Redundant Redundant Labels for Inattentive Consumers

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Abstract

Many daily purchase choices are aided by the use of labels with simple information about products. In this project I study the "redundant label effect:" simple labels that are not adding new information can still affect consumer behavior.

In the domain of food choice, observational studies and experiments show that redundant labels can generate healthier choices, but little is known about which features of the labels generate this effect. I conduct a field-framed experiment to separate the effect of four features of the labels: position, comparison, precision, and interpretation.

The experiment allows to answer the following questions:
1) which features of the labels generate the redundant label effect?
2) how does price elasticity vary under different labeling regimes?
3) in order to promote healthy food habits, what is the effectiveness of price manipulation (sugar tax) and information provision (labels)?

Redundant Labels

Redundant Labels: Example

Nutrition Facts

5 servings per container

Serving size 3/4 cup (170g)

Amount Per Serving

Calories 110

	% Daily Value*
Total Fat 1.5g	**2%**
Saturated Fat 1g	**5%**
Trans Fat 0g	
Cholesterol 10mg	**3%**
Sodium 95mg	**4%**
Total Carbohydrate 19g	**7%**
Dietary Fiber 0g	**0%**
Total Sugars 16g	
Includes 9g Added Sugars	**18%**
Protein 6g	**12%**
Vitamin D 1.9mcg	10%
Calcium 230mg	20%
Iron 0mg	0%
Potassium 310mg	6%

*The % Daily Value (DV) tells you how much a nutrient in a serving of food contributes to a daily diet. 2,000 calories a day is used for general nutrition advice.

Back-of-Package (BOP)

Nutrition facts

Detailed: 1.5g fat

Front-of-Package (FOP)

Nutrition label

Coarse: low fat

Redundant Labels: Definition

Today we focus on this particular type of redundant labels:

1. Continuous Variable	relevant for the DM
2. Observable	available for the DM
3. Shown as Categorical	based on objective criteria

Commonly used, not only in purchase settings:

- Food nutrient claims: low-fat, rich in fiber
- Energy efficiency: energy star (US), A-E scale (EU)
- Health: test results, risk categories
- Finance: high-risk investment funds

Redundant labels present a puzzle for standard economic models...

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Redundant Label Puzzle: Standard Models

- Suppose we want to increase the consumption of healthy food, for example food low in sugar
- ECON 101: Two types of incentives used to change agents' behavior under asymmetric information: price and information
  - **Price incentive**: sugar tax
  - **Information incentive**: mandatory labeling
- *Redundant* information should have no effect...

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Redundant Label Puzzle: Evidence

Observational studies

- FOP label reform in Chile (2016): warning labels mandatory for high level of sugar, calories, fat, sodium Chilean reform

- Reduction in sugar consumption (Barahona et al. 2020), especially for low SES (Araya et al. 2020), price response (Pachali et al. 2020)

Experimental studies

- Food labels increase demand for healthy products
  - Laboratory experiments: Ikonen et al. 2020, Crosetto et al. 2020
  - Field experiments: Dubois et al. 2020, Cadario & Chandon 2020

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Redundant Labels: Why do they matter?

We don't know (yet). Nutrition labels have multiple *features*:

1. Position — Information accessible on the FOP
2. Comparison — Facilitate comparison with other products
3. Precision — Fewer categories simplifies the information
4. Interpretation — High-sugar interpreted as unhealthy

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Redundant Labels: Do they help consumers?

Recent papers highlight possible limitations of “positive” labels

- Labels and overall nutritional value, weak relation (Tallie et al. 2017)
- Labels with no real information increase WTP (Wilson and Lusk 2020)
  Examples: non-GMO sea salt, gluten-free orange juice

Does Truth-in-Advertising labeling help or hurt consumers?

The answer depends on which “advertising” function they cover

1. INFORMATION — Illustrate nutrient content
2. PERSUASION — No informative message

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1. Information — Illustrate nutrient content
2. Persuasion — No informative message

In This Paper

Use a field-framed experiment with consequential choices to study:

1. **How do redundant labels affect consumer behavior?**
   Separate the effects of the features of the label

2. **How does price elasticity vary across label regimes?**
   Estimate nutrient demand elasticity

3. **Compare effectiveness of price vs. info manipulation**
   Estimate the impact on welfare of different interventions

Possibly complement with empirical analysis - but labeling is not random!

1. **How do we include redundant labels in demand estimation?**
   Incorporate through information or persuasion in a demand model

2. **Should we maintain the truth-in-advertising labeling regime?**
   Compare counterfactuals: mandatory, TIA, or no labeling regimes

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Cases that does not follow under the definition of redundant labels

1. *Unraveling* — e.g. mandatory info provision
   Not available before, new info
2. *Verification* — e.g. organic food labels
   External verification process, new info

Other interesting questions about redundant labels (for the future)

1. *Signaling strategy* — e.g. firm choosing what to display
   Choose strategically what to display [firms]
2. *Categories definition* — e.g. FDA defining ranges for claims
   Define thresholds for categories [regulator]
3. *Awareness campaign* — e.g. tobacco danger campaign
   Additional information about risks

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- **Experimental**

  Established stylized facts about food labels

  - Field RCT (Dubois et al. 2020), Lab exp. (Bix et al. 2015, Ono & Ono 2015, Newman et al. 2016), Meta-analysis (Ikonen et al. 2019, Cadario & Chandon 2020)
  - Which *features* of the label generate the effect?

- **Theory & Behavioral**

  Introduced candidate models to explain the effect

  - Contextual inference (Kamenica 2008), salience (Chetty et al. 2009), rational inattention (Matejka & McKay 2015), search cost (De Los Santos et al. 2012)
  - Which families of models are falsified by the observed behavior?

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  Provided tools to measure the effect and study counterfactuals

  - Food information (Abaluck 2011, Kiesel 2007), Chilean labels reform (Pachali et al. 2020, Ale'-Chilet & Moshary 2020, Araya et al. 2020, Barahona et al. 2020)
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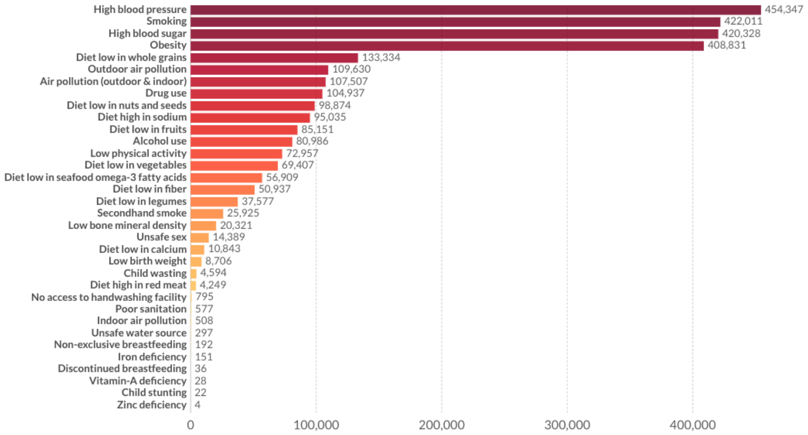
Background

Number of Deaths by Risk Factor, USA 2017

Food-related risk factors include high blood pressure, diabetes, obesity



SOURCE: Institute for Health Metrics and Evaluation (IHME), Global Burden of Disease (GBD)

FDA Mission: Protect and promote the public health

- Food-related health concerns (US adults, CDC data):
  - Obesity: 42% (2018), up from 30% (2000)
  - High cholesterol: 29% (2016), up from 25% (2000)
  - Diabetes: 12% (2016), up from 6% (2000)

- FDA mission. Interventions to help consumers:
  - 1990 Nutrition Labeling and Education Act
  - Subsequent reforms on content and display format

- **How can we help consumers?**
  Ban, Taxation, Consumer education, or Package information

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Nutrition Labels - Institutional Background

- FDA, Code of Federal Regulations, Title 21, Volume 2, Chapter 1, Subchapter B, Part 101 - Food Labeling
- FDA, Food Labeling Guide for Industry
  Much easier to navigate
- Nutrition Facts mandatory since 1994
  - Subpart B - Specific food labeling requirements
- Nutrition Labels *(claims)* truth-in-advertising
  - **General rule: optional, do not lie or misrepresent info**
  - Subpart D - Specific requirements for nutrient content claim
  - E.g. *low-fat* claim only with fat ≤ 3 g

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Nutrition Labels - Institutional Background

Nutrient content claims related to total fat

Nutrient	*Free*	*Low*	*Reduced/Less*	*Comments*
Total Fat *21 CFR 101.62(b)*	Less than 0.5 g RACC and per labeled serving (or for meals and main dishes, less than 0.5 g per labeled serving) (b)(1) Contains no ingredient that is fat or understood to contain fat, except noted below (*).	3 g or less per RACC (and per 50 g if RACC is small) *(b)(2)* Meals and main dishes: 3 g or less per 100 g and not more than 30% of calories from fat *(b)(3)*	At least 25% less fat per RACC than an appropriate reference food (or for meals and main dishes, at least 25% less fat per 100 g) *(b)(4)* & *(5)* Reference food may not be "Low Fat"	"__% Fat Free": may be used if food meets the requirements for "Low Fat" *21 CFR 101.62(b)(6)* 100% Fat Free: food must be "Fat Free" *(b)(6)(iii)* "Light"—see previous Calorie comments For dietary supplements: total fat claims cannot be made for products that are 40 calories or less per serving *21 CFR 101.62(a)(4)*

SOURCE: FDA Food Labeling Guide for Industry

Redundant Label Effect: Hypotheses

- **No effect**
  - Traditional model with perfect information processing
  - Attention model: Sims '03 RI, Bordalo et al. '12 salience (based on value)
- **Position**: front position, immediately accessible info
  - Costly search: De Los Santos et al. '12
  - Salience: Chetty et al. '09 (based on position)
- **Comparison**: facilitate comparison between products
  - Reference dependence: Kahneman & Tversky 1980
  - Bayesian learning: Barahona et al. '20 (uncertainty about prior)
- **Precision**: fewer categories simplify search
  - Limited attention: Abaluck & Adams '21
  - Costly cognitive resources: Stahl 1990
- **Interpretation**: interpretative message, e.g. good, healthy
  - Inference from the message: Kamenica '09
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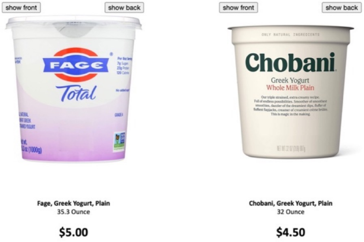
Online Experiment

Experiment: Overview Task

- **Discrete choice with real products**: yogurt, cereals, juice
- Incentivized: receive the product, pay the price
- Collect choices and information acquisition (mousetracking)



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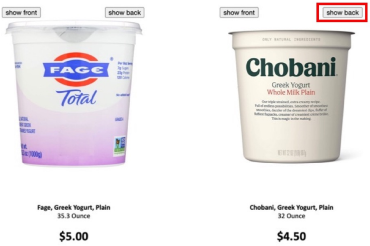

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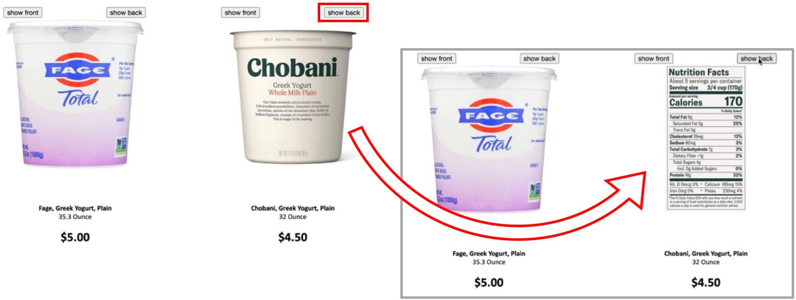

Experiment: Label Manipulations

Label manipulation across treatments

- Manipulate FOP Label features (incrementally)
- Randomly assign treatment, between-subject

Experiment: Price Manipulations

Price manipulation across trials (colors not in the experiment)

- Manipulate product prices within-subject
- Three relative prizes for Healthy/Unhealthy products
  - $p_H > p_U$ Healthy premium
  - $p_H = p_U$ Constant price
  - $p_H < p_U$ Sugar tax

Plan for Analysis

Plan for Analysis - Manipulations

- **Do labels affect food choice?**
  - Compare treatments 1 (control) and 5 (traffic lights). Use a Wald test, H0: the prob. of choosing the healthy product is not affected.
- **Which label features affect food choice?**
  - Compare adjacent treatments (1 vs 2, 2 vs 3, etc.). Use a Wald test for the four separate hypotheses: each feature has no effect.
- **Do label regimes affect price elasticity?**
  - Estimate the nutrient elasticity to price in the different label regimes, use a Wald test for the hypothesis: no effect of labels.
- **Do labels affect the likelihood of BOP consultation?**
  - Use a Wald test for the hypothesis of no effect of labels on Back-Of-Package consultation.

Plan for Analysis - Binary Choice Model

Simple setup for **binary choices** (healthy vs unhealthy products), capture the different perceived evaluation (based on Taubinsky and Allcott 2015)

- Denote products as H healthy and U unhealthy
- p_j price of good j, $p = p_H - p_U$ the relative price
- v_j true utility of good j, $v = v_H - v_U$ the relative utility
- An optimizing consumer chooses H iff $v \geq p$

- Introduce choice bias b (affects choice, not utility)
- Inattentive consumer chooses H iff $v - b \geq p$
- $F(v)$ is the CDF of v (true relative utility)
- $G(b|v)$ is the CDF of b conditional on v
- $H(\hat{v})$ is the CDF of the perceived valuation $\hat{v} = v - b$

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Plan for Analysis - Binary Choice Model

Simple setup for **binary choices** (healthy vs unhealthy products), capture the different perceived evaluation (based on Taubinsky and Allcott 2015)

- Demand curves based on biased and unbiased choices
- $D_B(p) = 1 - H(p)$ with biased choices
- $D_N(p) = 1 - F(p)$ with unbiased choices

- Given the two demand curves we can compute $B(p) = E_G(b | v - b = p)$, i.e. the average marginal bias at price p
- Nudge experiments compute $B(p)$ directly by using *pure nudges* (information manipulation, no price change: Chetty et al. 2009, Taubinsky and Allcott 2015)

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Which Feature matters? Models' Predictions

Multiple families of models can explain the redundant-label effect, but disagree on the mechanism: position, comparison, precision, interpretation

Assumption	Example	POS	COM	PRE	INT
Perfect information					
Rational inattention	Sims 2003				
Salience (value)	Bordalo et al. 2012				
Costly search	DeLosSantos et al. '12	X			
Salience (position)	Chetty et al. 2009	X			
Reference point	Kahneman & Tversky		X		
Bayesian learning	Barahona et al. 2020		X		
Limited attention	Abaluck & Adams '20			X	
Cognitive cost	Stahl 1990			X	
Inference	Kamenica 2009				X
Salience (color)	Wilson et al. 2016				X

Examples of assumptions that are consistent with the redundant-label effect.

Demand Estimation Model

Demand Model: Nutritional Characteristics

- Utility obtained by individual i when purchasing product j

$$u_{ijt} = \underbrace{\phi_i \mathbf{n}_j}_{\text{nutrients}} + \underbrace{\alpha_i p_{jt}}_{\text{price}} + \underbrace{\omega_i \beta_{jt}}_{\text{brand}} + \epsilon_{ijt}$$

- Assumption: decompose product characteristics $\mathbf{X}_{jt}$
  - $\mathbf{n}_j$ nutrients vector, known (product data)
  - p_{jt} price, known (store data)
  - β_{jt} brand component, observable by consumers

- Consider store-period t (market)

- Outside option $j = 0$ with normalized utility $u_{i0t} = \epsilon_{i0t}$

Literature: demand models with nutrients Abaluck 2011 Barahona 2020

Demand Model: Include Redundant Labels

- Define the nutrient vector $\mathbf{n}_j$ based on n_j^k (n_j^1 fat, n_j^2 sugar, n_j^3 protein...)
- Introduce labels: $\mathbf{l}_j$ indicate claims for each nutrient
  - $l_j^1 = 1$ if a fat label is used
  - $l_j^1 = 0$ if no fat label is not used (or not possible based on n_j^1)

INFORMATION SPECIFICATION

- Labels make nutrition information more salient (Chetty et al. 2009)

$$u_{ijt} = \underbrace{\gamma_j \phi_i \mathbf{n}_j}_{\text{nutrients}} + \underbrace{\alpha_i p_{jt}}_{\text{price}} + \underbrace{\omega_i \beta_{jt}}_{\text{brand}} + \epsilon_{ijt}$$

$$\text{with } \gamma_j^k = 1 \text{ if } l_j^k = 0 \qquad \text{and} \qquad \gamma_j^k = \underbrace{\bar{\gamma} \geq 1}_{\text{salient}} \text{ if } l_j^k = 1$$

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with $\gamma_j^k = 1$ if $l_j^k = 0$ and $\gamma_j^k = \underbrace{\bar{\gamma} \geq 1}_{\text{salient}}$ if $l_j^k = 1$

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Persuasion Specification

- Labels provide consumption utility (Pachali et al. 2020)

$$u_{ijt} = \underbrace{\phi_i \mathbf{n}_j}_{\text{nutrients}} + \underbrace{\alpha_i p_{jt}}_{\text{price}} + \underbrace{\omega_i \beta_{jt}}_{\text{brand}} + \underbrace{\rho_j}_{\text{label}} + \epsilon_{ijt}$$

$$\text{with } \rho_j = 0 \text{ if } l_j^k = 0 \ \forall k \qquad \text{and} \qquad \rho_j = \underbrace{\bar{\rho} \geq 0}_{\text{label}} \text{ if } \exists \ l_j^k = 1$$

Demand Estimation: Identification Problem!

A classic market to analyze would be the cereal one

- The decision to **display** the label is arguably not exogenous
- We do not have the time variation as in the Chilean papers!

- Other related decisions, e.g. **formulation** to be below threshold
- Barahona et al. 2020 have a simplified supply model that includes reformulation costs (change recipe)

- **Strong assumption** on the supply side: restrict on the pricing strategy, assume that nutrient characteristics and labels are given

Supply Side

- Nash-Bertrand competition between cereal manufacturer
- Define market t as the week-retailer combination
- Restrict β_{jt} (fixed within year and across retailers)
- Assume M multi-product manufacturer,
  each manufacturer m maximizes profits in market t

$$\pi_{mt} = \sum_{j \in S_{mt}} \left[p_{jt} - c_{jt} \right] s_j(p^t) D_t$$

with s market share, c marginal cost, D market size, S set of manufacturer's products

- Gives he FOC for all j in every market t

$$s_j(p^t) + \sum_{k=1}^{J_t} \Omega_t(k, j) \left[p_{jt} - c_{jt} \right] \frac{\partial s_k^t}{\partial p_{jt}} = 0$$

with Ω_t being the ownership structure matrix

Demand Model: Recap of Parameters

Demand for nutrients:

- ϕ_i (vector) nutrient elasticity
- α_i price elasticity
- ω_i brand preference
- β_{jt} brand fixed effect (replaces usual δ_{jt})
- $\bar{\gamma}$ salience parameter
- $\bar{\rho}$ label utility parameter

Observed heterogeneity:

- p_{jt} choice sets and prices across markets
- $\mathbf{n}_j$ nutrients (within and across brands)
- $\mathbf{l}_j$ labels (across products with same nutrients)
- β_{jt} labels (across products with same nutrients)

Redundant Labels: Counterfactuals

Compare welfare in current Truth-in-Advertising regime and...

1. Information interventions
   - Abolish redundant labels
   - Mandatory redundant label (health halo only)
   - Mandatory redundant label (health halo + warning)
2. Price interventions
   - Sugar tax
   - Calorie tax

Ex-ante utility can differ from the experienced one: adapt consumer surplus as in Allcott 2013 (welfare effect of misperceived characteristics)

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Datasets

- Retail data ✓
  - **Nielsen Retail Scanner Data**
    Weekly sales (SKU level), quantity, price (2004-2018)
- Nutrients data ✓
  - **USDA Nutrient Database for Standard Reference**
    Calories, protein, fat, sugars, ... (per 100g) [good coverage, 200 cereals]
- Label data ✗
  - **Mysterious Kilts/Nielsen dataset**
    Estimated to be released by Spring. Might save tons of time.
  - **Gladson UPC Information Dataset**
    Used in Amano-Patino 2019 (Yale) [Gladson is now Syndigo]
  - **IRI Product Dictionary**
    Used in Tallie et al. 2017 (UC Irvine)
- Focus on one or few product categories with sufficient label heterogeneity (e.g. cereals)

Conclusions

Conclusions & Next Steps

- Redundant labels used in everyday decisions (food, energy, health...)
- Why do they matter? Do they help or harm consumers?
- Experiment: manipulate labels and product prices
- Incorporate redundant labels in standard demand model
- Policy implications: compare price and information interventions

Next Steps

- **Experimental study**
  - Conduct the experiment!
  - Analyze data: price vs. info manipulation
  - Possible follow-up study (based on NSF grant)
- **Dataset**
  - Get label data (various options), merge with Nielsen dataset
  - Incorporate labels in demand estimation (easier said than done)
  - Counterfactual simulations

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Redundant Redundant Labels for Inattentive Consumers

Silvio Ravaioli

Industrial Organization Colloquium
February 11, 2021

Experiment: Overview Task

- **Discrete choices between food items** (yogurt, cereals, juice)
  - Choice data (preferred item)
  - Mousetracking (information collected)
- Debriefing questionnaire (food literacy & habits)
- Incentivized
  - All participants receive \$ 3.50
  - 1/10 participants also receive own choice

Treatments

- Between-subjects: vary the labeling regime
  $\rightarrow$ Test hypotheses on label features
- Within-subject: vary prices and choice set
  $\rightarrow$ Estimate price elasticity

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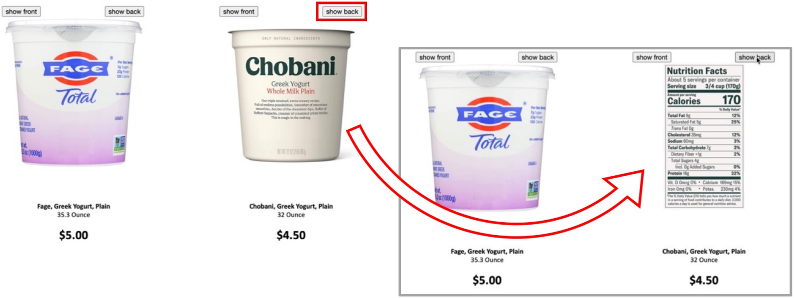
Experimental Interface (no labels)



- Two real products per trial
- Package image, Prices (based on market prices)
- Mousetracking: click to read nutrient facts
- Select the preferred item (no outside option)

Field-framed Experiment

- Choices are consequential
  (deliver grocery for 1 out of 10 participants)
- Screen participants based on relevant categories
  (do not recruit participants uninterested in the products)
- Categories: products with heterogeneity in sugar content
  (yogurt, cereals, juice)
- Binary choice
  1) statistical power, 2) large icons, facilitate reading the labels
- Manipulate prices (estimate local demand elasticity)

Treatments

1. Vary FOP label regimes
   - Between-subjects
   - 5 treatments: 1 control + 4 types of labels
   - Introduce gradually the features

2. Vary product prices
   - Within-subject
   - 3 levels: same prices, healthy premium, sugar tax

Experiment - Main

Label Treatments - Example Product - Treatment 1

Label Treatments - Example Product - Treatment 2

Label Treatments - Example Product - Treatment 3

0g (min) **Sugar** 20g (max)

Sugar content (Yogurt, per portion)

Label Treatments - Example Product - Treatment 4

Sugar content (Yogurt, per portion)

Label Treatments - Example Product - Treatment 5

LOW	MED	HIGH

0g (min) **Sugar** 20g (max)

Sugar content (Yogurt, per portion)

Price Manipulation

- Three product categories in the experiment
  Selected based on price and nutrient heterogeneity

- Twenty different choice sets
  Compare low-low sugar, low-high sugar, etc...

- 3 price levels for each choice set
  - Starting from a benchmark price $\bar{p}$
  - $p_A = \bar{p} = p_B$
  - $1.1 \cdot p_A = \bar{p} = 0.9 \cdot p_B$
  - $0.9 \cdot p_A = \bar{p} = 1.1 \cdot p_B$

Final Questionnaire

- Food literacy
  - Nutritional labels (habits) Poelmann et al. 2018
  - Nutritional labels (ability) Weiss et al. 2005 (NVS test)
- Purchase habits
  - Drivers of purchase (price, brand, taste, healthiness)
  - Beliefs about usage of FOP labels
- Screening and control questions
  - Allergies and dietary restrictions
  - Interested in the products displayed
  - Demographic survey

Experiment - Main

Chile 2016 - Labeling reform

Back to Introduction

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Chile 2016 - Labeling reform

Table 1: Law 20.606 thresholds for Stage 1

	Solids	Liquids
Sugar (g/100g[ml])	22.5	6
Energy (kcal/100g[ml])	350	100
Sodium (mg/100g[ml])	800	100
Saturated fat (g/100g[ml])	6	3

Notes: The table shows the level of sugar, calories, sodium, or saturated fat at which products receive each label after the implementation of Stage 1. For solids, the thresholds are calculated as a function of grams of product (e.g. kcal/100g). For liquids, the formula uses millilitres in the denominator (e.g. kcal/100ml).

Back to Introduction

Demand Model: Abaluck 2011

N_{ijt} is the number of grams of product j consumed by i at t
The utility of consuming diet $d_{it} = \{N_{i1t}, \ldots, N_{iJt}\}$ is

$$U_{it} = \sum_j (\gamma_j + \rho_{jt} + \epsilon_{ijt}) \frac{(K + N_{ijt})^{1-\frac{1}{\eta_j}}}{1 - \frac{1}{\eta_j}} + \sum_n \alpha_n(X_{in}) \left(\sum_j N_{ijt} E_{ijt}(x_{nj}) \right) + \theta I_{it}$$

as a sum of preference for variety, nutrients of the diet, and income

- $\gamma_j, \rho_j, \epsilon_{ijt}$ capture taste for food
- η determines elasticity of demand for food j
- x gives the content of nutrient n
- I is the individual's income
- X_n is the average consumption of nutrient n
- $\alpha(X_n)$ is a piecewise linear function
- Maximization wrt budget constraint and food weight constraint

Back to Demand Model

Demand Model: Barahona 2020

Utility of consumer i when purchasing product j

$$u_{ijt} = \delta_{ijt} + \alpha_i p_{jt} + \phi_i w_{jt}$$

as a sum of taste, price, and health consequences

- δ_{ijt} is the direct utility from consuming j
- Separate product, period, and store fixed effects
- p is the price of the product
- ϕ_i is the elasticity to *health*
- w_{jt} is the long-term health consequences of consumption
- The consumer replaces w with beliefs π_{ji}
- Consumers of the same type have the same π (multivariate normal)
- Split consumers into two bins (above vs below median income)

Back to Demand Model