NOWCASTING PRIVATE CONSUMPTION: TRADITIONAL INDICATORS, UNCERTAINTY MEASURES, CREDIT CARDS AND SOME INTERNET DATA

2018

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**Documentos de Trabajo
N.º 1842**

BANCO DE ESPAÑA
Eurosistema

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(*) The views expressed in this paper are the authors' and do not necessarily reflect those of the Banco de España or the Eurosystem. We thank participants at the WGF-Eurosystem WP meeting (Frankfurt am Main, January 2017), Banco de España seminar (Madrid, June 2017), the XX Applied Economics Meeting (Valencia, June 2017), the ISI2017 Conference (Marraketch, July 2017), the Workshop Nowcasting & Big Data (Banco Central de la República Argentina, Buenos Aires, November 2017), the 18th IWH-CIREQ-GW Macroeconometric Workshop (Halle, Germany, December 2017), the 11th Int. Conference on Computational and Financial Econometrics (London, December 2017), the 5th SEM Conference (Xiamen, June 2018), and the IFC-Bank of Indonesia Workshop Building Pathways for Policy Making with Big Data (Bali, July 2018), in particular Marta Banbura, Luis J. Álvarez, Diego J. Pedregal, Massimiliano Marcelino, Stefan Neuwirth, and Domenico Giannone, for helful comments and suggestions. We also thank Ivet Ramírez, Alejandro Fiorito and Diego Vila for their help with Google data. Sánchez-Fuentes acknowledges the financial support of the Regional Government of Andalusia (project SEJ 1512). (**)
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Documentos de Trabajo. N.º 1842

2018

ISSN: 1579-8666 (on line)

Abstract

The focus of this paper is on nowcasting and forecasting quarterly private consumption. The selection of real-time, monthly indicators focuses on standard ("hard" / "soft" indicators) and less-standard variables. Among the latter group we analyze: i) proxy indicators of economic and policy uncertainty; ii) payment cards' transactions, as measured at "Point-of-sale" (POS) and ATM withdrawals; iii) indicators based on consumption-related search queries retrieved by means of the Google Trends application. We estimate a suite of mixed-frequency, time series models at the monthly frequency, on a real-time database with Spanish data, and conduct out-of-sample forecasting exercises to assess the relevant merits of the different groups of indicators. Some results stand out: i) "hard" and payments cards indicators are the best performers when taken individually, and more so when combined; ii) nonetheless, "soft" indicators are helpful to detect qualitative signals in the nowcasting horizon; iii) Google-based and uncertainty indicators add value when combined with traditional indicators, most notably at estimation horizons beyond the nowcasting one, what would be consistent with capturing information about future consumption decisions; iv) the combinations of models that include the best performing indicators tend to beat broader-based combinations.

Keywords: private consumption, nowcasting, forecasting, uncertainty, Google Trends.

JEL classification: E27, C32, C53.

Resumen

Este documento se centra en la predicción a corto y medio plazo del consumo privado. La selección de indicadores mensuales en tiempo real se realiza sobre la base de las variables habituales (indicadores cualitativos versus cuantitativos) y de otras menos habituales. Entre las variables de este último grupo se analizan las siguientes: i) variables *proxy* de la incertidumbre económica y sobre las políticas económicas; ii) operaciones con tarjetas de crédito, medidas tanto en TPV como en cajeros; iii) indicadores basados en búsquedas de términos relacionados con el consumo obtenidas con la herramienta Google Trends. Se estima un conjunto de modelos de frecuencias mixtas (mensual y trimestral) utilizando una base de datos en tiempo real, y se realizan ejercicios empíricos para valorar la capacidad predictiva de los diferentes grupos de indicadores. Los principales resultados son los siguientes: i) los indicadores cuantitativos y los relativos al uso de tarjetas de crédito son los que presentan mejor capacidad predictiva cuando se utilizan individualmente, y esta mejora cuando se combinan; ii) a pesar de lo anterior, los indicadores de opinión son de utilidad para captar señales cualitativas a muy corto plazo (en el horizonte del *nowcast);* iii) los indicadores de Google y los de incertidumbre añaden información cuando se combinan con los indicadores tradicionales, sobre todo en horizontes de proyección más allá del *nowcast,* lo que sería consistente con el hecho de que estos indicadores pueden contener información acerca de futuras decisiones de consumo; iv) la combinación de los modelos que incluyen los indicadores que arrojan los mejores resultados tiende a mejorar los resultados obtenidos con combinaciones más amplias de modelos.

Palabras clave: consumo privado, *nowcasting,* predicción macroeconómica, incertidumbre económica, Google Trends.

Códigos JEL: E27, C32, C53.

1 Introduction

Private consumption represents between 60% to 80% of an average OECD country gross domestic product. Thus the importance for applied forecasters of having accurate estimates of this GDP component in real-time. Benchmark data to approximate private households' spending decisions are normally provided by the national accounts, and are available at the quarterly frequency. Nevertheless, usually, there exists a significant publication lag, typically of 90 days after the quarter of reference ended. More timely data is usually published, mostly, but not only, by National Statistical Institutes, in the form of economic indicators, both covering quantitative information on observed spending decisions (so-called "hard" indicators), and qualitative information provided by households' surveys on consumer sentiment and consumption plans (so-called "soft" indicators). These standard leading indicators of private consumption used by practitioners and academics alike, are typically available in real-term with a 1 to 3 months delay, depending on the country, and are available at the monthly frequency.

Nowdays, in addition, technological progress has enabled the development of other sources of data usable for monitoring and forecasting real-time economic activity[1] and, in particular, private consumption decisions, in many occasions from private sector sources, such as Google Trends (see e.g. Choi and Varian, 2012), data on granular payment instruments, like payment cards (see, e.g. Galbraith and Tkacz, 2018; Duarte et al., 2017), or indicators based on textual analysis, including media news (see e.g. Backer et al., 2017). In our paper, from a forecasting point of view, we analyze the information content of some of these new source of information, but in a context in which we ascertain their value in conjunction with traditional, more proven, sources of short-term information, such as the "hard" and "soft" ones mentioned above.

In particular, among these new data sources we look, first, at data collected from automated teller machines (ATMs), encompassing cash withdrawals at ATM terminals, and points-of-sale (POS) payments with debit and credit cards, given the increasing and widespread use of electronic payment systems by economic agents. Typically, electronically recorded data are available in a quite timely fashion and are free of measurement errors (see e.g. Galbraith and Tkacz, 2018, Duarte et al., 2017, Aprigliano et al., 217, Ardizzi et al.,

[1]See Bok et al. (2017) or Baldacci et al. (2016).

2018, and the references quoted therein)[2]. Secondly, in line with a recent and very active branch of the literature, we construct indicators of consumption behavior on the basis of internet search patterns as provided by Google Trends. Over the past decade, the number of Internet users has increased dramatically, and also their buying patterns. In this way *intentions to buy*, as reflected in Internet searches of certain categories of goods and services, might be useful to anticipate *actual* buying behavior. While indicators linked to income reflect the *ability to spend* of consumers, and survey-based indicators capture the *willingness to spend*, Google-searches-based variables based on consumption-related search queries may provide a measure of consumers' *preparatory steps to spend* (see Vosen and Schmidt, 2011, 2012; Choi and Varian, 2012). Finally, we use measures of economic and policy uncertainty, in line with another recent strand of the literature that has highlighted the relevance of the level of uncertainty prevailing in the economy for private agents' decision-making (see, among others, Backer et al., 2017). This is all the more relevant in the field of modeling consumption decisions, as prescribed by the existing theoretical literature.

Building on these strands of the literature, in this paper we focus on nowcasting quarterly private consumption for the case of Spain, the fourth largest euro area economy. To exploit the data in an efficient and effective manner, we build models that relate data at the quarterly and monthly frequencies. We follow the modeling approach of Harvey and Chung (2000).[3] The mixture of frequencies, and the estimation of models at the monthly frequency, implies combining variables that at the monthly frequency can be considered as stocks with those being pure flows. The quarterly private consumption series cast into the monthly frequency is a set of missing observations for the first months of the quarter (January and February, in the case of Q1) and the observed value assigned to the last month of each quarter (say, March). Theoretically, the quarterly National Accounts series would be obtained from monthly National Accounts series by aggregation of the three months of a quarter (January to March) had them been available. We estimate such mixed-frequency

[2]Other recent applications on the usefulness of credit card data are Bodas et al. (2018), that mimic the standard retail sales index for Spain, or Dong et al. (2018), that use credit card transaction data for measuring the economic effects of a series of protests on consumer actions and personal consumption.

[3]Other approaches for modeling data at different sampling intervals are the methods based on regression techniques (Chow and Lin, 1971, Guerrero, 2003), the MIDAS (MIxed DAta Sampling) approach (see Ghysels et al., 2006, Clements and Galvão, 2008), the state space approaches of Liu and Hall (2001) and Mariano and Murusawa (2003), or the ARMA model with missing observations of Hyung and Granger (2008).

models on a mixed real-time and pseudo-real-time database, for the period that starts in the early 2000s and runs through to 2017Q4, and conduct out-of-sample forecasting exercises to assess the relevant merits of different groups of indicators.

Some results stand out from our empirical exercises. First, traditional "hard" indicators are in general difficult to beat by other individual indicators for nowcasting (and 1-quarter ahead forecasting) purposes, with the exception of payment card-related, that turn out to be the ones most useful among the new sources. Second, "soft" indicators are helpful to detect qualitative signals in the nowcasting horizon. Next, uncertainty and Google-based sources add value when combined with traditional indicators, most notably at estimation horizons beyond the nowcasting one, what would be consistent with capturing information about *future* consumption decisions. Finally, the combination of models that include the best performing indicators tends to beat broader-based combinations of models.

The rest of the paper is organized as follows. In Section 2 we describe the data sources. In sections 3 and 4 we describe, respectively, the econometric methodology and all the choices that condition the statistical experiments performed (timing of the information set, alternative models, forecast accuracy statistics), while in Section 5 we present and discuss the main results of the empirical exercise. Finally, in Section 6 we provide a summary with the key conclusions.

2 The data

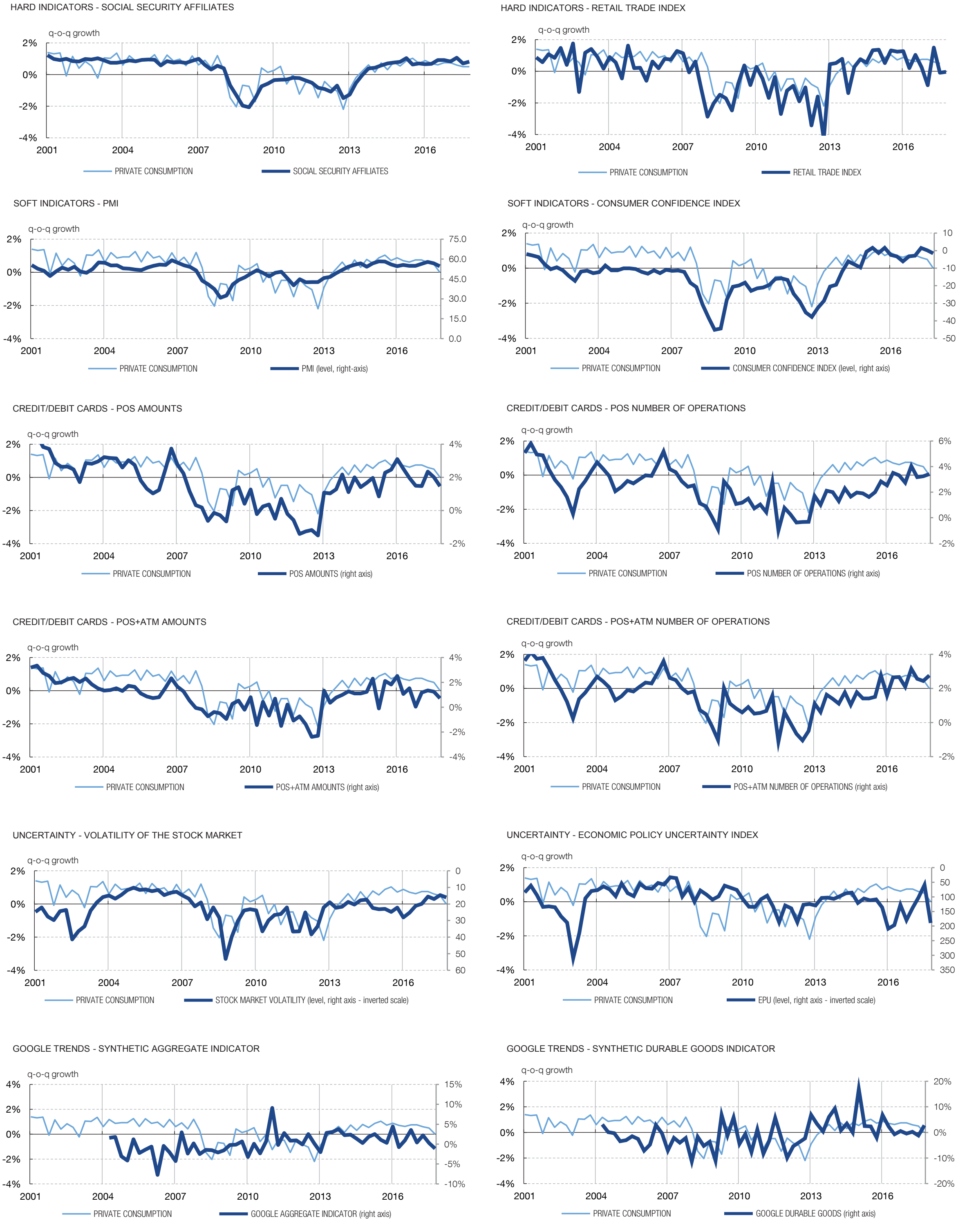
2.1 Traditional indicators

Within this set of commonly used variables we include quantitative ("hard") and qualitative ("soft") indicators (see Figure 1). Among the first group, we select, first, the monthly number of Employees Registered in the Social Security System ("Social Security Registrations") at month t, published in the very initial days of month $t+1$ by the Ministry of Employment and Social Security.[4] Employment growth is a usual indicator of ability to consume. Secondly, we use an index of retail sales, the Retail Trade Index, published at the monthly frequency by the National Statistical Institute of Spain (INE henceforth).[5] The index reflects the evolution of

[4]For more information and data see http://www.seg-social.es/Internet_1/Estadistica/Est /AfiliacionAltaTrabajadores /SeriesAfiliacion /index.htm.

[5]For more information and data see http://www.ine.es/en/prensa/icm_prensa_en.htm.

Figure 1: Main variables used in the paper.



the sales and employment in the retail trade sector in Spain. Finally, we select the monthly Services Sector Activity Indicator (published by INE[6]), given the significant weight of the services sector in the Spanish economy (some 50% of GDP and 45% of employment). The index measures the turnover and employment of services companies. The turnover captures the amounts invoiced by each economic activity unit for the provision of services and sale of goods.

As regards "soft" indicators, we focus on two. On the one hand, the Purchasing Manager's Index (PMI) of Services (elaborated by the private company Markit Economics), an index based on monthly questionnaire responses from panels of senior purchasing executives (or similar).[7] On the other hand, we use the Consumer Confidence Indicator published each month by the European Commission. This indicator is built on selected questions addressed to consumers according to the Joint Harmonised EU Programme of Business and Consumer Surveys.[8]

From a real-time perspective, Social Security Registrations, the PMI Services' index, and the Consumer Confidence Indicator are available with a one-month lag, while the Retail Trade Index presents a lag of two months, and the Services Sector Activity Indicator is published with a three months delay.[9]

2.2 Household's payment cards data

Data on ATM withdrawals with payment cards — debit, delayed debit and credit cards — (nominal amounts and number of operations), and payments made at POS (nominal amounts spent and transactions) by residents, are made available by the main card service providers (*SERVIRED*, *Sistema 4B* and *Euro6000*) to the Bank of Spain under strict confidentiality conditions. They include both "card-not-present transactions" and "card-present" transactions.[10] Data can only be used for research purposes, and are received in aggregated form (from anonymized original files). Card payments are a widespread means of payment

[6]See http://www.ine.es/en/prensa/iass_prensa_en.htm.

[7]See https://ihsmarkit.com/products/pmi.html. The questions included in the PMI Services cover the following economic variables: Business activity, new business, backlogs of work, prices charged, input prices, employment, expectations for activity.

[8]More details on the consumer confidence indicator as well as long time series can be found via the following link: http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm

[9]All variables are available since, at least, the mid-1990s, with the exception of the Services Sector Activity Indicator that starts in January 2002.

[10]See Banco de España (2017).

by Spanish consumers. In 2017, in Spain, these means of payments accounted for around 25% of private consumption. In addition, there are 51,000 ATMs and 1,800,000 POS, while the number of payment cards is close to 80 million (for a population of 47 million inhabitants). Data in the Spanish case is available in yearly terms since 1996, on a quarterly basis since 2006, and at the monthly frequency since 2009.[11] As ATM/POS data are not seasonally-adjusted, we use the TRAMO-SEATS software[12] to remove the seasonal component. In addition, nominal amounts are deflated by means of the headline Consumer Price Index (CPI).

2.3 Uncertainty indicators

By now it is well established in the theoretical and empirical literature that heightened economic uncertainty has the potential to harm economic activity, mainly through the effects on households' consumption, and firm's investment, decisions (see, among others, Bloom, 2014). In the recent empirical literature, a number of works have dealt with the hurdle of finding proxy measures of economic uncertainty, being the later a non-observable variable. The extant studies tend to focus on one specific proxy or method, the most popular ones being: (i) stock market volatility (see, e.g. Leahy and Whited, 1996; Bloom, 2009; Caggiano et al, 2014); (ii) the variance of forecasters' expectations, in many cases approximated by a concept of disagreement (see, e.g., D'Amico and Orphanides, 2008; Bachmann et al., 2013; Balta et al., 2013; Popescu and Smets, 2010) ; (iii) the frequency of news related to policy uncertainty to form a proxy of policy uncertainty (Baker et al., 2016); (iv) the common components of the volatility of the forecast errors from several macroeconomic time series (see e.g. Jurado et al., 2013); on related grounds, some authors compute uncertainty measures on the basis of real-time forecasting models (see, e.g. Scotti, 2016). In the current paper we

[11]Following the methodological approach described in section 3 of this paper, we use the data sampled at the three different frequencies to generate an interpolated monthly time series for the time period of reference for our study, using also as indicators the time series on "Cash and cash equivalents" (i.e. cash and deposits: current accounts, savings accounts and deposits redeemable at up to 3 months' notice), that are available on a monthly basis for the whole period (see page 50 of Banco de España's Statistical Bulletin https://www.bde.es/f/ webbde/SES/Secciones/ Publicaciones/ InformesBoletinesRevistas/ BoletinEstadistico/ 2018/Files/ie_mayo2018_en.pdf).

[12]See Gómez and Maravall (1996).

focus on measures covering (i), (ii) and (iii). In particular, as regards (i) we use the volatility of the Spanish Stock Market (IBEX-35)[13], as regards (iii) we focus on the textual indicator known as Economic Policy Uncertainty Index (EPU) for Spain elaborated by Baker, Bloom and Davis (2015)[14], and as to measures of disagreement, we construct several, standard ones on the basis of: (a) private sector forecasts of private consumption and of consumption prices; (b) European Commission's consumer surveys, focusing on forward looking questions, namely unemployment prospects.[15]

Specifically, regarding the forward-looking indicators on "Unemployment perspectives over next 12 months", we follow the approach of Bachmann et al. (2013) to construct measures of uncertainty that exploit the information contained in the dispersion of responses. Specifically, respondents to the above-mentioned questions can be grouped in three answers: "decrease", "unchanged" or "increase". Let $Frac_t^+$ denote the weighted fraction of consumers in the cross section with "increase" responses at time t, and $Frac_t^-$ the weighted fraction of consumers with "decrease" responses. Then the "uncertainty indicator" is computed as

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

As to the measure of disagreement about private consumption among forecasters, we take as starting point the month t cross section of current and one-year-ahead forecasts about national accounts' private consumption produced by analysts that do respond to the "FUNCAS panel" of private sector analysts of the Spanish economy. FUNCAS is a private sector institute that has been compiling forecasters' views since 1999.[16] At each point in time, the measure of "disagreement" is computed as the standard deviation of such cross-section of n forecasters from the mean ("consensus") forecast $\hat{C}_A$, $\frac{1}{n}\sum_{i=1} n\left(\hat{C}_i - \hat{C}_A\right)^2$. Given that each analyst i provides growth rates of two fixed-event forecasts (current and year-ahead) m months ahead, it is necessary to correct each time-t value by the fact that it is computed on an evolving information set. For that, we follow the methodology of Dovern et al. (2012).

[13] As computed every month by the International Center for Decision Making (ICDM) and IESE Business School: see https://blog.iese.edu/icdm/que-es-el-i3e/.

[14] Available for the period that starts in January 2001.

[15] See Gil et al. (2017) and Ghirelli et al. (2018).

[16] For more information on the panel see https://www.funcas.es/Indicadores/Index.aspx.

Table 1: Consumption categories according to the National Accounts and Google Trends searches.

Classification by national product and income accounts (NIPAs)	Google categories
Durable goods	
Motor vehicles and parts	Automotive, 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 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
Nondurable goods	
Food and beverages	Food and beverages, food, drink
Clothing & footwear	Clothing, second hand clothing, footwear, second hand footwear, female lingerie, undergarments, T-shirts
Gasoline and energy goods	Electricity, energy, gaoline, gas
Other nondurable goods	Beauty, chemicals, medications, face & body care, beauty products, tobacco
Services	
Household consumption expenditures	
Housing and utilities	Home & auto insurance, interior decoration, interior design, real estate agency
Health care	Health, health insurance, medical services, mobile phone, wireless
Transportation services	
Recreational services	Leisure, video games, online movie, to buy a movie, watch online movie, ticket sales
Food services and accommodation	Hotels, accommodation, restaurant, restoration, terrace, welfare
Financial services and insurance	
Other services	Telecommunications, life insurance, social services

SOURCE: National Accounts, Google Trends.

2.4 Internet search query data (Google Trends)

We construct indicators of private consumption based on internet search data queries through Google Trends. Google Trends provides an index of the relative volume of search queries conducted through Google. The application provides aggregated indexes of search queries which are classified into categories and sub-categories using an automated classification engine. Google Trends provides a time series index of the volume of queries users enter into Google in a given geographic area. The query index is based on query share: the total query volume for the search term in question within a particular geographic region divided by the total number of queries in that region during the time period being examined. The maximum query share in the time period specified is normalized to be 100, and the query share at the initial date being examined is normalized to be zero. We select 61 consumption-relevant categories that in our view are best matches for the product categories of personal consumption expenditures of the BEA's national income and product accounts, as described in Table 1.

It is possible to obtain raw data from Google Trends for the period starting in 2004, on a monthly basis. Data are non-seasonally adjusted, and thus seasonality is removed by using the TRAMO-SEATS software.[17] The so corrected series are summarized in groups, following a conceptual approach, as in Table 1, in order to calculate synthetic indicators of (i) durable goods' consumption, (ii) non-durable goods' consumption, and (iii) services goods' consumption; (iv) an aggregate of all consumption categories. The weights used to combine the Google indicators are calculated on the basis of the classification tables of consumption expenditure by purpose of the National Accounts (COICOP tables). In addition, we also aggregate the 61 Google Trends indicators using principal components analysis, as it is standard in the literature (see, e.g., Vosen and Schmidt, 2011, 2012).[18]

2.5 A first, standard look at the explanatory power of the data

In this section we present an exploratory analysis of the contribution of non-traditional indicators by means of standard bridge equations.[19] First, we estimate an equation for real private consumption C_t, in which households' disposable income, the interest rate and lagged consumption are included as explanatory variables, to provide a simple baseline. Then, we augment the latter with short-term indicators. Let X_{it} denote the corresponding stationary short-term monthly indicator i, time-averaged to the quarterly frequency. Then, we estimate the following model (by ordinary least squares)

$$\Delta \log(C_t) = \alpha_1 + \alpha_2 \Delta \log(C_{t-1}) + \alpha_3 \Delta \log(INC_{t-1}) + \alpha_4 r_t + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \epsilon_t$$

where INC denotes disposable income and r_t the short-term interest rate. In columns [1] to [5] of Table 2 we first show the results of including in the bridge equation two indicators from each block at a time, namely quantitative, qualitative, credit cards, uncertainty, and Google Trends. In all cases, both or at least one of the indicators of each block turns out

[17] The data is downloaded and seasonally-adjusted following a pseudo-real-time scheme, as follows. First, time series are downloaded by sub-samples using Google Trends, so that they can be accommodated to the timing convention and structure of the forecasting exercise described in Section 4. This amounts to downloading sequentially the data for the time period January 2004 to January 2008, January 2004 to February 2008, ..., January 2004 to December 2017. In a second step, each data series for each sub-sample is seasonally-adjusted.

[18] See also Götz and Knetsch (2017). For a critical view, see, among others, Liu (2016).

[19] For comparability, we follow closely the approach by Vosen and Schmidt (2011, 2012).

to be relevant to explain changes in consumption in a given quarter. Nevertheless, when we include in the regression one indicator of each block (column [6]), the "Hard" and the POS ones are the only ones that turn out to be significant from a statistical point of view. When the "Hard" indicator is excluded (column [7]), the "Soft" and the Google-Trends indicators capture part of the variance of consumption that the former indicator was able to explain.

Thus, in this modeling framework, at the quarterly frequency, and not giving any publication advantage to any data source, "hard" and payment cards' indicators seem to dominate the rest. In what follows, we further explore the information content of the different sources of information, but in a more comprehensive set-up in which the advanced information with which these variables are available may play a role in its potential usefulness for the applied, real-time forecaster. Beyond timeliness, some indicators may have anticipatory power, insofar as they capture information on agents' expectations (like the uncertainty and Google-Trend-based ones).

Table 2: Preliminary exploration: regressions of $\Delta \log(C_t)$ on its own lag and different indicators. P-Values.

p-values Sample: 2001Q1-2016Q4	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Constant	0.060 *	0.052 **	0.000 ***	0.047 **	0.288	0.280	0.001 ***
Interest rate: Euribor 3-months^a	0.635	0.674	0.829	0.513	0.370	0.523	0.782
Households' disposable income^b	0.952	0.564	0.267	0.338	0.265	0.761	0.487
Lagged $\Delta \log(C_t)$	0.772	0.100 *	0.002 ***	0.000 ***	0.000 ***	0.660	0.2969
<u>*Short-term Indicators:*</u>							
"Hard": Social Security Registrations^b	0.000 ***					0.010 **	
"Hard": Retail Trade Index^b	0.020 **						
"Soft": PMI-Services^c		0.007 ***				0.258	0.000 ***
"Soft": Consumers' Confidence Index^c		0.162					
Credit cards: POS amounts (real)^b			0.003 ***			0.007 ***	0.000 ***
Credit cards: POS number of transactions^b			0.252				
Uncertainty: Stock market volatility^c				0.0951 *		0.872	0.970
Uncertainty: Economic Policy^d				0.0000 ***			
Google Trends: Durable Goods^b					0.037 **	0.192	0.086 *
Google Trends: Non-durable Goods^b					0.207		
R-squared statistic	0.72	0.62	0.60	0.51	0.49	0.74	0.71

Notes:
a. Deviation from trend (HP-filter).
b. $\Delta \log(\bullet)$.
c. Variable in levels.
d. $\Delta(\bullet)$.

3 The mixed-frequencies, times series models

The starting point of the modeling approach is to consider a multivariate Unobserved Components Model known as the Basic Structural Model (BSM, Harvey, 1989)[20]. A given (seasonally-adjusted) time series is decomposed into unobserved components which are meaningful from an economic point of view (trend, T_t, and irregular, e_t). Equation (1) displays a general form, where t is a time sub-index measured in months, z_t denotes the variable in National Accounts terms expressed at a quarterly sampling interval for our objective time series (private consumption), and u_t represents the vector of monthly indicators.

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \mathbf{T}_t + \mathbf{e}_t \tag{1}$$

The general consensus in this type of multivariate models in order to enable identifiability is to build SUTSE models (Seemingly Unrelated Structural Time Series). This means that components of the same type interact among them for different time series, but are independent of any of the components of different types. In addition, statistical relations are only allowed through the covariance structure of the vector noises, but never through the system matrices directly. This allows that trends of different time series may relate to each other, but all of them are independent of the irregular components. The full model is a standard BSM that may be written in State-Space form as

$$\mathbf{x}_t = \mathbf{\Phi x_{t-1}} + \mathbf{E w_t} \tag{2}$$

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \begin{bmatrix} \mathbf{H} \\ \mathbf{H}^u \end{bmatrix} \mathbf{x}_t + \begin{bmatrix} \epsilon_t \\ \mathbf{v}_t \end{bmatrix} \tag{3}$$

where $\epsilon_t \sim N(0, \Sigma_\epsilon)$ and $\mathbf{v}_t \sim N(0, \Sigma_{\mathbf{v}_t})$. The system matrices $\mathbf{\Phi}$, $\mathbf{E}$, $\mathbf{H}$ and $\mathbf{H}^u$ in equations (2)-(3) include the particular definitions of the components and all the vector noises have the usual Gaussian properties with zero mean and constant covariance matrices (ϵ_t and $\mathbf{v}_t$ are correlated among them, but both are independent of $\mathbf{w}_t$). The particular structure of the covariance matrices of the observed and transition noises defines the structures of correlations among the components across output variables. The mixture of frequencies, and the estimation of models at the monthly frequency, implies combining variables that at

[20]The exposition in this section follows closely Pedregal and Pérez (2010) and Harvey and Chun (2000). For some examples of applications of this approach to the field of forecasting see, among many others, Grassi et al. (2015), Moauro (2014), or Durbin and Koopman (2012), and the references quoted therein.

the monthly frequency can be considered as stocks with those being pure flows. Thus, given the fact that our objective variables are observed at different frequencies, an accumulator variable has to be included

$$C_t = \begin{cases} 0, & t = \text{first month of the quarter} \\ 1, & \text{otherwise} \end{cases} \tag{4}$$

so that the previous model turns out to be

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} = \begin{bmatrix} C_t \otimes \mathbf{I} & \mathbf{H\Phi} \\ \mathbf{0} & \mathbf{\Phi} \end{bmatrix} \begin{bmatrix} \mathbf{z}_{t-1} \\ \mathbf{x}_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & \mathbf{HE} \\ \mathbf{0} & \mathbf{E} \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \mathbf{w}_t \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{H}^u \end{bmatrix} \begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{I} \end{bmatrix} \mathbf{v}_t \tag{6}$$

Given the structure of the system and the information available, the Kalman Filter and Fixed Interval Smoother algorithms provide an optimal estimation of states. Maximum

Table 3: High frequency variables used in the study and information flow: information available at each nowcasting origin.

Information available at nowcasting time…	… m1 (1st month of the quarter)						… m2 (2nd month of the quarter)						… m3 (3rd month of the quarter)					
	Previous quarter			Current quarter			Previous quarter			Current quarter			Previous quarter			Current quarter		
	1st month	2nd month	3rd month	1st month	2nd month	3rd month	1st month	2nd month	3rd month	1st month	2nd month	3rd month	1st month	2nd month	3rd month	1st month	2nd month	3rd month
Private consumption (QNA)																		
Social security registrations																		
Retail trade index																		
Services activity index																		
PMI. Services																		
Consumers confidence index																		
Credit cards - ATMs																		
Credit cards - POSs																		
Disagreement - consumption																		
Disagreement - inflation																		
Unemploymeny expectations																		
Economic policy uncertainty																		
Stock market volatility																		
Google Trends																		

a. Dark colour in a horizontal line denotes lack of availability of the indicator in a particular point in time within the quarter.

likelihood in the time domain provides optimal estimates of the unknown system matrices, which in the present context are just covariance matrices of all the vector noises involved in the model. The use of the selected modeling approach, allows the estimation of models with unbalanced data sets, i.e. input variables with different sample lengths, an issue relevant for the application at hand given the different timing of publication of incoming monthly indicators.

4 The empirical exercise

4.1 Timing of the (pseudo) real-time exercise

We build up a real-time database for the target variable, quarterly private consumption as measured by the National Accounts, for the period 1995Q1-2017Q4. The size of the sample for our empirical exercises, though, is restricted by the availability of some of the monthly indicators, in particular as regards Google Trends, the EPU index, and the Services Sector Activity Indicator, available for the sample starting in January 2004, January 2001, and January 2002, respectively. As regards the indicator variables we could not replicate a truly real-time dataset, so we proceeded to built up a pseudo real-time one, namely we adjusted for each point in time (month) the information set that had been available given the timing rules that we describe in the next paragraph. It is worth mentioning that the indicators that we use are not revised, which means that the pseudo-real-time approximation should be a fair representation of data available in real-time. The only discrepancy may arise from seasonal-adjustment. While we seasonally-adjust the series that are published on non-seasonally-adjusted terms following our pseudo-real-time approach, we take official series that are published in a seasonally-adjusted form as the latest available vintage of official data.

As regards the rules governing the timing of availability of the data, this is illustrated in Table 3. At the time the first month of each quarter (denoted by $m1$ in the table) is over (i.e. at the very beginning of the subsequent month) the official quarterly national accounts has not yet been released by the statistical agency. Within the group of quantitative indicators, only employment (Social Security Registrations) is available at that moment of time, while the most recent figure for the Retail Trade Index does correspond to the second month of the previous quarter, and the Services Activity Indicator presents a lag of two months. In turn, "soft" indicators are published more timely, and at $m1$ they both already cover the whole $t-1$ quarter. The same happens with the uncertainty indicators computed from surveys, while the EPU index presents a delay of two months. The more timely indicators are the payment cards ones, the volatility of the stock market, and the internet-based variables. Given their daily production process, they would be available to the real-time forecasters at the very beginning of the next month (what we denote by $m1$).

4.2 Alternative models and comparison criteria

In order to test the relevant merits of each group of indicators, as mentioned above, we consider several models, that differ in the set of indicators included in each one. We estimate models that include indicators from each group at a time, several groups at a time, and different combinations of individual models. We only provide results for a selection of all possible combinations, that were chosen for its better forecasting performance.[21] In particular, we focus on the following models for quarterly private consumption:

- Models including indicators of only one group: (i) Quantitative ("hard") indicators; (ii) Qualitative ("soft") indicators; (iii) Payment cards: aggregate of POS and ATM - amounts; (iv) Payment cards: aggregate of POS and ATM - number of operations; (v) Uncertainty indicators: Stock Market Volatility and EPU; (vi) Google Trends: aggregate of all indicators; (vii) Google Trends: durable goods aggregate (with one lag).

- Models including indicators of different groups: (i) Quantitative and qualitative; (ii) Quantitative and POS-ATM amounts; (iii) Quantitative and Uncertainty; (iv) Quantitative and Google Trends (aggregate); (v) Quantitative and Google Trends (durables, with one lag).

- Combination of models that do include indicators of only one group: (i) Suite of 30 models[22]; (ii) "Hard" and aggregate of POS and ATM amounts; (iii) "Hard", aggregate of POS and ATM amounts, and "Soft"; (iv) "Hard" and "Soft"; (v) "Hard" and Google.

We perform a rolling forecasting exercise in which the selection of the forecast origin and the information set available at each date are carefully controlled for. In particular we evaluate the forecasts generated from three forecast origins per quarter ($m1$, $m2$, $m3$) for the time window 2008Q1 to 2017Q4. This makes up to 40 projections from each forecast origin, and a total of 120 projections at each forecast horizon. In addition, we break down the sample in two sub-samples, to broadly capture the most recent economic crisis period (2008-2012), and the subsequent economic recovery (2013-2017).

[21] All the results are available upon request.

[22] These models include those described in the two groups before (plus a version of each one in which the variables are included with 1 lag), and the additional bilateral combinations of "Hard" and other indicators not covered above (plus a version of each one in which the variables are included with 1 lag).

As a mechanical benchmark we use a random walk model, whereby we repeat in future quarters the latest quarterly growth rate observed for private consumption. Beyond being a usual benchmark in statistical works, the random walk model of consumption is a classical one from a theoretical point of view (see the seminal paper of Hall, 1978). Rational expectations together with the hypothesis of constant expected real interest rates implies that any changes in consumption should be unpredictable, i.e. evolve as a random walk, which is consistent with the permanent income hypothesis of consumption. According to the random walk model for consumption, no information known to the consumer when the consumption choice at t was made can have any predictive power for how consumption will change between period t and $t + 1$ (or for any date beyond $t + 1$).[23]

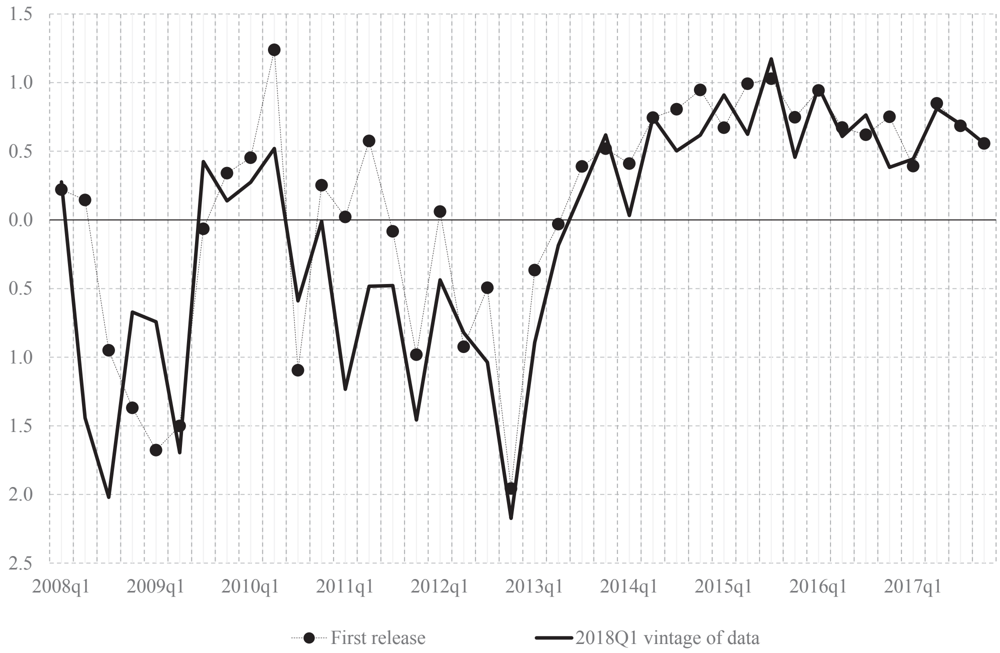
We focus on the forecast performance at the nowcasting horizon (current quarter), but also explore forecasts at 1 to 4 quarters-ahead from each one of the current quarter forecast origins ($m1$, $m2$ and $m3$).

As regards forecasting performance statistics, we present three standard quantitative measures. First, the ratio of the Root Mean Squared Errors (RMSE) of the different alternative models with respect to the quarterly random walk alternative. Second, we also look at the Diebold and Mariano test (using the finite sample modification of Harvey *et al.*, 1997), and test for the null hypothesis of no difference in the accuracy of two competing forecasts. The Diebold-Mariano test could be biased when parameter uncertainty is taken into account (see for example Clark and McCraken, 2001). We make sure that a reasonable proportion of the sample is employed when the first out-of-sample forecast is computed to reduce the bias generated by ignoring parameter uncertainty (the forecasting exercise is performed on the moving window 2008-2017, while the full sample covers 2001-2017). Finally, we compare model/indicator performance by means of the Pesaran-Timmermann test (see Pesaran and Timmermann, 1992), that determines the accuracy in predicting the change in direction of a time series, i.e. its directional accuracy.

In all cases, errors are computed as the difference of the nowcast/forecast value from two vintages of data: the first release of each quarterly figure, and the 2018Q1 vintage of data. As illustrated by Figure 2, differences can be quite significant depending on the reference

[23] As regards the link with the empirical specification chosen, please notice that the prescriptions of the usual theoretical sugmodels are derived for variables that fluctuate in a stationary fashion around a deterministic steady-state.

Figure 2: Quarterly private consumption: first release of each quarterly figure versus the 2018Q1 data vintage (quarter-on-quarter growth rates). 2008Q1-2017Q4 sample.



point taken to compute the forecast error. While first released figures are the ones of concern from the perspective of a real-time forecaster, they tend to be produced with a more limited informational base than subsequent data publications. From this perspective subsequent revisions of initially published figures can be sizeable, beyond changes due to methodological improvements of statistical sources.[24]

5 Results

The main results of the empirical exercises are shown in Table 4, that display RMSE statistics of each model with respect to the quarterly random walk alternative, figures 3 and 4, that provide an illustration of the behavior of model nowcasts/forecasts around turning points, figures 5 and 6, presenting RMSEs for selected models, and in "good" vesus "bad" times, tables 5, 6, 7, that show pairwise RMSEs and Diebold-Mariano statistics, and tables 8 and 9, that present Pesaran-Timmermann tests. Forecast errors in all cases are computed using the first released figure. Additional tables based on the 2018Q1 vintage are presented in Appendix A (tables A.1, A.2, A.3, A.4, A.5, and A.6).

[24]For a cross-country overview of revisions to quarterly national accounts data see, for example, http://www.oecd.org/sdd/na/revisions-of-quarterly-gdp-in-selected-oecd-countries.htm

First, from tables 4 (relative RMSEs) and 5 to 7 (Dieblod-Mariano tests), the following results can be highlighted. As regards models that use only indicators from each group (first panel of the table), the ones that use quantitative indicators and payment cards (amounts) tend to perform best than the others at the nowcasting and, somewhat less so, forecasting (1-quarter- and 4-quarters-ahead) horizons. Relative RMSE are in almost all cases below one, even though from a statistical point of view they are only different from quarterly random walk nowcasts and forecasts in a few instances. In general, the other models do not beat systematically the quarterly random walk alternative. The two main exceptions are the model with qualitative indicators for the nowcasting horizons, and the Google-Trends-based ones for the longer-horizon forecasts. The latter results might be consistent with the prior that Google-based indicators deliver today information on steps to prepare purchases in the future. Lastly, it is worth mentioning that nowcast/forecast accuracy does not always improve monotonically as the information set expands, i.e. as we move from nowcast/forecast origins m_1 to m_3. This is explained by the real-time nature of the information set used in each case. Following the standard publication calendar, at m_2-time the quarterly figure of private consumption corresponding to the previous quarter is published. This has two implications. On the one hand, the quarterly random walk alternative moves from a situation in which the reference was the $t-2$ figure to one in which the $t-1$ quarter is used. On the other hand, quarterly data corresponding to previous quarters tend to be revised at m_2, which may affect the estimation of models in real-time, and eventually the accuracy of the generated nowcasts/forecasts, or at least the comparability of estimations based on different information sets. The revision of past, quarterly national accounts figures is quite apparent when going through the different pannels of figures 3 and 4 in a chronological order.

Second, in the middle panel of Table 4 we show the results of the estimation of models that include quantitative indicators while adding, in turn, variables from the other groups (qualitative, payment cards - amounts, uncertainty, Google-Trends-based). The improvement in nowcast accuracy is not generalized when adding more indicators, with the exception of the "soft" ones (m_1 and m_3 origins). Nonetheless, there is a significant improvement for longer forecast horizons of expanding the baseline model. In particular, for the 4-quarters-ahead one, uncertainty and Google-based indicators add significant value to the core "hard"-only-based model.

Finally, as regards the third panel of results of Table 4, and the corresponding Diebold-Mariano test results in tables 5 to 7, it seems clear that the combination (average) of models with individual groups of indicators improves the forecasting performance in all cases and at all horizons. Most notably, the combination of the forecasts of models including quantitative indicators with those with payment cards (amounts), delivers, in general, the best nowcasting/forecasting performance at all horizons. At the same time, adding the "soft" forecasts seems to add value in the nowcasting phase, when more information for the current quarter is available (m_2 and m_3 origins). In turn, the combination of a broad set of models (first line of the panel) produces the lowest RMSE relative to the quarterly random walk at the four quarters ahead forecast horizon. Nevertheless, the bilateral DM-test results with respect to combinations of simpler models do not tend to be, in general, significantly different from zero from a statistical point of view. In addition, according to this metric, also the models with only quantitative, qualitative and payment cards indicators individually, beat the combination of the broad set of models at the nowcasting horizons.

Regarding the ability of models to correctly anticipate the sign of changes in private consumption (Pesaran-Timmerman test) we present two exercise. In the first one (shown in Table 8), the aim is to capture the sign of the growth rate of private consumption (i.e. whether it is positive or negative). In the second one (shown in Table 9), in turn, we provide results for the percentage of correctly anticipated accelerations or decelerations in private consumption, i.e. the second derivative, that tends to be of more interest to the applied forecaster. As regards the first exercise, the results shown in Table 8 indicate that: (i) the model that only includes "soft" indicators dominates the other at the nowcasting horizons, with gains of some 5% of correctly predicted signs; (ii) for longer forecast horizons, models based on quantitative and payment cards indicators tend to present a better record, also when combined with qualitative indicators. As to the second exercise (Table 9), the following results are worth highlighting: (i) At the nowcasting horizons, models using quantitative and, to a lesser extent, payment cards indicators (amounts) are the best at anticipating accelerations/decelerations in private consumption growth; (ii) payment card indicators (amounts and numbers) present a good behaviour for foreasting horizons; (iii) Google-Trends based indicators (durable goods) are the best performers at long forecast horizons (4-quarters-ahead) within the group of single-indicator models.

Turning again to figures 3 and 4, some additional facts can be highlighted. First, as regards figure 3, that shows the results for the double-dip of private consumption (and economic activity, more generally), the model selected for the illustration (with quantitative indicators) adequately capture, and subsequently adapt to, the downturn in consumption that burst in the first quarter of 2008. Second, as of the second quarter of 2009 the recovery starts to be signalled for the subsequent quarters, but forecasts for more distant horizons tend to be flat, which ex post was consistent with the observed double-dip of economic activity that occurred as of 2011. All this said, forecasts for longer horizons during the 2008Q1 to 2009Q4 period perform relatively poorly. Thus, in figure 4, we show the behaviour of the selected model for the period that encompasses the end of the second recession (2011) and the start of the economic recovery phase (end of 2013). It is clear from the figure that the model starts signalling the turn (recovery phase) as of 2011Q4, despite the observed negative growth rates of private consumption on which the information set conditions at that moment. Discrepancies with first-released outcomes, particularly at forecasting horizons, tend to be smaller in the 2013 recovery phase than in the crisis period. This is also the case for the subsequent years, not shown in the figure for the sake of brevity. The worst nowcast/forecast performance in crisis times is illustrated by figure 6, in which we show relative RMSEs of different models in the crisis (2008-2012) and recovery (2013-2017) phases of the cycle, with respect to the whole sample.

Past data revisions do not appreciably affect the main results described above. This is clear from the tables in Appendix A that present all the results for nowcast and forecast errors computed on the basis of the 2018Q1 vintage of data, instead of the first released figure. Interestingly, though, past data revisions in our real-time setting somehow affect the interpretation of some of the results, in particular as regards the expected increase in accuracy when the information set expands and, less so, the expected reduction in forecast accuracy for longer-horizons. This is illustrated in Figure 5, where we present the RMSEs of some selected models: the quarterly random walk, the model with only "hard" indicators, the combination of "hard" and payment cards (amounts)-based models, and the broader combination with a set of 30 models. The RMSE of each model does not get monotonically reduced as we move from the nowcast/forecast origin m_1 to m_2 and then to m_3. As mentioned above, this might be partly related to the change on the past private consumption data that enters the information set at each point in time, including in some cases significant past data revisions.

6 Conclusions

We estimate a suite of mixed-frequency models on an (almost) real-time database for the period January 2001 - December 2017, and conduct out-of-sample forecasting exercises to assess the relevant merits of different groups of indicators. The selection of indicators is guided by the standard practice ("hard" and "soft" indicators), but also expand this practice by looking at non-standard variables, namely: (i) a suite of proxy indicators of uncertainty, calculated at the monthly frequency; (ii) two additional sets of variables that are sampled at a much lower frequency: payment card transactions and indicators based on search query time series provided by Google Trends. The latter set of indicators is based on factors extracted from consumption-related search categories of the Google Trends application. Our study shows that, even though traditional indicators make a good job at nowcasting and forecasting private consumption in real-time, novel data sources add value, most notably those based on payment cards-related, but also, to a lesser extent, Google-based and uncertainty indicators when combined with other sources.

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Table 4: Relative RMSE statistics: ratio of each model to the quarterly random walk.[a]

Models including indicators of only one group

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative ("hard") indicators [b]	0.84	0.75 *	0.79	0.75 **	0.81	0.80	0.98	0.97	1.00
Qualitative ("soft") indicators [c]	1.01	0.85	0.85	1.11	1.05	1.05	1.09	1.10	1.29 *
Payment cards (amounts, am)[d]	0.79	0.82	0.88	0.65 ***	0.84	0.69 **	0.74 **	0.84	0.83
Payment cards (numbers)[d]	1.05	1.15	1.13	0.90	1.10	0.98	0.75 **	0.81	0.79
Uncertainty indicators [e]	1.06	0.97	0.99	1.00	1.05	1.06	0.94	1.00	1.02
Google: aggregate of all indicators	1.04	1.06	1.06	0.85	1.03	1.03	0.71 **	0.79	0.79
Google: durable goods (lagged)	1.04	0.97	0.98	0.96	1.04	1.04	0.85 *	0.93	0.93

Models including indicators from different groups

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative & Qualitative	0.69 **	0.78	0.77	0.67 ***	0.76 *	0.72 *	0.79 *	0.82 *	0.80 *
Quantitative & Payment cards (am)[d]	0.90	0.82	0.91	0.67 ***	0.79	0.78	0.86	0.89	0.91
Quantitative & Uncertainty	0.88	0.86	0.75	0.74 **	0.91	0.93	0.69 **	0.76	0.76
Quantitative & Google (aggregate)	0.85	0.76	0.77	0.81 *	0.94	0.89	0.77 **	0.81 *	0.82
Quantitative & Google (durables)	0.91	0.95	0.87	0.69 **	0.83	0.88	0.72 **	0.76 *	0.77 *

Combination of models

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
All models [f]	0.66 **	0.71 **	0.69 **	0.68 ***	0.77 *	0.68 **	0.73 **	0.78 *	0.78 *
Hard & Payment cards (am)[d]	0.62 **	0.69 **	0.71 **	0.53 ***	0.69 **	0.52 ***	0.79 *	0.86	0.84
Hard, Payment cards (am)[d] & Soft	0.65 **	0.67 **	0.67 **	0.68 ***	0.74 **	0.59 ***	0.83 *	0.89	0.92
Hard & Soft	0.68 **	0.66 **	0.66 **	0.77 **	0.75 **	0.69 **	0.91	0.94	1.02
Hard & Google (durables)	0.77 **	0.78 **	0.76 **	0.74 ***	0.83	0.78 *	0.85	0.91	0.90

Notes:
The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the quarterly random walk alternative. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
a. Nowcast/forecast errors computed as the difference to the first released vintage of private consumption data. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$).
b. Social Security Registrations; Retail Trade Index; Activity Services Index.
c. PMI Services; Consumer Confidence Index.
d. Aggregate of payment cards via POS and ATMs.
e. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

Table 5: Pairwise relative RMSEs and Diebold-Mariano tests: nowcasts.

Nowcast origin - $m1$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.19	0.99	1.26	0.95	0.94	0.96	1.52**	1.62**	1.55**
Quantitative[a] [2]	—	0.83	1.06	0.80*	0.79*	0.81	1.27*	1.35**	1.30*
Qualitative[b] [3]	—	—	1.27*	0.96	0.95	0.97	1.53**	1.63**	1.56***
Payment cards[c] [4]	—	—	—	0.75**	0.74*	0.76	1.20	1.28*	1.23*
Uncertainty[d] [5]	—	—	—	—	0.99	1.01	1.60***	1.70***	1.63***
Google[e] [6]	—	—	—	—	—	1.03	1.62***	1.72***	1.65***
Comb: All models[f] [7]	—	—	—	—	—	—	1.58***	1.68**	1.61***
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	1.06	1.02
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.96

Nowcast origin - $m2$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.33*	1.18	1.23	0.87	1.03	1.03	1.41**	1.45**	1.48***
Quantitative[a] [2]	—	0.89	0.92	0.65**	0.77*	0.77	1.06	1.09	1.12
Qualitative[b] [3]	—	—	1.04	0.73**	0.87	0.87	1.19	1.22	1.26**
Payment cards[c] [4]	—	—	—	0.71**	0.84	0.84	1.15	1.18	1.21*
Uncertainty[d] [5]	—	—	—	—	1.18	1.18	1.62***	1.66***	1.71***
Google[e] [6]	—	—	—	—	—	1.00	1.37**	1.41**	1.44**
Comb: All models[f] [7]	—	—	—	—	—	—	1.37**	1.41**	1.45**
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	1.03	1.05
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	1.03

Nowcast origin- $m3$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.27	1.18	1.14	0.89	1.01	1.02	1.46**	1.42**	1.49**
Quantitative[a] [2]	—	0.93	0.89	0.70**	0.79	0.81	1.15	1.11	1.17
Qualitative[b] [3]	—	—	0.97	0.75**	0.85	0.87	1.24	1.20	1.26**
Payment cards[c] [4]	—	—	—	0.78*	0.88	0.90	1.28*	1.24**	1.30**
Uncertainty[d] [5]	—	—	—	—	1.13	1.15	1.64***	1.60***	1.67***
Google[e] [6]	—	—	—	—	—	1.02	1.45**	1.41*	1.48**
Comb: All models[f] [7]	—	—	—	—	—	—	1.42**	1.38*	1.45**
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.97	1.02
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	1.05

Notes:
Each cell shows the relative RMSE of the model in its horizontal line as compared to the model in the vertical column.The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the method in the vertical column. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from 2008Q1 ($m1$) to 2017Q4 ($m3$). Nowcast/forecast errors are computed as the difference to the first released vintage of private consumption data.
a. Social Security Registrations; Retail Trade Index; Activity Services Index.
b. PMI Services; Consumer Confidence Index.
c. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
d. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
e. Google Trends, durables' goods indicator (lagged).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.
g. Combination of Quantitative (see note a) & Google Trends, durables' goods indicator (lagged).

Table 6: Pairwise relative RMSEs and Diebold-Mariano tests: 1-quarters-ahead forecasts.

Forecast origin - $m1$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]^g
Q-Random Walk [1]	1.34**	0.90	1.54***	1.11	1.00	1.04	1.47***	1.87***	1.48***
Quantitative^a [2]	—	0.67***	1.15	0.83	0.75**	0.77*	1.09	1.40***	1.11
Qualitative^b [3]	—	—	1.70***	1.23*	1.11	1.15	1.62***	2.07***	1.64***
Payment cards^c [4]	—	—	—	0.72***	0.65***	0.67***	0.95	1.22	0.96
Uncertainty^d [5]	—	—	—	—	0.90	0.93	1.32**	1.68***	1.33**
Google^e [6]	—	—	—	—	—	1.03	1.46***	1.86***	1.47***
Comb: All models^f [7]	—	—	—	—	—	—	1.41***	1.80***	1.43**
Comb: Quant.^{a} & Cards^c [8]	—	—	—	—	—	—	—	1.28***	1.01
Comb: Quant.^{a} & Qual.^{b} [9]	—	—	—	—	—	—	—	—	0.79***

Forecast origin - $m2$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]^g
Q-Random Walk [1]	1.24	0.96	1.19	0.91	0.95	0.96	1.30*	1.45**	1.36**
Quantitative^a [2]	—	0.77	0.96	0.73*	0.76*	0.77*	1.05	1.17	1.10
Qualitative^b [3]	—	—	1.25*	0.95	0.99	1.01	1.36**	1.51**	1.42***
Payment cards^c [4]	—	—	—	0.76*	0.80	0.81	1.09	1.22*	1.14
Uncertainty^d [5]	—	—	—	—	1.04	1.06	1.43**	1.59**	1.49**
Google^e [6]	—	—	—	—	—	1.01	1.37**	1.53**	1.44***
Comb: All models^f [7]	—	—	—	—	—	—	1.35**	1.51**	1.41**
Comb: Quant.^{a} & Cards^c [8]	—	—	—	—	—	—	—	1.11	1.05
Comb: Quant.^{a} & Qual.^{b} [9]	—	—	—	—	—	—	—	—	0.94

Forecast origin- $m3$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]^g
Q-Random Walk [1]	1.24	0.95	1.45**	1.02	0.94	0.96	1.47**	1.93***	1.69***
Quantitative^a [2]	—	0.76*	1.17	0.82	0.76*	0.77*	1.19*	1.56***	1.36**
Qualitative^b [3]	—	—	1.53***	1.07	0.99	1.01	1.55**	2.04***	1.78***
Payment cards^c [4]	—	—	—	0.70**	0.65***	0.66**	1.02	1.33	1.17
Uncertainty^d [5]	—	—	—	—	0.93	0.94	1.45**	1.90***	1.66**
Google^e [6]	—	—	—	—	—	1.02	1.56***	2.05***	1.79***
Comb: All models^f [7]	—	—	—	—	—	—	1.53***	2.01***	1.76***
Comb: Quant.^{a} & Cards^c [8]	—	—	—	—	—	—	—	1.31**	1.15
Comb: Quant.^{a} & Qual.^{b} [9]	—	—	—	—	—	—	—	—	0.88

Notes:
Each cell shows the relative RMSE of the model in its horizontal line as compared to the model in the vertical column.The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the method in the vertical column. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from 2008Q1 ($m1$) to 2017Q4 ($m3$). Nowcast/forecast errors are computed as the difference to the first released vintage of private consumption data.
a. Social Security Registrations; Retail Trade Index; Activity Services Index.
b. PMI Services; Consumer Confidence Index.
c. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
d. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
e. Google Trends, durables' goods indicator (lagged).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.
g. Combination of Quantitative (see note a) & Google Trends, durables' goods indicator (lagged).

Table 7: Pairwise relative RMSEs and Diebold-Mariano tests: 4-quarters-ahead forecasts.

Forecast origin - $m1$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.19	0.92	1.35**	1.33**	1.07	1.17*	1.38***	1.26*	1.21*
Quantitative[a] [2]	—	0.90	1.33	1.31	1.05	1.15	1.35*	1.24*	1.19
Qualitative[b] [3]	—	—	1.48***	1.45**	1.16	1.28*	1.50***	1.38**	1.32***
Payment cards[c] [4]	—	—	—	0.98	0.79*	0.86	1.02	0.93	0.89
Uncertainty[d] [5]	—	—	—	—	0.80**	0.88	1.03	0.95	0.91
Google[e] [6]	—	—	—	—	—	1.10***	1.29***	1.19	1.14
Comb: All models[f] [7]	—	—	—	—	—	—	1.17**	1.08	1.03
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.92	0.88**
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.96

Forecast origin - $m2$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.03	0.91	1.19	1.24	1.00	1.07	1.29**	1.17	1.13
Quantitative[a] [2]	—	0.88	1.16	1.21	0.98	1.05	1.26*	1.14*	1.10
Qualitative[b] [3]	—	—	1.31**	1.37**	1.11	1.18**	1.42***	1.29**	1.24***
Payment cards[c] [4]	—	—	—	1.04	0.85	0.90	1.08	0.98	0.95
Uncertainty[d] [5]	—	—	—	—	0.81	0.87	1.04	0.94	0.91
Google[e] [6]	—	—	—	—	—	1.07*	1.28**	1.16*	1.12*
Comb: All models[f] [7]	—	—	—	—	—	—	1.20*	1.09	1.05
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.91	0.88**
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.96

Forecast origin- $m3$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.00	0.78**	1.21	1.27	0.98	1.07	1.29**	1.19	1.08
Quantitative[a] [2]	—	0.78	1.21	1.27	0.98	1.08	1.29	1.19*	1.09
Qualitative[b] [3]	—	—	1.55***	1.63***	1.26*	1.38**	1.66***	1.53***	1.40***
Payment cards[c] [4]	—	—	—	1.05	0.81	0.89	1.07	0.98	0.90
Uncertainty[d] [5]	—	—	—	—	0.77*	0.85	1.01	0.94	0.85
Google[e] [6]	—	—	—	—	—	1.10**	1.32**	1.22	1.11
Comb: All models[f] [7]	—	—	—	—	—	—	1.20*	1.11	1.01
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.92	0.84**
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.91

Notes:
Each cell shows the relative RMSE of the model in its horizontal line as compared to the model in the vertical column.The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the method in the vertical column. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from 2008Q1 ($m1$) to 2017Q4 ($m3$). Nowcast/forecast errors are computed as the difference to the first released vintage of private consumption data.
a. Social Security Registrations; Retail Trade Index; Activity Services Index.
b. PMI Services; Consumer Confidence Index.
c. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
d. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
e. Google Trends, durables' goods indicator (lagged).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.
g. Combination of Quantitative (see note a) & Google Trends, durables' goods indicator (lagged).

Table 8: Pesaran-Timmermann statistic of directional accuracy:[a] sign of private consumption growth rate.

Models including indicators of only one group

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quarterly Random Walk	0.70**	0.80***	0.80***	0.64	0.69**	0.69**	0.50	0.56	0.56
Quantitative ("hard") indicators [b]	0.78***	0.78***	0.73***	0.77***	0.82***	0.77***	0.64***	0.69***	0.67***
Qualitative ("soft") indicators [c]	0.78***	0.85***	0.83***	0.69**	0.79***	0.77***	0.50	0.61	0.53
Payment cards (amounts,am)[d]	0.78***	0.78***	0.80***	0.74***	0.79***	0.85***	0.56	0.58	0.61
Payment cards (numbers)[d]	0.75***	0.75***	0.75***	0.72**	0.69**	0.77***	0.50	0.69**	0.67**
Uncertainty indicators [e]	0.73***	0.78***	0.78***	0.67**	0.72***	0.69**	0.50	0.56	0.56
Google: aggregate of all indicators	0.40	0.80***	0.80***	0.26	0.51	0.41	0.25	0.28	0.44
Google: durable goods (lagged)	0.73***	0.73***	0.73***	0.69**	0.72***	0.72***	0.53	0.58	0.58

Models including indicators from different groups

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative & Qualitative	0.78***	0.78***	0.78***	0.77***	0.87***	0.85***	0.64***	0.67***	0.67***
Quantitative & Payment cards (am)[d]	0.78***	0.83***	0.78***	0.74***	0.77***	0.77***	0.61**	0.67***	0.61**
Quantitative & Uncertainty[e]	0.75***	0.73***	0.75***	0.79***	0.74***	0.74***	0.56	0.61	0.61
Quantitative & Google (aggregate)	0.78***	0.78***	0.70***	0.74***	0.77***	0.82***	0.58	0.58	0.64**
Quantitative & Google (durables)	0.78***	0.78***	0.78***	0.77***	0.82***	0.79***	0.64**	0.61	0.61*

Combination of models

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
All models [f]	0.88***	0.83***	0.78***	0.74***	0.85***	0.85***	0.56	0.58	0.67***
Hard & Payment cards (am)[d]	0.83***	0.78***	0.78***	0.85***	0.87***	0.85***	0.61*	0.69***	0.69***
Hard, Payment cards (am)[d] & Soft	0.83***	0.85***	0.78***	0.74***	0.82***	0.87***	0.53	0.61*	0.67**
Hard & Soft	0.83***	0.80***	0.80***	0.74***	0.79***	0.82***	0.50	0.64**	0.58
Hard & Google (durables)	0.78***	0.78***	0.75***	0.77***	0.77***	0.79***	0.56	0.58*	0.61**

Notes:
The asterisks denote the PT test results for the null hypothesis. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
a. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$).
b. Social Security Registrations; Retail Trade Index; Activity Services Index.
c. PMI Services; Consumer Confidence Index.
d. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
e. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

Table 9: Pesaran-Timmermann statistic of directional accuracy:[a] acceleration/deceleration of private consumption growth rate.

Models including indicators of only one group

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quarterly Random Walk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Quantitative ("hard") indicators [b]	0.55	0.73***	0.73***	0.54	0.54	0.62**	0.56	0.53	0.53
Qualitative ("soft") indicators [c]	0.48	0.55	0.55	0.49	0.54	0.56	0.64**	0.47	0.50
Credit cards: POS+ATM, amounts	0.55	0.63*	0.65**	0.59	0.67**	0.64**	0.53	0.50	0.50
Credit cards: POS+ATM, numbers	0.55	0.53	0.53	0.54	0.51	0.56	0.64**	0.61*	0.61*
Uncertainty indicators [d]	0.50	0.38	0.48	0.38	0.44	0.46	0.53	0.50	0.47
Google: aggregate of all indicators	0.53	0.55	0.55	0.59*	0.59*	0.56	0.53	0.44	0.50
Google: durable goods (lagged)	0.48	0.53	0.53	0.46	0.46	0.49	0.64**	0.67**	0.67**

Models including indicators from different groups

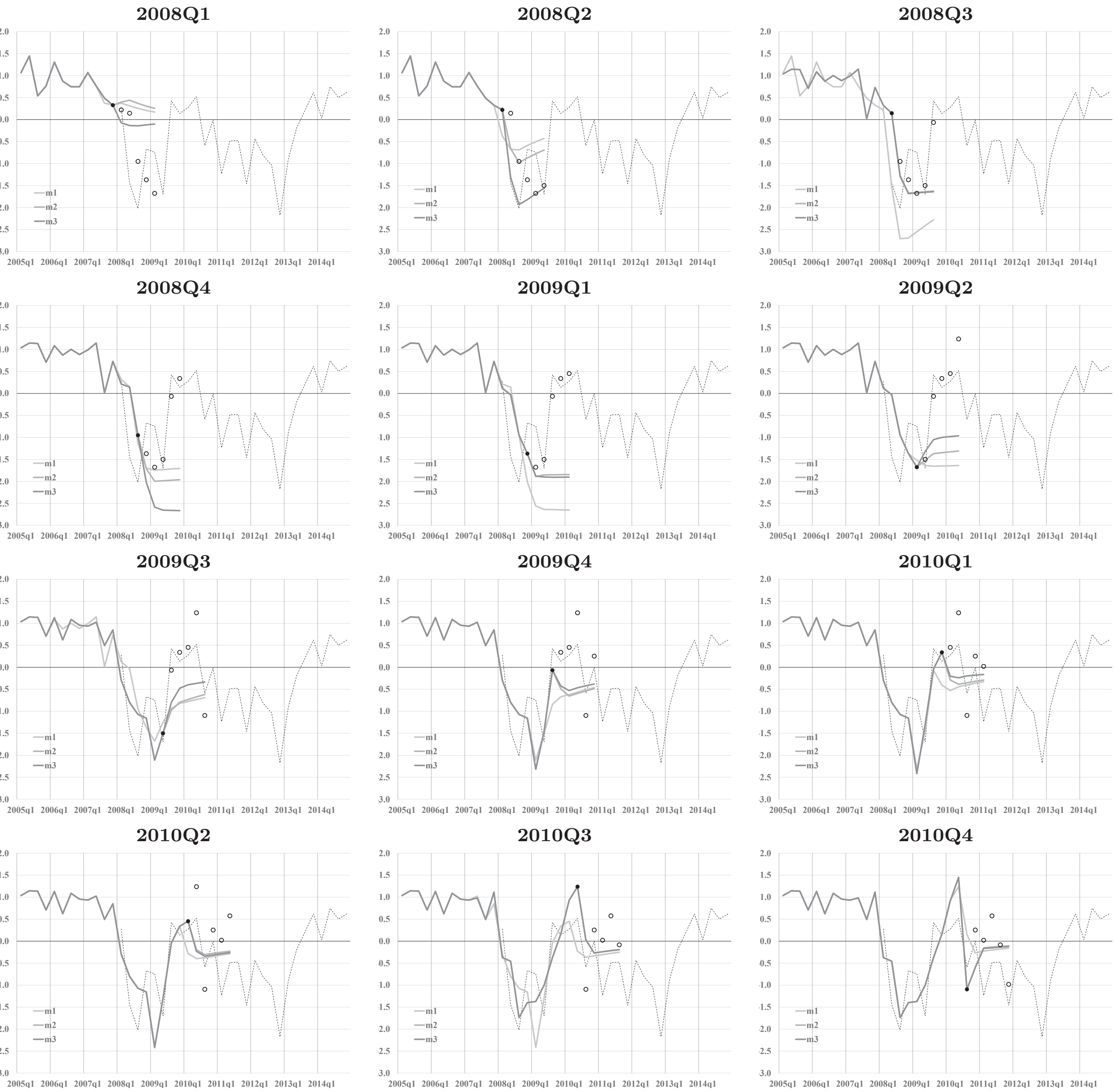
	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative & Qualitative	0.63*	0.68***	0.63**	0.51	0.56	0.64**	0.64*	0.64*	0.64*
Quantitative & POS+ATM amounts	0.58	0.68***	0.68***	0.51	0.49	0.59*	0.64**	0.69***	0.67**
Quantitative & Uncertainty	0.45	0.68**	0.70***	0.59*	0.56	0.62*	0.44	0.53	0.56
Quantitative & Google (aggregate)	0.65**	0.68**	0.60*	0.46	0.56	0.59	0.69***	0.67**	0.67**
Quantitative & Google (durables)	0.48	0.65**	0.65**	0.59*	0.59*	0.62**	0.50	0.53	0.53

Combination of models

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
All models [e]	0.60	0.68***	0.65**	0.59*	0.62**	0.64**	0.61*	0.58	0.56
Hard & POS+ATM amounts	0.50	0.78***	0.78***	0.56	0.64**	0.59	0.58	0.53	0.53
Hard, POS+ATM amounts & Soft	0.65**	0.60*	0.73***	0.62*	0.62*	0.69***	0.58	0.58	0.39
Hard & Soft	0.58	0.63*	0.63**	0.54	0.59	0.67**	0.53	0.53	0.36
Hard & Google (durables)	0.60*	0.65**	0.68***	0.54	0.59*	0.62**	0.67**	0.58	0.58

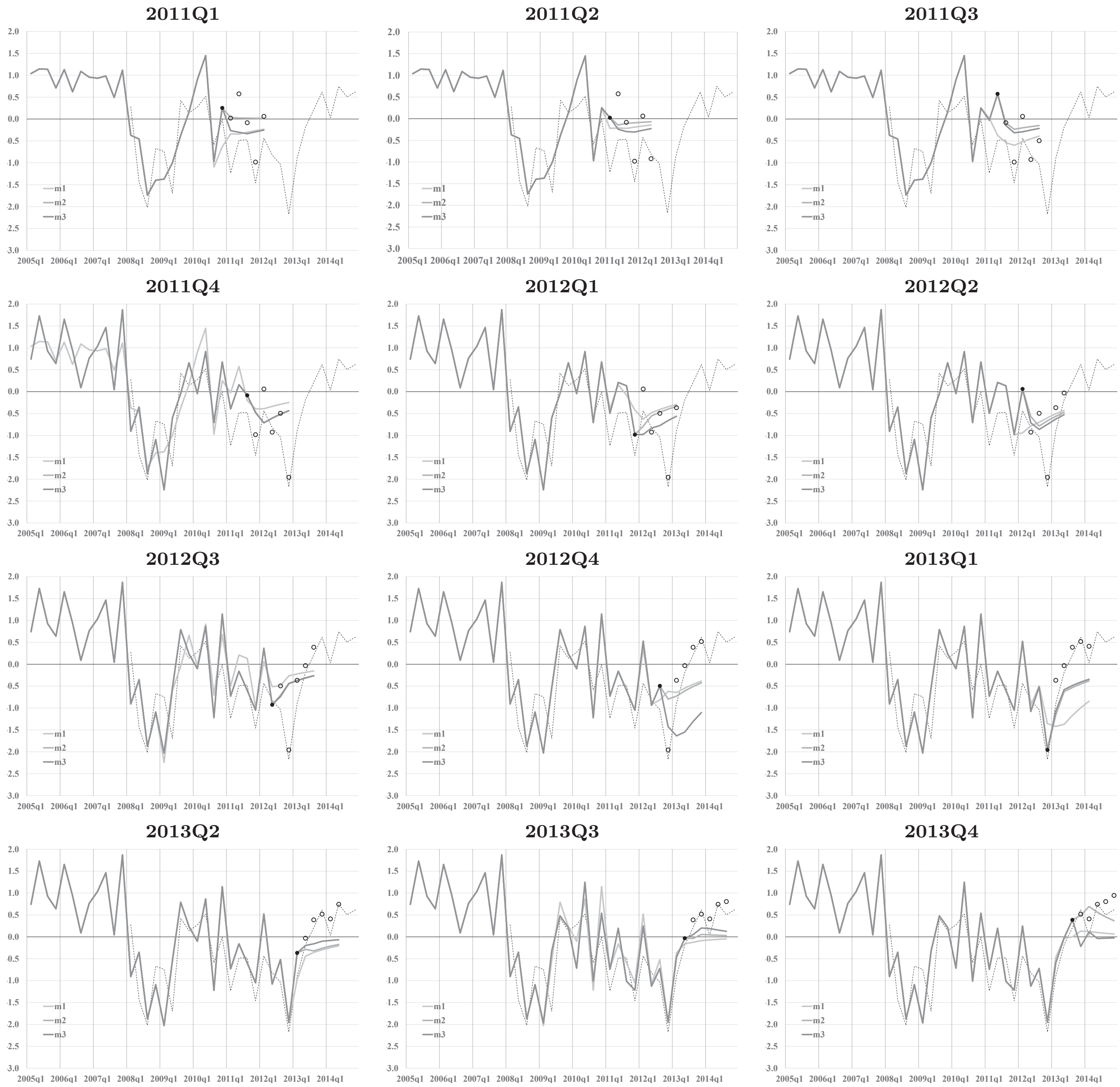
Notes:
The asterisks denote the PT test results for the null hypothesis. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
a. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$).
b. Social Security Registrations; Retail Trade Index; Activity Services Index.
c. PMI Services; Consumer Confidence Index.
d. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
e. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

Figure 3: Intuitive vision of nowcast/forecast behavior from the crisis to the recovery (2008-2010): illustration based on the model with only quantitative indicators.



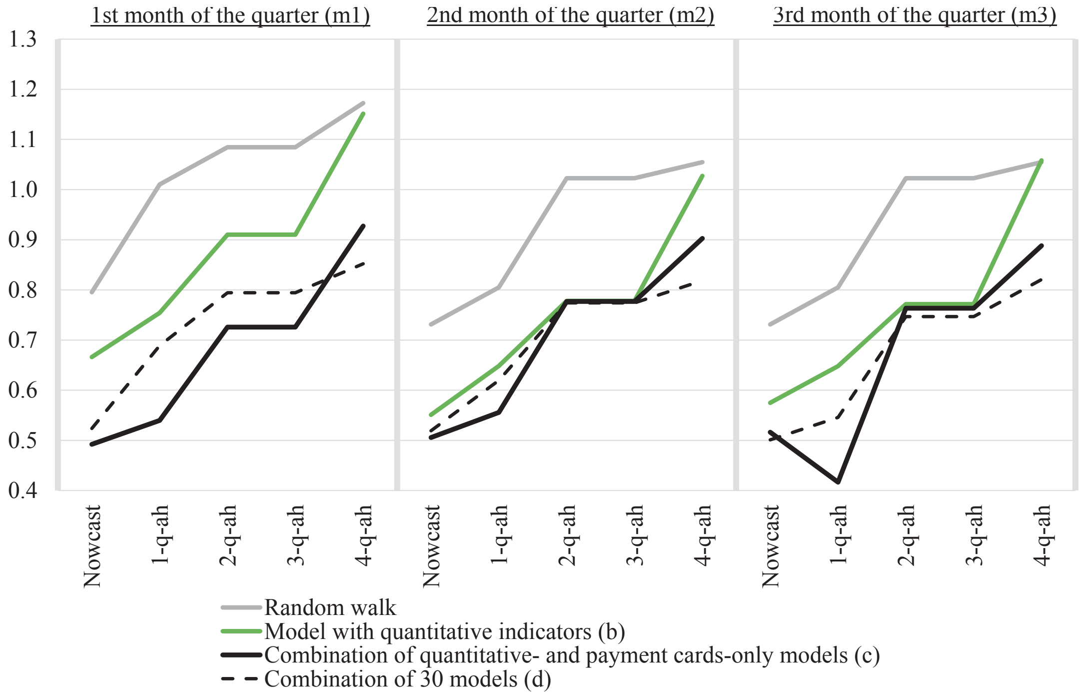
Notes: (i) Nowcasts/forecasts from origins $m1$, $m2$ and $m3$ in the quarter marked at the top of each pannel; (ii) The dotted line denotes the 2018Q1 vintage of data, while the empty circles refer to the first released quarterly figure; (iii) the filled-in dot denotes the available quarterly figure at $m2$ of each quarter.

Figure 4: Intuitive vision of nowcast/forecast behavior from the crisis to the recovery (2011-2013): illustration based on the model with only quantitative indicators.



Notes: (i) Nowcasts/forecasts from origins $m1$, $m2$ and $m3$ in the quarter marked at the top of each pannel; (ii) The dotted line denotes the 2018Q1 vintage of data, while the empty circles refer to the first released quarterly figure; (iii) the filled-in dot denotes the available quarterly figure at $m2$ of each quarter.

Figure 5: Root Mean Squared statistics of selected models by forecast origin and forecast horizon.



Notes:

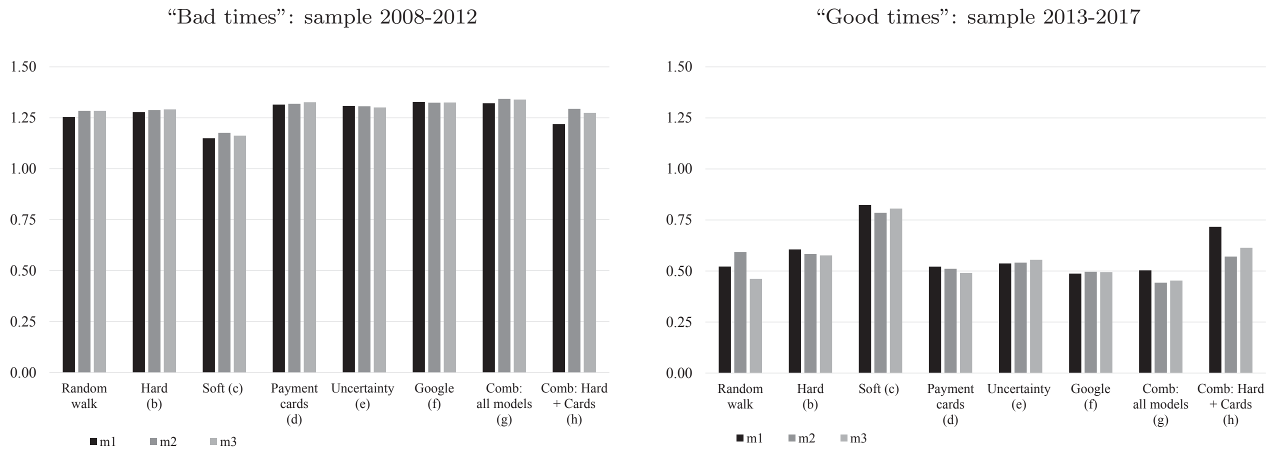
a. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$). Forecast errors computed from first vintage of released, private consumption data.

b. Model with quantitative indicators: ocial Security Registrations; Retail Trade Index; Activity Services Index.

c. Combination of quantitative-only (see footnote a) and payment cards-only (POS and ATM amounts) models.

d. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

Figure 6: Ratio of RMSEs of errors computed for two sub-samples over RMSEs computed using the whole sample.



Notes:

a. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$). Forecast errors computed from first vintage of released private consumption data.

b. Model with quantitative indicators: Social Security Registrations; Retail Trade Index; Activity Services Index.

c. Model with qualitative indicators: PMI Services; Consumer Confidence Index.

d. Model with payment card data (aggregate of POS and ATMs amounts).

e. Model with uncertainty indicators: Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).

f. Model with Google-Trends indicators: searches of durable goods, with one lag.

g. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

h. Combination of quantitative-only (footnote b) and payment cards-only (footnote d) models.

A Additional tables

Table A.1: Relative RMSE statistics: ratio of each model to the quarterly random walk. Nowcast/forecast errors computed as the difference to the 2018Q1 vintage of private consumption data.[a]

Models including indicators of only one group	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative ("hard") indicators [b]	0.71 *	0.78 **	0.72 **	0.85	0.83	0.74	0.90	0.90	0.93
Qualitative ("soft") indicators [c]	0.99	1.02	1.02	1.17	1.05	1.05	1.05	1.08	1.23
Payment cards (amounts,am)[d]	0.75 *	0.90	0.94	0.76 *	0.83	0.76 *	0.70 **	0.81	0.84
Payment cards (munbers)[d]	1.06	1.29 *	1.27	0.98	1.00	0.98	0.72 **	0.82	0.80 *
Uncertainty indicators [d]	1.05	1.11	1.12	1.09	1.04	1.04	0.90	0.95	0.98
Google: aggregate of all indicators	0.98	1.15	1.15	0.92	0.98	0.98	0.68 **	0.77 *	0.77 *
Google: durable goods (lagged)	1.02	1.10	1.10	1.05	1.02	1.02	0.81 *	0.89	0.89
Models including indicators from different groups	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative & Qualitative	0.68 *	0.80 *	0.75 **	0.78	0.80	0.72 *	0.73 **	0.77 *	0.76 **
Quantitative & Payment cards (am)[d]	0.78	0.83	0.85	0.79	0.81	0.75	0.77 **	0.81 *	0.84
Quantitative & Uncertainty	0.84	0.94	0.86	0.80	0.87	0.87	0.67 **	0.75 *	0.75 *
Quantitative & Google (aggregate)	0.80	0.87	0.88	0.84	0.88	0.78	0.69 **	0.76 *	0.77 *
Quantitative & Google (durables)	0.80	0.90	0.83	0.80	0.87	0.84	0.67 **	0.73 **	0.73 **
Combination of models	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
All models [e]	0.66 **	0.79 *	0.76 *	0.77 *	0.78 *	0.69 **	0.68 **	0.74 **	0.74 **
Hard & Payment cards (am)[d]	0.56 **	0.76 *	0.72 **	0.66 **	0.73 **	0.59 ***	0.73 **	0.80 *	0.81 *
Hard, Payment cards (am)[d] & Soft	0.63 **	0.80	0.77 *	0.78 *	0.79 *	0.67 **	0.77 **	0.84	0.88
Hard & Soft	0.66 **	0.80	0.76 *	0.86	0.82	0.72 **	0.85	0.89	0.95
Hard & Google (durables)	0.74 *	0.88	0.82	0.85	0.86	0.78 *	0.78 *	0.85	0.84

Notes:
The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the quarterly random walk alternative. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
a. Nowcast/forecast errors computed as the difference to the 2018Q1 vintage of private consumption data. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$).
b. Social Security Registrations; Retail Trade Index; Activity Services Index.
c. PMI Services; Consumer Confidence Index.
d. Aggregate of payment cards via POS and ATMs.
e. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

Table A.2: Pairwise relative RMSEs and Diebold-Mariano tests: nowcasts. Nowcast errors are computed as the difference to the 2018Q1 vintage of private consumption data.

Nowcast origin - $m1$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.19	1.01	1.33*	0.94	0.95	0.98	1.52**	1.78**	1.58**
Quantitative[a] [2]	—	0.71*	0.94	0.67**	0.67**	0.69**	1.07	1.26	1.11
Qualitative[b] [3]	—	—	1.32***	0.94	0.94	0.97	1.50**	1.76***	1.56***
Payment cards[c] [4]	—	—	—	0.71***	0.71**	0.74**	1.14	1.33*	1.18
Uncertainty[d] [5]	—	—	—	—	1.00	1.04	1.61***	1.88***	1.67***
Google[e] [6]	—	—	—	—	—	1.04	1.60***	1.87***	1.66***
Comb: All models[f] [7]	—	—	—	—	—	—	1.55***	1.81***	1.60***
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	1.17	1.04
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.89

Nowcast origin - $m2$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.29**	0.98	1.11	0.77*	0.90	0.91	1.26*	1.31*	1.25
Quantitative[a] [2]	—	0.76	0.87	0.60***	0.70*	0.71*	0.98	1.02	0.97
Qualitative[b] [3]	—	—	1.14	0.79**	0.92	0.93	1.29*	1.34*	1.28**
Payment cards[c] [4]	—	—	—	0.69***	0.81*	0.82	1.14	1.18	1.12
Uncertainty[d] [5]	—	—	—	—	1.17	1.17	1.64***	1.70***	1.61***
Google[e] [6]	—	—	—	—	—	1.01	1.40**	1.46**	1.38**
Comb: All models[f] [7]	—	—	—	—	—	—	1.39**	1.45**	1.37**
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	1.04	0.99
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.95

Nowcast origin- $m3$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.40**	0.98	1.06	0.79*	0.89	0.91	1.32*	1.38**	1.30*
Quantitative[a] [2]	—	0.70	0.76	0.57***	0.64**	0.65*	0.94	0.99	0.93
Qualitative[b] [3]	—	—	1.08	0.81*	0.91	0.92	1.34*	1.41*	1.33**
Payment cards[c] [4]	—	—	—	0.74**	0.84	0.85	1.24*	1.30**	1.23**
Uncertainty[d] [5]	—	—	—	—	1.13	1.15	1.67***	1.75***	1.65***
Google[e] [6]	—	—	—	—	—	1.02	1.48***	1.55**	1.46**
Comb: All models[f] [7]	—	—	—	—	—	—	1.46***	1.53**	1.44**
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	1.05	0.99
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.94

Notes:
Each cell shows the relative RMSE of the model in its horizontal line as compared to the model in the vertical column.The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the method in the vertical column. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from 2008Q1 ($m1$) to 2017Q4 ($m3$). Nowcast/forecast errors are computed as the difference to the first released vintage of private consumption data.
a. Social Security Registrations; Retail Trade Index; Activity Services Index.
b. PMI Services; Consumer Confidence Index.
c. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
d. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
e. Google Trends, durables' goods indicator (lagged).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.
g. Combination of Quantitative (see note a) & Google Trends, durables' goods indicator (lagged).

Table A.3: Pairwise relative RMSEs and Diebold-Mariano tests: 1-quarters-ahead forecasts. Forecast errors are computed as the difference to the 2018Q1 vintage of private consumption data.

Forecast origin - $m1$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]^g
Q-Random Walk [1]	1.34**	0.85	1.31*	1.02	0.92	0.95	1.30*	1.50**	1.28*
Quantitative^a [2]	—	0.72**	1.11	0.87	0.78**	0.81*	1.10	1.27**	1.08
Qualitative^b [3]	—	—	1.54***	1.20**	1.08	1.12	1.52***	1.76***	1.50***
Payment cards^c [4]	—	—	—	0.78***	0.70***	0.73***	0.99	1.15	0.98
Uncertainty^d [5]	—	—	—	—	0.90	0.93	1.27***	1.47***	1.25**
Google^e [6]	—	—	—	—	—	1.04*	1.41***	1.63***	1.39***
Comb: All models^f [7]	—	—	—	—	—	—	1.36***	1.58***	1.34***
Comb: Quant.^{a} & Cards^c [8]	—	—	—	—	—	—	—	1.16***	0.99
Comb: Quant.^{a} & Qual.^{b} [9]	—	—	—	—	—	—	—	—	0.85***

Forecast origin - $m2$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]^g
Q-Random Walk [1]	1.20	0.95	1.21	1.00	0.96	0.98	1.28*	1.36**	1.27*
Quantitative^a [2]	—	0.79*	1.01	0.83	0.80*	0.82*	1.07	1.14	1.06
Qualitative^b [3]	—	—	1.27**	1.05	1.01	1.03	1.35**	1.43***	1.34***
Payment cards^c [4]	—	—	—	0.83*	0.80**	0.81*	1.06	1.13*	1.05
Uncertainty^d [5]	—	—	—	—	0.96	0.98	1.28**	1.36**	1.27**
Google^e [6]	—	—	—	—	—	1.02	1.33***	1.42***	1.32***
Comb: All models^f [7]	—	—	—	—	—	—	1.31**	1.39***	1.30***
Comb: Quant.^{a} & Cards^c [8]	—	—	—	—	—	—	—	1.06	0.99
Comb: Quant.^{a} & Qual.^{b} [9]	—	—	—	—	—	—	—	—	0.93

Forecast origin- $m3$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]^g
Q-Random Walk [1]	1.34	0.95	1.31*	1.03	0.96	0.98	1.46**	1.71***	1.50***
Quantitative^a [2]	—	0.71*	0.98	0.76	0.71*	0.73*	1.08	1.27*	1.11
Qualitative^b [3]	—	—	1.38***	1.08	1.01	1.03	1.53***	1.80***	1.58***
Payment cards^c [4]	—	—	—	0.78*	0.73**	0.75**	1.11	1.30*	1.14
Uncertainty^d [5]	—	—	—	—	0.93	0.96	1.42**	1.66***	1.46**
Google^e [6]	—	—	—	—	—	1.02	1.52***	1.78***	1.56***
Comb: All models^f [7]	—	—	—	—	—	—	1.48***	1.74***	1.52***
Comb: Quant.^{a} & Cards^c [8]	—	—	—	—	—	—	—	1.17**	1.03
Comb: Quant.^{a} & Qual.^{b} [9]	—	—	—	—	—	—	—	—	0.88

Notes:

Each cell shows the relative RMSE of the model in its horizontal line as compared to the model in the vertical column.The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the method in the vertical column. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.

We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from 2008Q1 ($m1$) to 2017Q4 ($m3$). Nowcast/forecast errors are computed as the difference to the first released vintage of private consumption data.

a. Social Security Registrations; Retail Trade Index; Activity Services Index.

b. PMI Services; Consumer Confidence Index.

c. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.

d. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).

e. Google Trends, durables' goods indicator (lagged).

f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

g. Combination of Quantitative (see note a) & Google Trends, durables' goods indicator (lagged).

Table A.4: Pairwise relative RMSEs and Diebold-Mariano tests: 4-quarters-ahead forecasts. Forecast errors are computed as the difference to the 2018Q1 vintage of private consumption data.

Forecast origin - $m1$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.19	0.95	1.42**	1.39**	1.11	1.24*	1.48***	1.38**	1.30**
Quantitative[a] [2]	—	0.86	1.28	1.25	1.00	1.11	1.33	1.24*	1.16
Qualitative[b] [3]	—	—	1.49***	1.46***	1.17	1.29*	1.55***	1.44**	1.36***
Payment cards[c] [4]	—	—	—	0.98	0.78**	0.87	1.04	0.97	0.91
Uncertainty[d] [5]	—	—	—	—	0.80***	0.89	1.06	0.99	0.93
Google[e] [6]	—	—	—	—	—	1.11***	1.33***	1.24*	1.16*
Comb: All models[f] [7]	—	—	—	—	—	—	1.20**	1.11	1.05
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.93	0.88**
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.94

Forecast origin - $m2$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.11	0.93	1.23	1.22	1.05	1.13	1.36**	1.25*	1.19
Quantitative[a] [2]	—	0.83	1.11	1.09	0.94	1.01	1.22	1.12	1.07
Qualitative[b] [3]	—	—	1.33***	1.31**	1.13	1.22**	1.46***	1.35***	1.28***
Payment cards[c] [4]	—	—	—	0.99	0.85*	0.91	1.10	1.01	0.96
Uncertainty[d] [5]	—	—	—	—	0.86	0.93	1.12	1.03	0.98
Google[e] [6]	—	—	—	—	—	1.07	1.30***	1.19*	1.13*
Comb: All models[f] [7]	—	—	—	—	—	—	1.20**	1.11	1.05
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.92	0.87**
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.95

Forecast origin - $m3$

	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10][g]
Q-Random Walk [1]	1.07	0.82	1.19	1.26*	1.02	1.13	1.35**	1.24*	1.14
Quantitative[a] [2]	—	0.76	1.11	1.17	0.95	1.05	1.26	1.15	1.06
Qualitative[b] [3]	—	—	1.46**	1.54***	1.25*	1.38**	1.65***	1.52**	1.40***
Payment cards[c] [4]	—	—	—	1.05	0.85	0.94	1.13	1.04	0.96
Uncertainty[d] [5]	—	—	—	—	0.81**	0.90	1.08	0.99	0.91
Google[e] [6]	—	—	—	—	—	1.10**	1.32***	1.22	1.12
Comb: All models[f] [7]	—	—	—	—	—	—	1.20**	1.10	1.02
Comb: Quant.[a] & Cards[c] [8]	—	—	—	—	—	—	—	0.92	0.85**
Comb: Quant.[a] & Qual.[b] [9]	—	—	—	—	—	—	—	—	0.92

Notes:

Each cell shows the relative RMSE of the model in its horizontal line as compared to the model in the vertical column.The asterisks denote the Diebold Mariano test results for the null hypothesis of equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in its horizontal line as compared to the method in the vertical column. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.

We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from 2008Q1 ($m1$) to 2017Q4 ($m3$). Nowcast/forecast errors are computed as the difference to the first released vintage of private consumption data.

a. Social Security Registrations; Retail Trade Index; Activity Services Index.

b. PMI Services; Consumer Confidence Index.

c. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.

d. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).

e. Google Trends, durables' goods indicator (lagged).

f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

g. Combination of Quantitative (see note a) & Google Trends, durables' goods indicator (lagged).

Table A.5: Pesaran-Timmermann statistic of directional accuracy: sign of private consumption growth rate. Nowcast/forecast errors computed as the difference to the 2018Q1 vintage of private consumption data.[a]

Models including indicators of only one group

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quarterly Random Walk	0.80***	0.90***	0.90***	0.69***	0.79***	0.79***	0.58	0.58	0.58
Quantitative (“hard”) indicators [b]	0.88***	0.83***	0.83***	0.82***	0.82***	0.87***	0.72***	0.72***	0.75***
Qualitative (“soft”) indicators [c]	0.68**	0.75***	0.78***	0.64*	0.69**	0.67**	0.58	0.53	0.56
Payment cards (amounts,am)[d]	0.78***	0.78***	0.80***	0.74***	0.74***	0.79***	0.64*	0.61	0.64*
Payment cards (numbers)[d]	0.75***	0.75***	0.80***	0.62	0.69**	0.82***	0.58	0.72***	0.69**
Uncertainty indicators [e]	0.73***	0.78***	0.78***	0.62*	0.67**	0.69***	0.53	0.53	0.58
Google: aggregate of all indicators	0.30	0.80***	0.80***	0.15	0.41	0.36	0.28	0.19	0.36
Google: durable goods (lagged)	0.73***	0.78***	0.78***	0.59	0.72***	0.72***	0.56	0.56	0.56

Models including indicators from different groups

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative & Qualitative	0.88***	0.88***	0.88***	0.82***	0.82***	0.85***	0.72***	0.69***	0.69***
Quantitative & Payment cards (am)[d]	0.83***	0.88***	0.83***	0.79***	0.82***	0.82***	0.69***	0.69***	0.69***
Quantitative & Uncertainty	0.70***	0.78***	0.80***	0.85***	0.79***	0.79***	0.53	0.58	0.56
Quantitative & Google (aggregate)	0.78***	0.78***	0.75***	0.69***	0.67**	0.77***	0.72***	0.61	0.78***
Quantitative & Google (durables)	0.83***	0.83***	0.83***	0.77***	0.77***	0.79***	0.72***	0.64*	0.69***

Combination of models

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
All models [f]	0.83***	0.85***	0.88***	0.74***	0.82***	0.85***	0.64**	0.58	0.69***
Hard & Payment cards (am)[d]	0.83***	0.83***	0.83***	0.85***	0.82***	0.85***	0.64**	0.67**	0.72***
Hard, Payment cards (am)[d] & Soft	0.78***	0.80***	0.83***	0.74***	0.77***	0.82***	0.56	0.58	0.64**
Hard & Soft	0.78***	0.85***	0.85***	0.69***	0.79***	0.77***	0.58	0.61*	0.56
Hard & Google (durables)	0.83***	0.88***	0.85***	0.77***	0.77***	0.79***	0.64**	0.67**	0.69***

Notes:
The asterisks denote the PT test results for the null hypothesis. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
a. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$).
b. Social Security Registrations; Retail Trade Index; Activity Services Index.
c. PMI Services; Consumer Confidence Index.
d. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
e. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

Table A.6: Pesaran-Timmermann statistic of directional accuracy: acceleration/deceleration of private consumption. Nowcast/forecast errors computed as the difference to the 2018Q1 vintage of private consumption data.[a]

Models including indicators of only one group

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quarterly Random Walk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Quantitative ("hard") indicators [b]	0.55	0.73***	0.73***	0.54	0.54	0.62**	0.56	0.53	0.53
Qualitative ("soft") indicators [c]	0.48	0.55	0.55	0.49	0.54	0.56	0.64**	0.47	0.50
Credit cards: POS+ATM, amounts	0.55	0.63*	0.65**	0.59	0.67**	0.64**	0.53	0.50	0.50
Credit cards: POS+ATM, numbers	0.55	0.53	0.53	0.54	0.51	0.56	0.64**	0.61*	0.61*
Uncertainty indicators [d]	0.50	0.38	0.48	0.38	0.44	0.46	0.53	0.50	0.47
Google: aggregate of all indicators	0.53	0.55	0.55	0.59*	0.59*	0.56	0.53	0.44	0.50
Google: durable goods (lagged)	0.48	0.53	0.53	0.46	0.46	0.49	0.64**	0.67**	0.67**

Models including indicators from different groups

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
Quantitative & Qualitative	0.63*	0.68***	0.63**	0.51	0.56	0.64**	0.64*	0.64*	0.64*
Quantitative & POS+ATM amounts	0.58	0.68***	0.68***	0.51	0.49	0.59*	0.64**	0.69***	0.67**
Quantitative & Uncertainty	0.45	0.68**	0.70***	0.59*	0.56	0.62*	0.44	0.53	0.56
Quantitative & Google (aggregate)	0.65**	0.68**	0.60*	0.46	0.56	0.59	0.69***	0.67**	0.67**
Quantitative & Google (durables)	0.48	0.65**	0.65**	0.59*	0.59*	0.62**	0.50	0.53	0.53

Combination of models

	Nowcast			1-q-ahead			4-q-ahead		
	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$	$m1$	$m2$	$m3$
All models [e]	0.60	0.68***	0.65**	0.59*	0.62**	0.64**	0.61*	0.58	0.56
Hard & POS+ATM amounts	0.50	0.78***	0.78***	0.56	0.64**	0.59	0.58	0.53	0.53
Hard, POS+ATM amounts & Soft	0.65**	0.60*	0.73***	0.62*	0.62*	0.69***	0.58	0.58	0.39
Hard & Soft	0.58	0.63*	0.63**	0.54	0.59	0.67**	0.53	0.53	0.36
Hard & Google (durables)	0.60*	0.65**	0.68***	0.54	0.59*	0.62**	0.67**	0.58	0.58

Notes:
The asterisks denote the PT test results for the null hypothesis. A single (double) [triple] asterisk denotes rejection of the null hypothesis at the 10% (5%) [1%] level of significance.
a. Forecasts generated recursively over the moving window 2008Q1 ($m1$) to 2017Q4 ($m3$).
b. Social Security Registrations; Retail Trade Index; Activity Services Index.
c. PMI Services; Consumer Confidence Index.
d. Aggregate of payment cards via POS and ATMs, amounts paid and withdrawn.
e. Stock Market Volatility (IBEX); Economic Policy Uncertainty Index (EPU).
f. Combination of the results of 30 models, that include models in which the indicators of each block are included separately, models that include the quantitative block and each other block, and version of all the previous models but including lags of the variables.

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