The Short-Term Effects of Monetary Policy

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Work in progress - please do not circulate

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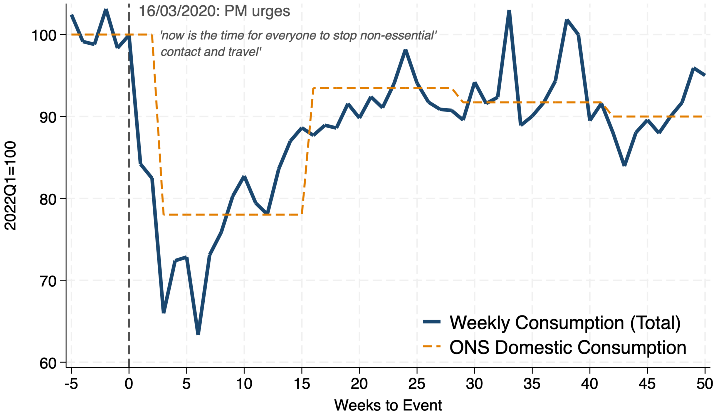
Consumer spending very responsive to news



Motivation

- The conventional wisdom in central banks is that monetary policy works with a lag
- This notion shapes the conduct of policy on many dimensions, inducing decision makers to try and act preemptively
- However, recent literature on causal effects of monetary policy has begun to challenge it

What we do

- We assemble a novel high-frequency dataset for the UK economy, covering credit and debit card spending, vacancy postings, and online prices.
- We study the transmission of monetary policy to macroeconomic activity at a weekly frequency.
- We rely on the monetary policy surprises by Braun et al. (2025) as instruments for Δ 1-year Gilt yield

Main findings

- We find that consumer spending falls quickly and its response to interest rate surprises is statistically significant
- The response seem to be concentrated in discretionary spending categories such as restaurants and hotels
- Online vacancies fall similarly fast after a monetary policy shock
- The aggregate price level falls more slowly and is permanently lower a year after the shock

Literature review

- **High-frequency indicator of economic activity**
  Eraslan and Götz (2021), Baumeister et al. (2024), Grigoli and Pugacheva (2024), ...

- **Monetary policy: High-frequency identification & effects**
  Kuttner (2001), Gürkaynak et al. (2005), Jarociński and Karadi (2020), Altavilla et al. (2019), Cesa-Bianchi et al. (2020), Braun et al. (2025), **Buda et al. (2023)**, ...

- **Fable Consumer Spending Data**
  Koeniger et al. (2024), Koeniger and Kress (2024), Grigoli and Sandri (2022), Grigoli and Pugacheva (2024), Askitas et al. (2024)

Data

Data: Overview

- **Consumption**: Fable (daily, 2017-2023)
- **Job Vacancies**: Indeed (daily, 2018-2023) Summary
  - most used page for online job search in the UK (≈50m visits per month)
- **Prices**: PriceStats (daily, 2008-2023) Summary
  - formerly Billion Prices Project (Cavallo and Rigobon, 2016)
  - scrapes daily online prices of goods and services (60% of CPI weights).
  - remaining "offline" prices proxied using related goods with similar developments.
  - weighted with CPI weights.
- **High-frequency UK monetary policy shocks** Braun et al. (2025)

⇒ **Final Sample**: 1 February 2018 - 30 June 2023

Data: Fable deep-dive

- $\approx$ 900mn transactions performed by more than 5mn cards
- Sample starting in early 2016 and ending at the end of 2023 (currently)
- For each transaction, the data set provides information on
  - Date of purchase
  - Merchant category code (MCC)
  - Location (zipcode level)
  - Card type (debit/credit), online/offline
  - Card holder age group, gender, income band
  - Often merchant tags (not our focus here)
- Not possible to link cards belonging to the same user, or the same household

Data: Fable sample selection

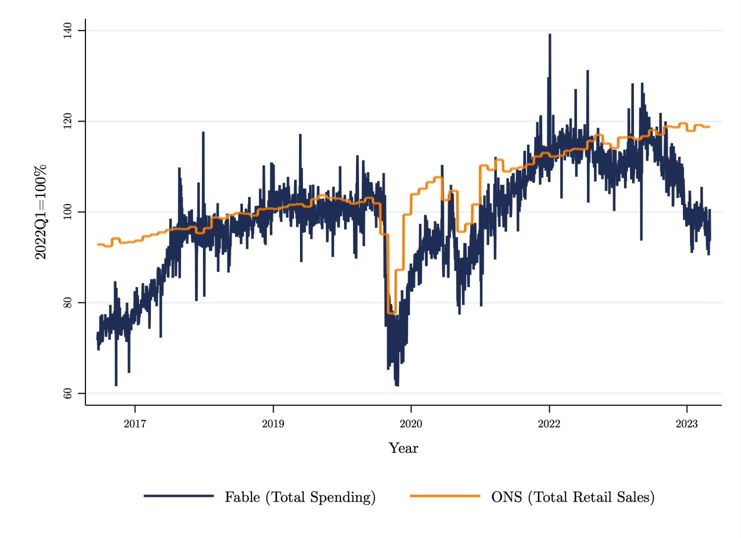
- Follow Koeniger et al. (2024) and select cards with at least one transaction per year 2017 to 2023
- Exclude expenditures that do not belong to consumption in national accounts (e.g. fines) based on the MCC, exclude those not in GBP
- $\approx$ 125mn transactions performed by $\approx$ 200k cards
- Deflate aggregate transaction value with the retail sales deflator, sectoral transaction data with the respective consumption deflators

Data: Fable summary statistics

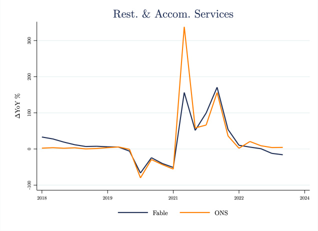
Table: Consumption per card by year

Year	min	p10	p25	median	p75	p90	max
2017	0.01	209	521	1,415	3,346	7,196	914,301
2018	0.04	215	652	1,824	4,191	8,689	1,100,582
2019	0.01	241	657	1,874	4,445	9,102	665,014
2020	0.01	204	556	1,586	3,898	8,136	463,776
2021	0.01	252	690	1,876	4,487	9,196	590,524
2022	0.01	305	840	2,217	5,012	9,939	814,058
2023	0.01	199	657	1,871	4,506	9,292	459,674

Data: Fable over time

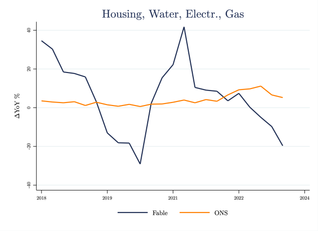


Data: Fable by category



(a) COICOP 11: Restaurants and accommodation services

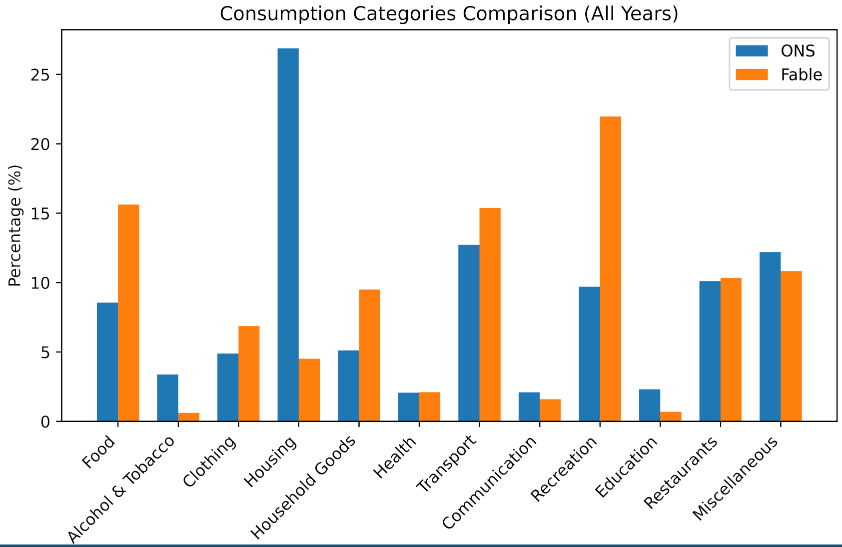
(b) COICOP 7: Transport



(c) COICOP 4: Housing, Water, Electricity, Gas

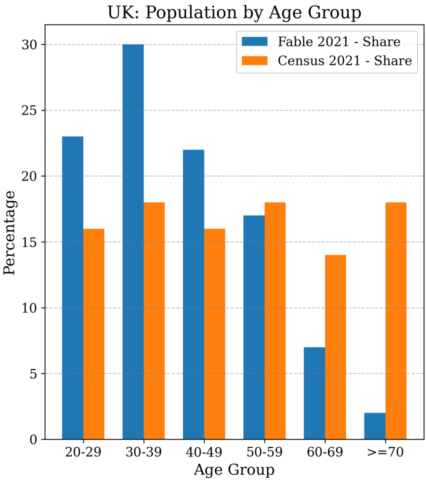
Data: Fable representativeness - consumption categories

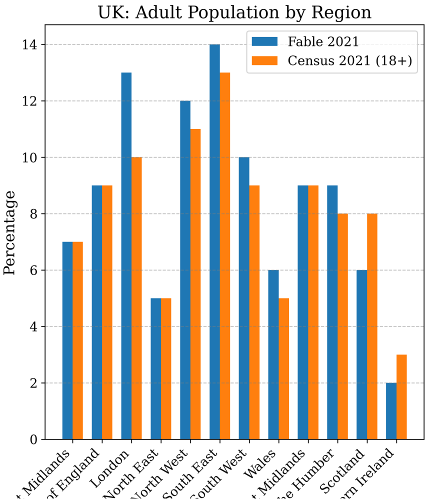
◂ By year



Data: Fable by age group

Data: Fable representativeness - age and regions





Data: Indeed over time

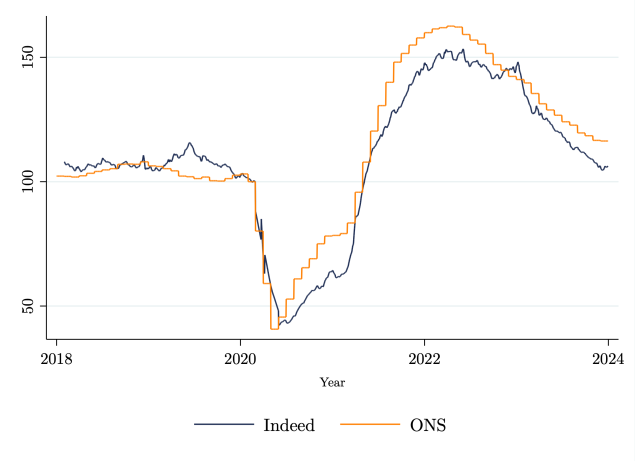


Figure: Indeed vs. ONS Vacancy Indices

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Data: PriceStats over time

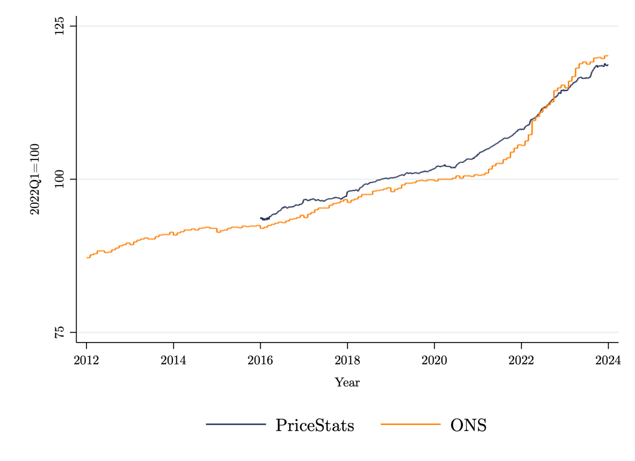

Figure: PriceStats Index vs. ONS CPI Index

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Data: Seasonal adjustment

- Consumer spending at daily frequency is highly seasonal.
- We adjust for four seasonal components:
  - Intra-weekly: weekdays versus weekends
  - Intra-monthly: consumption spikes at start of month
  - Intra-annual: consumption is strong in Q4 and then falls back after Christmas
  - Finally, irregular moving holidays: Easter, bank holidays ...
- We use the routine of Ollech (2021) which is designed for daily data as implemented in the R package `dsa` to perform the adjustment

Data: Seasonal adjustment

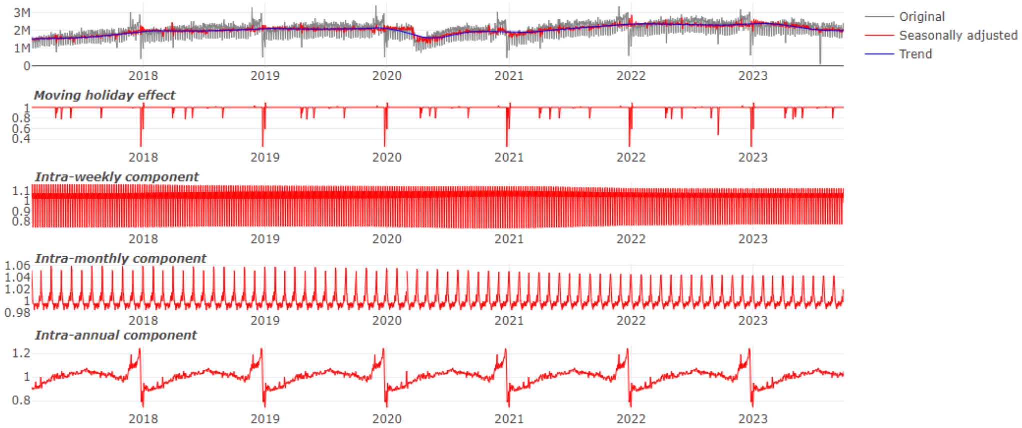


Figure: Seasonal components of total spending

Empirical Approach & Results

Bayesian VAR: Specification

We start with a four-variable VAR at **weekly** frequency. Let

$$\mathbf{X}_t = \begin{bmatrix} \ln(\text{consumption}_t) \\ \ln(\text{vacancies}_t) \\ \ln(\text{prices}_t) \\ \text{1-year Gilt}_t \end{bmatrix}.$$

Where each variable is an average over the week t. Then we estimate:

$$\mathbf{X}_t = \mathbf{A}_0 + \sum_{p=1}^{P} \mathbf{A}_p \mathbf{X}_{t-p} + \mathbf{B}\,\varepsilon_t^{\text{MP}} + \mathbf{u}_t, \tag{1}$$

- $\varepsilon_t^{\text{MP}}$ is the monetary policy surprise, the path factor in Braun et al. (2025)
- $\mathbf{A}_p$ are VAR coefficients capturing lagged dynamics, with $P = 8$ weeks
- $\mathbf{B}\,\varepsilon_t^{\text{MP}}$ transmits the shock into 1-year Gilt changes.

Results: Consumption

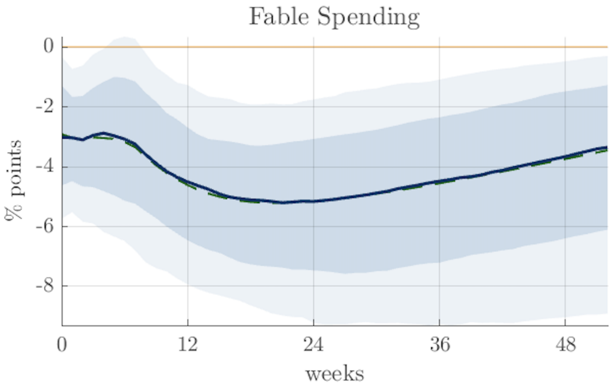


Figure: Total Real Consumption Response to Path Factor

Results: Vacancies

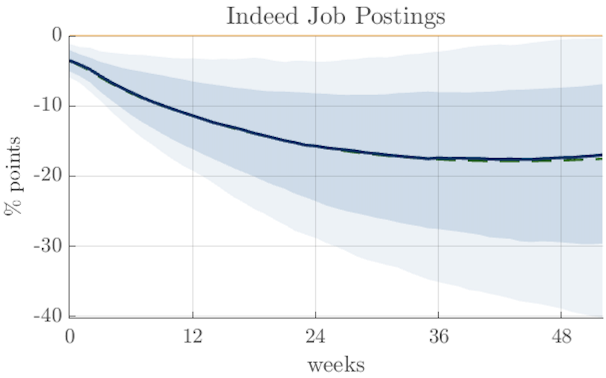


Figure: Job Posting Response to Path Factor

Results: Prices

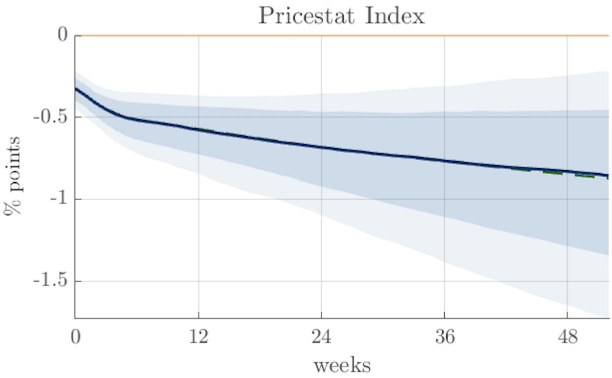


Figure: Total Price Response to Path Factor

Results: 1-year Gilt

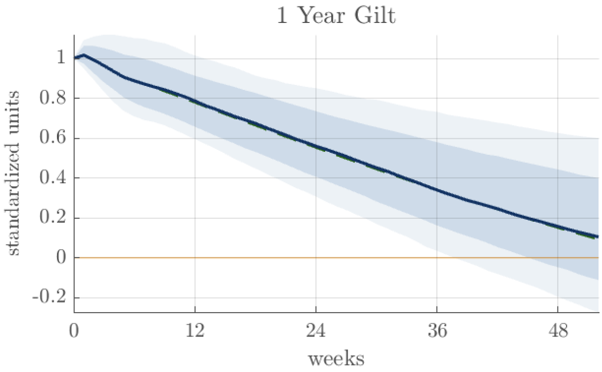
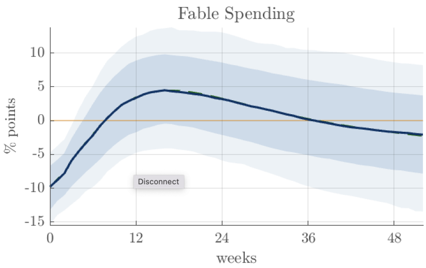
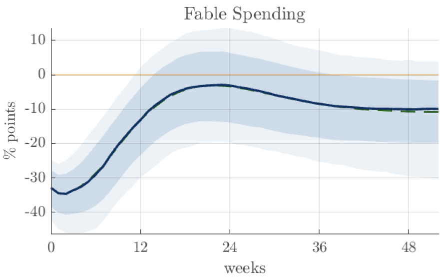


Figure: 1-Year Gilt Response to Path Factor

Results: Consumption components



(a) COICOP 7: Transport



(b) COICOP 11: Restaurants and accomodation

Alternative: Local Projection

We estimate the short-run effects of UK monetary policy for up to $H = 52$ weeks using local projections:

$$y_{t+h} = \alpha_h + \beta_h \text{path}_t + \sum_{\ell=1}^{8} \varphi_{h,\ell} \mathbf{X}_{t-\ell} + \varepsilon_{h,t} \tag{2}$$

where

- y_{t+h} is the h-week ahead log-level of average consumption, vacancies, or prices
- path_t is the monetary policy shock
- X_t is a vector containing the 1-year Gilt yield and log-levels of consumption, vacancies, prices (all as weekly averages).

LP Results: Consumption

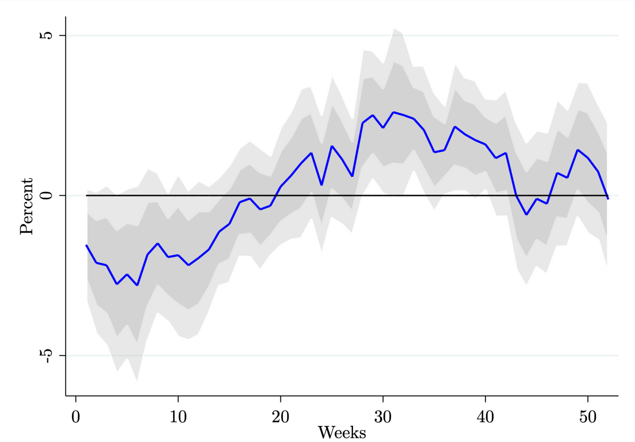
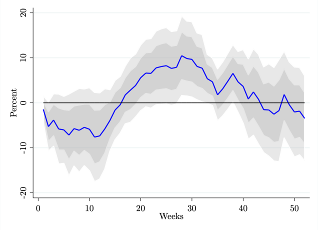
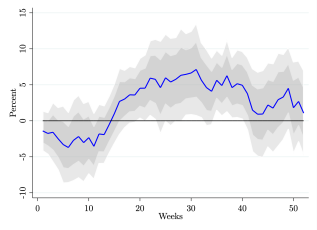


Figure: Total Real Consumption Response to Path Factor

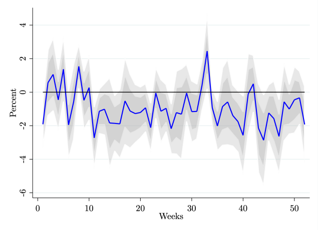
Results: Consumption components



(a) COICOP 11: Restaurants and accommodation services



(b) COICOP 7: Transport



(c) COICOP 1: Food and non-alcoholic beverages

Conclusion

Conclusion

- Using a novel dataset of UK card spending we show that consumer spending falls quickly and significantly in response to interest rate surprises
- The response seem to be concentrated in discretionary spending categories such as restaurants and hotels
- Online vacancies fall similarly fast after a monetary policy shock
- Prices also fall and are still lower after a year

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Appendix: Consumption response by COICOP

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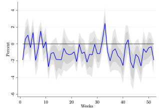
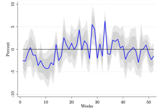
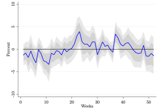


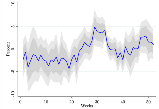
(a) Food and non-alcoholic beverages



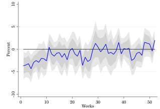
(b) Alcoholic beverages, tobacco and narcotics



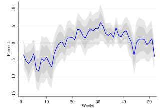
(c) Clothing and footwear



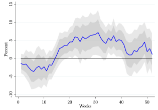
(d) Housing, water, electricity, gas and other fuels



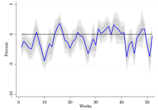
(e) Furnishings, household equipment and routine household maintenance



(f) Health



(g) Transport



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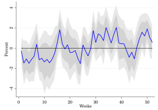
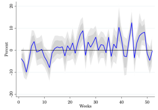
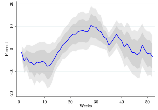


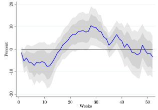
(i) Recreation, sport and culture



(j) Education



(k) Restaurants and accommodation services



(l) Insurance and Finance

Figure: High Frequency Response of Consumption Across Sectors

Data: Fable representativeness - consumption categories

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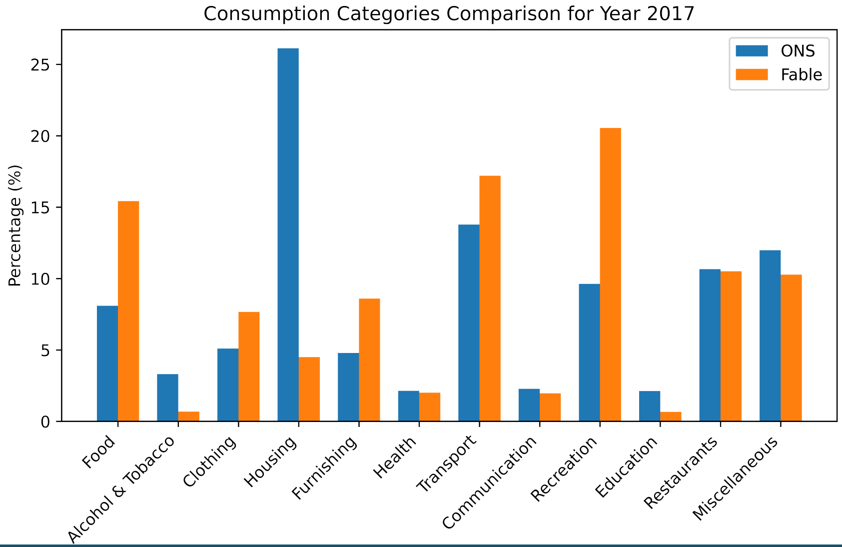

Data: Fable representativeness - consumption categories

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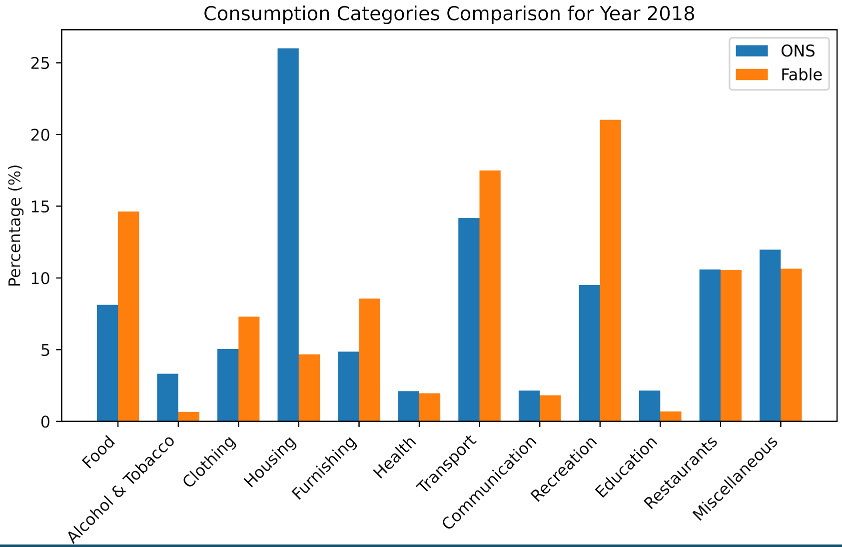

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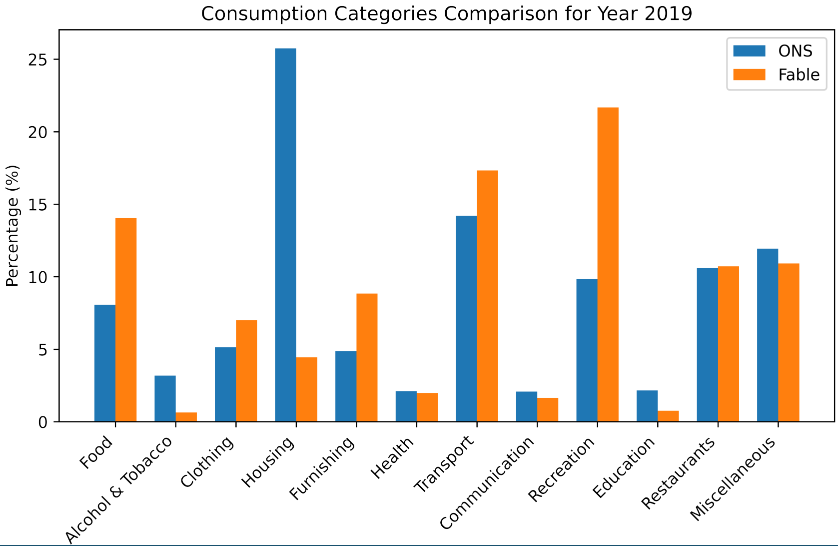

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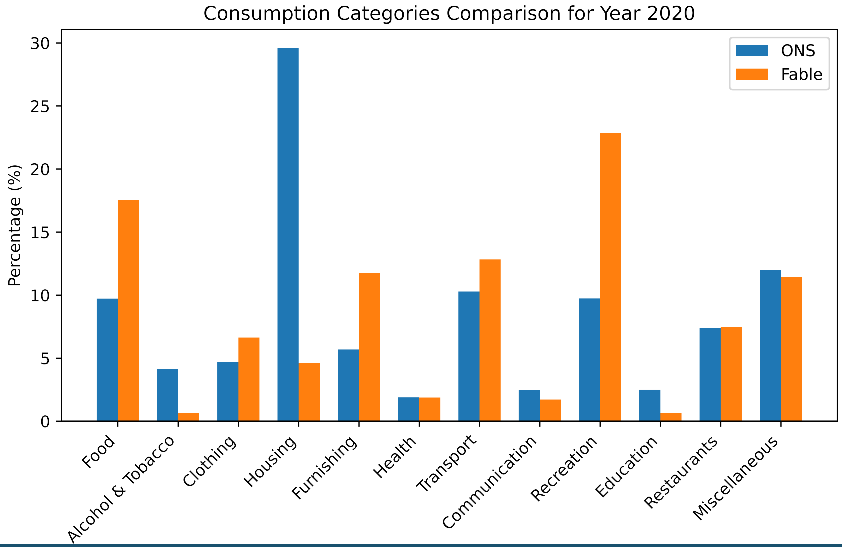

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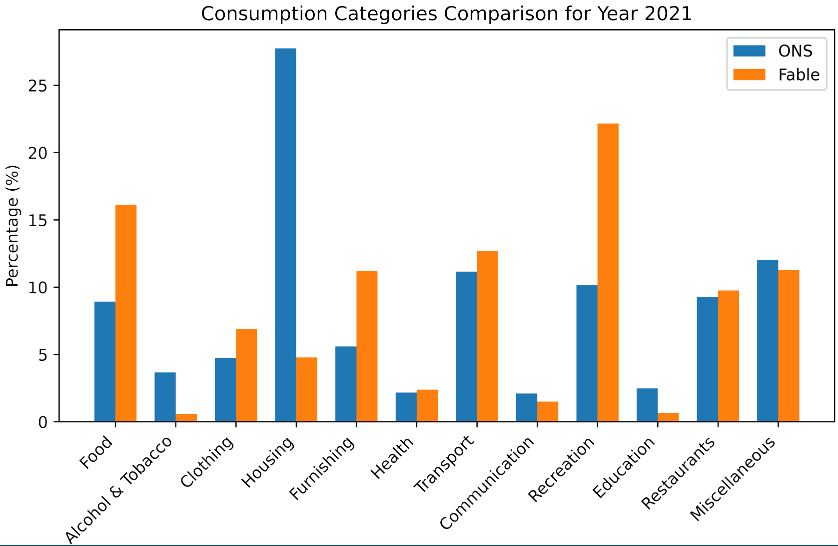

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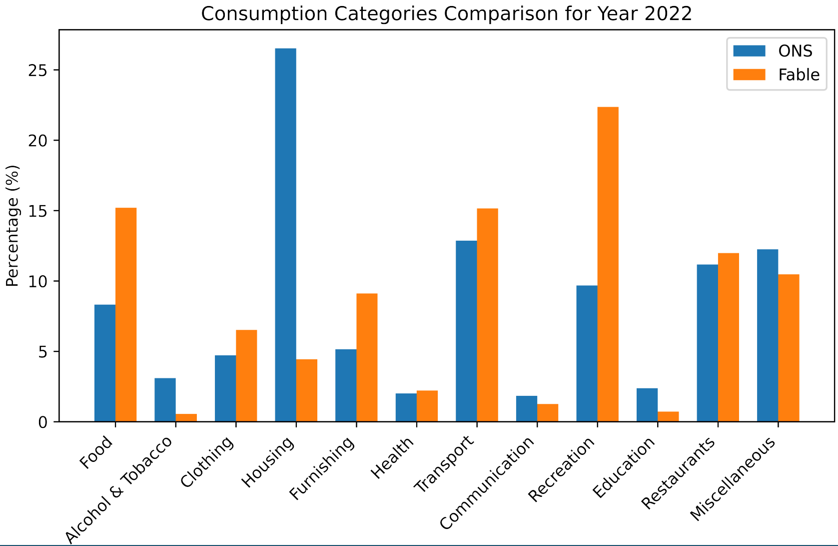

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