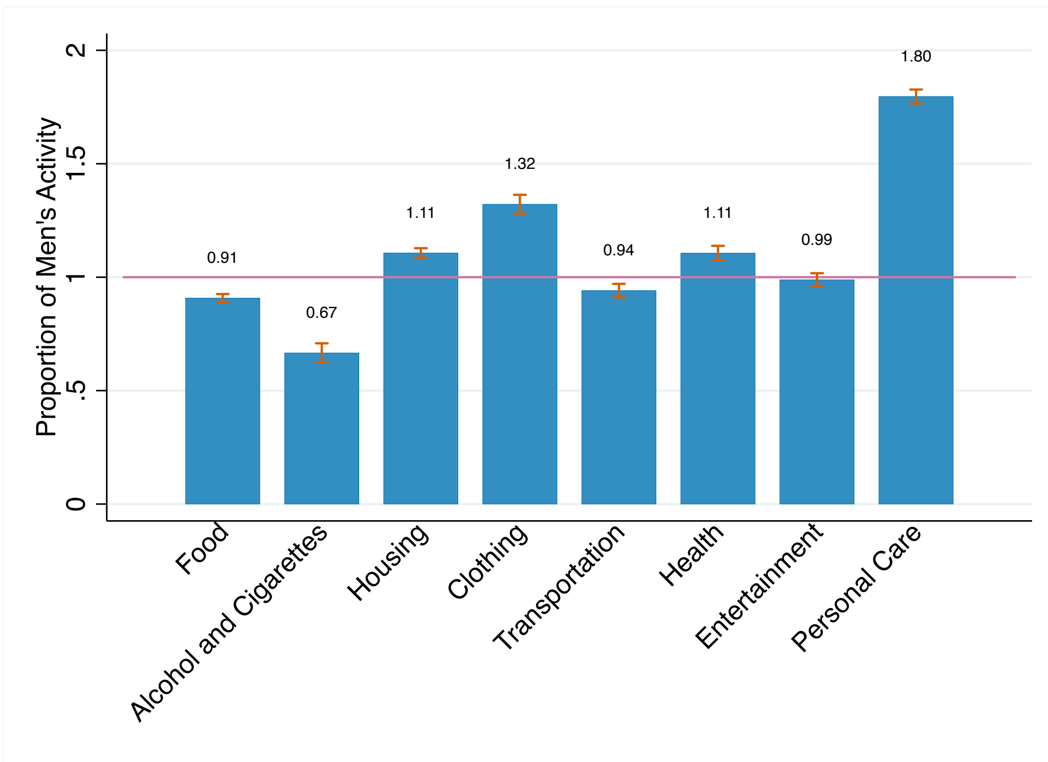
	(1)	(2)	(3)	(4)	(5)
Woman	0.0230***	0.0467***	0.0512***	0.0419***	0.0402***
	(0.0035)	(0.0033)	(0.0028)	(0.0020)	(0.0018)
Observations	153,333,409	153,333,409	150,059,493	143,532,160	139,739,839
Adjusted R^2	0.829	0.831	0.868	0.889	0.877
ModuleXUnits FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No
County FE	No	No	Yes	Yes	Yes
Retailer FE	No	No	No	Yes	Yes
Month FE	No	No	No	No	Yes
Demographic FE	No	Yes	Yes	Yes	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

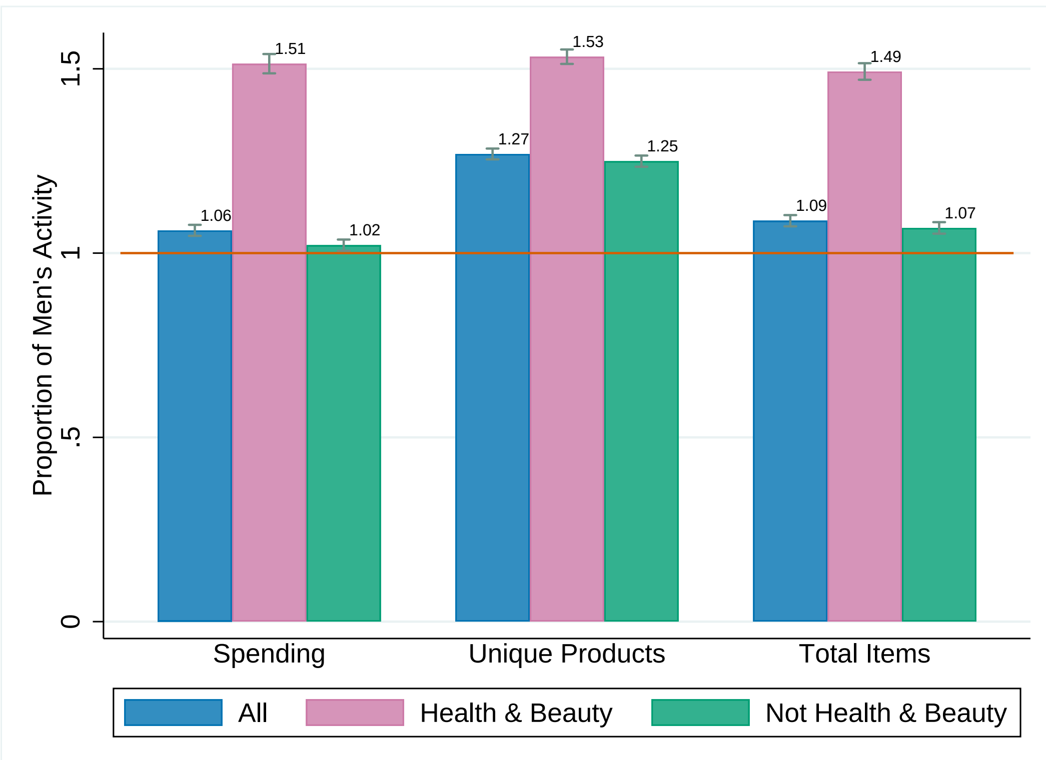
Note: This table presents estimates from the regression: $log(P_{ijt}) = \phi_{t(j)} + \beta \mathbf{1}_{w(i)} + \gamma X_i + \epsilon_{ijt}$ where P_{ijt} is the per-unit price of a UPC. $\mathbb{1}\{woman_i = 1\}$ is an indicator for whether the individual is a woman, ϕ_t is a market-time fixed effect and X_i is a vector of demographic controls including income, county, age, race and education which we add in sequentially. Standard errors are clustered at the individual-level. Column 1 can be thought of as a raw gap between single men and single women, each subsequent column demonstrates the contribution of controlling for an additional market or demographic factor.

Figure 1.1: Women's yearly consumption spending relative to men's



Note: This figure plots the coefficients estimated from a regression of log expenditure on an indicator for the individual being a woman and demographic controls: $\log y_{it} = \beta \cdot \mathbb{1}\{woman_i = 1\} + \Gamma X_{i,t} + \varepsilon_{i,t}$, for spending categories food, alcohol and cigarettes, housing, clothing, transportation, health entertainment and personal care using the CE PUMD from 2010 to 2017. $\mathbb{1}\{female_i = 1\}$ is an indicator for whether the individual is a woman, and $X_{i,t}$ is a vector of time- and time-id-varying controls including income, age, race and education. Standard errors are clustered at the individual-level.

Figure 1.2: Women's yearly retail consumption spending relative to men's



Note: This figure plots the coefficients estimated from a regression of log expenditure on an indicator for the individual being a woman and demographic controls: $\log y_{it} = \alpha + \beta \cdot \mathbb{1}\{woman_i = 1\} + \Gamma X_{i,t} + \varepsilon_{i,t}$, for dependent variables including yearly spending, unique products purchased, and total items purchased. $\mathbb{1}\{woman_i = 1\}$ is an indicator for whether the individual is a woman, and $X_{i,t}$ is a vector of time- and time-id-varying controls including income, county, age, race and education. Standard errors are clustered at the individual-level.

Table 1.4: Unit prices for the same product

	(1)	(2)	(3)	(4)	(5)
Women	-0.0089***	-0.0055***	-0.0060***	-0.0075***	-0.0080***
	(0.0017)	(0.0017)	(0.0015)	(0.0010)	(0.0010)
Observations	151,188,750	151,191,277	139,671,522	138,165,657	135,154,990
Adjusted R^2	0.952	0.840	0.860	0.878	0.879
UPC FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No
County FE	No	No	Yes	Yes	Yes
Retailer FE	No	No	No	Yes	Yes
Month FE	No	No	No	No	Yes
Demographic FE	No	Yes	Yes	Yes	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

This table estimates reduced forms specified as $log(P_{ijt}) = \phi_{jt} + \beta \mathbf{1}_{w(i)} + \gamma X_i + \epsilon_{ijt}$ where P_{ijt} is the per-unit price of a UPC. $\mathbb{1}\{woman_i = 1\}$ is an indicator for whether the individual is a woman, ϕ_t is a UPC-market-time fixed effect and X_i is a vector of demographic controls including income, county, age, race and education which we add in sequentially. Standard errors are clustered at the individual-level. Column 1 can be thought of as a raw gap between single men and single women, each subsequent column demonstrates the contribution of controlling for an additional market or demographic factor.

Table 1.5: Prices paid across departments

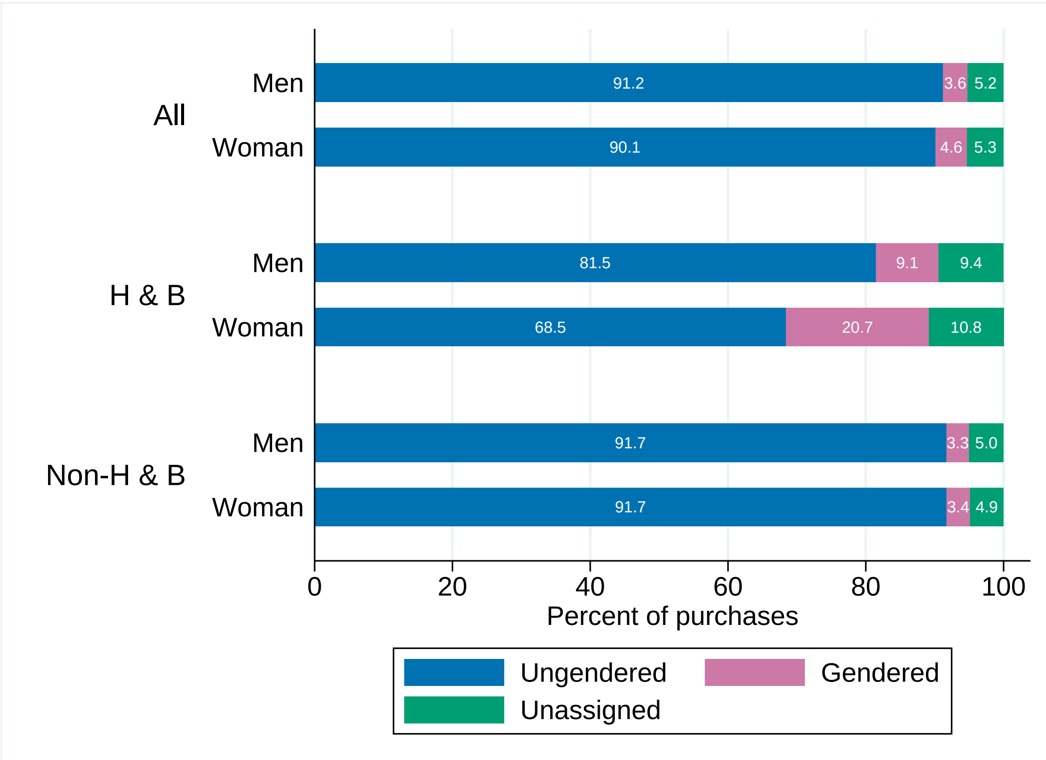
	(1) H&B	(2) Dry Groc.	(3) Frozen	(4) Dairy	(5) Deli	(6) Pack. Meat	(7) Produce	(8) Non-food Groc.	(9) Alcohol	(10) Gen. Merch.
Panel A: Per unit prices within product module										
Female	0.0534***	0.0546***	0.0489***	0.0374***	0.0348***	0.0485***	0.0182***	0.0348***	-0.1450***	-0.0484***
	(0.0029)	(0.0019)	(0.0025)	(0.0022)	(0.0063)	(0.0031)	(0.0037)	(0.0021)	(0.0204)	(0.0039)
Observations	10504032	55328879	14261546	16609254	5270903	4094787	10769045	12467554	1991861	6719882
Adjusted R^2	0.836	0.860	0.903	0.934	0.900	0.798	0.779	0.870	0.637	0.780
ModXUnitXRetXLocXMonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Per unit price for same UPC										
Woman	-0.0212***	-0.0034***	-0.0050***	-0.0012	-0.0258***	-0.0070***	-0.0160***	-0.0133***	-0.0031	-0.0016
	(0.0022)	(0.0009)	(0.0014)	(0.0010)	(0.0055)	(0.0015)	(0.0030)	(0.0010)	(0.0019)	(0.0049)
Observations	9668836	61456951	12812841	15406630	5381334	3922662	10758430	10671760	1891549	6259655
Adjusted R^2	0.817	0.891	0.842	0.875	0.637	0.813	0.654	0.933	0.930	0.854
UPCXRetXLocXYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

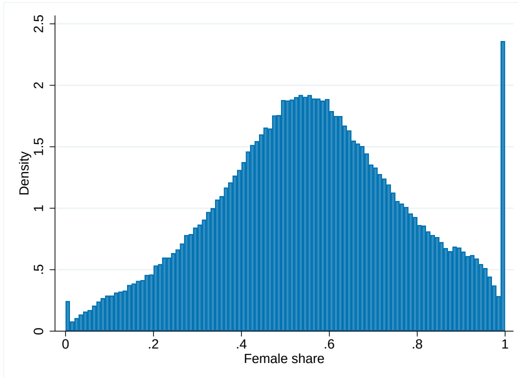
This table estimates $log(P_{ijt}) = \phi_t + \beta \mathbf{1}_{w(i)} + \gamma X_i + \epsilon_{ijt}$, stratifying by department across columns. P_{ijt} is the per-unit price of a UPC. $\mathbb{1}\{woman_i = 1\}$ is an indicator for whether the individual is a woman and and X_i is a vector of demographic controls including income, county, age, race. In panel A, ϕ_t is a vector of fixed effects for the interaction of product module, units, retailer chain, county, and half-year. In Panel B ϕ_t is a vector of fixed effects for the interaction of product (UPC), retailer chain, county, and half-year.

Figure 1.3: Consumption basket composition by product gender

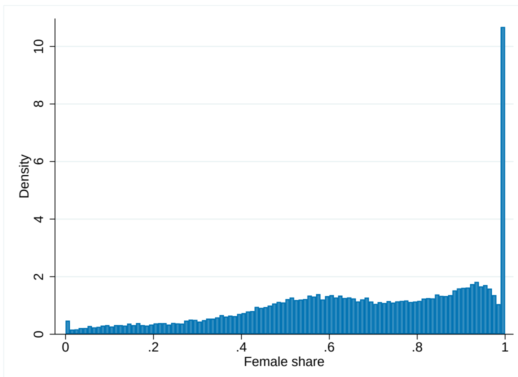


Note: This figure presents plots the decomposition of purchases made by men and women into gendered, ungendered and unassigned products. The first rows show this for all product departments while the next two separate out health and beauty products.

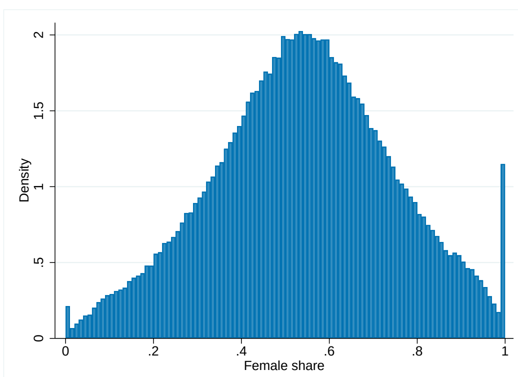
Figure 1.4: Distribution of female purchase share across UPCs



(a) All Departments



(b) Health and Beauty



(c) Non-Health and Beauty

Note: This figure plots a histogram of the share of times a UPC is bought by women. We restrict to UPCs that have above a varying cutoff number of purchases by unique individuals over the panel, this cutoff number corresponds to 95% confidence that a product's true purchase share is within a 10 percentile bin centered around its observed share.

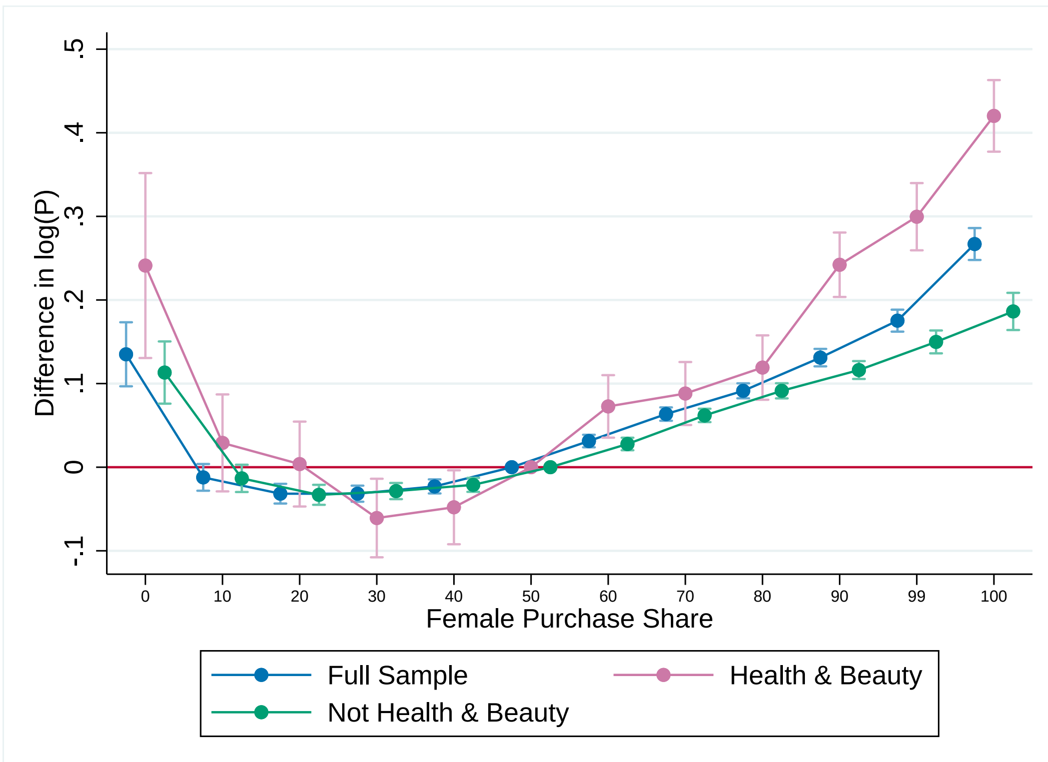


Figure 1.5: Prices of UPCs by female purchase share

Note: This figure presents plots of the results of the regression $\log P_{u,t} = \alpha + \sum_{b\in\mathcal{B}} \gamma_b \mathbb{1}\{g_u \in Bin_b\} + \theta_{m,l,t} + \varepsilon_{u,m,c,l,t}$. Bins $b \in \mathcal{B}$ include ten-percentile-width bins and two bins for pure gender stratification at the tails partitioning the interval $[0, 1]$. The regression includes fixed effects for product module, county and half-year. Results are presented for the whole sample and also separating out Health and Beauty and Dry Grocery. Standard errors are clustered at the UPC-county level.

Table 1.6: Unit prices by gender of product and consumer

	(1)	(2)	(3)
	All	H & B	Non-H & B
Woman consumer	0.0383***	0.0407***	0.0328***
	(0.0019)	(0.0030)	(0.0017)
Gendered Product	-0.0104*	0.0363***	-0.0158**
	(0.0054)	(0.0062)	(0.0072)
Woman Consumer & Gendered Product	0.1139***	0.1014***	0.0879***
	(0.0059)	(0.0065)	(0.0081)
Observations	131609099	9306618	120577845
Adjusted R^2	0.884	0.844	0.888
ModXUnitXRetXLocXMonth FE	Yes	Yes	Yes
Demographic FE	Yes	Yes	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimates from the regression: $log(P_{ijt}) = \phi_{t(j)} + \beta_1 \mathbf{1}_{w(i)} + \beta_2 \mathbf{1}_{g(j)} + \beta_3 \mathbf{1}_{w(i)} \cdot \mathbf{1}_{g(j)} + \gamma X_i + \epsilon_{ijt}$. $\phi_{t(j)}$ is a vector of fixed effects for the interaction of product module, units denomination, retailer chain, county, and half-year. X_i includes with demographic controls for income, age, race and education. Columns 2 and 3 separate out Health and Beauty products.

Table 1.7: Elasticities of substitution

	County		County-Retailer	
	(1)	(2)	(3)	(4)
$1-\sigma_m$		0.3055***	0.2777***	0.2548***
		(0.0193)	(0.0219)	(0.0181)
$\sigma_m-\sigma_w$	-0.0445***	-0.1161***	-0.1097***	-0.0686***
	(0.0091)	(0.0221)	(0.0257)	(0.0209)
Observations	1,054,187	18,271,669	11,007,333	12,431,472
F-Stat		12,764	8,184	5,397
UPCXTimeXCountyXGen FE	Yes	No	No	No
ModXTimeXCountyXGen FE	No	Yes	No	No
ModXTimeXCountyXRetXGen FE	No	No	Yes	Yes
Hausman IV	No	Yes	No	Yes
DellaVigna Gentzkow IV	No	No	Yes	Yes

UPC-County level clustered standard errors in parentheses

* $p<.10$, ** $p<.05$, *** $p<.01$

This table presents the results of estimating elasticities of substitution by regressing changes in the log budget share of a product on changes in log price for men and women controlling for the location, retail chain, and half-year corresponding to the following regression: $\Delta log(b_{gjt}) = (1-\sigma_t(g))\Delta log(\bar{P}_{gjt}) + \eta_{gt} + \varepsilon_{gjt}$. Column (1) estimates differential price responses for men and women on the same price change for the same UPC. Columns (1) and (2) do not control for retail chain, taking the market definition to be a county-module-half year. Column (2) utilizes only Hausman instruments. Columns (3) and (4) control for retail chain in the definition of market. Column (3) instruments for price with DellaVigna-Gentzkow instruments only. Column (4) instruments for prices with both Hausman and DellaVigna-Gentzkow instruments.

Table 1.8: Elasticities of substitution by department

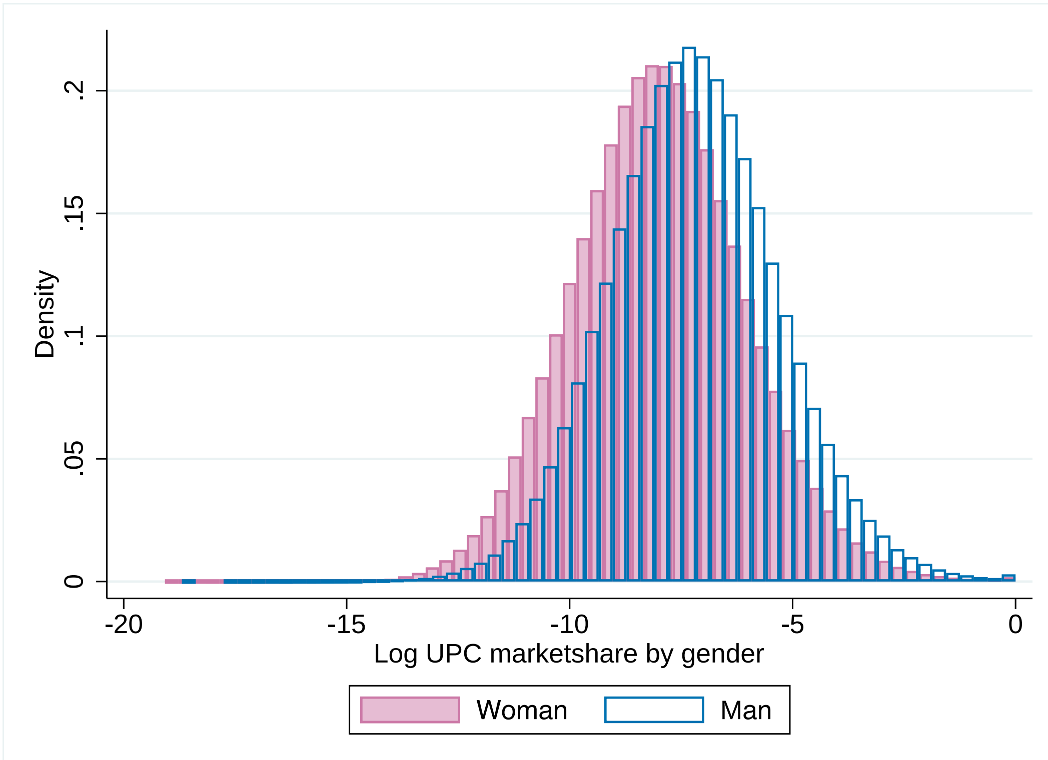
	(1) H&B	(2) Dry Groc.	(3) Frozen	(4) Dairy	(5) Deli	(6) Meat	(7) Produce	(8) Non-food Groc.	(9) Alcohol	(10) Gen. Merch.
$1-\sigma_m$	0.4347***	0.2619***	0.4946***	0.1788***	0.1447	0.1667*	0.0001	0.2238***	-0.5720	0.4893***
	(0.0867)	(0.0315)	(0.0717)	(0.0357)	(0.1310)	(0.0953)	(0.0974)	(0.0672)	(0.5679)	(0.1156)
$\sigma_m-\sigma_w$	0.1037	-0.2682***	-0.4578***	-0.2709***	-0.1488	-0.2688**	-0.2145***	0.0161	0.7583	-0.0384
	(0.0974)	(0.0369)	(0.0907)	(0.0456)	(0.1650)	(0.1204)	(0.0798)	(0.0744)	(0.6057)	(0.1251)
Observations	718302	5335802	1314605	1680282	401229	467441	1084136	1144523	63143	265534
Adjusted R^2	-0.256	-0.287	-0.280	-0.192	-0.278	-0.212	-46.792	-0.275	-0.337	-0.333
ModuleXTimeXDMAXRetXGender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA IV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Retailer IV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

UPC-DMA level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

This table presents the results of estimating elasticities of substitution by regressing changes in the log budget share of a product on changes in log price for men and women controlling for the location, retail chain, and half-year corresponding to the following regression: $\Delta log(b_{gjt}) = (1 - \sigma_t(g))\Delta log(\bar{P}_{gjt}) + \eta_{gt} + \varepsilon_{gjt}$. Results are pooled at the department level. Markets are defined at the product module-retail chain-DMA-half year level.

Figure 1.6: Market competition by gender



Note: This figure presents histograms of log market share of products for men and women separately.

Table 1.9: Purchase-weighted differences in price elasticities between men and women

	(1) All	(2) Health & Beauty	(3) Non-Health & Beauty
$\Delta\varepsilon$	0.0137***	0.0175***	0.0064**
	(0.0025)	(0.0031)	(0.0026)
Observations	146718945	8907946	137810996
Adjusted R^2	0.006	0.003	0.007
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Income FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table plots the results of a regression of estimated product own price elasticities from the CES model on whether or not a purchase was made by a woman and fixed effects for county, month and demographics. The regression is weighted with Nielsen's projection weights. The coefficient can be interpreted as the average difference in price elasticity of the average purchase that a woman makes and the average purchase that a man makes.

Transition to Chapter 2

Chapter 1 studies the phenomenon of the Pink Tax across all purchases made by a household. This more aggregated analysis allowed us to speak to systemic differences in demand that can contribute to differences in inflation and price indices between men and women. By analyzing all of the consumer packaged goods markets, we captured the scope of the Pink Tax and showed that it is not just an issue of razors and personal care products but something that affects almost every market. The benefits of this aggregation come at the cost of model complexity. We do not allow for flexible substitution patterns or complex oligopolistic market structure. Chapter 2, in turn, zooms in on a small number of markets in order to estimate supply and demand in a flexible way. This added complexity allows us to better pin down the mechanisms by which the Pink Tax comes to exist. Specifically, we are able separate out contributions of demand and preferences from compeititve structure in explaining why women's products have higher prices.

Chapter 1 utilizes a constant elasticity of substitution demand model to estimate demand elasticity differences between men and women across all the product markets they consume from. The simple functional form of the model lends itself to estimation across many product markets however, we estimate one elasticity for men and one elasticity for women within each market. In reality, demand elasticities are product specific and depend on the characteristics of the product and the other products in the market as well as being variable by consumer. Chapter 2 explicitly allows individual and product level variation in demand elasticities. This extra complexity requires that we narrow the number of markets to be focused on, this means that we view chapters 1 and 2 as striking a balance in the trade off of speaking to the scope of the Pink Tax while still allowing for sufficient complexity.

Chapter 2

Estimating the causal components of the Pink Tax using a Differentiated Products model of Demand

Authors: Kayleigh Barnes and Jakob Brounstein

"I'm all lost in the supermarket
I can no longer shop happily
I came in here for the special offer
Guaranteed personality"
— The Clash, *London Calling*

2.1 Introduction

This chapter studies whether the observed "Pink Tax" price premium on products purchased and consumed by women is a form of price discrimination or if it is a phenomenon sustained by differences in preferences or competition. In Chapter 1 we have shown that, on average, women are more elastic consumers than men, but in order to better understand product specific demand and decompose prices into markups and marginal costs we estimate a differentiated products demand and supply model. This model incorporates market structure and allows for flexible substitution patterns based on how "gendered" a product is. We focus on five markets: yogurt, protein bars, disposable razors, deodorant and shampoo. We selected yogurt because its pricing patterns mirror the descriptive analysis of the full consumption basket, it is representative of the most commonly bought item in the data, a packaged food item, and it has a moderate amount of differential sorting by gender. The other four markets were selected because gender is an explicit component of marketing and product design, allowing for identification of demand for explicitly gendered products which might not be well captured in the CES model.

To estimate the model, we use store-level data on quantities and prices. With this data, we gain improved inference on markets where purchase frequencies make individual-level data sparse, like personal care items. We allow for heterogeneity in preferences for the gender of a product and instrument for prices with Hausman instruments and retail chain-level leave-out mean prices following evidence from DellaVigna and Gentzkow (2019). To map our results back to consumer demographics, we analyze how our results vary with the product's woman purchase share observed in the individual-level purchase data. We find that women's products are either more elastic or have no significant differences in elasticities from ungendered or men's products and that women's products have lower markups and higher marginal costs. These results, while allowing for more granular identification and flexible demand, are largely consistent with the CES demand analysis. Overall, our findings imply that observed price differences between men and women are primarily driven by women sorting into higher cost products.

Though our results are all consistent in terms of patterns and direction, we estimate that, for Health and Beauty products, elasticities are relatively inelastic (elasticities between 0 and -1) and thus our estimates of marginal costs are negative. We explore how this result may arise by reviewing the theory on brand loyal consumers and forward looking firms. Brand loyalty makes consumers less elastic, as they will incur a switching cost when deviating from their previous choice. If firms are not forward looking, then brand loyal customers should lead to higher equilibrium prices. However, if firms are forward looking, then brand loyalty can lead to lower equilibrium prices because the firm now has incentive to keep prices low to attract customers that will provide value in future periods. This could explain our findings for Health and Beauty products, where there is likely a high level of brand loyalty or inertia in general.

We validate our finding that women's products are associated with higher costs of production and lower markups with two additional analyses. First, we use data on wholesale prices to construct retailer level markups. These wholesale prices represent the marginal cost to retailers that do not self distribute. We find that women's products are associated with higher wholesale prices and lower markups. This finding is consistent with our demand analysis. Theory on double marginalization predicts that both retailers markup products to the demand elasticity of the final consumer base, so theory would predict that retailer markup differentials should mirror manufacturer markup differentials. Second, we hand collected product attributes for disposable razors in our sample. By searching Universal Product Codes and brand descriptions we were able to gather information on the number of blades, presence of a moisture strip, whether the head pivoted, and the ergonomic shape and material used in the handle for the vast majority of razor purchases in our sample. We chose these attributes because they are easily identifiable from images or product descriptions and are generally associated with differences in cost of production due to different amounts of input materials used. We find that women's razors are associated with having more blades, more likely to have a moisture strip and are more likely to have an ergonomic handle that utilizes soft rubber or plastic. This is consistent with our findings that women's products have higher marginal costs of production than men's.

We contribute to the large literature in industrial organization on the role of product differentiation within markets. Berry, Levinsohn, and Pakes (1995) developed the method that we use to estimate a discrete choice model in the presence of product differentiation. We incorporate the gendered-ness of a product as a characteristic over which individuals may have heterogeneous tastes. We use a revealed preference approach to identifying product gender, which means we do not need existing product characteristic data which enables us to estimate demand in multiple markets. Economists have long thought about the role of heterogeneous tastes and product differentiation in welfare. (George J Stigler and Becker 1977; Spence 1976) Product differentiation and price discrimination are sometimes thought of as separate phenomenons but in a broad view of price discrimination as any markup difference between consumers groups (like that of George J. Stigler 1987) the two are linked. Shapiro (1982) discusses second degree price discrimination through versioning, but there is no clear line of where versioning ends and product differentiation begins. Our paper contributes to this literature by analyzing how demand composition for differentiated products may lead to higher markups placed on a particular demographic group.

Though we do not estimate a general equilibrium model that incorporates endogenous product entry and exit, our findings suggest a natural next step of examining firms decisions to produce gendered products. Wollmann (2018) models entry and exit decisions of truck models finding that allowing for entry and exit moderates price increases resulting from mergers. Barahona et al. 2020 finds that firms decision to reformulate after a policy that affects demand depends on expected profits that face a tradeoff between bunching product characteristics that appeal to a larger demand group but face higher competition or differentiating a product to a smaller consumer base but facing less competition. Firm's incentives to innovate and introduce new products have also been studied in the trade literature. Work on firm and product heterogeneity stemming from differences in demand and costs among firms finds implications for innovation and competition. (Hottman, Redding, and Weinstein 2016, Faber and Fally 2022, and Atkeson and Burstein 2008) Broda and Weinstein (2010) and Bernard, Redding, and Schott (2010) also substantiate the role of innovation and turnover in driving evolution in prices, finding a substantial amount of product innovation: namely that half of firms switch their products within a span of five years and that product creation is a much stronger component of net product entry than product destruction. Although these works do not focus on gender or gendered product spaces explicitly, their findings have important implications for how we understand and motivate study of men's and women's consumer goods markets.

2.2 Data

This paper primarily relies on the Retail Scanner Data, henceforth referred to as RMS, from Nielsen IQ. The RMS data contain product-store-week level average prices and sales volumes of products purchased by consumers from 2004 to 2018. This dataset is not tied to the consumer identifiers; rather, the strength of the RMS data is in its relative comprehensiveness of US sales. We use the RMS data to model demand in select markets that have a high level of gendered products. These markets include yogurt, health and protein bars, deodorant, disposable razors and shampoo. To identify gendered products, we use data from Nielsen's HomeScan Panel (HMS). The HMS data serves as the primary data source for Chapter 1, which is focused on documenting gender differences in consumption behavior. This chapter is focused on explaining pricing strategies in markets where products are highly segregated by gender to uncover whether there is systemic price discrimination against women in these markets. The HMS data is described in detail in Chapter 1, as is the method for identification of gendered products.

The RMS data contains complete sales information for a specific store while the HMS offers complete purchase information for a given individual. As such, they offer different but complementary information on consumption of consumer packaged goods. The HMS contains information about products and prices made at stores that are not part of large chains, while the RMS is tracks information generally for only large national or regional chains. The RMS data can also be prohibitively large to use, as such we restrict our attention to five primary markets with a high degree of gender segregation in the product space: yogurt, protein bars, disposable razors, deodorant, and shampoo. In addition to focusing on these five markets we also restrict our attention to two years, 2010 and 2011, and take a random sample of retail chains to include. This gives between 500,000 and 3.5 million product-store-week observations depending on the product market of focus.

In addition to the RMS, we utilize data on wholesale prices through PriceTrak PromoData. The PriceTrak PromoData data allow us to validate retailer markups relative to wholesaler price. A critical component of this work consists of assigning the source of the observed differences in prices of goods consumed by women and by men to differences in marginal costs and differences in markups. While this data does not feature information on production costs, it does provide on the intermediary costs to retailers. The PriceTrak PromoData ultimately serves to facilitate a cross-validation against our structural demand estimation that uses solely price and consumption information from NielsenIQ. The PriceTrack data features retailer cost-data of individual UPCs for a variety of time- and geographic-denominations from 2006 and 2012, with the geographic disaggregations covering 48 markets (coinciding with the metropolitan areas around large US cities). The match rate of UPCs in the Promodata to the NielsenIQ datasets is relatively low—with only about 18% of the 430,000 distinct UPCs in the RMS data matching to PromoData. We combine the data from PriceTrak on wholesaler prices with Nielsen data on post-deal consumer prices to compute retailer markups relative to wholesaler prices following B. J. Bronnenberg et al. (2015).

Finally, we also collected product attribute data for disposable razors as a way to further validate our findings. Each disposable razor in the data contains a Universal Product Code (UPC) along with a product description and a brand description. We began identifying razors by looking up the UPC on the internet, however many UPCs are jumbled in the data collection process or were sold long enough ago that there are not great online records. For razors unidentifiable through UPC we utilized the product and brand descriptions in the data, searching the internet for listings of the product. In all we were able to identify and visually assess about 300 unique disposable razor products which account for the vast majority of razor purchases. Most razors were identified through online market places such as amazon or big box retailers but some older razors were identified through eBay listings. From these listings we gathered information on the number of blades, presence of a moisture strip, whether the razor head pivoted, and if the handle had an ergonomic shape or soft rubber used for comfort from either pictures of the razor or from the product description. We also collected information on the intended gender of the razor. We chose these product attributes because they are likely closely related to the costs of production of the razor. While we can't measure cost differences due to these attributes directly, their association with costs helps validate the direction of our findings.

2.3 Empirical Strategy

Our constant elasticity of substitution demand model in Chapter 1 speaks to differences in demand elasticities between men and women across their retail consumption baskets. To do this, we leveraged individual level purchase data aggregated to the by-gender market level. This method allowed us to capture consumer level average demand differences across a broad scope of products, but at the cost of model complexity in terms of flexible substitution patterns and market structure. Additionally, individual level purchase data faces sparsity issues in markets where purchases are relatively infrequent, like Health and Beauty products. To structurally decompose prices into markups and marginal costs, we allow for significantly more model complexity at the cost of narrowing our focus to less markets. To do this, we use weekly store level data that does not face the same sparsity issue that the aggregated individual level data does. This lack of sparsity comes at the cost of no longer being able to attribute purchases to a specific gender. To overcome this, we rely on our observed woman purchase share, $\hat{w}_j$ that we calculate using the individual level purchase data and map to the products in the weekly store level data.

We model demand in five product markets: yogurt, protein bars, deodorant, disposable razors, and shampoo. We focus on these markets because they have a high level of dispersion of $\hat{w}_j$ across their product spaces. Specifically, we select yogurt because prices and consumer behavior look similar to descriptive results of the entire grocery consumption basket. We think of the yogurt market as representative of grocery food markets generally. While yogurt seems to have significant heterogeneity in preferences across gender, marketing and advertising is less explicitly gendered than the other markets we focus on. The four other markets were selected because they contained a large amount of explicitly gendered products while also matching the price and consumption trends that we see in descriptive section. Figure 2.1 plots histograms of woman purchase share in each of the selected markets. Yogurt follows a similar normal distribution to what we see across the data at large, but the other four markets are either bimodal (deodorant and disposable razors) or somewhat uniform (protein bars and shampoo).

In the descriptive analysis, we found evidence that products explicitly gendered to men or women had higher prices than ungendered products in the same market (see Figure 1.5). Suggesting the potential for price discrimination on gendered products as a whole, rather than just women's products. Because of this we select two markets that have very few ungendered products, deodorant and razors, and two markets that have a relatively high amount of both gendered and ungendered products, protein bars and shampoo. Deodorant and razors allow us to test for price discrimination on women's products versus men's products while shampoo and protein bars are additionally able to test for price discrimination relative to ungendered products. Finally, three of the markets we analyze, deodorant, shampoo and razors are discussed in concurrent work on gender price discrimination by Moshary, Tuchman, and Bhatia (2021).

We structurally estimate markups and marginal costs with a differentiated products market demand model, the model validates our findings from the CES model while also incorporating market structure, flexible substitution patterns across a product's gender, as well as identification in markets where purchases are infrequent. To estimate the model we use store level weekly sales data from the RMS, this data is subject to considerably less sparsity than the individual purchases which allows us identification in markets with products are purchased relatively infrequently, namely Health and Beauty products. However, using store level data comes at the cost of not being able to attribute purchases to a specific gender. To overcome this we study how elasticities, marginal costs and markups vary with woman purchase share within a product market. Allowing for flexibility in substitution patterns requires significant computational power, therefore we restrict our analysis to five product markets that have significant dispersion of woman purchase share across the product space.

Differentiated Products Demand Model and Estimation

We follow the standard differentiated products market demand model presented in Berry, Levinsohn, and Pakes (1995) (BLP). Our main departure is that instead of typical product characteristics, we include our measure of the woman purchase share of a product, $\hat{w}_j$ and allow for heterogeneity in preferences for how gendered a product is. For each product module, consider $t = 1, ..., T$ markets defined as a retail store-month combination each with

$i = 1, ..., I_T$ customers. The indirect utility that customer i receives from choosing product j in market t is:

$$u_{ijt} = \alpha p_{jt} + \beta_{\mathbf{i}} \mathbf{x_j} + \xi_{jt} + \epsilon_{ijt}, \tag{2.1}$$

where p_{jt} is the price of product j in market t, x_j is vector of a constant term and the woman purchase share of the product, $\xi_{jt} = \xi_{jr(t)} + \xi_{m(t)} + \Delta\xi_{jt}$ are product-retail chain fixed effects, month fixed effects, and unobservable product characteristics, and ϵ_{ijt} is a mean-zero idiosyncratic error term that takes a Type I Extreme Value distribution. The key deviation from our CES model or a logit demand is that the coefficients on the product characteristics, β_i, are individual specific coefficients. We can parameterize these individual coefficients as a population mean preference parameter, that is eaten up by the fixed effects, and an individual random taste shock that captures unobserved heterogeneity in preference for the outside option and the woman purchase share of the product:

$$\beta_{\mathbf{i}} = \mathbf{\Sigma} \cdot \mathbf{v_i}, \qquad \mathbf{v_i} \sim N(0, \mathbf{I_2})$$

Heterogeneity in preferences for product gender will generate more reasonable substitution patterns than our CES demand model does. Under CES demand, price increases on a woman's razor will lead to equal levels of substitution from the women's razor into other women's razors and men's razors. Now, the random coefficient on women purchase will generate substitution patterns that have men's razors substituting to men's razors and women's razors substituting to women's razors. Allowing for heterogeneity in preferences for the outside option is important as the value of the outside option is likely different between men and women in many of these of these markets. For example, the value of the outside option for disposable razors depends on the social stigma attached to shaving for men versus women. Many papers that estimate differentiated products demand models include demographic moments as in Nevo (2001), here we do not because our product characteristic is effectively a demographic moment and will be mechanically correlated.

The resulting market share for product j in market t can be written as:

$$s_{jt} = \int \frac{\exp(\alpha p_{jt} + \beta_i \mathbf{x_j} + \xi_{jt})}{1 + \sum_k (\exp(\alpha p_{kt} + \beta_i \mathbf{x_k} + \xi_{kt}))} d\beta_i \tag{2.2}$$

We estimate the model using the Python package, *pyBLP* Conlon and Gortmaker (2020), which solves for the parameters of interest using two step generalized method of moments. The methods used for estimation of this class of models is standard and well documented in the industrial organization literature. The indirect utility that an individual receives from consuming product j can be written as a linear component and a non-linear component:

$$u_{ijt} = \delta_{jt} + \Sigma \cdot v_i + \epsilon_{ijt},$$

where $\delta_{jt} = \alpha p_{jt} + \beta \mathbf{x_j} + \xi_{jt}$ is the fixed component of utility from product j. Given a guess of the variances of the taste parameters for the woman purchase share and outside option,

$\hat{\Sigma}$, we can construct estimates of the market shares:

$$\hat{s}_{jt} = \int \frac{\exp(\delta_{jt} + \hat{\Sigma} v_i)}{1 + \sum_k (\exp(\delta_{kt} + \hat{\Sigma} v_i))} dv_i \tag{2.3}$$

Using our estimated market shares and observed market shares, we iteratively solve for δ_{jt} using the contraction mapping:

$$\delta'_{jt} = \delta_{jt} + \log(s_{jt}) - \log(\hat{s}_{jt}).$$

From the converged estimates of δ_{jt}, we can recover the price parameter, α, and the mean taste parameters, β from a regression of δ_{jt} on prices. In practice, we include product-retail chain fixed effects as well as time fixed effects in our specification which allows the mean taste parameters to vary at the product-retail chain level. This regression also provides estimates of ξ_{jt}, which we use to estimate the variance of taste parameters, Σ with the following moment condition:

$$\mathbb{E}[\xi_{jt} Z_{jt}] = 0,$$

where ξ_{jt} and Z_{jt} are the residuals of the unobserved product characteristics and demand side instruments after all fixed effects have been partialled out.

We instrument for prices with the same instruments we use for our aggregate elasticity analysis, Hausman instruments that are a national level leave out mean of prices and Dellavigna-Gentzkow instruments that are a retail level leave out mean of prices. The Hausman instruments rely on the assumption that demand shocks are uncorrelated across markets while supply shocks are correlated across space and time. The Dellavigna-Gentzkow instrument's validity relies on retail chain level pricing being largely exogenous from local demand shocks. In addition to price instruments, we identify substitution patterns across products with quadratic differentiation instruments developed by Gandhi and Houde (2019). The instruments take the form $Z^{diff}_{jt} = \sum_k d^2_{jkt}$, where $d_{jkt} = x_{kt} - x_{jt}$ and x_{jt} is the woman purchase share of product j. We utilize two versions of this instrument, one where differences are summed over products that are true rivals, that is, products that are owned by other firms and one for products produced by the same firm. The instrument captures "closeness" in the product space in terms of woman purchase share and is rooted in the idea that substitution likely happens among products that are similar in gender.

We fit the supply side of the model by assuming firms, f, maximize their profits across the set of products they produce, $\mathcal{J}_f$ given the demand that they face.

$$\pi_{ft} = \sum_{j \in \mathcal{J}_f} (p_{jt} - mc_{jt}) s_{jt},$$

We construct an ownership matrix, Ω, that maps each product in our data to a common owner so that element jk is 1 if product j and product k are owned by the same firm and 0 otherwise.[1] Let J be the matrix of estimated demand derivatives, so that element jk is $\frac{\partial s_j}{\partial p_k}$.

[1]We construct the ownership matrix through manual search, Capital IQ, and newspaper articles.

The price-cost markup is then given by:

$$\frac{p^* - mc}{p^*} = -(\Omega J)^{-1} \frac{s(p^*)}{p^*} \tag{2.4}$$

Because price is observed, identified markups also identify marginal costs. The estimated parameters are presented in Table 2.2.

2.4 Differentiated Products Demand Model Results

We begin by plotting prices by decile of woman purchase share for each market. These prices are observed in the data and we normalize them relative to the size of the good.[2] We plot the median price of a product within a woman purchase share decile along with the interquartile range. Figure 2.2 presents the data. Generally, we find that prices are increasing in woman purchase share. The average men's razor in our data priced at about \$1.2, while the average women's razor is priced at about \$1.5. We find that women's yogurt is generally priced about 5 cents higher per ounce than ungendered yogurt, women's protein bars are priced about 5 cents higher per ounce as well. Women's deodorant is priced about 20 cents more per ounce than men's.[3] Finally, women's shampoo can cost 20-25 cents more per ounce than men's or ungendered shampoo.

We plot median estimated own price elasticities and interquartile range by woman purchase share in Figure 2.3. Own price demand elasticities in our model are given by $\varepsilon_{jt} = \frac{\partial s_{jt}}{\partial p_{jt}} \frac{p_{jt}}{s_{jt}}$. Generally we find that women's products are either more elastic or no differently elastic than men's or ungendered products. Most of the markets exhibit a downward trend in elasticities along woman purchase share. These findings are generally inconsistent with a price discrimination story, where we would expect to find that women's products or gendered products in general have less elastic demand. Instead we find that women's products are much more elastic and men's products are either slightly more elastic (yogurt and shampoo) or are no differently elastic than ungendered products (deodorant and razors). Our results are generally consistent with our CES demand estimation and suggest that women as a consumer base seem to be generally more elastic consumers than men across both gendered and ungendered products.

Firm's pricing decisions and markups are made based on the own price elasticity of the product, the cross elasticities with other products owned by the firm and marginal cost.

[2] Yogurt, protein bar, deodorant and shampoo prices are all presented as price per ounce while razors are presented as price per count.

[3] An interesting finding about the price discrepancy in deodorant is that it is mostly generated by women's deodorant in slightly smaller amounts but having the same list price. The outlier in the 70th decile for deodorant is primarily driven by the brand Tom's of Maine, it is a natural health product that is generally priced higher than other deodorants.

Even though women's products have more elastic demand, they could face higher markups through substitution patterns or the competitive structure of the market. Multiproduct firms have incentives to price higher because some of the lost demand is funneled into other products that they own. Women's products could still face higher markups if they are more likely to be owned by large multiproduct firms and consumers strongly substitute to other products owned by the firm.

We plot median estimated markups along with interquartile range by woman purchase share decile in Figure 2.4. We find that markups are generally decreasing in woman purchase share in all product markets except for protein bars. Protein bars are the only product market where we find that women pay significantly higher markups than men. Looking at the elasticities in Figure 2.3, women's own price elasticities are slightly more elastic than men's. That means that this result is generated by substitution patterns and the competitive structure of market. When we look into this, we find that this result is driven entirely by substitution of Luna bars into Clif bars, Luna is Clif's woman oriented protein bar brand and both Clif command's a significantly large share of the market. Because of this, we do not take this as evidence of price discrimination but rather the result of a single firm's market power. Overall, the results suggest that women's products are associated with lower markups.

From the markups we directly calculate marginal costs and present them in Figure 2.5. Among yogurt, razors, and shampoo we find that marginal costs are increasing in woman purchase share, that is the products that women sort into are more expensive to produce. We find weakly higher marginal costs for women's deodorant but this is dwarfed by higher marginal costs in ungendered deodorants. Ungendered deodorants make up a small share of the market, and tend to be either natural products, like Tom's of Maine, or clinical strength products, like Certain Dri, that seem reasonable to have higher marginal costs. Again, the only market where women are not sorting into higher marginal cost products is protein bars, but this is primarily driven by competitive structure and does not seem to be consistent with the narrative across the consumption basket.

A consistent result that we encounter in our differentiated products model is that we generally estimate health and beauty products to have negative marginal costs, while the food items we analyze have positive marginal costs. There are many reasons why this could arise related to both supply and demand side behavior. Our partial equilibrium model assumes firms maximize profits statically, and that consumers are rational in their decisions. Deviations from our assumed competitive structure as well as behavioral demand factors may result in equilibrium prices and elasticities that are lower than what is rationalizeable in the standard static setting. In the next section, we discuss in detail one possible explanation: brand loyalty and dynamic, forward looking firms. Dubé, Hitsch, and Rossi (2009) find that when consumers have brand loyalty and firms price to maximize their future stream of profits, equilibrium prices can be lower than in the static case. It is also possible that other dynamic competitive factors may drive prices down, like threat of entry of other firms or products. Overall, equilibrium prices are a result of price elasticities and competitive structure.

Brand Loyalty and Forward Looking Firms

In our differentiated products demand model, we consistently estimate demand elasticities for Health and Beauty products that yield negative marginal costs under static competition over prices. While many alternate models of firm conduct can could rationalize the pricing decisions of firms and produce positive marginal costs, in this section we explore how brand loyalty and forward looking firms could lead to less elastic demand and lower equilibrium prices. We build on the model presented in Dubé, Hitsch, and Rossi (2009), where brand loyalty is incorporated as a psychological switching cost and firms maximize their present discounted stream of profits. The individual's indirect utility from consuming product j in market t is now:

$$u_{ijt} = \alpha p_{jt} + \beta_{\mathbf{i}} \mathbf{x_j} + \xi_{jt} + \gamma \mathbb{1}(state_{it} \neq j) + \epsilon_{ijt}, \tag{2.5}$$

where γ is a negative number that represents the utility cost of switching to a product not consumed in the previous period. The individual's probability of choosing product j is given by:

$$s_{ijt} = \frac{\exp(\alpha p_{jt} + \beta_i \mathbf{x_j} + \xi_{jt} + \gamma \mathbb{1}(state_{it} \neq j))}{1 + \sum_k (\exp(\alpha p_{kt} + \beta_i \mathbf{x_k} + \xi_{kt} + \gamma \mathbb{1}(state_{it} \neq k)))} \tag{2.6}$$

To arrive at population level choice probabilities, or market shares, we integrate over the distribution of random taste shocks as well as the distribution of the state space.

$$s_{jt} = \int \int \frac{\exp(\alpha p_{jt} + \beta_i \mathbf{x_j} + \xi_{jt} + \gamma \mathbb{1}(state_{it} \neq j))}{1 + \sum_k (\exp(\alpha p_{kt} + \beta_i \mathbf{x_k} + \xi_{kt} + \gamma \mathbb{1}(state_{it} \neq k)))} d\beta_i df(i), \tag{2.7}$$

where $f(i)$ is the state space distribution and maps to the previous period's market share. Incorporating brand loyalty provides firm's with an additional dimension over which they can increase market shares. In the standard BLP model, firm's can increase their market shares by adjusting prices in that time period. Now, firm's market shares are not only dependent on current period prices, but also indirectly by previous periods' prices through the previous period's market share. Note that the existence of brand loyalty means we will observe consumers being less elastic, as it would take a larger price change to incentive a consumer to switch products than without switching costs.

If we kept the static model of competition that is standard in BLP, the existence of brand loyalty and inertia should always lead to higher equilibrium prices. This is because in a one shot game, there is a benefit of cannibalizing on existing inertial customers. The effect on prices for forward looking firms, however, is ambiguous. We now assume that firms maximize the present discounted stream of future profits, making supply dynamic rather than static.

The firm's problem is given by:

$$V(\pi_{ft}) = \sum_{j \in \mathcal{J}_f} \sum_{l} \beta^l (p_{jt} - mc_{jt}) s_{jt},$$

Firms compete over prices and the solution is defined by a set of strategies, $\sigma(f)$, that satisfy Markov perfect equilibrium. Because the supply side is now dynamic, the game does not have a closed form solution and must be solved with computational methods. However, we can build intuition for how strategies change. In a static supply model, firms maximize profit in a single period and face a trade off between prices and market shares. If a firm raises prices, it makes more money on the marginal consumer that stays, but loses out on the consumers that leave. Firms set prices such that the marginal benefit of raising prices is exactly offset by the marginal loss of losing customers. When consumers are brand loyal and firms are forward looking, prices in the current period have an enduring effect on market shares in the future. That is, lower prices today not only increases today's market shares but tomorrow's as well.

This additional incentive expands the range of potential equilibrium price outcomes relative to the static model. That is because there is now an additional trade off decision being made: firms may have incentive to cannibalize on their inertial consumer base with higher prices, but they also may have incentive to lower prices in order to gain and maintain a larger consumer base in future periods. Dubé, Hitsch, and Rossi (2009) simulate equilibrium prices for consumers with a standard logit utility function and assuming single product firms and find that at very high levels of brand loyalty equilibrium prices are higher than in static equilibrium, but at lower levels of brand loyalty equilibrium prices are lower than they would be in static competition.They find that equilibrium prices are initially decreasing in brand loyalty then the trend inverts and prices begin increasing in brand loyalty. Empirically, they find that the level of brand loyalty observed in orange juice and margarine markets is consistent with lower equilibrium prices.

These results are consistent with our finding that prices for Health and Beauty products are low given their observed demand elasticities. Estimating this model is ongoing work and will be included in future iterations of this paper. We now discuss how our results in the main body of the paper can be interpreted in the context of brand loyalty and a dynamic supply side. Our paper finds that marginal costs tend to be increasing in woman purchase share, that is products that are more often bought by women have higher marginal costs. The introduction of brand loyalty has the potential to change this relationship if women and men are heterogeneously brand loyal.

Holding the level of brand loyalty constant between men and women would likely lead to a level shift up of our marginal cost estimates, as the pricing incentives for men's products and women's products would change in the same way. In order for our results to be flipped, women would need to have significantly different brand loyalty levels than men. Specifically, men would need to have moderate brand loyalty levels with women either having close to no brand loyalty or fairly high levels of brand loyalty.

2.5 Marginal Cost Validation: Razors Case Study

We validate our finding that women's products have higher marginal cost of production for disposable razors using attributes and measures that are associated with marginal costs. We use wholesale prices as well as information on the number of blades, moisture strip and ergonomic shape and contents of the handle to do this.

Wholesale Prices

First, we use PriceTrak PromoData that contains information on the wholesale price of razors to grocery retailers. These wholesale prices are the marginal cost to the retailer, though not the true marginal cost of the product as there is a manufacturer level markup that factors into the wholesale price. However, assuming a standard double marginalization setup similar to Spengler (1950), markups at each stage are proportional to the demand of the consumer base and so, it is likely that markup differences downstream correspond to markup differences upstream as well.

We merge the PriceTrak PromoData to Nielsen data via matching on UPCs and are able to successfully match about 40% of disposable razor units sold in the store level retail scanner data in years 2006 through 2011. We merge purchases to national level averages of wholesale prices in a given year. We are disproportionately able to match women's razors (successfully match 47% of purchases) as opposed to men's razors (successfully match 35% of purchases). A significant portion of the missing matches are generic, store brand razors which are not sold through wholesalers, about 30% of sales, which means we are able to match about 60% of branded razors that may be sold through wholesalers.

We classify razors as women's and men's products using our women purchase share measure and ensure that we are correctly inferring gender by manually checking product and brand descriptions. We calculate markups as $\frac{P-MC}{P}$ where MC is the average wholesale price of the product that year after deals and discounts. There are a few important caveats to mention that go into constructing these markups. The first is that we are computing the wholesale cost as fixed nationally within a year, when in reality there is some variation in prices both regionally and temporally. Because of this we take these markups as representations of likely averages rather than exact markup calculations. We present comparisons of purchase weighted average prices, wholesale costs to the retailer, and markups in Table 2.3.

From Table 2.3 we can see that the median women's razor is priced about 20 cents higher than the median men's razor, this 20 cent difference also occurs in the wholesale prices, where the median women's razor is priced at about 80 cents and the median men's razor is priced about 58 cents. This translates to the women's razors having a lower markup over wholesale prices than men's razors. We find that women's razors have markups of about 16% and men's razors have markups of about 21%. These patterns are maintained when we look at differences within the major razor manufacturers that we identify.

In addition to comparing medians, we regress our imputed markups on an indicator for whether a razor is a women's razor along with fixed effects for the parent brand (i.e. Gillette, Bic, and Schick) as well as market fixed effects for the store and year. The coefficient on the indicator for whether a razor is a women's razor represents the average difference in markup between men's and women's razors for products in the same market and same parent company/brand. We weight observations by their total sales volume to get purchase weighted differences in markups. We find that women's razors are associated with 7.6% lower markups than men's razors and the result is significant at the 1% level.

Men's and Women's Razor Attributes

In addition to wholesale prices, we validate our marginal cost findings with information about product characteristics that are likely correlated with the costs of production. Specifically, we scrape information on a razor's number of blades, the existence of a moisture strip, and the shape an contents of the handle. We create an indicator for whether the handle is ergonomic based on it having a shape that requires more plastic in comparison to a straight handle or whether it has additional rubber grip in the handle. We are able to gather information on product attributes for 90 out of the 176 razor product lines in our data, however we capture those products that have the largest market share and are able to capture information for 73% of purchases that are made on private label razors.

We present purchase weighted comparisons of the product characteristics of the average women's razor to the average men's razor in Table 2.4. We can see that women's razor purchases have 0.3 more blades than men's, with the average razor purchase having between two and three blades. Women's razor purchases are slightly more likely to have a moisture strip, by about 1.4%. Finally, women's razor purchases are about 19% more likely to have a ergonomic handle. We take this as evidence that the razors that women purchase have characteristics associated with having higher cost of production as they require more materials to produce than men's razor purchases.

Overall, we find that both the wholesale price data and the product attribute data support our finding that women's razors have higher marginal costs of production. This should give confidence that while our marginal cost estimates may be biased downwards due to using a static model or other competitive factors, the trend lines and elasticity estimates are capturing meaningful differences in firm's pricing and production of products.

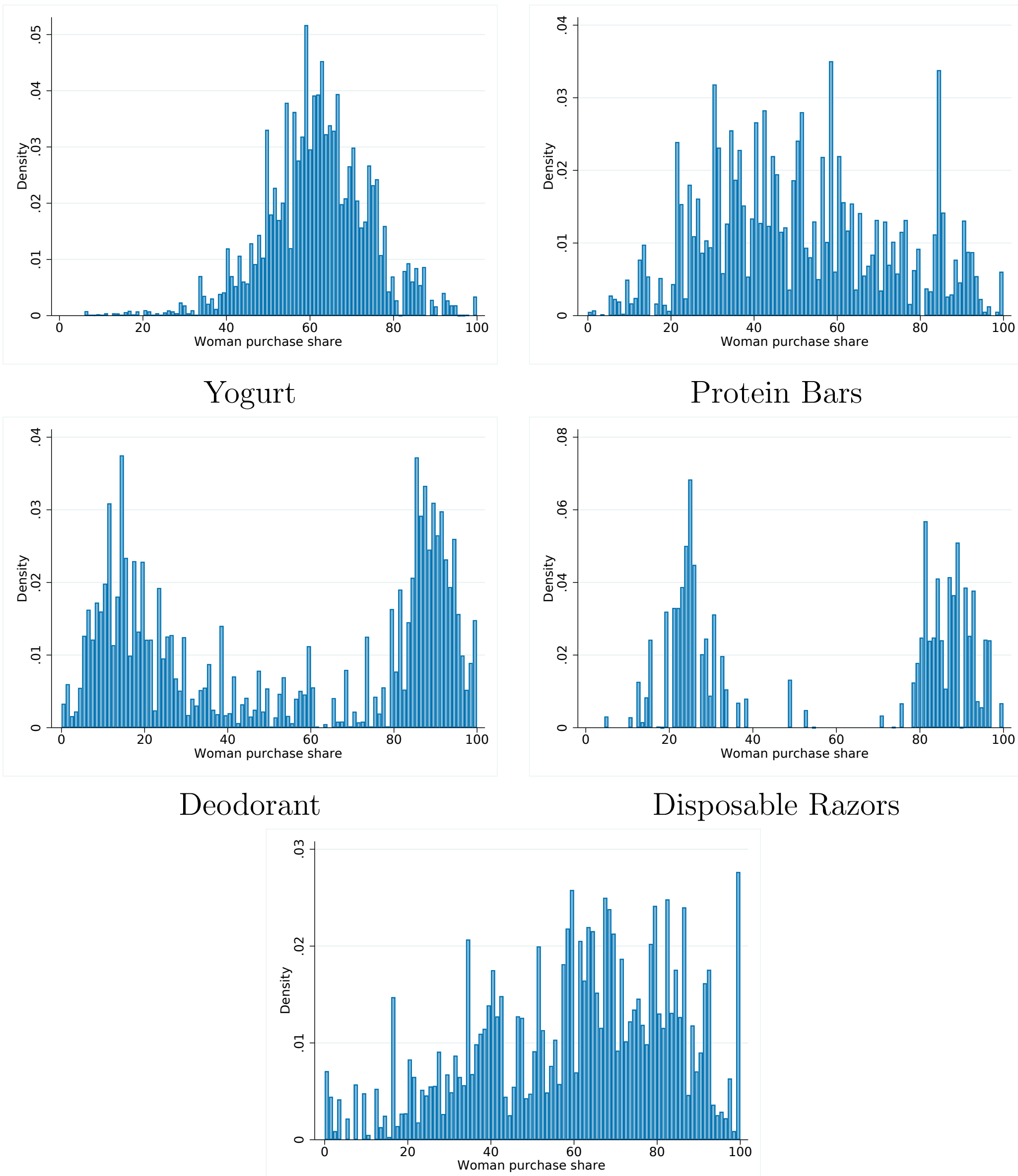
2.6 Discussion

To understand if observed price premiums are driven by markups (price discrimination) or preferences for goods with higher marginals costs, we formally model demand in two ways, incorporating methods from the international trade and industrial organization literature. Our first model, documented in Chapter 1, allows us to attribute demand elasticities to the gender of the consumer and speaks to the entire consumption bundle. Our second model, documented in Chapter 2, allows us to identify elasticities for explicitly gendered products that are not well captures in the first model and more carefully models demand by allowing for more flexible substitution patterns and competitive structure. Our CES demand model finds that women are generally more elastic consumers than men are, this finding suggests that women are sorting into products that have higher marginal costs, at least among the most frequently bought ungendered products. Our differentiated products demand model allows for heterogeneity in preferences for the gender of a product and finds that women's products are either more elastic or not significantly differently elastic than men's products or ungendered products. Taken together, our demand estimations show that price premiums paid by women are generated by women sorting into higher marginal cost goods.

The policy implications of our findings are nuanced. We can confidently state that existing and proposed legislation that bans pricing differences based on gender is likely to have little to no effect on the observed pink tax paid by women, a finding supported by related work by Moshary, Tuchman, and Bhatia (2021). It is harder to prescribe optimal policy or welfare improving policy when the underlying mechanism is differences in preferences for quality or marginal costs. Classical economic theory that assumes rational consumers and that revealed preferences are utility maximizing would suggest that policy that interferes with markets here would be welfare decreasing. However, growing literature on biased beliefs in retail consumption suggest that consumer preferences do not necessarily map to utility, its possible that men and women may be biased to different degrees and this could affect optimal policy.(B. J. Bronnenberg et al. 2015; Allcott, Lockwood, and Taubinsky 2019) Ultimately, our work describes gender differences in consumption behavior and the product space but does not address how these differences come to be.

Preference formation has long been a topic of interest in economics, since George J Stigler and Becker (1977) first put forth their theory of accumulated consumption capital. More recently this theory has been applied to study generational differences in preferences (B. Bronnenberg, Dubé, and Joo (2022)). Given that men and women are socialized to consume and value goods in very different ways, one would expect that a woman's accumulated consumption capital would be very different from a man's. The relevant policy, welfare and research questions then become how are preferences shaped, can preferences be changed, and can changing preferences increase utility? Finally, we estimate a partial equilibrium model where we take the set of products produced as given. A natural question to arise is how do systematically different preferences between men and women shape product entry and exit along with innovation (and vice versa)?

Figure 2.1: Woman purchase share distribution



Note: This figure presents the distribution of products across woman purchase share for the five selected product markets.

Table 2.1: Most popular brands by product gender - deodorant

Ungendered	**Woman Gendered**	**Man Gendered**
Arrid	Secret	Mennen Speed Stick
Sure	Mennen Lady Speed Stick	Right Guard Sport
Ban Classic	Degree	Old Spice High Endurance
Arm & Hammer UltraMax	Dove	Gillette
Suave	Mitchum for Women	Old Spice

Table 2.2: Differentiated Products Model Results

	(1) Yogurt	(2) Deodorant	(3) Protein Bars	(4) Razors	(5) Shampoo
Price (α)	-13.778***	-0.201***	-2.710**	-0.563***	-0.612
	(0.198)	(0.0045)	(0.171)	(0.125)	(0.392)
σ_1	10.187***	9.386***	7.262	62.911***	4.417
	(1.377)	(1.849)	(15.661)	(25.780)	(6.575)
σ_W	15.509*	1.906	23.738	19.833	17.670
	(8.611)	(5.603)	(17.414)	(13.808)	(68.242)
Observations	728,428	3,425,548	1,443,840	466,059	694,939
$\bar{\varepsilon}$	-1.875	-0.329	-1.716	-0.766	-0.215
$\bar{\mu}$	0.879	5.278	0.925	3.377	11.109

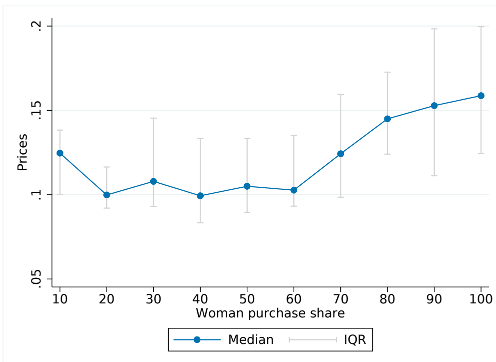
Market level clustered standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.3: Median prices, wholesale prices, and markups for disposable razors

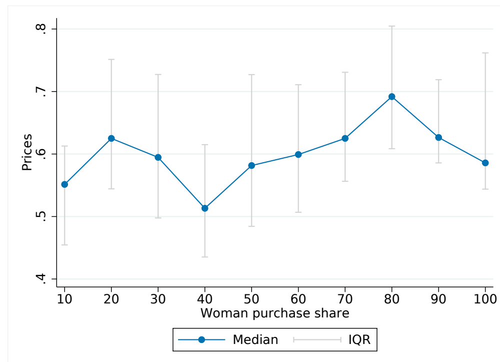
	Unit Price	Unit Wholesale Price	Imputed Markup
Women's Razors	0.94	0.802	0.16
	(1.058)	(0.747)	(0.201)
Men's Razors	0.73	0.58	0.21
	(0.367)	(0.159)	(0.207)

Note: Median values reported and interquartile ranges presented in parentheses below. All values are reported in 2016 dollars. Unit prices are from Nielsen's retail scanner data and wholesale prices are from PriceTrak PromoData.

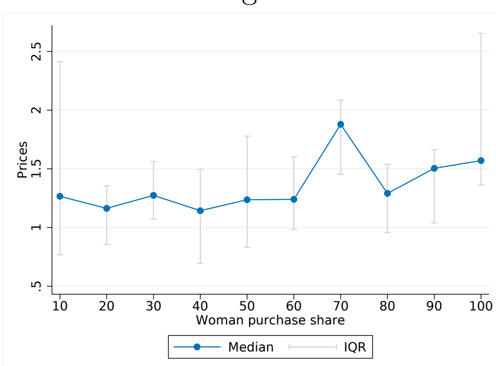
Figure 2.2: Observed prices



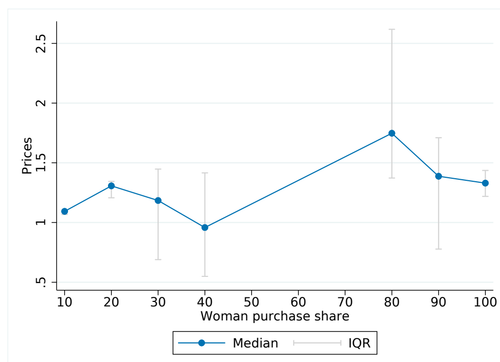
Yogurt



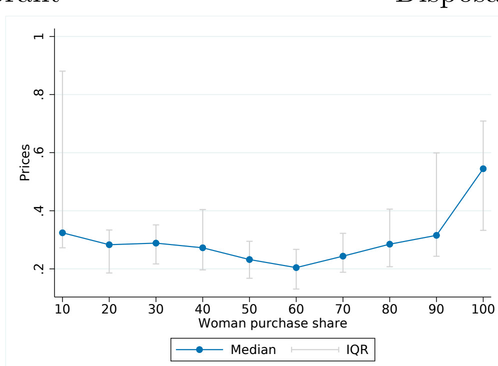
Protein Bars



Deodorant



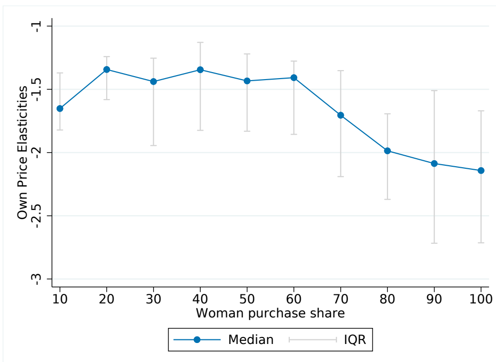
Disposable Razors



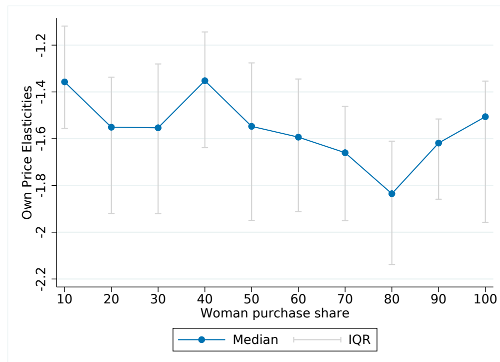
Shampoo

Note: This figure presents median prices of products by decile of woman purchase share. Prices are observed in the data and are not estimated. Grey bars represent the inter quartile range.

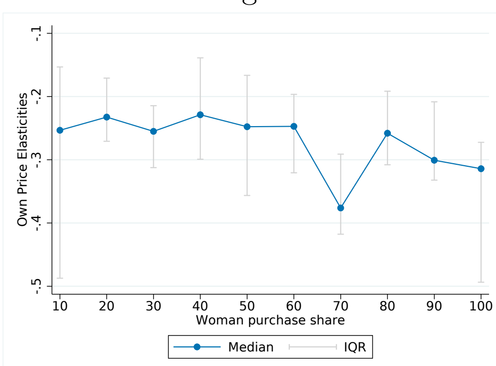
Figure 2.3: Own price elasticities



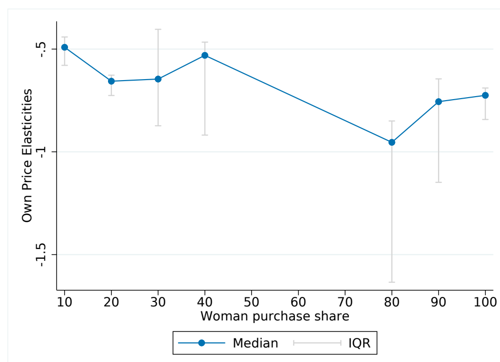
Yogurt



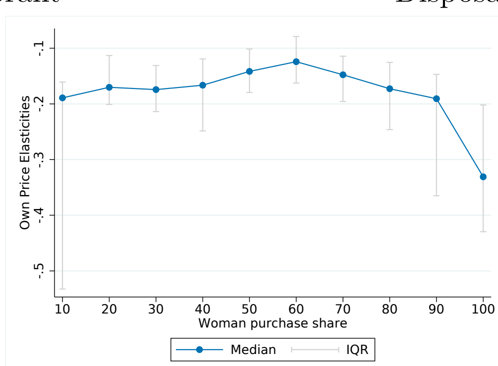
Protein Bars



Deodorant



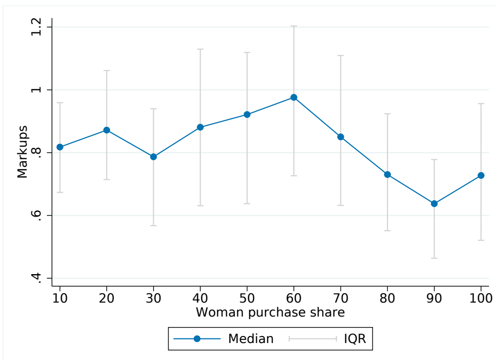
Disposable Razors



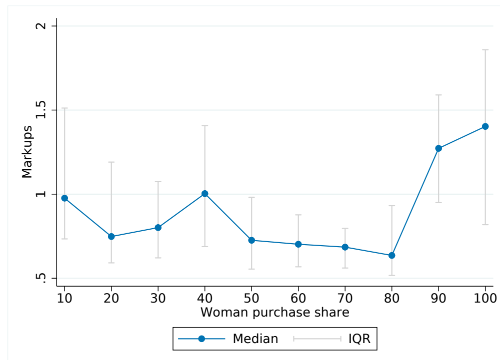
Shampoo

Note: This figure presents median estimated own-price elasticities of products by decile of woman purchase share. Grey bars represent the inter quartile range of the estimates.

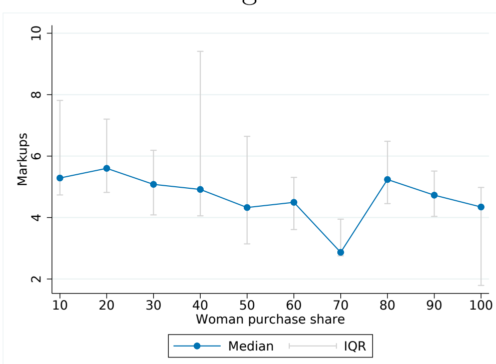
Figure 2.4: Markups



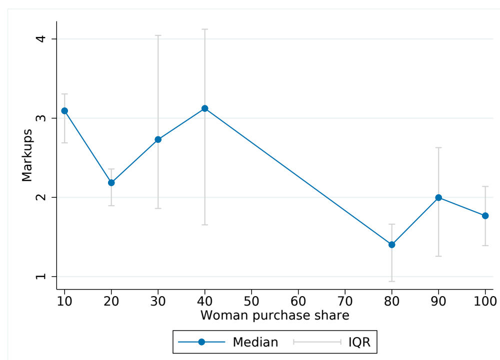
Yogurt



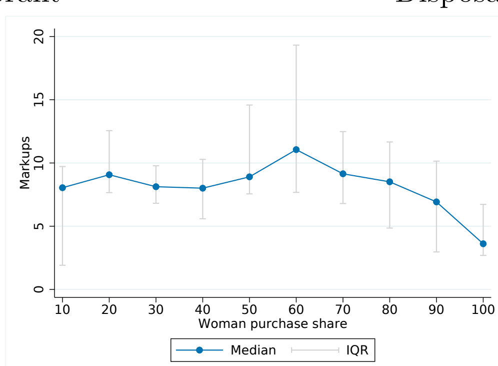
Protein Bars



Deodorant



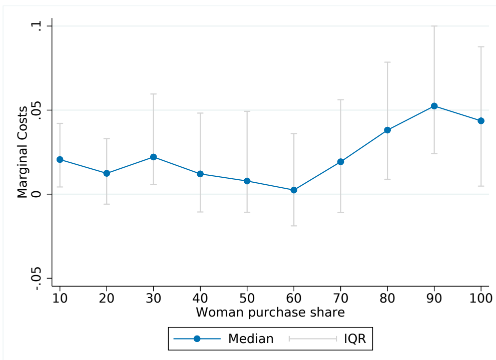
Disposable Razors



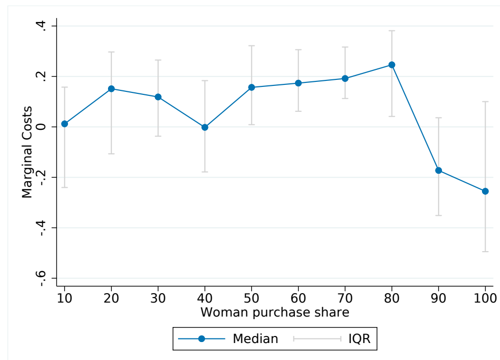
Shampoo

Note: This figure presents median estimated markups of products by decile of woman purchase share. Grey bars represent the inter quartile range of the estimates.

Figure 2.5: Marginal costs



Yogurt



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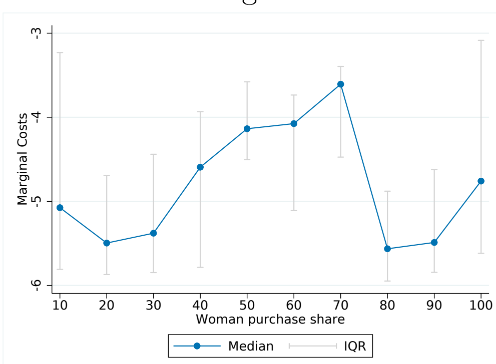
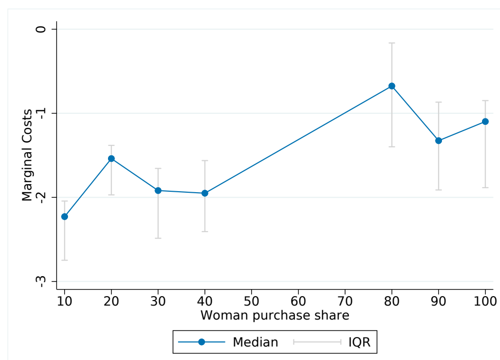
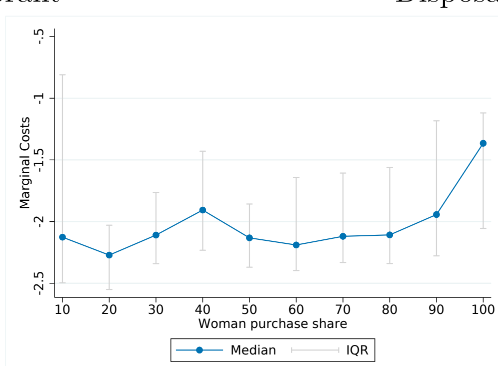


Deodorant



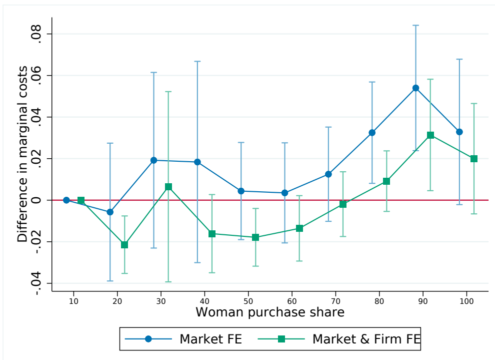
Disposable Razors



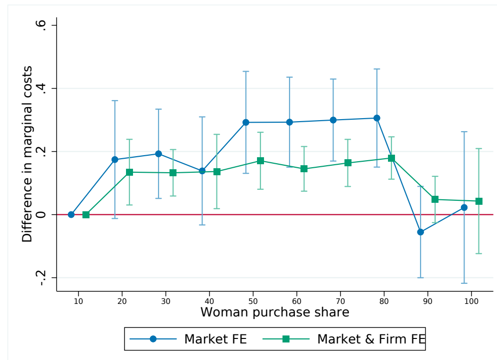
Shampoo

Note: This figure presents median estimated marginal costs of products by decile of woman purchase share. Grey bars represent the inter quartile range of the estimates.

Figure 2.6: Marginal costs with market and firm FE



Yogurt



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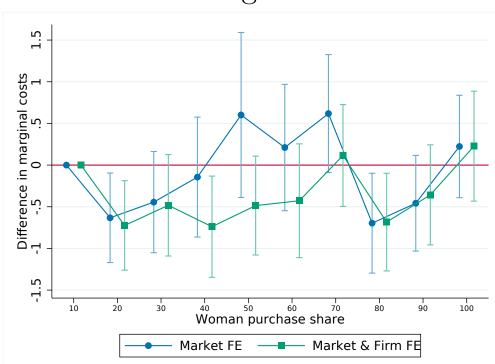

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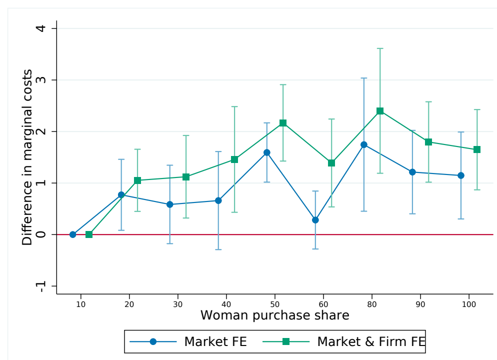
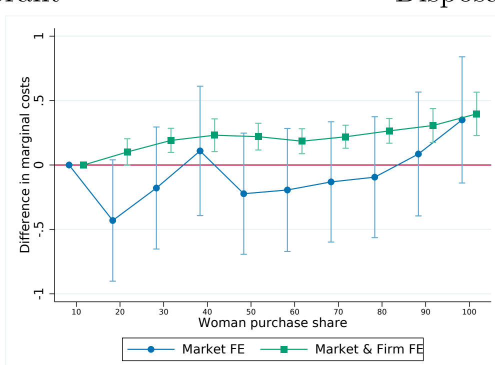


Disposable Razors



Shampoo

Note: This figure plots average average markups for each decile of woman purchase share relative to goods that are bought up to 10% of the time by men within a market and within a market and firm. Standard errors bars were computed taking estimated values as truth.

Table 2.4: Women's and men's razor attributes

	# of Blades	Moisture Strip	Ergonomic Handle
Women's Razors	0.30***	0.014***	0.19***
	(0.00003)	(0.00002)	(0.00002)
Men's Average	2.17	0.72	0.24
N	2,219,026,905	2,214,004,663	2,214,004,663

Note: This table plots coefficients from regressions of a given product characteristic on whether or not the product is a women's razor. We weight the regression by the total number of sales volume of the razor. Robust Standard errors are presented in parentheses.

Transition to Chapter 3

Chapters 1 and 2 are unified by focus on the same topic and setting, but taking different empirical approaches. This dual approach has the goal of being able to speak to both the scope and mechanisms involved in the Pink Tax. Chapter 3 offers a departure in terms of setting and topic but is still intimately related to the topic of industrial organization and the study of demand and supply. In chapters 1 and 2 we study the effects of demand heterogeneity, but are are always assuming perfect information on the part of consumers and producers. This is because information is largely available and list prices are posted publicly. There are many markets, however, where information about prices or characteristics are shrouded. Health care is just one of these markets and offers an interesting setting to study the effects of revealing information. In this sense, chapter 3 builds upon chapters 1 and 2 by incorporating the role of imperfect information.

Chapters 1 and 2 highlight the role of demand heterogeneity in generating disparities in equilibrium prices and quantities. Chapter 3 highlights how fixing existing information asymmetries can have unintended effects on the supply side of the market, not just the demand side. All three chapters showcase how supply adjusts to demand factors or information that is present as a way to maximise profits. Though we model chapters 1 and 2 as having perfect information, other work has shown that imperfect information also exists in consumer packaged goods markets. Chapter 3 can therefore offer interesting insights to the setting of chapters 1 and 2. Similarly, chapters 1 and 2's focus on demand heterogeneity is relevant to the findings of chapter 3, particularly the heterogeneity analysis showing that groups with different characteristics respond differently to the information treatment.

Chapter 3

The Impact of Price Transparency in Outpatient Provider Markets

Authors: Hunt Allcott, Kayleigh Barnes, Sherry Glied, Ben Handel, Grace Kim

3.1 Introduction

Health care policymakers, insurers, and private companies have frequently discussed the transparency of health care pricing information as a way to reign in rising health care spending (Reinhardt 2006; Sinaiko, Kakani, and Rosenthal 2019; Volpp 2016). Prices in health care markets are notoriously variable, opaque, and confusing and price transparency has the potential to reduce search costs and information asymmetries for consumers seeking cheap, high value health care. Most consumers purchasing services, especially those who intentionally or inadvertently purchase services outside their insurer networks, have no easy way to ascertain or compare prices charged by different providers. Recently, the federal government has sought to use regulatory levers to make healthcare prices more transparent, including upholding a CMS 2019 Final Rule that mandates hospitals release comprehensive information regarding negotiated rates, and was in effect as of 2021 (Wilensky 2019; Kullgren and Fendrick 2021; Glied 2021; UnitedHealthcare 2023).

Proponents of price transparency note the substantial potential benefits in (i) making price information available to consumers and (ii) reducing consumer search costs by making this information easily accessible. They also note the potential benefits for provider pricing: if consumers are more price elastic then providers may lower prices in this more competitive landscape. This may result either from providers choosing prices freely or as the result of insurer-provider bargaining if price transparency provides a competitive advantage to insurers.

However, despite these evident benefits, skeptics are concerned that the release of pricing information might lead to higher prices either via collusion among providers (tacit or explicit) or via providers gaining a competitive advantage from realizing that they are systematically under-pricing relative to similar-quality peers. In a market with clear capacity constraints, as in health care, information may help motivate providers to raise prices under the realization that they can charge more without decreasing their quantity of services. Alternatively, if consumers equate price with quality, providers might raise prices to signal quality. Albæk, Møllgaard, and Overgaard (1997) document exactly this phenomenon in the context of the Danish concrete industry, where the publishing of transaction prices produced a 15-20% increase in concrete prices, as producers stopped offering confidential discounts to purchasers. With these kinds of issues in mind, some policymakers and economists have urged caution in promoting price transparency (see, e.g., Cutler and Dafny 2011).

In this study, we examine price transparency for providers across the state of New York, using a randomized controlled trial embedded in the information provision platform run by FAIR Health, a non-profit organization dedicated to promoting price transparency in health care markets. Prior to our intervention, FAIR Health provided market-level information on typical prices for a given procedure, but did not provide information for specific individual providers. We partnered with FAIR Health to implement a statewide randomized intervention providing individual-level provider billed charge information on their platform. We randomized whether this information would be provided for providers at the procedure-geozip level. For a given kind of procedure in a given market, all providers of that procedure are either randomized into our individual-level price information treatment or randomized out of the treatment.[1]

The design was set up specifically to capture market-level pricing and demand effects as well as the effects for specific kinds of individual providers. Our intervention applies to 107 procedures and all geozips in New York and was in place for two years so that we could assess its medium-run effects. The data captured all commercial claims in the FAIR Health data warehouse related to these procedures and geozips and encompassed over 110 million claims and over 205,000 providers. We present a series of descriptive statistics showing (i) that our intervention is well-balanced across treatment and control arms (ii) that there is meaningful heterogeneity across procedure-geozip markets in market power, out-of-network claims, and ex ante price dispersion and (iii) that usage of the information tool we study averages just fewer than 10,000 uses per month.

Our randomized intervention allows us to cleanly identify the net price and quantity effects of our information-provision tool while also allowing us to study heterogeneous effects related to (i) initial absolute procedure prices (ii) initial prices relative to peers (iii) specific types of medical procedures and (iv) specific kinds of market structures. Importantly, since our information provision focuses on individual provider billed charges, rather than

[1] The trial was submitted to the AEA RCT registry.

negotiated rates between insurers and providers, our analysis is especially relevant for the out-of-network services that these charges are germane to. However, since billed charges also feed into negotiated rates with insurers, and are meaningfully correlated with them (Batty and Ippolito 2017). we also study services that are shoppable but typically received in-network. To our knowledge, this is the first randomized intervention of a price transparency tool that is specifically designed to address market-level effects as well as the effects on consumers and specific providers.[2]

Our randomized intervention directly guides our econometric approach to estimating our effects of interest. We use a difference-in-differences approach with different configurations of the fixed effects that compares key price and quantity outcomes for providers in treated procedure-location pairs to the same outcomes for providers in control procedure-location pairs. In our primary difference-in-differences specification, we control for procedure, geozip, and trimester fixed effects and also time fixed effects interacted with the procedure and geozip indicators, which leverage any procedure or geozip specific time-series variation spanning the periods pre- and post-intervention. We conduct a number of robustness analyses to our main difference-in-differences specification including, e.g., a difference-in-differences version without time fixed effects, and find similar results for these alternatives.

In our primary difference-in-differences specification, we find that, across all procedures and locations, providing individual-level provider charge information increases prices by 1.2% and has no statistically significant impact on quantity. We assess these impacts separately for providers whose prices were initially above or below the median for a given procedure in their geozip and find modest but larger increases in prices for providers who were initially below the median. In addition, we find no quantity impacts for providers who were initially high-priced as opposed to low-priced, suggesting that our intervention had no meaningful impact on the extent of consumer price shopping. We also find that providers located in procedure markets that are above median market concentration, measured with procedure-geozip HHI, have slightly larger price increases than those below median, with no statistically significant quantity differences.

Given that our intervention provides information on billed charges, rather than insurer-contracted prices, we focus especially on out-of-network claims, for which billed charges are relevant.[3] We find that procedures with a high proportion of out-of-network claims have

[2]Several prior major studies in health economics rely on randomized controlled trials as a "gold standard" for identification. See, for example, the 1974 RAND Health Insurance Experiment (HIE) studying the price elasticity of demand for health care and the Oregon Health Insurance Experiment studying the effects of expanding access to public health insurance (Manning et al. 1987; Newhouse 1996; Finkelstein et al. 2012).

[3]Consumers going out-of-network could pay the entire billed charge as given in our intervention or some reduced version of that billed charge if negotiated down between themselves and the provider or their insurer and the provider. The latter case is relevant for consumers whose insurance covers some portion of out-of-network claims, which is more typical in generous health plans, such as preferred provider organization

essentially no price change while procedures with a low proportion of out-of-network claims have a 2.5% price increase as a result of our intervention. This suggests that, for procedures where billed charges are much closer to final prices, there is no impact of our intervention, while for procedures that are more likely to be covered by insurance, prices increase. This could be, e.g., because providers serving out-of-network patients suspect that those patients will respond to prices in the medium to long run and thus be less willing to raise prices relative to other providers.

We also investigate the effects of our intervention for specific procedure categories. We find larger price increases for specific categories that are almost always insured and less elective in nature, including MRI (+6%) and radiology (+3%) services. We find price decreases for several categories that are less often insured and more elective in nature, including psychology (-2%) and chiropractor (-3%) services, though physical therapy services have a 1.6% price increase. Categories that we investigate that have reasonably precise zero price effects include CT scans, gastrointestinal, and eye care. Orthopedic services have a large point estimate (+3%) but a large standard error (2.5%) so we cannot rule out zero nor large effects for that category. While most category-specific quantity effects are fairly precise zeros, there are some notable impacts on radiology procedures (+6%) OB procedures (+4%) and physical therapy procedures (-7%). Since, ex ante, one would expect quantity effects to reflect consumer updating to more precise information, the quantity effects of price information revelation are theoretically ambiguous, even conditional on no price changes. Consequently, when quantities decrease, as with physical therapy, that is consistent with a theory where consumers believed out-of-pocket prices were lower than they actually are, and vice-versa for the procedures with positive quantity impacts. We utilize the sharpened False Discovery Rate (FDR) q-values to adjust for testing multiple hypotheses.

Taken together, these results are consistent with our intervention having (i) a minimal effect on consumer price shopping, except for the physical therapy category and (ii) a meaningful effect driving provider price increases, especially for less elective services that are almost always covered by insurance. These price increases are consistent with both tacit collusion between providers in an environment with greater provider-specific price information or with reduced information asymmetries that generally push providers towards realizing that they are under-charging relative to their peers.

Our results should be viewed with a number of caveats. It is important to note that the results of our intervention should be viewed in a short-run context since we measure the effects for two years. Many hypothesized impacts of price transparency relate to systemic, long-run impacts which we do not study here. In addition, our results are specific to the information

(PPO) plans. See, e.g., Bai and G. F. Anderson 2016; Bai and G. F. Anderson 2017; Bai and G. F. Anderson 2015; Bai and G. F. Anderson 2018 for an extended discussion of consumer payments when accessing out-of-network providers.

provision tool provided by FAIR Health and how many providers and consumers use the tool. While website utilization average around 10,000 people per month during our sample period, the impacts of the intervention depend on the type of user. If providers carefully use the site to examine prices, there is potential for significant impacts on prices, while if users are primarily consumers, any impact is more likely to be on the quantity and price shopping dimensions. Finally, our intervention applies to billed charges, which, though relevant for out-of-network claims and potentially relevant via what they signal about negotiated rates, ultimately are a noisy signal of insurer-provider negotiated rates. Given this, it is possible that many providers will not find this information to be very valuable or they may misinterpret its relevance to their patient panels. Despite these potential difficulties our results shed light on important market-level issues related to price transparency that prior studies (who also share some of these difficulties) are not able to address and we are able to do so using a gold standard randomized design.

Relevant prior work in the literature on price transparency has mostly focused on the impact of insurer-provided price transparency tools on consumer price shopping, with equivocal results (Mehrotra, Brannen, and Sinaiko 2014). Robinson and Brown J. C. Robinson and T. T. Brown (2013) and Robinson and MacPherson J. C. Robinson and MacPherson (2012) show that information provision about prices has a meaningful impact on the providers patients choose in the context of a reference-pricing payments model implemented in California where consumers have a lot of money at stake in a context where the potential for price differences is quite salient. Several studies focused on homogeneous services (e.g. lab services and MRIs) find some evidence of price shopping behavior in some populations (Christensen, Floyd, and Maffett 2017; J. C. Robinson, T. Brown, and Whaley 2015; Sinaiko, Joynt, and Rosenthal 2016). There is also evidence that consumers respond to price information in the context of tiered networks (Prager 2020). However, most studies find both relatively low use of price shopping tools by health plan members and, even when accessing such information, little impact on price shopping behavior (S. Desai et al. 2016; Mehrotra, Brannen, and Sinaiko 2014; Sinaiko and Rosenthal 2016; Brot-Goldberg et al. 2017; M. Chernew et al. 2018; Cooper, Scott Morton, and Shekita 2020).

For consumers utilizing insurer-provided tools, the availability of price information could have large impacts on prices, but these impacts are mitigated by insurance coverage that shields true exposure to prices (Lieber 2017). Since these studies focus on insurer-provided tools, they typically don't address out-of-network price shopping, where consumers typically face larger price differentials and thus may be more responsive to price information.

While there have been quite a few studies on short-run consumer responses to price transparency tools there have been only a few studies that examine provider responses to price transparency. Robinson and Brown J. C. Robinson and T. T. Brown (2013) and Wu et al. Wu et al. (2014) both find some evidence that providers lower prices after the introduction of reference pricing/price shipping tools. Both of these studies focused on enrollees in specific-insurance plans (Whaley, T. Brown, and J. Robinson 2019) exploit the staggered deployment of an online transparency tool to a large pool of insured consumers and finds that robust consumer use of the tool can drive providers to reduce prices for homogeneous services but not for differentiated services. There are two prior studies on market-wide deployment of price transparency tools in New Hampshire (S. M. Desai, Shambhu, and Mehrotra 2021; Z. Y. Brown 2019).

These studies find that price transparency led to more aggressive bargaining by insurers that had medium-run impacts lowering the prices of high-priced hospitals. To our knowledge, there are no prior papers studying a market-wide deployment of a price transparency tool focused on individual provider prices and certainly none where price transparency information was implemented in a randomized controlled trial together with researchers.

The introduction of the New York Healthcare Online Shopping Tool (NY HOST) offers a unique opportunity to conduct such a trial and systematically and rigorously examine the effects of charge transparency on consumers and providers. The paper proceeds as follows. We provide an overview of the background and setting for the experiment in Section 3.2. Section 3.2 describes the experimental design and randomization. We discuss the the mechanism by which the information provided by the tool might change the shopping behavior by consumers and price-setting by providers in Section 3.2. Section 3.3 describes the empirical strategy. Section 3.4 provides an overview of the datasets utilized and construction of the datasets for analyses. Section 3.5 provides the results of the empirical tests of the impact of the tool on providers' charges at both the individual provider level and aggregated market level. Section 3.6 examines the mechanisms behind the results and concludes.

3.2 Background

About FAIRHealth

FAIR Health is an independent non-profit organization that was established in 2009 as a replacement for Ingenix, a database owned by the insurance giant United Healthcare. FAIR Health maintains the nation's largest data repository of privately billed health insurance claims.[4] Its principal purpose is to provide insurers with an unbiased source of information on usual, customary, and reasonable rates to support the adjudication of out-of-network claims. The database contains claims information from insurers covering approximately 75% of the privately insured population of New York State, including information on both fully-insured claims and claims administered by insurers on behalf of self-insured plans.

In early 2011, FAIR Health created a consumer website that displayed educational infor-

[4]Information on FAIRHealth can be accessed via https://www.fairhealth.org.

mation on providers and services but did not contain price information. In April 2011 this website was transformed into an independent, publicly-accessible consumer price transparency tool that displayed aggregate estimates of the charge and insurer allowed amount for a given procedure in each geozip across the country. Charges are posted by providers as the list price for services, typically the actual price to be paid by uninsured or out-of-network patients. The insurer allowed amount reflects the reimbursement rate that is negotiated between a provider and a health plan.

On September 12, 2017, FAIR Health re-launched a revamped version of its website for New York State as the New York Healthcare Online Shopping Tool (NYHOST).[5] The rollout was accompanied by an extensive, multi-pronged marketing effort to raise awareness of and draw people to the new consumer facing website. A statewide advertising campaign was estimated to have reached over 6 million consumers in New York State through traditional media, online advertising, and social media channels. The traditional media campaign included several components. In New York City and Albany, large billboards displayed ads in prominent places, including Times Square. Public service ads (featuring well-known personalities Larry King, Mandy Patinkin, and Nancy Grace) ran in New York City taxicabs; paid advertisements were featured in health clubs and shopping malls throughout the state; and magazine ads were featured in nearly two dozen national magazines (e.g. Harper's Bazaar, InStyle, Fortune, Food Network). The distribution of paid print advertising in malls and health clubs was focused on the most highly populated areas of the State, including New York City and Albany. FAIR Health distributed press releases about the launch to websites with heavy internet traffic, such as Crain's New York and PR Newswire. A Facebook advertising campaign was estimated to have reached nearly two million people from September 2017 to July 2018, and Facebook click-throughs accounted for over a quarter of website hits. A digital banner campaign from September 2017 to January 2018 generated approximately an additional five percent of website hits. According to FAIR Health's analytics, direct searches (such as users typing the url), which may have been generated by the advertising and online media campaigns, generated the remaining website hits. FAIR Health also maintains an active social media presence, with accounts on Facebook and Twitter, and frequent updates featuring its events, services and publications (Kim and Glied 2021).

Experimental Design: New York Healthcare Online Shopping Tool (NYHOST)

In conjunction with the 2017 update, a randomized experiment was embedded within the website design of NYHOST that varied the level of charge information available to users across procedures and location. Based on data from FAIR Health, we identified 100 frequently performed procedures for professional outpatient medical services in New York

[5] The consumer tool is publicly accessible on the FAIR Health website via `https://www.youcanplanforthis.org/`

State, spanning 30 different categories. Due to Current Procedural Terminology (CPT) code changes during the 2017 calendar year, another 7 CPT codes were added for a total of 107 procedure codes included in the experiment. This set of categories and procedures were selected because they were both common and had a high rate of out-of-network use.[6] Working with the FAIR Health web development team, 19 categories spanning 50 procedures were assigned to have specific provider-level charge information featured in all the 3-digit zipcodes (referred henceforth as "geozip") in New York State, 31 in total, and those procedure codes were excluded from the randomization. For the other 57 procedures in the 11 remaining categories, specific provider-level charge information was released for a randomized set of geozip-procedure pairs. This randomization occured across a set of 1767 procedure-geozip pairs with 948 procedure-geozips included in the treatment arm and 819 procedure-geozips included in the control arm. Each geozip was randomly allocated a set of procedures where provider-level charge information was displayed, with a range of 25 to 37 procedures in each geozip, for an average of 31 procedures treated procedures per geozip. The randomization process occurred as follows: first, the randomization algorithm assigned a random number to each procedure category and, within each geozip, assigned categories with progressively larger random numbers until the treatment group has 25 or more procedures. Next, the randomization algorithm chooses the maximum over 1000 trials of minimum p-values in t-tests of equality of mean covariates between the treatment and control groups. A timeline describing the rollout and outcome of the experiment can be found in Figure 3.1. The experiment ran from September 12, 2017 through August 30, 2019, and during this time period, provider-level charge information was only available on the randomized geozip-procedure pairs.[7]

For procedure-geozips in the treatment group, the website featured provider-level charge information. Specifically, each provider listed on the website was given a range that their average billed charges for a procedure fell into. See Figure 3.3 for a screenshot of a sample search in the treatment group. In the treated procedure-geozips, the website displays only providers with above median volume based on the claims data, updated twice a year based on a rolling 12 months of data.[8] The provider charge ranges were created around actual charges to make sure the website was providing an estimate as opposed to an exact charge. FAIR Health chose this particular methodology to ensure the end user did not assume that the charge seen on the website would be what the provider would charge in exact amounts.

[6]Because of CPT codes that were discontinued in 2017, specifically mammogram codes, we restricted our analysis to a "balanced panel" of procedures, which included the set of 104 procedure codes that were actively billed during the time period examined, CY 2016 through the second quarter of 2019.

[7]The experiment ended on August 2019, and for select procedures, provider-level price information was released in all geozips in New York State.

[8]In the "unbalanced panel dataset", the median volume for each provider and procedureXgeozip combination, each trimester was 5 claims, which aligns with our decision to truncate our"balanced panel dataset to those providers who rendered at least 5 services for each procedureXgeozip pair in each trimester. After restricting the observations to the balanced panel (as referenced in A.2.4), the median volume posted for each provider and procedureXgeozip combination, each trimester was 33 claims.

The exact method of the construction of the charge ranges was not made public, so providers would be unlikely to be able to game the system (i.e. adjusting their charges to remain within a certain range). The range of the charges varied by the charge posted. [9]

The remaining procedure-geozip combinations were randomized to the control group. Searches for price information in the procedure-geozip combinations assigned to the control group would yield only the aggregated median charge information posted on the website - provider-specific charges were not available during the study period. See Figure 3.2 for a screenshot of a sample search in the control group. The aggregated charge information featured in the procedure-geozip combinations in the control group was not subject to any minimum volume requirements.

How price transparency might affect prices and quantity at the provider and market levels

There is considerable variation in billed charges ("list prices") within specialty within geographical markets. Prior to the introduction of price transparency tools, most consumers might have, at best, a sense of what average charges for a service in their market might be (and even this information would typically be difficult to find). While providers are aware of their own billed charges and the in-network rates that are offered to them by insurers, except in small, highly-concentrated markets, they typically lack information on their competitors' billed charges or negotiated rates. In response, a large trade literature and an army of consultants in the industry exists to advise doctors on how to set their prices. Revealing billed charges publicly provides new, much more accurate information on charges at the provider level both to consumers and to providers themselves. We outline the potential market-wide effects of price revelation in Table 3.1.

The availability of new information on prices at the provider level would ordinarily be ex-

[9] The logic behind the construction of the charge bins was as follows: (1) Charge less than or equal to 25, set range 1-25; (2) charge greater than 25 but less than or equal to 50, set range to 26-50; (3) charge greater than 50 but less than or equal to 75, set range to 51-75; (4) charge greater than 75 but less than or equal to 100, set range to 76-100; (5) charge greater than 100 but less than or equal to 500, set range to (amount minus 50 and round down to nearest 10th to amount plus 50 round up to nearest 10th); (6) charge greater than 500 but less than or equal to 2000, set range to (amount minus 100 and round down to nearest 100th to amount plus 100 round up to nearest 100th); (7) charge greater than 2000 but less than or equal to 10000, set range to (amount minus 200 and round down to nearest 100th to amount plus 200 round up to nearest 100th); (8) charge greater than 10000 but less than or equal to 20000, set range to (amount minus 500 and round down to nearest 100th to amount plus 500 round up to nearest 100th); (9) charge greater than 20000 but less than or equal to 50000, set range to (amount minus 1000 and round down to nearest 100th to amount plus 1000 round up to nearest 100th); (10) charge greater than 50000, set range to (amount minus 5000 and round down to nearest 100th to amount plus 5000 round up to nearest 100th); (11) If price doesn't match any of above, set bottom range by taking current charge minus 100 and round down to nearest 100, set top charge to current charge plus 100 and round up to nearest 100th.

pected to shift demand toward lower-priced providers and to encourage providers to reduce their prices to attract additional demand, but that might not occur in this context. Three features of the out-of-network health care market may lead to unexpected results. First, information on quality in health care markets is inadequate. Consumers may perceive higher priced providers to be of higher quality (as they have in some other contexts where information on quality is poor) (Rao and Monroe 1989; Leavitt 1954). Providers, aware of this perception, might then choose to raise their own prices when they observe those of their peers. Second, billed charges are only relevant to insured consumers if they seek care out-of-network. For care provided in-network, consumers will pay cost-sharing based on prices negotiated between insurers and providers, which are generally well below list prices, and any such out-of-pocket payments will draw down remaining deductible and out-of-pocket maximums. A consumer choosing to use services out-of-network, then, will generally do so only because of a strong non-financial preference (emergency, perceived quality, convenience, referrals) for a specific provider, consistent with evidence that consumers even in high-deductible plans choose high cost options for MRIs that were recommended by the referring provider, despite nearby cheaper options (M. Chernew et al. 2018). This suggests that the demand for out-of-network care from any specific monopolistically-competitive provider is relatively inelastic in price (completely inelastic to price in a surprise billing situation). Revealing competitors' price information to providers facing relatively inelastic demand could lead them to raise their prices. Finally, the availability of information on competitors' prices can facilitate collusion (Albæk, Møllgaard, and Overgaard 1997; Edlin 1997). Such collusion may be particularly valuable because market-level average billed charges have historically been used as a starting point for price negotiations with insurers. If providers within a market can maintain high levels of billed charges for out-of-network care, they may be able to command both higher out-of-network rates, and, perhaps higher negotiated rates.

3.3 Empirical Strategy

To capture the effect of the FAIR Health price transparency tool on both charges and volume of services provided, we estimate a difference-in-differencess approach at the provider and market level. The provider-level analysis examines effects on the log of the modal charge that a provider bills over a trimester as well as the log of the total volume of a procedure performed by the provider. We choose to define the "price" as the modal charge because the mode is least insensitive to outliers and represents the price most likely to be faced by any given patient. As a sensitivity analysis, we confirmed that our resuts are consistent when the price is defined as the median or average charge. Providers in NYS are required to have one charge for a given procedure at a point in time (e.g. charge discrimination is not allowed), and our use of the modal charge reflects that requirement. Our market level anaysis is conducted at the geozip-procedure level and captures volume-weighted effects on charges as well as charge dispersion. We estimate effects on the log of the average billed charge of a procedure in a given geozip in a trimester and on the total volume of services in a market.

Difference-in-differences specification

Our preferred specification is a difference-in-differences specification that accounts for time trends in procedure and geozip effects, referred to throughout the paper as a "triple difference-in-differences" estimator (Berck and Villas-Boas 2016). Because the randomization was conducted at the procedure-geozip level and the randomization units are not equal in size, geographic and procedure changes over time could bias our results because of compositional effects. The triple difference-in-differences specification reduces potential bias due to geozip or procedure-specific changes over time. Because of these considerations, we utilize a difference-in-differences specification that includes the "year by trimester" time variable interacted with the treatment effect to assess the impact over time. The provider-level triple difference-in-differences specification is as follows:

$$Y_{igpt} = \beta \cdot T_{gp} \cdot Post_t + \lambda_t \cdot \mathbb{1}(yrtri = t) + \gamma_{gp} \cdot \mathbb{1}(gp) + \pi_i \cdot \mathbb{1}(i) + \kappa_{pt} + \alpha_{gt} + \pi_i \cdot \mathbb{1}(i) + \varepsilon_{igpt} \quad (3.1)$$

Where Y_{igpt} is the outcome variable for provider i for procedure p in geozip g in trimester t, and is either $ln(P)_{igpt}$, the log of the modal charge for a provider, or $ln(Q)_{igpt}$, the log of total volume for a provider. In the triple difference-in-differences estimate, β specifies the treatment effect, T_{gp} is the treatment indicator (equal to 1 for the randomized procedure and geozips) which is interacted with $Post_t$, the indicator for the post-period (equal to 1 for the trimesters encompassing the period after September 2017). The model includes controls for time fixed effects λ_t, procedure-geozip fixed effects γ_{gp}, procedure dummy variables interacted with the time dummy variables κ_{pt}, the geozip dummy variables interacted with the time dummy variables α_{gt} , and provider fixed effects π_i. The error term, ε_{igpt}. , are robust standard errors and clustered at the category-geozip level.

In addition to our preferred triple difference specification 3.1, we also estimate a standard difference-in-differences framework with the treatment and post indicators, time fixed effects λ_t, procedure-geozip fixed effects γ_{gp}, and an error term, ε_{igpt}. (Equation 3.2)

$$Y_{igpt} = \beta \cdot T_{gp} \cdot Post_t + \lambda_t \cdot \mathbb{1}(yrtri = t) + \gamma_{gp} \cdot \mathbb{1}(gp) + \varepsilon_{igpt} \quad (3.2)$$

Due to volume differences between providers, a market-level model enables capturing effects on the volume-weighted price. Thus, we also estimate the difference-in-differences analyses at the market-level, with procedure-geozip-time as the unit of observation.

$$Y_{gpt} = \beta \cdot T_{gp} \cdot Post_t + \lambda_t \cdot \mathbb{1}(yrtri = t) + \gamma_{gp} \cdot \mathbb{1}(gp) + \kappa_{pt} + \alpha_{gt} + \varepsilon_{gpt} \quad (3.3)$$

In Equation 3.3, the dependent variable Y_{gpt} is either $ln(P)_{gpt}$ the log of the average volume-weighted actual billed charge in the market for procedure p in geozip g in time period t, $ln(Q)_{gpt}$ the log of total volume for a market, or CoV_{gpt} the coefficient of variation of billed charges within a market. The difference-in-differences estimate β specifies the treatment effect of interest, T_{gp} interacted with $Post_t$, and estimates the treatment effect on the market average charge for procedure p in geozip g after the launch of the tool. The treatment variable T_{gp} and time variable $Post_t$ has the same construct as in the provider-level model. The market-level triple difference-in-differences specification includes the time and procedure-geozip fixed effects separately and interacted with the time dummy variable, similar to the provider-level regressions in Equation 3.1. The model includes the error term, ε_{gpt} and robust standard errors are clustered at the procedure-geozip level.

We generate event study graphs that correspond to equations 3.1 and 3.3. These graphs plot the difference in outcome variable between treatment and control units over time, controlling for procedure-geozip, time, geozip-time and procedure-time fixed effects. The event studies allow us to visually interpret the treatment effect of NYHOST as well as compare pre-trends across our specifications.

Heterogeneity Tests

To complement and better understand our main results, we examine heterogeneity in our results along a variety of economically meaningful dimensions. Specifically, we examine how our results differ for providers that are above or below median for billed charges, number of services provided out-of-network and a provider's Herfindahl-Hirschman index (HHI) for a given procedure. Additionally, we test heterogeneity by type of procedure. We group procedures into those that receive continuous care (a patient repeatedly visits a provider for the procedure at regular intervals) and non-continuous care (patient visit tends to be a one-off) as well grouping CPT codes into broader categories like psychological services or MRIs. We chose these provider characteristic dimensions for heterogeniety because they correspond to competitive forces that may increase the bite of the information policy change. Our analysis for above and below median price providers allows us to decompose overall price effects into high priced providers potentially lowering their prices or low price providers raising prices to match the market rate. The information provided by the tool likely has the most relevance for procedures rendered out-of-network or for providers that provide more out-of-network care because billed charges represent actual prices paid by patients. Analyzing heterogeneity by HHI examines the role that market competition plays; if there are relatively more providers to compare, the information treatment may have a stronger effect. For these provider characteristics we rerun our triple difference (Equation 3.1) specification and our differences in difference (Equation 3.2) specification.

CPT codes themselves vary widely in out-of-network usage, market prevalence and frequency of usage which may contribute to heterogeneous treatment effects. We group CPT codes into continuous use codes (codes for psychological, physical therapy or chiropractic services) and non-continuous use codes (MRIs, CT scans and radiology). Across this cut we run both the difference in differences specifications with different configurations of the fixed effects.

We then run a series of analyses examining each category of CPT codes, of which there are 10 included in our experiment. Because of the implementation of the experiment, for these analyses stratified by category, we are only able to fit our difference in differences specification.

3.4 Data

Our analyses utilize the FAIR Health database, which is comprised of medical claims in New York State with dates of services between January 1, 2016 to June 30, 2019, totalling over 110 million claims (110,422,511 claims in total). Our data covers about 75% of private insurance claims in New York. The data includes National Provider Identifier (NPI), 3-digit zipcode ("geozip"), date of service, procedure code (Current Procedural Terminology (CPT)), billed charge, place of service code, the patient's gender, and the patient's age group.

We matched NPI data to the CMS Physician Compare and the National Plan and Provider Enumeration System (NPPES) files to obtain information on provider characteristics. There were 205,023 unique NPIs in the FAIR Health data extract. We linked the provider NPIs represented in the FAIR Health data to the information in the 2017 CMS Physician Compare Downloadable File in order to access provider-level information, including gender, years in practice, medical school, group size, and hospital affiliation. The 2017 CMS Physician Compare File contains information on the providers who are participating in the CMS quality program, which encompasses all eligible providers (EPs) that qualify or participate in the program.[10] Since providers were able to be credentialed in multiple specialties and practice in several different locations, the specialty and location was chosen as the first that appeared when sorted in alphabetical order. We also utilized U.S. Census Data to access population and geographic information.

We define our time periods at the trimester level, or a third of a year, with four months in each trimester because the experiment went into effect in September 2017, which was two-thirds of the way into the calendar year. The post randomization period spanned from September 2017 through June 2019 period. Because we had incomplete data for the last trimester, spanning as May 2019 through August 2019, we restricted our final analyses to the 10 trimesters for which we had complete claims data. Thus, the time period examined in our study dates from January 2016 through April 2019, with five trimesters in the pre-randomization period (from January 2016 through August 2017), and five trimesters in the post-randomization period (from September 2017 through April 2019).

[10]Table A.2.1 shows the procedure categories that were included for the study. Table A.2.2 shows the datasets utilized and time periods encompassed. Table A.2.3 shows the match between the FAIR Health dataset and the CMS Physician Compare dataset. Approximately 58% of all of the provider NPIs in our FAIR Health data extract were captured in the 2017 CMS Physician Compare file.

For the provider level analysis, we collapsed the original claims data to the provider-geozip-procedure-trimester level, which encompassed 3,598,866 observations. Our billed charge outcome variable was constructed as the modal charge reported by each provider for each procedure in each trimester of the period studied. Given potential billing errors, we utilized the modal charge as our primary outcome variable to capture the most frequently billed unit charge for a given procedure for each trimester as the list price for that provider. As robustness checks, we also include the median, 95th percentile and 5th percentile of the billed charges for each provider in a given trimester, procedure, and geozip. To account for outliers and billing errors (since several claims had billed charges that ranged as high as $70,000), we winsorized the provider-level panel dataset at the 95th percentile, conditional upon the procedure code.[11]

To create a balanced panel of providers, we restricted our analysis to providers with at least five claims in each trimester. We also restricted to only physicians, dropping providers with credentials identifying them as a physicians assistant or a nurse practitioner, since these practitioners often submit separate claims for procedures and services they may have rendered supporting services for rather than as the primary provider. We also removed any CPT codes that were added or discontinued throughout the study period keeping only procedures for which charges were posted continuously across all the trimesters included in our study period.[12]

To assess the overall market impact of the tool, we created a panel dataset at the procedure and geozip level for each trimester, and constructed the aggregate volume-weighted charge and total volume for a given procedure and geozip in each time period. The market level dataset is based on all claims in the FAIR Health claims database, not only those included in the construction of the provider level data set. Our main outcome variables for the market level dataset include total volume of procedures, average billed charge and the coefficient of variation of charges within a market.

We present summary statistics for our provider and market level datasets in Table 3.2. We examine a variety of procedures, ranging from lower cost psychotherapy and physical therapy services to higher cost orthopedic and radiology services, resulting in substantial heterogeneity in the billed charge. Each provider had an average of 102 claims each trimester, with an average billed charge of $420. Providers' billed charges ranged from $2 to $59,000, with a standard deviation of $1,279. The volume of services rendered by providers ranged from 6 to 22,329, with a standard deviation of 198 claims.[13]

[11]Table A.2.4 shows the steps involved in the construction of the balanced panel.

[12]The codes were removed from the balanced panel because they were either discontinued or added to the CPT® (Current Procedural Terminology) list between 2016 and 2019. Those codes were 76641, 76642, 77052, 77056, 77065, 77066, 97161, 97162, and 97163.

[13]The billed charge for a given procedure varies widely across providers, and even for the same provider, the billed charge can vary over time since providers can update their chargemasters at will. There is significant

Figure 3.5 plots the histogram of normalized charge dispersion, the ratio of a provider's modal charge to the market's average charge, and documents heterogeneity in prices within a given market. This heterogeniety suggests theat there is scope for the information treatment to affect equilibrium prices. At the market level, there was significant underlying price heterogeneity with the average inter quartile range of prices within a market of $735. In our sample of procedures, there was an average of 5,956 claims rendered in a given procedure and geozip market in a single trimester, and of those claims, approximately 20% were rendered by a provider who was out-of-network with a given insurance product.[14]

We conducted balance checks to validate the randomization process of the experiment and compare market characteristics between the treatment and control groups, including measures of price, volume, and market concentration based on the claims with dates of service in 2016, the baseline period prior to the launch of the tool (Table 3.3). There was no statistically significant difference between the treatment and control groups on aggregate charges, the interquartile range of charges, volume of claims, volume out-of-network claims, insurer market concentration, and population density. Although most of the market characteristics were comparable, the control group had more concentrated provider markets at baseline (provider HHI of 860 in the control group compared to provider HHI of 732 in the treatment group), and the treatment group had slightly higher within market charge dispersion, defined as the standard deviation of charges in a given procedure-geozip market (0.09 in the treatment group compared to 0.08 in the control group), and slightly higher charge dispersion at the 90th quantile (1.10 in the treatment group compared to the 1.09 in the control group).

We compare market characteristics of procedures included in the randomization to other procedures for which FAIR Health receives claims. The subset of procedures that were selected for the experiment had a relatively high percentage of out-of-network claims; although most procedures were performed out-of-network less than 10% of the time, some procedures have an out-of-network percentage that ranged as high as 40 percent (Figure 3.6). Figure 3.7 demonstrates the market concentration of providers for each procedure and geozip market. The provider market concentration for each procedure and geozip was calculated using the Herfindahl-Hirschman Index (HHI), with the market share for each provider represented in the dataset by the National Provider Identification number (NPI). Prior research suggests

dispersion in the distribution of the charge updates (presented as the change in the log of the price in Figure A.2.8). Approximately 15% of providers updated their charges in the first trimester of 2017 and 2018, but providers continue to update their charges later in a given calendar year (Figure A.2.9). This underlying price heterogeneity points to meaningful scope for price changes.

[14]We also calculated the insurer HHI as the sum of the square of the market share for each insurer within each each procedure and geozip market. Over 30 insurance companies in NYS represented in the claims data, with each insurer represented in the data by a FAIR Health "key" that kept the identity of each insurer confidential. The distribution of insurance market HHI shows that most markets are highly concentrated, and for most of the procedures in our sample, the insurer HHI was well above 4000 (Figure A.2.11).

that concentration of provider markets is associated with higher charges (Roberts, M. E. Chernew, and McWilliams 2017), and the variation in the provider market HHI demonstrates substantial heterogeneity in provider market concentration and corresponding price dispersion.

3.5 Results

First Stage Website Usage

The "first stage" analysis assesses utilization of the price transparency tool prior to and after the launch of the revamped tool in September 2017. Figure A.2.6 demonstrates the distribution of the utilization of the website, measured as the total number of searches, over years and months. Figure 3.4 depicts the distribution of website utilization across the treatment and control groups by month between January 2016 and June 2019. The persistently higher number of searches in the control group can be attributed to the number of searches that occurred in New York City for the procedures in that geozip that were assigned to the control group. When we exclude the 3-digit geozip that corresponds to the borough of Manhattan (geozip = 100), the number of searches between the treatment and control groups is more comparable (see Appendix). Because we randomized 57 different procedures across 31 geozips to the treatment and control groups, and the zipcodes are of different sizes in population density, random assignment to a highly populated zipcode can lead to a higher number of searches.

Web utilization of the tool by consumers appears to have been relatively consistent over time and low compared to the New York State overall population of over 19 million residents, with fewer than 15 searches on average for each procedure in a given month (Kim and Glied 2021). This suggests that demand side forces are unlikely to be a large contributor to any observed price or volume changes after the roll out of the experiment. Low numbers of searches relative to the population would be consistent with our theory that supply side forces played a larger role in use of the tool, where providers search to gain information on competitor's prices.

Provider-level Outcomes

We present the results of our analysis specified in equations 3.1 and 3.2 in Table 3.4. Our preferred specification results are presented in columns (3) and (6). We find that treatment is associated with a 0.75% increase in prices and no significant changes to the quantity of services provided. [15] Our difference-in-differences estimates presented in columns (1) and (3) are not significant. Figure 3.8 presents the event study plot associated with Table 3.4 column (2). Overall, our results suggest that meaningful changes to market prices or quantity of

[15]This estimate increases to 1.2% without the provider fixed effects (Table A.2.2).

procedures are small and any changes that we do see are likely attributable to supply side market forces. Our main results show the impact of the tool in aggregate but may mask heterogeneity in the effect on price and quantity. We test for heterogeneity across provider and procedure characteristics. Table 3.5 presents our results for heterogeneity across potentially meaningful cuts of the data. Specifically we analyze how our results vary for above versus below median charge providers (with the median determined at the procedure X geozip level), continuous versus non-continuous procedures, above versus below median out of network visits, above versus below median HHI and above versus below median website usage. Panel A presents the results for charges while Panel B presents the results for quantity treatment effects. We find that our overall results are primarily driven by increases in prices for below median price providers, consistent with providers raising their prices to match their peers. Additionally, we find that price increases are higher for non-continuous procedures (procedures that are not repeted for a patient) and for procedures that are less frequently provided out-of-network. For out-of-network claims, we find that procedures with a high proportion of out-of-network claims have essentially no price change while procedures with a low proportion of out-of-network claims have a 2.5% price increase as a result of our intervention. We find significant charge increases for low volume out-of-network procedures across the course of the experiment, with price increases driven entirely by "low price" providers, defined as those with billed charges below the median charge for a procedure X geozip X trimester. Figure 3.10 depicts this upward trend in the modal charge posted by "low price" providers for the low out-of-network volume procedures. Figures 3.9 and A.2.13 feature event study graphs that highlight these trends over the course of the study period.

Table 3.5 Panel B presents our heterogeneity analysis for quantity effects. While overall we find null quantity effects, we do find some evidence that would support consumers price shopping. We find that volume of services decrease by about 3.4% for markets with above median website usage. Additionally, we find that the volume of services decreases by about 3.6% for continuous procedures. For continuous procedures, patients are likely to repeatedly pay for care which may increase the value of price shopping.

We also investigate the effects of our intervention for specific procedure categories and present the findings in Table 3.6. We find larger price increases for specific categories that are almost always insured and less elective in nature, including MRI (+6%) and radiology (+3%) services. We find price decreases for several categories that are less often insured and more elective in nature, including psychology (-2%) and chiropractor (-3%) services, though physical therapy services have a 1.6% price increase. Categories that we investigate that have reasonably precise zero price effects include CT scans, gastrointestinal, and eye care. Orthopedic services have a large point estimate (+3%) but a large standard error (2.5%) so we cannot rule out zero nor large effects for that category. While most category-specific quantity effects are fairly precise zeros, there are some notable impacts on radiology procedures (+6%) OB procedures (+4%) and physical therapy procedures (-7%). To adjust for the fact that we are testing multiple hypotheses, we utilize the sharpened False Discovery Rate

(FDR) q-values for multiple hypothesis testing (M. L. Anderson 2008). Table A16 provides a comparison of the calculated q-values with the p-values from the heterogeneity tests by procedure category for price effects, and Table A17 provides the comparison for quantity effects.

The provider-level models utilize the balanced panel of providers constructed from providers with a minimum of 5 claims in a given trimester. As a robustness check, we present the results generated from the market-level dataset constructed at the geozip X procedure X trimester level. The market-level panel dataset utilizes the entirety of the dataset and thus captures the volume-weighted charge and aggregate market level effects. Table A.2.5 shows the results from the market-level specifications (Equation 3.3), which captures the aggregate charge and quantity effect. We find that the overall price effect is similar to the provider-level models, with no significant market level effects on overall volume. To test for heterogeneity in our market-level outcomes, we stratified the market-level dataset upon dimensions of market concentration, procedures with high vs. low out-of-network use, coefficient of variation, website utilization and for continuous vs. non-continuous services (Table A.2.6). Just as we did for the provider level results, we test for heterogeneity along continuity of care for continuous and non-continuous services. Similar to the provider-level results, our most significant result is that in procedure markets with low out-of-network claims at baseline, there is a 2.9% price increase. Table A.2.7 presents the effects of our intervention for specific procedure categories, and find a market-level price increase for MRI services (+8%) but no significant effects for all other categories. For our market level analysis, our heterogeneity tests involved separate analyses of results for markets with high or low price dispersion, measured as above median or below median coefficient of variation on billed charges.

3.6 Discussion

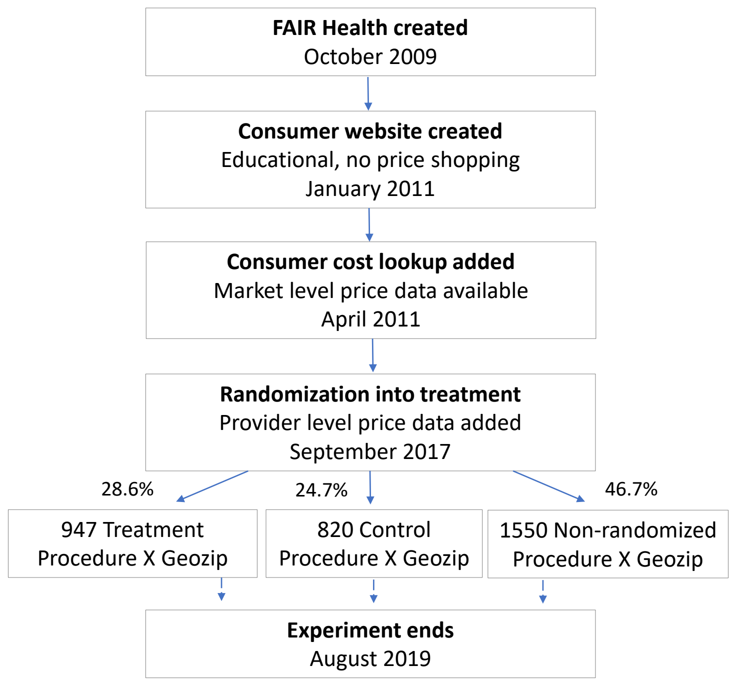
Our findings support the hypothesis that effects of the NYHOST price shopping tool were dominated by provider responses and price adjustments rather than consumer price shopping. Overall, provider-level prices and aggregated market prices increased more in the treated markets than in untreated markets. Our findings that providers with a lower percentage of their services rendered out of network were more likely to raise their charges in the post-randomization period suggests that the tool yielded useful information for providers with limited out-of-network experience. The providers who were already rendering a larger proportion of their services out-of-network may already have been aware of their competitors' charges or had set their charges optimally. For providers with limited out-of-network experience, the presence of the tool enabled them to see the charge information posted by their competitors in a given market and increase their charges accordingly.

Overall, these results are consistent with our intervention having (i) a minimal effect on consumer price shopping and (ii) a meaningful effect driving provider price increases, especially for less elective services that are almost always covered by insurance. These price increases are consistent with both tacit collusion between providers in an environment with greater provider-specific price information or with reduced information asymmetries that generally push providers towards realizing that they are under-charging relative to their peers.

Although price transparency is a laudable goal in a healthcare market dominated by information asymmetries, there may be perverse price effects due to supply constraints, the inelastic nature of the demand for healthcare services and opportunity for providers to engage in price-setting. Our results suggest caution about price transparency if physicians are more likely to leverage that information than consumers to set prices. Our results should be viewed with a number of caveats, including the limited time window during which we can study the effects of the intervention, and the application to billed charges, which, though relevant for out-of-network claims and potentially relevant via what they signal about negotiated rates, are not indicative of insurer-provider negotiated rates. The NY HOST price transparency tool is not representative of all price transparency interventions, and this is just one limited example. Further research is necessary to more fully assess how different kinds of interventions impact prices, quantities, and welfare. Recent policy actions, including the CMS price transparency rule mandating that insurers reveal provider-negotiated rates, necessitates future work investigating the impact of that rule.

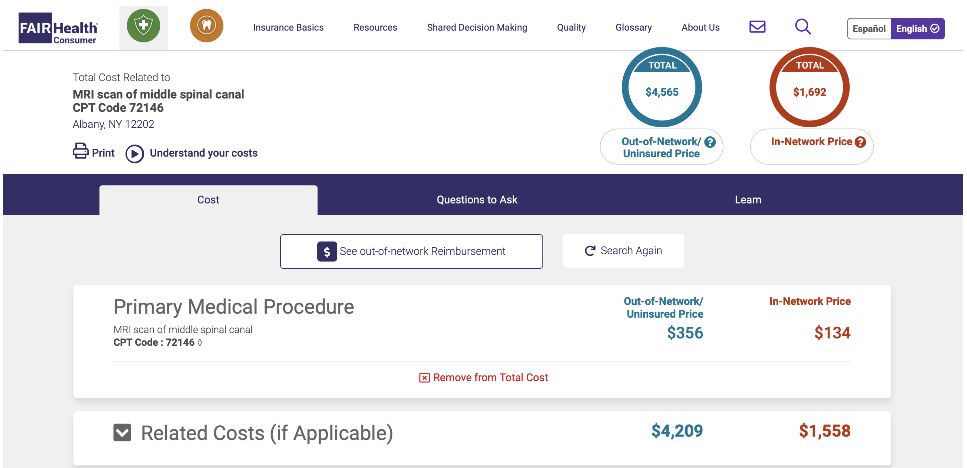
Tables and Figures

Figure 3.1: Timeline and Experimental Design



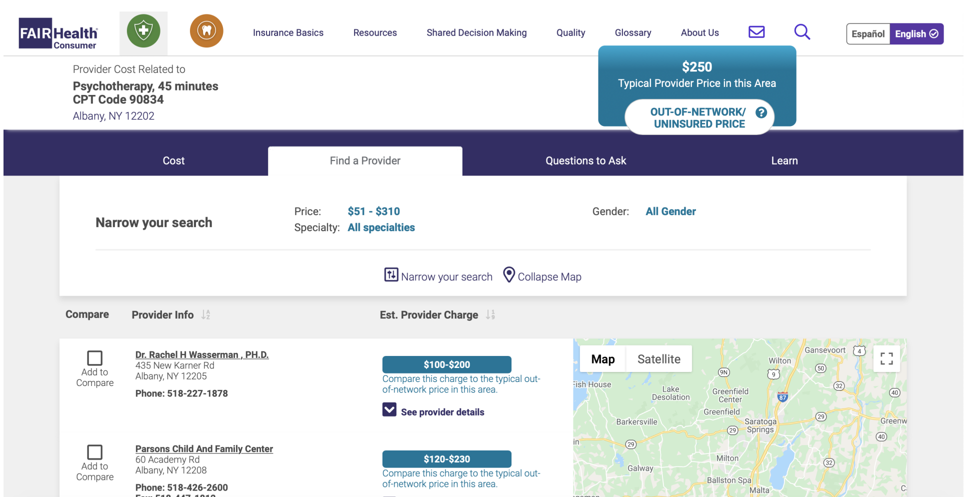
Notes: This shows the timeline of the implementation and randomization of the website.

Figure 3.2: NYHOST Website: Control Website Search Result



Notes: A snapshot of the FAIRHealth consumer shopping tool for a control procedure and geozip that does not contain provider-level information.

Figure 3.3: NYHOST Website: Treatment Website Search Result



Notes: A snapshot of the FAIRHealth consumer shopping tool for one of the randomized procedure and geozips that released provider-level price information.

Table 3.1: Theorized Impact of the Price Transparency Tool on Market-Level Charges and Volume

Market conditions	**Initial volume effect**	**Initial charge effect**	**Equilibrium volume at the market-level**	**Equilibrium charge at the market-level**	**Equilibrium out-of-network charge at the market-level**	**Average charge at the provider-level**	**Average out-of-network charge at the provider-level**
Price elastic consumers	Volume shifts to lower price providers.	Providers reduce prices.	Shift to lower price providers.	Lower charges.	Lower charges.	Lower charges.	Lower charges.
Price inelastic consumers	No volume shifts	Providers raise prices.	Dependent on charge dispersion.	Higher charges.	Higher charges.	Higher charges.	Higher charges.
Monopolistic competitive producers	—	Providers raise prices	Shift to lower price providers.	Higher charges.		Higher charges.	Higher charges.

Table 3.2: Provider and Market Summary Statistics

	Mean	SD	Min	Max
Panel A: Provider summary statistics				
Unit Charge	420	1,279	2	59,000
Volume	103	198	6	22,329
N	583,693			
Panel B: Market summary statistics				
Average charge	985	2,173	14	42,611
Average volume	4,562	19,349	6	350,776
Average volume out-of-network	688	4,446	0	96,661
Provider HHI	756	901	5	10,000
Website usage	2	11	0	565
N	13,141			

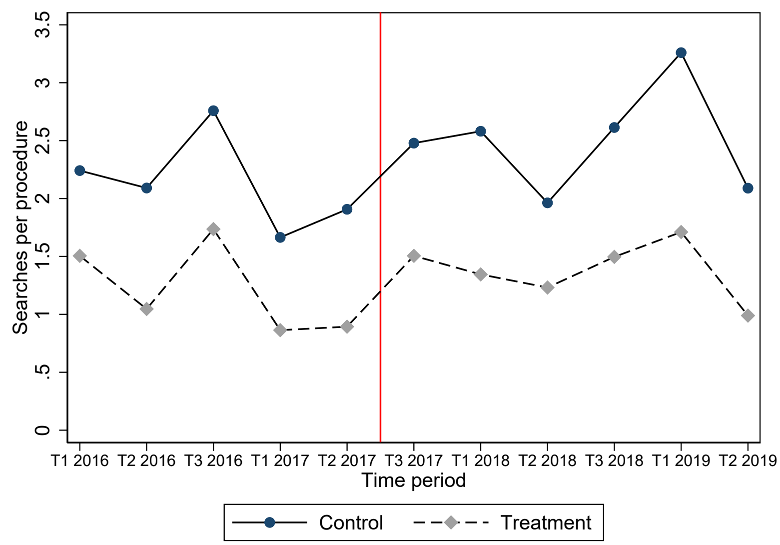
Notes: This table shows the summary statistics for charge and volume information for the provider-level dataset at the NPI X procedure X geozip X trimester level as well as market level summary statistics of charges, volume and market characteristics.
Data source: FAIRHealth.

Table 3.3: Balance Check

Variable	(1) Treatment Mean/SD	(2) Control Mean/SD	T-test P-value (1)-(2)
Average charge	1,025.13	918.30	0.58
	(7,045.04)	(5,282.47)	
Average volume	4,251.48	4,980.21	0.69
	(51,717.63)	(60,955.76)	
Average volume out-of-network	574.69	900.36	0.46
	(9,550.12)	(16,700.61)	
Provider HHI	716.19	812.44	0.18
	(2,061.27)	(2,399.04)	
Website usage	1.43	2.36	0.31
	(13.62)	(37.43)	
N	2175	1822	
Clusters	165	144	
F-test of joint significance (p-value)			0.01**
F-test, number of observations			3997

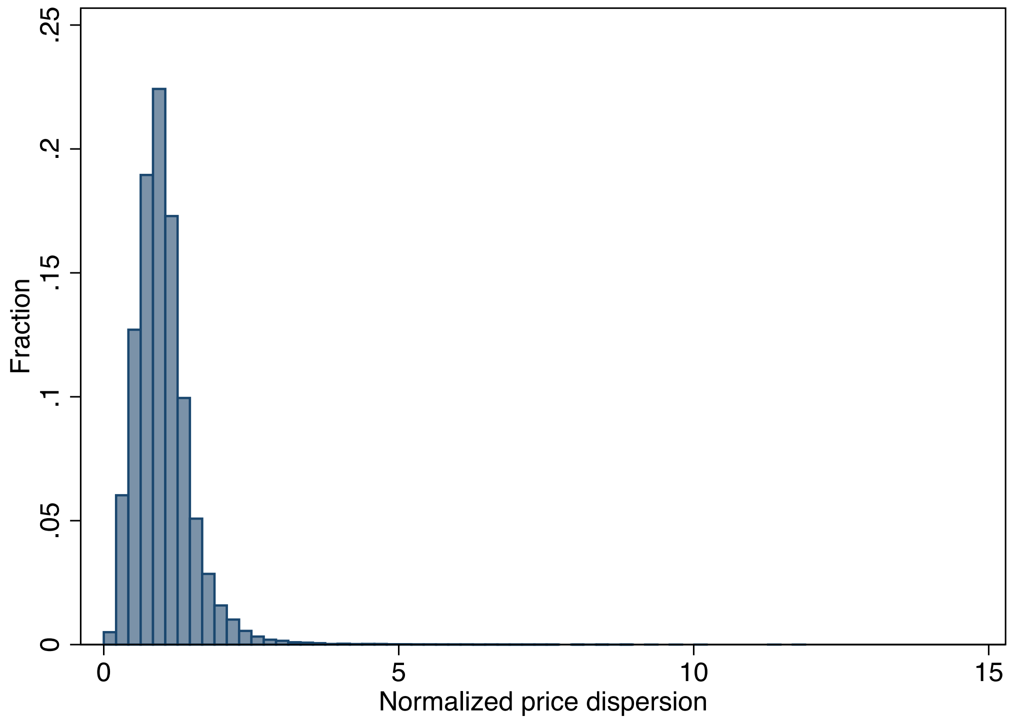
Note: This table checks for balance of market level summary stats in the pre-period for treatment and control markets.

Figure 3.4: Website Utilization Between Treatment and Control Groups



Notes: This figure plots the average monthly website utilization (data on NYHOST web searches provided by FAIRHealth) for procedures in treatment and control groups. The persistently higher searches in the control group can be attributed to the number of searches that occurred in New York City for the procedureXgeozip combinations in the control group.

Figure 3.5: Normalized Charge Dispersion



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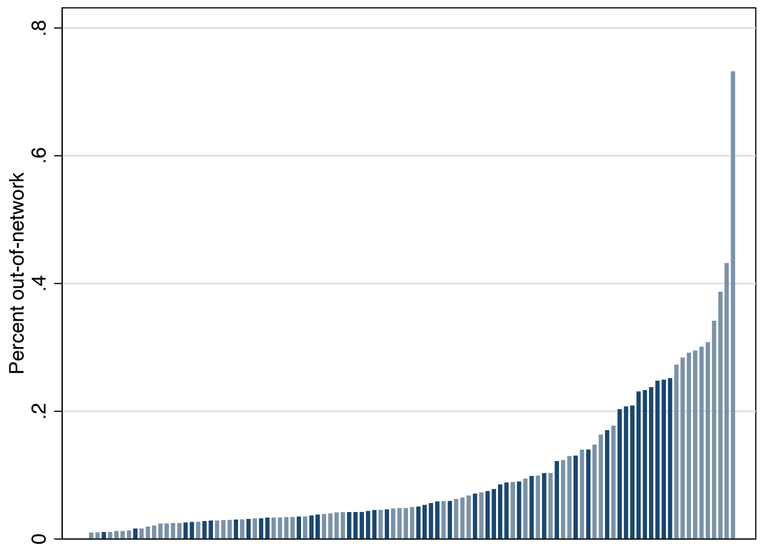
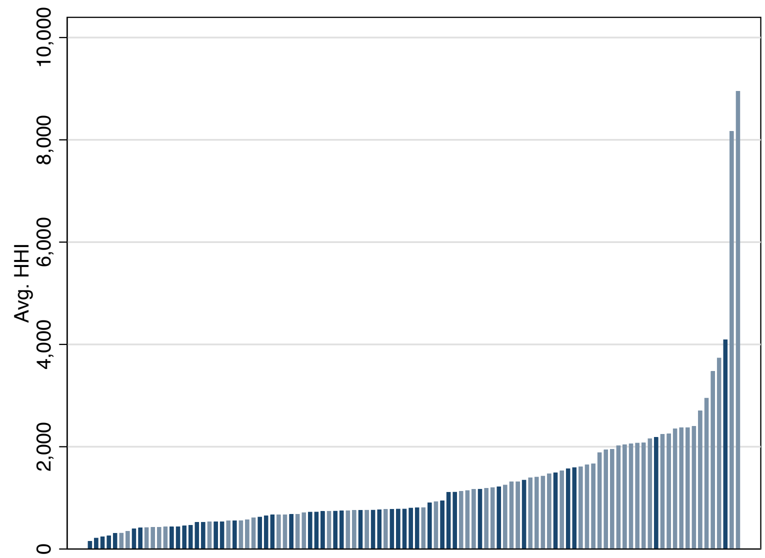
Notes: This graph presents the histogram of normalized modal charge dispersion by trimester. Normalized modal charge is calculated as the ratio of a provider's modal charge to the procedureX-geozip mean. The histogram is restricted to normalized charges below 10.

Figure 3.6: Percentage of Claims Out-of-Network, by Procedure Code



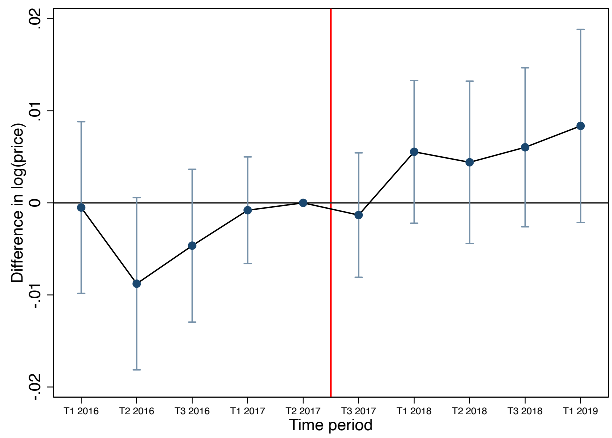
Notes: The graph represents the distribution of the percentage of out-of-network claims for procedure codes ordered lowest to highest. Dark blue bars indicate procedure codes used in the final analysis sample.

Figure 3.7: Physician Market Concentration



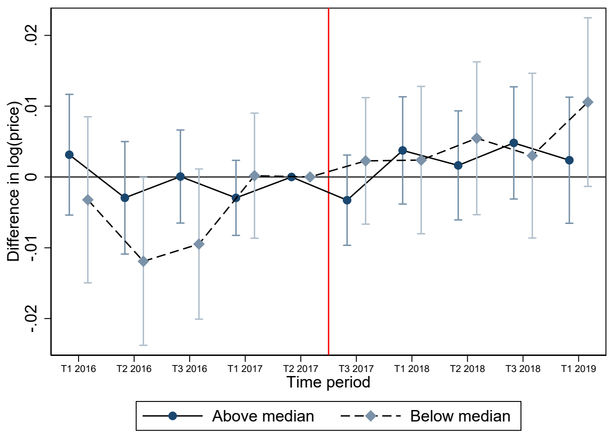
Notes: This figure represents the distribution of physician market concentration by procedure code in 2016. Provider market concentration was constructed as the HHI for each procedure and geozip, with the market share constructed as each provider, defined by the NPI.

Figure 3.8: Event Study: Difference between Treatment and Control with Triple Difference-in-Differences Specification



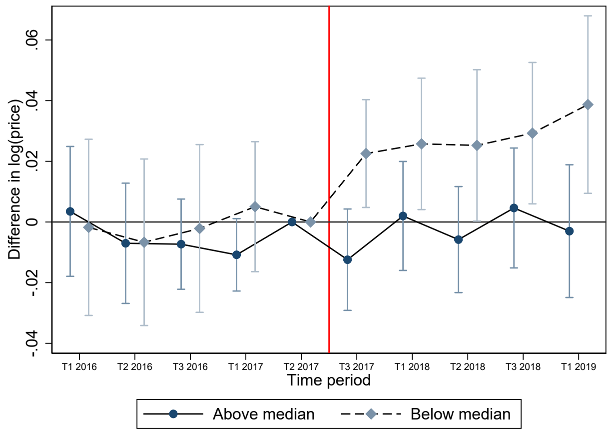
Note: This figure plots coefficients from a regression of log(price) on an interaction between treatment and trimester, with time (trimester-year), market (procedure X geozip), procedure X trimester, geozip X trimester, and provider fixed effects. Treatment began at the start of trimester 3 in 2017. This event study corresponds to a triple difference-in-differences regression model specification. Standard errors are clustered at the category X geozip level.

Figure 3.9: Event Study: Treatment Effect for High vs. Low Price Providers



Note: This figure plots coefficients from triple difference-in-differences regressions of log(price) on an interaction between treatment and trimester, with time (trimester-year), market (procedure X geozip), procedure X trimester, geozip X trimester, and provider fixed effects. The figure plots the trends for high vs. low price providers, with high price providers defined as providers with a billed charge in that trimester above the median charge for that procedure X geozip X trimester, and low price providers defined as providers with a billed charge below the median charge. Treatment began at the start of trimester 3 in 2017. This event study corresponds to a triple difference in differences regression model specification. Standard errors are clustered at the category X geozip level.

Figure 3.10: Event study: Treatment Effect for Low Out-of-Network Volume Procedures, High vs. Low Price Providers



Note: This event study graph plots the difference in log(price) between the treatment and control group for high price (above median charge) and low price (below median charge) providers by trimester, with a triple differences-in-differences specification. This figure plots coefficients from a regression of log(price) on an interaction between treatment and trimester, with time (trimester-year), market (procedure X geozip), procedure X trimester, geozip X trimester, and provider fixed effects. Treatment began at the start of trimester 3 in 2017. This event study corresponds to a triple difference regression. Standard errors are clustered at the category X geozip level.

Table 3.4: Provider-Level Regressions: Treatment Effect of NYHOST

	log(Price)			log(Quantity)		
	(1)	(2)	(3)	(4)	(5)	(6)
	DiD	DiD	DiD	DiD	DiD	DiD
Treatment effect	0.0013	0.0012	0.0075*	-0.0071	-0.0040	0.0009
	(0.0052)	(0.0046)	(0.0042)	(0.0113)	(0.0083)	(0.0071)
Observations	583469	583469	583469	583469	583469	583469
Adjusted R^2	0.945	0.946	0.946	0.601	0.601	0.601
ProcedureXGeozip FE	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes
ProcedureXTime FE		Yes	Yes		Yes	Yes
GeozipXTime FE			Yes			Yes
Provider FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table contains coefficients from a difference-in-differences regression of log(price) on an interaction between the treatment variable and a post indicator with different fixed effects configurations, including time (trimester-year), market (procedure X geozip), procedure X time, geozip X time, and provider. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the category X geozip level.

Table 3.5: Provider-Level Regressions: Heterogeneity Tests for the Treatment Effect of NYHOST

	Provider prices		Continuous procedures		OON procedures		Market HHI		Website use	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	>Median	<Median	Non-continuous	Continuous	>Median	<Median	>Median	<Median	>Median	<Median
Panel A: Charge treatment effects										
log(P) effect	0.0023	0.0095	0.0103	0.0027	0.0062	0.0128*	0.0065	0.0084*	0.0064	0.0114**
	(0.0040)	(0.0064)	(0.0079)	(0.0044)	(0.0043)	(0.0075)	(0.0083)	(0.0044)	(0.0052)	(0.0055)
Observations	313057	242724	156491	333587	407252	175987	86596	496188	293394	288071
Adjusted R^2	0.972	0.950	0.941	0.903	0.922	0.945	0.952	0.950	0.955	0.942
ProcedureXGeozip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ProcedureXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GeozipXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Quantity treatment effects										
log(q) effect	0.0001	0.0125	0.0153	-0.0190*	-0.0066	0.0006	0.0174	-0.0000	-0.0112	-0.0004
	(0.0096)	(0.0099)	(0.0097)	(0.0113)	(0.0084)	(0.0104)	(0.0159)	(0.0080)	(0.0127)	(0.0081)
Observations	313057	242724	156491	333587	407252	175987	86596	496188	293394	288071
Adjusted R^2	0.657	0.684	0.435	0.540	0.578	0.564	0.685	0.609	0.604	0.612
ProcedureXGeozip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ProcedureXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GeozipXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table contains coefficients from a regression of log(price) on an interaction between treatment and a post indicator with fixed effects for time (trimester-year), market (procedure X geozip), procedure X time and geozip X time corresponding to a difference in difference in difference regression testing for heterogeneity. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the category X geozip level.

Table 3.6: Provider level regressions: Treatment effect of NYHOST by procedure category

	(1) CT	(2) MRI	(3) RAD	(4) GI	(5) EYE	(6) ORTHO	(7) OB	(8) PSYCH	(9) PTOT	(10) CHIRO
Panel A: Charge Treatment Effects										
log(P) effect	-0.03433	0.03651	0.03000	-0.01443	-0.00265	0.03838*	-0.02067	-0.01720**	0.00653	-0.00660
	(0.02346)	(0.02591)	(0.02154)	(0.02572)	(0.00808)	(0.02250)	(0.01539)	(0.00662)	(0.00919)	(0.00690)
Observations	33868	33405	55382	27315	65897	20298	13285	129105	159101	45266
Adjusted R^2	0.850	0.807	0.869	0.866	0.835	0.951	0.970	0.818	0.836	0.860
ProcXZip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Quantity Treatment Effects										
log(Q) effect	0.01567	0.05155	0.06113**	0.01341	-0.00281	-0.00142	0.04034*	0.00346	-0.04116*	-0.00416
	(0.03661)	(0.03439)	(0.02358)	(0.03201)	(0.01858)	(0.02011)	(0.02363)	(0.01281)	(0.02069)	(0.02523)
Observations	33868	33405	55382	27315	65897	20298	13285	129105	159101	45266
Adjusted R^2	0.536	0.537	0.482	0.632	0.509	0.640	0.546	0.619	0.449	0.509
ProcXZip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provider FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table contains coefficients from a regression of log(price) and log(quantity) on an interaction between treatment and a post indicator with fixed effects for time (trimester-year) and market (procedure X geozip) corresponding to a difference in difference regression for each procedure category. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the category X geozip level.

Conclusion

The chapters of this dissertation explore the unintended and sometimes unwanted market outcomes of demand heterogeneity and information frictions. The first two chapters use two different methods to understand why the products that women buy are priced higher than the products that men buy. We find that women systematically exhibit more demand elasticity while also showing preference for higher cost of production goods. This means that the observed Pink Tax is largely explained by women sorting into products that cost more to produce as opposed to products that have higher markups. The third chapter studies the effects of an information treatment that revealed prices for healthcare services and finds that consumers respond very little but that providers do respond, sometimes by increasing prices. This increase in prices after the information treatment showcases the potential of information increasing the possibility of collusion.

All three chapters study topics that policy makers or the general public may misperceive. In the first two chapters the Pink Tax is typically thought of as price discrimination, where women are charged higher prices based on their demand elasticities. We find, however, that its not a form of price discrimination but rather differences in preferences between men and women. In the third chapter, price transparency in health care is typically thought of as a way to reduce health care costs by making consumers better shoppers. Throughout this research, a common thread emerges - the critical role of understanding consumer and supplier behavior in shaping market outcomes and informing optimal policy design. Whether discussing gender disparities in pricing or the impacts of price transparency in healthcare, the importance of a nuanced understanding of market dynamics is clear. This dissertation, therefore, not only provides specific insights into these areas but also underscores the broader applicability of a behavioral approach in economics, offering a foundation for future research and policy-making.

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Appendix A

Additional Figures and Tables

A.1 Pink Tax Additional Figures and Tables

Table A.1.1: Nielsen panelist behavior per month

	Total	Women	Men	Difference
Months in Panel	53.35 (48.378)	50.85 (46.675)	56.26 (50.1261)	-5.407** (.4468)
Trips	9.395 (6.5983)	9.018 (6.0547)	9.833 (7.1526)	-.815** (.0609)
Spending	258.8 (177.0685)	259.6 (175.8798)	257.9 (178.4388)	1.644 (1.6378)
Spending inc. share	0.0120 (.0208)	0.0140 (.0235)	0.0100 (.017)	.004** (.0002)
Purchases	53.95 (32.122)	55.78 (32.2948)	51.84 (31.7906)	3.941** (.2966)
Unique products	25.67 (14.7973)	28.44 (15.2127)	22.45 (13.6116)	5.985** (.1341)
Unique modules	6.597 (15.3426)	7.516 (16.422)	5.531 (13.9114)	1.986** (.1416)
Unique groups	3.500 (7.0203)	3.955 (7.3166)	2.973 (6.6215)	.982** (.0648)
Coupon value	11.65 (15.3496)	12.80 (15.6305)	10.31 (14.9068)	2.487** (.1415)
Coupon use	8.229 (5.4355)	9.159 (5.6248)	7.150 (4.995)	2.009** (.0494)
Deal use	2.972 (2.1307)	3.223 (2.2144)	2.682 (1.9902)	.541** (.0196)

Note: This table features shopping behavior of single-individual household Nielsen panelists per month and unconditional differences between genders. Monetary values are expressed in 2016 USD.
$*p < .05$, $**p < .01$.

Table A.1.2: Nielsen panelist behavior per shopping trip

	Total	Women	Men	Difference
Spending	25.61	26.82	24.46	2.357**
	(34.2295)	(35.1908)	(33.2481)	(.013)
Spending inc. share (%)	0.104	0.123	0.0860	.037**
	(.2522)	(.2911)	(.207)	(.0001)
Purchases	5.402	5.851	4.974	.877**
	(6.7014)	(7.1709)	(6.1916)	(.0025)
Unique products	5.183	5.613	4.773	.84**
	(6.341)	(6.806)	(5.8349)	(.0024)
Unique modules	4.507	4.869	4.163	.707**
	(5.2263)	(5.6165)	(4.8006)	(.002)
Unique groups	3.884	4.160	3.622	.538**
	(4.0665)	(4.3455)	(3.7633)	(.0015)
Coupon value	0.731	0.873	0.596	.277**
	(3.321)	(3.7914)	(2.7942)	(.0013)
Coupon use	0.398	0.470	0.330	.14**
	(1.5169)	(1.6698)	(1.3519)	(.0006)
Deal use	1.347	1.530	1.173	.357**
	(3.0739)	(3.333)	(2.7942)	(.0012)

Note: This table features descriptive statistics of shopping behavior of single-individual household Nielsen panelists per trip and unconditional differences between genders. Monetary values are expressed in 2016 USD.
$*p < .05$, $**p < .01$.

Table A.1.3: Price paid per good unit by department

	Total	Women	Men	Difference	Log difference
All departments	1.737	1.859	1.601	.258**	.091**
	(21.7607)	(27.6795)	(12.0798)	(.0035)	(.0003)
Health and beauty	5.907	7.442	3.541	3.901**	.261**
	(76.3566)	(95.0937)	(29.4796)	(.0488)	(.0013)
Dry grocery	0.302	0.317	0.286	.031**	.109**
	(3.0293)	(1.6098)	(4.0436)	(.0007)	(.0003)
Frozen foods	0.983	0.993	0.972	.021**	.056**
	(2.7548)	(2.7258)	(2.7834)	(.0015)	(.0007)
Dairy	0.419	0.432	0.405	.027**	.142**
	(1.0206)	(1.0247)	(1.0158)	(.0005)	(.0006)
Deli	3.101	3.011	3.188	-.176**	-.004**
	(5.5958)	(5.5005)	(5.6842)	(.005)	(.0015)
Packaged meat	0.606	0.617	0.597	.021**	.071**
	(1.3595)	(1.3252)	(1.388)	(.0014)	(.001)
Fresh produce	1.474	1.473	1.476	-0.00200	.002*
	(2.2024)	(2.2308)	(2.1655)	(.0014)	(.0008)
Non-food grocery	1.210	1.243	1.164	.079**	-.058**
	(17.1235)	(17.4589)	(16.6564)	(.0099)	(.001)
Alc. beverages	2.092	1.997	2.143	-.146**	-.283**
	(4.7644)	(4.3439)	(4.9772)	(.0072)	(.0039)
General merch.	9.850	8.777	11.12	-2.348**	-.238**
	(31.9754)	(32.0002)	(31.899)	(.0247)	(.0015)

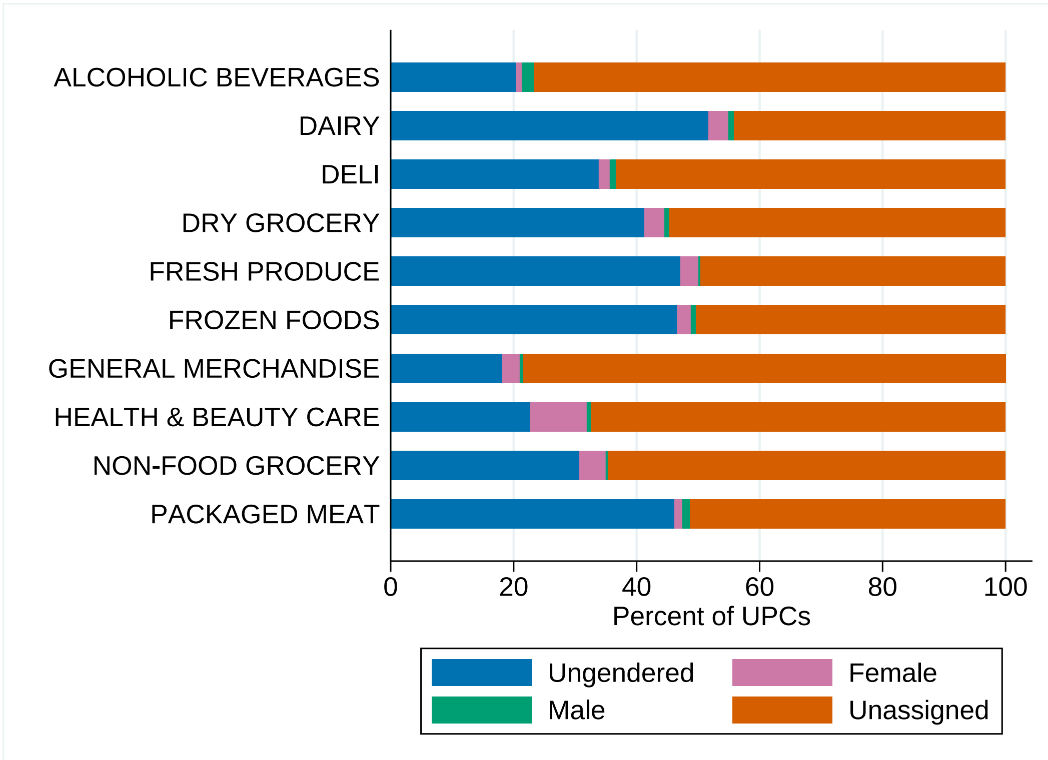
Note: This table displays per-unit prices within each department as well as the descriptive difference in per-unit prices calculated for men's and women's purchases separately. Level units are expressed as 2016 USD per unit-amount.
$*p < .05$, $**p < .01$.

Table A.1.4: Demographics of CE PUMD single-member households

_	Total	Women	Men	Difference
Income	30530	26950	34665	-7715.418**
	(42896.3)	(36923.05)	(48568.25)	(335.0263)
Age	54.72	58.93	49.86	9.071**
	(20.2861)	(20.2295)	(19.2376)	(.1516)
High school	0.482	0.478	0.486	-.008*
	(.4997)	(.4995)	(.4998)	(.0038)
College	0.284	0.278	0.291	-.013**
	(.4508)	(.448)	(.4541)	(.0035)
Post-grad	0.0980	0.103	0.0920	.01**
	(.2971)	(.3035)	(.2894)	(.0023)
White	0.792	0.788	0.797	-.009**
	(.4058)	(.4086)	(.4024)	(.0031)
Black	0.146	0.152	0.140	.012**
	(.3536)	(.3591)	(.3469)	(.0027)
Asian	0.0400	0.0390	0.0410	-0.00200
	(.1957)	(.1937)	(.198)	(.0015)
Hispanic	0.0830	0.0750	0.0920	-.017**
	(.2761)	(.2636)	(.2895)	(.0021)
No. observations	67950	36417	31533	4884

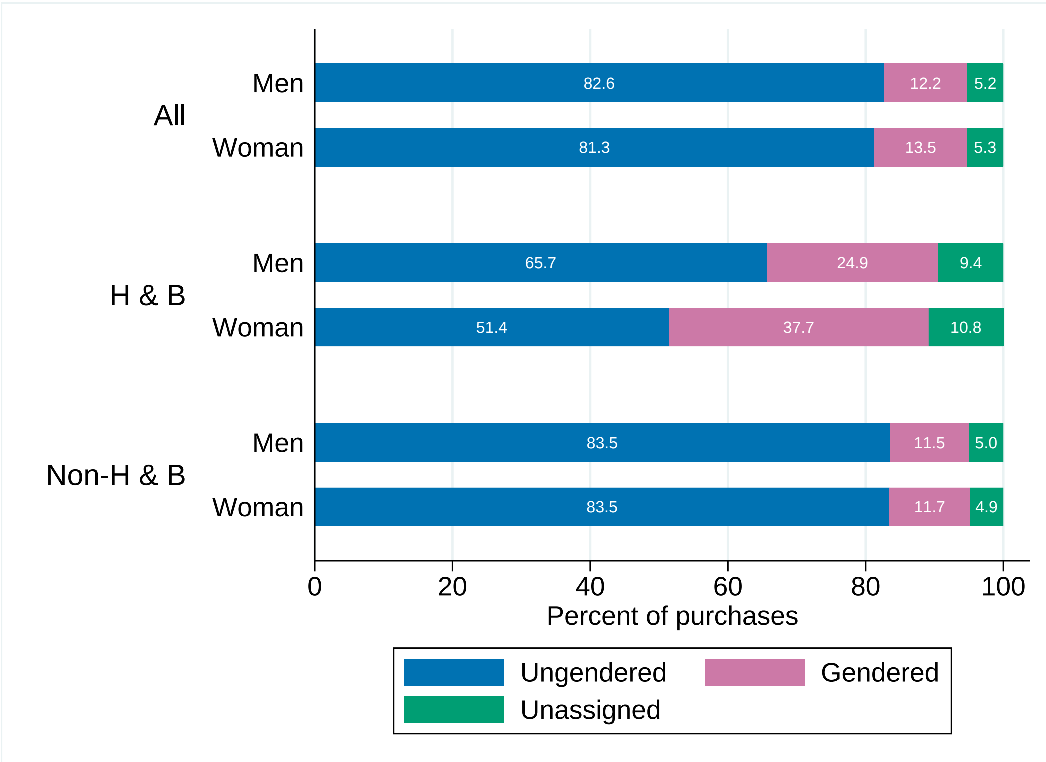
This table displays demographic data of men and women constituting single-member households as well as their differences. Dollar amounts are expressed in USD 2016.
$*p < .05$, $**p < .01$

Figure A.1.1: Assigned UPC Gender Across Departments



Note: This figure plots the percentage distribution of UPCs assigned to Ungendered, Female, and Male across departments. We restrict to UPCs that are observed with great enough purchase frequency to be assigned a UPC gender with false positive probability of 5% . Unassigned UPCs are those excluded by the purchase cutoff.

Figure A.1.2: Consumption basket composition as share of purchases, 75-25 Cutoff



Note: This figure presents plots the decomposition of purchases made by men and women into gendered, ungendered and unassigned products. The first rows show this for all product departments while the next two separate out health and beauty products.

Table A.1.5: Unit prices in same product module by UPC and consumer gender, 75-25 Cutoff

	(1) All	(2) H & B	(3) Non-H & B
Woman Consumer	0.0322***	0.0182***	0.0286***
	(0.0019)	(0.0032)	(0.0017)
Gendered Product	0.0084***	0.0817***	0.0066***
	(0.0022)	(0.0038)	(0.0024)
Woman Consumer & Gendered Product	0.0848***	0.1002***	0.0648***
	(0.0024)	(0.0042)	(0.0026)
Observations	131501221	9299678	120478978
Adjusted R^2	0.884	0.844	0.888
ModXUnitXRetXLocXMonth FE	Yes	Yes	Yes
Demographic FE	Yes	Yes	Yes

Individual level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimates from the regression:
$log(P_{ijt}) = \phi_{t(j)} + \beta_1 \mathbf{1}_{w(i)} + \beta_2 \mathbf{1}_{g(j)} + \beta_3 \mathbf{1}_{w(i)} \cdot \mathbf{1}_{g(j)} + \gamma X_i + \epsilon_{ijt}$. $\phi_{t(j)}$ is a vector of fixed effects for the interaction of product module, units denomination, retailer chain, county, and half-year. X_i includes with demographic controls for income, age, race and education. Columns 2 and 3 separate out Health and Beauty products. This table corresponds to table 6 in the paper but with the gendered product cutoff at 25-75 rather than 10-90.

Table A.1.6: OLS Elasticities (No Instruments)

	(1) County-Half Year	(2) County-Retailer-Half Year
$1 - \sigma_m$	0.6886***	0.7784***
	(0.0170)	(0.0075)
$\sigma_m - \sigma_w$	-0.0181***	-0.0073*
	(0.0065)	(0.0044)
Observations	17,010,404	14,939,386
Adjusted R^2	0.016	0.000
ModXTimeXCountyXRetXGen FE	Yes	Yes
County IV	No	No
Retailer IV	No	No

UPC-County level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A.1.7: First Stage

	(1) Hausman	(2) Dellavigna-Gentzkow
Hausman	0.3280***	
	(0.0044)	
Dellavigna-Gentzkow		0.2215***
		(0.0036)
Observations	16,351,076	11,018,742
Adjusted R^2	0.008	0.006
ModuleXTimeXCountyXRetXGender FE	Yes	Yes
County IV	Yes	No
Retailer IV	No	Yes

UPC-County level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

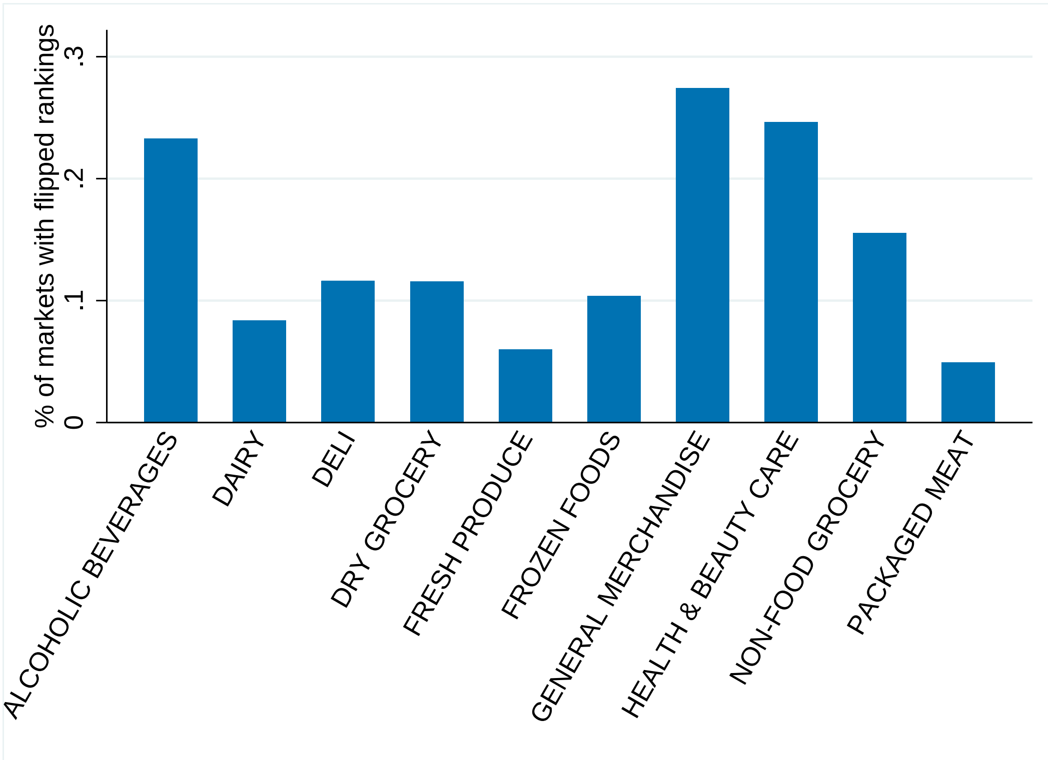
Table A.1.8: Reduced Form Results

	(1) Hausman	(2) Dellavigna Gentzkow
Hausman	0.0650***	
	(0.0077)	
WomanXHausman	0.0102	
	(0.0076)	
Dellavigna-Gentzkow		0.0568***
		(0.0052)
WomanXDellavigna-Gentzkow		-0.0198***
		(0.0060)
Observations	16,336,260	11,007,333
Adjusted R^2	-0.022	-0.052
ModuleXTimeXCountyXRetXGender FE	Yes	Yes
County IV	Yes	No
Retailer IV	No	Yes

UPC-County level clustered standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.1.3: Markets with Flipped Product Rankings between Men and Women



Note: This figure displays the percentage of markets with flipped product rankings across departments. We define flipped product rankings as markets where items that are in the top 25% of products by market share for women are in the bottom 25% of products for men and vice versa.

A.2 Price Transparency Additional Figures and Tables

Figure A.2.1: Categories of service for procedures examined

Category	Randomized	Number of Procedures
Acupuncture	N	4
Allergy	N	4
Bone Density	N	1
Cardiology	N	2
Chemotherapy	N	1
Chiropractic	Y	4
CAT Scan (Radiology)	Y	4
Dermatology	N	4
ENT	N	5
Gastroenterology	Y	3
Infusion	N	1
Mammogram	Y	8
MRI	Y	5
Neuromuscular	N	1
Obstetrics & Gynecology	Y	4
Ophthalmology	Y	4
Orthopaedic	Y	6
Pain	N	5
Plastic Surgery	N	1
Psychotherapy	Y	5
Physical Therapy/Occupational Therapy	Y	8
Pulmonology	N	3
Radiology	Y	6
Sleep Medicine	N	2
Spine	N	4
Surgery	N	3
Urology	N	1
Ultrasound	N	4
Ultrasound-OB	N	2
Vascular Radiology	N	2

Notes: These categories were selected on the basis of encompassing procedures that were commonly serviced and non-emergent.

Figure A.2.2: Description of the datasets utilized

Dataset	**Description**
FAIRHealth	2016-2019
FAIRHealth NYHOST Website data	2016-2019
CMS Physician Compare	2017
CMS National Plan and Provider Enumeration System (NPPES)	2017

Notes: These datasets were utilized to conduct the analyses of the impact of the NYHOST price transparency tool. The CMS Physician Compare file utilized is the most recent dataset that was able to be accessed on 2/20/2020.

Figure A.2.3: Data on provider characteristics

Dataset	**# Distinct NPI in FAIRHealth Data**	**# Distinct NPI in CMS Compare (2017)**
Total number of providers in each dataset.	205,258	1,142,428
Providers in both FAIRHealth + CMS Physician Compare	119,583	119,583
# Distinct NPI in FAIRHealth Data and CMS Physician Compare, with specialties associated with the MD/DO credential.	78,509	78,509
Number of providers represented in the balanced panel (subset of the total number of providers)	21,601	14,146

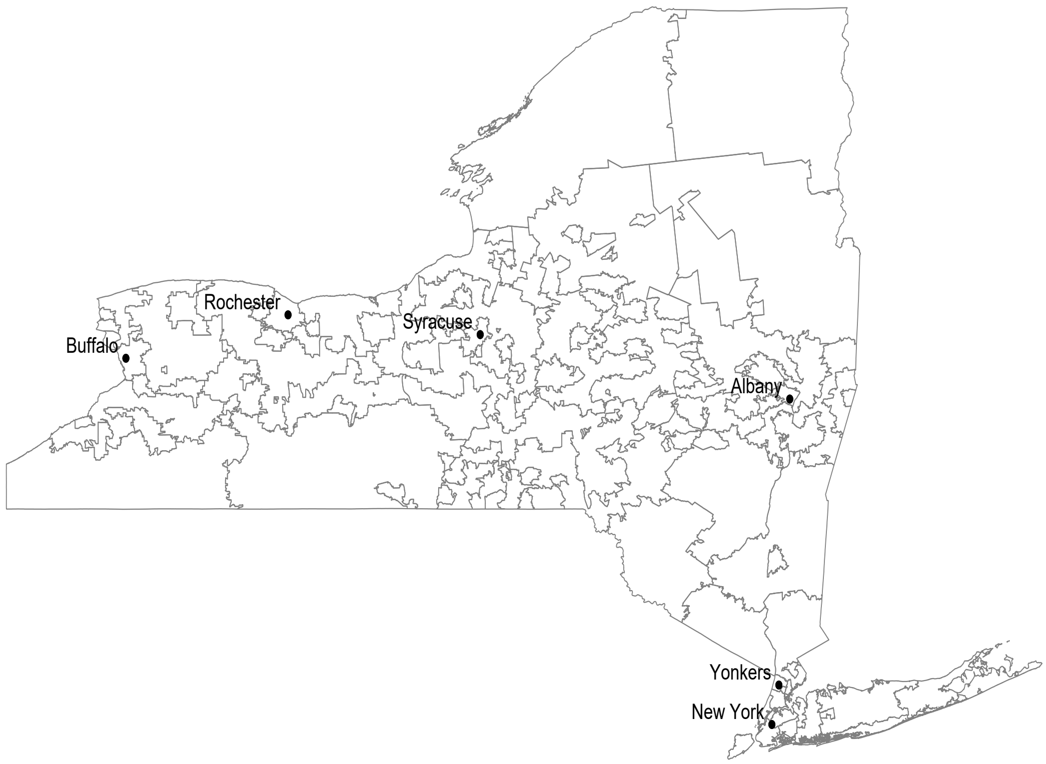
Notes: This table demonstrates the number of providers represented in the FAIR Health dataset, and the match of the NPIs in the FAIRHealth dataset with the 2017 CMS Physician Compare File. The CMS Physician Compare File includes information on providers, including credentials, medical school, gender, and affiliated hospitals.

Figure A.2.4: Construction of the Balanced Panel

Steps to Create Balanced Panel	**# Observations**	**# Observations dropped**
1. Total number of observations for the provider-level dataset with the modal charge (NPI X geozip X procedure X year X trimester).	3,598,866	
2. Drop any observation with fewer than 5 claims in a trimester.	1,708,771	1,890,095
3. Create a balanced panel of providers by restricting the sample to providers with at least five claims in each trimester for the study period.	1,083,963	624,808
4. Create a balanced panel of procedures (drop any procedures that were added or discontinued during this time period).	1,028,785	55,178
5. Drop any procedures for which provider-level charges were released across the state.	667,014	361,771
6. Drop any observations where the volume is above the 99th percentile of the volume for a given procedureXgeozipXtrimester.	654,425	12,589
7. Drop any observations where the modal charge is above the 99th percentile of the charge for a given procedureXgeozipXtrimester.	628,428	25,997

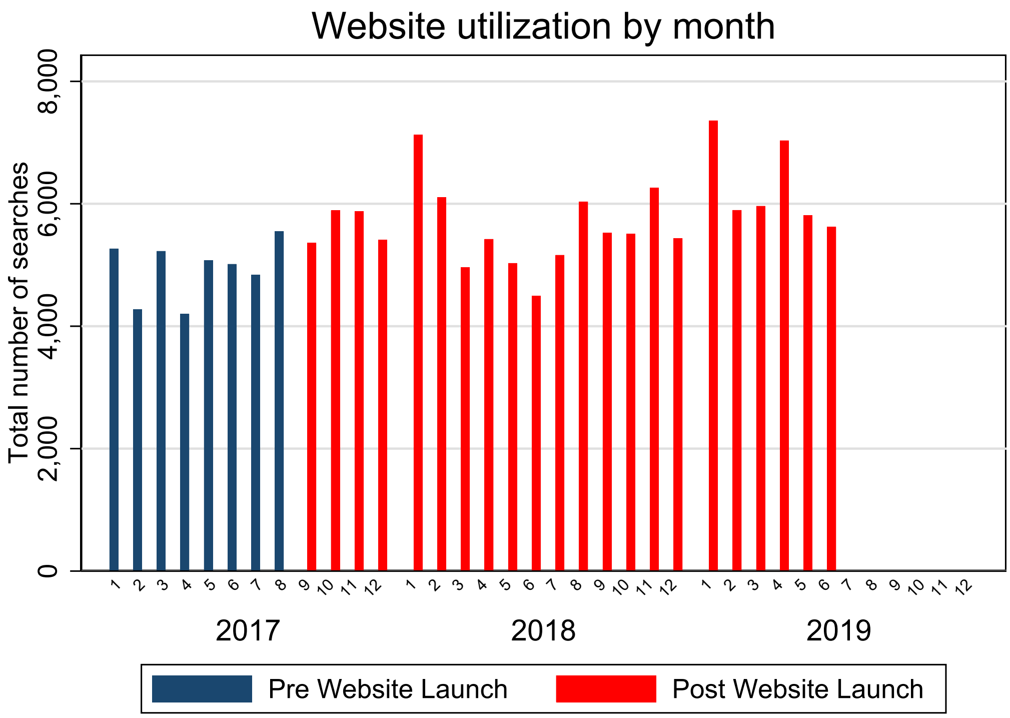
Notes: We constructed a balanced panel of providers and procedures in order to ensure that we were following the same panel of providers over time to assess the impact of the randomization on their billed charges over time after the release of the price transparency tool. The balanced panel was constructed by restricting the sample to the procedures that were randomized across geozips, to providers with at least five claims in each quarter, and procedures that were active throughout the study period.

Figure A.2.5: Map of New York Geozips



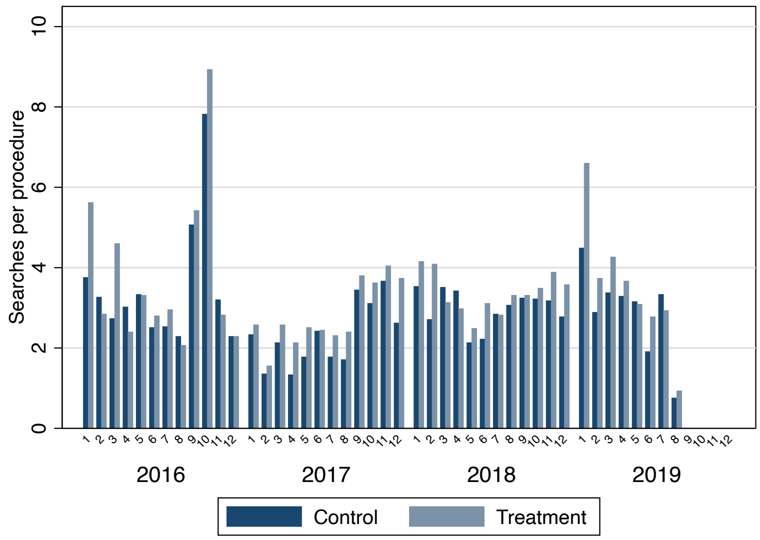
Notes: Map of New York State geozips, with select cities indicated.

Figure A.2.6: Website Utilization by Month



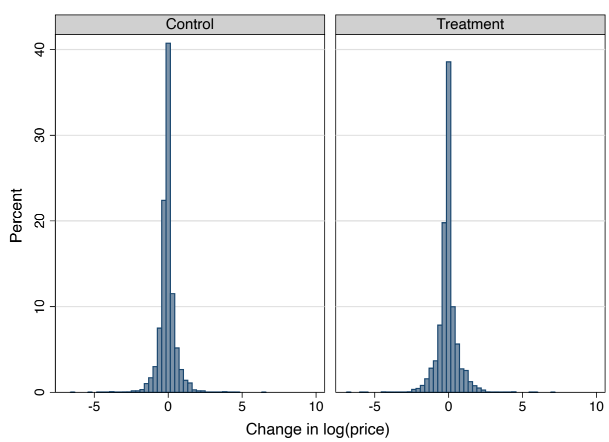
Note: This figure plots total number of monthly searches across the pre- and post- period. Large spikes in 2016 and 2019 are associated with major website overhauls and marketing changes.The experiment was in effect from 9/2017 through 6/2019.

Figure A.2.7: Website Utilization by Month Excluding Manhattan



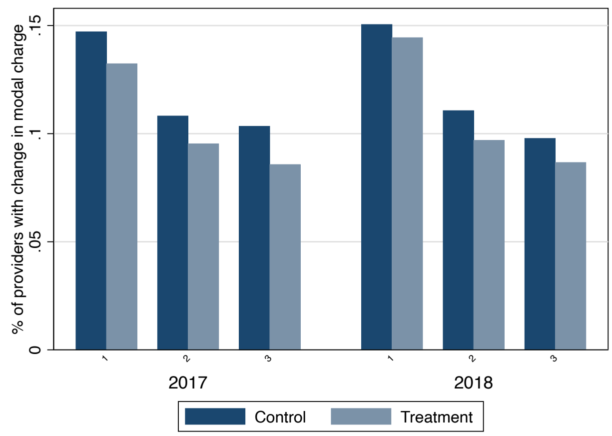
Notes: This figure plots the average monthly website utilization (data on NYHOST web searches provided by FAIRHealth) for procedures in treatment and control groups when the geozip corresponding to Manhattan (geozip = 100) is excluded.

Figure A.2.8: Changes in log(Price) in Treatment and Control Groups



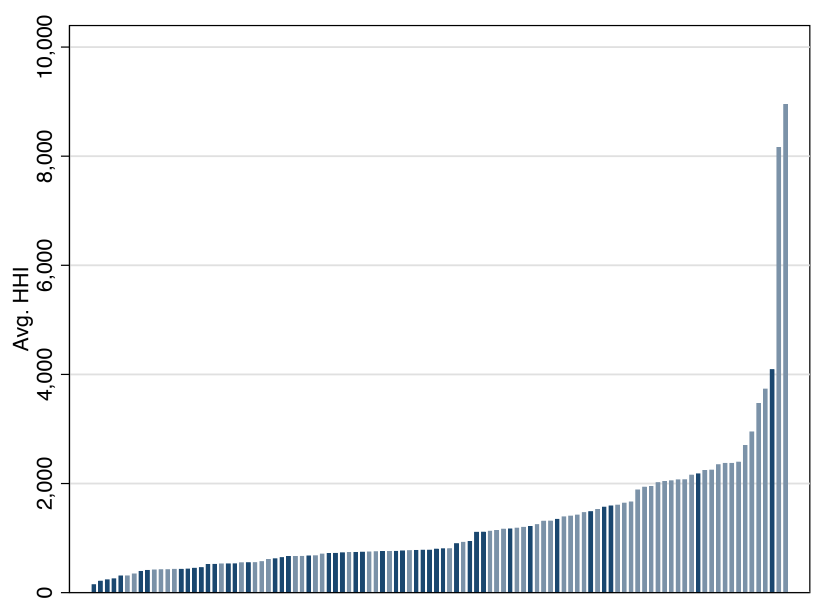
Note: This figure presents histograms of charge updates for providers in the treatment and control groups.

Figure A.2.9: Changes in log(Price) over Time (2017-2018)



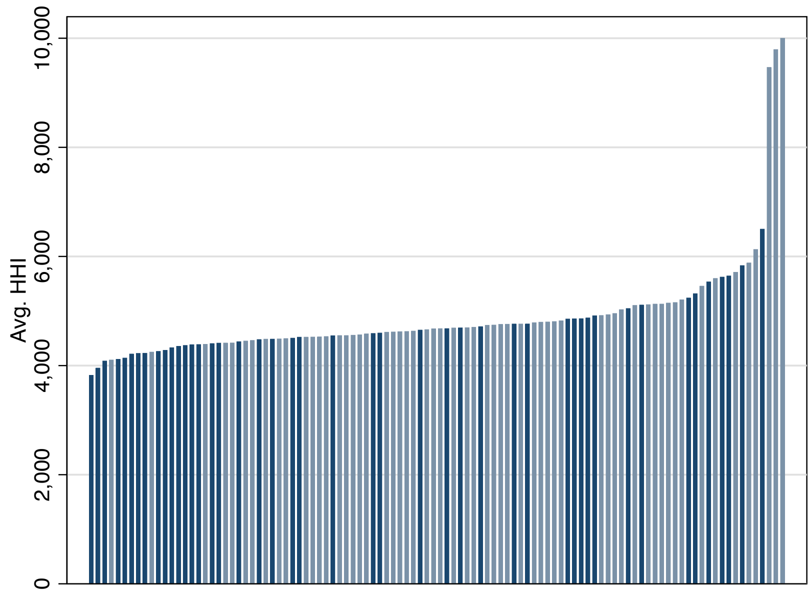
Data source: FAIRHealth.
Note: This figure presents histograms of charge updates for providers in the treatment and control groups. This displays the percentage of providers who update their charges each trimester.

Figure A.2.10: Provider Market Concentration



Notes: Provider market concentration in 2016, by procedure code, with each provider identified by the National Provider Identifier (NPI).

Figure A.2.11: Insurer Market Concentration



Notes: Insurer market concentration in 2016, by procedure code, with each insurer identified by a FAIR Health "key".

Table A.2.1: Provider-Level Results: Treatment Effect of NYHOST with Alternative Fixed Effects Specification

	log(Price)		log(Quantity)	
	(1)	(2)	(3)	(4)
	DiD	Triple Diff	DiD	Triple Diff
Treatment effect	0.0013	0.0075*	-0.0071	0.0009
	(0.0052)	(0.0042)	(0.0113)	(0.0071)
Observations	583469	583469	583469	583469
Adjusted R^2	0.945	0.946	0.601	0.601
ProcedureXGeozip FE	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes
ProcedureXTime FE		Yes		Yes
GeozipXTime FE		Yes		Yes
Provider FE	Yes	Yes	Yes	Yes

Notes: This table contains coefficients from a difference-in-differences regression of log(price) on an interaction between the treatment variable and a post indicator with different fixed effects configurations, including time (trimester-year), market (procedure X geozip), procedure X time, and geozip X time. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the category X geozip level.

Table A.2.2: Provider-Level Results: Robustness Test of the Treatment Effect on the Percentile of Providers' Charges

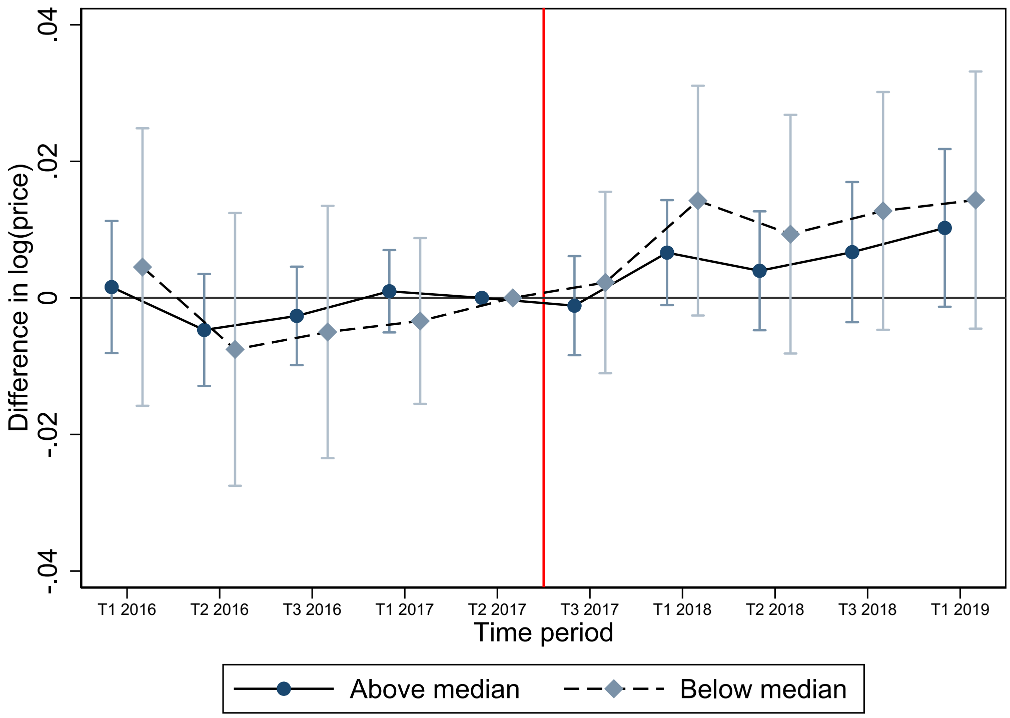
	(1)	(2)	(3)	(4)	(5)	(6)
	95th	95th	50th	50th	5th	5th
Treat*Post	0.003	0.012***	0.003	0.012***	0.007	0.016***
	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)
Constant	5.016***	5.013***	4.948***	4.945***	4.839***	4.837***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	510815	510815	510815	510815	510815	510815
Adjusted R^2	0.848	0.848	0.846	0.846	0.815	0.816
ProcedureXGeozip Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
ProcedureXPost Dummies		Yes		Yes		Yes
GeozipXPost Dummies		Yes		Yes		Yes

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

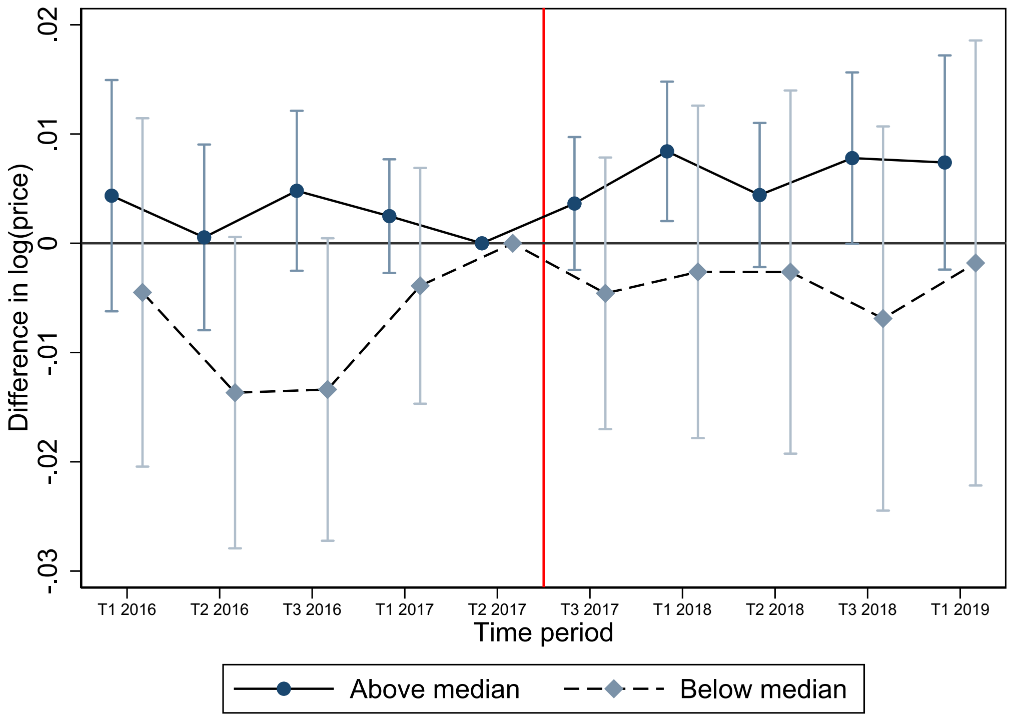
Notes: Fixed effects models with procedureXgeozip and time fixed effects. The DD estimates demonstrate the overall impact of NY HOST on the log of the percentile of a provider's charge (5th, 50th, and 95th percentile) each trimester as the outcome variable. The time fixed effects are measured the by the"Post"dummy variable, signifying the time period after the experiment went into effect. The triple difference-in-differences specification includes postXprocedure dummy variables and postXgeozip dummy variables.

Figure A.2.12: Event Study: Difference between Treatment and Control with Triple Differences-in-Differences Specification, for High vs. Low OON Volume Procedures



Note: This figure plots coefficients from a regression of log(price) on an interaction between treatment and trimester, with time (trimester-year), market (procedure X geozip), procedure X trimester, geozip X trimester, and provider fixed effects, for above and below median OON procedures. Treatment began at the start of trimester 3 in 2017. This event study corresponds to a triple difference-in-differences regression model specification. Standard errors are clustered at the category X geozip level.

Figure A.2.13: Event Study: Difference between Treatment and Control with Triple Differences-in-Differences Specification, for High Out-of-Network Procedures



Note: This figure plots coefficients from a regression of log(price) on an interaction between treatment and trimester and fixed effects for time (trimester-year), market (procedure X geozip), procedure X trimester and geozip X trimester for high OON procedures across above and below median price providers. Treatment began at the start of trimester 3 in 2017. This event study corresponds to a triple difference regression. Standard errors are clustered at the category X geozip level.

Table A.2.3: Provider-level results: Multiple Hypothesis Testing for Heterogeneity Tests by Category, for Price Effects

	(1)									
	CHIRO	CT	GASTRO	MRI	OB	OPHTHO	ORTHO	PSYCH	PTOT	RAD
P-Values	0.347	0.154	0.579	0.169	0.189	0.745	0.0980	0.0140	0.483	0.174
Q-Values	0.608	0.516	0.804	0.516	0.516	0.865	0.516	0.177	0.674	0.516

Notes: This table presents the p-values from the heterogeneity tests by category, from triple difference-in-differences specification with log(price) as the dependent variable, and the sharpened False Discovery Rate (FDR) q-values for multiple hypothesis testing.

Table A.2.4: Provider-level results: Multiple Hypothesis Testing for Heterogeneity Tests by Category, for Quantity Effects

	(1)									
	CHIRO	CT	GASTRO	MRI	OB	OPHTHO	ORTHO	PSYCH	PTOT	RAD
P-Values	0.870	0.672	0.678	0.144	0.0980	0.881	0.944	0.789	0.0560	0.0150
Q-Values	0.865	0.825	0.825	0.516	0.516	0.865	0.894	0.865	0.507	0.177

Notes: This table presents the p-values from the heterogeneity tests by category, from triple difference-in-differences specification with log(quantity) as the dependent variable, and the sharpened False Discovery Rate (FDR) q-values for multiple hypothesis testing.

Table A.2.5: Market-Level Regressions: Treatment Effect of NYHOST on Outcomes

	log(Price)		log(Quantity)	
	(1)	(2)	(3)	(4)
	DiD	Triple Diff	DiD	Triple Diff
Treatment effect	0.0127**	0.0176***	-0.0111	0.0149
	(0.0063)	(0.0055)	(0.0272)	(0.0131)
Observations	15871	15864	15871	15864
Adjusted R^2	0.994	0.995	0.940	0.987
ProcedureXGeozip FE	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes
ProcedureXTime FE		Yes		Yes
GeozipXTime FE		Yes		Yes

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table contains coefficients from difference-in-differences regression of log(price) on an interaction between treatment and a post indicator with time (trimester-year), market (procedure X geozip), procedure X time, and geozip X time fixed effects. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the procedure X geozip level.

Table A.2.6: Market-Level Regressions: Heterogeneity Tests for the Treatment Effect of NYHOST

	Coefficient of Variation		Continuous Procedures		OON Procedures		Market HHI		Website Use	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	¿Median	¡Median	Non-Continuous	Continuous	¿Median	¡Median	¿Median	¡Median	¿Median	¡Median
log(P) effect	0.0164*	0.0189***	0.0120	-0.0046	0.0083	0.0286***	0.0196**	0.0141**	0.0148**	0.0282**
	(0.0088)	(0.0069)	(0.0089)	(0.0088)	(0.0072)	(0.0083)	(0.0097)	(0.0058)	(0.0060)	(0.0121)
Observations	8045	7801	7653	4750	7827	8037	7922	7922	13406	2159
Adjusted R^2	0.994	0.996	0.995	0.984	0.996	0.993	0.993	0.998	0.995	0.997
ProcedureXGeozip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ProcedureXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GeozipXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$

Panel B: Quantity treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(Q) effect	0.0201	0.0183	0.0612***	-0.0506	-0.0213	0.0600***	0.0194	0.0086	0.0148	-0.0159
	(0.0154)	(0.0226)	(0.0171)	(0.0488)	(0.0219)	(0.0170)	(0.0270)	(0.0088)	(0.0151)	(0.0183)
Observations	8045	7801	7653	4750	7827	8037	7922	7922	13406	2159
Adjusted R^2	0.990	0.985	0.984	0.988	0.989	0.981	0.969	0.996	0.985	0.994
ProcedureXGeozip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ProcedureXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GeozipXTime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table contains coefficients from a regression of charges (constructed here as the log(price)) on an interaction between treatment and a post indicator with fixed effects for time (trimester-year), market (procedure X geozip), procedure X time and geozip X time corresponding to a difference in difference in difference regression testing for heterogeneity. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the procedure X geozip level.

Table A.2.7: Market-Level Regressions: Treatment Effect of NYHOST by Category

	(1) CT	(2) MRI	(3) RAD	(4) GI	(5) EYE	(6) ORTHO	(7) OB	(8) PSYCH	(9) PTOT	(10) CHIRO
Panel A: Charge treatment effects										
log(P) effect	-0.01550	0.08102***	-0.02828	-0.00601	-0.00679	0.02856	0.00558	-0.00928	-0.00500	0.02081
	(0.02119)	(0.02502)	(0.02057)	(0.02529)	(0.01567)	(0.02107)	(0.01726)	(0.01009)	(0.01224)	(0.01465)
Observations	1240	1550	1766	930	1240	1858	1239	1549	1985	1219
Adjusted R^2	0.955	0.887	0.936	0.965	0.997	0.984	0.995	0.939	0.980	0.937
ProcXZip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
* $p < .10$, ** $p < .05$, *** $p < .01$										
Panel B: Quantity treatment effects										
log(Q) effect	0.06304*	0.08516***	-0.21411	-0.00588	0.06716**	-0.04532	0.11407**	0.01925	-0.03083	-0.09618
	(0.03725)	(0.02756)	(0.13690)	(0.02968)	(0.03316)	(0.03495)	(0.05126)	(0.03232)	(0.05479)	(0.09246)
Observations	1240	1550	1766	930	1240	1858	1239	1549	1985	1219
Adjusted R^2	0.980	0.974	0.613	0.989	0.982	0.977	0.968	0.990	0.965	0.970
ProcXZip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trimester FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table presents the regression results when stratifying the procedures by category. This table contains coefficients from a regression of log(price) and log(quantity) on an interaction between treatment and a post indicator with fixed effects for time (trimester-year) and market (procedure X geozip) corresponding to a difference in difference regression for each procedure category. Treatment began at the start of trimester 3 in 2017. Standard errors are clustered at the procedure X geozip level.