Eye-opening products: Uncertainty and surprise in cataract surgery outcomes

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- Leverage patient-level data from a large private provider in Mexico City.
- Forward-looking, two-eyed consumers; information revealed after first surgery.
- Evaluate counterfactual policies to increase take-up.

Motivation

- Cataracts = eye lens gets clouded; factors: age, co-morbidities, risky behavior.
- In the US, 45% incidence in ages 75-79; 60% for ages 80+.
- Estimated 30-40% of Mexicans have cataracts; 350k new cases each year.
- But only around 50% are treated.
- Low take-up due to access, cost, and uncertainty. (Lewallen and Courtright, 2000; Syed et al., 2013)

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- Counterfactual 1: information provision to eliminate uncertainty.
- Patients have a high option value.
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- Counterfactual 2: revenue-neutral price change: $p_1 \downarrow, p_2 \uparrow$.
- With 10% price changes: take-up increases by 7%.

Contributions

Contributions

- Dynamics in experience goods markets (Bergemann and Välimäki, 2006; Gowrisankaran and Rysman, 2012; Jing, 2011; Yu, Debo and Kapuscinski, 2016).
  - We study a limited and small number of repeated interactions.
- Demand uncertainty and expert advise. (Berger, Sorensen and Rasmussen, 2010; Reinstein and Snyder, 2005; Hilger, Rafert and Villas-Boas, 2011; Foubert and Gijsbrechts, 2016; Sunada, 2020).
  - We model uncertainty, implied option value; perform counterfactuals.
- Dynamic healthcare treatment choices: adoption of health products in developing countries; search and learning costs for pharmaceutical products. (Dupas, 2014; Oster and Thornton, 2012; Dupas and Miguel, 2017; Ching, 2010; Crawford and Shum, 2005; Dickstein, 2021; Maurer and Harris, 2016).
  - We find: once patients are aware of the benefits, they respond more inelastically.
- Medical lit: why take-up rates of cataract surgeries are low. (Zhang et al., 2013; Mailu et al., 2020; Adhvaryu et al., 2020).
  - Focus on inherent dynamics and how to increase surgical rates.

Empirical setting

- Most patients develop cataracts in both eyes; operated sequentially.
- Cataracts require surgery to replace the lens with an artificial one.
- Method of replacement: phacoemulsification or small incision surgery.
- Lens and surgery type set exogenously by physiological and medical factors.

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- Public healthcare system offers heterogenous quality, long wait times, but free.
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- Most private services are paid for out-of-pocket.
- Private: $\sim$1,500 USD per eye, $\sim$160% median monthly HH income in Mex City.

Empirical setting: Our partner firm

- The Firm is a private, ocular healthcare provider.
- Provides regular check-ups, lab analyses, eye surgery, and an optical store.
- Specializes in diagnosing and operating cataracts.
- Based in Mexico City: 20 clinics, HQ in downtown.
- All* of surgeries are carried out in HQ.
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- We observe all first-time patients of 2018 and through 2019.
- Offered prices, cataract scores, age, gender, sales agent, proxy for income, proxy for risk aversion.
- Avg price is $\sim$700 USD.

quotes by surgery

Patients sum stats

Has a cataract surgery	0.65
	(0.48)
Age	69.24
	(12.24)
Female	0.61
	(0.49)
Private insurance	0.07
	(0.26)
Social security	0.22
	(0.41)
Uninsured	0.72
	(0.45)
Right eye cataract potential	2.68
	(1.61)
Left eye cataract potential	2.64
	(1.61)
Observations	3,894

Consumer's journey

1. Consumer arrives, ophthalmologist diagnoses cataracts with 0 to 6 scale.
2. Physician prescribes the type of surgery and lens. No posted prices.
3. Sales agent discusses prices; some discretion over price.
   - Agents earn commissions. Max price conditional on sale.
4. If consumer agrees, surgery is scheduled and performed.
5. The patient might return, at the physician's discretion, for follow ups.

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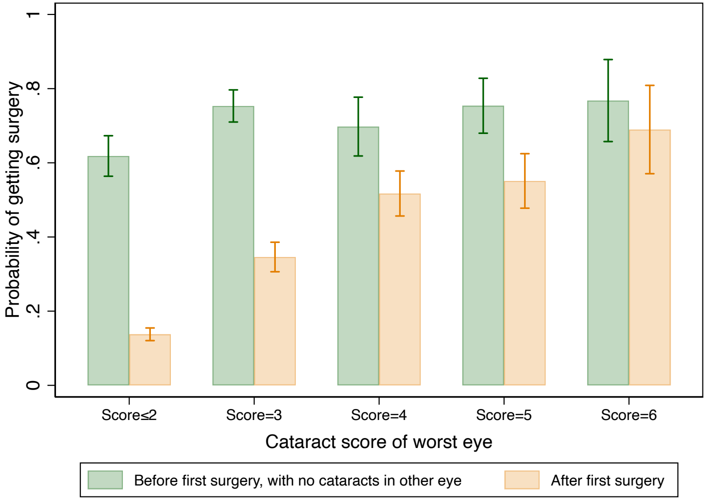
Note: We take prescriptions as exogenous. (Finkelstein et al., 2021; Johnson and Rehavi, 2016; Gruber and Owings, 1996).

Consumer's learning

- From literature: Cataract patients do update their beliefs. (Cheung and Sandramouli, 2005; Henderson and Schneider, 2012)

	Before first surgery		After first surgery	
	Alice	Bob	Alice	Bob
First eye score:	4	6	0	0
Second eye score:	0	4	0	4

Consumer's learning



Model

1. Consumer i observes $\boldsymbol{x}_{i1}$, ε_{i1}, and ε_{i01}.
2. Decides to operate or not.
3. Gets $u_{i1} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i1} + \varepsilon_{i1}$ or outside option ε_{i01}.
4. Consumer i observes α_i, $\boldsymbol{x}_{i2}$, ε_{i2}, and ε_{i02}.
5. Decides to operate or not.
6. Gets $u_{i2} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2}$ or outside option ε_{i02}.

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5. Decides to operate or not.
6. Gets $u_{i2} = \alpha_i + \boldsymbol{\beta}'\boldsymbol{x}_{i2} + \varepsilon_{i2}$ or outside option ε_{i02}.

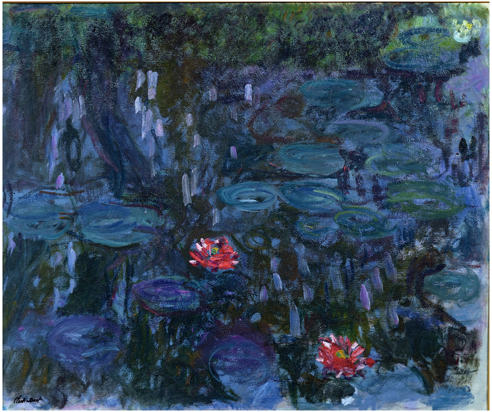
- $\alpha_i \sim G_i$ to allow for heterogeneity.
- Variance measures the size of uncertainty that consumer i faces.
- Allow for partial learning: knowable and an unknowable components

$$\alpha_i \equiv \alpha_i^k + \alpha_i^u.$$

- Do not learn nor observe $\alpha_i^u \Rightarrow \alpha_i = \alpha_i^k$ in relevant time-frame.

Claude Monet's α_i

Giverny period c.1897



With cataracts c.1916

Model: Backward induction

- Let $y_{i2} = 1$ indicate if i operates at $t = 2$, which happens iff

$$u_{i2} > u_{i02} \iff \alpha_i + \boldsymbol{\beta}' \mathbf{x}_{i2} + \varepsilon_{i2} - \varepsilon_{i02} > 0.$$

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Then, the demand for the second surgery is

$$s_{i2} \equiv P\left[y_{i2} = 1 | y_{i1} = 1\right] = P\left[u_{i2} - u_{i02} > 0\right].$$

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- Expected marginal utility of the second surgery is

$$\mathbb{E}\left[u_{i2} - u_{i02}\right] = \mathbb{E}\left[u_{i2} - u_{i02} | u_{i2} - u_{i02} > 0\right] P\left[u_{i2} - u_{i02} > 0\right]$$

  where the expectations are with respect to $\alpha_i + \varepsilon_{i2} - \varepsilon_{i02}$.

Model: Backward induction

- Before α_i, ε_{i2}, ε_{i02} are known, the expected marginal utility from first surgery is

$$\mathbb{E}_{\alpha_i}\Big[u_{i1} - u_{i01} + \underbrace{\mathbb{E}\left[u_{i2} - u_{i02}\right]}_{\text{option value}}\Big].$$

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Model: Estimation and identification

Assumption

$\varepsilon_{i1} - \varepsilon_{i01}$ and $\varepsilon_{i2} - \varepsilon_{i02}$ are iid $\mathcal{N}(0, 1)$, and α_i are iid $\mathcal{N}(0, \sigma_{\alpha,i})$.

- Simplify to analytic expressions, Φ, inverse Mills ratio.

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- Simplify to analytic expressions, Φ, inverse Mills ratio.
- Parameterize $\sigma_{\alpha,i} \equiv \exp(\boldsymbol{\theta}' w_i)$.
- Estimate $(\boldsymbol{\beta}, \boldsymbol{\theta})$ via maximum likelihood estimation.

$$\ell = \sum_{i=1}^{N} y_{i1} \log s_{i1} + (1 - y_{i1}) \log(1 - s_{i1}) + y_{i1} y_{i2} \log s_{i2} + y_{i1}(1 - y_{i2}) \log(1 - s_{i2}).$$

Model: Estimation and identification

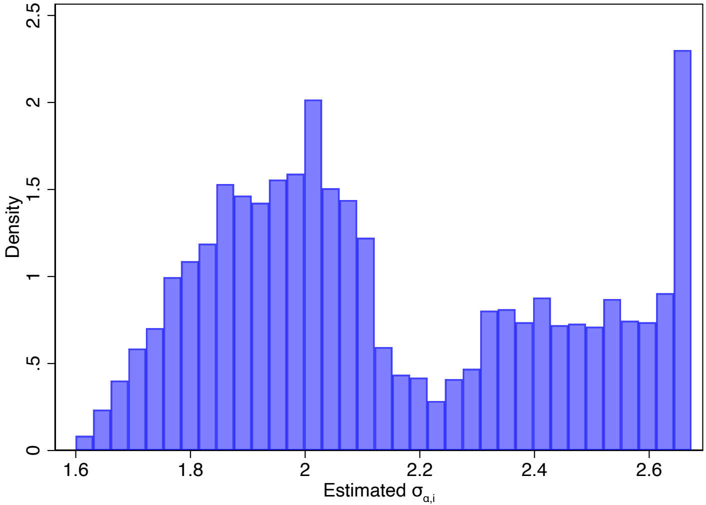
- **Price endog**: control function (Petrin and Train, 2010) Control function.
  - IV: daily percentage of operations sold just before price quote.
- **Risk aversion**: visits per price quote as proxy.
- **Decreasing marginal returns**: cataract scores.
- **Income effects**: type of insurance (proxy for SES).
- Further controls: sales agent fixed effects, log age, gender, type/characteristics of surgery.
- Identify level of $\sigma_{\alpha,i}$ given that shocks at $t = 1, 2$ have the same variance. (Gowrisankaran and Rysman, 2012; Arcidiacono and Ellickson, 2011)
- Identify $\boldsymbol{\theta}$ from the correlations between $\sigma_{\alpha,i}$ and w_i.
- **Selection bias**: machine learning to predict unobserved p_{i2}. lasso
- Bootstrapped standard errors.

Results

Dep var: Operates$_{it}$	(1)	(2)	(3)	(4)
log price	−3.85	−0.93	−3.92	−3.92
	(0.068)	(0.077)	(0.070)	(0.071)
log Age	0.08	−0.11	0.07	0.05
	(0.074)	(0.084)	(0.078)	(0.104)
Female	−0.04	−0.09	−0.05	0.12
	(0.025)	(0.041)	(0.025)	(0.135)
Dep var: $\sigma_{\alpha,i}$				
log Age				−1.98
				(0.243)
Female				−2.57
				(0.358)
Elasticities				
All ops	-3.64	-7.99	-6.31	-3.56
First ops	-3.72	-11.39	-8.62	-4.07
Second ops	-3.57	-4.53	-3.96	-3.04
Other controls	yes	yes	yes	yes
Controls ($\sigma_{\alpha,i}$)	no	no	no	yes
Control function	yes	no	yes	yes
mpe	0.43	0.41	0.39	0.34
R_p^2	-0.06	0.00	0.04	0.16
First-stage IV's F	50.48		50.48	50.48
Patients	3,894	3,894	3,894	3,894
Quotes	7,848	7,848	7,848	7,848

Notes: Bootstrapped standard errors with 500 repetitions.

Results



Distribution of $\widehat{\sigma}_{\alpha,i}$, winsorised at 95th percentile.

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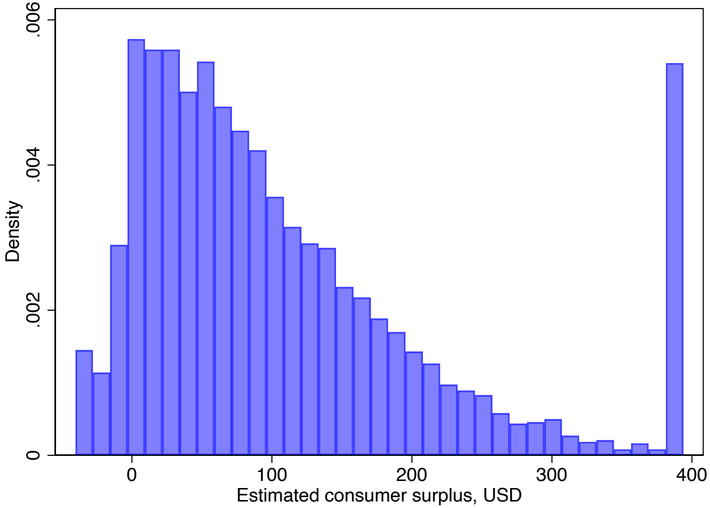
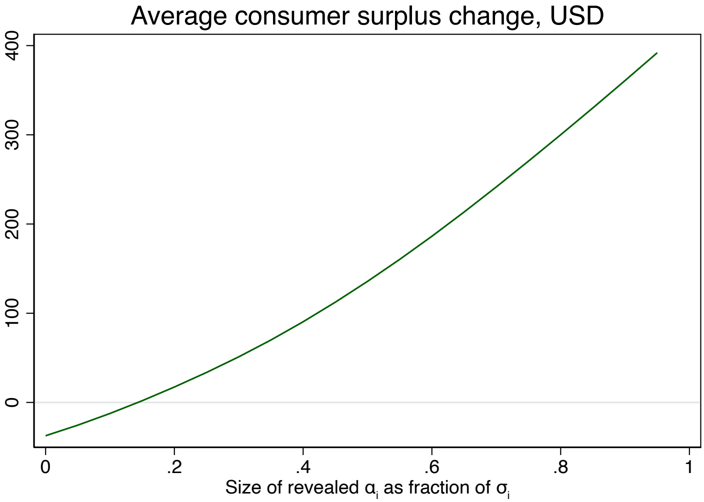


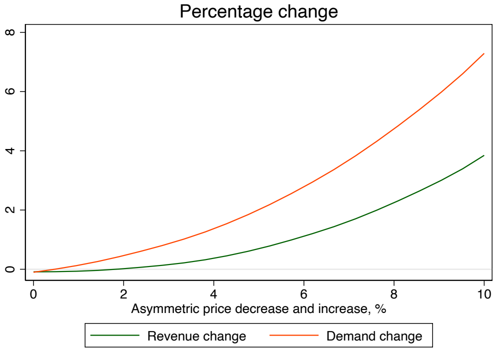
Distribution winsorised at 1st and 99th percentiles.

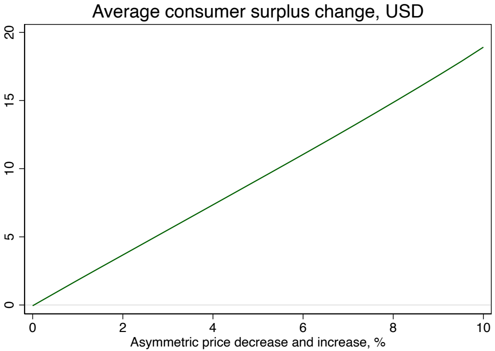
Counterfactuals: Champions



Persuasive advertising: removing uncertainty by revealing $\alpha_i \in [0, \widehat{\sigma}_{i,\alpha}]$

Counterfactuals: Revenue-neutral price cross-subsidy





Asymmetric changes: For example, if p_1 drops in 1%, then p_2 increases in 2%.

Symmetric change

Concluding remarks

- Elastic demand for surgeries; first op more elastic.
- Sizable uncertainty about surgery outcomes: 2x as big as unobservables.
- Persuasive advertising not very effective to increase take-up.
- Budget-neutral price changes are more efficient.
- A 10% price change increases surgeries in 7%, and consumer welfare in $20.

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Thank you!

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Price quotes by number of surgery and patient outcomes

	Number of surgery		
	1st eye	2nd eye	Total
Patients with zero surgeries	1,480	-	1,480
Patients with one surgery	1,981	93	2,074
Patients with two surgeries	679	678	1,357
Total	4,140	771	4,911

back

Prince endogeneity and control function I

To deal with endogenous prices, we use a control function (Petrin and Train, 2010). We assume:

Assumption

Shocks can be decomposed as $\varepsilon = \gamma\rho + \widetilde{\varepsilon}$, where prices $p \perp \widetilde{\varepsilon}$, and ρ is correlated with prices, with $\mathbb{V}[\rho] = 1$.

Then,

$$\mathbb{V}[\varepsilon] = 1 = \gamma^2 + \mathbb{V}[\widetilde{\varepsilon}] \Rightarrow \mathbb{V}[\widetilde{\varepsilon}] = 1 - \gamma^2.$$

Define

$$\sigma_{\widetilde{\varepsilon}} \equiv \sqrt{1-\gamma^2}.$$

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Prince endogeneity and control function II

Therefore, by decomposing ε in the preceding derivations, we have

$$\begin{aligned}\mathbb{E}\left[u_{i2}|\alpha_i, u_{i2}>0\right] &= \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i2} + \gamma\rho_{i2} + \mathbb{E}_{\widetilde{\varepsilon}_{i2}|\alpha_i}\left[\widetilde{\varepsilon}_{i2}|\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i2} + \gamma\rho_{i2} + \widetilde{\varepsilon}_{i2} > 0\right] \\ &= \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i2} + \gamma\rho_{i2} + \sigma_{\widetilde{\varepsilon}}\lambda\left(\frac{\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i2} + \gamma\rho_{i2}}{\sigma_{\widetilde{\varepsilon}}}\right).\end{aligned}$$

Then,

$$\begin{aligned}P\left[y_{i1}=1\right] &= P\left[\int \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i1} + \gamma\rho_{i1} + \widetilde{\varepsilon}_{i1} + \mathbb{E}\left[u_{i2}|\alpha_i, u_{i2}>0\right] dG_i(\alpha_i) > 0\right], \\ &= \Phi\left[\frac{1}{\sigma_{\widetilde{\varepsilon}}}\int \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{i1} + \gamma\rho_{i1} + \mathbb{E}\left[u_{i2}|\alpha_i, u_{i2}>0\right] dG_i(\alpha_i)\right].\end{aligned}$$

Prince endogeneity and control function III

Also,

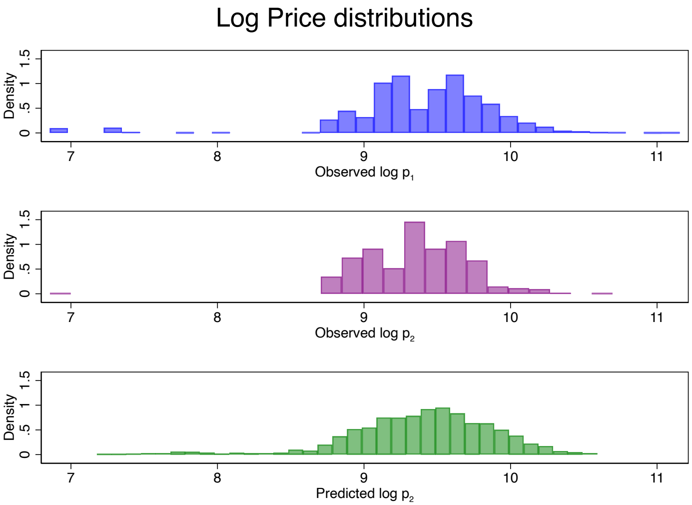
$$
\begin{aligned}
P\left[y_{i2}=1|y_{i1}=1\right] &= P\left[\alpha_i+\boldsymbol{\beta}'\mathbf{x}_{i2}+\gamma\rho_{i2}+\widetilde{\varepsilon}_{i2}>0|y_{i1}=1\right] \\
&= \Phi\left(\frac{\mu_{\alpha,i}+\boldsymbol{\beta}'\mathbf{x}_{i2}+\gamma\rho_{i2}}{\sqrt{\sigma^2_{\widetilde{\varepsilon}}+\sigma^2_{\alpha,i}}}\right), \\
&= \Phi\left(\frac{\mu_{\alpha,i}+\boldsymbol{\beta}'\mathbf{x}_{i2}+\gamma\rho_{i2}}{\sigma_{\widetilde{\varepsilon}}\sqrt{1+\frac{\sigma^2_{\alpha,i}}{\sigma^2_{\widetilde{\varepsilon}}}}}\right),
\end{aligned}
$$

Prince endogeneity and control function IV

We see every parameter of the model is rescaled by $1/\sigma_{\widetilde{\varepsilon}}$, which needs to be accounted for to report the parameters in the original scale. Indeed, from an estimate of $\widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}$, we can back out

$$\widehat{\gamma} = \frac{\widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}}{\sqrt{1 + \widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}^2}} \Rightarrow \widehat{\sigma_{\widetilde{\varepsilon}}} = \sqrt{\frac{1}{1 + \widehat{(\frac{\gamma}{\sigma_{\widetilde{\varepsilon}}})}^2}}.$$

Sample selection and LASSO I



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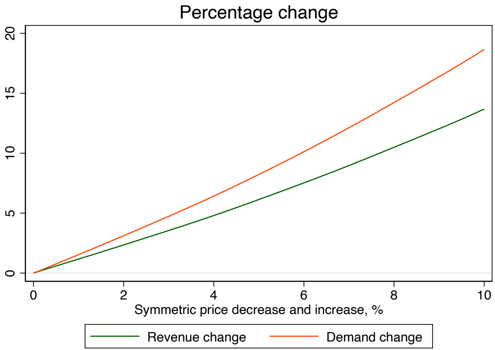
Sample selection and LASSO II

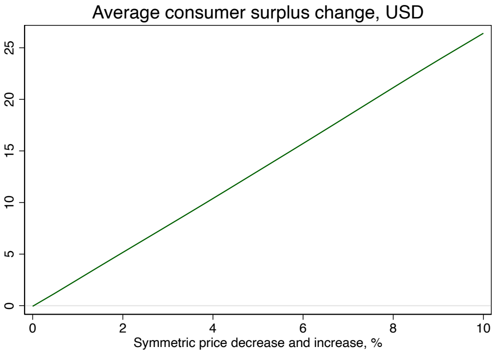
We predict log prices using:

- Patient's characteristics: age, gender, access to private insurance, social security, cataract scores, and ocular conditions, namely, ampliopia, anisometropia, astigmatism, myopia, presbyopia, hypermetropia, and emmetropia.
- Surgery's characteristics: type of intraocular lens and type of surgery.
- Personnel: identity of sales agents, optometrists, and ophthalmologists who interacted with the patient.

LASSO selected 156 out of 291 predictors; penalty parameter selected by cross-validation, 10 folds. Mean prediction error of .07, which is small, given the average log price is about 9.4. We further shock predicted prices to match the empirical distribution of non-missing prices, in order to estimate meaningful standard errors.

Counterfactuals: Revenue-neutral price cross-subsidy





Symmetric changes: For example, if p_1 drops in 1%, then p_2 increases in 1%. back

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