Joint macro/econometrics seminar
Indiana University
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Responses of Households' Expected Inflation to Oil Prices and the Exchange Rate: Evidence from Daily Data

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Acknowledgement

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1. Research Questions

Question (1) = Central theme

Can daily data help predict changes

in monthly data

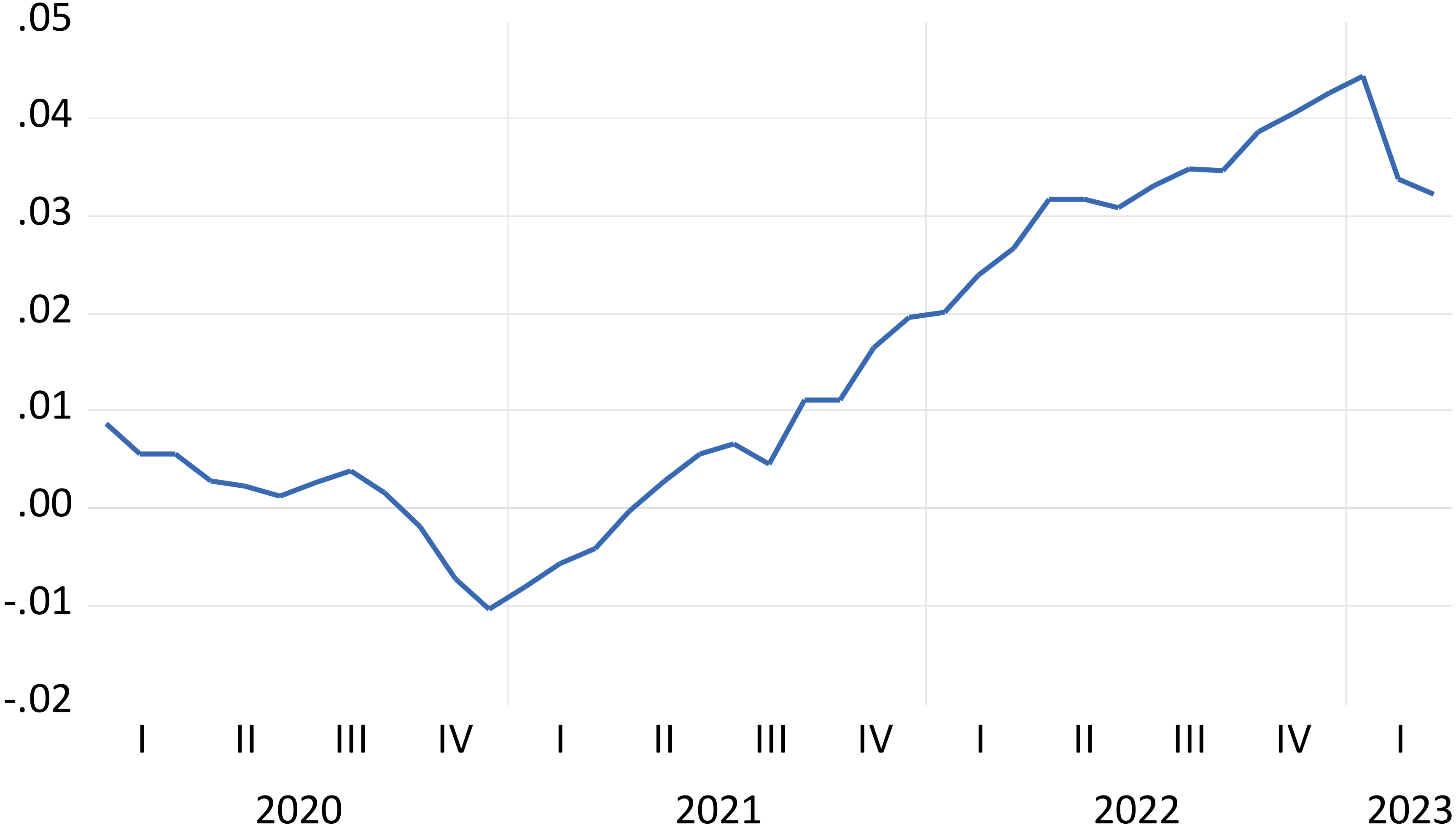
on household inflation expectations (π^e)?

Background

Inflation (π) has finally come,

EVEN TO JAPAN!

CPI in Japan (headline)



Excludes fresh food; starting from 2020, I excluded mobile phone fees and lodging.

Background (continued)

- Policy-makers worry: will π become pervasive?
- Macro theory: π^e holds the key.
- Recent experiences: π^e can change abruptly.
- Implication: we need <u>timely</u> monitoring.

Methodology

- **MIDAS** regressions
  - "Mixed Data Sampling"
  - Ghysels et.al. (2004)

Question (2)

Market π^e vs Households π^e :
Are they different?

- Literature: Consumer perceptions are influenced by prices of goods that they purchase frequently.

- If so, daily data on those prices might help.

Utilize

Barcode price data

at supermarkets

(called **"CPINOW"**)

Question (3)

Construct new indices
="Daily CPI of frequently purchased products"

- CPINOW includes items that are rarely sold.

- Can we do even better by focusing only on frequently purchased products?

Literature :determinants of HH π^e

- Jonung (1981)
  - HH π^e is heavily influenced by perceived π.
- D'Acunto et. al. (2021, 2022)
  - Importance of frequently purchased items.

- Coibion et. al. (2015)
  - Importance of oil prices
- Kilian et. al. (2022)
  - Criticism

Structure of talk

1. Research question
2. Data on daily indicators
3. Do the daily indicators help predict **actual** inflation?
4. Data on inflation expectation
5. Do the daily indicators help predict **expected** inflation?
6. Summary

2. Daily data

[2-1] Existing series

We consider two types of daily series:

- **Market** indices
  - Oil futures
  - Exchange rate

Known to affect BEI.

- **Retail** prices
  - Gasoline prices (weekly)

and…

Nikkei CPINOW

(purchased from Nowcast, Inc.)

- POS data, from 1,200 supermarkets.

- Composition
  - Dominated by processed food (80%).
  - Few fresh food items: eggs & mushrooms.
  - Others: toilet papers, detergents, etc.

CPINOW: Ingredients

- Products: 217 “**Categories**”

- Example of a category:

  “Instant Cup Chinese Noodles”

  - It consists of 13,766 “**items**” = barcodes (as of 2022).

    e.g. “Nissin Cup Noodle: Brazilian Chicken Noodle Cup 74G”.

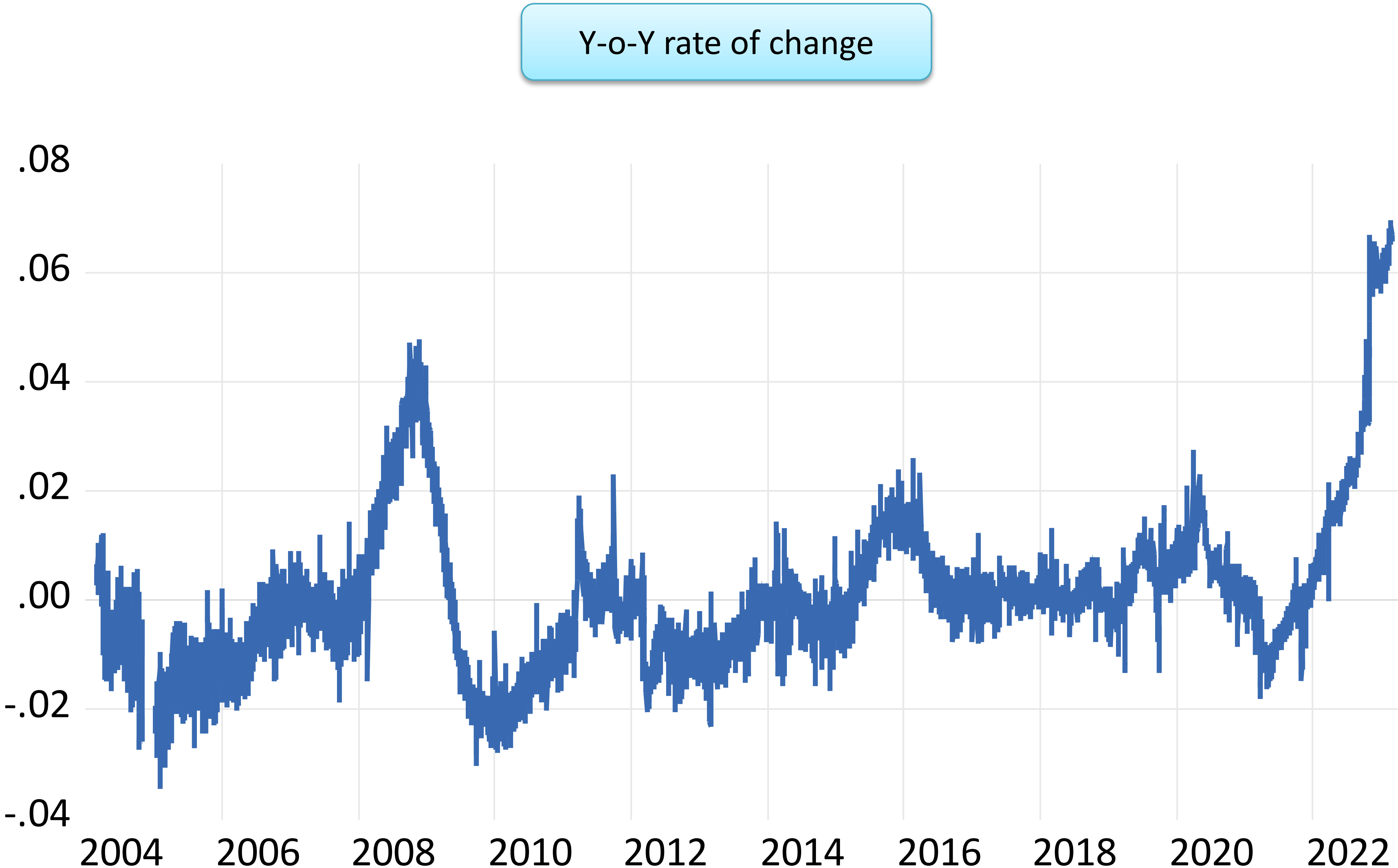
CPINOW: How it's made

- **Unit = (shop) X (item)**
  - E.g., "Nissin Cup Noodle: Italian Curry: Cup 83G" sold at "Supermarket #843"

- For each of (shop)x(item), they record daily sales values and quantities.

→ Compute YoY rate of change of (value/quantity).

- Take their weighted averages across (shop)x(item).


Y-o-Y rate of change
.08
.06
.04
.02
.00
-.02
-.04
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022

[2-2] CPINOW: possible drawbacks

- CPINOW includes items that are rarely sold.
- They go in and out of the sample.
- Problems?
  - Buyers do not observe their prices frequently.
  - They may make the series noisier.

[2-3] Our new indices
= Daily CPI of Frequently Purchased Products

- Choose categories frequently purchased.
  - Like **"Instant Cup Chinese Noodles"**.

- Within category, pick (shop)x(item) that appear frequently in the data.

Data for our new indices

- Obtained underlying data for CPINOW
  - from Prof. Tsutomu Watanabe = Founding Father of CPINOW.
  - Drawback: consists of only around 300 shops.
    - = Those that have agreed to academic usage.

- Frequently purchased categories are chosen based on Household Survey.

Our index (1) **P_ALL**

- Computed in the same way as CPINOW, from our narrower data set, for the sake of comparison.

Our index (2) P_FREQ

- Includes only categories of goods that are purchased at least once a month.

- Categories are weighted according to their purchase frequencies in Household Survey.

- Within each category, (shop)x(item) are weighted according to the number of their appearances in the data per month (computed for each year).

Our index (3) **P_VERYFREQ**

- Same as P_FREQ but only those categories that are purchased <u>at least twice a month</u>.

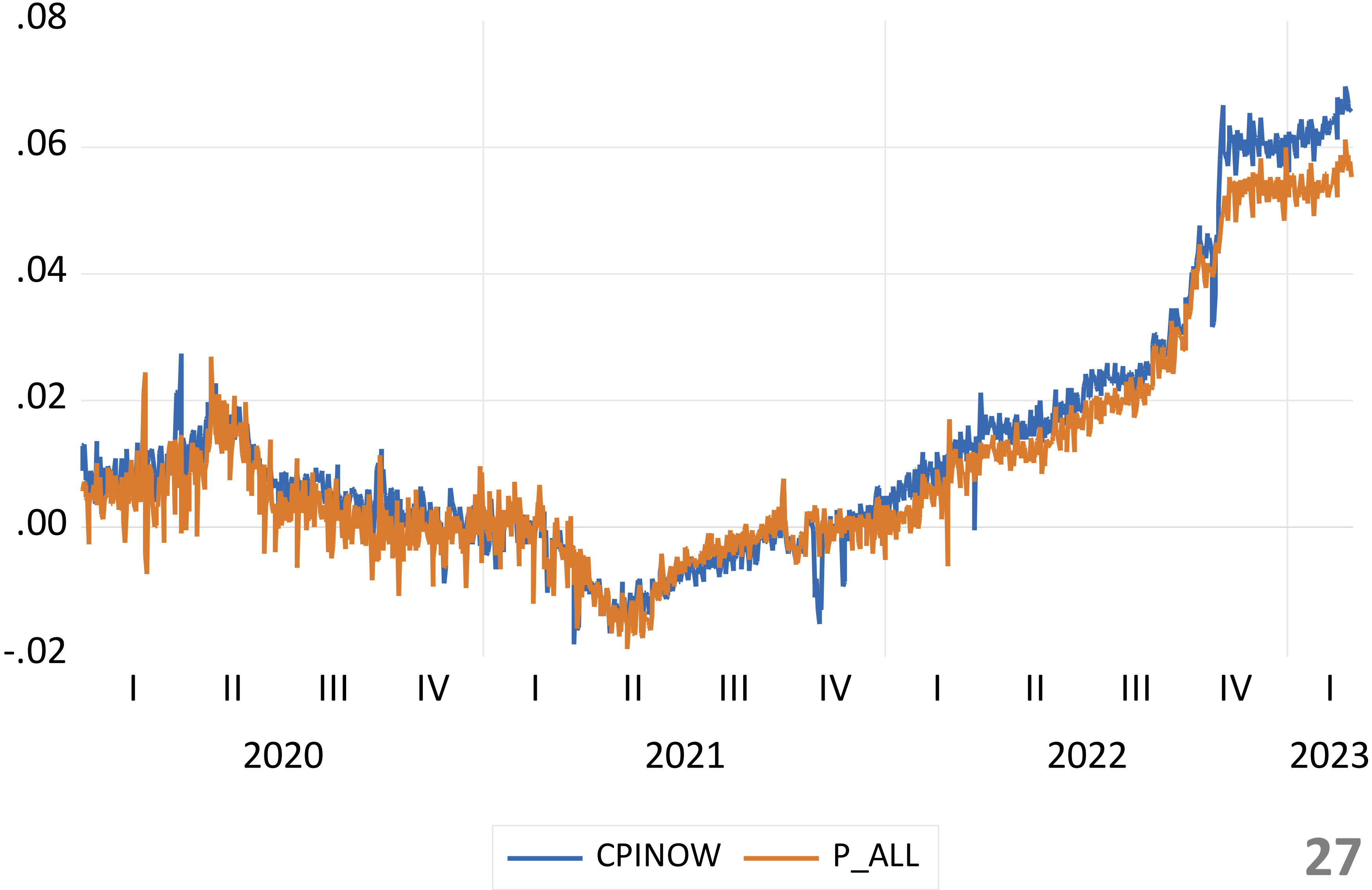
- Examples of VERYFREQ
  - Tofu, Onigiri, Yogurt, Cup Noodles, Bread, Soda, Ice Cream, Egg, Milk, Plastic Bags, …
- Examples, FREQ but not VERYFREQ:
  - Chinese Noodle, Ham, Cheese, Chocolates, Sanitary Item…

Our index (4) P_FREQ**N**, P_VERYFREQ**N**

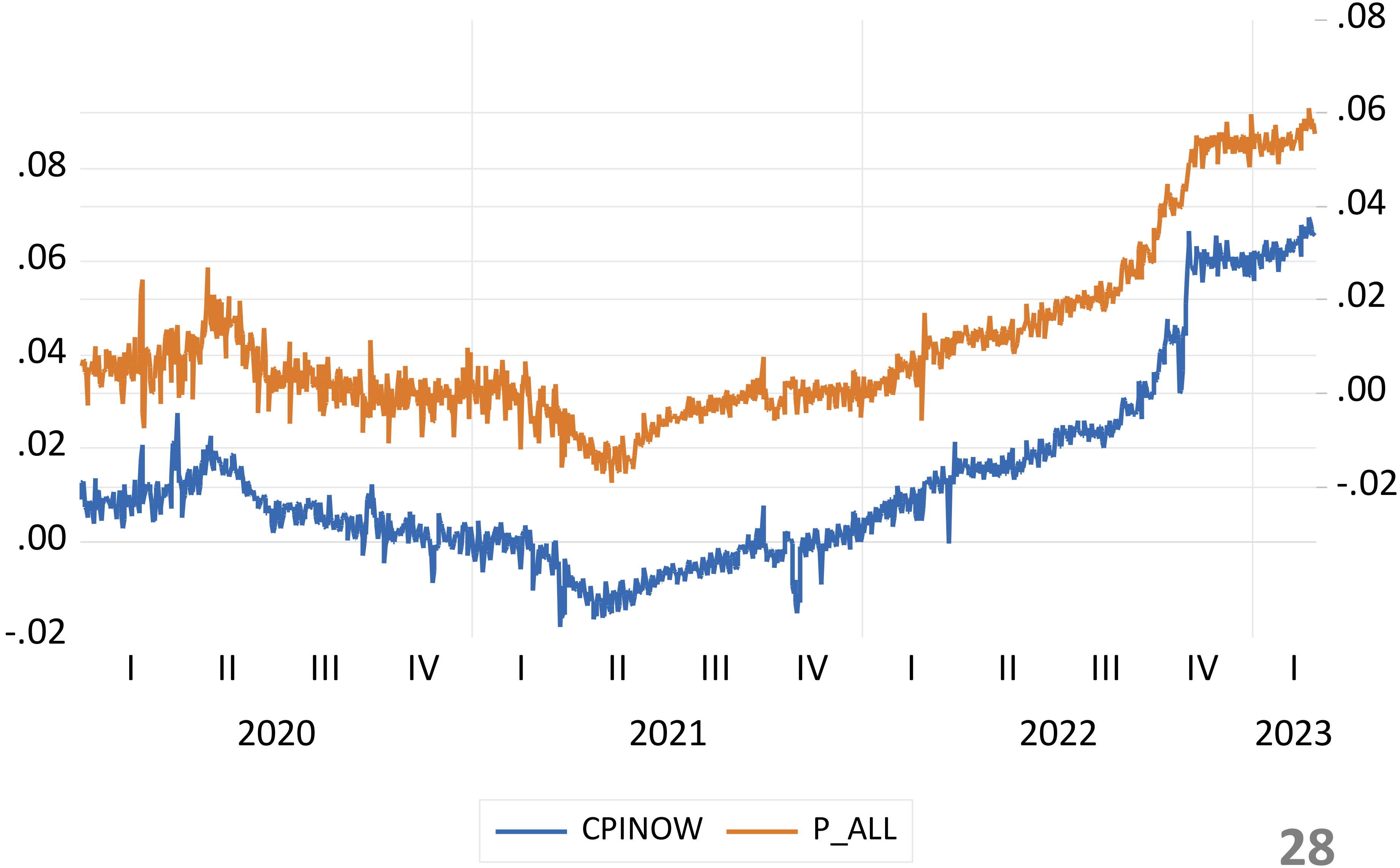
- N = number

- Within each category, include only (shop)x(item) that appeared at least N times per month (in a given year).

[2-4] Comparison of daily indices



Same graph, different axes



3. Do they help explain **actual** inflation?

MIDAS estimation

$$\Delta CPI_m = a_1 \Delta CPI_{m-1} + a_2 \Delta CPI_{m-2} + other\ controls$$

"m" is a month.

$$+ \quad \boxed{\text{Daily Data Part}}$$

"m_d" is a day in month m.

$$f(0) \cdot DAILY_{m_d} + f(1) \cdot DAILY_{m_d-1} + f(2) \cdot DAILY_{m_d-2} + \cdots$$

For *f*, use “polynomial distributed lag (PDL)” (or Almon) weighting.

$$f(i) = \theta_0 + \theta_1 \cdot i + \theta_2 \cdot i^2$$

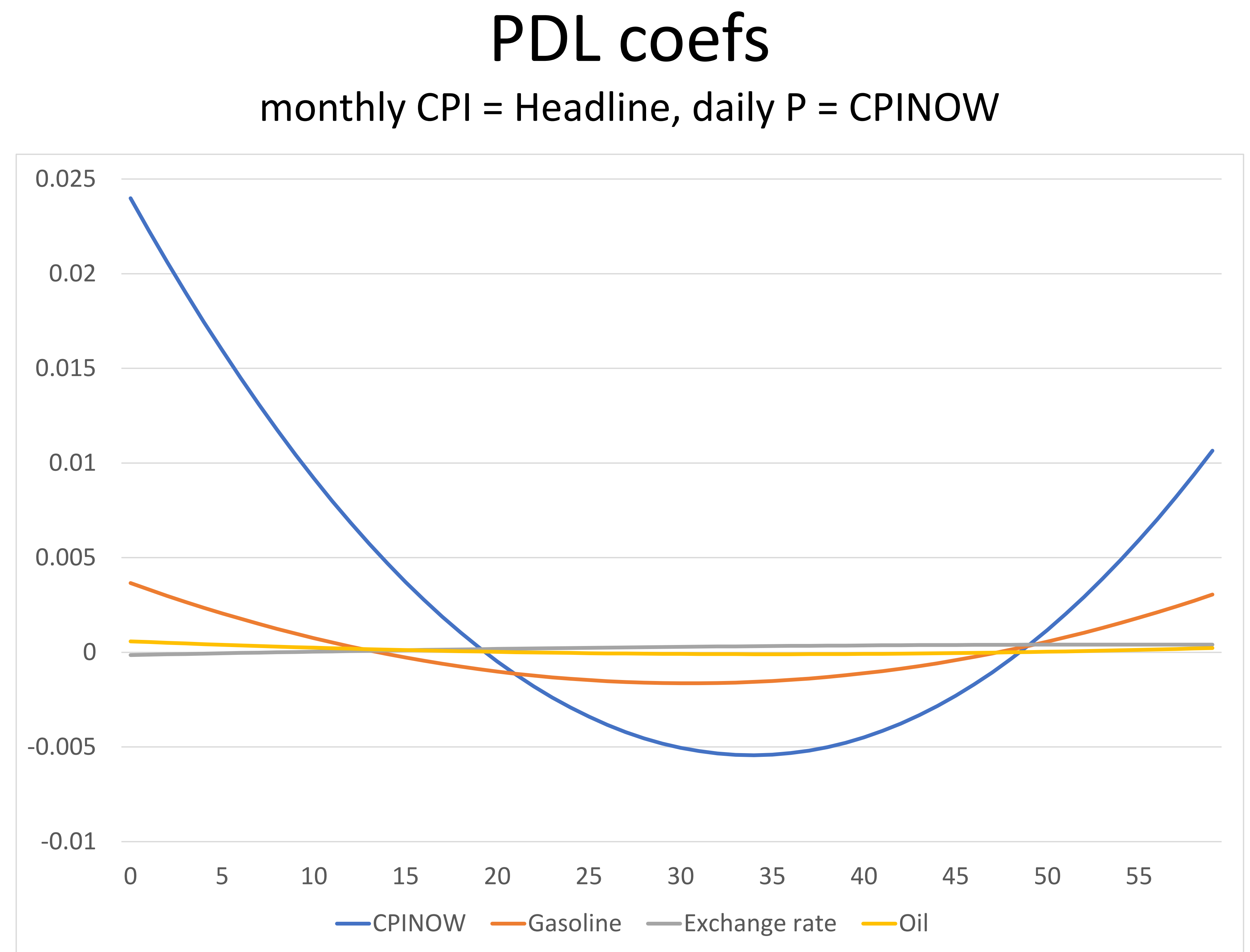
Estimation

- Sample period: Apr 2005 – Feb 2023

- Other controls:
  - Two dummies for consumption tax hikes.

Monthly CPI = Headline
Daily P = CPINOW

		CPI, Headline	
		Coef	t-Stat
LHS(-1)		0.838	11.85
LHS(-2)		-0.122	-1.81
CPINOW	Intercept	3.E-02	2.99
	Slope	-2.E-03	-2.32
	Quadratic	3.E-05	2.05
Gasoline	Intercept	4.E-03	3.90
	Slope	-4.E-04	-4.28
	Quadratic	6.E-06	4.42
Exchange Rate	Intercept	-2.E-04	-0.18
	Slope	2.E-05	0.24
	Quadratic	-2.E-07	-0.13
Oil	Intercept	6.E-04	2.68
	Slope	-4.E-05	-1.86
	Quadratic	6.E-07	1.55
Adjusted R-squared		0.955	


PDL coefs
monthly CPI = Headline, daily P = CPINOW
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
0
5
10
15
20
25
30
35
40
45
50
55
CPINOW
Gasoline
Exchange rate
Oil

Monthly CPI = Various
Daily P = CPINOW

	Total, less Fresh Food		Total, less Food & Energy		Goods		Frequently Purchased Items	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	1.E-02	1.76	4.E-03	0.62	2.E-02	1.79	2.E-02	1.79
Slope	-5.E-04	-0.84	-2.E-04	-0.31	-9.E-04	-0.98	-9.E-04	-0.85
Quadratic	5.E-06	0.53	3.E-06	0.29	1.E-05	0.66	6.E-06	0.37

	Fresh Food		Food, less Fresh Food		Frequently Purchased Food	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	3.E-01	2.09	5.E-02	7.26	7.E-02	7.58
Slope	-2.E-02	-1.99	-3.E-03	-4.79	-4.E-03	-4.91
Quadratic	4.E-04	1.89	4.E-05	3.82	5.E-05	3.70

(Note) Frequently purchased items exclude fresh food.

Monthly CPI = Food less fresh food

Daily P = Various

	CPINOW		P_ALL		P_FREQ		P_VERYFREQ	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	5.E-02	7.26	5.E-02	6.96	5.E-02	5.91	5.E-02	5.45
Slope	-3.E-03	-4.79	-3.E-03	-4.51	-4.E-03	-4.29	-3.E-03	-4.05
Quadratic	4.E-05	3.82	4.E-05	3.58	5.E-05	3.65	4.E-05	3.49
Adj. R sq.	0.983		0.983		0.979		0.977	

	P_FREQ30		P_VERYFREQ30	
	Coef	t-Stat	Coef	t-Stat
Intercept	4.E-02	4.91	4.E-02	4.71
Slope	-3.E-03	-3.48	-2.E-03	-3.42
Quadratic	4.E-05	2.91	3.E-05	2.89
Adj. R sq.	0.977		0.976	

4. Data on expected inflation

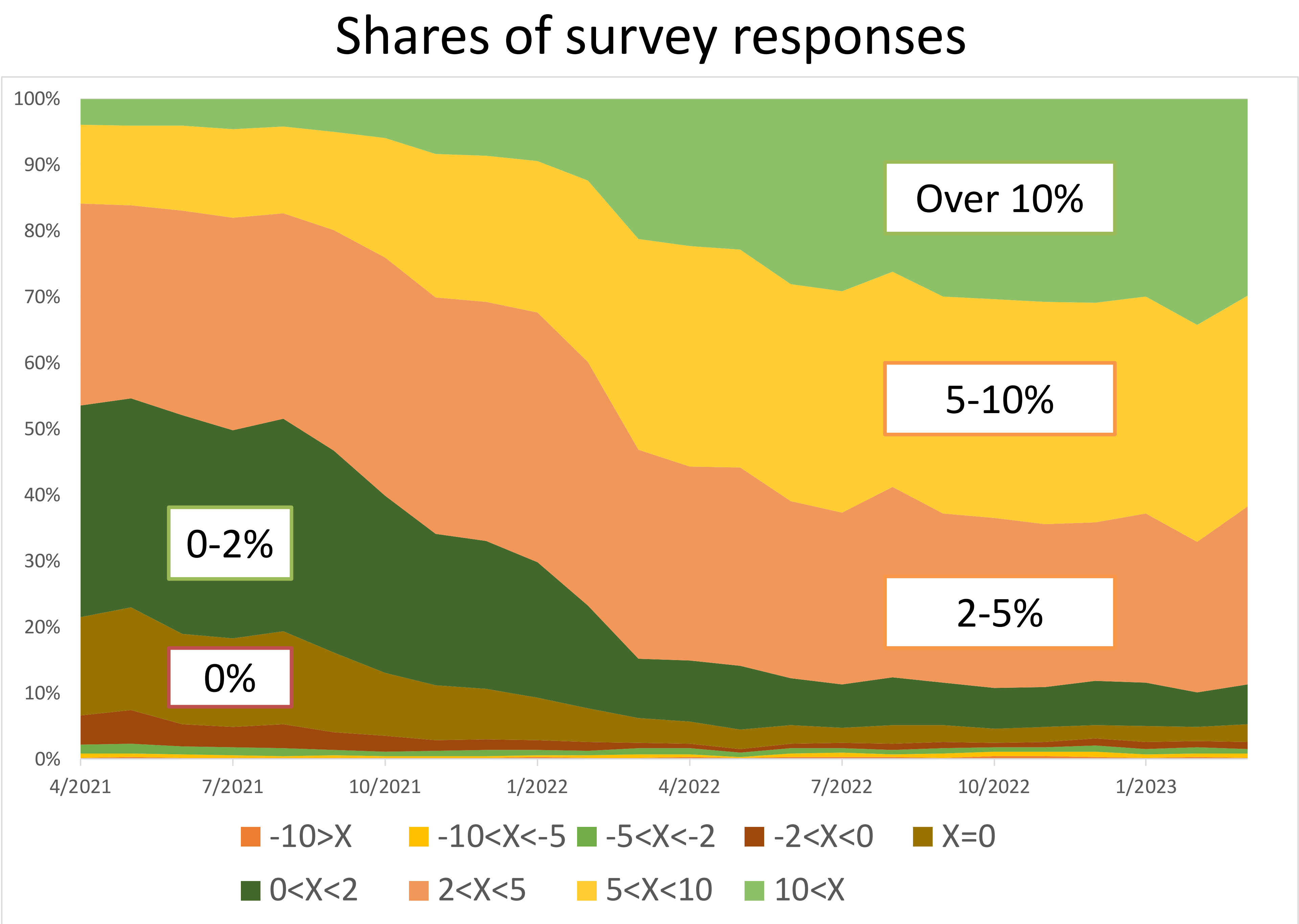
Consumer Confidence Survey

by the Cabinet Office of Japan

- Monthly, 15^{th} day of the month.

- Q: “What do you think about prices of goods that your household regularly purchases frequently one year from now?”

- Since April 2004
- Two important survey design changes.
  - Use dummy variables to control for their effects.



Shares of survey responses
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
4/2021
7/2021
10/2021
1/2022
4/2022
7/2022
10/2022
1/2023
Over 10%
5-10%
2-5%
0-2%
0%
-10>X
-10<X<-5
-5<X<-2
-2<X<0
X=0
0<X<2
2<X<5
5<X<10
10<X

Household inflation expectations

5. Do the daily indicators help predict expected inflation?

Estimation

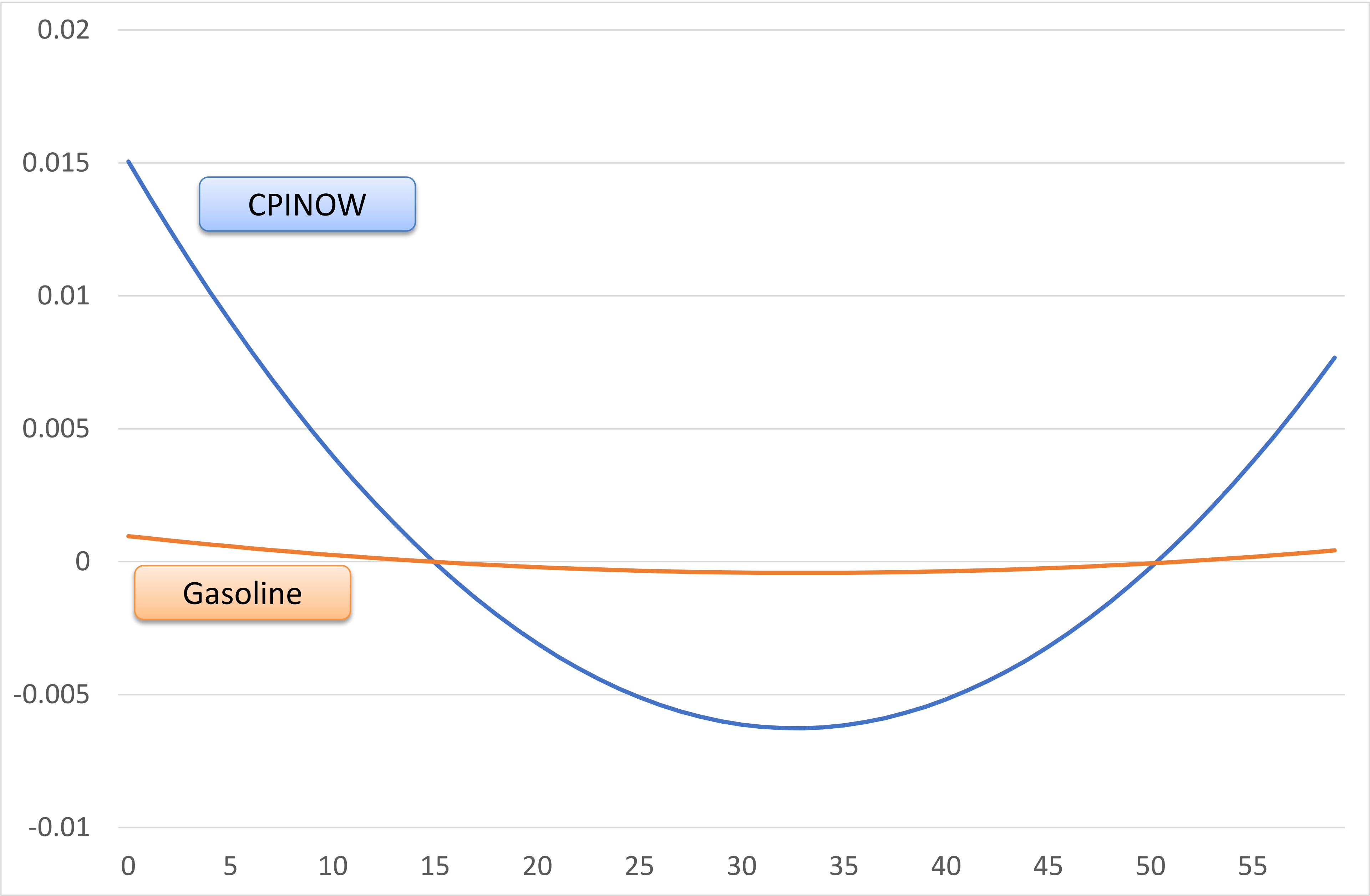
- Sample period: Apr 2005 – Feb 2023

- Other controls:
  - Two dummies for consumption tax hikes.
  - Two dummies for survey design changes.
  - CPI for Energy, lagged 2 months.
    - I tried including various lagged CPI's, and this one turned out to be significant.

Estimation result with CPINOW

		Expected Inflation			
		Coef	t-Stat	Coef	t-Stat
LHS(-1)		1.117	15.93	1.123	16.08
LHS(-2)		-0.221	-3.02	-0.204	-2.81
CPI energy (-2)		0.012	1.87	0.015	2.50
CPINOW	Intercept	2.E-02	2.74	2.E-02	2.51
	Slope	-2.E-03	-2.59	-1.E-03	-2.34
	Quadratic	2.E-05	2.45	2.E-05	2.16
Gasoline	Intercept	5.E-04	0.65	1.E-03	1.92
	Slope	-5.E-05	-0.78	-9.E-05	-1.72
	Quadratic	8.E-07	0.79	1.E-06	1.54
Exchange Rate	Intercept	4.E-04	0.63		
	Slope	-5.E-05	-0.76		
	Quadratic	9.E-07	0.87		
Oil	Intercept	2.E-04	1.10		
	Slope	-1.E-05	-0.66		
	Quadratic	1.E-07	0.47		
Adjusted R-squared		0.975		0.975	

PDL coefs



0.02
0.015
0.01
0.005
0
-0.005
-0.01
CPINOW
Gasoline
0
5
10
15
20
25
30
35
40
45
50
55

Monthly LHS var. = Expected Inflation
Daily P = Various

	CPINOW		P_ALL		P_FREQ		P_VERYFREQ	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	2.E-02	2.51	2.E-02	2.76	2.E-02	2.37	1.E-02	1.85
Slope	-1.E-03	-2.34	-2.E-03	-2.73	-2.E-03	-2.39	-1.E-03	-1.90
Quadratic	2.E-05	2.16	2.E-05	2.61	3.E-05	2.33	2.E-05	1.87
Adj. R sq.	0.975		0.975		0.975		0.975	

	P_FREQ30		P_VERYFREQ30	
	Coef	t-Stat	Coef	t-Stat
Intercept	2.E-02	2.50	1.E-02	2.16
Slope	-1.E-03	-2.53	-1.E-03	-2.28
Quadratic	2.E-05	2.47	2.E-05	2.28
Adj. R sq.	0.975		0.975	

7. Summary

Conclusions

- CPINOW helps explain HH inflation expectations.
- Gasoline prices also, to some extent.
- But **not** oil prices or the exchange rate.
  - **BIG CONTRAST** with expectations of the **market**.

⇒ Consumers seem to base their expectations on what they directly observe.

Seeing is believing

Future work

- Our new indices did not make much difference (after so much time and efforts): we must find out why.
- Add more daily indicators
  - Text data such as newspaper articles (Shintani & Yamamoto 2023).
- Automatic selection of regressors.
  - MIDAS + LASSO.
- Forecast performance evaluation.

Thank you!

Appendix (A): Literature Review on the determinants of inflation expectation in Japan

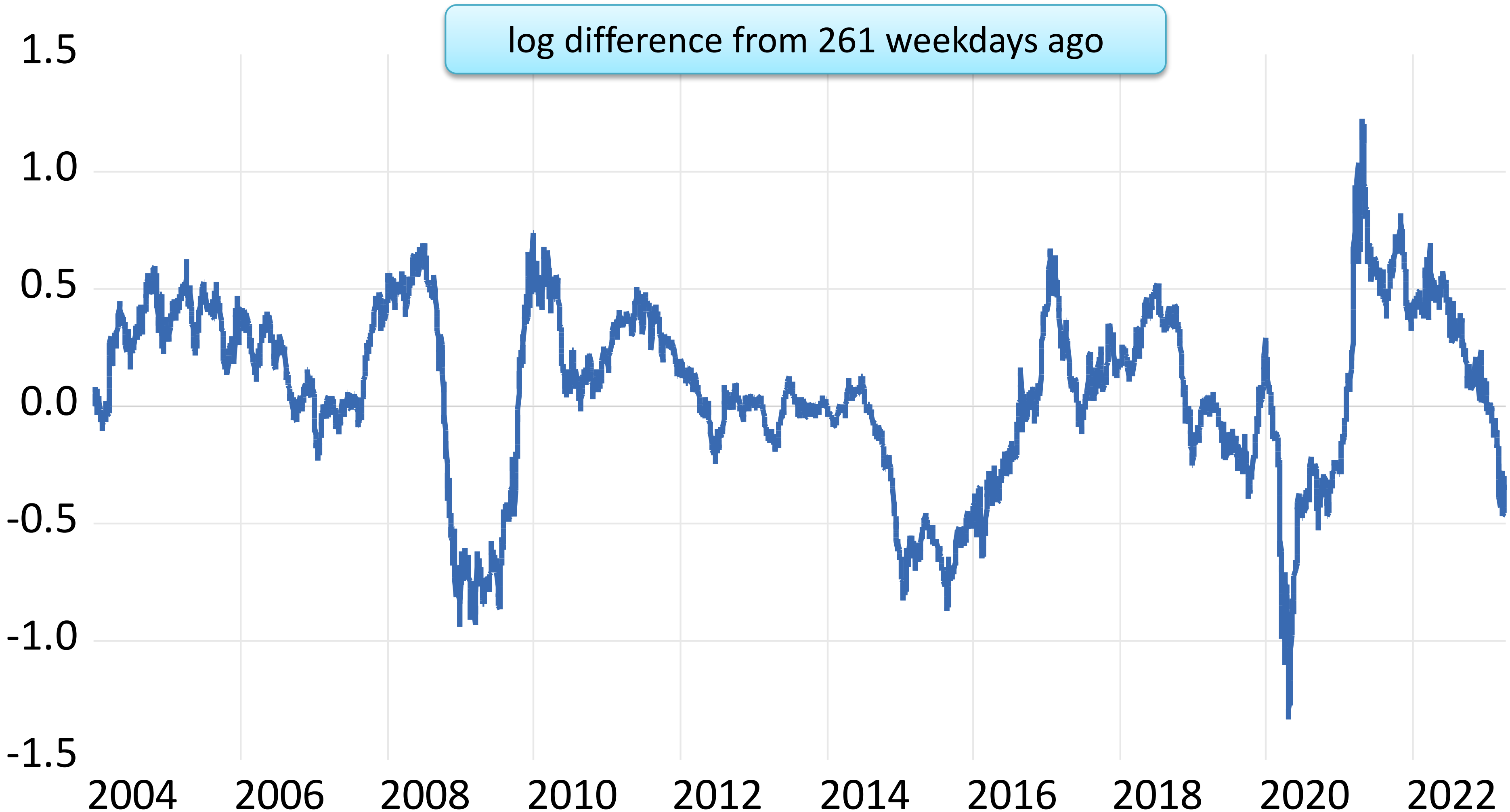
- Ueda (2010)
  - VAR with output gap, r, π & π^e (US & JPN)
- Nishiguchi, Nakajima & Imakubo (2014)
  - VAR with π of frequently purchased items, π of less frequently purchased items, HH's perceived π, & π^e .
- Kamada, Nakajima & Nishiguchi (2015)
  - how means and higher moments of π^e react to monetary policy announcements and actual π.
- Shintani & Yamamoto (2023)
  - How HH π^e responds to newspaper articles.

Appendix (B)
More on daily data other than CPINOW

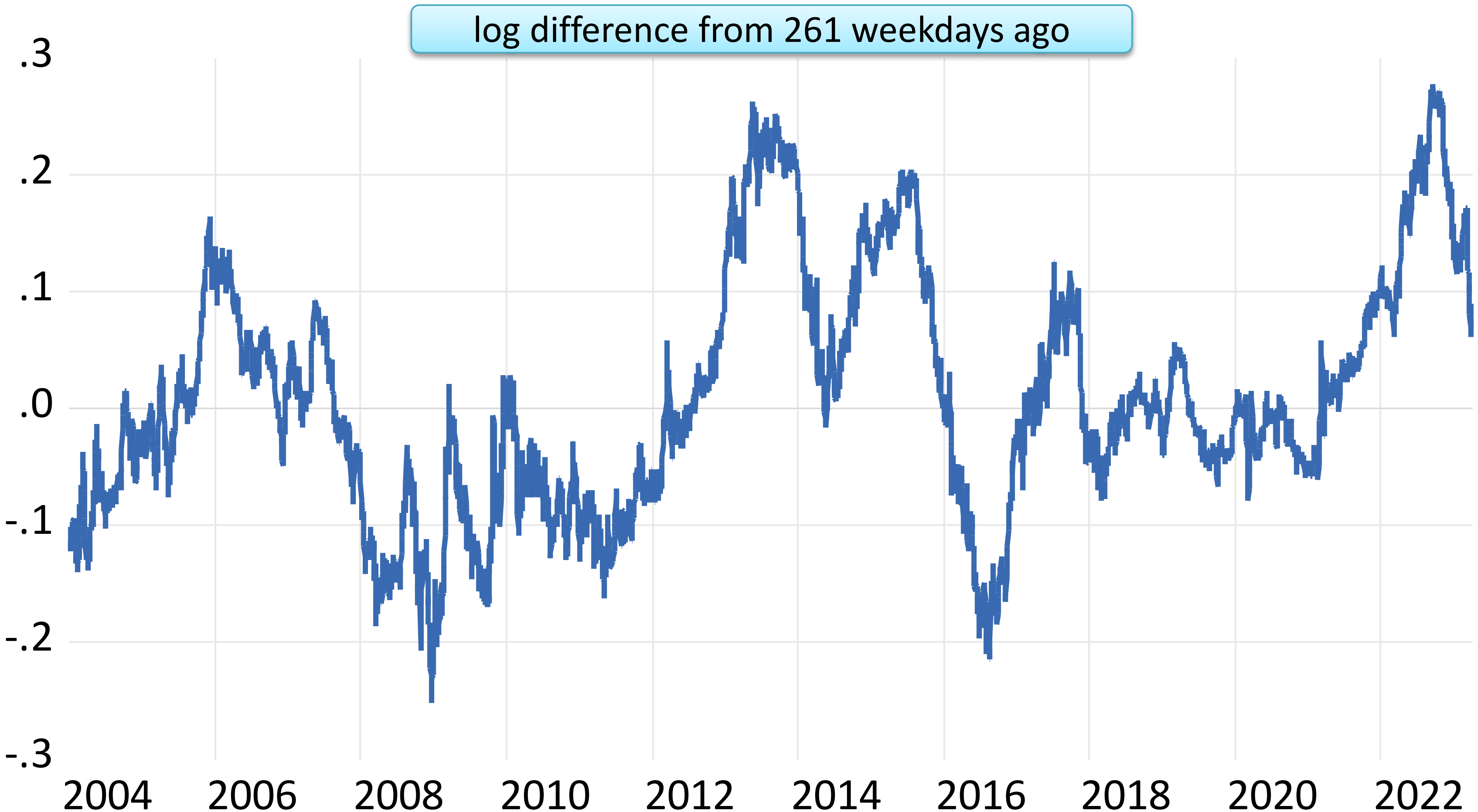
Data handling issues

- Exclude weekends (5 days per week).
- Missing data due to a holiday: the value for that day is set equal to that of the previous day.
- For variables other than CPINOW, I take log differences from 261 weekdays (≈ 1 year) ago.

Market indicator 1: Oil Price (Brent)

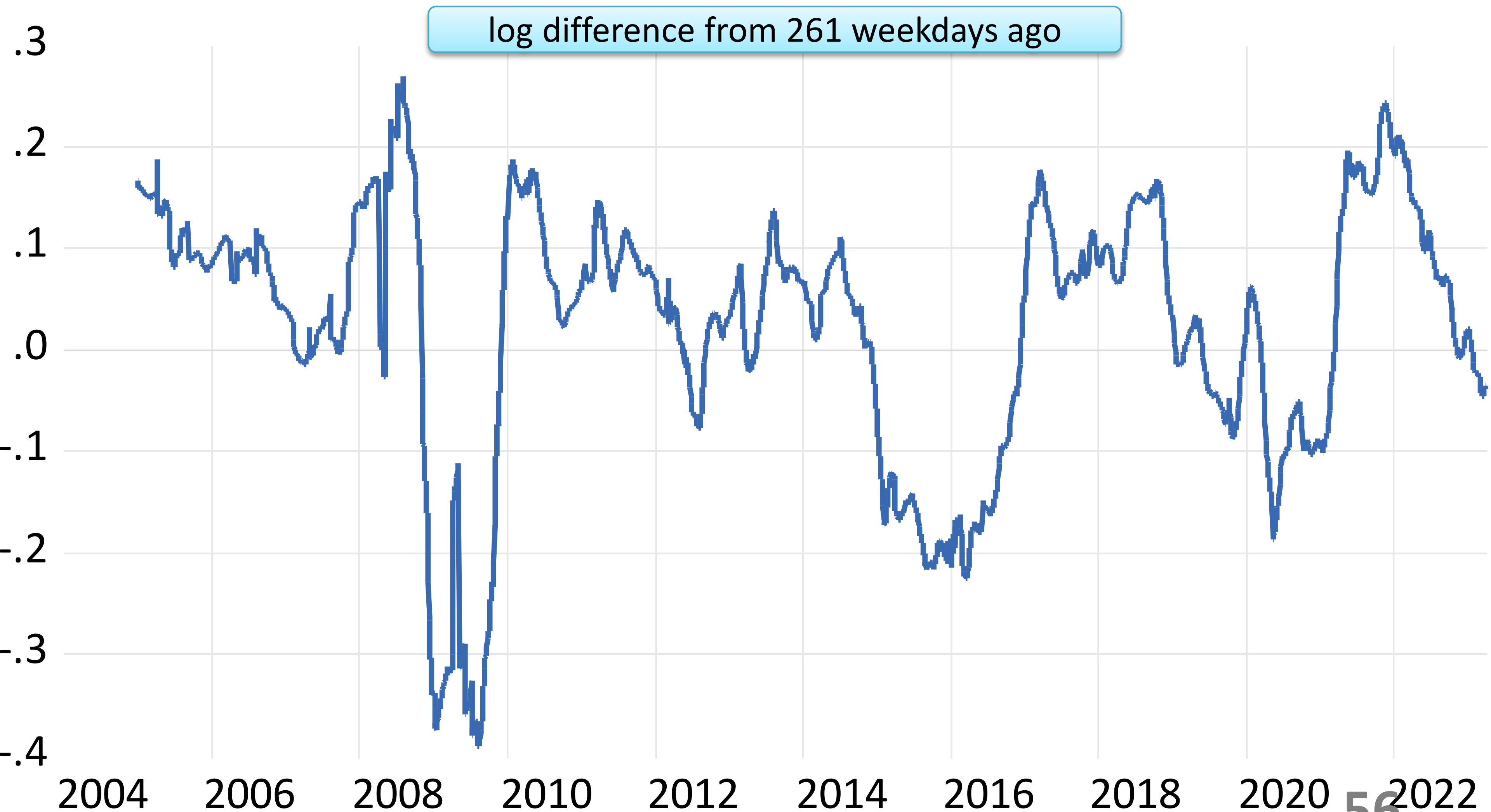


Market indicator 2: Exchange Rate (USD-JPY)

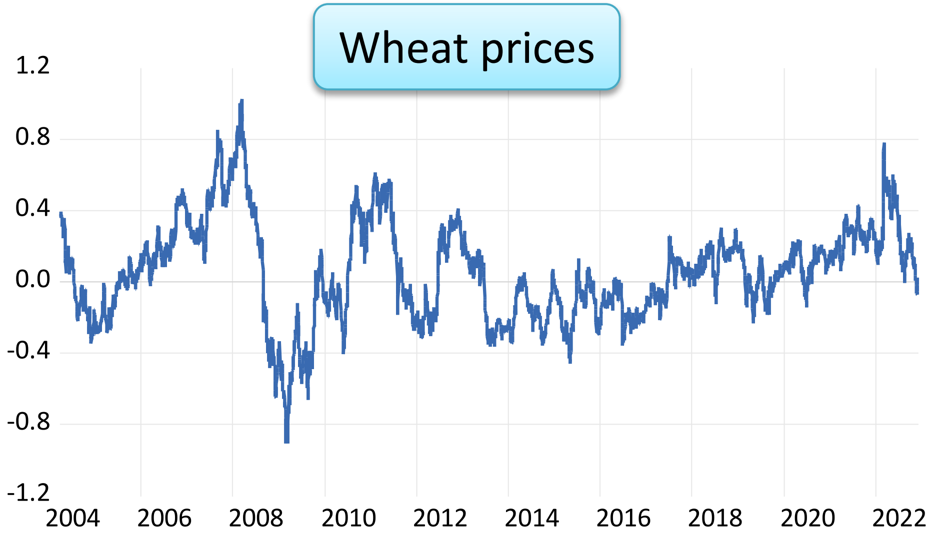


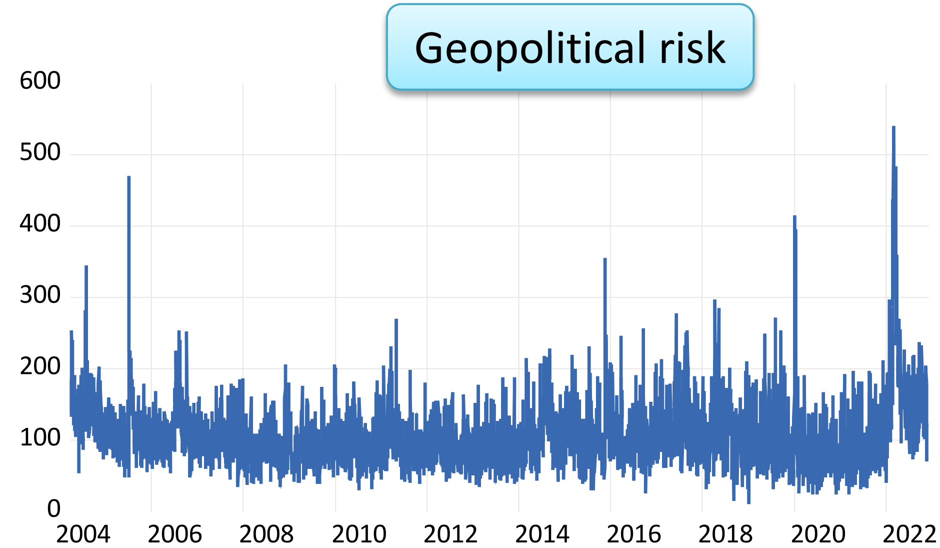
Retail indicator 2: Gasoline price

weekly data converted into daily



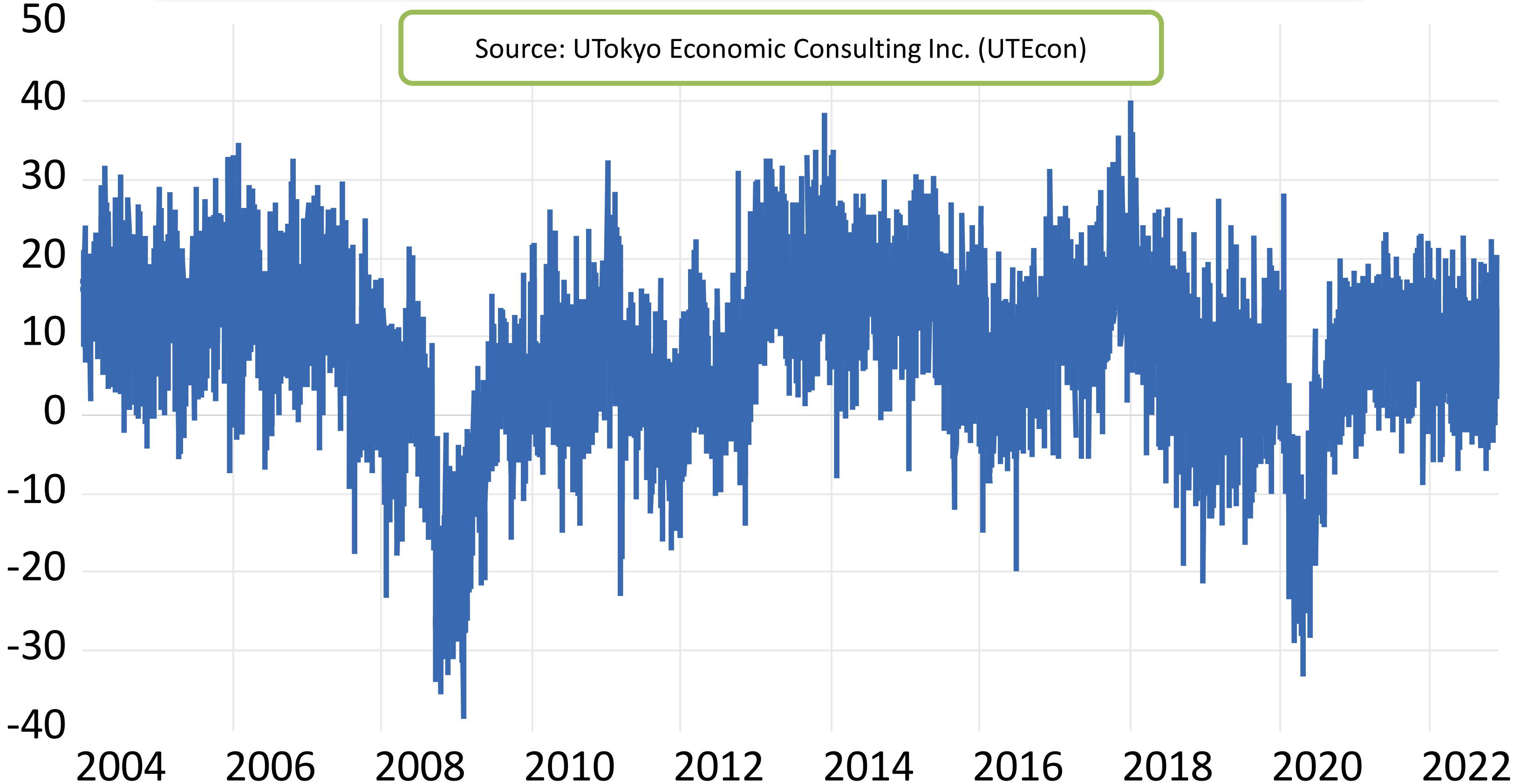
Additional indicators that did not help





Daily Business Cycle Indicator

Nikkei-UTEcon Daily Economic Indicator



Unfortunately, it was insignificant…

Appendix (C)
Adjustment to
daily barcode price data

It matters how you define "YoY".

- CPINOW is defined as "rate of change from **365** days ago" (even for leap years).
- We follow them.
- Note 365 is not a multiple of 7 (364 is).
- "Seasonality" pattern is likely to be different for leap years.

We detect 3 notable patterns in the un-adjusted data.

- (1) Day-of-week effect: amplified by taking the 365-day-difference as opposed to 364.
- (2) Zero effect: things tend to be cheaper on the 10^{th} , the 20^{th}, and the 30^{th} days of the month.
- (3) New year effect: things tend to be cheaper on January 1. (why??)

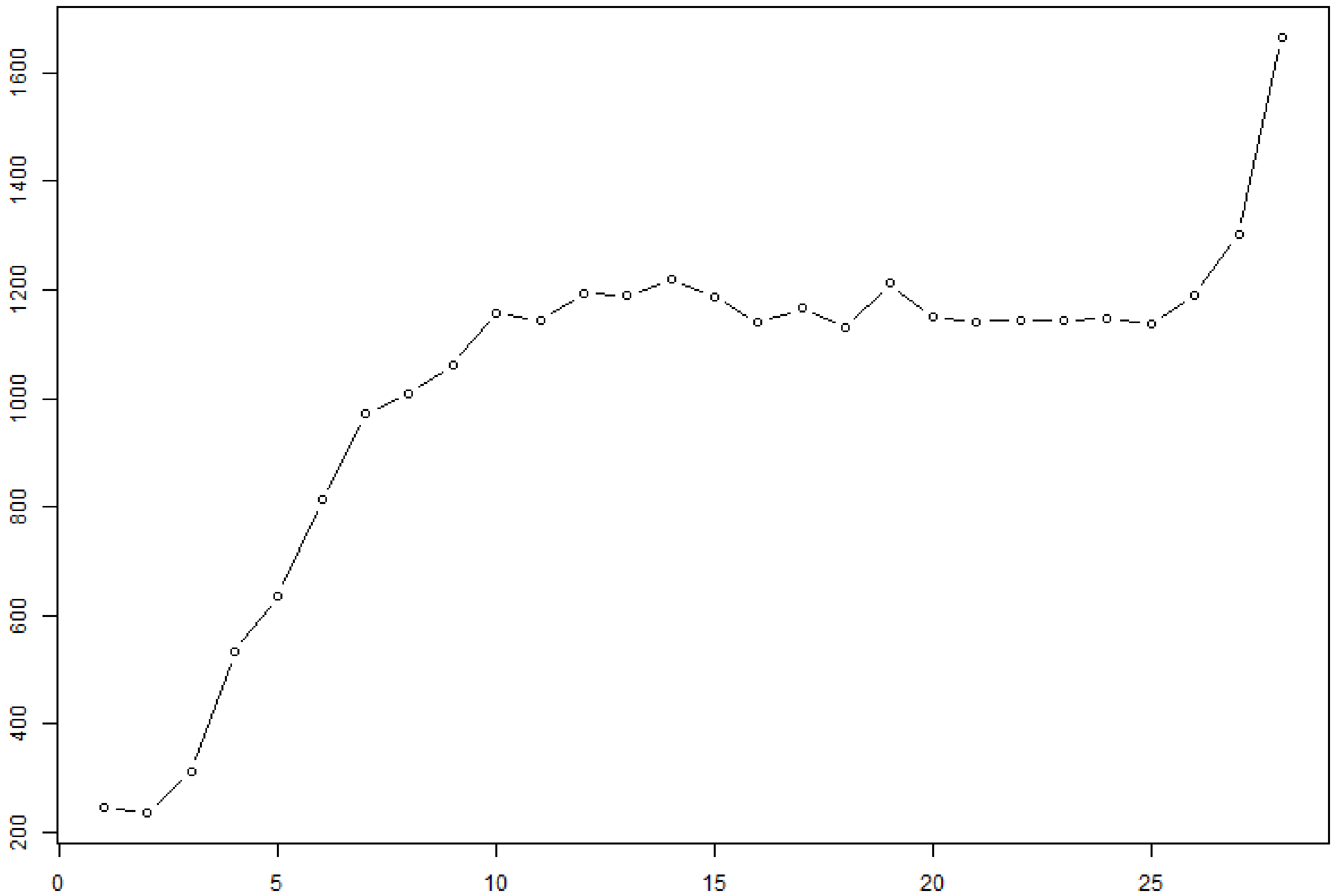
We adjust for the three effects, year-by-year.

- Here, "year" is defined as "from the day after Feb 28 of this year" "until Feb 28 of the next year".
- Regress "P" on its own lags (up to the 7^{th}) and dummies for the three effects. Take out the effects of those dummies.
  - For leap years, add dummies for the "9 effects" and "New year's eve effects".

Appendix (D)
Within-month frequency distributions of (shop)x(item), typical examples

Ice cream etc., Feb 2022

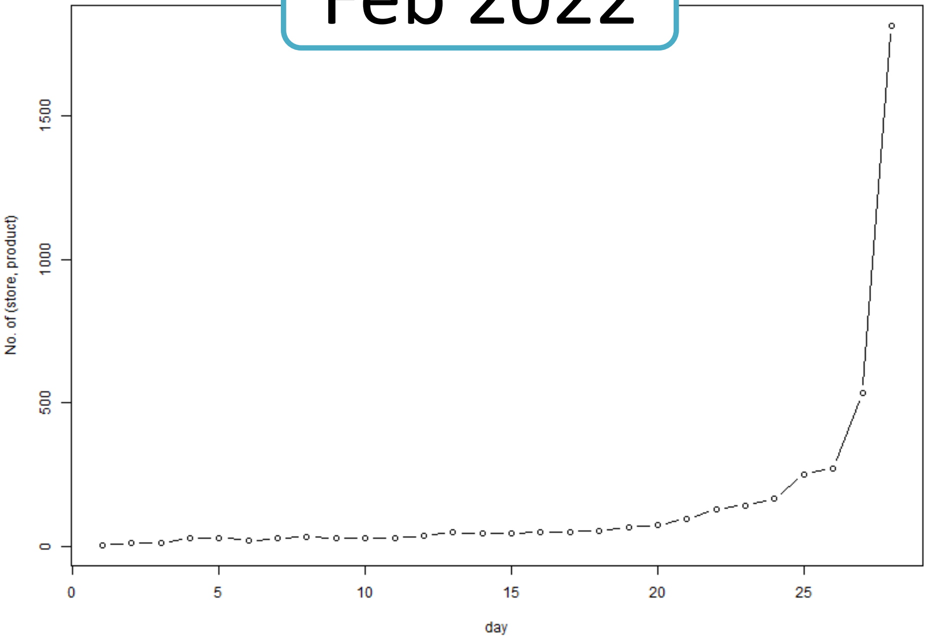
Number of (shop)x(item) that fall into a group



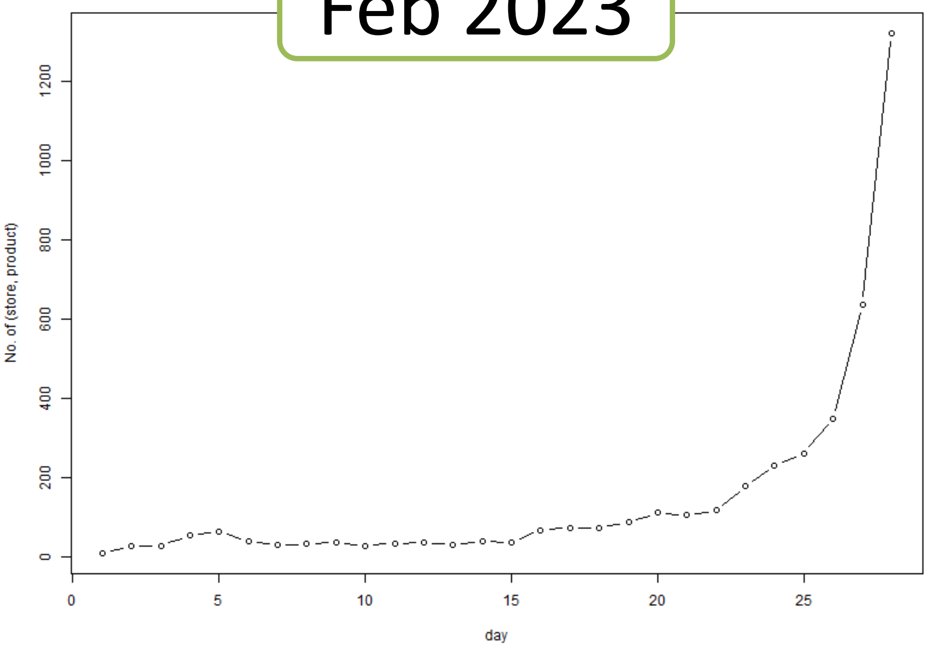
Number of days on which a particular (shop)x(item) appeared in the data set (i.e., sold at least 1 unit)

Eggs

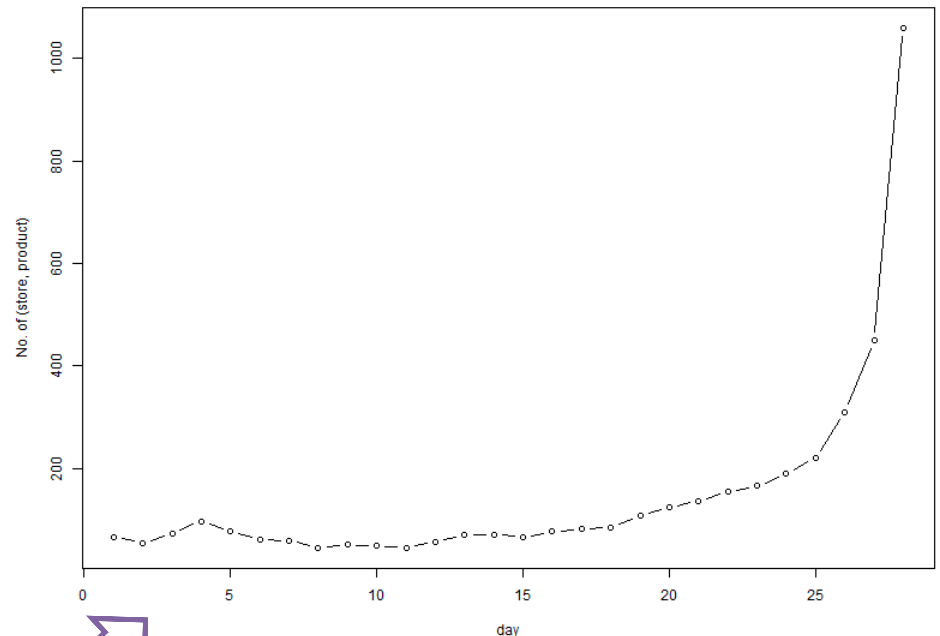
Feb 2022



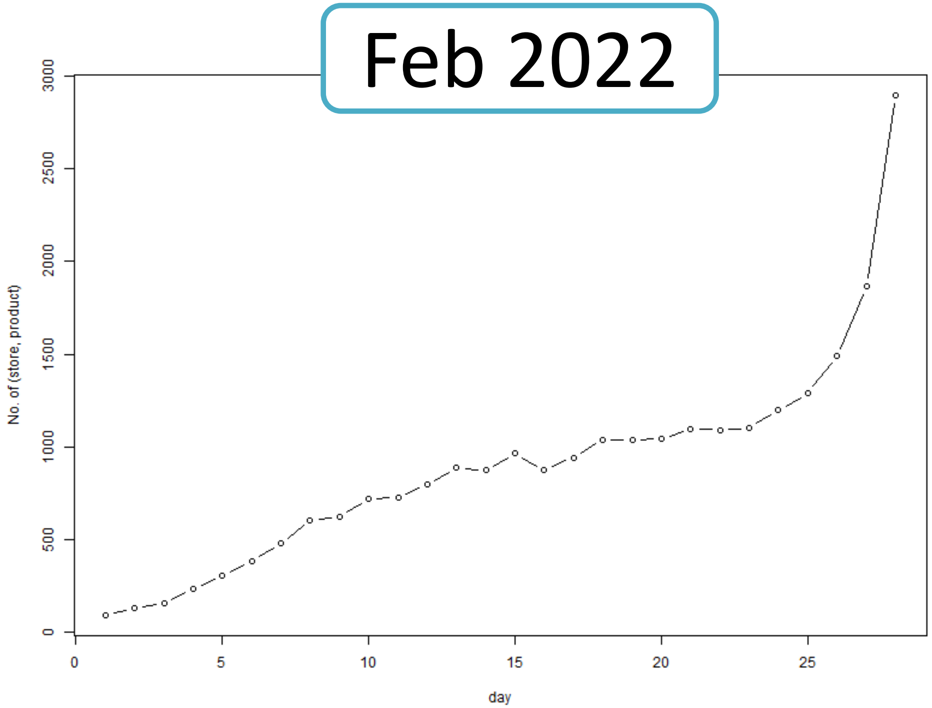
Feb 2023

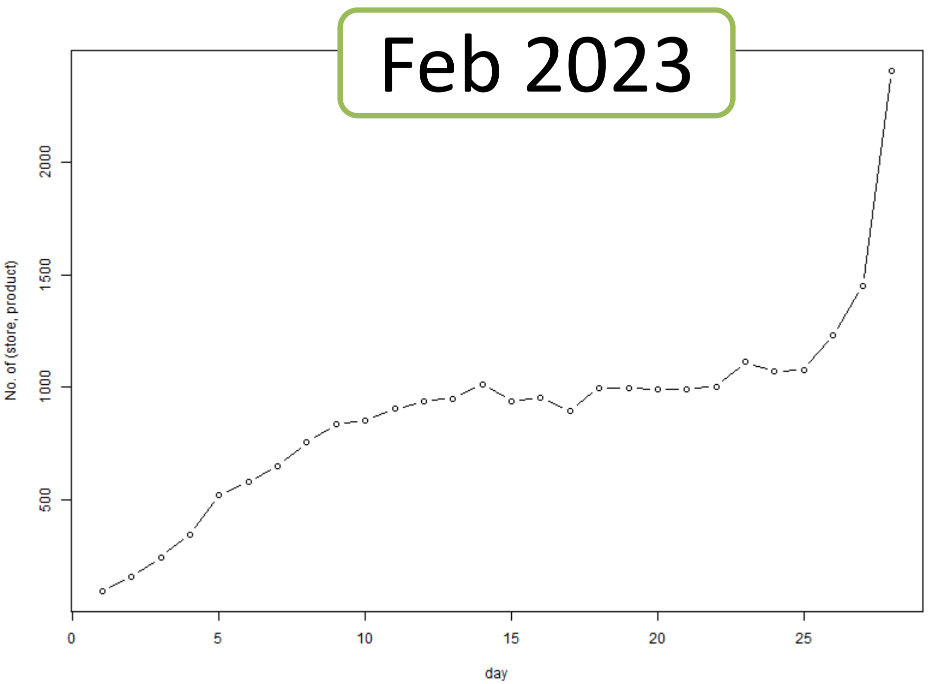


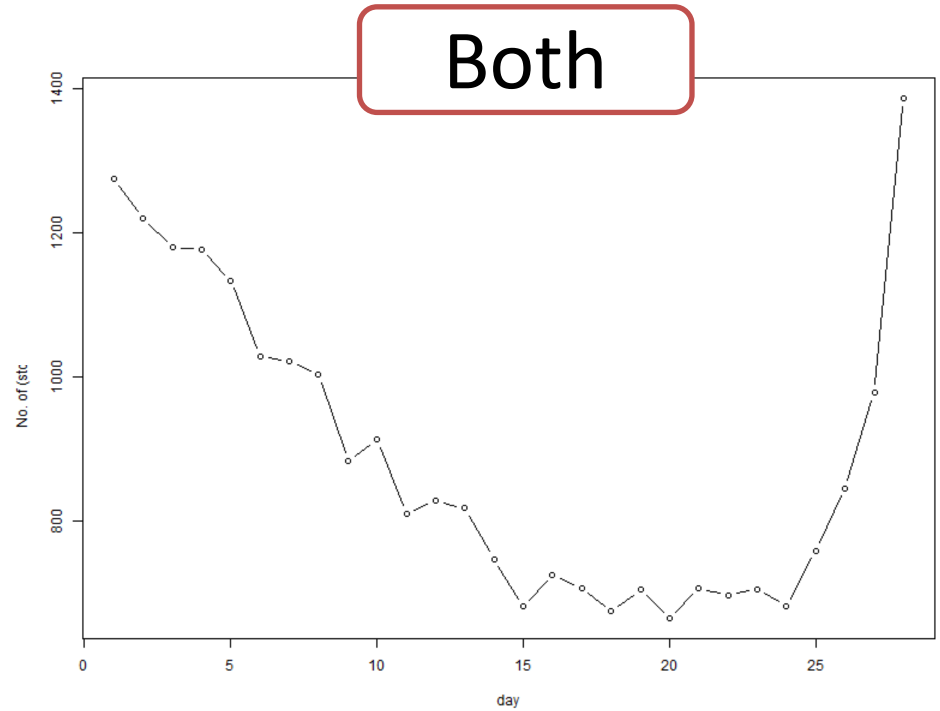
Both



Cup Noodles


Feb 2022
No. of (store, product)
0
500
1000
1500
2000
2500
3000
0
5
10
15
20
25
day


Feb 2023
No. of (store, product)
500
1000
1500
2000
0
5
10
15
20
25
day


Both
No. of (stc
800
1000
1200
1400
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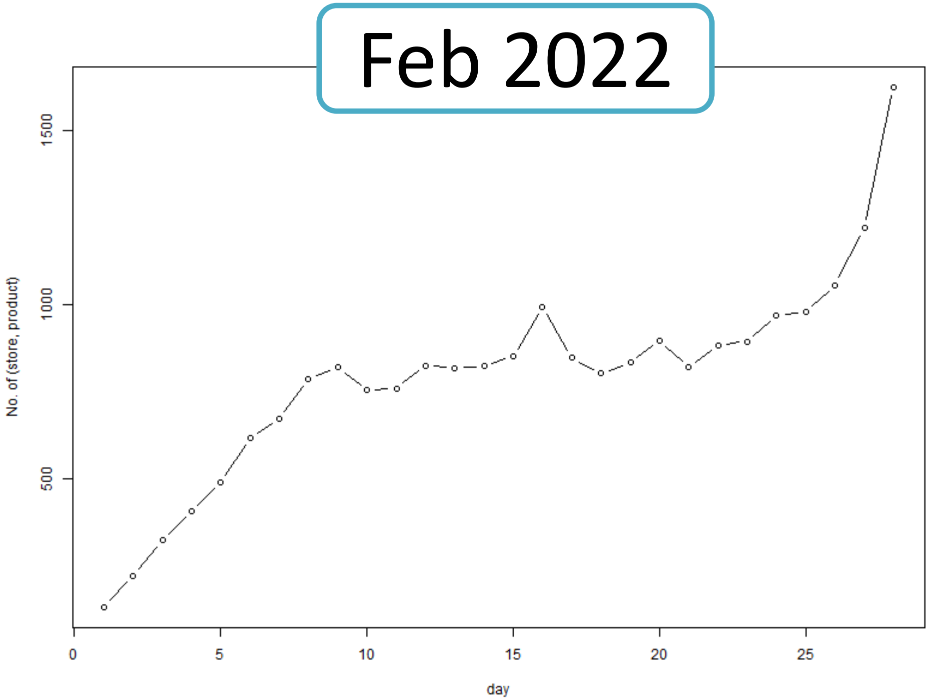
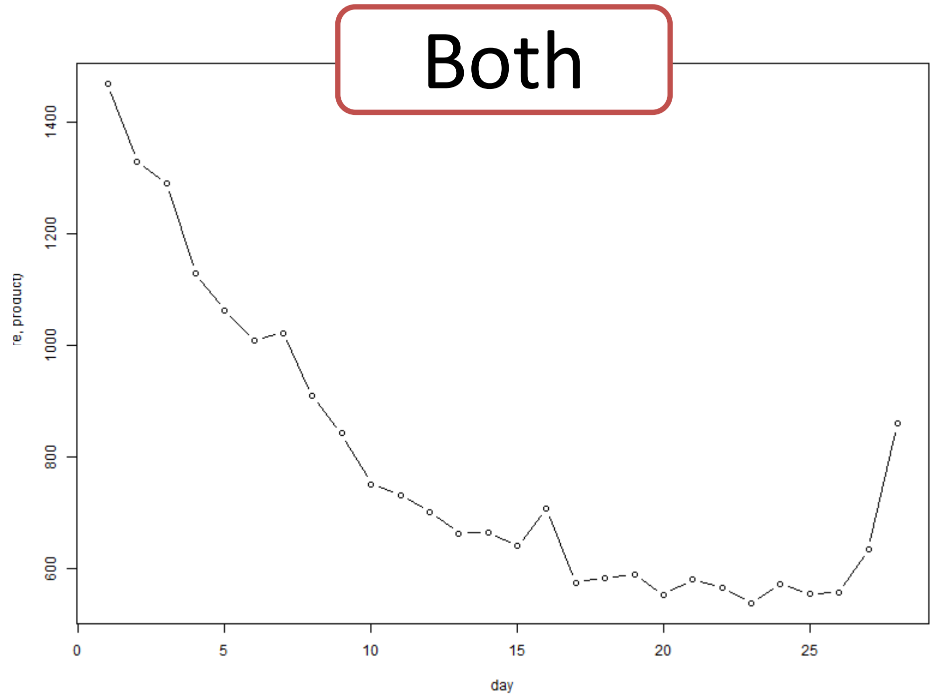
5
10
15
20
25
day

Snacks


Feb 2022
No. of (store, product)
1500
1000
500
0
5
10
15
20
25
day


Both
1400
1200
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600
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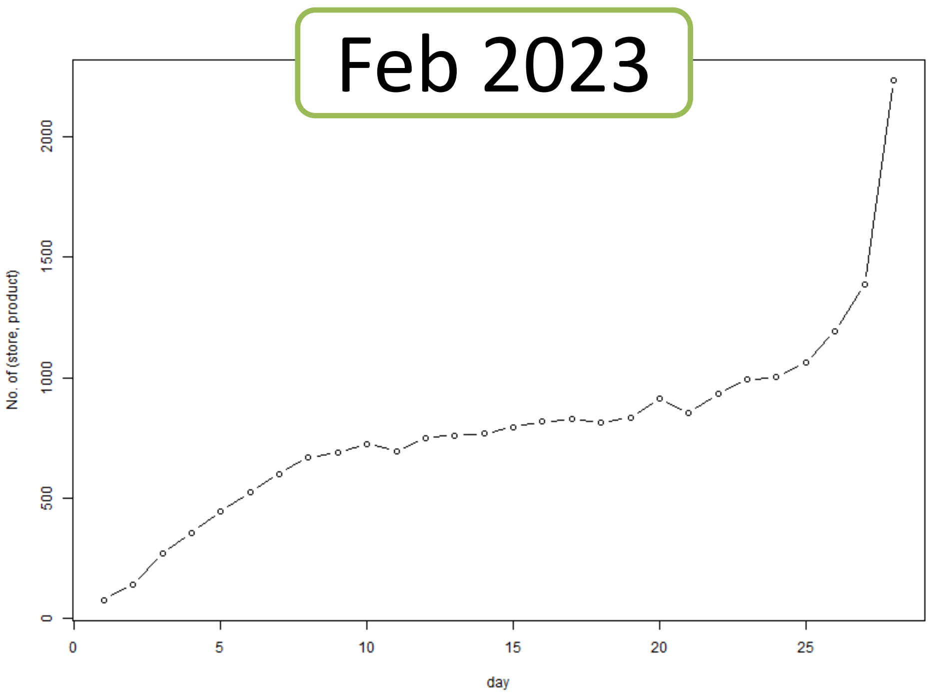
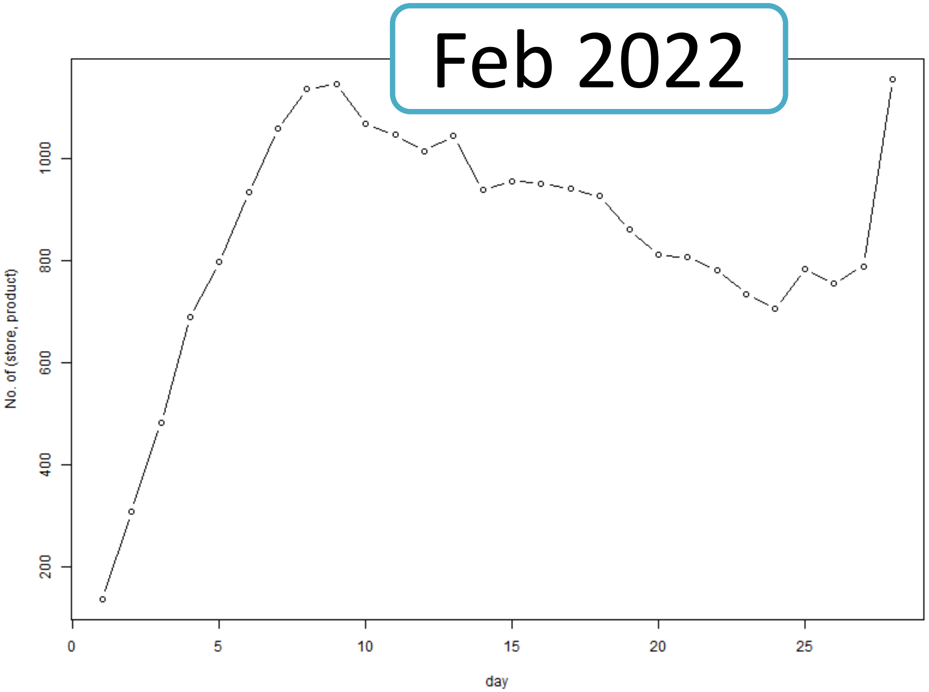
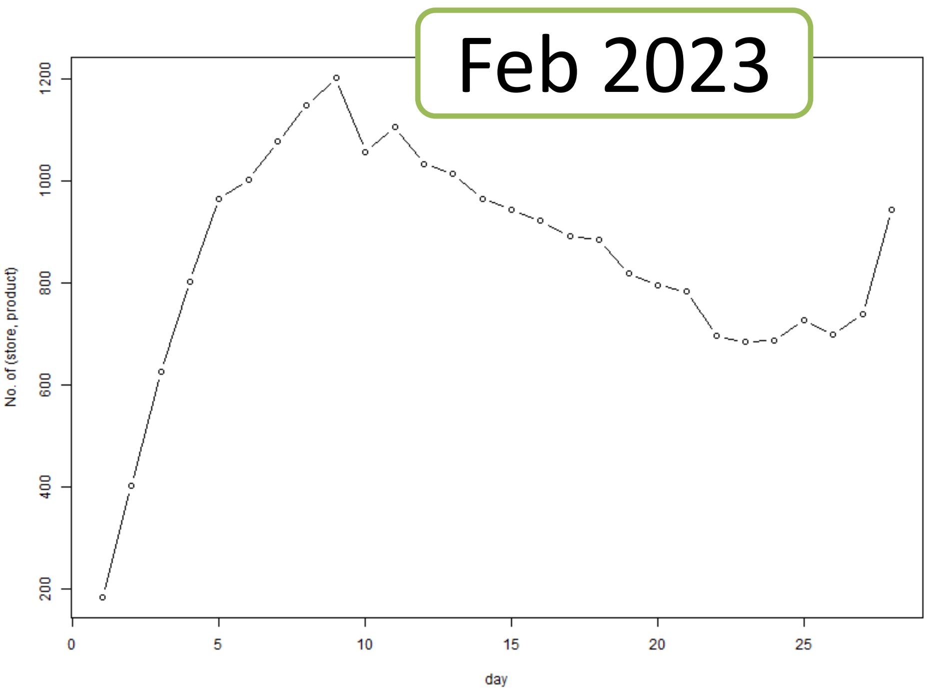
20
25
day


Feb 2023
No. of (store, product)
2000
1500
1000
500
0
0
5
10
15
20
25
day

Chocolates


Feb 2022
No. of (store, product)
200
400
600
800
1000
0
5
10
15
20
25
day


Feb 2023
No. of (store, product)
200
400
600
800
1000
1200
0
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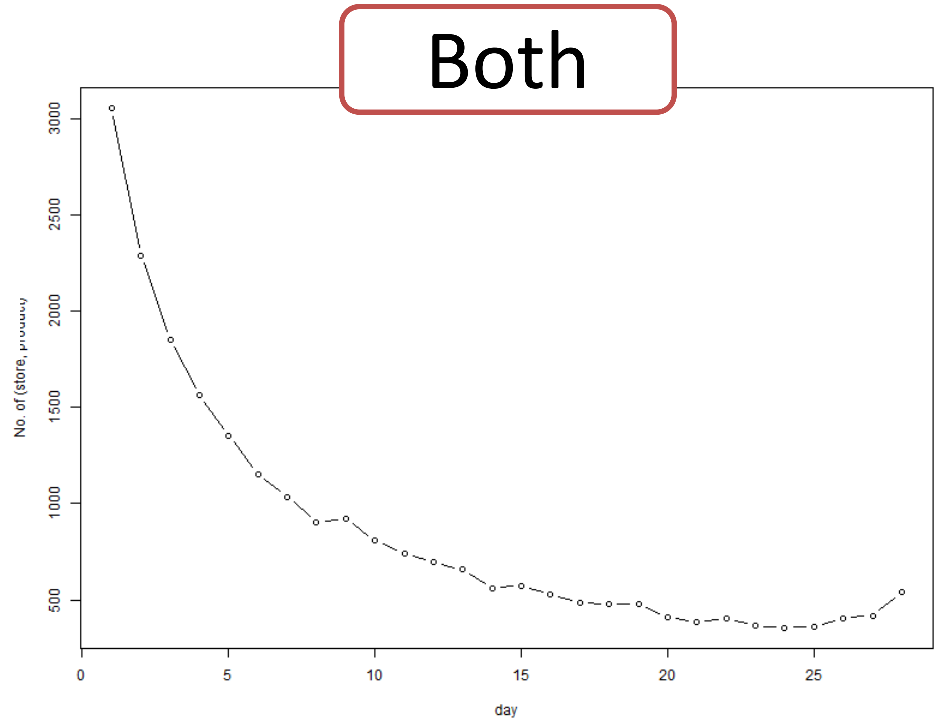
15
20
25
day


Both
500
1000
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2000
2500
3000
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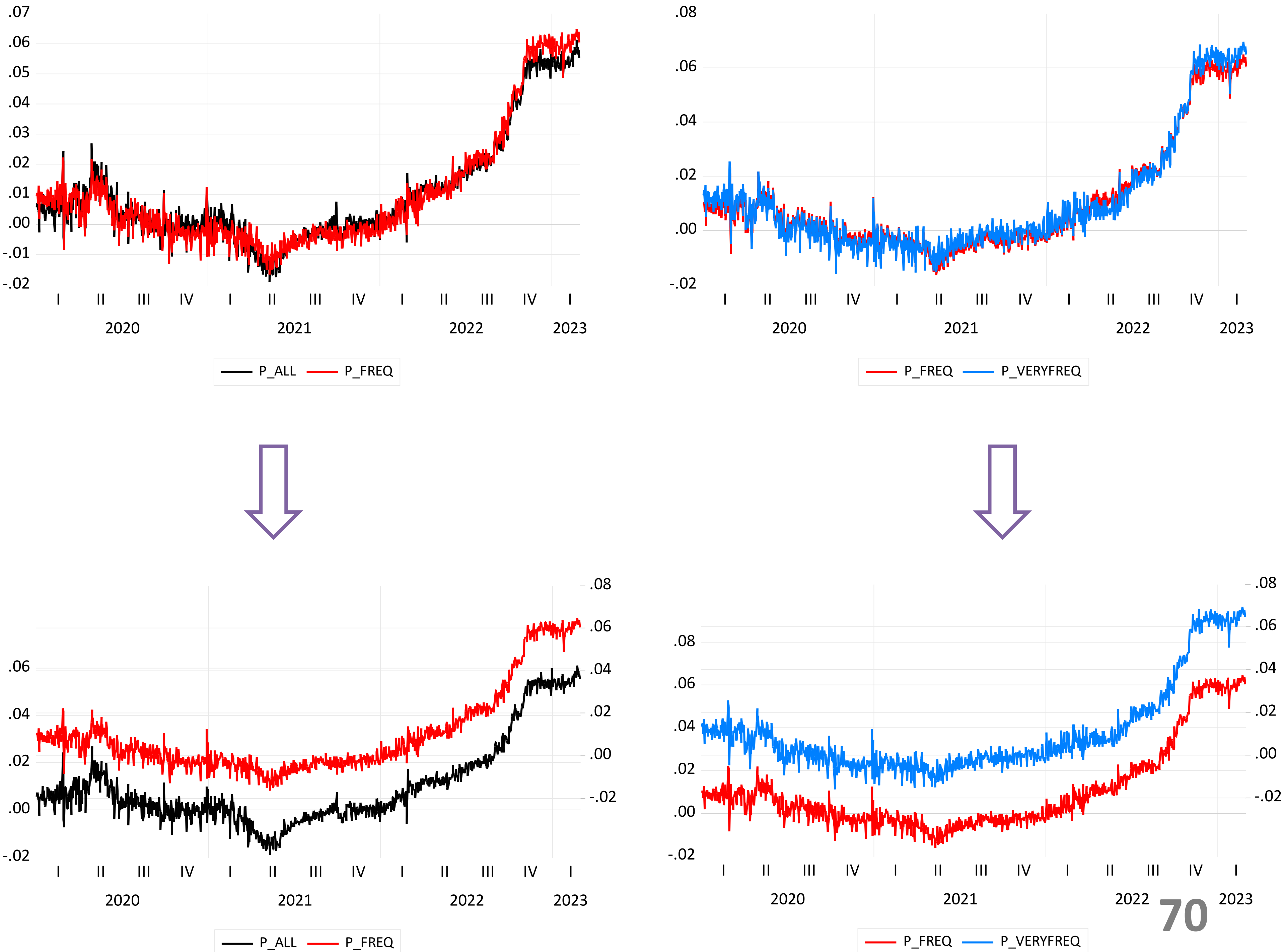
Appendix (E)
Daily indices, visual inspection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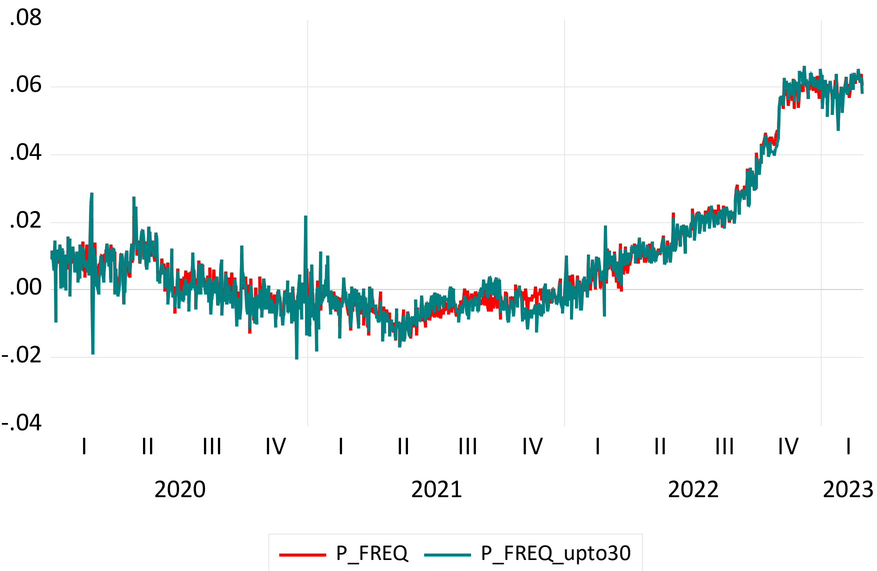
P_FREQ P_VERYFREQ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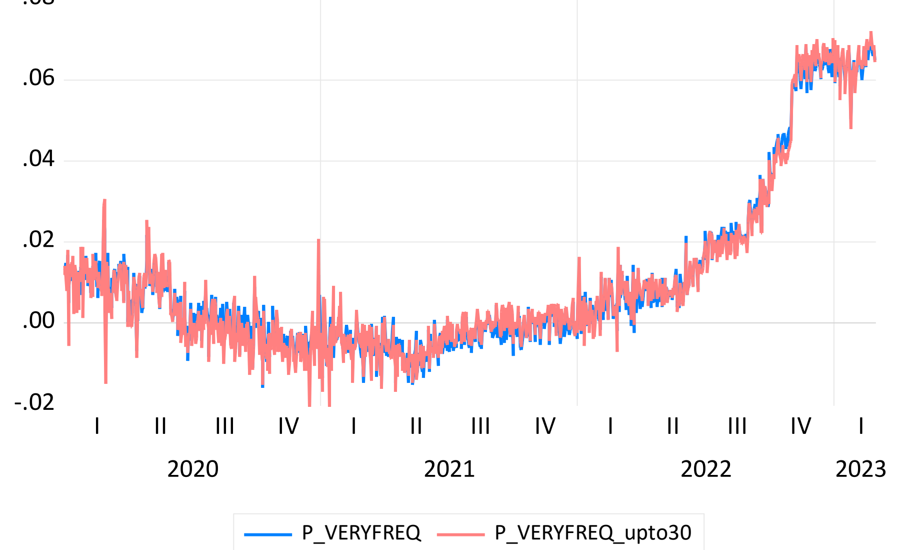
P_FREQ
P_FREQ_upto30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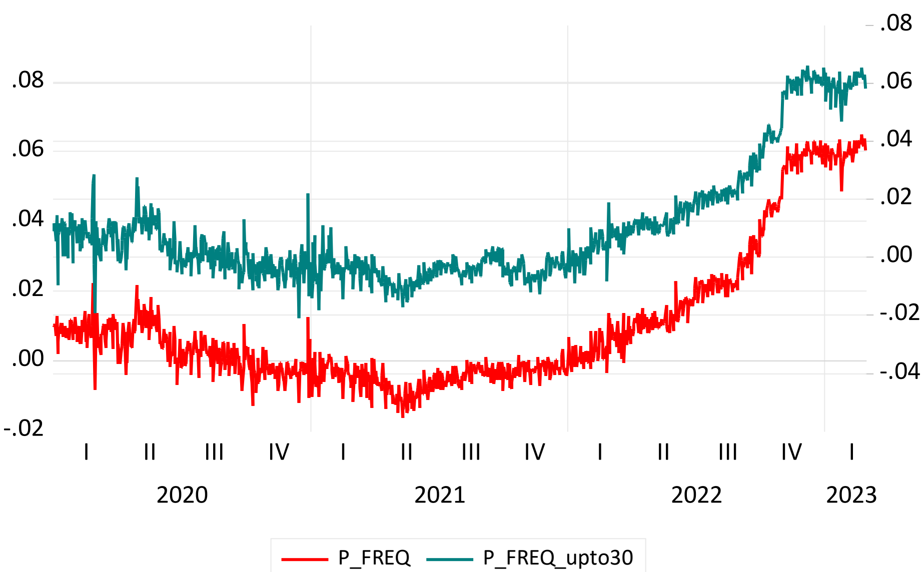
P_VERYFREQ
P_VERYFREQ_upto30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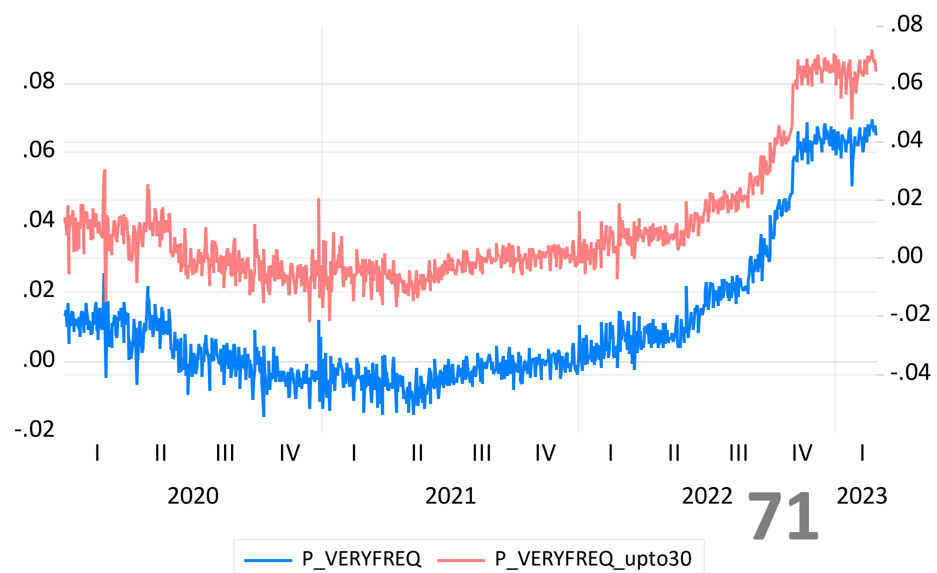
P_FREQ
P_FREQ_upto30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I II III IV I II III IV I II III IV I
2020 2021 2022 2023
P_VERYFREQ
P_VERYFREQ_upto30

Appendix (F) More on data on inflation expectations

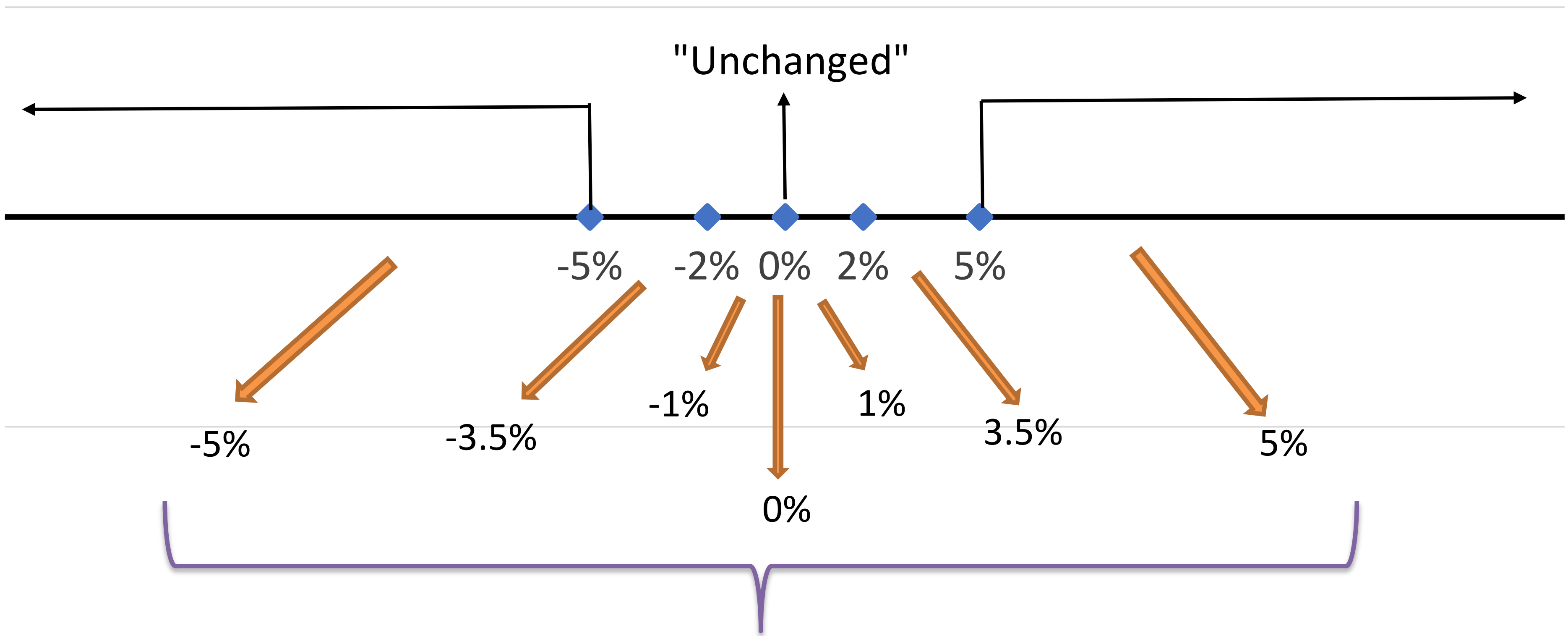
(1) April 2013
Change of survey method

- Before: direct-visit and self-completion questionnaires

- After: Mail Survey Method.

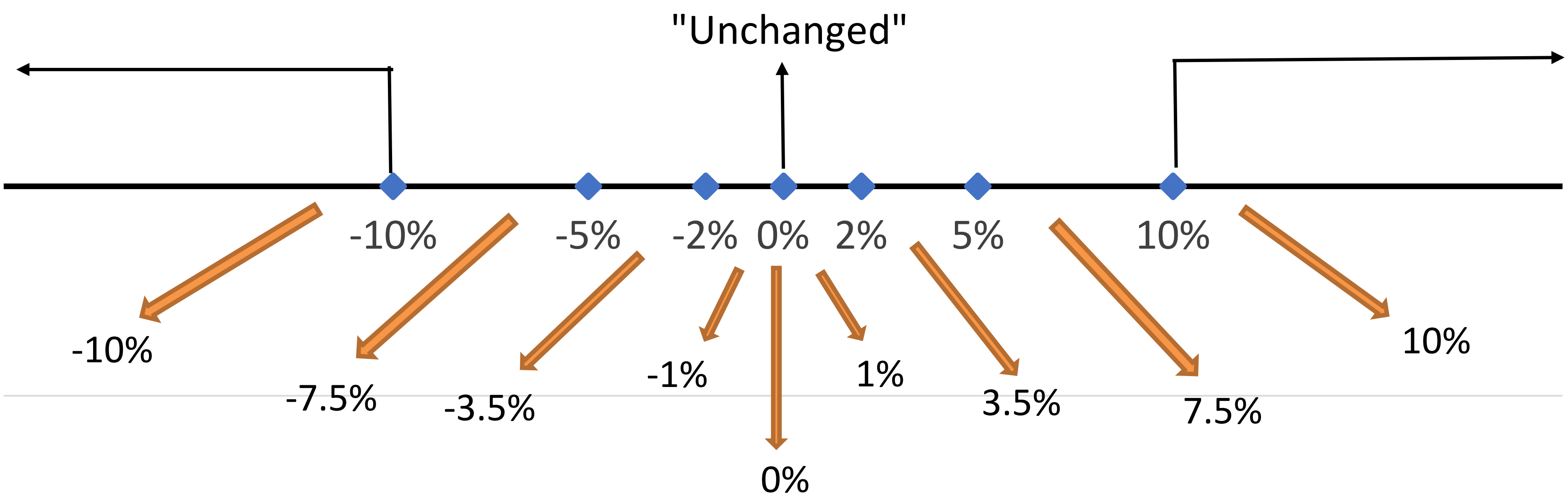
(2) April 2009: Range change

Before

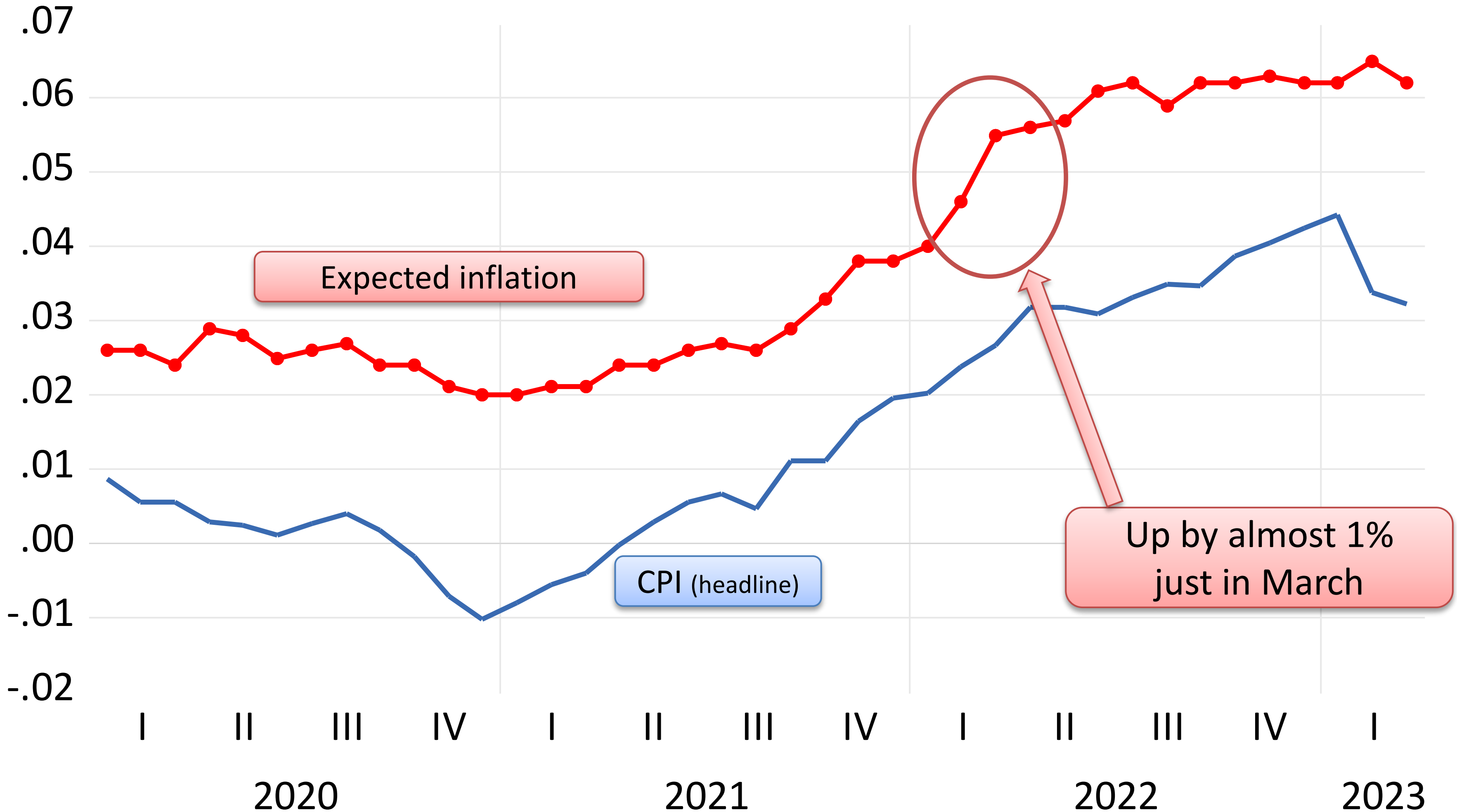


I assign conventional numerical values to each range to compute expected inflation as a weighted average.

After



Data shows that expectations can change abruptly.



Note: CPI is core, adjusted for mobile phone fees

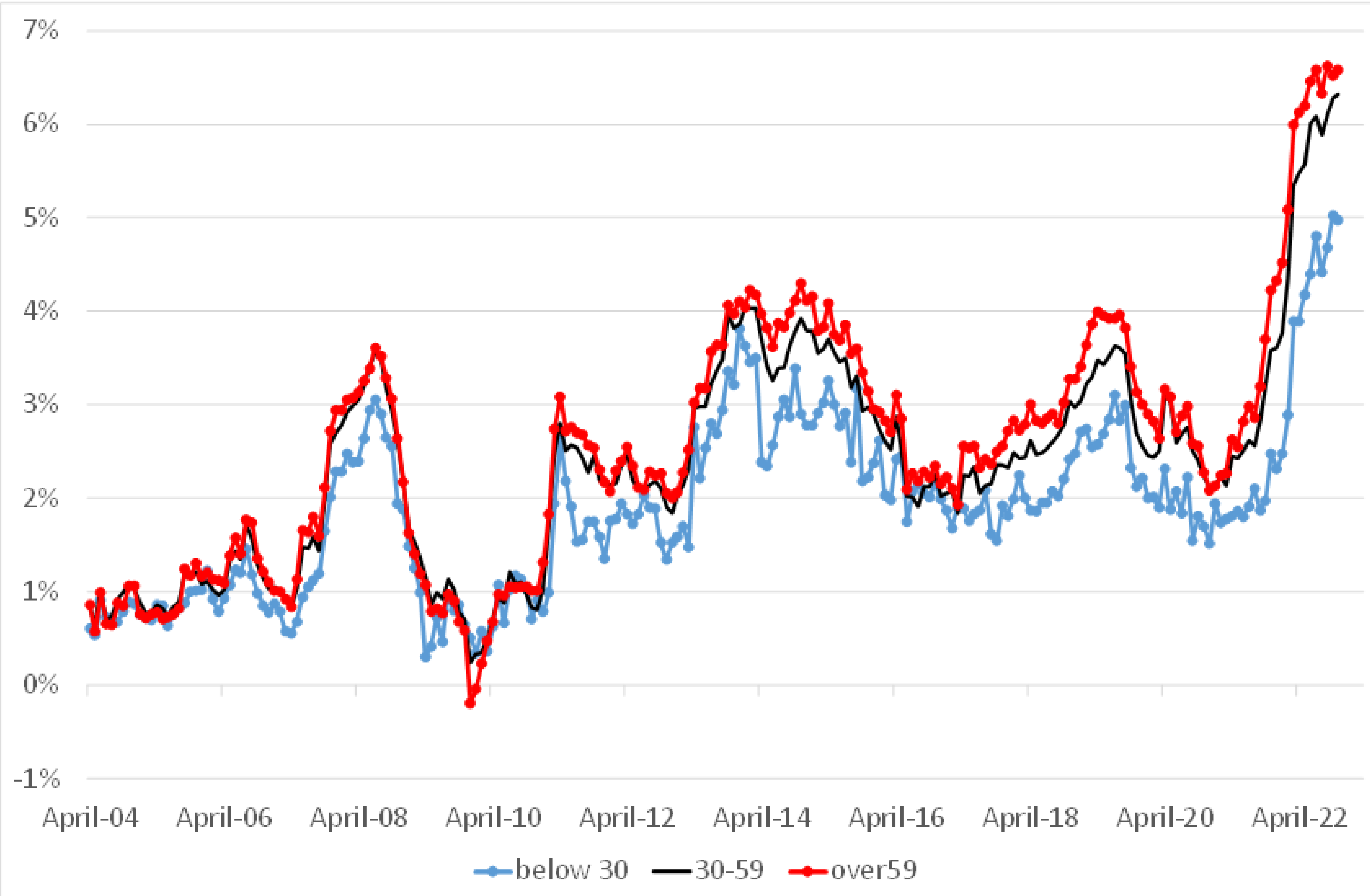
Appendix (G) Heterogeneity of expectations across age groups

3 groups: below 30, 30-59, above 60

- Older people are most responsive to gasoline prices (puzzling).

- Younger people are most sensitive to CPINOW.

Inflation expectations by age group



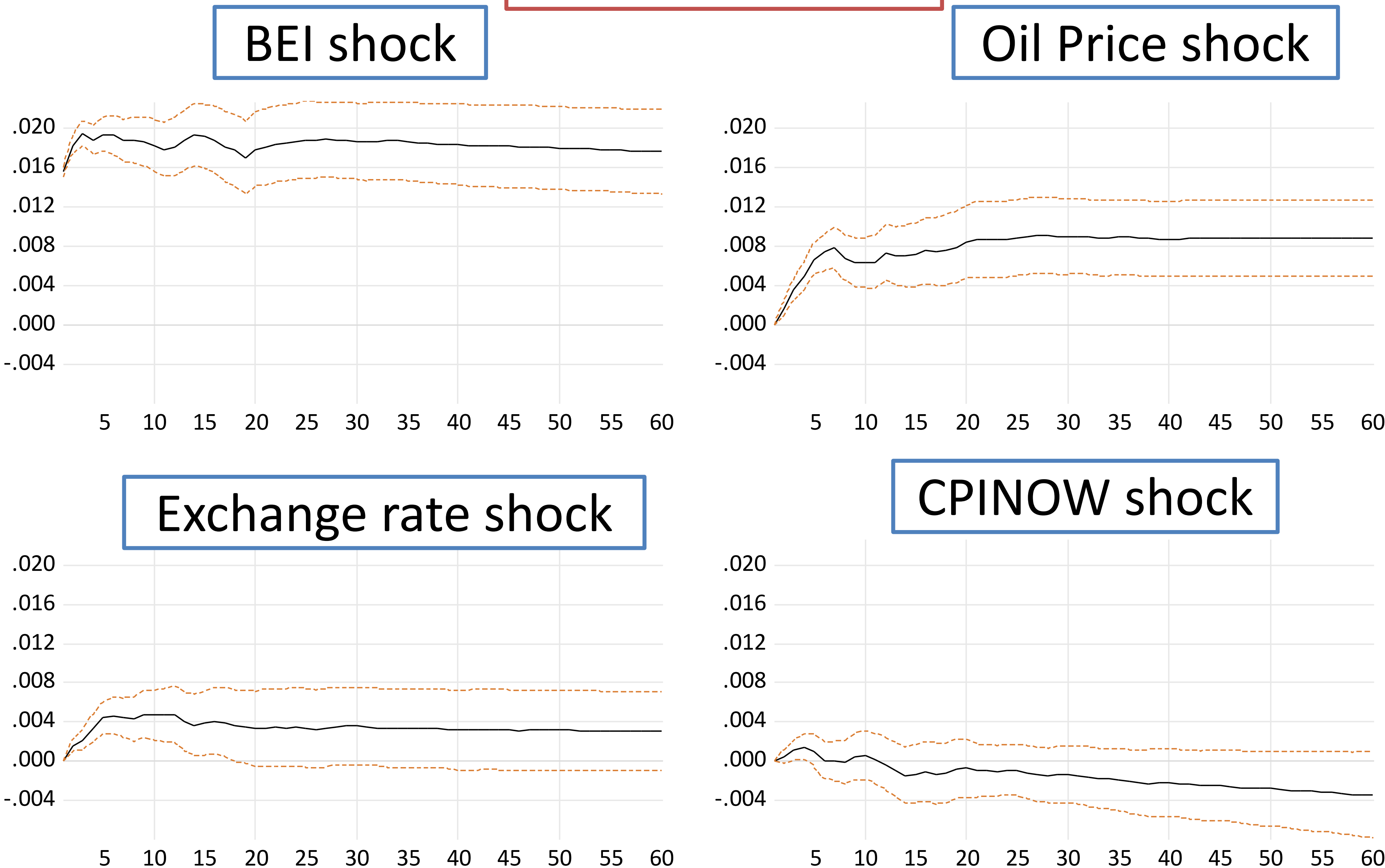
		Below 30		30-59		Over 59	
		Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
LHS(-1)		0.718	10.49	1.154	16.61	1.099	15.68
LHS(-2)		0.164	2.29	-0.184	-2.54	-0.124	-1.69
CPINOW	Intercept	0.019	2.10	0.015	2.25	0.014	2.06
	Slope	-0.001	-1.29	-0.001	-2.13	-0.001	-2.06
	Quadratic	0.000	0.80	0.000	1.99	0.000	1.98
Gasoline	Intercept	0.000	0.28	0.001	1.28	0.001	1.90
	Slope	0.000	-0.33	0.000	-1.19	0.000	-1.75
	Quadratic	0.000	0.38	0.000	1.19	0.000	1.71
Adjusted R-squared		0.920		0.973		0.974	

Appendix (H): Determinants of Market Expectations (BEI)

VAR with 4 variables

- Oil Price, Exchange Rate, CPINOW, **BEI**
- Oil Price and Exchange Rate are in first differences.
- Lag length = 20
- Sample period: November 2013 – March 2022

Response of BEI



Oil and exchange rate are much more important.