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Torsten Schmidt and Simeon Vosen[1]

A monthly consumption indicator for Germany based on internet search query data

Abstract

In this study we introduce a new monthly indicator for private consumption in Germany based on search query time series provided by Google Trends. The indicator is based on unobserved factors extracted from a set of consumption-related search categories of the Google Trends application Insights for Search. The predictive performance of the indicator is assessed in real time relative to the European Commission's consumer confidence indicator and the European Commission's retail trade confidence indicator. In out-of-sample nowcasting experiments the Google indicator outperformed the survey-based indicators. In comparison to the other indicators, the new indicator also provided substantial predictive information on consumption beyond that already captured in other macroeconomic variables.

JEL classification: C53, E21, E27

Keywords: Google Trends, Private Consumption, Forecasting, Consumer Sentiment Indicator

October 2010

1 Both RWI, Hohenzollernstr. 1-3, D-45128 Essen, Germany - This paper initiated in a project to the German Federal Ministry of Finance. We thank Thomas K. Bauer, Roland Döhrn and Hal. C. Varian for helpful comments and advise, György Barabas and Karl-Heinz Herlitschke for technical support.-All correspondence to Simeon Vosen, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: simeon.vosen@rwi-essen.de.

I. Introduction

Since private consumption represents about 60 percent of German Gross Domestic Product (GDP), timely information about consumer spending is important to assess and predict overall economic activity. Data on German private consumption are published quarterly and with a lag of two month. Leading indicators can therefore be helpful not only in predicting the future but also by allowing better predictions for current unobserved consumption (nowcasts). This study introduces a new monthly consumption indicator for Germany that is based on search query data provided by Google Trends.

Conventional leading indicators for private consumption are typically sentiment indicators based on household surveys. These indicators try to account for both economic and psychological (Katona, 1951) aspects of consumer behaviour by asking households to assess their own and the general economy's current and upcoming economic conditions. However, there is little consensus in the empirical literature about these indicators' ability to collect information that is not already captured in fundamental macroeconomic variables such as income, wealth and interest rates. Fuhrer (1993) finds that in the US roughly 70 percent of the variation in the Michigan Consumer Sentiment Index (MCSI) can be explained by other macroeconomic variables, suggesting that a large part of consumers' sentiment might simply reflect their knowledge of general economic conditions. Carroll et al. (1994) and Ludvigson (2004) find in in-sample regressions that consumer sentiment indicators nevertheless have explanatory power for US consumption additional to that contained in other macroeconomic variables. Croushore (2005) on the other hand, using real-time data for out-of-sample forecasting experiments, finds that the MCSI and the Conference Board Consumer Confidence Index are not of significant value in forecasting consumer spending. Research on consumption indicators for European countries – except for the UK – is rather rare. Nahuis and Jansen (2004) examined the in-sample explanatory power of the European Commission's consumer confidence and retail confidence indicators for eight European countries. They found that for most countries – including Germany – both indicators embody valuable information. However, the out-of-sample explanatory power was not examined in this study.

This paper introduces a new monthly indicator for private consumption in Germany, which is constructed using data on internet search behaviour provided by Google Trends. The study builds on Schmidt and Vosen (2009) in which Google Trends data were used to predict US private consumption. Other applications of Google Trends data include Choi and Varian (2009a, 2009b) who conducted nowcasting experiments for retail, auto, and home sales, travel and initial unemployment claims using search categories of Google Insights for Search. Ginsberg et al. (2009) used large numbers of Google Trends search queries to estimate the current level of influenza activity in the US. Askitas and Zimmermann (2009) found selected queries associated with job search activity to be useful in forecasting the German unemployment rate.

Due to the increasing popularity of the internet, it is quite certain that a substantial amount of people use the internet to collect information on goods they intend to buy. Reflecting the research and selection phase of the consumption process, data on web search queries as provided by Google Trends might be even closer related to actual spending decisions of private households than data on consumer sentiment. To employ the Google data for consumption forecasts, we extract common unobserved factors from time series of web search categories of the Google Trends application *Insights for Search*. The Google-Indicator then reflects nowcasts of real monthly consumption that are made based on these factors.

The new indicator's usefulness to economic forecasters is assessed by testing to what extent the Google factors improve an iterated autoregressive model compared to common survey-based sentiment indicators. Any new indicator for private consumption should also be examined with regard to its ability to improve forecasting models that already contain other macroeconomic variables. We therefore repeat the exercise using a model that includes several other macroeconomic variables related to consumer spending. To get a realistic impression of the indicators' usefulness in actual forecasting, real-time data are used in all experiments.[1]

The remainder of this paper is structured as follows: The next section describes the data, the Google indicator and the survey-based indicators used as benchmark

[1] Diebold and Rudebusch (1991) demonstrated the particular importance of using real-time data for indicator constructions and evaluations. They showed that the good track record of the U.S. index of leading economic indicators in predicting recessions was mainly due to the fact that the index was constructed to fit the past. In several revisions over time, components were added or removed in order to improve the index's performance retrospectively. If assessed using real-time data, its performance deteriorated substantially, suggesting that its high predictive ability ex-post was merely spurious. The use of latest available data for indicator construction can therefore lead to an inclusion of variables that have only little predictive power in real time.

indicators. Section 3 describes the nowcasting methodology and the empirical approach to assess the predictive accuracy of the Google indicator. Section 4 presents the results. Section 5 concludes.

II. Indicators and data

According to a survey by the German Federal Statics Office (Destatis, 2009), 86 % of the German internet users in 2009 used the internet to obtain information on products and services. This share has been rising continuously. In 2006 it was still at 83 %. 56 % of all persons and 75 % of those who used the internet in 2009:Q1 have already purchased products and services online. In addition, 40 % of all persons and 55 % of the internet users in 2009:Q1 had conducted online purchases within the last three month before the interview, suggesting a high frequency of online purchases. Search engines should play a substantial role in gathering information on the internet as well as online-shopping. This applies in particular to Google's search engine, which has an almost monopolistic position among search engines in Germany.[2]

Google Trends provides an index of the relative volume of search queries conducted through Google. The *Insights for Search* application of Google Trends provides aggregated indices of search queries which are classified into 27 main categories which contain a total of 578 sub-categories on two further levels using

[2] According to the web statistics provider Webhits (2010), Google currently has a market share of 90 %. See: http://www.webhits.de/deutsch/index.shtml?webstats.html, downloaded on June 25th, 2010.

an automated classification engine.[3] We selected 46 consumption-relevant categories that constitute best matches for the components of private consumption in the national accounts of the Federal Statistics Office (Table 1).[4] To avoid multiple usage of the same information, only series from either main categories or sub categories were used.

The Google time series are not subject to revisions but the data are based on random samples. This means, when a query is send to Google Insights for Search, the software underlying the Google Trends application draws a random sample from all search queries conducted through the Google search engine. Google caches the data for a given day, so that samples drawn on the same day don't differ. However, there is some non-negligible variation between samples drawn on different days. This poses a potential problem for our purposes as the identified model parameters can vary with the respective data samples. For our estimations, we addressed this problem by using averages of 52 samples drawn on different days. This exercise, which is similar to bootstrapping, enabled us to indirectly increase the sample size and thus obtain much more stable and reproducible estimates.

Google Trends data are provided on a weekly basis. However, we only used monthly averages since the data on other indicators and macroeconomic variables

[3] See http://www.google.com/insights/search/?hl=en-US# for a comprehensive description.

[4] This approach is based on Choi and Varian (2009a) who assigned search categories to components of US retail sales. We think that using search categories more useful for our purposes than using specific key words. The latter are likely to be more vulnerable to shocks caused by special events unrelated to consumption which could bias the indicator.

used in our nowcasting models are on a monthly basis. The Google time series are not seasonally adjusted. It is, however, hardly possible to compute accurate seasonal factors because the data is available only back to 2004 and economic development has been quite turbulent in the past 2 years due to the financial and subsequent economic crisis. Therefore year on year growth rates were used instead of seasonally adjusted data in levels or monthly growth rates. A disadvantage of this approach is, of course, that 12 months of observations are lost.

To use as much information from the Google data as possible without running out of degrees of freedom in our forecasting models, we extracted common unobserved factors from the Google data and used these factors as exogenous variables in our regression. To extract the factors, the method of principal components analysis was employed. The number of factors to be included into the forecasting model was selected through a scree-test (Cattell, 1966) using the complete sample of data (Fig. 1). This criterion suggested retaining three factors which explain 50 % of the total variance of the 46 Google time series. Following a similar exercise of Stock and Watson (2002) table 2 displays the average factor loadings of the Google categories grouped by components of private consumption. This rough characterization suggests that the first factor loads primarily on “traffic and transportation”, “education”, and “alcoholic beverages and tobacco products”; the second, on “telecommunication” (with negative sign), “food and non-alcoholic beverages”, and “hotel and restaurant services” (with negative sign); and the third, again on “hotel and restaurant services” (with positive sign), “traffic and transportation”, and “housing water, electricity, gas and other fuels”.

Two survey-based indicators are used as benchmark indicators: The European Commission’s consumer confidence (CCI) and retail trade confidence indicators (RTI). The CCI is a composite indicator which is based on surveys conducted by the German market research institute GfK on behalf of the European Commission. The CCI is derived from four forward looking questions that cover expectations of a household’s own economic situation as well as the general economy:

- How do you expect the financial position of your household to change over the next 12 months?
- How do you expect the general economic situation in this country to develop over the next 12 months?
- How do you expect the number of people unemployed in this country to change over the next 12 months?
- Over the next 12 months, how likely is it that you save any money?

The RTI is based on surveys of retail traders. Nahuis and Jansen (2004) showed that perceptions of sellers of consumption goods, measured by retail trade surveys, may also improve short-term monitoring of consumption. Although the retail trade sector accounts for just about 30 % of total consumer expenditures in Germany, its share of the cyclical part of consumption has been much bigger. We therefore used the RTI as a second benchmark indicator. It is based on the following three questions from the retail trade survey:

- How has (have) your business activity (sales) developed over the past 3 months?
- Do you consider the volume of stock you currently hold to be too large/adequate/too small?
- How do you expect your orders placed with suppliers to change over the next 3 months?

Both survey-based indicators are constructed by averaging the scores obtained for the respective questions which are computed as the balances of positive and negative answers. The correlation coefficients between consumption growth and the survey-based indicators are higher if the latter are used in levels rather than growth rates. Unlike the Google indicator, the survey-based indicators therefore enter the forecasting equations in levels.

Destatis publishes only quarterly consumption data. It was our intention, however, to construct an indicator that reflects estimates of monthly consumption. Since the Google time series only go back to 2004, estimating the forecasting models on monthly basis was also highly desirable as otherwise the sample-size would have been rather small. We therefore employed the random walk-Markov model of Litterman (1983) to generate a consumption time series at monthly frequency. This disaggregation method builds on the linear disaggregation procedures of Chow and Lin (1971) and Fernández (1981) using related monthly time series as indicator of the monthly dynamics of the quarterly series.[5]

Monthly series on real turnover in retail trade, which accounts for about a third of German consumption, are a natural candidate for the required reference indicator series. We used a series of turnover in retail trade published by Destatis that also includes automobile trade, which accounts for another ten percent of German consumption. Figure 2 shows the quarterly aggregates of this composite monthly indicator series and quarterly consumption between 1994:Q1 and 2010:Q2. For this period, the correlation coefficient between the quarterly aggregates of this monthly indicator series and quarterly consumption is 0.52 which does not indicate a strong correlation. The indicator series is nevertheless helpful, as retail trade accounts for much of consumption's seasonal pattern. Figure 3 plots the time series in first differences. The corresponding correlation coefficient is 0.93. The Litterman method does not require cointegration relationships between the two series (which Engle-Granger tests did not indicate in our case). By modelling the disturbance terms as ARIMA(1,1,0) processes, it corrects the serial correlation in the residuals of the lower frequency estimates. It should therefore allow us to get adequate estimates of monthly consumption. To obtain the real-time data of monthly consumption, we compiled a real-time data set of turnover in retail-trade including automobile trade that goes back to 1994 and is available upon request.

[5] Moauro and Savio (2005) carried out an extensive empirical comparison among methods of timely disaggregation using seasonally unadjusted data. They find that Litterman's approach outperforms both other standard univariate disaggregation methods. The paper also demonstrated that structural time series models formulated in state space representation can produce even better results than univariate models. However, these methods are not yet fully corroborated by empirical applications (Chen, 2007, Hall and McDermott, 2009).

III. Nowcasting methodology

To determine the predictive power of the Google factors relative to that of the survey-based indicators, a simple iterated AR(4) model of consumption growth is first estimated as a baseline model. Nowcasts for the current month t are made at each month's end. Quarterly data for private consumption, which can be disaggregated to monthly data, are published with a lag of two month. Let m be the number of month since the end of the quarter. Then m=2 is the first month in which nowcasts can be made using the newest consumption data lasting until m=0. For nowcasts in m=2 an intermediate nowcast for m=1 is first computed using a simple AR(4) model:

$$\hat{C}_t^{m=1} = \hat{\alpha} + \sum_{i=1}^{4} \hat{\beta}_i C_{t-i} \, , \tag{1}$$

where $\hat{C}_t$ denotes the nowcasts of the monthly year-on-year growth rates of real private consumption. Subsequently, consumption in m=2 is nowcasted again through an AR(4) model using the one-period ahead nowcast for the intervening period. For m=3 and m=4 we proceed analogously:

$$\hat{C}_{t|t-m} = \hat{\alpha} + \sum_{i=m}^{4} \hat{\beta}_i C_{t-i} + \sum_{i=1}^{m-1} \hat{\chi}_i \hat{C}_{t-i|t-m} \, . \tag{2}$$

The models thus differ depending on the month in which the nowcasts are made. Figure 3 sketches the time structure of nowcasting. Next, the survey-based consumer confidence indicator, the retail trade confidence indicator, and the Google factors respectively are added to the baseline model in order to explore to what extent its predictive power is improved by these indicators alone. We always include current values and two lags of the indicators. Again, for the indicator augmented model an intermediate nowcast is made first for m=1:

$$\hat{C}_t^{m=1} = \hat{\alpha} + \sum_{i=1}^{3} \hat{\beta}_i C_{t-i} + \sum_{i=0}^{2} \hat{\gamma}_i G_{t-i}^k \,, \tag{3}$$

where G^k denotes the respective indicator. The iterated nowcasts for m=2,3,4 are made as in equation (2):

$$\hat{C}_{t|t-m} = \hat{\alpha} + \sum_{i=m}^{4} \hat{\beta}_i C_{t-i} + \sum_{i=1}^{m-1} \hat{\chi}_i \hat{C}_{t-i|t-m} + \sum_{i=0}^{2} \hat{\gamma}_i G_{t-i}^k \,. \tag{4}$$

To assess whether these indicators provide information beyond that already captured in other macroeconomic variables typically embedded in forecasting models, an extended baseline model that also includes selected macroeconomic variables is estimated subsequently. Since the selection of these variables is somewhat arbitrary, we refer to the consumption models of Carrol et al. (1994), Bram and Ludvigson (1998) and Croushore (2005) that are widely applied in the literature and add measures of real income and interest rates as additional variables to equation (1).[6] The income measure that becomes first available with a publication lag of two month, are monthly negotiated wages and salaries (w). Due

[6] Initially, the DAX as a proxy for wealth was also included, but dropped as it was insignificant and reduced the forecasting performance of the extended baseline model.

to its timely availability by the end of each month, the consumer price index is used as deflator. In addition, interest rates on three-month treasury bills (r) are included in the extended model. The latter two variables are also available by the end of each month. For the interest rates, the year-on-year differences are used, for all other macroeconomic variables year-on-year growth rates. To keep the models parsimonious, only the latest available values and one additional lag are considered. For m=1 the extended model takes the form:

$$\hat{C}_t^{m=1} = \hat{\alpha} + \sum_{i=1}^{3} \hat{\beta}_i C_{t-i} + \sum_{i=1}^{2} \hat{\delta}_i w_{t-i} + \sum_{i=0}^{1} \hat{\phi}_i r_{t-i} \tag{5}$$

and for m=2,3,4

$$\hat{C}_{t|t-m} = \hat{\alpha} + \sum_{i=m}^{4} \hat{\beta}_i C_{t-i} + \sum_{i=1}^{m-1} \hat{\chi}_i \hat{C}_{t-i|t-m} + \sum_{i=2}^{3} \hat{\delta}_i w_{t-i} + \sum_{i=0}^{1} \hat{\phi}_i r_{t-i} \,. \tag{6}$$

Finally the extended model is again augmented with the indicators already discussed for the baseline model. This gives us a total of eight nowcasting models to be assessed – four based on the simple baseline model and four based on the extended model.

Real-time out-of-sample nowcasting experiments were conducted using recursive methods to determine to what extent the indicators help nowcasting movements in consumer spending.[7] Nowcasts were evaluated for the period from February 2008 (in which data on quarterly consumption in the 2007:Q4 was released)

[7] Though a rolling window can better account for structural shifts, it would be inappropriate given the small sample size.

to June 2010. For the initial February 2008 nowcasts, the models were first estimated using the data from January 2004 to December 2007.[8] Subsequently the intermediate nowcasts for January 2008 were computed. For the remaining nowcasts we extended the estimation period by one month at a time, re-estimate the models and thus obtain a series of nowcasts.

IV. Empirical results

Table 3 displays the results of the out-of-sample experiments. The nowcasts of the indicator augmented models are evaluated by their mean squared errors (MSE). The table also displays the prediction errors of the quarterly nowcasts that result from aggregating the monthly predictions. In computing the respective MSEs we used the first releases (diagonal of the real-time data matrix) rather than the latest available data as "actuals".[9] For the simple and the extended baseline models and for both monthly and quarterly nowcasts, the Google-model performed best, producing MSEs that are 3 to 71 % lower than the ones of the other models. In the simple baseline specification, it is the only indicator that improved the baseline AR(4) model. Both other indicators actually deteriorated the predictive performance of the baseline model. The extended model was substantially improved by the Google factors and only slightly by the RTI, which indicates that

[8] For both survey-based indicators earlier data are also available. However, to maintain a basis of comparison across regressions, we use this period as the largest sample for which year-on-year growth rates of all indicators are available.

[9] Although the latest available data may be the best overall measure of the "true" values, early releases may affect the decisions of households, businesses and policy makers much more than the finally revised data released years later. Besides this, forecasters cannot be expected to forecast methodological changes and redefinitions of variables by the statistical agencies publishing the data.

at least the Google indicator contains predictive information beyond that already captured in other macroeconomic variables. Again, the CCI model's predictive accuracy has been much worse. Overall, the Google augmented baseline model produced the lowest MSEs in predicting monthly consumption. For quarterly consumption the extended model augmented with the Google factors performed best.

Significance is determined in table 4 through the Harvey-Leybourne-Newbold (1997) modification of the Diebold-Mariano (1995) test statistic for equal forecast accuracy. Only the indicator-augmented models are compared with one another, since in recursive experiments the Diebold-Mariano statistic is only applicable to non-nested models. Relative MSEs lower than one indicate that the first model outperforms the second one. The Diebold-Mariano statistic has a student's t-distribution and shows whether differences in MSEs are statistically significant. The table shows that although the Google model outperformed all other indicators, the Diebold-Mariano statistics are not significant if the simple baseline model was used. If the extended model was used instead, the Google model significantly outperformed the CCI model. If compared with the RTI model, differences are again not significant.

Figure 5 provides a visual impression of real consumption as predicted by the Google model and the actual values. Overall, the co-movement looks quite remarkable. Apart from some overshooting in December 2007 and January 2008 and an underestimated consumption drop in early 2010 the Google-Indicator's predictions were pretty close to the actual values.[10] In four out of fourteen quarters the actual level of consumer spending was almost exactly predicted by the Google-Indicator.

V. Conclusions

This study showed that a consumption indicator based on internet search query data might be a very attractive alternative to conventional consumption indicators in Germany. In all conducted out-of-sample experiments, the Google indicator's predictive performance was better than that of conventional survey-based indicators, although not all differences were significant. Once longer time series are available and nowcasts can be made based on longer estimation windows, the indicator's predictive power might well be improved even further. Nevertheless, the study should have demonstrated the enormous potential of a consumption indicator, which simply reflects search behaviour on the internet rather than consumer sentiment or macroeconomic conditions.

[10] The former were associated with a base effect caused by a value added tax reform the year earlier, the latter by an unpredictable jump in the consumption deflator that had purely statistical causes.

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Appendix

Figure 1

Scree plot (ordered eigenvalues)

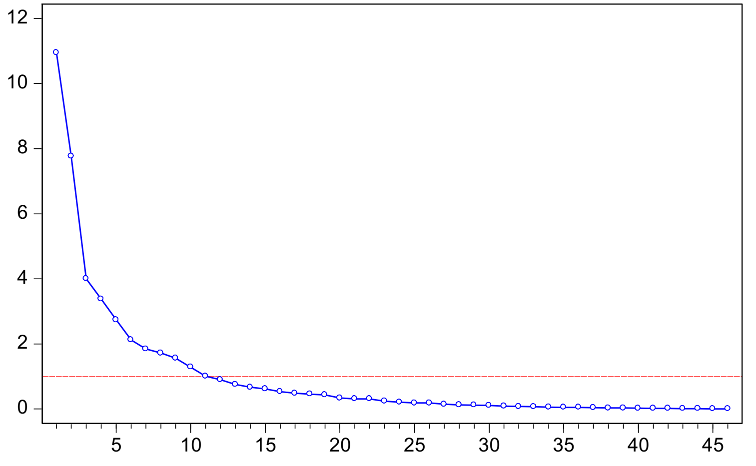
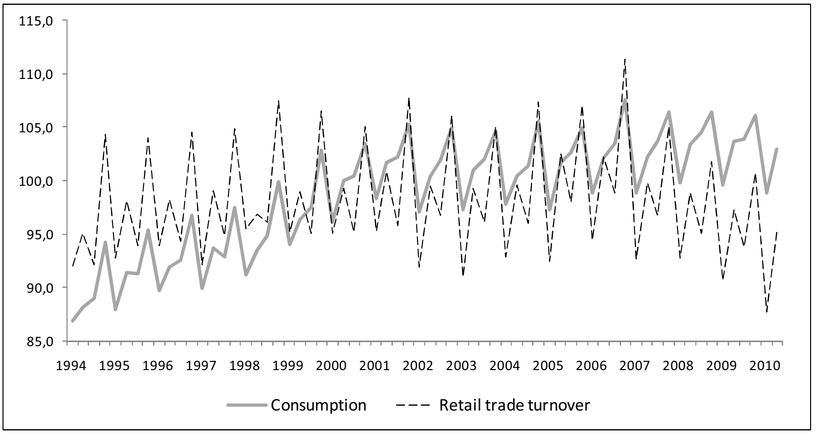


Figure 2

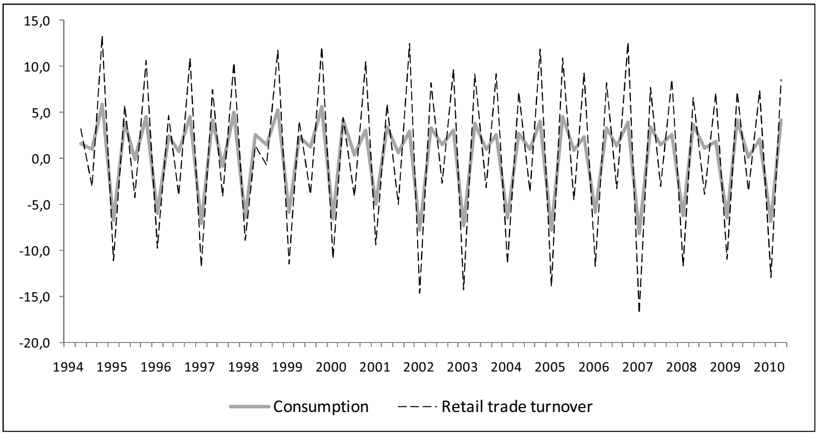
Consumption and quarterly aggregates of real turnover in retail trade



Source: Destatis

Figure 3

Consumption and quarterly aggregates of real turnover in retail trade (first differences)



Source: Destatis

Figure 4

Time structure of nowcasting

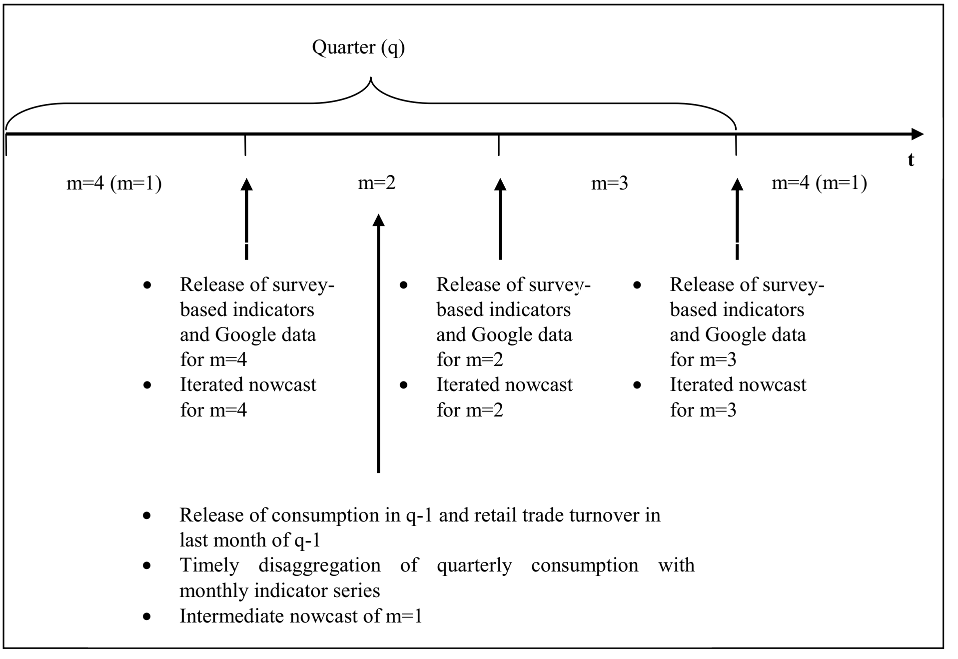


Figure 5

Google indicator (baseline model) and actual levels of real private consumption

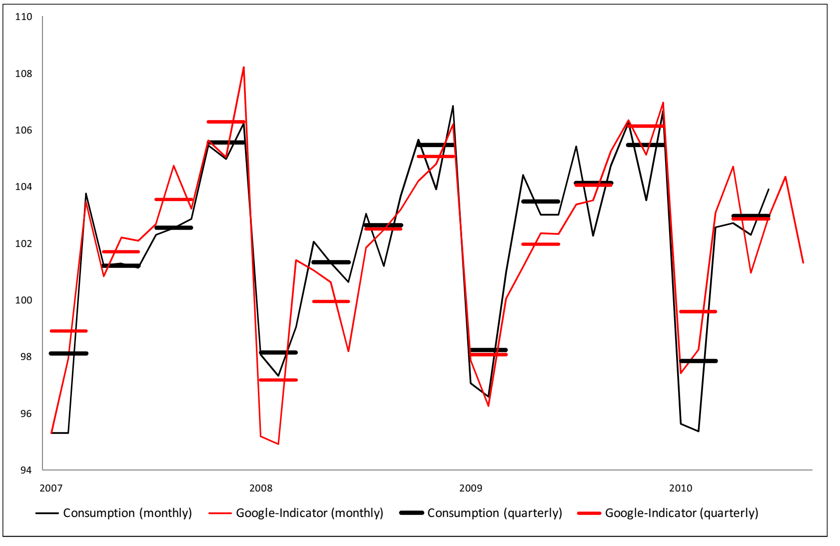


Table 1

Components of private consumption in national accounts and matching Google categories

Component of consumption (National Accounts)	Google categories
Food and non-alcoholic beverages	Food Retailers, Nonalcoholic Beverages
Alcoholic beverages and tobacco products	Alcoholic Beverages, Tobacco Products
Apparel and footwear	Clothing Labels & Designers, Clothing Retailers, Footwear, Lingerie & Undergarments, T-Shirts
Housing, water, electricity, gas and other fuels	Energy & Utilities, Electricity, Oil & Gas, Real Estate Agencies, Home Insurance, Rental Listings & Referrals, Waste Management
Fixtures, household appliances	Home Appliances, Home Furnishings, Home Improvement, Homemaking and Interior Decoration, Interior Design
Health care	Drugs & Medications, Health Insurance, Medical Facilities & Services
Traffic and Transportation	Auto Financing, Auto Parts, Freight & Trucking, Vehicle Brands, Vehicle Shopping
Telecommunication	Mobile & Wireless, Service Providers
Leisure, entertainment, culture	Book Retailers, Consumer Electronics, Entertainment Industry, Movies, Newspapers, Photo & Video, Ticket Sales, Video Games,
Education	Education
Hotel and restaurant services	Hotels & Accommodation, Restaurants
Other	Face & Body Care, Finance & Insurance, Hair Care & Products, Social Services

Table 2

Average factor loadings of Google categories grouped by components of private consumption

Component of consumption (National Accounts)	Average factor loading		
	F1	F2	F3
Food and non-alcoholic beverages	-.01	.11	.12
Alcoholic beverages and tobacco products	.23	-.02	-.07
Apparel and footwear	.04	.09	-.01
Housing, water, electricity, gas and other fuels	.12	.03	.12
Fixtures, household appliances	.10	.05	.01
Health care	.12	.06	-.06
Traffic and Transportation	.15	-.06	.12
Telecommunication	.05	-.16	-.03
Leisure, entertainment, culture	.11	.02	-.09
Education	.24	.01	-.06
Hotel and restaurant services	.13	-.11	.14
Other	.08	-.02	-.06

Table 3

Out-of-sample predictive power (MSE)

	Month		Quarters	
Indicator	Baseline	Extended	Baseline	Extended
No indicator	2.55	2.98	.84	1.15
CCI	2.71	4.52	.92	2.46
RTI	2.62	2.88	.90	1.05
Google	2.25	2.33	.81	.72

Table 4

Relative out-of-sample performance (baseline model)

	Month		Quarters	
	Rel. MSE[1]	DM Statistic[2]	Rel. MSE[1]	DM Statistic[2]
Baseline Model				
Google/CCI	.83	-.92	.86	-.37
Google/RTI	.86	-.88	.89	-.38
Extended Model				
Google/CCI	.52	-1.79**	.30	-1.55*
Google/RTI	.82	-1.11	.70	-.77

[1] Mean squared error of Google model relative to CCI model and RTI model.
[2] Harvey-Leyborne-Newbold (1997) modified Diebold-Mariano test statistic.
*, **, *** denote significance at the 10 %, 5 %, 1 % level.
Hypothesis tests were conducted using a heteroskedasticity and serial correlation robust covariance matrix