NOWCASTING PRIVATE CONSUMPTION: TRADITIONAL INDICATORS, UNCERTAINTY MEASURES, AND THE ROLE OF INTERNET SEARCH QUERY DATA

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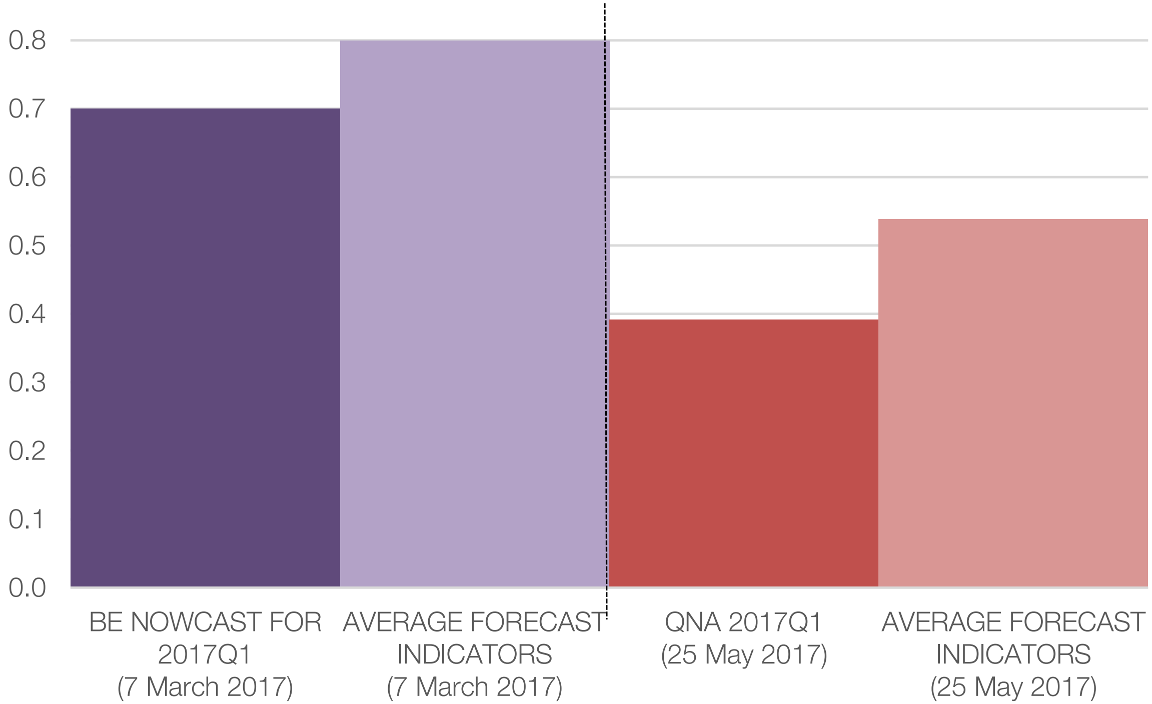
Outline

1. Motivation
2. Literature review
3. The data
4. Modeling approach
5. The empirical exercise
6. Selection of results and conclusions

1. Motivation

- Relevance of private consumption: some 60% of GDP
- Key variable from both a forecasting and a policy perspective
- Real-time assessment limited by availability of statistical information (QNA and monthly, traditional indicators)

Example: Nowcasting of q-q growth rates of QNA private consumption in the first quarter of 2017 (Spain)



1. Motivation: traditional vs. “new” indicators

- There is more data around than what is typically exploited in many short term forecasting models

Target variable: QNA private consumption

“Hard” indicators

- *Available at the monthly frequency … but released with significant lags*

“Soft” indicators

- *More timely*
- *Typically more correlated with hard indicators than with QNA variables*
- *Contemporaneous, leading or lagging behavior?*

Other (less standard) sources?

- *Credit cards’ spending / withdrawals*
- *Indicators of “uncertainty”*
- *Google searches*
- *…*

AIM OF THE PAPER:

Explore the relative merits of…

… hard vs. soft

… traditional vs. “new” indicators

to “nowcast” Spanish real private consumption

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1. Motivation
2. **Literature review**
3. The data
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2. Literature review

- Traditionally, the literature on “nowcasting” has been quite focused on GDP
- Few exceptions of papers in which GDP is modelled together with its demand and/or supply components
- More recently, the literature has started to explore “new” sources
  - ✓ Not so much for the case of private consumption
  - ✓ **GOOGLE SEARCHES**
  - ✓ **ATM/Point Of Sale DATA**
  - ✓ **UNCERTAINTY MEASURES**

Outline

3. The data

- Quarterly private consumption,

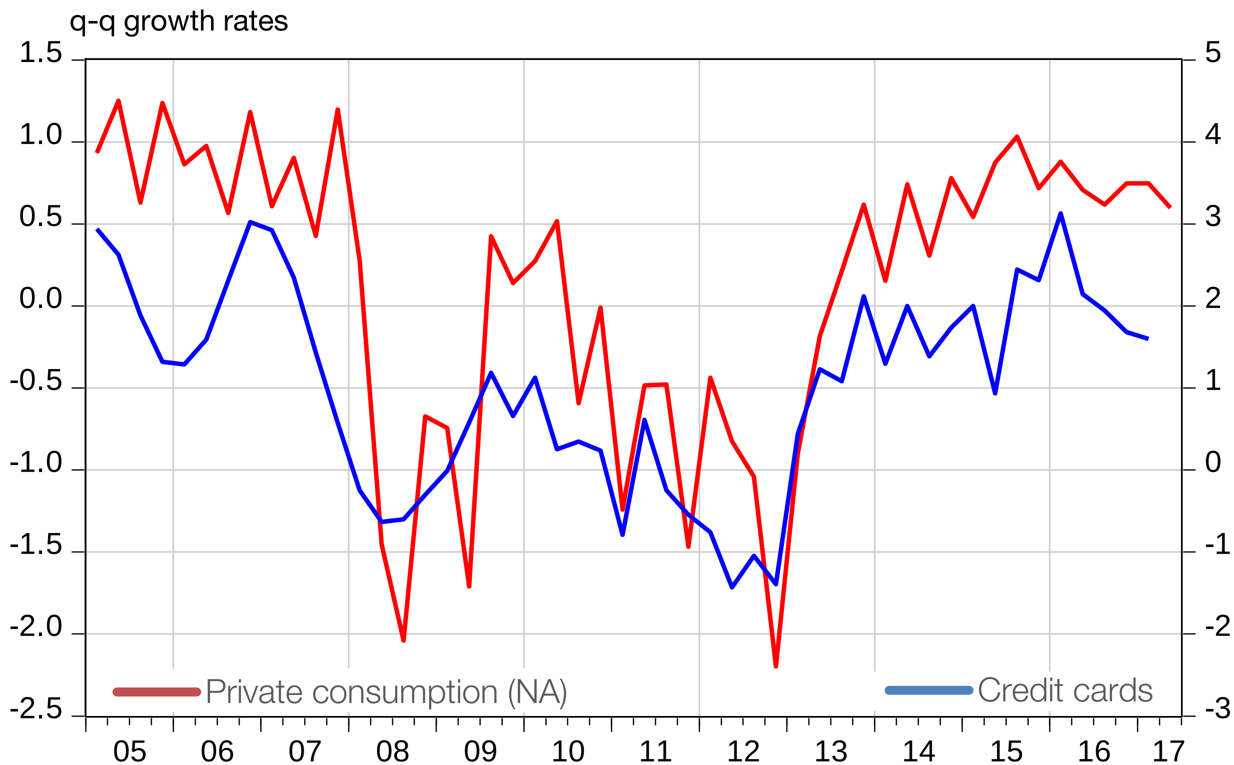
  monthly indicators

  (lower frequencies not exploited yet)

Quarterly private consumption	
Social sec. registrations **Retail trade index** **Services activity index** **PMI – services** **Consumers confidence index**	"Traditional" indicators
Credit cards' payments **Amounts** **Number**	ATM/POS
Disagreement consumption **Disagreement about inflation** **Uncertainty on unemployment** **Economic Policy Uncertainty** **IBEX-35 volatility index**	Uncertainty
Google Trends	Google search queries

3. The data: ATM/POS

- Widespread use of electronic payment systems
- Timeliness [daily/weekly frequency, in theory]
- Credit cards: payments by means of credit/debit cards in points of sales [seasonally adjusted and deflated by national CPI]
- Other options: ATMs; cash withdrawals; Cash and equivalents



3. The data: Google Trends

- Households use internet to buy goods and services
  - ✓ Willingness to buy
  - ✓ Info easily available.
- Evidence of usefulness in the literature: robustness?
- "Google Trends" provides an index of the relative volume of search queries conducted through Google (daily/weekly)
  - ✓ It provides aggregated indexes of search queries which are classified into categories and sub-categories using an automated classification engine
  - ✓ We select consumption-relevant categories (~60) that match the product categories of personal consumption expenditures of the BEA's national income and product accounts

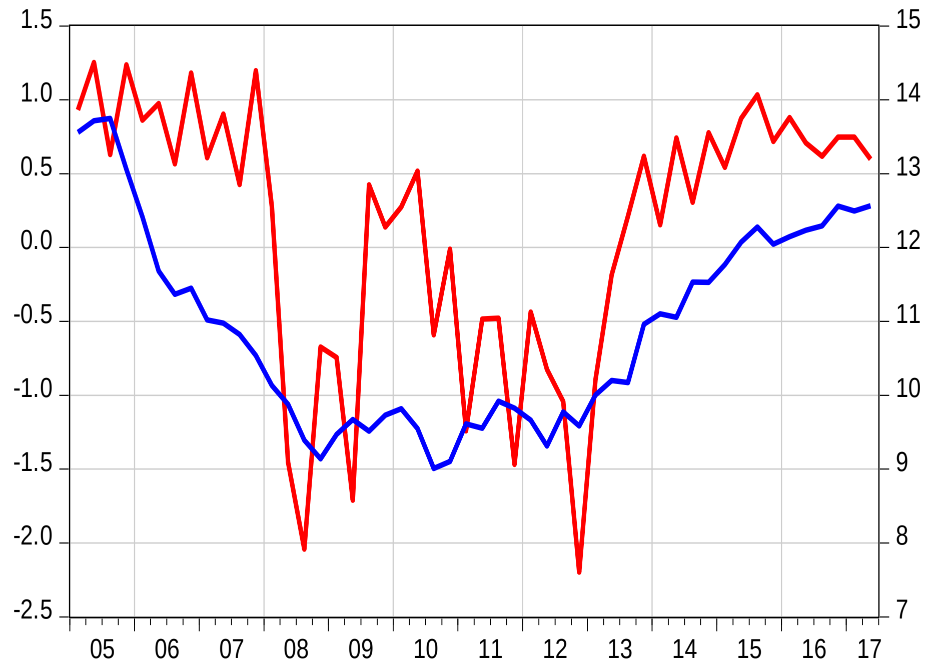
3. The data: Google Trends

- Example

Classification by national product and inco	Google categories
Durable goods	
Motor vehicles and parts	Automotive, auto financing, automotive parts, auto insurance, Seat, Mercedes Benz, Mercedes offer, second hand car, car, to buy a car
Furnishing and durable household equipment	Electrical appliance, home insurance, home remodel, home furnishing, interior decoration, interior design
Recreational goods and vehicles	Online movie, to buy a movie, watch online movie, video games
Other durable goods	Telecommunications, router wifi, mobile phone, electronic book, novel

3. The data: Google Trends

- Data available since January 2004 [not seasonally adjusted → TRAMO-SEATS]
- Distinguish durable/ non durable/ services
  - ✓ "Aggregation": (i) Principal Components Analysis (literature); (ii) **NA weights**



Private consumption
q-q growth rates

Google: durables
levels

3. The data: Uncertainty

- **Economic Policy Uncertainty Index (EPU)** (Baker, Bloom, Davis, 2016): it measures the frequency of news related to economic policy uncertainty in two of the most popular Spanish newspapers.

- **European Commission Business and Consumer Surveys**: “unemployment expectations for the next 12 months”, indicator computed as

$$\sqrt{Frac_t^{+} + Frac_t^{-} - (Frac_t^{+} - Frac_t^{-})^2}$$

where $Fract^{+/-}$ is the weighted fraction of consumers in the cross section with increase/decrease responses at time t.

- **Indicators of disagreement about consumption and inflation forecasts**, calculated using the information provided by the FUNCAS panel of forecasters. At each point in time, this measure is computed as the standard deviation of such cross-section of forecasters

$$\frac{1}{n}\sum_{1}^{n}(\hat{C}_i - \hat{C}_A)^2$$

- Preliminary exploration: regressions of Δlog C on determinants and indicators
  - ✓ Indicators by blocks add value

p-values, Sample: 2001Q1-2016Q4	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Constant	0.000 ***	0.017 **	0.174	0.077	0.000 ***	0.086 *	0.001 ***
Interest rate: Euribor 3-months	0.066 *	0.065 *	0.558	0.301	0.862	0.882	0.903
Households' disposable income	0.023 **	0.239	0.842	0.226	0.438	0.609	0.270
Lagged Household Consumption		0.001 ***	0.531	0.899	0.095 *	0.295	0.006 ***
Short-term Indicators:							
"Hard": Social Security Registrations			0.000 ***	0.001 ***			
"Hard": Retail Trade Index				0.002 ***			
"Hard": Services Activity Index				0.069 *			
"Soft": PMI-Services					0.000 ***	0.053 *	
"Soft": Consumers' Confidence Index						0.029 **	
Credit cards: amounts (real)							0.000 ***
Credit cards: number of transactions							

$$\Delta \log(C_t) = \alpha_1 + \alpha_2 \Delta \log(C_{t-1}) + \alpha_3 X_t + \epsilon_t$$

3. The data

- Preliminary exploration: regressions of Δlog C on determinants and indicators
  - ✓ Indicators by blocks add value

p-values, Sample: 2001Q1-2016Q4	[8]	[9]	[10]	[11]	[12]
Constant	0.000 ***	0.041 **	0.290	0.006 ***	0.235
Interest rate: Euribor 3-months	0.430	0.065 *	0.144	0.839	0.834
Households' disposable income	0.298	0.984	0.977	0.977	0.690
Lagged Household Consumption	0.088 *	0.006 ***	0.000 ***	0.000 ***	0.036 **
Short-term Indicators:					
"Hard": Social Security Registrations					
"Hard": Retail Trade Index					
"Hard": Services Activity Index					
"Soft": PMI-Services					
"Soft": Consumers' Confidence Index					
Credit cards: amounts (real)	0.001 ***				
Credit cards: number of transactions	0.067 *				
Uncertainty: Unemployment		0.196			
Uncertainty: disagreement on consumption		0.229			
Uncertainty: disagreement about inflation		0.044 **			
Uncertainty: Stock market volatility		0.616			
Uncertainty: Economic Policy Uncertainty		0.052 *	0.032 **		
Google Trends: Total Consumption Index				0.005 ***	
Google Trends: Durable Goods					0.003 ***
Google Trends: Non-durable Goods					0.577
Google Trends: Services					0.834

3. The data

- Preliminary exploration: regressions of Δlog C on determinants and indicators
  - ✓ But compete when used jointly

p-values, Sample: 2001Q1-2016Q4	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Constant	0.000 ***	0.041 **	0.290	0.006 ***	0.235	0.587	0.000 ***
Interest rate: Euribor 3-months	0.430	0.065 *	0.144	0.839	0.834	0.887	0.369
Households' disposable income	0.298	0.984	0.977	0.977	0.690	0.483	0.859
Lagged Household Consumption	0.088 *	0.006 ***	0.000 ***	0.000 ***	0.036 **	0.715	0.952
Short-term Indicators:							
"Hard": Social Security Registrations						0.046 *	
"Hard": Retail Trade Index							
"Hard": Services Activity Index							
"Soft": PMI-Services						0.496	0.001 ***
"Soft": Consumers' Confidence Index							
Credit cards: amounts (real)						0.009 **	
Credit cards: number of transactions							
Uncertainty: Unemployment							
Uncertainty: disagreement on consumption							
Uncertainty: disagreement about inflation							0.089 **
Uncertainty: Stock market volatility							
Uncertainty: Economic Policy Uncertainty						0.830	
Google Trends: Total Consumption Index							
Google Trends: Durable Goods						0.977	0.001 ***
Google Trends: Non-durable Goods							
Google Trends: Services							

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4. Modelling approach

- Different sampling frequency: monthly (indicators), quarterly (consumption)
- Publication delays cause missing values for some of the variables at the end of the sample ("ragged-end" problem)

4. Modelling approach

- Mixed-frequencies models, in the vein of Harvey and Chun (2000)

  ✓ Multivariate setup: Unobserved Components Model

  – *Flexibility: aggregation and modelling using the State Space representation*

  – *Models in levels: no need to worry about ex ante stationarity or cointegration*

  ✓ Seemingly Unrelated Structural Time Series Models (SUTSE)

  ✓ Different sampling intervals: cumulator variable

  ✓ Optimal interpolation using the Kalman Filter and the Smoothing Algorithm

  ✓ Robust estimation

  – *Use of last estimation as initial condition up to the moment when there is no estimation improvement*

  – *Estimate using random points around the solution to ensure that we end up in the same solution*

4. Modelling approach

The basic model is of the Unobserved Component Model class known as the Basic Structural Model (Harvey 1989), that decomposes a set of time series in unobserved though meaningful components from an economic point of view (mainly trend, seasonal and irregular). The model is multivariate, and may be written as

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \mathbf{T}_t + \mathbf{e}_t .$$

State-Space representation

Trend: **<u>SRW</u>** (no seasonal)

$$\mathbf{x}_t = \Phi \mathbf{x}_{t-1} + \mathbf{E}\mathbf{w}_t$$

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \begin{bmatrix} \mathbf{H} \\ \mathbf{H}^u \end{bmatrix} \mathbf{x}_t + \begin{bmatrix} \epsilon_t \\ \mathbf{v}_t \end{bmatrix}$$

where

$$\mathbf{w}_t \sim N(0, \Sigma_{\mathbf{w}_t}), \qquad \epsilon_t \sim N(0, \Sigma_\epsilon),$$
$$\mathbf{v}_t \sim N(0, \Sigma_{\mathbf{v}_t}).$$

Aggregation

Cumulator variable

$$C_t = \begin{cases} 0, & t = \text{every January (monthly data)/} \\ & \quad \text{first quarter (quarterly data)} \\ 1, & \text{otherwise.} \end{cases}$$

Thus, the model turns out to be:

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} = \begin{bmatrix} C_t \otimes \mathbf{I} & \mathbf{H}\Phi \\ \mathbf{0} & \Phi \end{bmatrix} \begin{bmatrix} \mathbf{z}_{t-1} \\ \mathbf{x}_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & \mathbf{H} \\ \mathbf{0} & \mathbf{E} \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \mathbf{w}_t \end{bmatrix}$$

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{H}^u \end{bmatrix} \begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{I} \end{bmatrix} \mathbf{v}_t .$$

$\mathbf{z}_t$: quarterly private consumption

$\mathbf{u}_t$: set of monthly indicators

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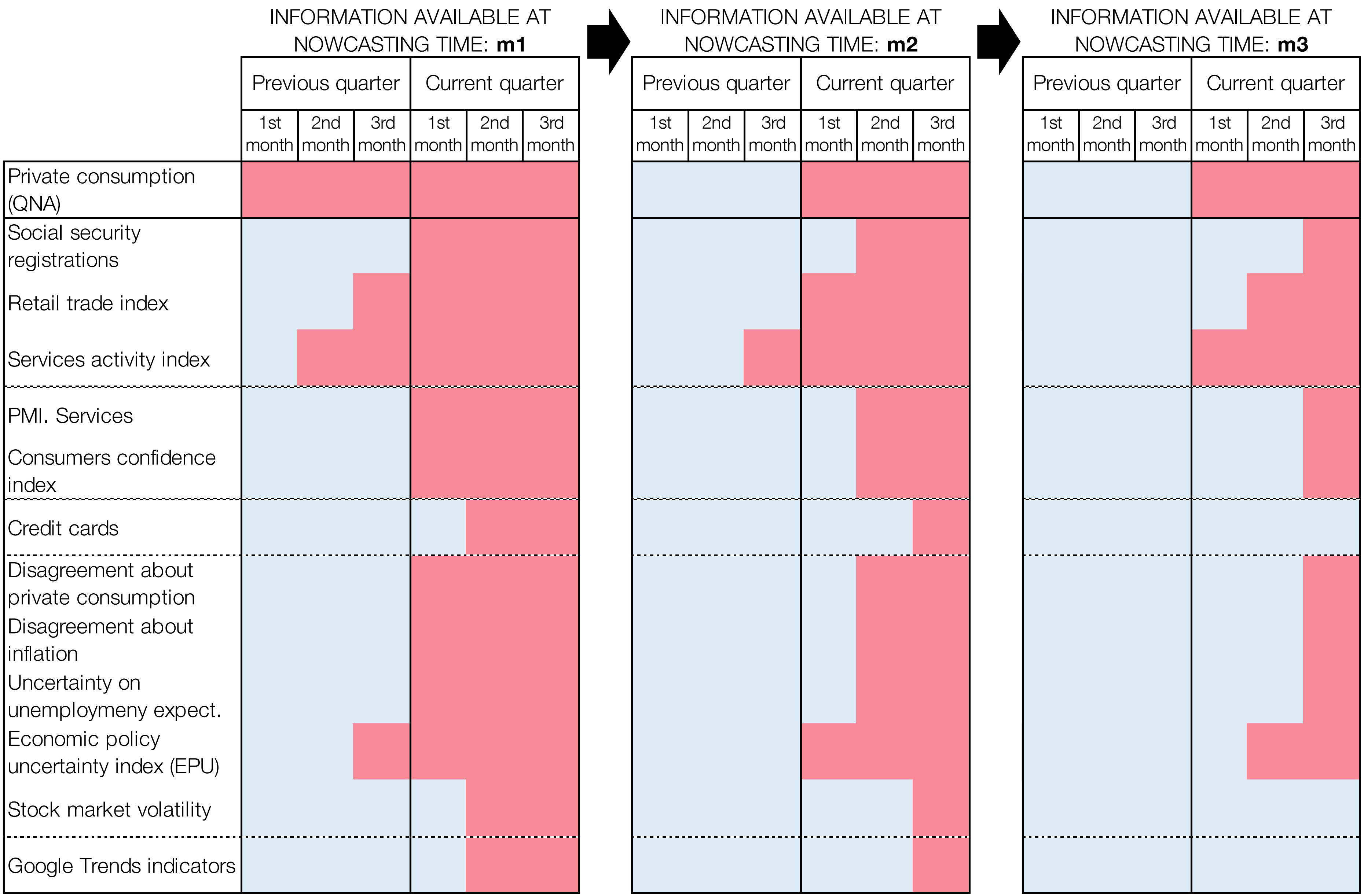
5. The empirical exercise

- Real-time database
  - ✓ Different forecast origins (information sets) within each quarter: m1, m2, m3
- Sample: 1995Q1-2016Q4 [2004-2016 - limitation due to "Google Trends"]
- Out-of-sample evaluation over 2008Q1-2016Q4 [35 obs. per forecast origin]
  - ✓ Quantitative: RMSEs
  - ✓ Quantitative: Diebold-Mariano
  - ✓ Qualitative: sign anticipation
  - ✓ Qualitative: turning point detection

4. Empirical exercise: real-time database



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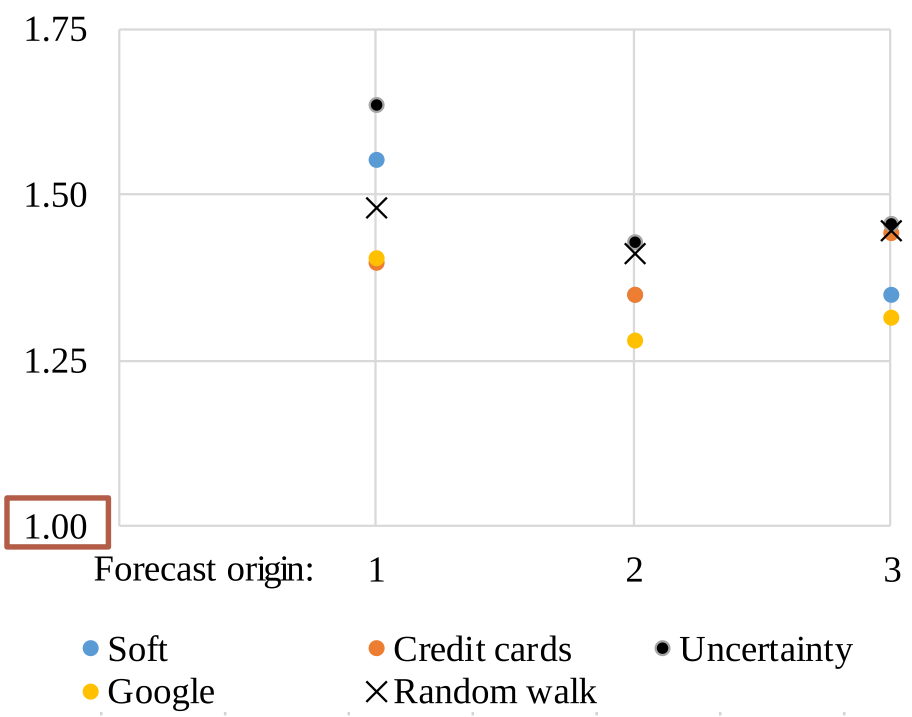
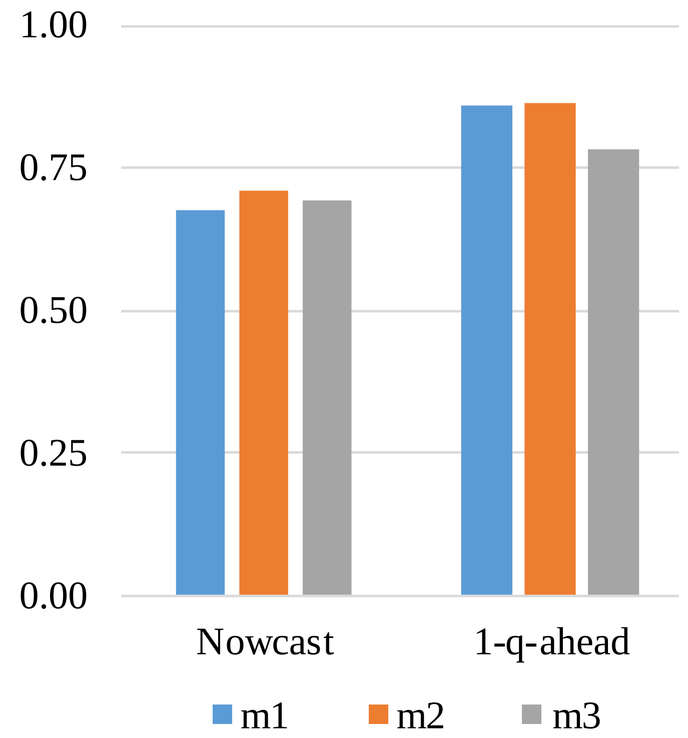
6. Selection of results and conclusions

- In terms of **quantitative measures** of forecast accuracy… traditional "hard" indicators tend to dominate the race…

Relative RMSE of *all* vs. "Hard": Nowcast



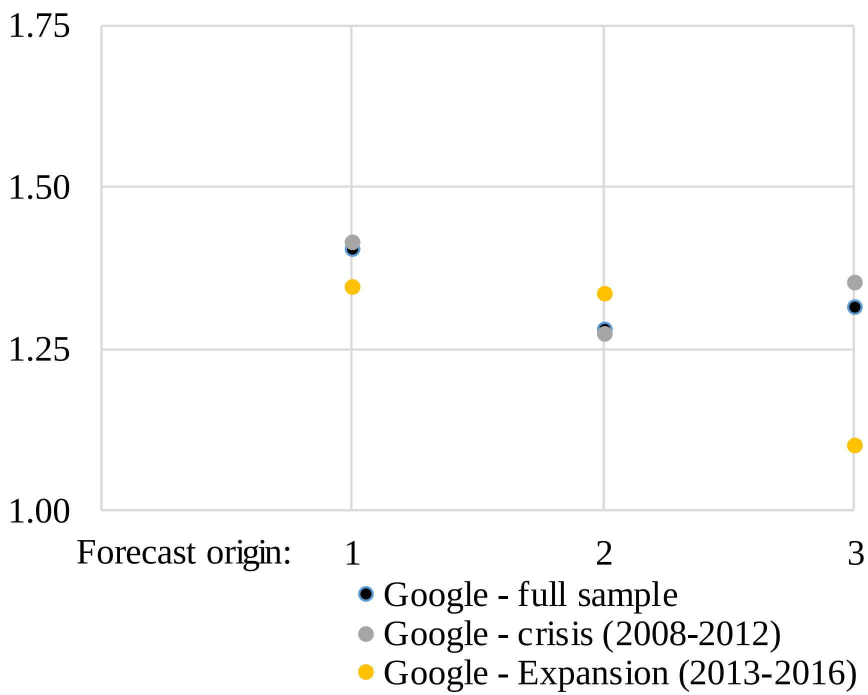
Relative RMSE: "Hard" vs. Q-RW: different forecast horizons



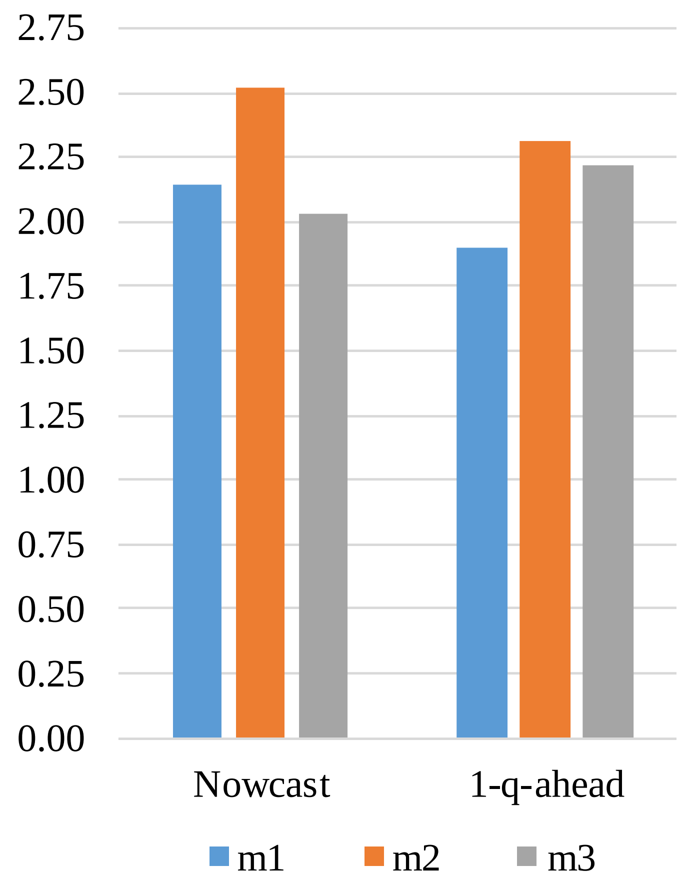
6. Selection of results and conclusions

- … but somewhat less so in the expansion period…

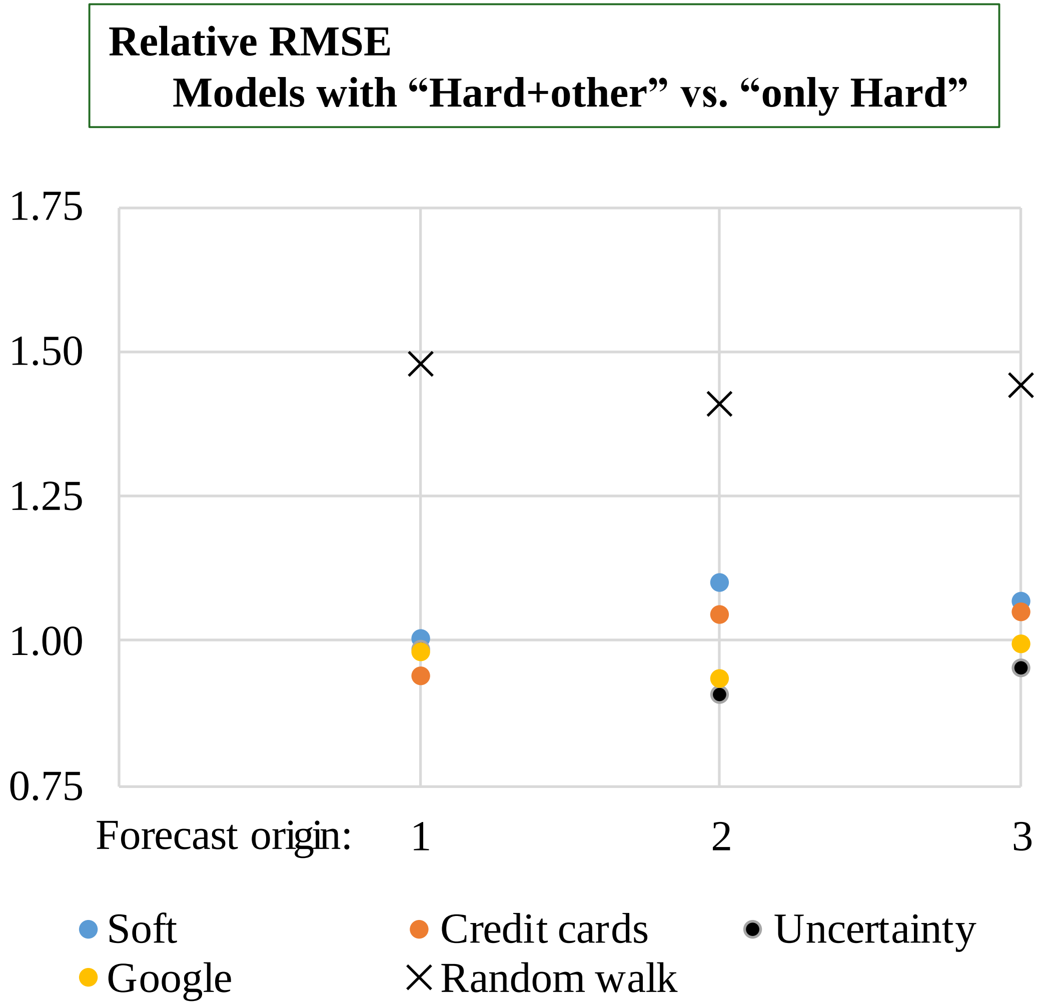
RMSE of GOOGLE vs. "Hard": Nowcast: crisis / expansion



Change of "Hard": relative RMSE crisis/expansion



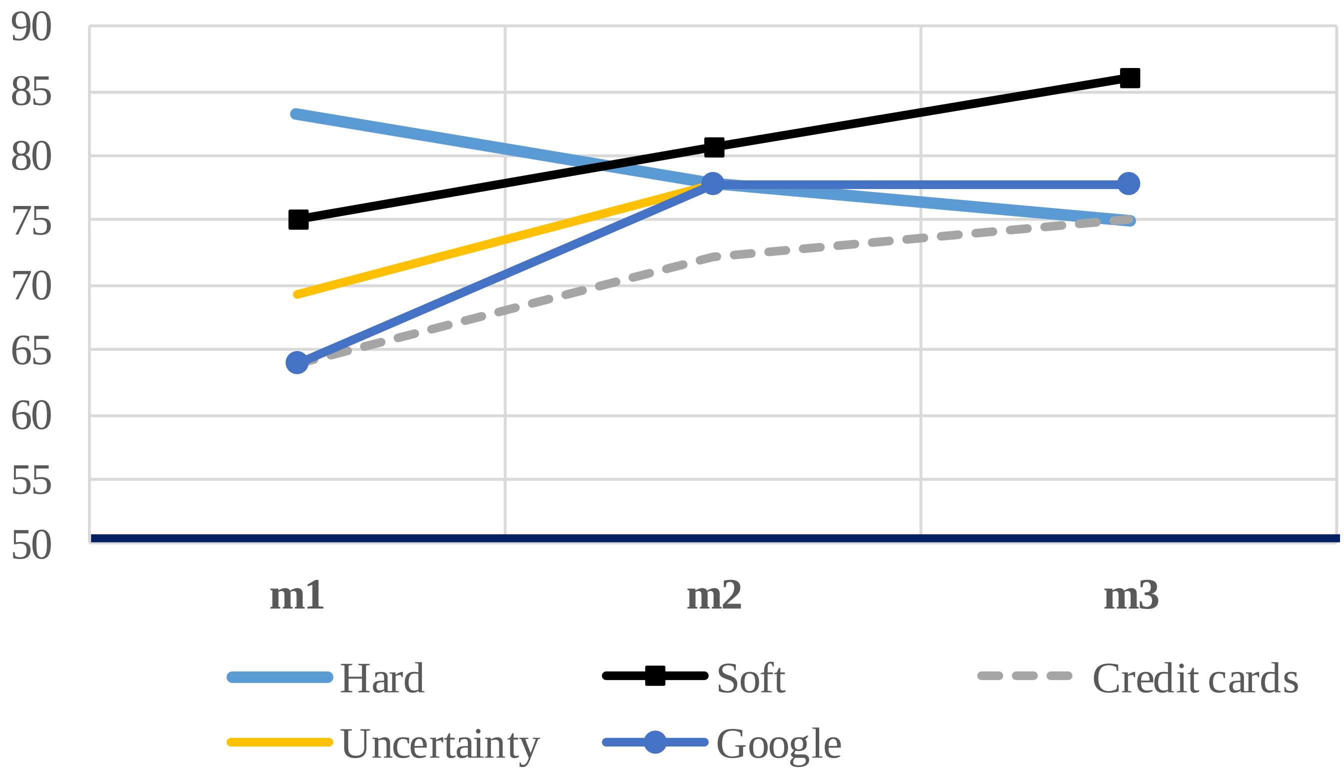
- … and "nesting" models helps



6. Selection of results and conclusions

- In terms of **qualitative measures** of forecast accuracy… "soft" (and Google)

Percent of correctly predicted accelerations or decelerations of quarterly private consumption



6. Selection of results and conclusions

- **Summing up:**
  - ✓ **Quantitative (Hard) indicators tend to dominate**
  - ✓ **But: other sources add value, when combined…**
  - ✓ **… and when looking at qualitative measures of forecast accuracy**
  - ✓ **Also (not shown), Google sources show potential to perform “event studies”**
  - ✓ **“New” indicators (Google, credit cards) may also be useful if more data frequencies are used (i.e. weekly data)**

THANKS FOR YOUR ATTENTION

- Some exceptions: papers in which GDP is modelled together with its demand and/or supply components

  - ✓ For example, Burriel and García-Belmonte (2013) for the euro area or Arencibia, Gómez-Loscos, de Luis and Pérez-Quirós (2017) for the case of Spain

  - ✓ The latter paper includes a block for QNA private consumption in which a number of hard/soft traditional indicators and *credit cards' transactions* are included

- More recently, the literature has started to explore “new” sources

  ✓ **GOOGLE SEARCHES**

  Camacho and Pacce (2016): application to tourism – including these indicators improves forecasting performance over models in which they are omitted

  Artola, Pinto and de Pedraza-García (2015): application to tourism / useful

  Bortoli and Combes (2015): general economic activity / limited usefulness

  Vosen and Schmidt (2011, 2012): private consumption/ useful compared to soft

  ✓ **ATM/Point Of Sale DATA**

  ✓ **UNCERTAINTY MEASURES**

2. Literature review

- More recently, the literature has started to explore “new” sources

  ✓ **GOOGLE SEARCHES**

  ✓ **ATM/Point Of Sale DATA**

    Duarte, Rodrigues and Rua (2016): private consumption

    Galbraith and Tkaz (2007): economic activity, consumption (non-durable)

    Gill, Perera and Sunner (2012): private spending

  ✓ **UNCERTAINTY MEASURES**

2. Literature review

- More recently, the literature has started to explore “new” sources

  ✓ **GOOGLE SEARCHES**

  ✓ **ATM/Point Of Sale DATA**

  ✓ **UNCERTAINTY MEASURES**

  Conceptually, they should help

  Gil, Pérez, Urtasun (2017): indicators of uncertainty (in particular, “financial”) influence consumption and investment, in the case of Spain

  Ferrara, Marsilli and Ortega (2013), Rossi and Sekhposyan (2015): useful to nowcast GDP

3. The data: additional slides

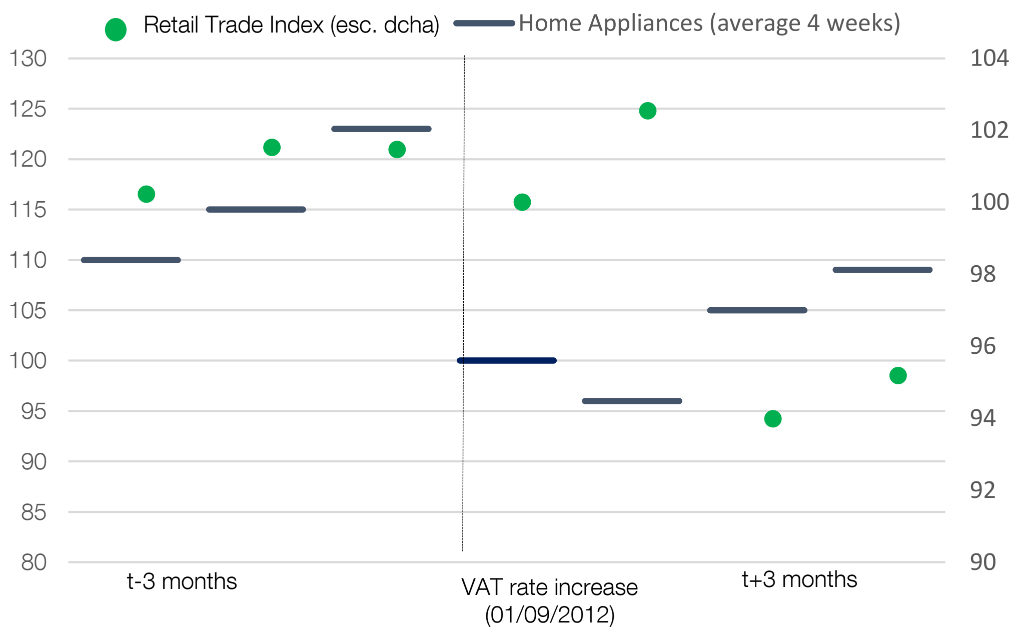
7. Further work

✓ **Event analysis: other uses of “Google Trends”**

Event studies: some illustrations

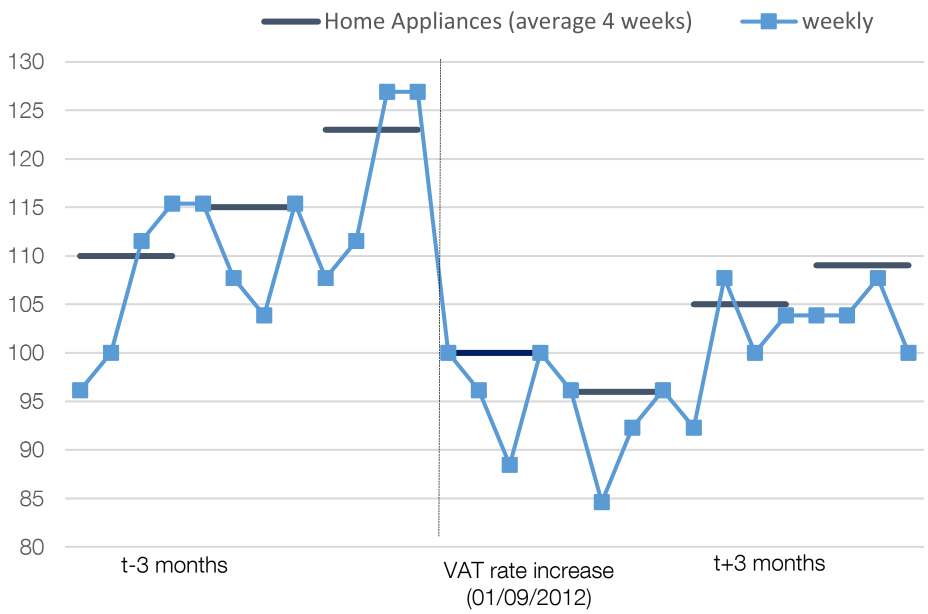
- Forecasters (and policy-makers) are occasionally confronted with unusual events (policy measures) that have the potential of affecting economic activity.
- The usual monthly-based indicators are in this case of little use, as the data are available only with a substantial lag.
- To assess the impact of these events on the economy, forecasters need to monitor indicators that are released on a timely basis: new high-frequency data (daily) sources that could provide accurate and timely information.
- Here we show that weekly google search data can be used to analyze the impact on consumer expenditure of different events (terrorist attacks, bankruptcies, political speeches etc.).
- We expect that the adjustment in the consumption of durables may be sharper after a VAT rate increase (2012).

Event studies: some illustrations



- Before the increase in VAT rates there was an increase in the consumption of durable goods (rational response to the expected increase in prices).
- This effect was transitory and was followed by a decline in consumption.
- In the case of the retail trade index you could see these effects with a lag of two months.

Event studies: some illustrations



- Although in this paper we are considering mainly monthly data, higher frequency data have also valuable information that can be used in the assessment of the response of consumption to a shock.