THE PINK TAX:
WHETHER AND WHY WOMEN PAY MORE IN CPG

Natasha Bhatia (Northwestern Kellogg)
Sarah Moshary (Chicago Booth)
Anna Tuchman (Northwestern Kellogg)

Rochester - QME Rossi Seminar (March 2021)

Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen 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.
WHAT IS THE “PINK TAX”? 

Alleged empirical regularity that goods and services marketed towards women have higher prices than comparable products marketed towards men.
∙ NY State Assembly banned pricing for goods on the basis of gender in 2019
  ∙ Mandates that retailers, distributors, and manufacturers cannot price “substantially similar” goods or services differently based on genders


∙ Reps. Jackie Speier (D-CA) and Tom Reed (R-NY) introduced a Pink Tax Repeal Act in Congress
How systematic are these price differences?

To understand the need for regulation, we need to understand how systematic these price differences are.
LIMITED EVIDENCE ON SYSTEMATIC PRICE DISPARITIES

· Academic
  · Established literature in markets with negotiated prices
    Ayres (1991) - Car purchases; Busse et al. (2017) - Car repair; Goldsmith-Pinkham and Shue (2020) - Real estate; Blau and Kahn (2017) - Wage gap
  · Limited evidence for posted price markets
    Duesterhaus et al. (2011) - Deodorant, dry-cleaning, haircuts; Wehner et al. (2017) - Rogaine

· Government
  · Government reports on shelf prices but ad hoc data collection
  · NYC report ➞ Women’s personal care items 13% more expensive
LIMITED EVIDENCE ON SYSTEMATIC PRICE DISPARITIES

· Academic
  · Established literature in markets with negotiated prices
    Ayres (1991) - Car purchases; Busse et al. (2017) - Car repair; Goldsmith-Pinkham and Shue (2020) - Real estate; Blau and Kahn (2017) - Wage gap
  · Limited evidence for posted price markets
    Duesterhaus et al. (2011) - Deodorant, dry-cleaning, haircuts; Wehner et al. (2017) - Rogaine

· Government
  · Government reports on shelf prices but ad hoc data collection
  · NYC report → Women’s personal care items 13% more expensive

This Study

· Systematic analysis of prevalence of price disparities
· Why do price differences exist?
  · Need to account for costs and quantities
1. Compare the shelf prices and prices paid of gendered CPG products across the US from 2006-2018
   · Today: focus on antiperspirant & deodorant
   · Find that women’s products are priced higher
1. Compare the shelf prices and prices paid of gendered CPG products across the US from 2006-2018
   - Today: focus on antiperspirant & deodorant
   - Find that women’s products are priced higher

Are men’s and women’s products comparable within the same category?
1. Compare the shelf prices and prices paid for gendered CPG products across the US from 2006-2018
   · Today: focus on antiperspirant & deodorant
   · Find that women’s products are priced higher

2. Investigate economic drivers of retail price differences
   · Attributes may differ systematically → higher manufacturing costs for women’s items?
     (Would not qualify as a pink tax under proposed legislation)
   · Or manufacturing costs may be similar, but demand for women’s products may be relatively inelastic
     (Pink tax as a differential markup for women’s items)
1. Costs
   - Explore attribute differences
   - Estimate retail price differences controlling for observables
   - Compare wholesale prices

2. Elasticities
   - Estimate a log-log demand specification
   - Advertising
Data
Data structure

- Weekly scanner data from 2006 – 2018 (Nielsen Kilts)
- Quantity and average price paid at a UPC/store/week in weeks with positive sales

Price Variables

- Price paid
- Shelf price
  - Fill in price in weeks with zero sales between first and last weeks a UPC sold in a store
  - Use “regular” price (similar to Hitsch et al. 2019) - max price paid at same store in 4 weeks before and after missing week
- Per unit and per ounce
DATA ON DEODORANT GENDER TARGETING

1. Search for gendered words in Nielsen brand description of each UPC (e.g., “his,” “women,” or “lady”)

2. Gender categorization from Walgreens.com

3. Gender targeting information from Label Insight

4. Hand-coding of products by undergraduates using pictures from Label Insight

5. Differential purchasing by all-male and all-female households in the Nielsen consumer panel dataset
- Uncategorized UPCs have small market share
- Almost all deodorant sales are for gendered UPCs
- Men’s and women’s shares similar
<table>
<thead>
<tr>
<th></th>
<th>Avg Shelf Price /Unit</th>
<th>/Oz</th>
<th>Avg Size Oz</th>
<th># Brands Nationally</th>
<th>Store</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>$4.04</td>
<td>$1.37</td>
<td>3.06</td>
<td>158</td>
<td>27</td>
</tr>
<tr>
<td>Women</td>
<td>$4.19</td>
<td>$1.73</td>
<td>2.55</td>
<td>114</td>
<td>20</td>
</tr>
</tbody>
</table>

- Price disparity in raw data
- Men’s products are larger
- Larger assortment of men’s products
Price Differences
· Aggregate 2006-2018 data to the UPC/store/year-level for computational feasibility

· Aggregating price variables:
  · Shelf price: simple average over weeks
  · Price paid: quantity-weighted average over weeks
  · No other pink tax study has information on what consumers actually buy
price disparities - national estimate

\[ p_{sjt} = \beta \text{Women}_j + \text{Year}_t + \text{Store}_s + \varepsilon_{sjt} \]
\[ p_{sjt} = \beta \text{Women}_j + \text{Year}_t + \text{Store}_s + \varepsilon_{sjt} \]

<table>
<thead>
<tr>
<th>DV</th>
<th>Shelf Price /Unit</th>
<th>Shelf Price /Oz</th>
<th>Price Paid /Unit</th>
<th>Price Paid /Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>0.17***</td>
<td>0.38***</td>
<td>-0.004**</td>
<td>0.34***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Avg Men’s DV</td>
<td>4.04</td>
<td>1.37</td>
<td>3.55</td>
<td>1.18</td>
</tr>
<tr>
<td>% Difference</td>
<td>4.2%</td>
<td>27.7%</td>
<td>-0.1%</td>
<td>28.8%</td>
</tr>
</tbody>
</table>

Notes: Shelf price regressions use number of weeks with non-missing shelf price as weights. Price paid regressions use unit sales as weights.

- Shelf price of women’s products is higher than men’s
- Price paid is not → women purchase cheaper products
- Larger price disparity on per ounce basis
# PRICE DISPARITIES - NATIONAL ESTIMATE

\[ p_{sjt} = \beta \text{ Women}_j + \text{Year}_t + \text{Store}_s + \epsilon_{sjt} \]

<table>
<thead>
<tr>
<th>DV</th>
<th>Shelf Price /Unit</th>
<th>Shelf Price /Oz</th>
<th>Price Paid /Unit</th>
<th>Price Paid /Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>0.17***</td>
<td>0.38***</td>
<td>-0.004**</td>
<td>0.34***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Avg Men’s DV</td>
<td>4.04</td>
<td>1.37</td>
<td>3.55</td>
<td>1.18</td>
</tr>
<tr>
<td>% Difference</td>
<td>4.2%</td>
<td>27.7%</td>
<td>-0.1%</td>
<td>28.8%</td>
</tr>
</tbody>
</table>

Notes: Shelf price regressions use number of weeks with non-missing shelf price as weights. Price paid regressions use unit sales as weights.

- Shelf price of women’s products is higher than men’s
- Price paid is not → women purchase cheaper products
- Larger price disparity on per ounce basis
- Not quite a pink tax: Products may have different characteristics
Drivers of Price Differences
(HOW) DO MEN’S AND WOMEN’S PRODUCTS DIFFER?

- Antiperspirant from RMS string parsing
- Other attribute data from Label Insight (26% of the RMS UPCs)
- Women’s products more likely to be antiperspirants & moisturizing
- Previously showed women’s items are smaller

<table>
<thead>
<tr>
<th>Attribute</th>
<th>% UPCs Within Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Women</td>
</tr>
<tr>
<td>Antiperspirant (RMS)</td>
<td>91.8%</td>
</tr>
<tr>
<td>Total UPCs (RMS)</td>
<td>2,126</td>
</tr>
<tr>
<td>Aluminum Free</td>
<td>8.6%</td>
</tr>
<tr>
<td>Antiperspirant (LI)</td>
<td>63.9%</td>
</tr>
<tr>
<td>Cruelty Free</td>
<td>3.1%</td>
</tr>
<tr>
<td>Deodorize</td>
<td>71.2%</td>
</tr>
<tr>
<td>Longlasting</td>
<td>26.6%</td>
</tr>
<tr>
<td>Made In USA</td>
<td>17.1%</td>
</tr>
<tr>
<td>Moisturizing</td>
<td>8.6%</td>
</tr>
<tr>
<td>Total UPCs (LI)</td>
<td>549</td>
</tr>
</tbody>
</table>
**OBSERVED ATTRIBUTES EXPLAIN 35% OF THE PRICE DIFFERENCE**

\[ p_{sjt} = \beta \text{Women}_j + X_j'\beta + \text{Year}_t + \text{Store}_s + \varepsilon_{sjt} \]

- \( X_j \): vector of product attributes
- Estimated on Label Insights UPCs

<table>
<thead>
<tr>
<th>DV</th>
<th>Shelf Price /Oz</th>
<th>Shelf Price /Oz</th>
<th>Price Paid /Oz</th>
<th>Price Paid /Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>0.44***</td>
<td>0.29***</td>
<td>0.36***</td>
<td>0.25***</td>
</tr>
<tr>
<td>Attributes</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Avg Men’s DV</td>
<td>1.40</td>
<td>1.40</td>
<td>1.21</td>
<td>1.21</td>
</tr>
<tr>
<td>% Difference</td>
<td>31.6%</td>
<td>20.7%</td>
<td>30.0%</td>
<td>20.7%</td>
</tr>
</tbody>
</table>

- Observed attributes account for 35% of the price difference per oz.
DATA ON RETAILERS’ WHOLESALE PRICES: PROMODATA FROM PRICETRAK

- Wholesale prices from 12 major grocery resellers across 30 markets in the U.S. from 2006-2011 for subset of UPCs

- Data at the UPC/market (DMA)/year level

- Average wholesale prices:
  - List wholesale prices
  - Deal wholesale prices: after manufacturer incentives

- If manufacturing costs drive price disparities, then should be echoed in PromoData
\[ c_{mjt} = \gamma \text{ Women}_j + \text{Year}_t + \text{Market}_m + \epsilon_{mjt} \]

\( c_{mjt} \): wholesale price of UPC j in market m in year t

<table>
<thead>
<tr>
<th></th>
<th>List Price /Unit</th>
<th>List Price /Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>-0.17*** (0.035)</td>
<td>0.17*** (0.018)</td>
</tr>
<tr>
<td>Avg Men’s DV</td>
<td>2.78</td>
<td>.98</td>
</tr>
<tr>
<td>% Difference</td>
<td>-6.2%</td>
<td>17.0%</td>
</tr>
</tbody>
</table>

Notes: Year and market clustered standard errors. 3,935 observations, 30 markets, and 6 years.

- Similar for deal prices net of promotional spend
- Retail shelf price difference for Promodata UPCs/Markets/Years is $0.13 per unit.
- Hard to reconcile wholesale and retail per unit results if price disparities are driven solely by differences in manufacturing costs
ELASTICITIES

- Classic economic rationale for price discrimination is demand heterogeneity

- Explore whether demand for women’s products is less elastic than for men’s products
Estimate own- and cross-price elasticities for top 5 brands $j$ of each gender in each county $m$ from 2016-2018

\[
\log(q_{jst} + 1) = \sum_{k \in J_m} \beta_{jkm} \log(p_{kst}) + \alpha_{js} + \tau_{jmt} + \varepsilon_{jst}
\]

- Estimate separately for each product (brand/gender) and county
- $q_{jst}$: quantity sold of product $j$ in store $s$ in week $t$
- $p_{kst}$: shelf price of product $k$ in store $s$ in week $t$
- $J_m$: set of top 10 products in market $m$
- $\beta_{jkm}$: own- and cross-price elasticities
- $\alpha_{js}$ and $\tau_{jmt}$ - store and week fixed effects

Identification argument relies on $\tau_{jmt}$ absorbing demand shocks that could lead to endogenous prices (Hitsch et. al (2019))
DEMAND FOR WOMEN’S PRODUCTS LESS ELASTIC

- Distribution of own-price elasticities across brands and markets

<table>
<thead>
<tr>
<th>Gender</th>
<th>Mean</th>
<th>25th Percentile</th>
<th>Median</th>
<th>75th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>men</td>
<td>-1.56</td>
<td>-2.07</td>
<td>-1.55</td>
<td>-1.03</td>
</tr>
<tr>
<td>women</td>
<td>-1.23</td>
<td>-1.74</td>
<td>-1.25</td>
<td>-0.72</td>
</tr>
</tbody>
</table>

- Women’s products less elastic
- Results robust to specification choices (e.g., number of brands included, promotion indicator)
Advertising can lead to higher prices

- Advertising could soften price competition within gender category:
  - Increases perceived product differentiation
  - Increases brand loyalty

- Today: women’s products are advertised more than men’s
Women’s products advertised more than men’s

- Ad Intel data on network and spot TV ads airing between 2010-2018
- Most advertising is for women’s products: ≈ 80% of deodorant ads feature women’s products

Figure 1: Spot

![Spot Ad Occurrences](image1)

Figure 2: Network

![Network Ad Occurrences](image2)
1. We estimate a 21% difference in average price per oz for women’s vs men’s deodorant products
   · If scales across personal care products, implies a $150 difference in spending per year between women and men (BLS)
1. We estimate a 21% difference in average price per oz for women’s vs men’s deodorant products
   - If scales across personal care products, implies a $150 difference in spending per year between women and men (BLS)

2. Despite price differences, we find women are significantly more likely to buy women’s products
1. We estimate a 21% difference in average price per oz for women’s vs men’s deodorant products
   · If scales across personal care products, implies a $150 difference in spending per year between women and men (BLS)

2. Despite price differences, we find women are significantly more likely to buy women’s products

3. Price differences are consistent with elasticity-based pricing
   · Potential role for policy intervention
NY state’s law prohibits differential pricing for “substantially similar” goods of the same brand.

- Many manufacturers sell men’s and women’s items under different brands (e.g. P&G with Old Spice and Secret)
- Controlling for manufacturer & attributes, price difference persists

<table>
<thead>
<tr>
<th>DV</th>
<th>Shelf Price /Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>0.23***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
</tr>
<tr>
<td>Avg Men’s DV</td>
<td>1.40</td>
</tr>
<tr>
<td>% Difference</td>
<td>16.4%</td>
</tr>
</tbody>
</table>
NY state’s law prohibits differential pricing for “substantially similar” goods of the same brand.

- Many manufacturers sell men’s and women’s items under different brands (e.g. P&G with Old Spice and Secret)
- Controlling for manufacturer & attributes, price difference persists

<table>
<thead>
<tr>
<th>DV</th>
<th>Shelf Price /Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>0.23***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
</tr>
<tr>
<td>Avg Men’s DV</td>
<td>1.40</td>
</tr>
<tr>
<td>% Difference</td>
<td>16.4%</td>
</tr>
</tbody>
</table>

Need to alter policy if goal is to reduce price differences

- Regulate within manufacturer rather than within brand
- Per oz instead of per unit
Set of products/attributes and prices are equilibrium objects

- Policies that restrict firms’ ability to set prices may inhibit entry or otherwise reduce assortments → may reduce welfare
  - Typical tradeoff: economies of scale vs match quality
  - Hard to identify empirically
Crux of the issue:
Why do women choose the pink product when the blue version is cheaper?

Two possibilities

1. Instrumental: Color is an important component of deodorant, razor, etc, and “sparks joy”
2. Spurious: Consumers believe color difference indicates other differences between the products (e.g., Shapiro (1982), Bronnenberg et al (2015))
   - Advertising as driver of spurious differentiation

If gender labeling is a case of spurious differentiation, then it potentially hurts all customers

- Softening price competition, leading to higher prices for everyone
1. Scale to other personal care products
2. Attribute-based demand specification
3. Welfare implications of policy
Thank You!
EXAMPLES FROM THE NYC REPORT

Schick Hydro Silk for Women Cartridges
4.0 ea
$18.49
Overview:
- Water activated moisturizing serum
- 5 curve sensing blades for closeness
- Hydrates longer than any other razor more

Schick Hydro 5 Cartridge Razor Refills
4.0 ea
$14.99
Overview:
- Hydrating gel reservoir
- 5 ultra glide blades
- With skin guards that smooth skin more

Ship to you
FREE shipping on orders of $35 or more. Details
Arrives in 1-3 business days*
EXAMPLES FROM THE NYC REPORT

**ITa-MED Rib Support for Women White**

1.0 ea

$26.99

**Overview:**
- Elastic Rib Support for Women (RSW-224) helps stabilize rib & sternum fractures by limiting expansion through compression
- Provides support & compression to the muscles & soft tissues of the rib cage weakened by strain, trauma, overuse, inactivity or surgery
- Limits the expansion for chest to promote healing

**ITa-MED Rib Support for Men White**

1.0 ea

$22.99

**Overview:**
- Elastic Rib Support for Men (RSM-223) helps stabilize rib & sternum fractures by limiting expansion through compression
- Provides support & compression to the muscles & soft tissues of the rib cage weakened by strain, trauma, overuse, inactivity or surgery
- Limits the expansion for chest to promote healing
USING NIELSEN CONSUMER PANEL TO CATEGORIZ GENDER

- Goal: Identify products whose customer base is significantly skewed towards one gender

- 2006-2018 Nielsen panelist data

- Subset to purchases by single-gendered households (“hh”)

- A sizeable sample:
  - 14,421 (30%) hh are single-gendered
  - Of which, 72% are all-female hh
  - 68% of all UPCs ever purchased in panelist data are included
For each UPC, count # of all-female (all-male) hh that ever purchase

Compute share of each UPC’s purchases from all-female (all-male) hh

Test whether share of all-female (all-male) hh purchases is significantly larger than 72% (38%)

Binomial test to avoid assignment for products purchased by few hh’s

If so, women’s (men’s) product. If not, leave unassigned.

<table>
<thead>
<tr>
<th>Category</th>
<th># UPCs</th>
<th>% Gendered</th>
<th>% Women’s of Gendered</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Categories</td>
<td>2,126,187</td>
<td>12%</td>
<td>64%</td>
</tr>
<tr>
<td>Deodorants</td>
<td>5,236</td>
<td>45%</td>
<td>47%</td>
</tr>
</tbody>
</table>

Table 1: Number and Percent of UPCs Categorized by Panelist Data
Distribution of Prices Across UPCs, Stores, and Years
DV: price_fillavg_oz
· Channel: Shelf price pink tax higher in
  · Drugstores
  · Grocery stores

· County Demographics: Shelf price pink tax higher
  · More urban
  · Higher income
  · Smaller share of population is female
  · More educated women
  · More employed women
### Heterogeneity: Channels

<table>
<thead>
<tr>
<th></th>
<th>(1) Shelf Price</th>
<th>(2) Shelf Price/Oz</th>
<th>(3) Price Paid</th>
<th>(4) Price Paid/Oz</th>
<th>Num Stores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women ×</td>
<td>-0.56***</td>
<td>0.10***</td>
<td>-0.46***</td>
<td>0.15***</td>
<td>11,965</td>
</tr>
<tr>
<td>Convenience</td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Women ×</td>
<td>0.24***</td>
<td>0.44***</td>
<td>-0.06***</td>
<td>0.39***</td>
<td>14,165</td>
</tr>
<tr>
<td>Drug</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Women ×</td>
<td>0.26***</td>
<td>0.38***</td>
<td>0.13***</td>
<td>0.33***</td>
<td>14,658</td>
</tr>
<tr>
<td>Food</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Women ×</td>
<td>-0.03***</td>
<td>0.27***</td>
<td>-0.09***</td>
<td>0.31***</td>
<td>15,166</td>
</tr>
<tr>
<td>Mass Merch</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Store FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Week FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>105,525,088</td>
<td>105,525,088</td>
<td>105,525,088</td>
<td>105,525,088</td>
<td></td>
</tr>
<tr>
<td>Stores</td>
<td>55,954</td>
<td>55,954</td>
<td>55,954</td>
<td>55,954</td>
<td></td>
</tr>
<tr>
<td>Years</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td></td>
</tr>
</tbody>
</table>

**Pink Tax by Retail Format** Standard errors are clustered at the store and week level and reported in parentheses. *** p < .01, ** p < .05, * p < .1. Price paid regressions use unit sales as regression weights. Shelf price regressions use number of weeks with non-missing price as regression weights. Not all stores are observed for the full sample period.
## Pink Tax by County Demographics

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1) Shelf Price</th>
<th>(2) Shelf Price/Oz</th>
<th>(3) Price Paid</th>
<th>(4) Price Paid/Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>0.161***</td>
<td>0.368***</td>
<td>-0.028***</td>
<td>0.317***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Women × % Urban Area</td>
<td>0.025***</td>
<td>0.017***</td>
<td>0.0002</td>
<td>0.016***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Women × Median Income</td>
<td>0.027***</td>
<td>0.013***</td>
<td>0.040***</td>
<td>0.018***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Women × Pop Share Female</td>
<td>-0.021***</td>
<td>-0.013***</td>
<td>-0.043***</td>
<td>-0.029***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Women × Share Female Employed</td>
<td>0.004**</td>
<td>-0.005***</td>
<td>0.022***</td>
<td>-0.008***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Women × Share Female College</td>
<td>0.042***</td>
<td>0.026***</td>
<td>0.038***</td>
<td>0.046***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Store FE: Yes, Year FE: Yes

Observations: 105,525,088
Stores: 55,954
Years: 13
# Wholesale Costs vs. Nielsen UPCs

<table>
<thead>
<tr>
<th>Sample</th>
<th>Gender</th>
<th>Mean Annual Qty</th>
<th>Shelf Price /Unit</th>
<th>Shelf Price /Oz</th>
<th>Size Oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Markets and UPCs</td>
<td>men</td>
<td>30.12</td>
<td>3.70</td>
<td>1.28</td>
<td>3.12</td>
</tr>
<tr>
<td></td>
<td>women</td>
<td>34.40</td>
<td>3.74</td>
<td>1.53</td>
<td>2.55</td>
</tr>
<tr>
<td>Wholesale Costs Markets</td>
<td>men</td>
<td>34.26</td>
<td>3.79</td>
<td>1.32</td>
<td>3.13</td>
</tr>
<tr>
<td>Wholesale Costs Markets and UPCs</td>
<td>women</td>
<td>39.01</td>
<td>3.86</td>
<td>1.58</td>
<td>2.56</td>
</tr>
<tr>
<td>Wholesale Costs Markets and UPCs</td>
<td>men</td>
<td>38.54</td>
<td>4.04</td>
<td>1.42</td>
<td>3.04</td>
</tr>
<tr>
<td></td>
<td>women</td>
<td>37.37</td>
<td>4.05</td>
<td>1.72</td>
<td>2.46</td>
</tr>
</tbody>
</table>

Table 2: Summary of UPCs in Wholesale Costs Data
· Show women’s products less elastic, which implies higher margins on women’s products (e.g., monopolist markups)

· Can we take wholesale data and calculate a pink tax in terms of markups?

\[ p_{sjt} = \mu_0 + \mu_1 w_{mjt} + \mu_2 w_{mjt} \times Women_j + Store_s + Year_t \]

where \( p_{sjt} \) is price in store \( s \), year \( t \), for UPC \( j \) and \( w \) is wholesale price in market \( m \), year \( t \), for UPC \( j \). \( \mu_1 \) is retailer’s margin on men’s products. \( \mu_2 \) is the additional margin on women’s products.

· Necessary assumption: wholesale prices for self-distributing Nielsen retailers vs. PromoData retailers is just a level shift
Table 3: Summary of Brands in Elasticities Estimation, 2016-2018

<table>
<thead>
<tr>
<th>Brand Description</th>
<th>Gender</th>
<th>Number of Markets</th>
<th>Share of Markets</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEGREE men</td>
<td>men</td>
<td>702</td>
<td>1.00</td>
</tr>
<tr>
<td>OLD SPICE men</td>
<td>men</td>
<td>702</td>
<td>1.00</td>
</tr>
<tr>
<td>OLD SPICE HIGH ENDURANCE men</td>
<td>men</td>
<td>701</td>
<td>1.00</td>
</tr>
<tr>
<td>MENNEN SPEED STICK men</td>
<td>men</td>
<td>697</td>
<td>0.99</td>
</tr>
<tr>
<td>DOVE MEN + CARE men</td>
<td>men</td>
<td>689</td>
<td>0.98</td>
</tr>
<tr>
<td>RIGHT GUARD SPORT men</td>
<td>men</td>
<td>6</td>
<td>0.01</td>
</tr>
<tr>
<td>ARRID men</td>
<td>men</td>
<td>4</td>
<td>0.01</td>
</tr>
<tr>
<td>GILLETTE ENDURANCE men</td>
<td>men</td>
<td>4</td>
<td>0.01</td>
</tr>
<tr>
<td>AXE men</td>
<td>men</td>
<td>3</td>
<td>0.00</td>
</tr>
<tr>
<td>ARM &amp; HAMMER ULTRAMAX men</td>
<td>men</td>
<td>1</td>
<td>0.00</td>
</tr>
<tr>
<td>POWER STICK men</td>
<td>men</td>
<td>1</td>
<td>0.00</td>
</tr>
<tr>
<td>DEGREE women</td>
<td>women</td>
<td>702</td>
<td>1.00</td>
</tr>
<tr>
<td>DOVE women</td>
<td>women</td>
<td>702</td>
<td>1.00</td>
</tr>
<tr>
<td>SECRET women</td>
<td>women</td>
<td>702</td>
<td>1.00</td>
</tr>
<tr>
<td>SECRET OUTLAST women</td>
<td>women</td>
<td>701</td>
<td>1.00</td>
</tr>
<tr>
<td>SUAVE women</td>
<td>women</td>
<td>697</td>
<td>0.99</td>
</tr>
<tr>
<td>LADY SPEED STICK women</td>
<td>women</td>
<td>3</td>
<td>0.00</td>
</tr>
<tr>
<td>TOM’S OF MAINE women</td>
<td>women</td>
<td>3</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Distribution of county-level elasticities by brand, sorted by median elasticity.
Combining Wholesale Prices and Elasticity Results

Suppose \( w \) is a women’s product and \( m \) is a men’s product. Monopolist FOC implies:

\[
\frac{p_w}{p_m} = \frac{c_w}{c_m} \cdot \frac{1 + \frac{1}{\epsilon_m}}{1 + \frac{1}{\epsilon_w}} \tag{1}
\]

From median elasticities estimates we know:

\[
\frac{1 + \frac{1}{\epsilon_m}}{1 + \frac{1}{\epsilon_w}} \approx 1.77 \tag{2}
\]

From wholesale price regressions per oz we know:

\[
\frac{c_w}{c_m} \approx 1.17 \tag{3}
\]

This implies that price of women’s products should be \( \approx 2 \times \) the price of men’s on a per oz basis. We find that price of women’s products are \( \approx 1.3 \times \) the price of men’s.
· If wholesalers and manufacturers apply markups based on elasticities

· And if wholesalers and manufacturers face similar demand elasticities as our estimates

· Then, markups on women’s products should be higher

· Wholesale prices for women’s products cheaper per unit  \[\Rightarrow\] women’s products are less expensive to manufacture per unit
Why don’t women substitute away from women’s products to cheaper men’s products?

- Estimate cross price elasticities of women’s products with respect to men’s
  - Current specification yields imprecise cross price elasticities
- Preferences over product characteristics?
  - Characteristics (e.g., scent) unobservable in scanner data

Next step: Attribute-based demand model (e.g., nested logit)

- Collected attributes from Label Insight for 26% of products
- Allow us to estimate welfare effects of policy proposals