# Price Norms and Consumer Behaviour

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# Introduction

- Pricing in retail markets is characterized by rigid regular prices and deep sales (Bils & Klenow 2004, Nakamura & Steinsson, 2008)
- Standard view of sales is price discrimination across heterogeneous rational consumers (Varian 1980)
  - even for repeated purchase of durable goods (Hendel & Nevo 2013)
- An alternative view is that valuation is unstable: experiencing high regular prices boosts valuation of the good on sale, by drawing attention to its low price (BGS 2013, 2020)
- Can we empirically distinguish these mechanisms? Are memory and attention quantitatively important in explaining demand?

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- Can we empirically distinguish these mechanisms? Are memory and attention quantitatively important in explaining demand?

# Overview

- Data and some facts about demand
- Model
- Testing novel predictions
- Estimation

# Data

# Data

- Large UK retail chain (approx. 600 large stores)
- Scanner data for all stores, over two years (March 2015 – March 2017)
- $\sim$ 15mln consumers with loyalty cards, 800mln shopping trips
- Unit of observation: consumer $i$ buys good $j$, at price $p$, time $t$, store $s$
  - Product characteristics (price, brand, type, size or weight)
  - Loyalty card information
    - panel structure
    - demographics: gender, age, household size, post code

# Memory, Attention and Choice (BGS 2020)

- Cues that bring high (low) prices to mind boost (dampen) demand

  Model of memory and attention in choice BGS (2020):

  1. choice to buy $(p, q)$ cues retrieval of norm $p^n$ from memory
     - retrieval based on similarity (Kahana 2012)
     - Memory acts as a reference for valuation
  2. If salient difference between $p$ and $p^n$: contrast $p$ away from $p^n$
  3. If no salient difference between $p$ and $p^n$: assimilate $p$ to $p^n$

$$u(q, p) = q - p^n - (p - p^n)\sigma(p, p^n)$$

  - Salience function $\sigma$ captures attention drawn to $p - p^n$

# This Paper

Empirically assess the role of consumers' price memory in choices:

- Use large dataset from UK retailer, covering universe of transactions over 2 years
- Heterogeneity in consumers' norms comes from variation in exposure to prices and to cues

Find systematic instability of valuation from memory-based norms

- sensitivity to differences from the norm double that to changes in price levels
- effect concentrated in large price changes; small price variation is neglected
- normatively irrelevant cues impact price sensitivity
- variables that might matter for price discrimination (inventory, income) have little effect

# Related Literature

**Contrast effects:**

- Lab choices (Tversky & Simonhson, 1995), rentals (Simonsohn & Loewenstein, 1999), speed dating (Barghava & Fishman, 2014), interviews (Schiprowski & Radbruch, 2021)

**Empirical estimation of models of sales**:

- Pesendorfer (2002), Boizot Robin Vissier (2004), Hendel Nevo (2006, 2013)
- Gentry Pesendorfer (2018), Mazumdar et al (2005)

**Relative to this literature, we document:**

- Role of memory: norms mediated by contextual cues, ex post
- Role of attention: contrast for large differences, neglect for small ones

# The Model

# Price Database and Cues

**Database**: good and time specific distribution $D_t(p)$

- Hedonic experiences of prices $p$ up to time $t$
- Assume that $p$ is bimodal: either regular $p_r$, or sale $p_s$
- if share of $p_r$ is $\eta$ then $\overline{p} = (1-\eta)p_s + \eta p_r$

**Cues** $k_t$: features of the choice setting that selective retrieve similar past experiences: reminders of regular price or of sale events

**Price norm**: average experience in $D_t$ weighted by similarity to $k_t$

$$p^n(k_t) = (1-\eta(k_t))p_s + \eta(k_t)p_r = \overline{p} + \Delta\eta(p_r - p_s)$$

where $\Delta\eta = \eta(k_t) - \eta > 0$ if cue is more similar to $p_r$

# Valuation

- Given norm $p^n$, valuation is $u(q,p) = q - V(p,p^n)$ where

$$V(p,p^n) = p^n + (p - p^n)\sigma(p,p^n)$$

- refer to $p - p^n$ as surprise
- $\sigma(p,p^n)$ is a salience function (BGS 2012, 2013, 2020)
  - homogeneous of degree zero, bounded by $\Sigma > 1$
  - large surprises attract attention $\sigma > 1$, small surprises are neglected $\sigma < 1$

# Empirical Approach

- Replacing $p^n(k_t) = \overline{p} + \Delta\eta\,(p_r - p_s)$ in $V$ yields:

$$V \approx \overline{p} + (p - \overline{p})\,\sigma\,(p, \overline{p}) - \Delta\eta\,(p_r - p_s)\,K(p, \overline{p})$$

  where

  - $\Delta\eta = \eta(k_t) - \eta > 0$ if cue $k_t$ disproportionately retrieves $p_r$
  - $K(p, \overline{p}) >)$ if $\sigma\,(p, \overline{p}) > 1$

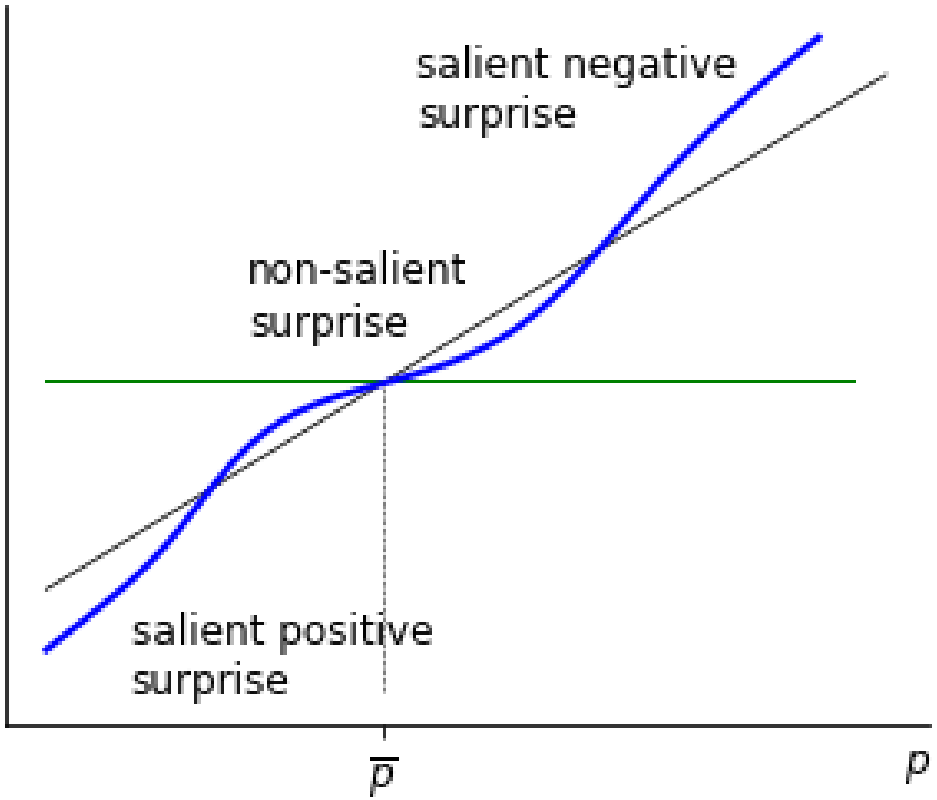
- Suggests the strategy:

  1. Neglect differences in similarity in memory ($\Delta\eta = 0$) and examine role of attention

$$V = \overline{p} + (p - \overline{p})\sigma(p, \overline{p})$$

  2. Then consider cues with clear similarity structure (sign $\Delta\eta$)

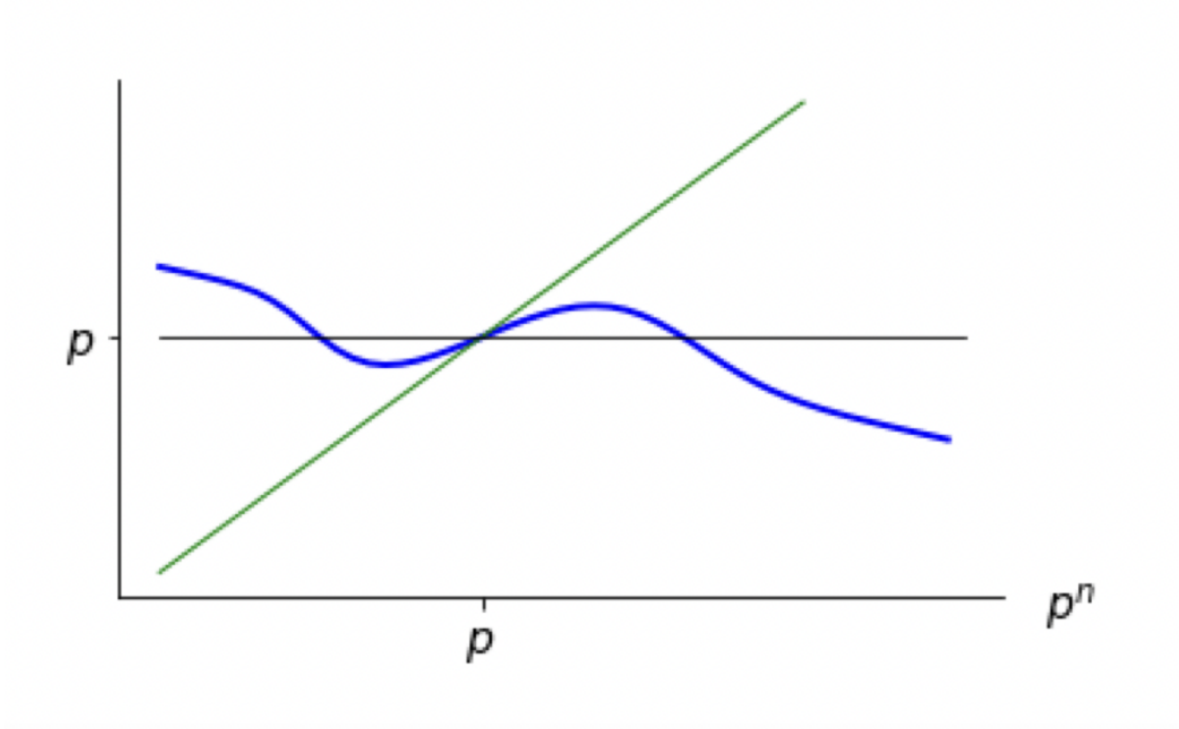
# The role of attention




- Inattention to small price changes, overreaction to large ones

# Cues and instability of valuation

- Conversely, for given $p$ and $\overline{p}$, valuation depends on cue $k_t$
- if $k_t$ retrieves regular prices (sales)$\rightarrow$ $p^n$ increases (drops)
- Valuation increases in $p^n$ if $\sigma > 1$ (contrast) but decreases if $\sigma < 1$ (assimilation)



# Summing Up

1. Consumers neglect price variation close to the average price they experienced
2. Consumers react strongly to large price changes relative to experienced prices
3. Contextual cues can move norms away from the average price, causing overreaction

# Empirical Analysis

# Approach

- For each individual $i$ extract price databases for each good $j$ over time
  - assess variation in average prices $\overline{p}$ and surprises $p - \overline{p}$
- Estimate the model in a flexible discrete choice approach

$$u(q, p) = q - \overline{p} - (p - \overline{p})\sigma(p, \overline{p}) + \Delta\eta(p_r - p_s)K(p, \overline{p})$$

- Test distinctive predictions of memory and attention mechanisms

# Individual price databases

- Define individual $i$'s price database for product $j$ at time $t$

$$D_{ijt} = \{p_{jt} \mid i \text{ visited store at } t' < t\}$$

- Summarize database by average price seen:

$$\overline{p}_{ijt} = E[p_{jt'} \mid p_{jt'} \in D_{ijt},\ t' \text{ in last 80 days}]$$

- To capture recency in recall, truncate distant experiences
- Assuming each visit entails experience may overstate the latter
  - this still entails large variation in norms
  - results robust to restricting database to purchases only

# Variation in price databases

Table 2: Experienced Prices and Surprises, Pooled Across Products

| Variable | Mean | Sd | P10 | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|---|
| Experienced Price (normalized) | 1.00 | 0.097 | 0.85 | 0.98 | 1.00 | 1.05 | 1.10 |
| Price Surprise (normalized) | 0.00 | 0.11 | -0.17 | 0.00 | 0.00 | 0.06 | 0.11 |

*Experienced price is normalized by dividing the experienced price by the average experienced price of the shopper*product combination. Price surprise is normalized by dividing the surprise value by the price norm in each trip. Column summary statistics pool all shopper trips together.*

- Databases vary over time, due to price changes
- Databases also vary across consumers ⏩ example
  - exogenous variation reflecting timing of visits to the supermarket
  - typically accounts for $> 1/4$ of total variance of $\overline{p}_{ijt}$ ⏩ hist

# Estimation

Mixed logit model:

$$\mu_{ijt} = \phi_i^n \overline{p}_{ijt} + \phi_i^s (p_{jt} - \overline{p}_{ijt}) + \alpha_{ij}\tau_j + \alpha_i^p c_{ijt} + \boldsymbol{\alpha_i^{hh}} f(X_{it}) + \epsilon_{ij}$$

- $\phi_i^X \sim \mathcal{N}\left(\overline{\phi}^X, \sigma_X^2\right)$ heterogeneity in sensitivity to price terms
- $\tau_j$ intercept captures fixed characteristics of good $j$, allows taste heterogeneity with random coefficients $\alpha_{ij}$ (Dube et al 2020)
- $c_{ijt} = 1$ if $i$ bought good $j$ before
- $X_{it}$ are household characteristics, including inventory inventory
- $\epsilon_{ij} \sim iid$ extreme value
- set outside option to $\mu_{i0t} = 0$ (static model)

# Baseline Result

Table 3: Baseline Results

| | Panel A: Mean Estimates | | | Panel B: Variance Estimates | | |
|---|---|---|---|---|---|---|
| | (rat) | (baseline) | (alt) | (rat) | (baseline) | (alt) |
| Price | -1.58*** | | | 0.13*** | | |
| Pricenorm | | -0.57*** | -1.44*** | | 0.07** | 0.38*** |
| Price-Pricenorm | | -1.77*** | -1.83*** | | 0.27*** | 0.14*** |
| Price * Inventory | -0.01*** | -0.01*** | | 0.01*** | 0.01*** | |
| Price * Inventory' | | | 0.01*** | | | 3.27*** |

- Past prices help predict choice, contrast dominates $|\phi_t^s| > |\phi_i^n|$
  - Sensitivity to surprises 2 to 3 times as large as to price levels
  - in (Alt), database restricted to purchases, similar results
- Inventory dampens demand but does not affect main result

# Robustness

- Definition of norms
  - all visits vs purchase only
  - different implementations of recency (past 80 to 120 days, last 7 to 10 visits)
  - directly assessing role of past prices table
- Proxying for consideration sets: restricting choice to goods bought by consumer
- Dynamics in reduced form: outside option given by price expectations fitted to $AR(n)$ process

# Rational Channels

In the model, past prices directly affect valuation. But past prices can also drive current demand by shaping the outside option:

- current inventory (controlled for)
- expectations about future prices (Handel & Nevo, 2013)

Crucial distinction: selective attention entails assimilation for small price surprises

1. Valuation may decrease with norm
2. Elasticity of demand is small around the norm, and large far from the norm

# Mechanism: Contrast and Assimilation

- Contrast for large surprises, assimilation for small surprises
- Piece-wise linear specification:

$$u_{ijt} = \phi_i^n \overline{p}_{ijt} + \phi_i^{S,s} \cdot S \cdot (p_{jt} - \overline{p}_{ijt}) + ...$$

where $S \in \{Low, Mid, High\}$ is a dummy for the level of percentage surprise

  - $S = Low$ for $\frac{p_{jt} - \overline{p_{ijt}}}{\overline{p}_{ijt}} <$ -0.07 (bottom 25pctile of surprises)
  - $S = High$ for $\frac{p_{jt} - \overline{p_{ijt}}}{\overline{p}_{ijt}} >$ 0.07 (top 10pctile of surprises)
  - Robust to other thresholds, e.g. 5%

# Results: Contrast and Assimilation

Table 4: Contrast and Assimilation

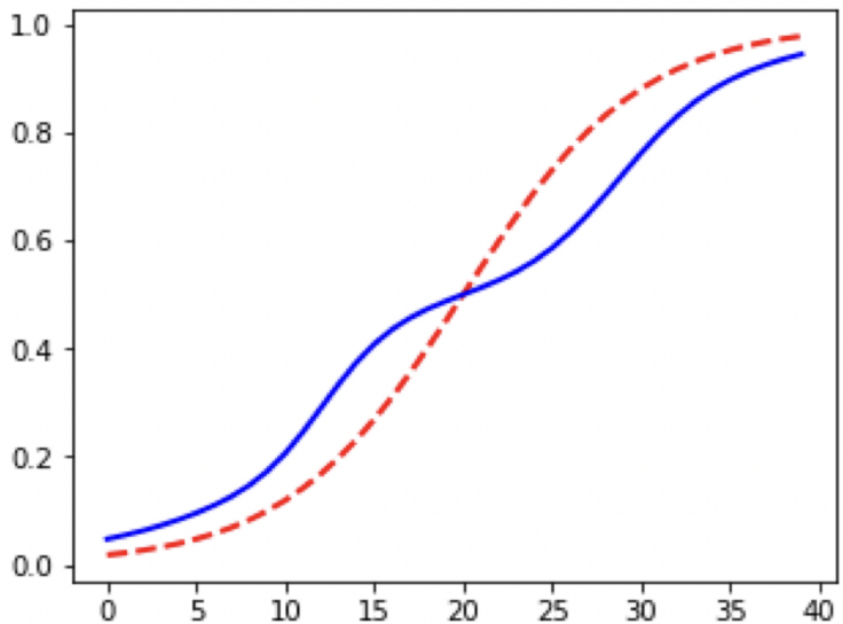
| | Panel A: Mean Estimates | | | Panel B: Variance Estimates | | |
|---|---|---|---|---|---|---|
| | (rat) | (baseline) | (alt) | (rat) | (baseline) | (alt) |
| Pricenorm | -0.57*** | -0.56*** | -1.41*** | 0.07*** | 0.11*** | 0.42*** |
| Price-Pricenorm | -1.77*** | | | 0.27*** | | |
| (Price-Pricenorm) * Low | | -2.05*** | -1.74*** | | 0.07** | 0.13*** |
| (Price-Pricenorm) * Mid | | 0.92*** | -0.54*** | | 0.78*** | 0.01 |
| (Price-Pricenorm) * High | | -1.50*** | -1.87*** | | 0.31 | 0.19*** |
| Price * Inventory | -0.01*** | -0.01*** | | 0.01*** | 0.01*** | |
| Price * Inventory' | | | 0.01*** | | | 0.00 |

- Valuation increases with norm (contrast) for large surprises, $\phi_i^{High,Low,s}/\phi_i^n > 1$ (where $\phi^s/\phi^n$ proxies for $\sigma$)
- Valuation drops with norm (assimilation) for small surprises, $\phi_i^{Mid,s}/\phi_i^n < 1$

# Norms and Price Elasticity

Consider the demand for $(q, p)$ given $(q, p^n)$ in a logit model of discrete choice

- If $(q, p^n)$ is the outside option (red line): $\frac{e^{q-p}}{e^{q-p}+e^{q-p^n}}$
- If $(q, p^n)$ is also the norm (blue line): $\frac{e^{q-V(p,p^n)}}{e^{q-V(p,p^n)}+e^{q-p^n}}$
- Qualitatively similar for more general mixed logit



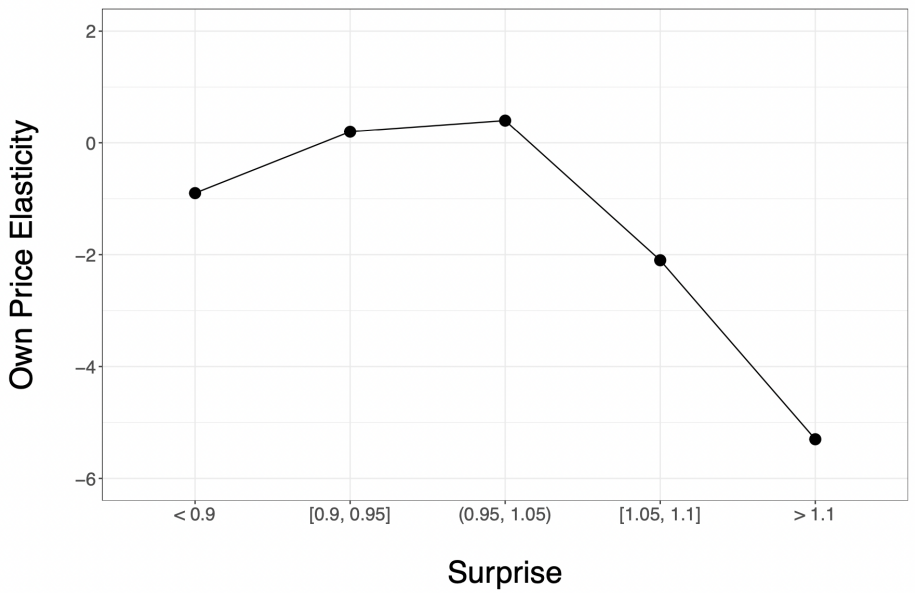
# Norms and Price Elasticity

To compute elasticity, use experimental price variation ($\pm 10\%$) in products treated in the experiment ⏩ experiment

- Sort consumers into norm bins of $\overline{p}$ around modal price $p$
- Compute demand $D(p', \overline{p})$ for each $p' \in \{0.9p,\ p,\ 1{,}1p\}$ and elasticity

$$\frac{P}{D(p, \overline{p})} \frac{D(p, \overline{p}) - D(p', \overline{p})}{p - p'}$$

- Plot average elasticity as a function of norm bin $\overline{p}$



# Cues and instability of valuation

- Norms are not mechanically determined by the database, rather they depend on cues

$$p^n(k_t) = \overline{p} + \Delta\eta(p_r - p_s)$$

where $\Delta\eta$ measures the impact of cues selective retrieval

We consider two naturally occurring cues:

1. When good $j$ is on sale, its regular price is shown $\rightarrow \Delta\eta > 0$.
   - inflates utility to buy at $p$ provided $\sigma > 1$
2. When goods similar to $j$ are on sale, it reminds consumers of $j$'s sales price $\rightarrow \Delta\eta < 0$
   - deflates utility to buy at $p$ provided $\sigma > 1$

# Cueing the Regular Price

- Specification:

$$u_{ijt} \sim \overline{p}_{ijt} + (p_{jt} - \overline{p}_{ijt}) + Sale_j \cdot (p_{j,r} - p_{j,s}) + ...$$

where $Sale_j$ is a dummy $= 1$ when $j$ is on sale

Table 5:Cueing the Regular Price

| | Panel A: Mean Estimates | | Panel B: Variance Estimates | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Pricenorm | -0.71*** | -0.50*** | 0.04*** | 0.14*** |
| Price-Pricenorm | -1.89*** | -1.43*** | 0.48*** | 0.19*** |
| ($Price_{j,r}$-$Price_{j,s}$)*$Sale_j$ | | 0.51*** | | 0.01 |
| Price * Inventory | -0.01*** | -0.01*** | 0.01*** | 0.01*** |

- Results suggest that sales events raise the price norm, increasing utility of purchase on sale
- Conversely, even given reminder, memory norms play a key role

# Cueing Sales

- Specification:

$$\mu_{ijt} \sim \overline{p}_{ijt} + (p_{jt} - \overline{p}_{ijt}) + Sale_{j,sim} \cdot (p_{j,r} - p_{j,s}) + ...$$

  where $Sale_{j,sim}$ is a dummy $= 1$ when $j$ is at its regular price and similar goods are on sale

- good $j$ is similar to $j'$ if equal in all characteristics but size. Analysis restricted to consumers who only purchase $j$

Table 6: Cueing Sales

| | Panel A: Mean Estimates | | Panel B: Variance Estimates | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Pricenorm | -0.71*** | -0.58*** | 0.04*** | 0.13*** |
| Price-Pricenorm | -1.89*** | -1.66*** | 0.48*** | 0.53*** |
| (Price$_{j,r}$-Price$_{j,s}$)*Sale$_{j,sim}$ | | -0.15** | | 0.01 |
| Price * Inventory | -0.01*** | -0.01*** | 0.01*** | 0.01*** |

- Valuation of $j$ is reduced if similar goods $j'$ are on sale

# Issues

1. Price endogeneity
   - Alleviated by using micro data, and randomized prices for 12% of market share
   - Variables are not prices but norms and surprises (which are randomized)
2. Could results reflect market segmentation?
   - Good fixed effects, substantial variation in norms and surprises within goods ⏩ norms ⏩ surprises, extra explanatory power from idiosyncratic variation in norms
3. Not all visits are active choices: partially accounted for with inventory, if anything may dampen results
4. None of these issues explains assimilation or effect of cues

# Taking stock

Memory of past experiences directly shapes valuation, in line with bottom up attention

- Large surprises draw attention, overvalued
- Irrelevant cues affect valuation and demand

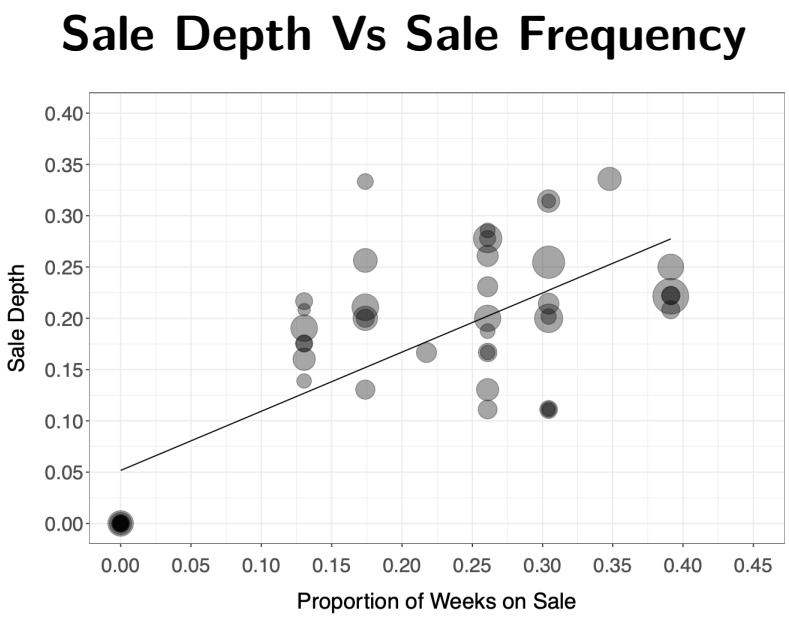
Memory databases and cues are measurable sources of heterogeneity in choice behavior

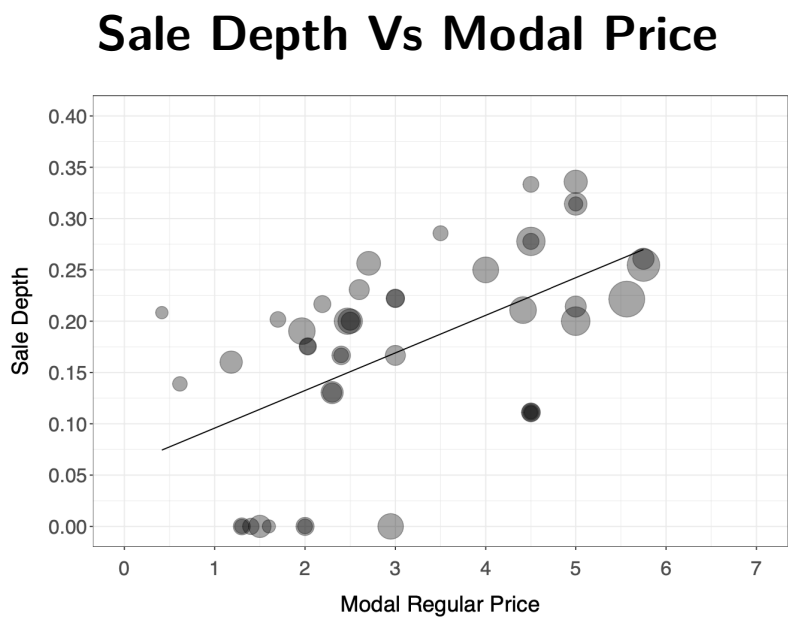
- Income effects matter little

Open issues:

- Ideal test of memory: effect of cues depend on database. Can this be documented?
- Calibrate similarity relations and memory process using choice data
- alternatives of choice can also shape attention to attributes
- optimal pricing strategies

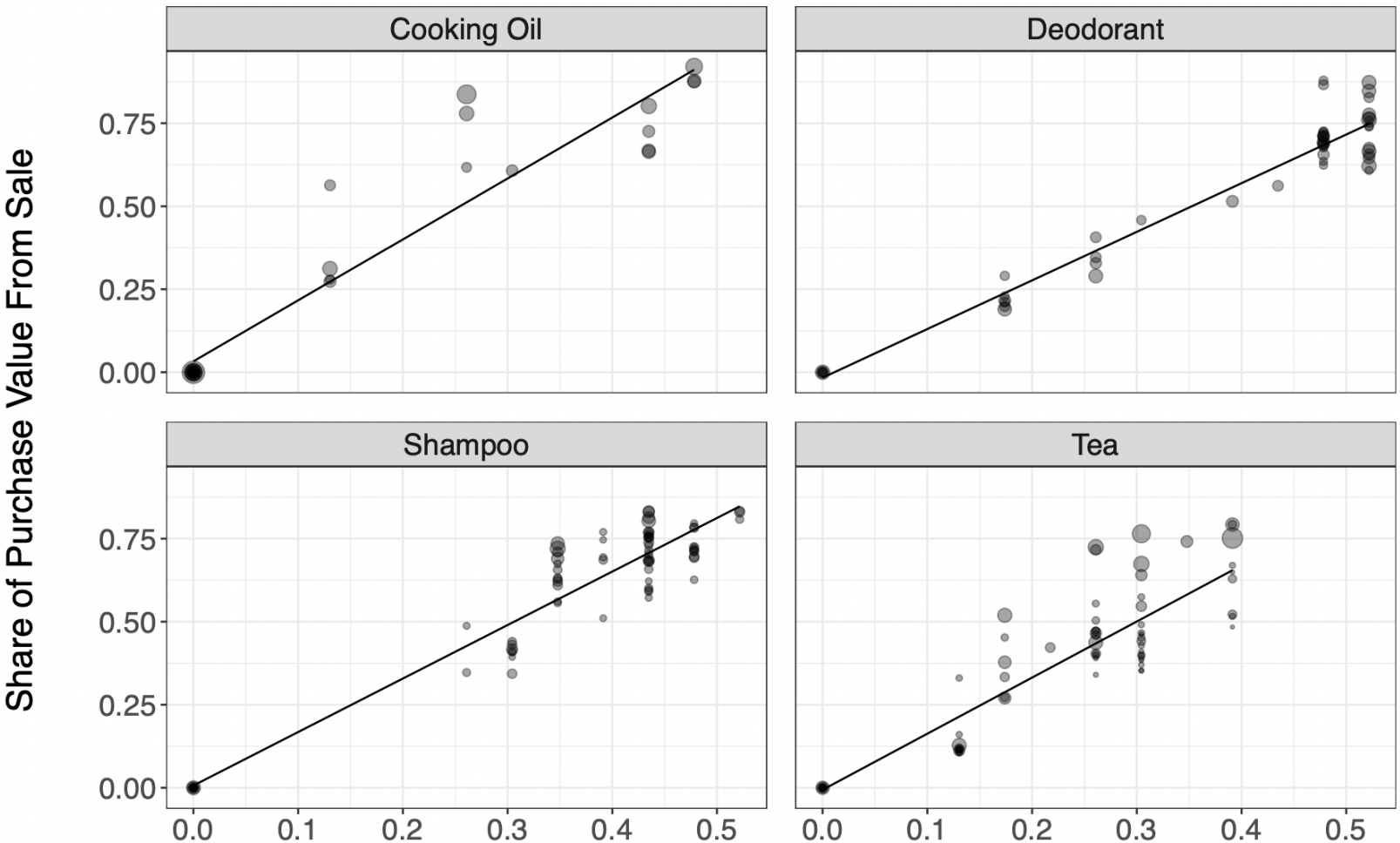
# Heterogeneity in sales




- More expensive teas tend to have larger and more frequent sales

# Share of Demand On Sale, Other Products

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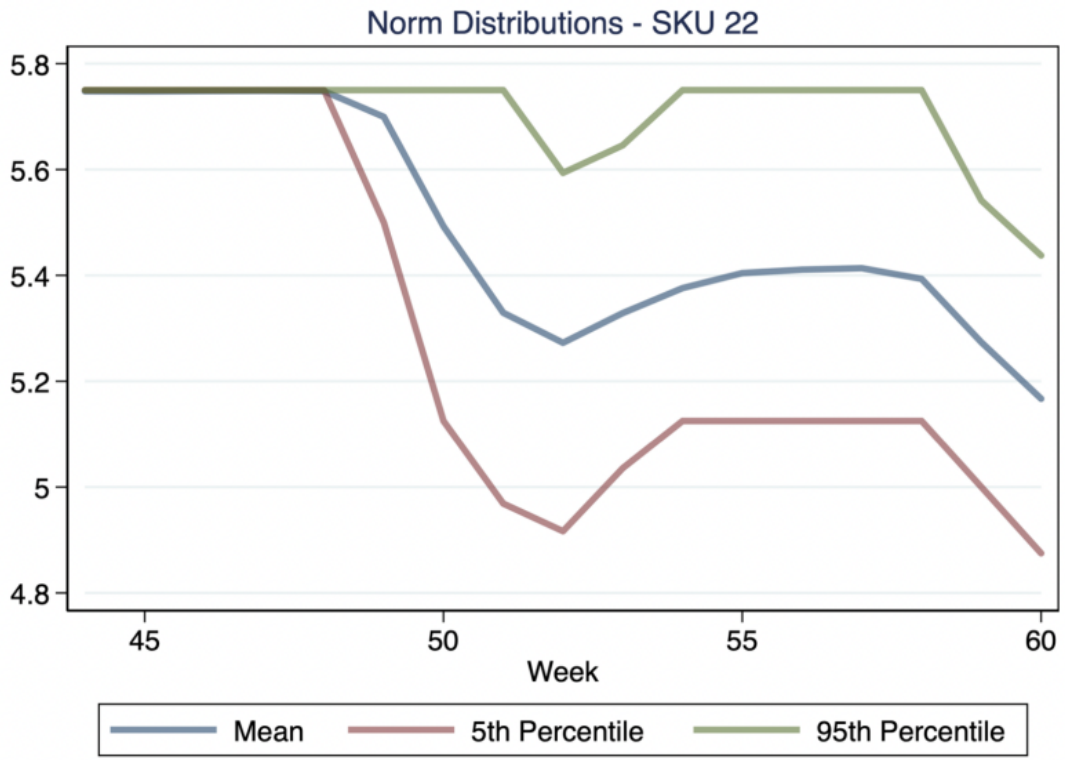
# Example of Price Database Variation

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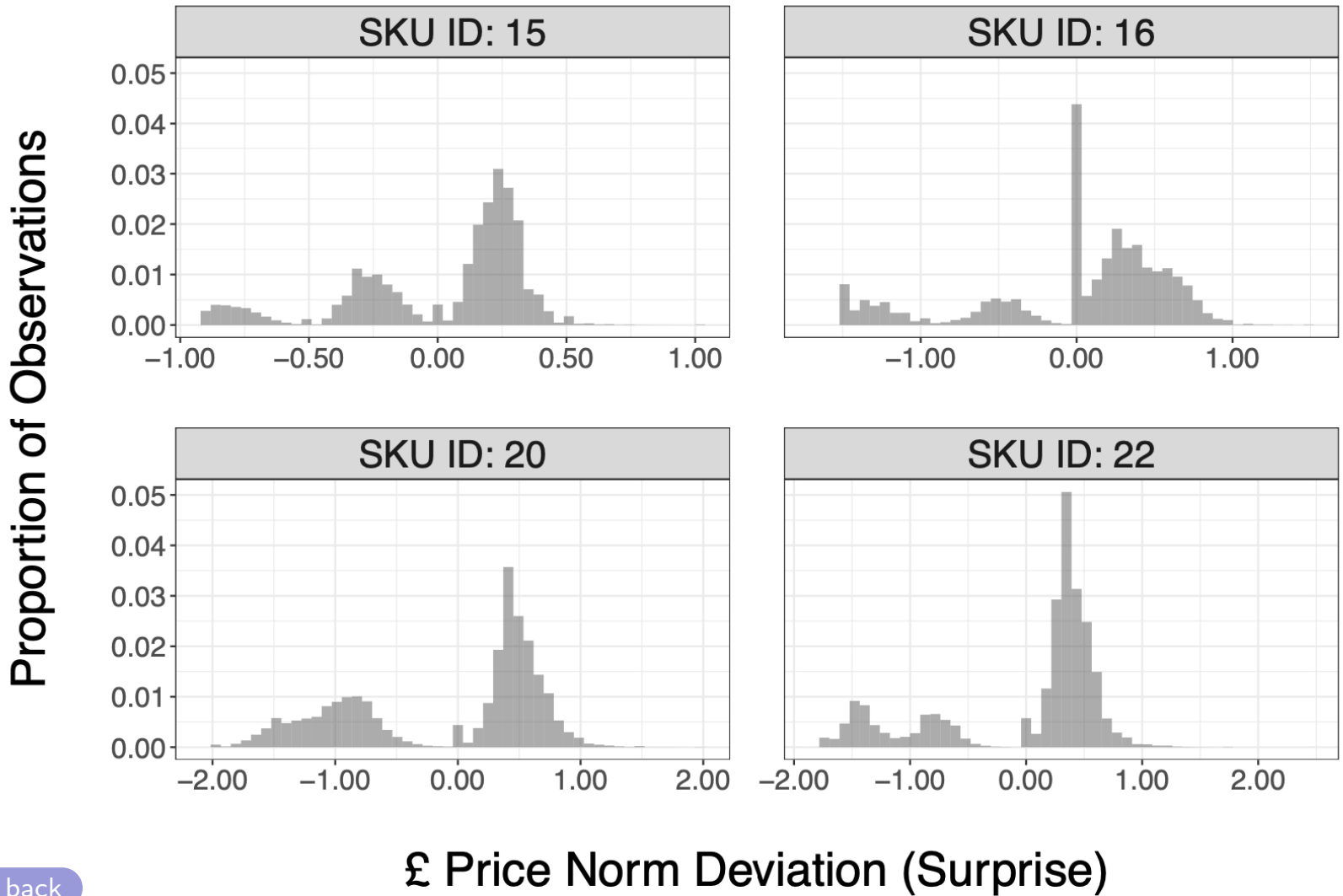
# Examples of Variation in Surprises Within Goods

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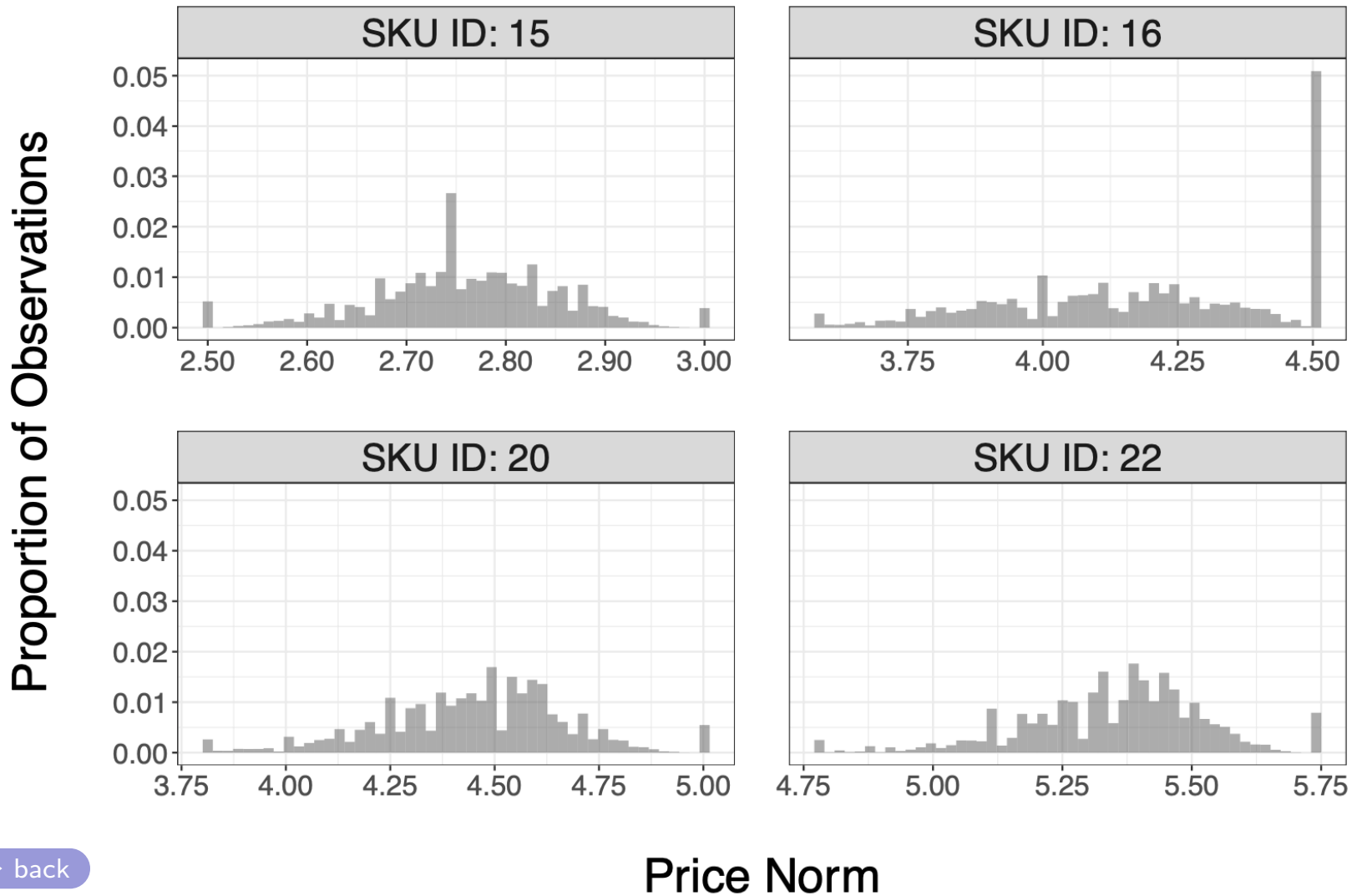
# Examples of Norm Variation

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# Inventory

Inventory proxied by:

$$I_{ijt} = \frac{weight_{i,j,prev}}{hhsize_i * days\ since\ prev\ purchase_{i,j}}$$

Estimation procedure is computationally very intensive

- dataset has approx 32mln rows, for 25k shoppers and 50+1 options
- 110 parameters

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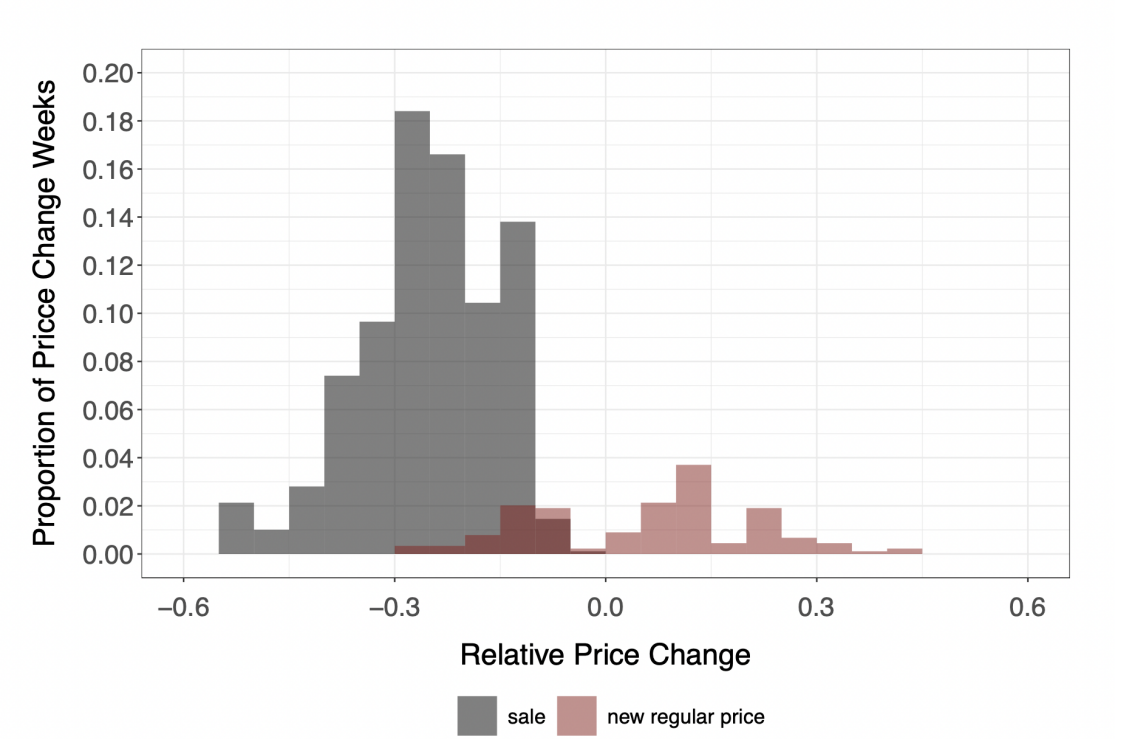
# Price Changes




- Sales are frequent and large: median is 24%
- Regular price changes are rare, mostly increases, and mostly small: median is 8%

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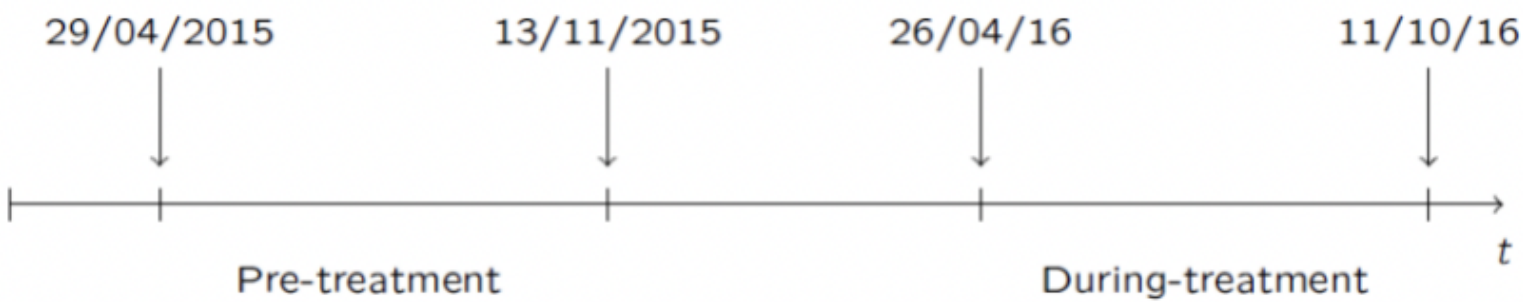
# Data Timeline

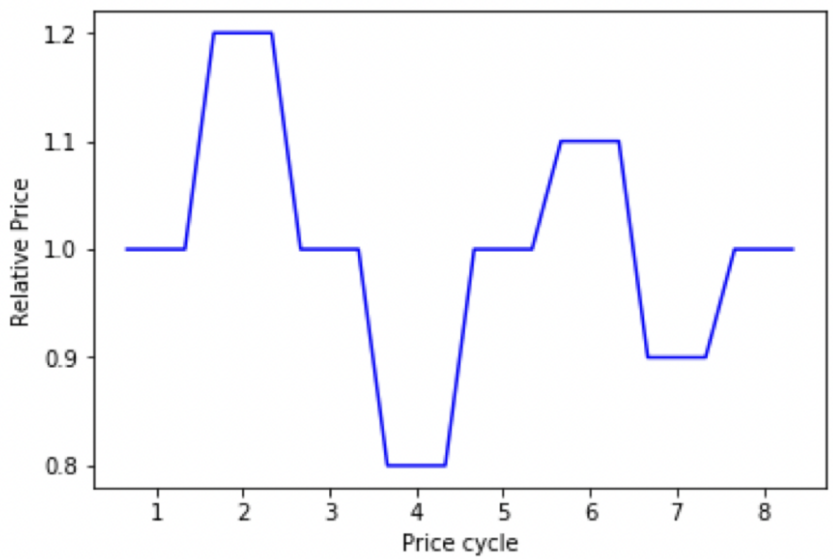
- **Experiment**: 8 cycles of 21 days (168 days), prices are randomized
- **Pre-treatment**: same length, also starting last Wednesday of April, prices set by the retailer



# Price Randomization

We manipulate tea prices within a range of approx. -20% +20% of baseline price

- 8 cycles of 3 weeks each
- 8 tea products, 12% of top 50 market share




elasticity

# Recency

Are past price effects concentrated on the most recent prices?

- prices several visit back still shape choice, but less strongly

Table 7: Recency

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| avg$(p_{n-1}, p_{n-2})$ | 0.44*** | | | |
| avg$(p_{n-3}, p_{n-4})$ | | 0.39*** | | |
| avg$(p_{n-5}, p_{n-6})$ | | | 0.15*** | |
| avg$(p_{n-7}, p_{n-8})$ | | | | 0.09*** |
| Price | -1.72*** | -1.54*** | -1.51*** | -1.50*** |
| Price * Inventory | -0.01*** | 0.01*** | 0.01*** | 0.01*** |
| Choice t-1 | 3.27*** | 3.27*** | 3.48*** | 3.31*** |

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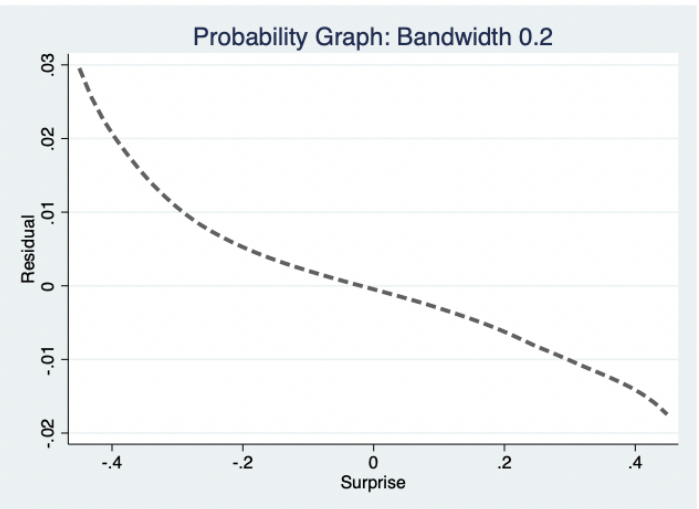
# Another View: Residuals From Linear Regression

Predictability of choice from surprise is easily seen

- Regress demand on price for consumers' modal tea in simple probit model
- Plot regression residuals against price surprise

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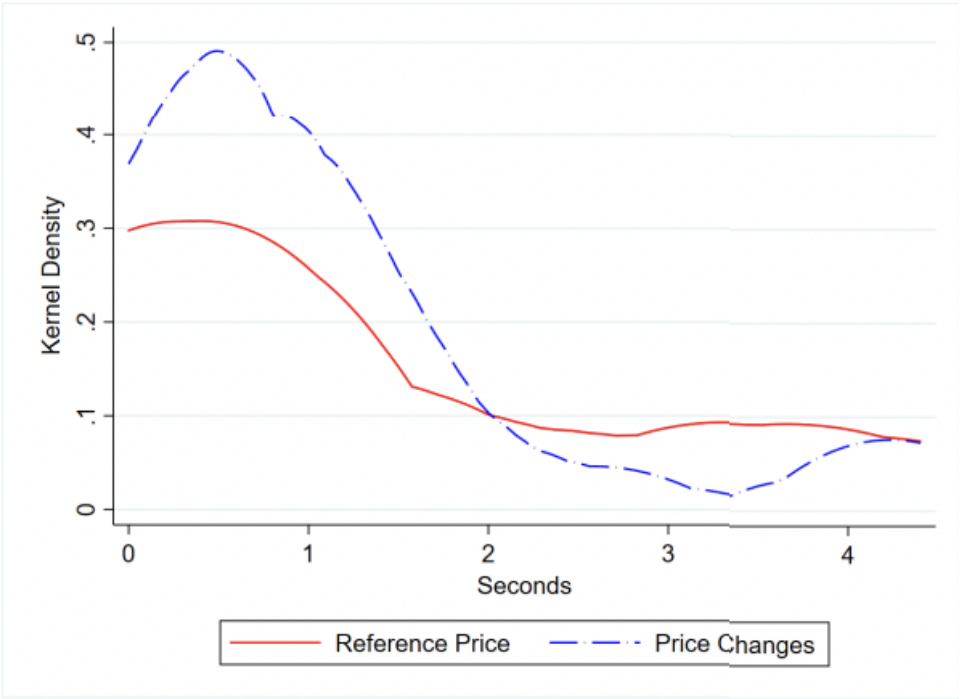
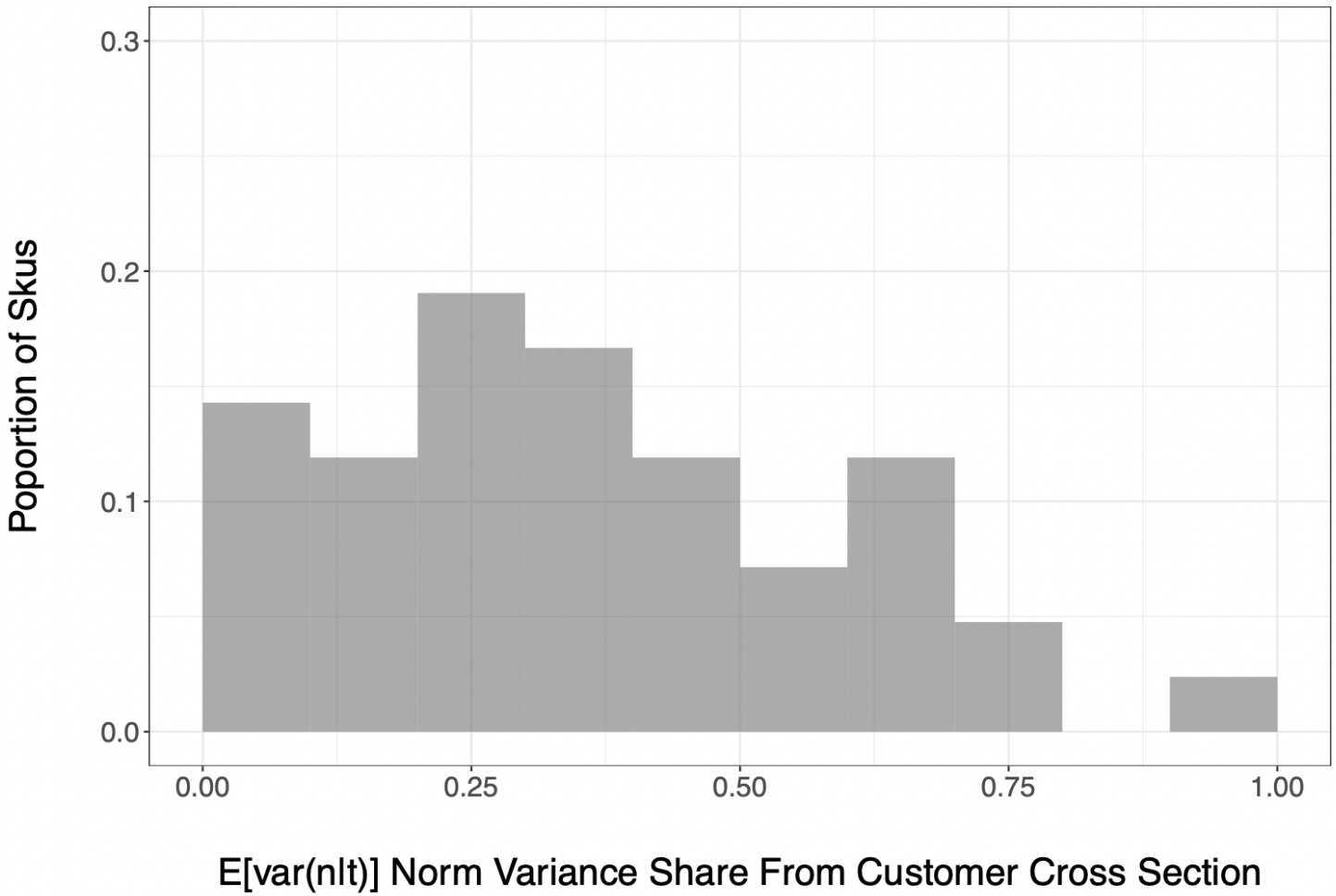
# Seeing Prices

Do consumers look at prices?
**Sample**: Eye-tracking with 68 consumers, usual tea shoppers

- 63% of consumers look longer than 0.3 secs (threshold to register  0.2s)
- Less time on price with price changes, more on other product attributes



# Cross Section Share of Price Norm Variance

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# Number of Teas Seen Per Purchase