PRODUCT REFORMULATION WITH ENDOGENOUS UNOBSERVABLES

Evidence from the UK's sugar levy on soft drinks

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*Not for circulation - Work in Progress

Corrective Taxes have raised as an effective way to promote healthier consumption choices, particularly in the context of sugary drinks.

Why sugary drinks?

Beverages are one of the main sources of sugar intake, specially across the young and the poor. Regular consumption of sugary drinks is linked to:

- Obesity
- Heart disease
- Diabetes
- Tooth decay
- Among other harmful effects

> *Obesity and overweight costs up to £98 billions per year (4% GDP) (Bell et al. 2023).*

UK introduced a sugar tax in 2018

Volume-based instead of flat rate.

- Three sugar concentration bands.

Extensively negotiated with the industry:

- 2012, firms make a voluntary pledge to cut sugars on their products.
- 2016, government announces a sugar-content tax on the industry with the Budget.
- 2018, the UK's Soft Drink Industry Levy gets implemented on April 6th, 2018.

Manufacturers' response

Irn-Bru cut sugar from 10.3g to 4.7g per 100ml

Pepsi no recipe change; remains at 11g per 100ml

Ribena cut sugar from 10g to less than 4.5g per 100ml

Lucozade cut sugar from 13g to less than 4.5g per 100ml

Coca-Cola no recipe change; remains at 10.6g per 100ml

Source: BBC - Article from 06/04/2018

This paper focuses on firms response

Estimate a structural model of product reformulation that accounts for overlooked changes in the unobserved product characteristics to study:

- What products get reformulated and why?
- How does the reformulation affect markups?
- How those the policy interact with the market structure?

Unobservables include the taste and experience of a particular brand, but they can also include others things, like changes to the advertisement strategy.

Literature (selection)

PRODUCT INTRODUCTION AND REFORMULATION

Draganska et al. (2009); Crawford (2012); Fan (2013); Sweeting (2013); Eizenberg (2014); Veiga & Weyl (2016); Sullivan (2017); Wollmann (2018); Crawford et al. (2019)

DEMAND ESTIMATION WITH ENDOGENOUS UNOBSERVABLES

Spence (1976); Bajari & Benkard (2005); Veiga & Weyl (2016); Petrin et al. (2022)

CORRECTIVE FOOD POLICIES AND SUPPLY SIDE RESPONSES

Ippolito & Mathios (1990, 1995); Griffith et al. (2017); Grogger (2017); Allcott *et al.* (2019); Griffith et al. (2019); Dubois et al. (2020); Villas-Boas *et al.* (2020); Abi-Rafeh et al. (2023); O'Connell & Smith. (2023) Barahona et al. (2023);

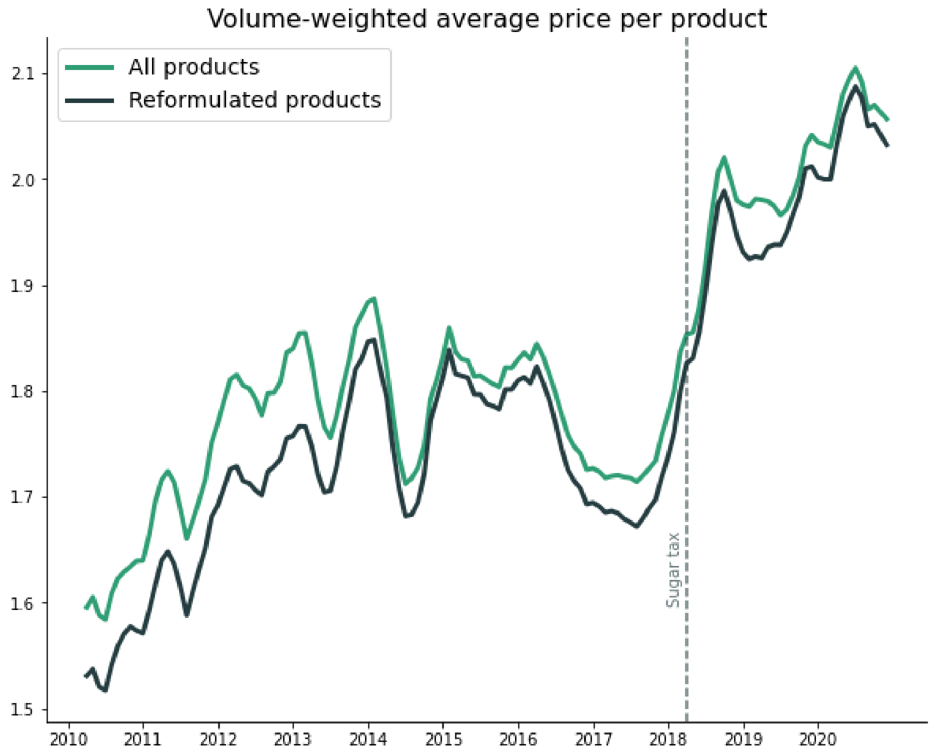
Data

Kantar Worldpanel survey

A commercial household consumption panel where participants employ hand-held scanners to scan all purchases brought into their home.

- Focused on fast-paced consumer goods
- ~35.000 households across the UK.
- Data available for +15 years *(using only 10)*.
- Non pecuniary incentives.
- Additional information available on:
    - Household demographics
    - Product nutritional values

Fact #1: The policy reduced sugar consumption



Sugars: -60% aprox

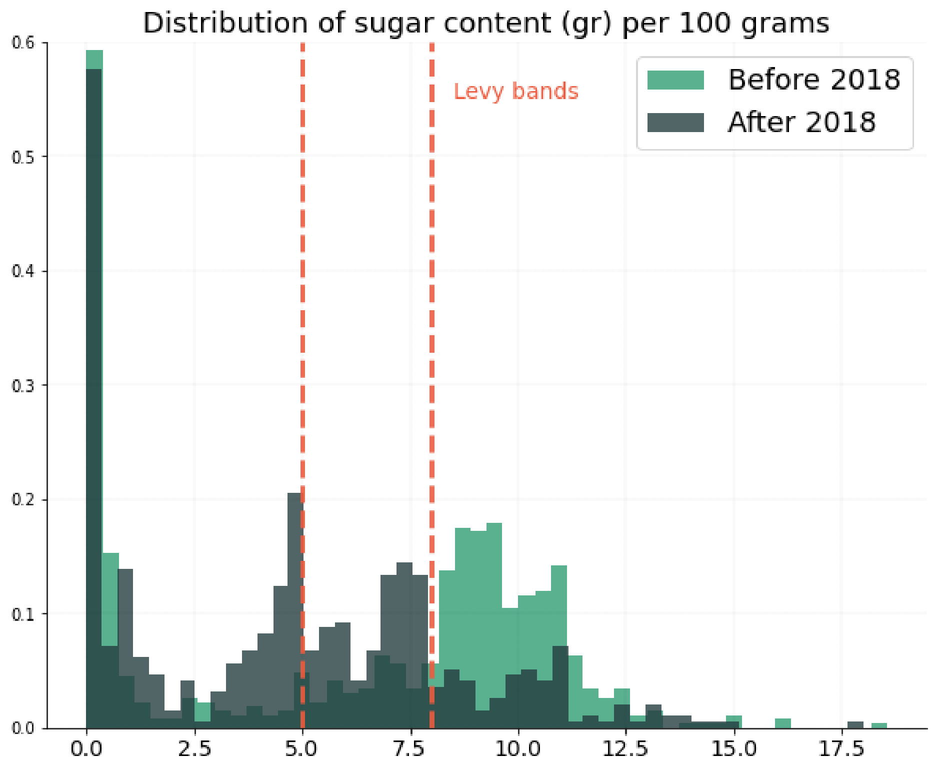
Prices: +10% aprox

Fact #2: Firms adjusted their product portfolios

Acting in anticipation to the policy, firms:

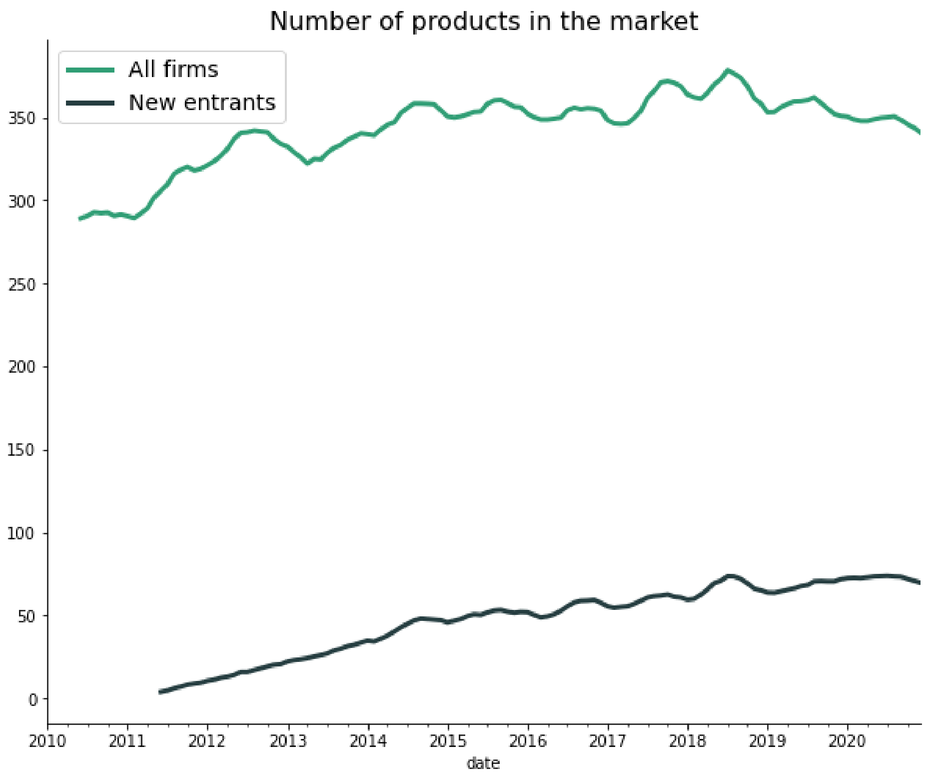
- Introduced new products.
- Removed existing ones.
- Reformulated others.

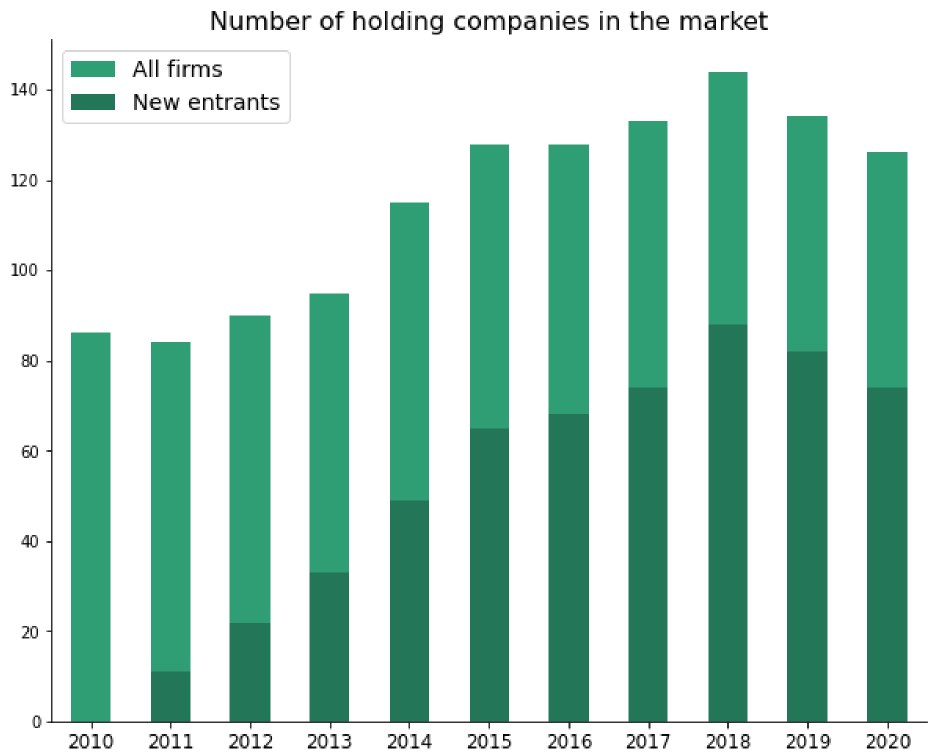
After the tax, products' sugar-content clusters below the tax thresholds.



Fact #3: Newcomers made many of these changes

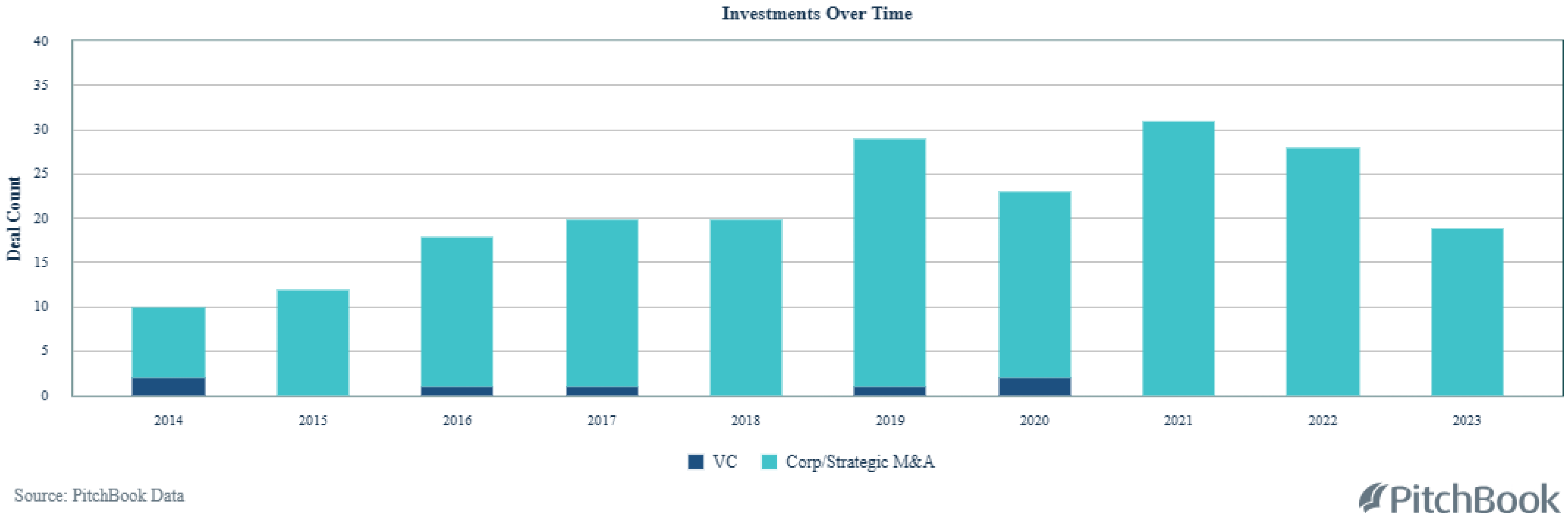
Most of the increase in the number of products is due to newcomer firms.



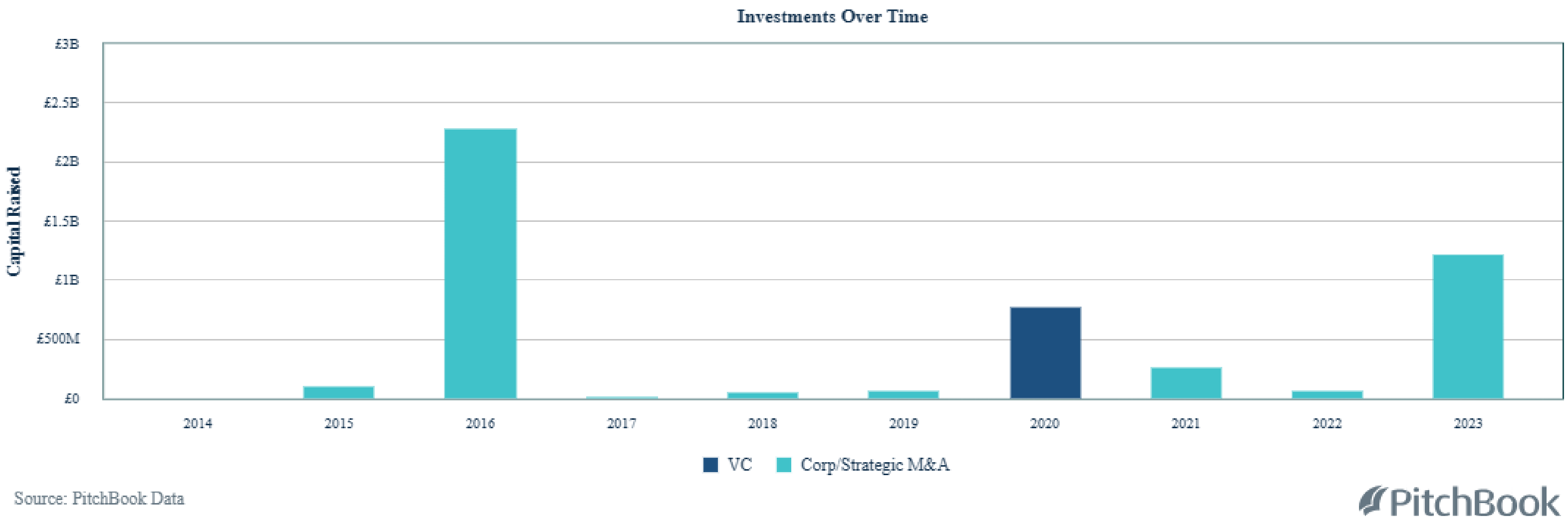


Fact #4: The industry structure also changed

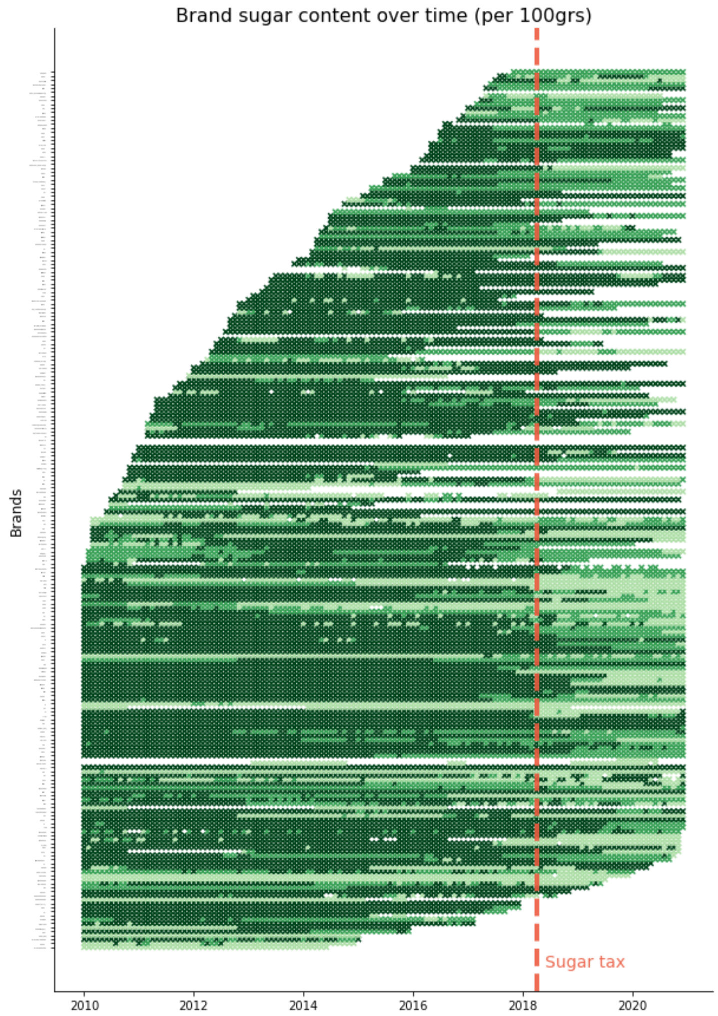
Mergers & Acquisitions



Deals total value



In a nutshell



What are we missing?

- What other changes are firms introducing to their products?
- How does reformulation affect costs and pass-throughs?
- How does reformulation affect policy outcomes?
- How does the policy affect merger incentives?

Model

Product reformulation with endogenous unobservables

RANDOM COEFFICIENTS DEMAND MODEL

Heterogenous preferences over the observed $(\boldsymbol{x}_j, \boldsymbol{p}_j)$ and unobserved $(\boldsymbol{f}_j)$ characteristics.

Following Berry *et al.* (BLP; 1995), I rewrite individual's utility in terms of the average utility of product j on market t (δ_{jt}).

$$U(i, j, t) = \underbrace{(\beta_t \cdot \boldsymbol{x}_j + \boldsymbol{\lambda}_t \cdot \boldsymbol{f}_j + \boldsymbol{e}_{jt})}_{\delta_{jt}} + \tilde{\beta}_i \cdot \boldsymbol{p}_j + \epsilon_{ijt}$$

with $\beta_t = \beta + \beta_w \cdot \boldsymbol{w}_t$ and $\tilde{\beta}_i \sim \boldsymbol{N}(\boldsymbol{0}, \Sigma)$

Market shares are obtained by aggregating individual choice probabilities.

$$\boldsymbol{s}_{jt}(\delta_{jt}, \delta_{-jt}, \Sigma) = \int \frac{e^{\delta_{jt} + \tilde{\beta}_i p_j}}{1 + \sum_{k \in J_t} e^{\delta_{kt} + \tilde{\beta}_i p_{kt}}} \, d\tilde{\beta}_i$$

Conditional on $\boldsymbol{\Sigma}$, there is a one-to-one mapping between $\boldsymbol{s}_{jt}$ and $\boldsymbol{\delta}_{jt}$ derived from solving the set of non-linear equations above (Berry et al., 1995; 2013).

The unobserved utility effect as a factor model

I allow arbitrary correlation between the utility of unobserved and observed product characteristics using Interactive Fixed Effects (IFE).

$$\xi_{jt} = \delta_{jt} - \beta_t \cdot x_j = \lambda_t \cdot f_j + e_{jt} \text{ with } E[\xi_{jt}|x_j] \neq 0$$

Moon et al. (2018) show $\lambda_t * f_j = \begin{bmatrix} \lambda_t f_j & \dots & \lambda_t^R f_j^R \end{bmatrix}$ can be jointly identified using only aggregated data on: market shares, some product characteristics (x_j), and demand instruments (z_{jt}).

Joint identification is not enough for welfare calculations of reformulation because Interactive Fixed Effects models are weakly identified:

- Only upon scaling & rotations: $\Lambda F = (\Lambda H^{-1})(HF)$.
- Relies in arbitrary regularization conditions:
    - Orthonormal factors: $F'F = \mathbb{I}_J$
    - Orthogonal loadings: $\Lambda'\Lambda$ diagonal

This gives them ambiguous, even inconsistent, economic interpretation: Can't differentiate changes to preferences from product changes.

I address these limitations by replacing the standard regularizations with moment conditions derived from a model of firms' product choices.

FIRMS PROBLEM: A TWO-STAGE GAME

$$\max_{N_{ft},\{x_j,f_j\}} \max_{\{p_{ft}\}} \Pi_{ft} = \sum_{j \in J_{ft}} (p_j - c_j) s_j(\cdot) - m(N_{ft})$$

Stage 1: Firms define their products simultaneously facing a menu size cost.

Stage 2: Determine prices after observing all competiting products.

Why focus only on the current period profits? (Static)

Low frictions to product reformulation allow firms to focus on the present:

- Low development costs *(relative to sales)*.
- High reaction capacity to introduce or remove products.

These assumptions are suitable for fast-moving goods, like soft drinks, but not for tech or industrial goods - where development costs are higher relative to sales.

Identification

Identification assumptions

The model preserves the main identification argument in Moon *et al.* (2018). In consequence, the model assumes their same conditions hold:

1. The second moments of $\delta(S|\Sigma, \lambda), X$ and Z exists for all Σ, λ, j, t.
2. $E_0[e_{jt}] = 0$.
3. $E_0[X_{jt}\epsilon_{jt}] = 0$ and $E_0[Z_{jt}\epsilon_{jt}] = 0$ for all j and t.
4. $E_0[(X, Z)'(I - f_0'(f_0'f_0)^{-1}f_0)(X, Z)] \geq b$ for some $b > 0$.
    - **Generalized Non-Collinearity condition**
5. $E_0[\Delta\xi\prime(\Sigma, f, \beta)(X, Z)]E_0[(X, Z)'(X, Z)]^{-1}E_0[(X, Z)'\Delta\xi(\Sigma, f, \beta)]$ is strictly greater than $E_0Tr([\Delta\xi(\Sigma, f, \beta)]'P_((\lambda_0, \lambda))[\Delta\xi(\Sigma, f, \beta)])$
    - **Generalized Relevance Condition**

Identification *(sketch)*

Then, it can be shown that:

1. The conditional factor model is identified.

$\boldsymbol{\delta}_{jt}(\boldsymbol{\Sigma}) = (\boldsymbol{\beta} + \boldsymbol{\beta}_w \cdot \boldsymbol{w}_t) \cdot \boldsymbol{x}_j + \boldsymbol{\lambda}_t \cdot \boldsymbol{f}_j + \boldsymbol{\gamma} \cdot \boldsymbol{z}_{jt} + \boldsymbol{\epsilon}_{jt}$ (Bai. 2009; Moon & Weidner, 2015)

2. $\boldsymbol{\Sigma}$ can be identified using the exclusion restriction.

$\mathbb{E}[\boldsymbol{\delta}_{jt} \cdot \boldsymbol{z}_{jt} | \boldsymbol{x}_j, \boldsymbol{f}_j] = \mathbf{0} \leftrightarrow \gamma_0 = \mathbf{0}$ (Moon *et al.* 2018)

Therefore, we can first identify $\boldsymbol{\Sigma}_0$ by finding the value that makes $\hat{\gamma} = \mathbf{0}$. Then use this value to identify the other parameters conditional on $\boldsymbol{\Sigma}_0$ by solving the factor model without the auxiliary regressors. *(Proof)*

Estimation

NON-LINEAR FACTOR MODEL WITH UNBALANCED PANEL

This is known as the Minimum Distance - Least Square estimator presented in Moon *et al.* (2018).

$$\min_{\Sigma} \arg_{\gamma} \min_{\beta,\beta_w,\gamma,\lambda,f} \mathbb{E}\left[(\delta(\Sigma) - (\beta + \beta_w \cdot w_t) \cdot x_j - \lambda_t \cdot f_j - \gamma \cdot z_{jt})^2\right]$$

Adapted to unbalanced panels using Norkutė *et al.* (2021) and Kripfganz & Sarafidis (2021) to account for the entry & exit patterns in the data.

How many factors to use?

I propose three criteria to choose the number of missing factors:

- **Prior knowledge:**
  Use industry knowledge to determine missing dimensions.
- **Econometric:**
  Use the *elbow criteria* to minimize the unexplained variance.
- **Economic:**
  Solve the endogeneity problem that raises need for factors.

$$\hat{\beta}^{(R+1)} = \hat{\beta}^{(R)}$$

DEMAND INSTRUMENTS

A simultaneity problem emerges when assuming jointly defined characteristics. Hence, BLP like instruments become invalid.

Therefore, inspired by Fan (2013), I use high-frequency proxies of *"other-market regional characteristics"*.

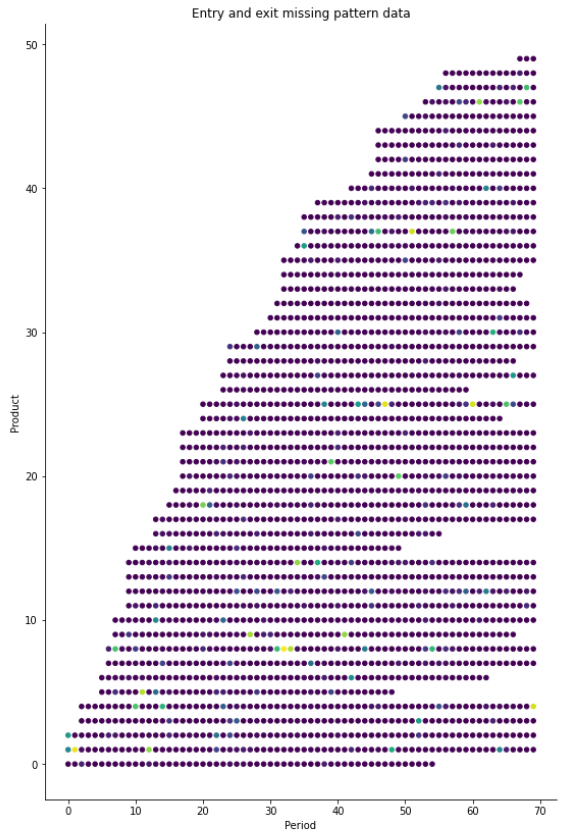
- Weather: Temperature and Rainfall (MET Office).
- House prices: House price indexes (ONS).

Results

Benchmark: Monte-Carlo simulation

To illustrate the necessity of accounting for endogenous unobservables when estimating from aggregated market data, I undertake the following steps:

1. Randomly generate products with exogenous characteristics.
2. Create a new variable correlated with the characteristics *(price)*.
3. Randomly simulate the entry & exit of products.
4. Simulate individual choices and compute market shares.
5. Recover simulation coefficients using BLP, deliberately omitting some product characteristics *(unobservables)*.



Simulation: Estimation results

	True	BLP	LSMD	BLP Bias (%)	LSMD Bias (%)
prices	2.0	-0.1128	2.4678	-105.64	23.39
x2	1.0	0.7065	0.8936	-29.35	-10.64

The LSMD estimator effectively recovers the coefficients with less bias.

Expected result: Change in coefficient estimates

Using a different approach, Petrin *et al.* (2022, NBER WP) reassess the original BLP (1995) results to account for endogenous unobservables, finding:

- *+31% increase* average in price elasticities.
- *-22% fall* in average markups.
- Fixes parameter inconsistency on efficiency.
- Helps explain the elasticity of the outside option.

THE KEY LIES IN THE CORRELATION BETWEEN OBSERVED AND UNOBSERVED CHARACTERISTICS.

For example, assuming taste is the only unobservable, a positive correlation with sugar content would likely lead to a lower coefficient estimates for sugar content.

Conclusion: Reformulation must account for unobservables

Product reformulation plays an important role for the policy outcomes of corrective taxes and other food related policies.

Firms know all their products' characteristics, irrespective of the analyst's ability to observe them.

This paper present a structural model that accounts for unobserved changes in product characteristics by combining factor models and moments derived from economic theory to get identification.

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Annex

Identification (I)

I show the model is fully identified by establishing a unique mapping between the distribution of observables and the true model parameters in three steps:

1.Use the instruments $(z_j t)$ to find the true Σ.

2.Conditional on Σ_0, identify the consumer preferences β and $\lambda_t * f_j$.

3.Conditional on $\Sigma_0, \beta_0, \lambda_0 * f_0$, use the supply side moments to find F and Λ
.

I assume the true number of factors (R) is known; Moon & Weidner (2015) look at the case when this is unknown.

THEOREM 3.1: IDENTIFICATION

Under assumptions (i)-(v), no two sets of parameters can be observationally equivalent. Thus, there is a unique mapping between the distribution of observables and the true model parameters.