Nowcasting food inflation with a massive amount of online prices

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Outline

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Summary

1. Precise nowcasts are crucial for providing accurate forecasts (Faust and Wright, 2013).
2. Analysing online prices gaining a lot of momentum in recent years.
3. The research is spearheaded by studies within the Billion Prices Project, launched at MIT in 2008 (Cavallo & Ribogon, 2016).
4. We show that online prices can be very effective in nowcasting inflation and macroeconomic practitioners can make use of them already after a couple of months of data collection.

This paper

1. We focus on inflation nowcasting.
2. We employ a unique, extensive dataset of online food and non-alcoholic beverages prices gathered from web since 2009.
3. Our database contains 159 millions of prices for around 640 thousands of products.
4. We perform a real-time nowcasting experiment among popular, simple univariate approaches using highly disaggregated framework.

Our contribution

- In the paper we:
  1. discuss how macroeconomic practitioners can improve inflation nowcasts.
  2. provide evidence for a large number of highly disaggregated inflation components.
  3. study the usefulness of online prices for a small, emerging economy.
  4. report how forecasting errors are related to the:
     - scale of the project, i.e. the number of stores being web scraped,
     - the approach towards data curation, i.e. the classification of products,
     - the variability in consumer prices.
  5. examine the accuracy of nowcasting with online prices during COVID-19 pandemic.

Key results

- We show that:
  1. pure estimates of online price changes is already effective in nowcasting food inflation.
  2. incorporating information on online prices into model-based frameworks delivers a substantial increase in the nowcast accuracy.
  3. this approach outperforms a variety of frameworks, including judgemental methods.
  4. marked improvement can be obtained for a number of inflation components, especially those experiencing high volatility throughout the year.
  5. during COVID-19 the nowcasting quality relatively improved and remained comparable with judgemental nowcasts.
  6. more data is not always better – product selection and expenditure weighing is essential for providing accurate both in-sample fit as well as out-of-sample nowcasts

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Usefulness of online data

- Literature on online prices is mushrooming (Lunnemann and Wintr, 2011; Cavallo, 2013; Cavallo & Ribogon, 2016; Cavallo, 2017; Gorodnichenko & Talavera, 2017; Cavallo, 2018; Gorodnichenko et al., 2018).
- Online prices are increasingly included in the compilation of the CPI (in the US, the UK, the Netherlands, New Zealand and Norway,).
- Evidence on the usefulness of scraped data in forecasting inflation remains scarce (Aparicio & Bertolotto, 2020).
  - Scraped data from July 2008 to September 2016.
  - Data for 10 advanced economies.
  - Parsimonious models with online prices beat traditional benchmarks and two leading survey of professional forecasters.
- Our work is conceptually similar but we:
  - provide evidence for a large number of highly disaggregated components,
  - study the usefulness of online prices for an emerging economy with the online market much less developed,
  - show how forecasting errors are related to the scale of the project, the approach towards data curation and the variability in online prices,
  - examine the nowcast accuracy during COVID-19.

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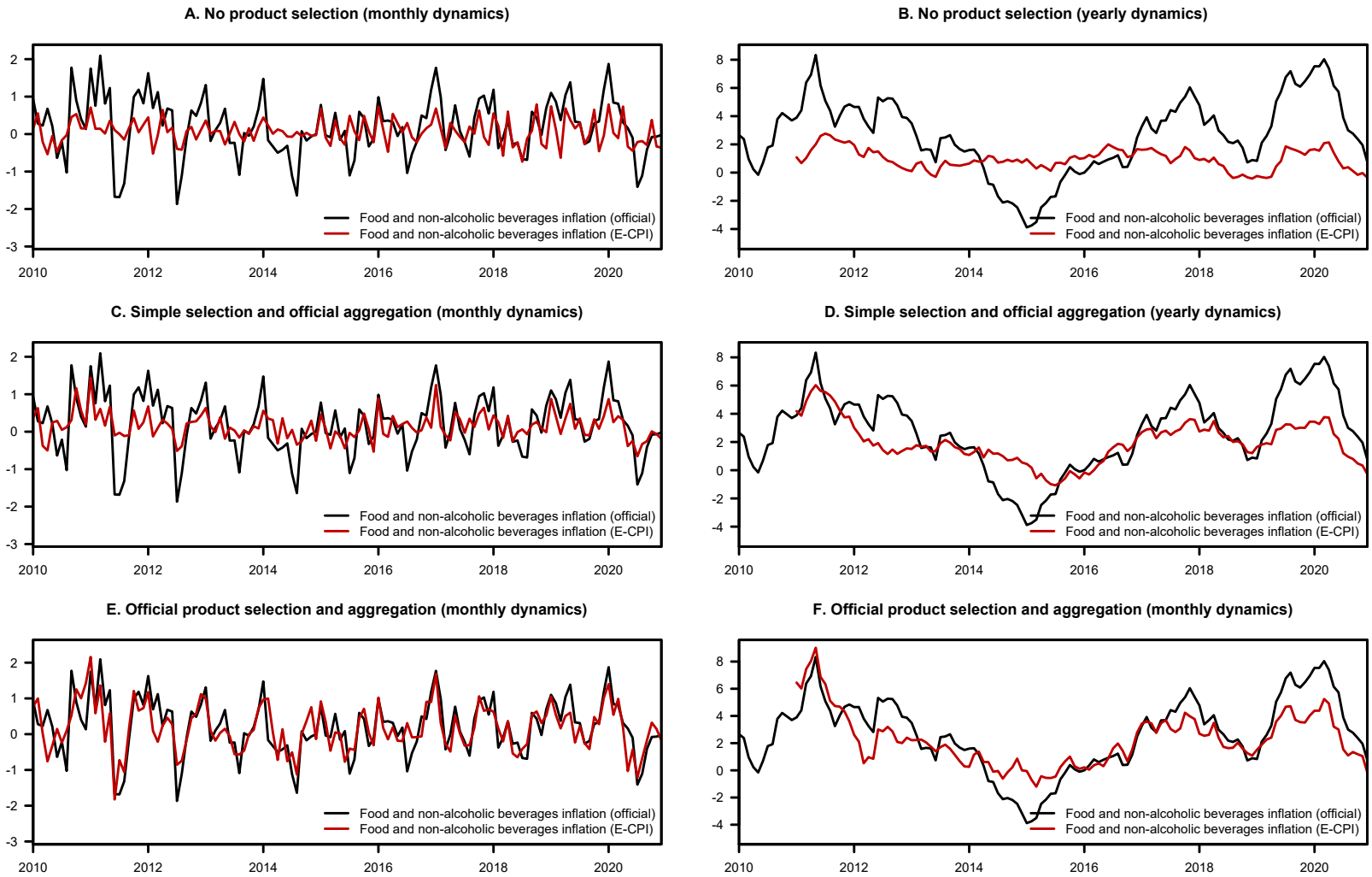
Online data

- E-CPI project aimed at collecting online prices launched in December, 2009.
- Frequency of operation changed to daily since 2017.
- Systematically expanding product categories to account for clothing, footwear, products, electronics, drugs, air plain tickets.

Store ID	q	q_s	n_p	$\bar{n}_p$	$\bar{n}_d$	$med\{n_d\}$
1	82,995	19,250	13,394,437	7,327	161	42
2	56,739	16,368	14,721,627	8,544	260	76
3	76,652	13,007	25,600,013	17,534	334	222
4	50,954	15,935	17,196,321	11,495	341	164
5	132,543	26,175	43,387,750	23,709	327	187
6	21,658	7,381	6,346,966	9,544	302	266
7	103,234	34,054	16,708,475	9,170	175	87
8	119,168	27,544	21,630,105	13,213	182	34
Total	643,943	159,714	158,985,694	12,759	250	102

q_s – number of selected products, n_p – number of observed prices, $\bar{n}_p$ – average number of prices per day, $\bar{n}_d$ – mean number of days price is observed, $med\{n_d\}$ – median number of days price is observed.

In-sample tracking accuracy of online data



Nowcasting competition (1)

- Inflation rate as the monthly, non-seasonally adjusted change in prices as the variable of interest.
- Change in the online price index defined as $o_{c,t}$.
- Baseline approach – recursive estimation strategy making use of expanding window.
  - Estimation sample spanning the period January 1999 - December 2016.
  - Evaluation sample spanning the period January 2017 - December 2020.
- Nowcast evaluation with MFE, RMSFE and Diebold-Mariano tests.
  - MFE reported in levels.
  - RMSFE reported as ratios - a value above 1 (below 1) that the competing approach produces on average less (more) accurate nowcasts than EC^{SX}.
- Sensitivity analysis for:
  - rolling window estimation,
  - store composition,
  - data curation,
  - forecast combinations,
  - the COVID-19 period (i.e. January 2020 - December 2020).

Nowcasting competition (2)

- Model entering the nowcasting competition:
  1. The simple random walk: $p_{c,t+1} = p_{c,t}$.
  2. The random walk à la Atkeson & Ohanian (2001): $p_{c,t+1} = \frac{1}{12}\sum_{j=1}^{12} p^{SA}_{c,t-j+1} + \hat{s}^{TS}_{c,t+1}$.
  3. The best SARMA model based on in-sample fit (BS^{IS}): $p_{c,t} = \mu_c + \varepsilon_{c,t} + \sum_{i=1}^{p}\phi_{c,i}p_{c,t-i} + \sum_{i=1}^{q}\theta_{c,i}\varepsilon_{c,t-i} + \sum_{i=1}^{P}\Phi_{c,i}p_{c,t-i*12} + \sum_{i=1}^{Q}\Theta_{c,i}\varepsilon_{c,t-i*12}$, assuming that $\varepsilon_{c,t} \sim NIID(0,\sigma_c^2)$ chosen from 64 specifications using BIC.
  4. The best SARMA model based on out-of-sample accuracy (BS^{OS}) using the minimal RMSFE criterion calculated on a pseudo validation set.
  5. The pure, ex-post E-CPI nowcast: $p_{c,t+1} = o_{c,t+1}$.
  6. The pure, real-time E-CPI nowcast (EC^{RT}): $p_{c,t+1} = o^{*}_{c,t+1}$.
  7. The best SARMAX model with online prices as the exogenous variable (EC^{SX}). The specification is the following: $p_{c,t} = \mu_c + \varepsilon_{c,t} + \sum_{i=0}^{B}\beta_{c,i}o_{c,t-i} + \sum_{i=1}^{p}\phi_{c,i}p_{c,t-i} + \sum_{i=1}^{q}\theta_{c,i}\varepsilon_{c,t-i} + \sum_{i=1}^{P}\Phi_{c,i}p_{c,t-i*12} + \sum_{i=1}^{Q}\Theta_{c,i}\varepsilon_{c,t-i*12}$ and $\varepsilon_{c,t} \sim NIID(0,\sigma_c^2)$ chosen from 256 specifications using the minimal RMSFE criterion calculated on a pseudo validation set.
  8. The simple combination of the EC^{SX} models (EC^{MC}).
  9. The combination of BS^{OS} models with equal weights (BS^{MC}).
  10. The combination of EC^{SX} models with weight inversely proportional to RMSFE (EC^{MCI}).
  11. The judgemental forecast (JD).

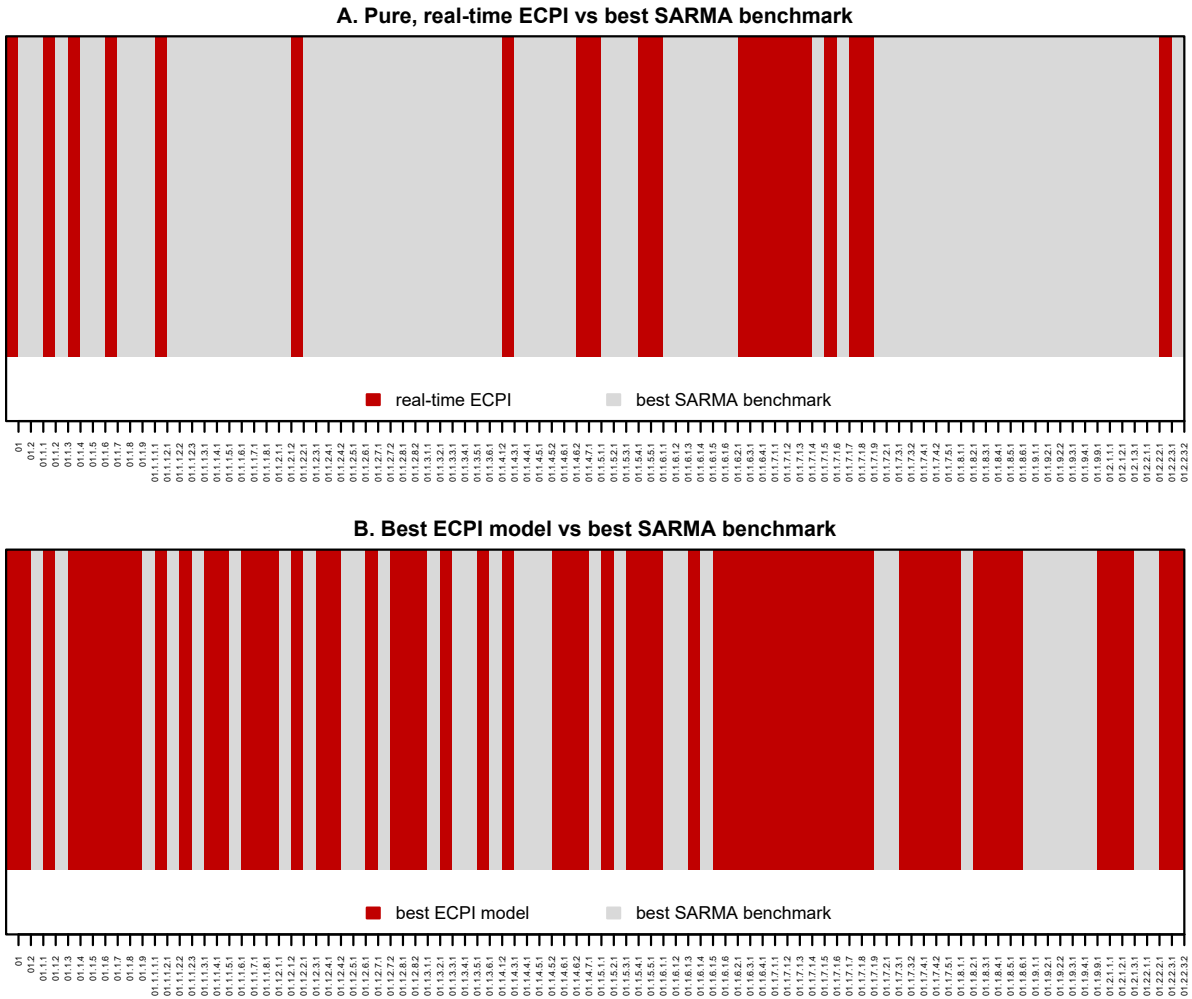
Outline

Baseline results – the aggregate

Error	Online prices			Traditional benchmarks				Forecast combinations		
	EC^{SX}	EC^{EX}	EC^{RT}	RW	AO^{SA}	BS^{IS}	BS^{OS}	BS^{MC}	EC^{MC}	EC^{MCI}
					Recursive estimation					
MFE	0.018	-0.106	-0.093	0.042	0.118	0.109	0.111	0.134	0.025	0.022
RMSFE	0.338	1.071	1.082	1.784^{a}	1.528^{a}	1.446^{a}	1.524^{a}	1.621^{a}	1.181^{b}	1.176^{b}
					Rolling estimation					
MFE	0.019	-0.106	-0.093	0.042	0.118	0.041	0.017	0.025	0.080	0.019
RMSFE	0.427	0.848	0.857	1.413^{b}	1.209^{c}	1.362^{b}	1.381^{b}	1.324^{b}	1.003	0.965
					COVID-19					
MFE	0.146	-0.076	-0.078	0.084	0.362	0.401	0.394	0.394	0.212	0.214
RMSFE	0.340	1.312	1.332	1.567	1.575	1.727	1.902	2.048	1.411	1.398

MFE reported in levels. RMSFE reported as ratios - a value above 1 (below 1) that the competing approach produces on average less (more) accurate nowcasts than EC^{SX}. ^{a} denotes significance at the 1 percent level, ^{b} denotes significance at the 5 percent level, ^{c} denotes significance at the 10 percent level.

Baseline results – low level disaggregation

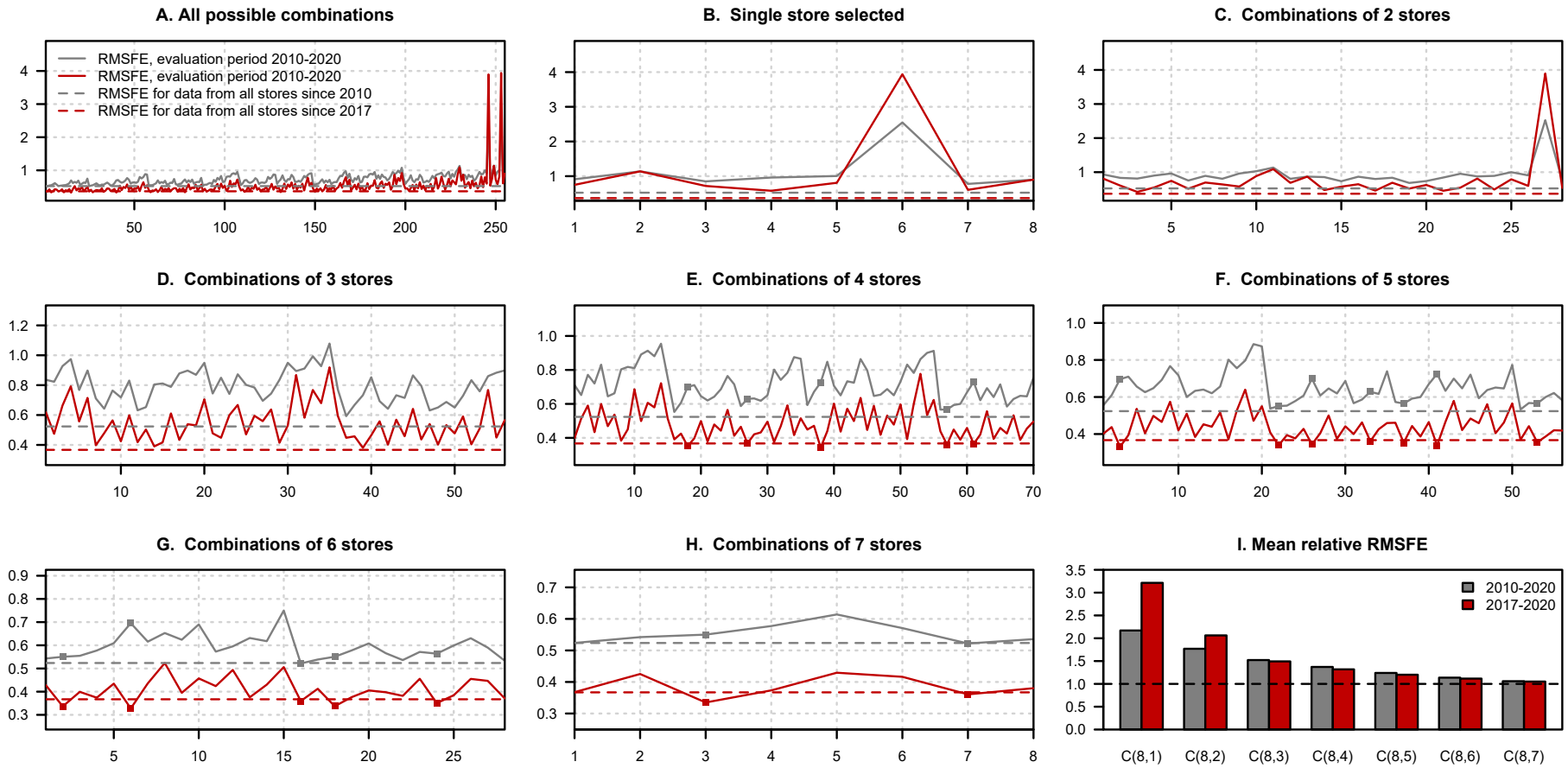


The comparison between online data approach and judgemental nowcasts

	Recursive estimation whole evaluation period		Rolling estimation		Recursive estimation COVID-19 period	
	EC^{SX}	JD	EC^{SX}	JD	EC^{SX}	JD
MFE	0.018	0.021	0.019	0.021	0.146	0.147
RMSFE	0.338	1.144^{c}	0.427	0.905	0.340	0.965

MFE reported in levels. RMSFE reported as ratios - a value above 1 (below 1) that the competing approach produces on average less (more) accurate nowcasts than EC^{SX}. ^{a} denotes significance at the 1 percent level, ^{b} denotes significance at the 5 percent level, ^{c} denotes significance at the 10 percent level.

Is more data better?



Not always – the importance of data curation

		RMSFE	MFE
Frameworks with online prices	EC^{SX}	0.338	0.018
	EC^{EX}	1.071	-0.106
	EC^{RT}	1.082	-0.093
Simple selection	EC^{SX}	1.299^{b}	0.036
	EC^{RT}	1.400^{a}	-0.117
Traditional benchmarks	RW	1.784^{a}	0.042
	AO^{SA}	1.528^{a}	0.118
	BS^{IS}	1.446^{a}	0.109
	BS^{OS}	1.524^{a}	0.111
Forecast combinations	BS^{MC}	1.621^{a}	0.134
	EC^{MC}	1.181^{b}	0.025
	EC^{MCI}	1.176^{b}	0.022

MFE reported in levels. RMSFE reported as ratios - a value above 1 (below 1) that the competing approach produces on average less (more) accurate nowcasts than EC^{SX}. Simple selection refers to the robustness check, where products are classified into respective groups using unsupervised learning based on word stems. ^{a} denotes significance at the 1 percent level, ^{b} denotes significance at the 5 percent level, ^{c} denotes significance at the 10 percent level.

The impact of price dispersion on the relative nowcast accuracy

	$RMSFE^{OS \to SX^*}$	$RMSFE^{SX^* \to SX}$	$RMSFE^{OS \to SX}$
log(SD)	-0.014	-0.046^{***}	-0.059^{***}
	(0.011)	(0.012)	(0.013)
C01.1.1	0.042	0.064^{*}	0.099^{**}
	(0.035)	(0.035)	(0.046)
C01.1.2	0.079^{**}	0.052	0.122^{***}
	(0.031)	(0.036)	(0.041)
C01.1.3	0.088^{***}	0.052	0.134^{***}
	(0.027)	(0.033)	(0.040)
C01.1.4	0.053	0.056	0.102^{**}
	(0.041)	(0.036)	(0.043)
C01.1.5	0.033	0.116^{***}	0.139^{***}
	(0.033)	(0.042)	(0.045)
C01.1.6	0.089^{**}	0.109^{*}	0.188^{***}
	(0.044)	(0.056)	(0.070)
C01.1.7	0.039	0.074	0.107^{**}
	(0.034)	(0.045)	(0.051)
C01.1.8	0.053^{**}	0.057	0.104^{**}
	(0.025)	(0.040)	(0.044)
C01.1.9	0.097^{***}	0.053	0.144^{***}
	(0.023)	(0.033)	(0.037)
C01.2	0.046	0.033	0.072^{*}
	(0.033)	(0.037)	(0.043)
Constant	-0.082^{***}	-0.079^{**}	-0.154^{***}
	(0.021)	(0.033)	(0.038)
Observations	95	95	95
R^2	0.156	0.311	0.401
F Statistic (df = 11; 83)	1.391	3.412^{***}	5.055^{***}

The table reports the outcomes of a simple regression of the dispersion in consumer prices measured with the standard deviation across all inflation components on the relative RMSFE measures, after accounting for group-specific fixed effects. C01.1.1 denotes *Bread and cereals*, C01.1.2 denotes *Meat*, C01.1.3 denotes *Fish and seafood*, C01.1.4 denotes *Milk, cheese and eggs*, C01.1.5 denotes *Oils and fats*, C01.1.6 denotes *Fruits*, C01.1.7 denotes *Vegetables*, C01.1.8 denotes *Sugar, jam, honey, chocolate and confectionery*, C01.1.9 denotes *Food products, n.e.c.* and C01.2 denotes *Non-alcoholic beverages*. Robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, * denotes significance at the 10 percent level.

Recursive versus rolling estimation

		EC^{SX}	EC^{MC}	EC^{MCI}	BS^{IS}	BS^{OS}	BS^{MC}	BS^{MCI}
RMSFE	rolling window	0.427	0.428	0.412	0.581	0.589	0.565	0.566
	expanding window	0.338	0.399	0.397	0.489	0.515	0.548	0.545
	ratio	26%	7%	4%	19%	14%	3%	4%
MFE	rolling	0.019	0.080	0.019	0.041	0.017	0.025	0.027
	expanding	0.018	0.025	0.022	0.109	0.111	0.134	0.131
	difference	0.001	0.054	-0.003	-0.068	-0.093	-0.109	-0.104

For the RMSFE statistics the ratio denotes the percent change in the RMSFE when the expanding windows estimation is switched to the rolling windows. For the MFE a simple difference is reported.

Nowcasting during the COVID-19 period (2020M1-2020M12)

Error	Online prices			Traditional benchmarks				Forecast combinations		
	EC^{SX}	EC^{EX}	EC^{RT}	RW	AO^{SA}	BS^{IS}	BS^{OS}	BS^{MC}	EC^{MC}	EC^{MCI}
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Outline

Main takeaways

1. Pure estimates of online price changes is already effective in nowcasting food inflation.
2. Incorporating information on online prices into model-based frameworks delivers a substantial increase in the nowcast accuracy.
3. This approach outperforms a variety of frameworks, including judgemental methods.
4. Marked improvement can be obtained for a number of inflation components, especially those experiencing high volatility throughout the year.
5. During COVID-19 the nowcasting quality relatively improved and remained comparable with judgemental nowcasts.
6. Meticulous product selection and expenditure weighing is essential for providing accurate both in-sample fit as well as out-of-sample nowcasts.