Consumer Preferences over Retail Channels: Evidence from Emergency Contraceptives *

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Abstract

I study the preferences of consumers over different retail channels (drug store, mass merchandiser, or grocery store) for purchasing over-the-counter emergency contraceptives (EC). Using monthly EC sales in Texas from 2017 to 2019, I estimate consumer preferences using a BLP discrete choice model. My results show that consumers are sensitive to prices, and that they exhibit preferences for specific retail channels but not for branded vs generic products. To address recent policy debates, I conduct counterfactual simulations banning the sale of EC from grocery or mass merchandiser stores. I find that this would result in 5-8% increase in the number of consumers who do not buy EC.

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

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1. Introduction

In the analysis of consumer preferences for products, the retail channel is frequently overlooked as a key aspect of product differentiation. However, the manner in which a product is showcased, marketed, and supported across various retail settings can significantly influence consumer perceptions and choices. This encompasses elements such as the in-store experience, quality of customer service, and product availability. Recognizing the importance of retail channels in differentiating products calls for a more integrated approach to understanding consumer preferences.

In this paper, I study the preferences of consumers over different retail channels (drug store, mass merchandiser, or grocery store) for purchasing over-the-counter emergency contraceptives (EC). I use monthly EC sales in Texas over the period 2017 to 2019 from the Nielsen's Retail Scanner (RMS) and estimate consumer preferences using a BLP discrete choice model.

Analyzing the consumers' preferences over retail channels for purchasing over-the-counter emergency contraceptives (EC) is interesting for several reasons. First, emergency contraceptives, often referred as the 'morning-after' pill, have been sold over-the-counter since 2006 and without age restriction since 2014. This imply that any retail store without a pharmacy inside could offer the pill. Second, from the consumers' perspective, the retail environment for purchase might matter significantly due to the existing stigma around buying this product. According to a survey carried by one of the manufacturers of EC, 12% of women said they would travel to a different town to buy EC to avoid seeing anyone they knew in the pharmacy. Third, emergency contraceptives have sparked controversy around their availability and there where instances where retail chains implemented corporate policies that restricted access to EC. For instance, in the late 1990's Wal-Mart chose not to sell the pill (The Ledger (1995) and ACSH (2006)). In 2006, the retail chain, Target, permitted its pharmacists to refuse filling EC prescriptions (NPR (2005)).

In order to examine the preferences of consumers over different retail channels, I estimate a discrete choice model in which consumers within a market can choose between two types of EC, branded or generic versions of the pill, in three different retail channels (drug, grocery, or mass merchandiser stores). I define a market as a county-year-month combination. Each consumer can choose one of the six differentiated options or an outside option, which accounts for not buying EC or from purchasing the pill from other place. The model follows the random coefficient discrete choice model proposed by Berry, Levinsohn, and Pakes (1995) (also called 'BLP' model) and allows substitution patterns to reflect consumer's heterogeneity in preferences for observed product characteristics, which include price, brand type, and indicator for the retail channel were they were purchased. Specifically, the heterogeneity in consumers' preferences are captured by coefficients on interactions of product characteristics with consumer demographics, which include income, an indicator for bachelor's degree or higher, and an indicator for age 20 to 34. The model allows me to recover consumers' marginal utility from price, brand type, and from using the three different channels. The analysis of marginal utilities associated with choosing specific retail channels can reveal whether consumers exhibit preferences for certain channels. Furthermore, using the estimated parameters, I calculate market share price elasticities to assess consumers' sensitivity to price changes.

To investigate the implications of past policy debates, wherein certain retail chains decided not to sell emergency contraceptives (EC), I simulate counterfactual scenarios where the sales of EC are banned from grocery or mass merchandiser stores. In these simulations, I examine the effects of such policies by quantifying the potential number of consumers who might refrain from purchasing EC if its sale were restricted in specific retail channels. Given that the outside option includes both consumers who opt not to purchase EC and those who would obtain it from alternative sources, my findings provide an upper limit estimate of the number of consumers who would avoid buying EC under these counterfactual scenarios.

Analyzing the demand for emergency contraceptives (EC) presents a significant challenge, primarily because the market size for this product is uncertain. Women do not use EC regularly, as it is typically needed following unexpected events. To address this, I estimate the model under varying assumptions about market size. Firstly, I consider the entire female population of reproductive age (15 to 44 years) in a specific county-year as the market size. This approach results in large market shares for the outside option (averaging 99.28 percent), highlighting it as a major substitute for the EC products and retail channels observed in the data. Secondly, I assume that the ECs captured in the data represent 83% of the total EC purchases that could have occurred in the market. This is grounded in findings from the 2017-2019 National Survey of Family Growth (NSFG), where 55% of women who have ever used EC obtained it from drug stores, and 28% from non-pharmacy retail outlets (such as Target, Walmart, etc.). This approach to estimating potential market size, often referred to as the 'potential market factor' method, has been employed in Gayle and Lin (2022) and in Ivaldi and Verboven

(2005).

The findings of this study reveal that consumers are sensitive to prices, and that they exhibit preferences for specific retail channels but not for branded vs generic products. Particularly, consumers with lower incomes exhibit a greater sensitivity to price changes compared to their higher-income counterparts. The counterfactual simulations, which involve banning the sale of emergency contraceptives from grocery or mass merchandiser stores, predict a 5-8% increase in the number of consumers choosing not to purchase emergency contraceptives as a result. Furthermore, an approximate calculation suggests that if sales of EC were prohibited in grocery and mass merchandise stores, there could be a monthly decrease of 18 and 30 EC purchases, respectively, in the analyzed Texas counties under the counterfactual scenario.

This paper represents a novel approach in the analysis of consumer preferences over retail channels for purchasing products, as it is the first, to my knowledge, to use market-level data and a BLP discrete choice model for this purpose. For example, Håkonsen et al. (2016) explored consumer preferences in the deregulated Swedish pharmacy market using an online survey of 2,594 adults, focusing on factors like geographic proximity and product range. Similarly, Titiloye et al. (2023) examined consumers' grocery shopping preferences in Florida during the Covid-19 pandemic, utilizing a hypothetical discrete choice experiment with 1,229 participants. However, in contrast to these studies that relied on stated preferences through surveys, my research employs observational data, specifically utilizing EC sales data from the NielsenIQ Retail Scanner. This approach not only reflects actual consumer choices but also offers a more direct and potentially accurate insight into consumer behavior in retail channels, differentiating it significantly from prior research methods that were based on hypothetical scenarios.

This paper contributes to the literature focused on understanding the dynamics of emergency contraceptive (EC) purchases in the United States. Mallatt (2019), for instance, investigates the impact of pharmacist refusal legislation on contraceptive purchasing behaviors. These laws delineate the rights of medical professionals to deny drugs and medical services due to personal objections. Mallatt's findings suggest that policies either broadening or limiting patients' access to contraception slightly increase the adoption of regular birth control pills, subsequently leading to decreased purchases of condoms and over-the-counter emergency contraceptives. Similarly, Fischer, Royer, and White (2018) research examines the effects of reduced access to abortion and family planning services in Texas. Their study reveals that such restrictions do not significantly alter emergency contraceptive purchasing patterns.

The structure of this paper is laid out across six sections for comprehensive analysis. Section 2 provides a historical and regulatory overview of emergency contraceptives. Section 3 details the data sources utilized in this study. Section 4 describes the discrete choice model used, including the identification and estimation strategies. Section 5 presents the results derived from the model's estimation. Section 6 explores various counterfactual scenarios and their implications. Finally, Section 7 concludes.

2. Background

Oral emergency contraceptives (EC) significantly increase the chance of preventing pregnancy when taken immediately after unprotected sex or contraceptive failure. For women, access to EC is crucial as it provides a last opportunity to prevent unwanted pregnancy before considering abortion. The accessibility of EC in the United States has evolved considerably over the past two decades.

In 1999, the FDA approved the first prescription drug for emergency contraception. Subsequent debates centered on whether the morning-after pill should be available without a prescription. In response, the FDA reclassified EC status in 2006, making it over-the-counter (OTC) for women aged 18 and older. Before this ruling, nine states had enacted Collaborative Practice Agreements (CPAs), enabling women to purchase EC from pharmacies without a doctor's appointment. Washington was the first state to allow OTC sales of EC in 1998, followed by California (2002), Alaska, Hawaii, and New Mexico (2003), Maine (2004), Massachusetts (2005), and New Hampshire and Vermont (2006).

Subsequently, there were three more significant federal regulatory changes. In July 2009, the FDA lowered the OTC age restriction to 17 years and older. This was followed by an expansion in April 2013 to include those 15 and older. Finally, in June 2013, the FDA removed all age restrictions, allowing unrestricted OTC access to EC.

Several studies have examined the impact of enhanced access to emergency contraceptives (EC) on fertility-related outcomes and risky sexual behaviors (Durrance 2013; Mulligan 2016; Cintina 2017; Zuppan 2012).[1] These studies generally indicate an increase in sexually transmitted diseases (STDs), particularly among teenagers. However, there is no definitive evidence regarding the effects on birth rates and abortions. Compta (2021) investigated the effects of the latest FDA's regulatory change that made emergency contraceptives available to women of all ages on teen birth rates and birth outcomes. His

[1] For a more detailed review on this literature see Bailey and Lindo (2017).

research found that removing the OTC age restriction for those aged 16 and under led to a 9.41% decrease in teen births. However, it did not significantly affect birth outcomes.

From a consumers' perspective, the retail environment for purchase might matter significantly due to the existing stigma around buying this product. A survey conducted by an EC manufacturer revealed that 58% of women felt embarrassed about obtaining the morning-after pill. Additionally, the survey found that one in eight women would travel to another town to purchase EC, avoiding recognition by acquaintances. Furthermore, 26% of women said they would wait until the pharmacy was empty before buying EC.[2]

Availability also poses a challenge: a 2018 survey by ASEC (2018) reported that 18% of sampled stores did not stock EC. Another study in Southwestern Pennsylvania in the same year found that 32% of pharmacies in the region did not carry EC (Orr et al. 2021). These findings highlight significant barriers to access, both in terms of social stigma and product availability.

In the wake of recent abortion restrictions in the US, emergency contraceptives (EC) have come into the spotlight, prompting policymakers to seek new ways to improve their accessibility and affordability. A significant legislative development in this area is the Illinois Public Higher Education Act (SB 1907), enacted in May 2023. This Act requires all public colleges and universities in the state to install at least one vending machine on campus that dispenses emergency contraception at a reduced price.

The use of emergency contraception (EC) among sexually experienced women has notably increased: from 4% in 2002 to 25% in 2017-2019. The highest usage is observed in young adult women aged 20–24, at 38%, followed by those aged 25 to 34. There's a clear correlation between educational attainment and EC usage; 27.9% of women with at least a bachelor's degree have used EC, compared to 12.6% among those without a high school diploma or GED. Furthermore, Hispanic and non-Hispanic black women are more likely to have used EC than non-Hispanic white women, with a usage rate of 23.9%. (See table A1 in Appendix).

3. Data

In this section, I describe data sources and sample construction. The primary dataset for this study is sourced from the NielsenIQ Retail Scanner Data, courtesy of the Kilts

[2] See: The Pharmaceutical Journal, PJ, October 2018, Vol 301, No 7918;301(7918):DOI:10.1211/PJ.2018.20205577 and ellaone.

Center for Marketing at the University of Chicago. In addition, I use data on county level economic and demographic characteristics collected from public sources.

3.1. NielsenIQ Retail Scanner Data

In this study, I utilize data from Nielsen's Retail Scanner ('RMS') to track purchases of OTC emergency contraceptives by product and retail channel for the period 2017-2019. The RMS dataset comprises weekly data on pricing, sales volume, and store environment, captured by point-of-sale systems from over 50,000 grocery, drug, mass merchandiser, and other stores across US markets. It provides detailed insights into weekly prices and units sold at the store level for a variety of products, including female contraceptives.[3]

However, it is important to note that the RMS data is not exhaustive; it does not cover the entire universe of stores in the United States, nor is it representative at the national, state, or county levels – its representativeness is limited to the store level. The coverage includes over half of the total sales volume for US grocery and drug stores, but only around 30% of the total sales volume for US mass merchandisers. For instance, in 2019, total OTC female contraceptive sales from Kilts-affiliated stores accounted for 51% of NielsenIQ's reported total U.S. sales across all outlets.[4] In this paper, I categorize drug stores as the 'pharmacy retail channel,' and grocery and mass merchandiser stores as the 'non-pharmacy retail channel'.

To construct the working sample, I aggregate prices and quantities purchased at the market-choice level, where 'market' is defined as a county-year-month combination, and 'choices' are unique combinations of emergency contraceptive type (branded or generic) and retail channel (drug, grocery, or mass merchandiser). Due to computational challenges associated with estimating the discrete choice model for a larger dataset, my analysis is focused on Texas. Specifically, I have created a panel comprising 81 counties over 36 months between 2017 and 2019, resulting in 2,916 market in my sample. Figure A2 in the Appendix A displays the counties included in the sample, and detailed information on sample construction is presented in the Appendix B.

Table 1 presents the means and standard deviations for price and units sold, categorized by choices. Prices are reported as volume sales-weighted average prices and have been deflated to 2019 dollars using the Consumer Price Index for Urban Consumers for all items. 'Units sold' represents the total number of emergency contraceptives sold in a

[3]See NielseIQ Retail Scanner Data, Kilts Center for Marketing for a detailed description of the data.
[4]Data on US total OTC sales for female contraceptives comes from Consumer Health Care Products Association.

Table 1. Market level summary statistics of six choices

	Generic Drug	Branded Drug	Generic Grocery	Branded Grocery	Generic Mass	Branded Mass
Price (dollars of 2019)	34.72	43.56	31.47	42.44	34.15	41.63
	(0.67)	(0.79)	(5.64)	(1.97)	(1.35)	(1.65)
Units Sold	248.83	248.32	33.63	33.06	43.30	54.74
	(610.67)	(691.62)	(58.10)	(59.94)	(71.39)	(90.55)

Notes: Table reports means and standard deviation in parentheses.
Prices are adjusted to 2019 dollars. N=10,458.

specific county-year-month for each choice.

On average, generic ECs are less expensive than the branded EC, irrespective of the retail channel. Price comparisons across store types reveal that, on average, branded ECs are marginally less expensive in grocery and mass merchandiser stores than in drug stores, while generic ECs cost less in food stores. Notably, there is considerable price dispersion among generic products in grocery stores, likely due to a broader selection of generic brands available compared to other channels. Within each retail channel, drug and grocery stores tend to have an equal split in volume sales between branded and generic ECs. However, in mass merchandiser stores, branded EC outsell generics. Drug stores dominate in terms of EC sales volume compared to non-pharmacy retailers, as also depicted in Figure A1 in the Appendix.

It is important to remember that the RMS data does not represent the entire national or Texas market and varies in coverage by retail channel, with only 30% of mass merchandiser sales captured. Therefore, the lower EC purchases from mass and grocery stores could be influenced by both the limited data coverage of non-pharmacy channels and consumer preferences. According to the 2017-2019 National Survey of Family Growth (NSFG), 55% of women who have used EC obtained it from drug stores, while 28% sourced it from non-pharmacy retail stores (like Target, Walmart, etc.). In contrast, in the RMS data, drug stores account for 88% of total EC sales volume, with mass merchandiser and grocery stores contributing only 12%. This suggests a potential oversampling of drug stores and undersampling of mass merchandiser and grocery stores in the RMS dataset.

Two key sources of variation in the data are instrumental in identifying the parameters of the model: firstly, the variation in prices across different products (branded vs. generic EC), retail channels, and markets; and secondly, the variation in the availability of choices across markets. In only 18% of the total markets are all choices available for consumers, while in 40% of the markets, consumers can only purchase EC from drug stores. Specifically, in 31 counties in Texas over the 36 months between 2017 and 2019, EC was available exclusively in drug stores. On average, each market offers 3.6 choices. Table A2 in the Appendix details the number of markets segmented by the number of choices available.

3.2. Choices

Before detailing the consumer choice model for purchasing over-the-counter (OTC) emergency contraceptives, it is essential to define what constitutes a 'choice' and a 'market' in this context. As with many pharmaceuticals, consumers of OTC emergency contraceptives face the decision between brand-name drugs (also referred to as 'branded') and their generic counterparts. Although both the branded and generic versions contain the same active ingredient and dosage, and generics are typically less expensive, consumers might still prefer the branded EC over generics. This preference may be attributed to the perception of higher quality associated with brand-name products, brand loyalty, or misconceptions regarding the efficacy of generic drugs.

Unlike prescription drugs, OTC drugs, including emergency contraceptives, are available through a multitude of retail channels. Consumers can acquire these from pharmacies, non-pharmacy retail outlets (such as grocery stores, mass merchandiser stores, convenience stores, vending machines), and online sources. In my model, a 'choice' is defined as a specific combination of the type of EC (branded or generic) and the retail channel. However, the scanner data I use only records purchases of OTC emergency contraceptives from drug stores, food stores, and mass merchandisers. Consequently, within a market, consumers have potentially six choices (branded or generic from each of the three retail channels) plus an 'outside option,' which represents purchasing from other retailers or not buying the product at all. The characteristics of each observed choice in the data include the price, an EC-type indicator (assigned a value of 1 for branded EC and 0 for generic), and retail channel type dummies (drug, grocery, and mass merchandiser).

3.3. Market Definition and Market Size

In estimating discrete choice models for products, it is standard practice to approximate observed choice probabilities with market shares of products and to include an 'outside option' in the choice set. For the purposes of my analysis, I define a 'market' as a county-year-month combination. This decision is driven by two factors: 1) the infrequency of emergency contraceptive purchases, and 2) the smallest geographic unit to locate the store in the Nielsen data is the county level. Since consumers have reported to travel to other towns to buy emergency contraceptives, the definition of the market at the county level is plausible. While data on total quantities purchased are available, the extent of the outside good remains unobserved. To address this, the common approach is to assume a market size, representing the number of potential purchases that could occur within a given market.

In the context of emergency contraceptives, it is difficult to know what is the market size as women do not use emergency contraceptives regularly and they need it after an unexpected event.[5] To address this, I estimate the model with different assumptions on the market size. Firstly, I consider the entire female population of reproductive age (15 to 44 years) in a specific county-year as the market size. This approach results in large market shares for the outside option (averaging 99.28 percent), highlighting it as a major substitute for the EC products and retail channels observed in the data. Secondly, I assume that the ECs captured in the data represent 83% of the total EC purchases that could have occurred in the market. This is grounded in findings from the 2017-2019 National Survey of Family Growth (NSFG), where 55% of women who have ever used EC obtained it from drug stores, and 28% from non-pharmacy retail outlets (such as Target, Walmart, etc.). Under this assumption, the potential market size (later denoted as M_m) is equal to the observed total quantities purchased in a market (Q_m) multiplied by the inverse of 83% (or 1.2). Thirdly, I assume that the market size is 30% larger than the total quantities purchased in the data, so I multiply Q_m by 1.3. This approach, known as the 'potential market factor' method has been used in Gayle and Lin (2022) and in Ivaldi and Verboven (2005).

3.4. Demographic and Socio-Economic Data

I complement the market level data with demographic and socioeconomic characteristics at the county-year level from diverse public sources. I utilize annual estimates of county populations by gender, age, and race from SEER (2016) to construct demographic variables. These include the proportion of the female population aged 15 to 44 who are 20 to 34 years old, and the fractions of Hispanic and black women. I use the American Community Survey (ACS) 5-year estimates to calculate the fraction of the female popu-

[5] It is not recommended to use emergency contraception as a routine birth control method.

lation aged 18 to 44 with a bachelor's degree or higher. I use per capita income from the Bureau of Economic Analysis and monthly unemployment rate from the Bureau of Labor Statistics. Finally, I use the 2013 Rural-Urban Continuum Codes from the U.S. Department of Agriculture to construct a metropolitan county indicator variable that takes the value of 1 for counties in metropolitan areas, and a value of zero for counties that are adjacent to a metro area. The Rural-Urban Continuum Codes distinguishes metropolitan counties by the population size of their metro area, and non-metropolitan counties by degree of urbanization and adjacency to a metro area.

Panel A to D in Table A3 reports pooled summary statistics of the primary variables used in the estimation of the model described in section 4 and Panel E provides summary statistics for the demographic variables used to simulate consumers.

4. Discrete Choice Model

To model the preferences of consumers over different retail channels (drug store, mass merchandiser, or grocery store) for purchasing over-the-counter emergency contraceptives (EC), I utilize an adapted version of the standard random coefficient discrete choice model proposed by Berry, Levinsohn, and Pakes (1995). In each market $m \in M$, there is a set of consumers, indexed by i and a set of choices, indexed by $j \in J$ and an outside option.[6] Consumers' choices in my model are determined by the combination of the type of emergency contraceptive — branded or generic — and the retail channel through which they purchase OTC EC, such as drug stores, grocery stores, or mass merchandisers. The outside option accounts for the choice of not purchase EC from any of the observed retailers, or from not buying EC at all. An example of a retail channel not included in the data would be online shopping (although only 1% get EC from on-line).

The utility of consumer i from choosing option j in market m is given by:

$$U_{ijm} = \boldsymbol{\beta_i x_{jm}} + \xi_{jt} + \varepsilon_{ijt} \tag{1}$$

where $\boldsymbol{x_{jm}} = (x^1_{jm}, ..., x^K_{jm})'$ is a vector of the observed choice's characteristics that includes price, an EC type indicator (assigned a value of 1 for brand-name EC and 0 for generic), and a comprehensive set of retail channel type dummies. The term ξ_{jt} represents choice characteristics that are observable to consumers but not to the econometrician. These characteristics may include factors like the store's distance from

[6] In the data there is variation across markets in the choice set. See Table A2 in the Appendix. To simplify the notation, I do not index J with m, i.e. the variation in the set of choices across markets.

the consumer, its opening hours, store's environment, and other similar aspects. ε_{ijt} is an individual random shock with mean zero drawn from a Type-I extreme value distribution.

Consumer preferences for the various choice characteristics in the model are captured by the parameters $\boldsymbol{\beta_i} = (\beta_i^1, ..., \beta_i^K)$, and these vary across consumers based on demographic variables $\boldsymbol{d_i}$ and unobserved individual attributes $\boldsymbol{\nu}_i$:

$$\beta'_{\boldsymbol{i}} = \beta + \boldsymbol{\Pi} \boldsymbol{d_i} + \boldsymbol{\Sigma \nu}_i \tag{2}$$

where $\boldsymbol{\beta}$ is a $(K \times 1)$ vector of preference parameters of choice characteristics that are common across consumers. Heterogeneity in consumer preferences for observed product characteristics is captured by the parameters in the matrix $\boldsymbol{\Pi}$ of size $(K \times D)$, and the scaling matrix $\boldsymbol{\Sigma}$ of size $(K \times K)$. The vector of 'observed' demographic variables for each individual, $\boldsymbol{d_i}$, includes the log of income, an indicator for age 20 to 34, and an indicator for bachelor's degree or higher.[7] I do not directly observe $\boldsymbol{d_i}$ for each individual, instead, I observe the joint non-parametric distribution of some demographics from the ACS. Finally, $\boldsymbol{\nu}_i = (\nu_i^1, ..., \nu_i^K)'$ are unobserved individual characteristics, which are drawn from independent standard normal distribution with mean zero.

Note that setting $\boldsymbol{\Pi}$ and $\boldsymbol{\Sigma}$ to zero in the equation (2) reduces it to a typical homogenous logit model, where $\boldsymbol{\beta}_i = \boldsymbol{\beta}$. However, the random coefficient model, by allowing for interactions between consumer demographic characteristics and product characteristics, yields more realistic substitution patterns compared to the logit model.

The choice set in the model is completed by defining the utility of the 'outside option' denoted by the index $j = 0$. I normalized the utility of the outside option by assuming that its price and other characteristics are zero. That is, $u_{i0m} = \varepsilon_{i0m}$.

By substituting (2) in (1), I can re-write the utility as:

$$\begin{aligned} U_{ijm} &= \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm} \quad \text{where,} \\ \delta_{jm} &= \boldsymbol{\beta x_{jm}} + \xi_{jm} \\ \mu_{ijm} &= (\boldsymbol{\Pi d_i} + \boldsymbol{\Sigma \nu}_i)\boldsymbol{x_{jm}} \end{aligned} \tag{3}$$

where δ_{jm} represents the utility from choice j that is common to all consumers in that market m, μ_{ijm} captures heterogeneity in consumer tastes for observed product characteristics, and ε_{ijm} is an idiosyncratic individual-specific taste that is assumed to

[7] I chose these demographics because they are correlated with a higher use of emergency contraceptives (see Table A1 in Appendix).

be independent and identically distributed. As in Nevo (2000), I denote the parameters of the model as $\theta = (\theta_1, \theta_2)$, where $\theta_1 = \beta$ are the linear parameters, and $\theta_2 = (\Pi, \Sigma)$ non-linear parameters. I estimate specifications of the model where I control for different sets of time fixed effects (FE) and county-level characteristics. These include the monthly unemployment rate, an indicator for metropolitan counties, and the proportions of black and Hispanic women of reproductive age (15 to 44 years old). These controls are integrated into the linear parameters of the model.

Each consumer chooses the option that gives her the highest utility, that is $U_{ijm} > U_{ilt}, \forall j \neq l$.[8] From the model, an individual is characterized by the vector $(\boldsymbol{d_i}, \boldsymbol{\nu_i}, \boldsymbol{\varepsilon_{im}})$, this implicitly defines the set of demographics and unobserved variables for which consumer i will choose option j: $A_{jm}(\boldsymbol{x}, \delta_m(\beta), \theta_2) = \{(\boldsymbol{d_i}, \nu_i, \boldsymbol{\varepsilon_i} \mid U_{ijm} > U_{ilt} \text{ for } l = 0, 1, ..., J)\}$, where $\boldsymbol{x}$ are the observed choice characteristics, $\boldsymbol{\delta_m} = (\delta_{1m}, ..., \delta_{Jm})$, and $\boldsymbol{\varepsilon_{im}} = (\varepsilon_{i1m}, ..., \varepsilon_{iJm})$.

The predicted market share of choice j can be obtained by integrating over the mass of individuals in region A_{jm}. Given the distribution of $(\boldsymbol{d_i}, \boldsymbol{\nu_i}, \boldsymbol{\varepsilon_{im}})$, and assuming that ε_{ijm} follows a Type I extreme value distribution, the predicted market shares from the model are given by:

$$s_{jm}(\boldsymbol{x}, \delta_m(\beta), \theta_2) = \int \frac{\exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{j=1}^{J} \exp(\delta_{jm} + \mu_{ijm})} dF(\boldsymbol{d_i}, \boldsymbol{\nu_i}) \tag{4}$$

The integral in equation (4) is computed through simulation. This is achieved in the standard manner by drawing a sample of $NS = 200$ consumers from the distribution of demographics in each market. For each simulated consumer, I calculate the predicted individual probabilities of choosing each option j. These probabilities are then averaged across simulations to obtain an approximated value for the integral:

$$\hat{s}_{jm} \approx \frac{1}{NS} \sum_{i=1}^{NS} \frac{\exp\left[\delta_{jm} + \boldsymbol{(\Pi d_i + \Sigma \nu_i) x_{jm}}\right]}{1 + \sum_{j=1}^{J} \exp\left[\delta_{jm} + \boldsymbol{(\Pi d_i + \Sigma \nu_i) x_{jm}}\right]} \tag{5}$$

where $\boldsymbol{\nu_i}$ and $\boldsymbol{d_i}$ are draws from $N(0, I)$ and $F_d^*(d)$, respectively. In the next section, I explain with more detail how I estimate the model parameters.

[8] Consumers are assumed to purchase one unit of the product.

4.1. Estimation and Identification

In the preceding section, I detailed a model of consumer behaviour and the parameters governing the distribution of consumer tastes. This subsection focuses on the methodology for estimating these model parameters, utilizing the aggregate market share data for over-the-counter (OTC) emergency contraceptives, as discussed in Section 3.1.

I estimate the model parameters employing the Generalized Method of Moments (GMM) estimator, in conjunction with the nested fixed point (NFXP) algorithm proposed by Berry, Levinsohn, and Pakes (1995).[9] Identification relies on moment conditions:

$$E[\xi_{jm}(\theta) \mid \boldsymbol{Z_{jm}}] = 0 \tag{6}$$

where ξ_{jm} are the unobserved choice characteristics, and $\boldsymbol{Z_{jm}}$ are excluded instruments. This, allows me to construct the following nonlinear GMM estimator by interacting the residuals with the instruments:

$$\hat{\theta} = \min_{\theta} = \boldsymbol{\xi(\theta)' Z W Z' \xi(\theta)} \tag{7}$$

where $\boldsymbol{\bar{\xi}(\theta)} = [\boldsymbol{\xi_1(\theta)}, ..., \boldsymbol{\xi_M(\theta)}]'$, $\boldsymbol{Z}$ is the matrix of instruments, and $\boldsymbol{W}$ is the weighting matrix. To obtain the estimates in (7), I use the standard two-step procedure for GMM estimation.[10] First, I set $\boldsymbol{W} = (\boldsymbol{Z'Z})^{-1}$, and run the full procedure to obtain θ^{step1}. In the second step, I recompute $W = (\frac{1}{J}\sum_j Z_j' \xi_j \xi_j' Z_j)^{-1}$ using the estimated values of $\hat{\xi}_j(\theta^{\text{step1}})$ from the first step, and re-run the full procedure using this optimal weighting matrix to obtain the final estimates, θ^{step2}.

Instruments play a crucial role in the estimation process for two key reasons. Firstly, they are necessary to generate sufficient moment conditions for identifying the nonlinear parameters θ_2 in the consumer's utility functions. Secondly, they address the potential endogeneity of prices ($cov(\xi_{jm}, p_{jm}) \neq 0$). This endogeneity issue arises because firms may set prices considering unobserved product characteristics. To tackle this, I use prices of the same product in geographically closed counties as indirect measures of cost (Hausman, Leonard, and Zona 1994, and Nevo 2001). The relevance of these instruments stems from the premise that prices across markets are likely correlated due to shared cost shocks.

[9] For further details about the BLP method see Berry (1994), and Nevo (2000).

[10] This is also known as the optimal GMM estimator (see Cameron and Trivedi 2005). The main benefit from using this procedure is that the optimal weighting matrix minimizes the variance of the GMM estimator.

The first set of instruments include the price in the second closest county, interacted with the average income in the market, along with the prices in the 8th, 9th, and 10th closest counties. To assist in the identification of the heterogeneity parameters, $\boldsymbol{\theta_2}$, I include average demographics characteristics as additional instruments. These include the average proportion of the female population with a bachelor's degree or higher, and the percentage of the female population aged 20 to 34.

4.1.1. NFXP Algorithm

The standard BLP approach uses a NFXP algorithm, where the minimization of the objective function in equation (7) is subject to the constraint that model predicted shares are equal to observed market shares from the data:

$$\hat{s}_{jm}(\boldsymbol{\delta}_{jm}, \theta_2) = S_{jm} \tag{8}$$

where the right hand side of equation (8) is calculated using equation (5), and the observed markets shares are calculated as:

$$S_{jm} = \frac{q_{jm}}{M_m} \tag{9}$$

where q_{jm} are units sold for option j in market m, and the *market size* M_m is either: 1) the female population in fertile age in a given county-year, or 2) the total quantities purchased of EC in a market Q_m multiply by a potential market factor $1+r$, where $r = 0.2$, or 3) $M_m = Q_m \times 1.3$. The market share of the outside option is just $S_{0m} = 1 - \sum_{j=1}^{J} S_{jm}$ for all m.

To solve for the system of equations in (8), Berry, Levinsohn, and Pakes (1995) show that for a given θ_2, $\delta(\beta)$ can be recovered by inverting (8) using the contraction mapping:

$$\delta_m^{h+1} = \delta_m^h + \log(\hat{s}_{jm}) - \log(S_{jm}) \quad h = 0, \ldots, H \tag{10}$$

where H is the smallest integer such that $\| \delta_m^{h+1} - \delta_m^h \|$ is smaller than some tolerance level, and $\delta_{.t}^H$ is the approximation to $\delta_{.t}$.

As in Nevo (2000), with $\delta(\theta_2)$ resulting from the contraction mapping, I can estimate $\boldsymbol{\beta}$ using linear IV-GMM:

$$\hat{\boldsymbol{\beta}} = [X_1' Z(Z'Z)^{-1} Z' X_1]^{-1} X_1' Z(Z'Z)^{-1} Z' \delta_{jm} \tag{11}$$

Then, to construct the objective function, I use $\hat{\beta}$ to compute the unobserved choice characteristics as:

$$\xi_{jm}(\theta) = \delta(\theta_2) - \hat{\beta}\boldsymbol{x_{jm}} \tag{12}$$

Finally, I perform a non-linear search of $\boldsymbol{\theta_2}$ that minimizes the objective function with the previous steps nested for every trial of θ_2. See Appendix C for details on the computational implementation of the BLP algorithm.

In the estimation, the standard errors allow for both heteroskedasticity and correlation of the errors ξ_{jm} across choices within a market.

5. Estimation Results

In this section, I present results of the estimated model based on two assumptions: 1) the market size is equivalent to the female population of fertile age, and 2) the market size is 20% larger than the total quantities of emergency contraceptives purchased, as recorded in the data. Additionally, for a sensitivity analysis of these results, Table A5 in Appendix A displays results based on the assumption that the market size is 30% larger than the total quantities purchased in the data.

5.1. Parameter estimates with market size as female population in fertile age

Homogeneous Logit. Results for the homogeneous logit model using three different sets of instruments are reported in Table A4. In this model, tastes do not vary across individuals, so $\boldsymbol{\Pi}$ and $\boldsymbol{\Sigma}$ are set to zero in equation (2). In this case, the mean utility can be recovered analytically with $\delta_{jm} = \log s_{jm} - \log s_{0m} = \boldsymbol{\beta x_{jm}} + \xi_{jm}$. The results from the homogeneous logit serve as benchmark to compare the full heterogeneity coefficient models. First, all coefficients on choice characteristics are statistically significant, indicating that these variables are relevant determinants of average consumer utility. As expected, a higher price generates dis-utility to consumers, and utility increases with the branded version of the pill. The coefficients on the retail channel type are negative and large in magnitude implying that consumers have strong preferences over the retail channel were they shop. I report the first stage F statistics in Table A4 to get a sense of the strength of the different instrument sets that I use in the estimation of the full coefficient model. The three instrument sets pass the conventional weak IV test (F > 10) indicating that the instruments are not week. However, because the full model I estimate is nonlinear, these tests are merely suggestive.

Random Coefficient Model. I present results of three sets of specifications of the BLP model. First, I model heterogeneity in consumers preferences through Normally distributed random coefficients, setting $\mathbf{\Sigma} \neq \mathbf{0}$ and $\mathbf{\Pi} = 0$ in equation (2). I allow random coefficients on price, constant, and on the indicators of EC type, drug, and mass merchandiser, while I omit the indicator variable for the grocery channel. Results from this model are reported in Table 2. Column (1) is the base-line specification, Column (2) includes quarter fixed effects, Column (3) controls for average county demographic characteristics (metropolitan county indicator, monthly-county level unemployment rate, fraction of Hispanic women, and fraction of black women in the county-year) and quarter FE. Column (4) includes the same set of county level controls and year-quarter FE, and Column (5) includes the same set of controls and year and quarter FE, separately. In columns (2) to (5), the time FE and additional county controls are included in the linear parameters. Because in my setting the number of markets is large relative to the number of choices, including market fixed effects will make estimation unfeasible. At the bottom of table 2, I report the J-test for the validity of the moment conditions, and the Newey-West D statistic for a test that the non-linear parameters are jointly zero. Overall, in all specifications, all linear parameters on the choice characteristics are statistically insignificant, with the exception of the grocery indicator in Column (3). Regarding the non-linear parameters there is mixed evidence. Note that across specifications the non-linear estimates are statistically and economically different. For example, all random coefficients in column (1) are statistically insignificant, but statistically significant and with opposite sign in column (5) when controlling for county average characteristics and including year and quarter FE. Nevertheless, in all random coefficient specifications in Table 2 the Newey-West D test fail to reject the null hypothesis that the non-linear parameters are jointly zero, providing consistent evidence that these specifications are inadequate.

In the second and third specifications, I relaxed the assumption of Normally distributed random coefficients (setting $\mathbf{\Sigma} = \mathbf{0}$) and allow for interactions of product characteristics with consumer demographics, which include income, an indicator for bachelor's degree or higher, and an indicator for age 20 to 34. $\mathbf{\Pi}$ are the coefficients on the interaction terms. Table 3 reports results for specifications where I allow for heterogeneity in consumer preferences for price, EC type, and the constant. Column (1) reports results without controls or FE, while columns (2) to (5) add FE and controls as indicated in the bottom of the Table. Estimates from Table 3 shows a consistent pattern regarding the non-linear coefficients. The positive coefficient on the interaction of price with income indicates that higher income makes mean price coefficient less negative. In other words, richer consumers are less sensitive to price. For example, looking at Column (1), the marginal dis-utility from price is $-1.237 + (0.719 \times 1.073) = -0.4655$. The positive coefficient on the interaction of EC-type and education suggest that high educated consumers value more the branded EC. The positive coefficient on the constant and age suggest that women aged 20 to 34 are more likely to purchase the product in any of the retail channels observed in the data compared to the outside option. In columns (1) to (3), all of the non-linear parameters are statistically significant, and only the linear parameter on brand type is not statistically significant. In specifications that control for year-quarter and year and quarter dummies, none of the price coefficients are statistically significant.

Finally, Table 4 shows results for a specification as in Table 3 plus allowing for heterogeneity in consumer preferences for drug stores. Similar to the previous table, I find that richer consumers are less sensitive to price and that women aged 20 to 34 are more likely to choose the inside options compared to the outside option. However, in all specifications the coefficient on the interaction of price and income is statistically insignificant. Regarding heterogeneity in consumer preferences over the EC type, I find that there is not convince evidence that higher educated consumers value more or less the branded EC. In all specifications, the non-linear coefficient on the interaction of EC-type and high education level is statistically insignificant. The coefficient in columns 1 to 3 is negative which would suggest that the marginal valuation for the branded EC decreases with high education level.[11] In contrast, in columns 4 and 5, the coefficient on the interaction of EC-type and high education is positive (and insignificant), while the average marginal valuation for EC-type is negative and statistically significant. Finally, the positive coefficient on the interaction of drug and income suggest that higher income makes mean drug coefficient less negative. So, richer consumers are more likely to purchase emergency contraceptives from drug stores compared to grocery and mass merchandiser stores. This is realistic as low income consumers are more price sensitive and, on average, compared to grocery and discount stores, pharmacies offer higher prices for emergency contraceptives. Overall, I find that the specifications that allow for consumer heterogeneity explained by demographics perform better than the random

[11] Previous studies have found that people with higher education levels are more likely to see generics positively. Bronnenberg et al. (2015) find that for some drugs, more informed consumers as proxy by education are more likely to buy store-brand drugs compared to national brands.

coefficient specification. In all specification in Table 3 and Table 4 the Newey and West (1987) D-test rejects the null that the nonlinear parameters included in the specifications are jointly 0.

A caveat from these specifications is that the assumption of the market size produces a large market share for the outside option. Loosely speaking, the model works by matching model-predicted to observed market shares, thus the model parameters need to explain why 99% of consumers choose the outside good. The implication is that the BLP model produces negative coefficients on the retail channel dummies so consumers preferred the outside good rather than the inside goods. To address this concern, in the next subsection, I present results with an alternative definition of the market size.

5.2. Parameter estimates with market size 20% larger than the total quantities purchased

Table 5 presents results from the same specification of the BLP model as presented in Column (1) of Table 3, with the key difference being the assumption regarding market size. In this case, it is assumed that the EC purchases recorded in the data represent 83% of the total potential EC purchases in a market. This assumption equates to multiplying the observed total quantities purchased by a factor of 1.2.

Homogeneous Logit. First column of Table 5 presents the results for the homogeneous logit model. Similar to previous specifications, a higher price generates dis-utility to consumers, and utility increases with the branded version of the pill. The coefficients on the retail channel type are larger in magnitude relative to the coefficients on price and EC-type, suggesting that consumers have strong preferences over retail channels for purchasing EC. Consumers' marginal utility increases with the pharmacy retail channel, and decreases with the non-pharmacy retail channel (grocery or mass merchandiser stores).

BLP model. The last four columns of Table 5 presents the estimates of a BLP model that allows for heterogeneity in consumer preferences for price, EC type, and the constant. This heterogeneity is captured by Π, the coefficients on the interactions of product characteristics with consumer demographics which include income, an indicator for bachelor's degree or higher, and an indicator for age 20 to 34. The coefficients on the retail channel type are positive and larger in magnitude compared to price and EC-type, reinforcing the argument that consumers have specific preferences for retail channels.

The positive coefficient on the interaction of price with income suggest that richer consumers are less sensitive to price. The average marginal dis-utility from price is $-0.119 + (0.035 \times 1.073) = -0.081$. The negative coefficient on the interaction of EC-type and education indicates that high educated consumers value less the branded EC. The negative coefficient on the constant and age suggest that women aged 20 to 34 are more likely to choose the outside option compared to any of the inside options. I perform the counterfactual analysis using estimates from the BLP model in Table 5 as my preferred specification.

TABLE 2. Two Step GMM Parameters Estimates using Normally Distributed random coefficients, ($\mathbf{\Sigma} \neq \mathbf{0}$, $\mathbf{\Pi} = 0$)

	(1)	(2)	(3)	(4)	(5)
Linear Parameters					
Price	-1.260	-1.324	-1.338	-2.577	-2.149
	(0.998)	(1.074)	(0.881)	(11.933)	(6.225)
EC-type	-6.835	-7.249	0.038	-0.970	-0.479
	(8.863)	(10.046)	(1.738)	(15.667)	(4.812)
Drug	-13.694	-14.596	-4.898	-10.211	-9.262
	(26.717)	(29.648)	(5.018)	(47.653)	(20.227)
Grocery	-16.026	-16.891	-7.691***	-12.870	-11.952
	(13.578)	(15.286)	(2.197)	(55.532)	(24.774)
Mass	-18.048	-19.180	-11.440	-15.109	-13.462
	(21.211)	(23.006)	(8.045)	(102.949)	(49.663)
metro			-0.076	-0.076	-0.088
			(0.105)	(1.730)	(0.689)
unemployment			-0.103***	-0.176	-0.161
			(0.020)	(0.675)	(0.346)
black			1.700*	3.598	3.208
			(0.905)	(26.695)	(13.469)
hispanic			0.904**	2.073	1.829
			(0.389)	(12.120)	(6.129)
Non-Linear Parameters ($\mathbf{\Sigma} \neq \mathbf{0}$, $\mathbf{\Pi} = 0$)					
price $\times\nu$	0.070	0.086	0.665***	-1.514	-1.308***
	(0.470)	(0.205)	(0.069)	(1.913)	(0.327)
EC-type $\times\nu$	7.000	7.406***	0.789***	-2.047	-1.006***
	(7.278)	(0.284)	(0.084)	(2.561)	(0.330)
drug $\times\nu$	-2.320	-2.461***	0.646***	0.945	0.808***
	(22.252)	(0.390)	(0.079)	(1.423)	(0.139)
mass $\times\nu$	3.938	4.242***	3.696***	3.713*	2.987***
	(8.668)	(0.472)	(0.274)	(2.240)	(0.833)
constant $\times\nu$	6.000	6.359	-1.656	-4.078	-3.620***
	(4.752)	(8.337)	(3.182)	(2.769)	(0.677)
FE	No	Quarter	Quarter	Year-Quarter	Year & Quarter
Controls	No	No	Yes	Yes	Yes
J	1.6307	0.60997	8.6438	0.92917	1.5848
p-value	0.2016	0.4348	0.0032818	0.33508	0.20808
Newey-West D	4.2444	1.7771	1.6245	0.91541	0.82074
p-value	0.51479	0.87904	0.89827	0.9691	0.97569

Notes: Market size is female population aged 15 to 44. ***, **, and * indicates significance at 1, 5, and 10 percent, respectively. J is the overidentification test statistic and p-value. Degrees of freedom=1. Newey-West D is a likelihood ratio test for the null hypothesis that the nonlinear parameters are jointly 0 with the corresponding p-value. N = 10,458.

TABLE 3. Two Step GMM Parameters Estimates of the BLP model using consumer demographics, ($\mathbf{\Sigma} = \mathbf{0}$, $\mathbf{\Pi} \neq 0$)

	(1)	(2)	(3)	(4)	(5)
Linear Parameters					
Price	-1.237**	-1.214**	-1.168**	-0.564	-0.557
	(0.494)	(0.492)	(0.561)	(0.536)	(0.533)
EC-type	0.017	-0.001	-0.582	-1.174***	-1.157***
	(0.243)	(0.243)	(0.355)	(0.450)	(0.444)
Drug	-6.876***	-6.967***	-5.789***	-7.870***	-7.705***
	(1.618)	(1.576)	(0.395)	(0.648)	(0.608)
Grocery	-9.930***	-10.017***	-8.780***	-10.792***	-10.627***
	(1.615)	(1.573)	(0.386)	(0.642)	(0.601)
Mass	-9.189***	-9.277***	-8.075***	-10.111***	-9.947***
	(1.618)	(1.576)	(0.390)	(0.645)	(0.604)
metro			-0.257***	-0.247***	-0.247***
			(0.022)	(0.022)	(0.022)
unemployment			-0.035***	-0.003	-0.006
			(0.012)	(0.011)	(0.011)
black			0.919***	0.699***	0.717***
			(0.110)	(0.108)	(0.108)
hispanic			0.727***	0.642***	0.647***
			(0.050)	(0.048)	(0.048)
Non-Linear Parameters ($\mathbf{\Sigma} = \mathbf{0}$, $\mathbf{\Pi} \neq 0$)					
price $\times$*income*	0.719*	0.715*	0.752*	0.511	0.502
	(0.397)	(0.396)	(0.451)	(0.428)	(0.427)
EC-type$\times$*higheduc*	1.197***	1.202***	2.066***	2.486***	2.468***
	(0.424)	(0.422)	(0.473)	(0.543)	(0.539)
constant $\times$*age*2034	3.228*	3.207*	1.559***	2.225***	2.143***
	(1.707)	(1.666)	(0.479)	(0.740)	(0.691)
FE	No	Quarter	Quarter	Year-Quarter	Year & Quarter
Controls	No	No	Yes	Yes	Yes
J	0.0562	0.042837	0.30972	3.826	3.6718
p-value	0.9723	0.97881	0.85653	0.14764	0.15947
Newey-West D	171.2795	173.0725	211.9657	222.732	220.5646
p-value	0	0	0	0	0

Notes: Market size is female population aged 15 to 44. ***, **, and * indicates significance at 1, 5, and 10 percent, respectively. J is the overidentification test statistic and p-value. Degrees of freedom=2. Newey-West D is a likelihood ratio test for the null hypothesis that the nonlinear parameters are jointly 0 with the corresponding p-value. N = 10,458.

TABLE 4. Two Step GMM Parameters Estimates of the BLP model using consumer demographics, ($\mathbf{\Sigma} = \mathbf{0}$, $\mathbf{\Pi} \neq 0$)

	(1)	(2)	(3)	(4)	(5)
Linear Parameters					
Price	-1.476*	-1.450*	-1.203	-0.356	-0.350
	(0.817)	(0.815)	(0.860)	(0.815)	(0.811)
EC-type	0.022	0.004	-0.583	-1.208**	-1.190**
	(0.252)	(0.252)	(0.377)	(0.492)	(0.486)
Drug	-5.279*	-5.391*	-5.476**	-9.250***	-9.079***
	(2.940)	(2.909)	(2.287)	(2.068)	(2.073)
Grocery	-10.000***	-10.085***	-8.779***	-10.797***	-10.633***
	(1.757)	(1.707)	(0.385)	(0.635)	(0.594)
Mass	-9.255***	-9.341***	-8.073***	-10.120***	-9.956***
	(1.759)	(1.710)	(0.389)	(0.637)	(0.597)
metro			-0.256***	-0.249***	-0.249***
			(0.022)	(0.022)	(0.022)
unemployment			-0.036***	-0.002	-0.005
			(0.010)	(0.010)	(0.010)
black			0.920***	0.693***	0.711***
			(0.108)	(0.105)	(0.105)
hispanic			0.726***	0.644***	0.650***
			(0.049)	(0.048)	(0.048)
Non-Linear Parameters ($\mathbf{\Sigma} = \mathbf{0}$, $\mathbf{\Pi} \neq 0$)					
price $\times$*income*	0.930	0.923	0.783	0.325	0.316
	(0.678)	(0.675)	(0.717)	(0.687)	(0.684)
EC-type$\times$*higheduc*	-1.505	-1.484	-0.281	1.252	1.247
	(2.086)	(2.079)	(2.024)	(1.920)	(1.913)
drug $\times$*income*	1.199***	1.203***	2.068***	2.526***	2.507***
	(0.421)	(0.420)	(0.497)	(0.593)	(0.588)
constant $\times$*age*2034	3.313*	3.290*	1.556***	2.212***	2.129***
	(1.860)	(1.811)	(0.481)	(0.736)	(0.688)
FE	No	Quarter	Quarter	Year-Quarter	Year & Quarter
Controls	No	No	Yes	Yes	Yes
J	0.0826	0.066185	0.32051	3.7333	3.5797
p-value	0.9595	0.96745	0.85192	0.15464	0.16699
Newey-West D	216.5186	218.3898	270.3623	292.7919	289.9777
p-value	0	0	0	0	0

Notes: Market size is female population aged 15 to 44. ***, **, and * indicates significance at 1, 5, and 10 percent, respectively. J is the overidentification test statistic and p-value. Degrees of freedom=2. Newey-West D is a likelihood ratio test for the null hypothesis that the nonlinear parameters are jointly 0 with the corresponding p-value. N = 10,458.

Table 5. Demand Parameter Estimates with market size 20% larger than the total quantities purchased

	Homogenous Logit with IV ($\mu_{ijm} = 0$)	BLP model ($\Sigma = 0, \Pi \neq 0$)			
		Mean θ_1	Income	HighEdu	Age2034
Price	-0.326***	-0.119	0.035		
	(0.080)	(0.479)	(0.399)		
EC-type	0.308***	0.211		-0.412	
	(0.070)	(0.175)		(0.571)	
Drug	1.948***	4.183***			
	(0.280)	(0.856)			
Mass	-0.472*	1.825**			
	(0.270)	(1.759)			
Grocery	-0.913***	1.260			
	(0.269)	(0.851)			
Constant					-3.972***
					(0.899)
FE	No	No			
Controls	No	No			
Week IV F-stat	112.56				
J		3.8456			
p-value		0.1462			
Newey-West D		225.43			
p-value		0			

Notes: Newey-West D is a likelihood ratio test for the null hypothesis that the nonlinear parameters are jointly 0 with the corresponding p-value.

6. Counterfactuals

In this section, I delve into the analysis of substitution patterns across retail channels, utilizing estimates derived from the discrete choice model. This analysis is conducted under various counterfactual scenarios. In the first scenario, I explore the market share-price elasticities resulting from a simulated 10% increase in prices. The second scenario involves removing certain retail channel options from the choice set and simulating new market shares in this altered environment. For these analyses, I focus on 512 markets where consumers have access to all six choices. These markets span 19 counties, with 18 of them being metropolitan counties (see Figure A2 (C) in the Appendix).

This straightforward exercise aims to shed light on the substitution patterns between pharmacy and non-pharmacy retailers in the context of emergency contraceptive purchases. It's important to note that the model presented in Section 4 primarily focuses on delineating consumer choices, representing the demand side of the market. In this paper, I do not delve into modeling the supply side of the OTC emergency contraceptives market. Consequently, in the counterfactual analysis, consumer behavior is examined with all other factors, including supply-side effects, held constant. A comprehensive analysis of the impact of these scenarios would necessitate modeling the supply side to account for potential responses from retailers to changes in the market environment.

Scenario 1: Substitution patterns due to a 10% in prices. Figure 1 illustrates how market share of product j would change due to a 10% increase in price of product k. In the matrix, rows represent product j while columns correspond to product k. The diagonal elements of the matrix indicate own-price elasticities, whereas the off-diagonal elements represent cross-price elasticities. This figure shows the average percentage changes in market shares (relative to actual market shares) due to a 10% in prices for a subsample of 512 markets where all six options are available. These market share price elasticities are derived using the estimated coefficients from column (1) in Table 3. To simplify the interpretation of the results, I exclude the outside option and recalculate both observed and counterfactual market shares, ensuring they sum to 100 percent in each scenario. Essentially, this counterfactual analysis is conducted under the assumption that the market size equates to the actual quantities purchased, rather than the total female population of reproductive age.

The primary insight from this analysis is that consumers purchasing emergency contraceptives are responsive to price changes. Notably, the generic EC option in drug stores exhibits the lowest own-price elasticity among all choices: a 10% price increase leads to an approximate 8% decrease in its market share. Additionally, consumer price sensitivity for branded EC is consistently higher than for generic EC across all retail channels, with the greatest own-price elasticity observed in food stores. Regarding cross-price elasticities, an increase in the price of generic EC in one retail channel prompts consumers to substitute towards generic options in the other two channels rather than switching to branded EC. Similarly, if the price of branded EC increases by 10% in any retail channel, consumers tend to switch to branded EC options in the alternative channels instead of opting for generic variants.

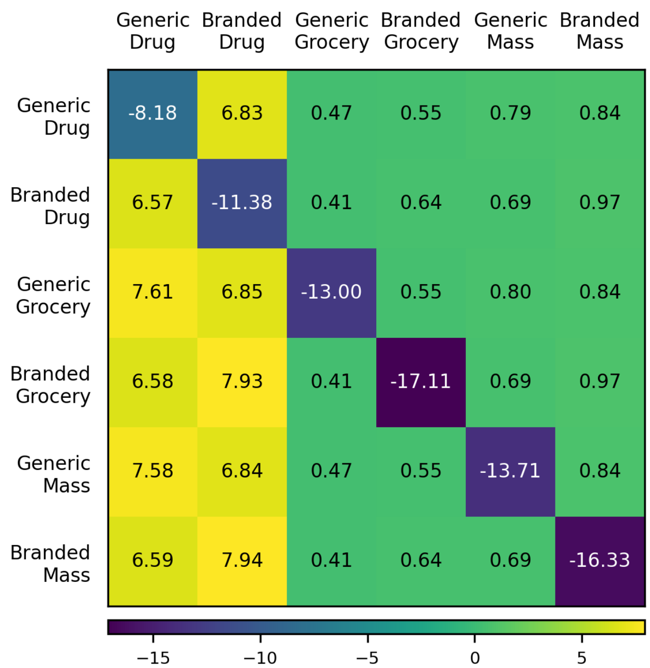


FIGURE 1. Changes in Market Shares (in percent) of product j (row) due to a 10% increase in price of product k (column).

Notes: Price elasticities calculated using estimates from column (1) in Table 3. In this counterfactual exercise, market shares are re-computed by removing the outside option, so inside shares sum to 100 percent. Sample is restricted to 512 markets with all choices. Percentage change is calculated as (counterfactual market share - observed market shares)/observed market shares *100.

To examine variations in price sensitivity among different consumer groups, Figure 2 displays the own-price elasticities categorized by retail channel, EC type, and income group, in response to a 10% increase in prices. It is observed that consumers with an annual income below $50,000 exhibit greater price sensitivity compared to those with higher incomes. The analysis reveals a range of own-price elasticities for emergency contraceptives, spanning from –6.72 to –19.23, varying according to the income group, type of EC, and the retail channel involved.

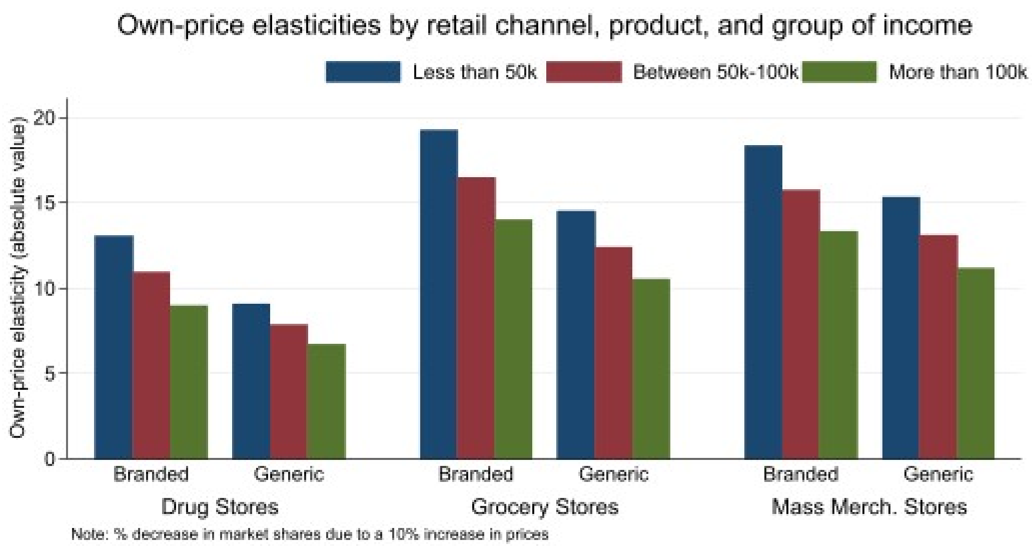


FIGURE 2. Own-price elasticities by retail channel, product, and group of income

Notes: Using estimates from column (1) in Table 3. In this counterfactual exercise, market shares are re-computed by removing the outside option, so inside shares sum to 100 percent. Sample is restricted to 512 markets with all choices. Percentage change is calculated as (counterfactual market share - observed market shares)/observed market shares *100.

Scenario 2: Substitution patterns due to changes in the choice set. In light of past policy debates, where some retail chains opted not to sell emergency contraceptives (EC) or restricted their sale, this scenario analyzes the impact of such policies. Specifically, it quantifies the potential number of consumers who might not purchase EC if its sale were prohibited in a particular retail channel. This is achieved by measuring changes in the market share of the outside option in scenarios where EC is unavailable from a specific retail channel, with all other factors held constant. The analysis involves three counterfactual scenarios: first, removing grocery store options; second, excluding mass merchandiser stores; and third, omitting drug stores from the choice set. Table 6 presents the actual market shares and the counterfactual market shares in each scenario. These results are obtained by utilizing the BLP model's estimated coefficients from Table 5. The table provides the average observed and counterfactual market shares for the 512 markets that initially offered both pharmacy and non-pharmacy retail options.

I find that banning the sale of emergency contraceptives from grocery or mass merchandiser stores would lead to a 5-8% increase in the number of consumers who opt not to purchase EC. For instance, a ban on EC sales in grocery stores would result in a 5% increase in the market share of the outside option relative to the baseline scenario. Since the outside option encompasses those who either choose not to buy EC or purchase it from alternative sources, this increase can be seen as an upper limit of the potential reduction in EC purchases. A back of the envelope calculation indicates that such a ban in grocery stores could result in an average decrease of 18 EC purchases per month across the 19 counties considered in this counterfactual scenario. Similarly, prohibiting EC sales in mass merchandiser stores is associated with an 8% increase in the outside option market share, equating to an average reduction of 30 EC purchases per month in the analyzed counties.

TABLE 6. Demand Impact of Removing Retail Channels from the Choice Set

	Generic Drug	Branded Drug	Generic Grocery	Branded Grocery	Generic Mass	Branded Mass	Outside Option
	Pharmacy Retailer		Non-Pharmacy Retailer				
Observed Market Shares (%)	34.51	34.59	2.51	3.05	3.95	4.73	16.67
A: Remove Grocery Options	36.60	36.67	0.00	0.00	4.22	5.05	17.47
B: Remove Mass Options	37.93	37.92	2.79	3.39	0.00	0.00	17.97
C: Remove Drug Options	0.00	0.00	10.53	12.73	16.35	19.75	40.63

Notes: Table reports average market shares for a sample of 512 markets. Counterfactual using Using BLP estimates from Table 5. Each row sums to 100%.

In Appendix A, Table A6 presents the counterfactual results using the estimated coefficients from column (1) in Table 3. These coefficients are based on the assumption that the market size equates to the female population of fertile age. To facilitate easier interpretation of these results, I exclude the outside option and recalculate both the observed and counterfactual market shares, ensuring they sum to 100 percent in each scenario. This approach effectively means that the counterfactual analysis is conducted under the assumption that the market size is equivalent to the actual quantities purchased, as opposed to the total female population of reproductive age

In a scenario where the sale of EC is banned in grocery stores, and the outside option is not available, the majority of consumers who previously bought EC from grocery stores are predicted to switch to drug stores, capturing 87% of the initial grocery store market share. The remaining market share would shift to mass merchandiser stores. In this scenario, the overall market share for generic EC is projected to increase only marginally by 0.26 percentage points (pp). Conversely, in a scenario where mass merchandiser stores do not sell EC, there is an even larger shift towards drug stores, with 92% of the initial mass merchandiser market share moving to drug stores. Here, the total market share for generic EC would increase by 0.47 pp. Finally, in a scenario excluding pharmacy channels, mass merchandiser stores are expected to capture 61% of the initial drug store market shares, with the remaining share going to grocery stores. In this situation, the total market share for generic EC would decrease by 3.73 pp, while the market share for branded EC correspondingly increases by the same amount.

7. Conclusion

In this paper, I have explored consumer preferences across various retail channels (drug stores, mass merchandisers, or grocery stores) for purchasing over-the-counter emergency contraceptives (EC). Utilizing data on monthly EC sales in Texas from 2017 to 2019, consumer preferences were estimated using a BLP discrete choice model. The findings reveal that consumers are sensitive to price changes, showing distinct preferences for specific retail channels, while demonstrating no marked preference between branded and generic EC products. Notably, consumers with lower incomes (below $50,000 per year) exhibit higher price sensitivity compared to those with higher incomes.

Further, in response to past policy debates where some retailers restricted EC sales, the impact of such policies was examined through counterfactual simulations. These simulations quantified the potential reduction in EC purchases if sales were banned in specific retail channels. The results indicate that prohibiting EC sales in grocery or mass merchandiser stores could lead to a 5-8% increase in consumers choosing not to purchase EC. Furthermore, an approximate calculation suggests that if sales of EC were prohibited in grocery and mass merchandise stores, there could be a monthly decrease of 18 and 30 EC purchases, respectively, in the analyzed Texas counties under the counterfactual scenario.

References

ASEC. 2018. "Not There Yet: ASEC's 2017 EC Access Study."Technical report, American Society of Emergency Contraception.

Bailey, Martha J, and Jason M Lindo. 2017. "Access and Use of Contraception and Its Effects on Women's Outcomes in the U.S.." Working Paper 23465, National Bureau of Economic Research.

Berry, S, J Levinsohn, and A Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2): 242–262.

Bronnenberg, Bart J, Jean-Pierre Dubé, Matthew Gentzkow, and Jesse M Shapiro. 2015. "Do pharmacists buy Bayer? Informed shoppers and the brand premium." *The Quarterly Journal of Economics* 130 (4): 1669–1726.

Cameron, A Colin, and Pravin K Trivedi. 2005. *Microeconometrics: methods and applications.*: Cambridge university press.

Cintina, Inna. 2017. "Behind-the-Counter, but Over-the-Border? The Assessment of the Geographical Spillover Effects of Emergency Contraception on Abortions." *Health Economics* 26 (10): 1249–1263.

Compta, Gael. 2021. "Impact of emergency contraception availability on teen pregnancy and birth outcomes." *Unpublished Third Year Paper*.

Dubé, Jean-Pierre, Jeremy T Fox, and Che-Lin Su. 2012. "Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation." *Econometrica* 80 (5): 2231–2267.

Durrance, Christine Piette. 2013. "The effects of increased access to emergency contraception on sexually transmitted disease and abortion rates." *Economic Inquiry* 51 (3): 1682–1695.

Fischer, Stefanie, Heather Royer, and Corey White. 2018. "The impacts of reduced access to abortion and family planning services on abortions, births, and contraceptive purchases." *Journal of Public Economics* 167: 43–68.

Gayle, Philip G., and Ying Lin. 2022. "Market effects of new product introduction: Evidence from the brew-at-home coffee market." *Journal of Economics and Management Strategy* 31 (3): 525–557.

Håkonsen, Helle, Karolina Andersson Sundell, Johan Martinsson, and Tove Hedenrud. 2016. "Consumer preferences for over-the-counter drug retailers in the reregulated Swedish pharmacy market." *Health Policy* 120 (3): 327–333.

Hausman, Jerry, Gregory Leonard, and J. Douglas Zona. 1994. "Competitive Analysis with Differenciated Products." *Annales d'Économie et de Statistique* (34): 159–180.

Ivaldi, Marc, and Frank Verboven. 2005. "Quantifying the effects from horizontal mergers in European competition policy." *International Journal of Industrial Organization* 23 (9): 669–691.

Knittel, Christopher R, and Konstantinos Metaxoglou. 2014. "Estimation of random-coefficient demand models: two empiricists' perspective." *Review of Economics and Statistics* 96 (1): 34–59.

Mallatt, Justine. 2019. "The Effect of Pharmacist Refusal Clauses on Contraception, Sexually

Transmitted Diseases, and Birthrates." *Sexually Transmitted Diseases, and Birthrates (May 8, 2019)*.

Mulligan, Karen. 2016. "Access to Emergency Contraception and its Impact on Fertility and Sexual Behavior." *Health Economics* 25 (4): 455–469.

Nevo, Aviv. 2000. "A practitioner's guide to estimation of random-coefficients logit models of demand." *Journal of Economics & Management Strategy* 9 (4): 513–548.

Nevo, Aviv. 2001. "Measuring market power in the ready-to-eat cereal industry." *Econometrica* 69 (2): 307–342.

Newey, Whitney K, and Kenneth D West. 1987. "Hypothesis testing with efficient method of moments estimation." *International Economic Review*: 777–787.

Orr, Katherine, Jennifer Chin, Maris Cuddeback, Jessica Zimo, Colleen Judge-Golden, Marian Jarlenski, and Sonya Borrero. 2021. "Pharmacy availability of emergency contraception in southwestern Pennsylvania: A simulated patient study." *Contraception: X* 3: 100068.

Titiloye, Ibukun, Md Al Adib Sarker, Xia Jin, and Brian Watts. 2023. "Examining channel choice preferences for grocery shopping during the Covid-19 pandemic." *International Journal of Transportation Science and Technology*.

Ujhelyi, Gergely, Somdeep Chatterjee, and Andrea Szabó. 2021. "None of the Above: Protest Voting in the World's Largest Democracy." *Journal of the European Economic Association* 19 (3): 1936–1979.

Zuppan, C. Andrew. 2012. "The Impact of Emergency Contraception on Dating and Marriage." *Unpublished Working Paper*.

Appendix A. Tables and Figures

Table A1. Percentage of Women Who Have Ever Used Emergency Contraception Among Women Who Have Ever Had Sexual Intercourse, 2017-2019

Characteristic	**Percent**	**SE**
Total (aged 15-49)	25	0.94
Age group		
15-19	25.9	3.2
20-24	37.9	2.3
25-29	35.7	2.3
30-34	35.9	2.3
35-39	22.5	2.2
40-49	9.6	1.1
Hispanic origin and race		
Hispanic	26.9	1.7
Non-Hispanic white	23.9	1.3
Non-Hispanic black	25.4	2.7
Marital Status		
Married	19.6	1.5
Never Married	32.9	1.3
*Education**		
No high school diploma or GED	12.6	1.9
High school diploma or GED	19.6	1.3
Some college, but no bachelor's degree	26.7	1.5
Bachelor's degree or higher	27.9	1.8
Income		
Under 25k	23.2	1.5
Between 25k and 50k	26.5	1.8
Between 50k and 100k	26.1	1.7
Higher than 100k	24	2.1
Religion		
No religion	33.1	1.6
Catholic	21.5	1.6
Protestant	21.4	1.4
Other religions	26.1	3.2

Note: All percentages expect for education are among women aged 15–49. Percentages for education are limited to women aged 22–49.
Source: National Survey of Family Growth, United States, 2017–2019.

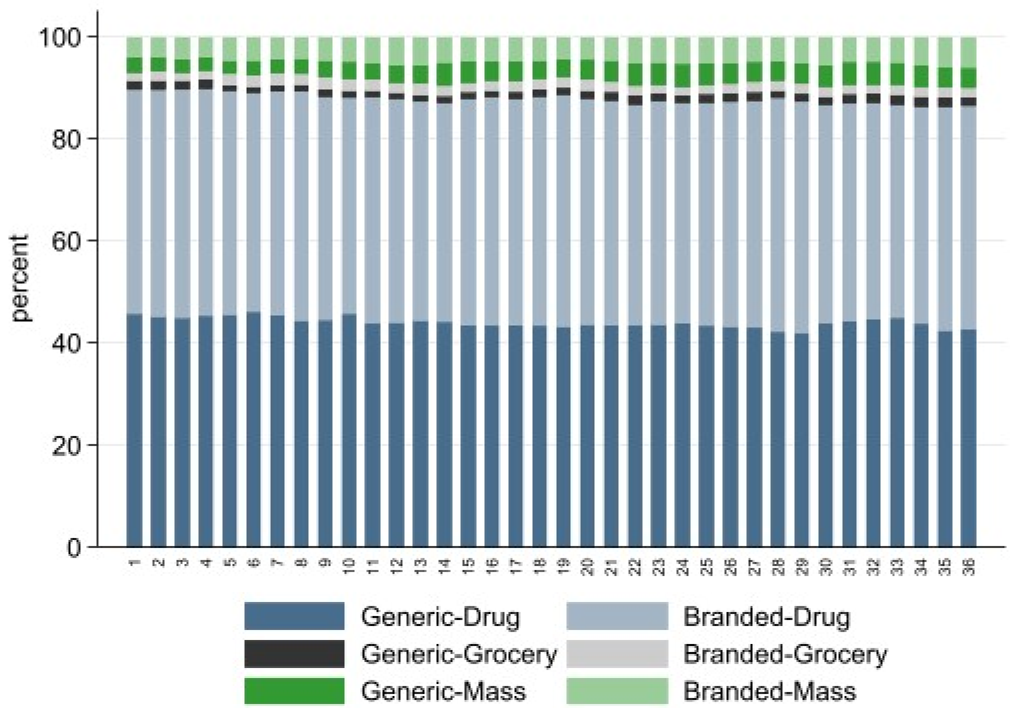
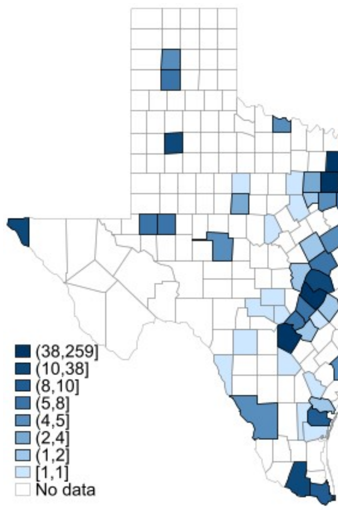
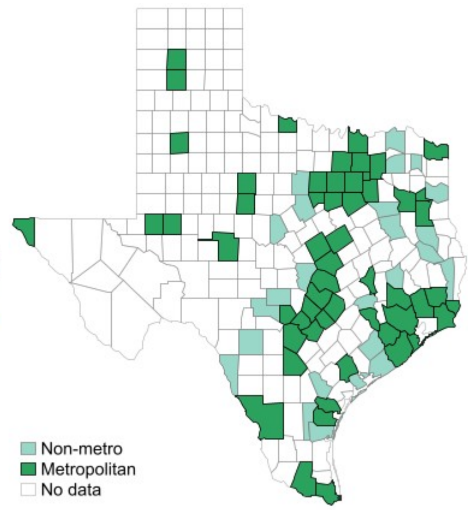


FIGURE A1. Volume shares by product and retail channel over time (Texas Sample)

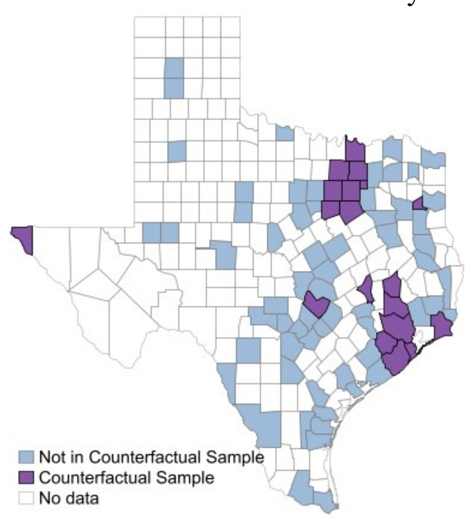
Notes: Each bar correspond to months from 2017 to 2019.



A. By number of stores



B. By Metropolitan



C. Counterfactual Sample

FIGURE A2. Counties in the Sample with EC sales

TABLE A2. Markets in the data by number of choices with non-zero sales

# / j	Generic Drug 1	Branded Drug 2	Generic Grocery 3	Branded Grocery 4	Generic Mass 5	Branded Mass 6	Number of markets	Percent
1	✓	✓					1,155	39.6%
2	✓	✓	✓				43	1.5%
3	✓	✓		✓			104	3.6%
4	✓	✓			✓		10	0.3%
5	✓	✓				✓	22	0.8%
6	✓	✓	✓	✓			136	4.7%
7	✓	✓	✓		✓		3	0.1%
8	✓	✓	✓			✓	1	0.0%
9	✓	✓		✓	✓		1	0.0%
10	✓	✓		✓		✓	4	0.1%
11	✓	✓			✓	✓	666	22.8%
12	✓	✓	✓	✓	✓		5	0.2%
13	✓	✓	✓	✓		✓	9	0.3%
14	✓	✓		✓	✓	✓	190	6.5%
15	✓	✓	✓		✓	✓	55	1.9%
16	✓	✓	✓	✓	✓	✓	512	17.6%
				Total number of markets			**2,916**	**100%**

TABLE A3. Summary statistics

	mean	sd	p10	p90
Panel A: Quantities Purchased and Market Size				
Units Sold	158	500	4	297
Female population aged 15 to 44	97,379	178,078	7,650	211,134
	mean	sd	p10	p90
Panel B: Market Shares (%)				
Inside options shares	0.19	0.19	0.02	0.44
Outside option share	99.28	0.33	98.87	99.66
	mean	sd	p10	p90
Panel C: Observe choice characteristics				
Price (dollars of 2019)	38.54	4.87	33.75	44.22
EC-type	0.51	0.50	0.00	1.00
drug store	0.56	0.50	0.00	1.00
grocery store	0.16	0.37	0.00	1.00
mass merchandiser	0.28	0.45	0.00	1.00
	mean	sd	p10	p90
Panel D: Controls				
Metropolitan county indicator	0.79	0.41	0.00	1.00
Monthly Unemployment Rate	3.99	1.21	2.80	5.60
Percent black among women aged 15 to 44	11.10	8.35	1.56	23.03
Percent Hispanic among women aged 15 to 44	36.23	21.58	16.82	68.66
	mean	sd	p10	p90
Panel E: Demographic Characteristics to Simulate Consumers				
Log of income (dollars of 2019)	10.73	0.24	10.47	11.02
Percent women with bacherlor's degree or higher	21.86	8.57	12.63	32.91
Percent women aged 20-34	50.62	3.51	47.12	54.83

Notes: In Panel A to D an observation is market-choice, N=10,458. In Panel E an observation is county-year, N=243. Percentages for education are limited to women aged 18–44, while percentage of female population correspond to women aged 15 to 44.

TABLE A4. Logit IV Estimates

	Dependent variable is δ_j					
	(1)	(2)	(3)	(4)	(5)	(6)
price	-0.289***	-0.155**	-0.167**	0.060	-0.211***	0.031
	(0.072)	(0.072)	(0.079)	(0.077)	(0.079)	(0.077)
EC-type	0.308***	0.189***	0.210***	0.015	0.244***	0.037
	(0.062)	(0.063)	(0.068)	(0.067)	(0.068)	(0.067)
drug	-4.904***	-5.258***	-5.306***	-5.975***	-5.146***	-5.831***
	(0.251)	(0.253)	(0.274)	(0.271)	(0.274)	(0.271)
grocery	-7.845***	-8.157***	-8.301***	-8.969***	-8.149***	-8.855***
	(0.242)	(0.245)	(0.262)	(0.258)	(0.262)	(0.259)
mass merchandiser	-7.134***	-7.490***	-7.539***	-8.203***	-7.390***	-8.078***
	(0.242)	(0.246)	(0.264)	(0.261)	(0.264)	(0.262)
Controls	No	Yes	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes	No	Yes
Instrument Set	1st	1st	2nd	2nd	3rd	3rd
Week IV F-stat	125.46	117.81	112.55	118.59	101.00	106.15

Notes: Two-step GMM estimates of the linear logit model. N=10458.

Standard errors robust to heteroskedasticity and intra-market correlation in parentheses.

Reported F-stat is the Kleibergen-Paap rk Wald F statistic. ***, **, and * indicates significance at 1, 5, and 10 percent, respectively.

TABLE A5. Two Step GMM Parameters Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Linear Parameters						
Price	-0.119	0.451	-0.117	0.454	0.178	0.185
	(0.479)	(0.522)	(0.479)	(0.521)	(0.833)	(0.832)
EC-type	0.211	0.050	0.208	0.047	0.054	0.051
	(0.175)	(0.161)	(0.174)	(0.161)	(0.169)	(0.169)
Drug	4.183***	3.852***	2.728***	2.827***	5.863**	4.848**
	(0.856)	(0.458)	(0.359)	(0.291)	(2.316)	(2.354)
Grocery	1.260	0.938**	-0.195	-0.087	0.854**	-0.130
	(0.851)	(0.452)	(0.347)	(0.279)	(0.428)	(0.275)
Mass	1.825**	1.547***	0.370	0.522*	1.464***	0.480*
	(0.857)	(0.458)	(0.353)	(0.285)	(0.434)	(0.281)
metro		-0.148***		-0.148***	-0.146***	-0.146***
		(0.014)		(0.014)	(0.013)	(0.013)
unemployment		-0.022*		-0.022*	-0.023**	-0.024**
		(0.012)		(0.012)	(0.011)	(0.011)
black		-0.607***		-0.610***	-0.606***	-0.609***
		(0.099)		(0.099)	(0.099)	(0.099)
hispanic		-0.509***		-0.509***	-0.515***	-0.515***
		(0.043)		(0.043)	(0.041)	(0.041)
Non-Linear Parameters ($\mathbf{\Sigma} = \mathbf{0}$, $\mathbf{\Pi} \neq 0$)						
price $\times$*income*	0.035	-0.459	0.034	-0.463	-0.200	-0.208
	(0.399)	(0.426)	(0.400)	(0.428)	(0.713)	(0.714)
EC-type$\times$*higheduc*	-0.412	0.131	-0.403	0.146	-1.937	-1.911
	(0.571)	(0.432)	(0.581)	(0.433)	(2.114)	(2.111)
drug $\times$*income*					0.099	0.117
					(0.457)	(0.459)
constant $\times$*age*2034	-3.972***	-3.286***	-2.946***	-2.686***	-3.214***	-2.656***
	(0.899)	(0.526)	(0.285)	(0.261)	(0.508)	(0.264)
Market Size	+20%	+20%	+30%	+30%	+20%	+30%
FE	No	Quarter	No	Quarter	Quarter	Quarter
Controls	No	Yes	No	Yes	Yes	Yes
J	3.8456	2.8577	3.8436	2.8402	3.0587	3.0365
p-value	0.1462	0.23959	0.14635	0.24168	0.21668	0.2191
Newey-West D	225.4291	232.5752	224.8979	232.9146	254.1136	253.8381
p-value	0	0	0	0	0	0

***, **, and * indicates significance at 1, 5, and 10 percent, respectively. J is the overidentification test statistic with corresponding degrees of freedom and p-value. Newey-West D is a likelihood ratio test for the null hypothesis that the nonlinear parameters are jointly 0 with the corresponding p-value. N = 10,458.

TABLE A6. Demand Impact of Removing Retail Channels from the Choice Set

	Generic Drug	Branded Drug	Generic Grocery	Branded Grocery	Generic Mass	Branded Mass
	Pharmacy Retailer		Non-Pharmacy Retailer			
Observed Market Shares (%)	45.06	37.95	3.31	3.33	5.15	5.21
A: Remove Grocery Options	48.23	40.61	0.00	0.00	5.55	5.62
B: Remove Mass Options	50.25	42.24	3.74	3.77	0.00	0.00
C: Remove Drug Options	0.00	0.00	19.44	19.39	30.35	30.82

Notes: Table reports average market shares for a sample of 512 markets. Shares are computed by removing the outside option, so each row sum to 100. Counterfactual market shares are computed using estimates from column (1) in Table 3.

Appendix B. Details of Sample Construction

The RMS data consist of weekly pricing, volume sales, and store environment information generated by point-of-sale systems from more than 90 participating retail chains across all US markets.[12] The data provides store-weekly level product data for 2.6-4.5 million universal product codes (UPCs) including food, nonfood grocery items, health and beauty aids, and select general merchandise aggregated into 1,100 product categories. All products include UPC code and description, brand, multi-pack, and size. The data covers around 60,600 unique stores distributed in 52 states and 2,764 counties across the U.S. The store information includes store chain code, retail channel type, and area location. The finest geographical identifier for each store is the county. The data also provides the first 3 digits of a store's zip code, and DMA code. The retail channels included are drug stores, grocery, mass merchandiser, convenience stores with gas stations, and liquor stores.

In the product-category 'female contraceptives', I identify eight brands of OTC emergency contraceptives with one dose of 1.5mg of levonorgestrel as an active ingredient. The data only cover sales for OTC medications, thus, sales for the oral emergency contraceptive pill that contains *ulipristal acetate* are not in the data because it is only available with prescription. For my analysis I classify EC into two mutually exclusive groups: branded EC or generic versions. The reason for the aggregation of different generic brands into one category is because volume sales for some generics brands are very small. Emergency contraceptives are mainly sold through drug, mass merchandiser, and grocery stores, thus my analysis focus on these three retail channels. According to Kilts Center for Marketing, pharmacies that are inside a grocery or mass merchandiser store are listed as drug store in the Nielsen data.

The RMS data for Texas include OTC emergency contraceptive sales from 1,230 stores (693 drug stores, 373 grocery stores, and 164 mass merchandiser stores) distributed in 95 counties. Further, I restrict the sample to create a panel of 81 counties over 36 months, so there are 2,916 markets in my sample. In the counterfactual analysis, I focus on 512 markets that have all six choices available. In the case of OTC emergency contraceptives, products are differentiated in terms of brand (generics vs branded-name) and price. There is no differentiation in size, formulation or content, as all EC are marketed as a single pill with 1.5mg of levonorgestrel.

[12] See NielseIQ Retail Scanner Data, Kilts Center for Marketing.

Appendix C. Computational Implementation of BLP algorithm

I estimate the model parameters in MATLAB using the Nested Fixed Point algorithm proposed by Berry, Levinsohn, and Pakes (1995). To ensure that the BLP estimator produces reliable estimates, I incorporate computational recommendations from Dubé, Fox, and Su (2012) and Knittel and Metaxoglou (2014) about the choice of the stopping rule for the contraction mapping and regarding the optimization solver. Specifically, for the contraction mapping (inner-loop), I use a tight convergence criterion (10^{-12}). For the optimization of the GMM objective function, I use the derivative-free optimizer *patternsearch* and a tight outer-loop tolerance (10^{-6}).

Additionally, I follow Ujhelyi, Chatterjee, and Szabó (2021) and eliminate a source of numerical instability in calculating the predicted market shares from the model that is present in the standard way of coding the BLP model in Matlab. Specifically, the function that computes the individual probabilities of choosing each product uses the *accumarray* function, instead of the *cumsum* and *diff* functions.[13]

[13] See their online appendix for more details about this issue.