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Forecasting Private Consumption: Survey-Based Indicators vs. Google Trends

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ABSTRACT
In this study we introduce a new indicator for private consumption based on search query time series provided by Google Trends. The indicator is based on factors extracted from consumption-related search categories of the Google Trends application Insights for Search. The forecasting performance of the new indicator is assessed relative to the two most common survey-based indicators: the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index. The results show that in almost all conducted in-sample and out-of-sample forecasting experiments the Google indicator outperforms the survey-based indicators. This suggests that incorporating information from Google Trends may offer significant benefits to forecasters of private consumption.

KEY WORDS Google Trends; private consumption; forecasting; consumer sentiment indicators

INTRODUCTION

Since private consumption represents about 70% of US gross domestic product (GDP), timely information about private household spending is important in assessing and predicting overall economic activity. Data on private consumption for the USA are published monthly and with a lag of 1 month. Leading indicators with high frequency can therefore be helpful not only in predicting the future but also the present month (nowcast). The high frequency and the publication lead of these indicators are of particular usefulness to economic forecasters in times of macroeconomic turbulences, great uncertainty or unique shocks when past values of other macroeconomic variables lose predictive power.

The leading indicators that are typically used to predict consumption are survey-based sentiment indicators. These indicators try to account for both economic and psychological[1] aspects of consumer behaviour by asking households to assess their own and the national economy's current and upcoming economic conditions. The empirical literature has long noted a strong correlation between consumer sentiment indicators and consumption in the USA. Indeed, the co-movement of the most

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[1] See Eppright *et al.* (1998) for a discussion of arguments from the economic psychology literature on how consumers' expectations relate to consumption behaviour.

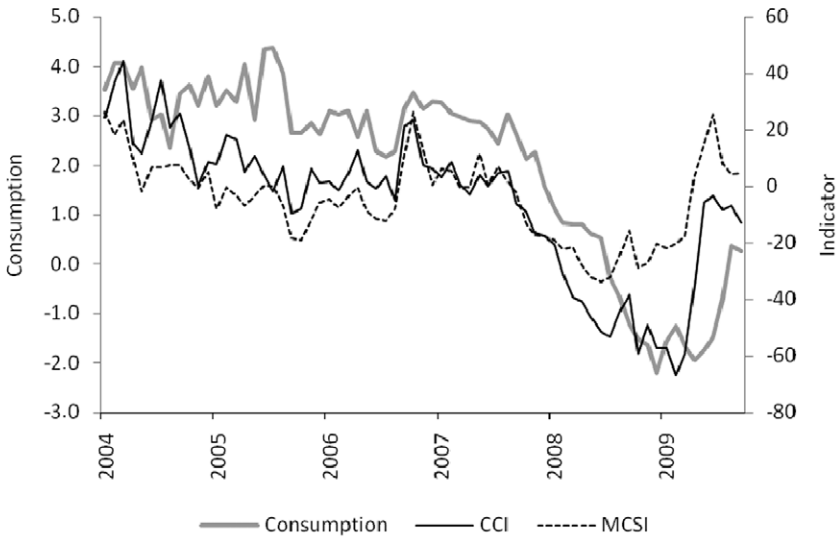

Figure 1. Consumption and survey-based indicators (monthly year-on-year growth rates)

common survey-based consumption indicators—the University of Michigan Consumer Sentiment Index (MCSI) and the Conference Board's Consumer Confidence Index (CCI)—and real consumption looks quite remarkable, although the time-lead of the indicators seems to vary (Figure 1). However, there is little consensus in the empirical literature about these indicators' ability to collect information that is not already captured in macroeconomic fundamentals such as income, wealth and interest rates. Fuhrer (1993) finds that roughly 70% of the variation in the MCSI can be explained by other macroeconomic variables, suggesting that a large part of sentiment might simply reflect respondents' knowledge of general economic conditions. A possible weakness of the survey-based indicators could be that they do not accurately capture the link between expectations and real spending decisions. 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. Other studies, including Croushore (2005), who uses real-time data for out-of-sample forecasting experiments, find that the MCSI and the CCI are not of significant value in forecasting consumer spending.

This paper introduces a new indicator for private consumption which is constructed using data on Internet search behaviour provided by Google Trends. Due to the increasing popularity of the Internet it is certain that a substantial number of people also use web search engines to collect information on goods they intend to buy. In 2008, US e-commerce retail sales (excluding travel) totalled \$132.3 billion, or 3.5% of total retail sales.[2] This share may appear relatively small, but the US market research firm eMarketers estimates that 86% of Internet users are online shoppers, which means they research and compare but not necessarily purchase products online.[3] As a result, eMarketers estimate store sales influenced by online research to be three times higher than e-commerce sales. Data about

[2] According to the Quarterly E-Commerce Report of the US Census Bureau, 4th Quarter, 2008.
[3] See in 'Retail E-Commerce Forecast: Cautious Optimism', June, 2009, http://www.emarketer.com/Report.aspx?code=emarketer_2000565.

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search queries could thus be more related to spending decisions of private households than sentiment indicators. While macroeconomic variables indicate consumers' *ability to spend* and survey-based indicators try to capture consumers' *willingness to spend* (Wilcox, 2007), the Google indicator intends to provide a measure for consumers' *preparatory steps to spend* by employing the volume of consumption-related search queries. Earlier applications of Google Trends data include Choi and Varian (2009a,b), who conducted nowcasting experiments for retail sales, auto sales, home sales, travel and initial unemployment claims using 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 USA. Askitas and Zimmermann (2009) found selected queries associated with job search activity to be useful in forecasting the German unemployment rate. Suhoy (2009) tests for Israel the predictive power of Google Trends queries for industrial production, retail trade, trade and services revenue, consumer imports and services exports, as well as employment rates in the business sector.

To use Google data for forecasting private consumption, common unobserved factors are extracted from time series of web search categories provided by the Google Trends application *Insights for Search*. We assess the new indicator's usefulness to economic forecasters by testing to what extent the Google factors improve a simple autoregressive model compared to common survey-based sentiment indicators. In line with the existing literature on consumption indicators, any new indicator for private consumption should also be assessed with regard to its ability to improve forecasting models that already include other macroeconomic variables. We therefore repeat the exercise using an extended baseline model that includes several other macroeconomic variables related to consumer spending. We conduct in-sample and out-of-sample forecasting experiments using monthly data from January 2005 to September 2009. The results show that in almost all experiments the Google indicator outperforms the survey-based indicators.

The remainder of this paper is structured as follows: The next section describes the data and the respective indicators. The third section presents the empirical approach to assess the forecasting performance of the Google indicator. The fourth section discusses the results. The fifth section concludes.

THE INDICATORS

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 a total of 605 categories and sub-categories using an automated classification engine.[4] We select 56 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 (Table I).[5] Google Trends data are provided on a weekly basis. We compute monthly averages since data on consumption are only available on a monthly basis. The Google time series are not seasonally adjusted. It is, however, hardly possible to compute accurate seasonal factors since data are available only since 2004 and times have been turbulent in the past 2 years due to the

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

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

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Table I. BEA classification of personal consumption expenditures (PCE) and matching Google categories

PCE by major type of product as classified by the national product and income accounts (NIPAs)	Google categories
Durable goods	
Motor vehicles and parts	Automotive, Auto Parts, Auto Financing, Auto Insurance, Vehicle Brands, Vehicle Shopping
Furnishings and durable household equipment	Computers and Electronics, Consumer Electronics, Home Appliances, Home Financing, Home Furnishings, Home and Garden, Home Improvement, Home Insurance, Homemaking and Interior Decoration, Interior Design
Recreational goods and vehicles	Book Retailers, Entertainment, Entertainment Industry, Movies, Video Games
Other durable goods	Book Retailers, Mobile and Wireless, Telecommunications
Nondurable goods	
Food and beverages purchased for off-premise consumption	Alcoholic Beverages, Food and Drink, Food Retailers, Nonalcoholic Beverages
Clothing and footwear	Apparel, Clothing Labels and Designers, Clothing Retailers, Footwear, Lingerie and Undergarments, T-Shirts
Gasoline and other energy goods	Electricity, Energy and Utilities, Oil and Gas
Other nondurable goods	Beauty and Personal Care, Chemicals, Drugs and Medications, Face and Body Care, Hair Care and Products, Health, Newspapers, Tobacco Products
Services	
Household consumption expenditures	
Housing and utilities	Home Financing, Home Improvement, Home Insurance, Homemaking and Interior Decoration, Interior Design, Real Estate, Real Estate Agencies
Health care	Drugs and Medications, Health, Health Insurance, Medical Facilities and Services, Mobile and Wireless
Transportation services	Auto Financing, Auto Insurance
Recreational services	Entertainment, Entertainment Industry, Movies, Ticket Sales, Video Games
Food services and accommodation	Food and Drink, Food Retailers, Hotels and Accommodation, Restaurant Supply, Restaurants
Financial services and insurance	Finance and Insurance, Home Financing, Home Insurance, Insurance
Other services	Retirement and Pensions, Social Services, Telecommunications, Waste Management
Final consumption expenditures of nonprofit institutions serving households	—

real-estate crisis and the subsequent financial crisis. We therefore use year-on-year growth rates instead of seasonally adjusted data in levels or monthly growth rates. A disadvantage of this approach is, of course, that we lose 12 months of observations.

To use as much information from the Google data as possible without running out of degrees of freedom in our forecasting models, we extract common unobserved factors from the Google data and use these factors as exogenous variables in our regression. To extract the factors we employ the method of unweighted least squares. The advantage of this method is that it does not require a posi-

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Table II. Goodness-of-fit indices for the factor model (whole sample)

	Model	Independence
Parameters	629	57
Degrees of freedom	1024	1596
Parsimony ratio	0.64	1.00
Discrepancy	1.27	174.56
Root mean square residual	0.03	0.33
Bollen relative (RFI)	0.99	
Bentler–Bonnet normed (NFI)	0.99	

Note: Model: factor model; Independence: zero common factor model.

tive definite dispersion matrix. This property is not guaranteed because it is possible that some of the search queries are negatively correlated. To select the number of factors we initially employed the Kaiser–Guttman criterion. Depending on the sample period this criterion suggests 11–13 factors which explain between 83% and 94% of the variance. The usual indices indicate that the resulting models fit the data quite well (Table II). However, with regard to the relatively short sample period it is necessary to reduce the number of factors further to avoid overfitting the forecasting models. We therefore estimated equations for each single factor and for all combinations from two to four factors and perform nowcasts and one-period-ahead forecasts. The best results were obtained using the four factors with the largest eigenvalues which still explain 61% of the total variance of the Google time series. In what follows we compare only these four factors with the other indicators.

The survey-based indicators we employ as benchmark indicators are the University of Michigan's Consumer Sentiment Index (MCSI) and the Conference Board's Consumer Confidence Index (CCI). Both indices try to measure the same concept—namely consumer confidence—and both are based on five questions that include current conditions and expectations components. The main difference is that the CCI puts a greater weight on labour market conditions, whereas the MCSI interviews households about their financial situation and their current attitude towards major purchases. The CCI thus slightly lags the MCSI as it is more related to the unemployment rate, which typically lags the business cycle. Due to differences in the construction methodology the CCI also displays larger movements than the MCSI. As a result of all these differences, both indicators can give conflicting signals, although overall they remain highly correlated (Figure 1).[6] For better comparability to the Google indicator we also use year-on-year growth rates instead of levels of the survey-based indicators.

FORECASTING EXPERIMENTS

To determine the predictive power of the Google factors relative to that of the survey-based indicators we first estimate a simple autoregressive model of consumption growth as a baseline model:

$$C_{t+h} = \alpha(L)C_{t-1} + \varepsilon_{t+h} \tag{1}$$

[6] See, for example, Ludvigson (2004) for a more detailed description of the characteristics of these indexes.

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where C denotes the monthly year-on-year growth rates of real private consumption and h is the forecast horizon (0 for nowcasts, 1 for 1-month-ahead forecasts). We use the Schwarz information criterion to determine the order of the autoregression, allowing up to three lags. Time aggregation and overlapping periods likely introduce an MA(1) error into the estimation. We therefore model the error term as an MA(1) process.

Next, we add the MCSI, the CCI or the Google Factors to the baseline model to see to what extent its predictive power is improved by these indicators alone:

$$C_{t+h} = \alpha(L)C_{t-1} + \beta(L)G_t^k + \varepsilon_{t+h} \tag{2}$$

where G^k is the respective indicator, again allowing up to three lags. To assess whether these indicators provide information beyond that already captured in other macroeconomic variables typically embedded in forecasting models, we estimate an extended baseline model that also includes macroeconomic variables. The selection of these variables is, of course, somewhat arbitrary. We employ a model that is also used by Bram and Ludvigson (1998) and Croushore (2005). It adds to equation (1) real personal income y, interest rates on 3-month Treasury bills i and stock prices s (measured by the S&P 500 index). The last two variables have the advantage of a publication lead of 1 month and can thus be used for nowcasting.[7] For all macroeconomic variables we also use year-on-year growth rates:

$$C_{t+h} = \alpha(L)C_{t-1} + \gamma(L)y_{t-1} + \delta(L)i_t + \eta(L)s_t + \varepsilon_{t+h} \tag{3}$$

Finally, the extended baseline model is again augmented with the respective indicators:

$$C_{t+h} = \alpha(L)C_{t-1} + \gamma(L)y_{t-1} + \delta(L)i_t + \eta(L)s_t + \beta(L)G_t^k + \varepsilon_{t+h} \tag{4}$$

We conduct in-sample and out-of-sample forecasts to determine to what extent the indicators help to predict movements in consumer spending. In-sample forecasts test the predictive power of the respective indicator over the entire sample period ranging from January 2005 to September 2009, while the out-of-sample tests investigate the stability of that predictive power over several subperiods. To test which indicator improves the baseline model best, we calculate the relative reduction in the unexplained variance (incremental R^2) of the respective indicator-augmented equation compared to that of the baseline models. We also compute the F-statistics to test whether the coefficients of the respective indicators and its lags are jointly zero. This test thus shows whether the relative reduction in unexplained variance is statistically significant.

We use recursive methods for the out-of-sample experiments.[8] We first estimate the models using data from January 2005 to December 2007. Then we conduct out-of-sample forecasts from January 2008 until September 2009, adding 1 month at a time, re-estimating the model and calculating a series of forecasts for the current (nowcast) or the following month. The forecasts of the indicator-augmented models are evaluated by their respective ratio of the root mean squared forecast errors (RMSFE) to that of the other models. Significance is determined using the Harvey–Leybourne–Newbold (1997) modification of the Diebold–Mariano (1995) test statistic.

[7] We use nominal instead of real stock prices to make use of the publication lead of the S&P 500 index. Bram and Ludvigson (1998) follow Carroll *et al.* (1994) in using labour income growth instead of personal income growth. For labour income, however, only quarterly data are available.

[8] Although a rolling window can better account for structural shifts, an expanding window leads to more parameter stability and precision, and it is more realistic for forecasters to use all available data.

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EMPIRICAL RESULTS

Table III displays the results of the in-sample assessment for the indicator-augmented models (2) relative to baseline model (1) for the sample period ranging from January 2005 to September 2009.[9] It reports the increment to the adjusted R^2 that results from augmenting the baseline equation with the respective indicator and the F-statistics for a test that the coefficients of the indicator and its lags are jointly zero. All indicators improve the baseline model significantly. The incremental R^2s are all of small size, since we are using overlapping growth rates and lags of the dependent variable already explain a large share of the variation. The Google-augmented model achieves the highest incremental R^2 of three percentage points for the nowcast and two percentage points for the 1-month-ahead forecast. With an incremental R^2 of two percentage points for both forecast horizons, the CCI indicator performs just slightly worse but the MCSI indicator is substantially inferior. If the extended baseline model (3) is used as the relevant benchmark (Table IV), the information content of the indicators diminishes but remains significant. For both forecast horizons all indicators increase the adjusted R^2 by one percentage point except for the MCSI, whose incremental R^2 for the 1-month-ahead forecast now falls close to zero.

Figures 2 and 3 provide a visual impression of the out-of-sample forecasting performance of the indicator-augmented models (2) and (4) respectively. Forecast values are compared with the actual

Table III. Information content of the indicators (baseline model)

	$h = 0$		$h = 1$	
	Increm. R^2	F-stat.	Increm. R^2	F-stat.
MCSI (2) vs. baseline (1)	0.01	8.30***	0.01	7.76***
CCI (2) vs. baseline (1)	0.02	40.46***	0.02	27.17***
Google (2) vs. baseline (1)	0.03	13.24***	0.02	12.56***

Note: Asterisks indicate significance at the *10%, **5% and ***1% significance level. Hypothesis tests were conducted using a heteroskedasticity and serial correlation robust covariance matrix. The sample covers the period from January 2005 to September 2009.

Table IV. Information content of the indicators (extended baseline model)

	$h = 0$		$h = 1$	
	Increm. R^2	F-stat.	Increm. R^2	F-stat.
MCSI (4) vs. baseline (3)	0.01	4.56**	0.00	3.52**
CCI (4) vs. baseline (3)	0.01	2.69*	0.01	6.72***
Google (4) vs. baseline (3)	0.01	2.38*	0.01	6.75***

Note: Asterisks indicate significance at the *10%, **5% and ***1% significance level. Hypothesis tests were conducted using a heteroskedasticity and serial correlation robust covariance matrix. The sample covers the period from January 2005 to September 2009.

[9] For both survey-based indicators earlier data are also available, but 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.

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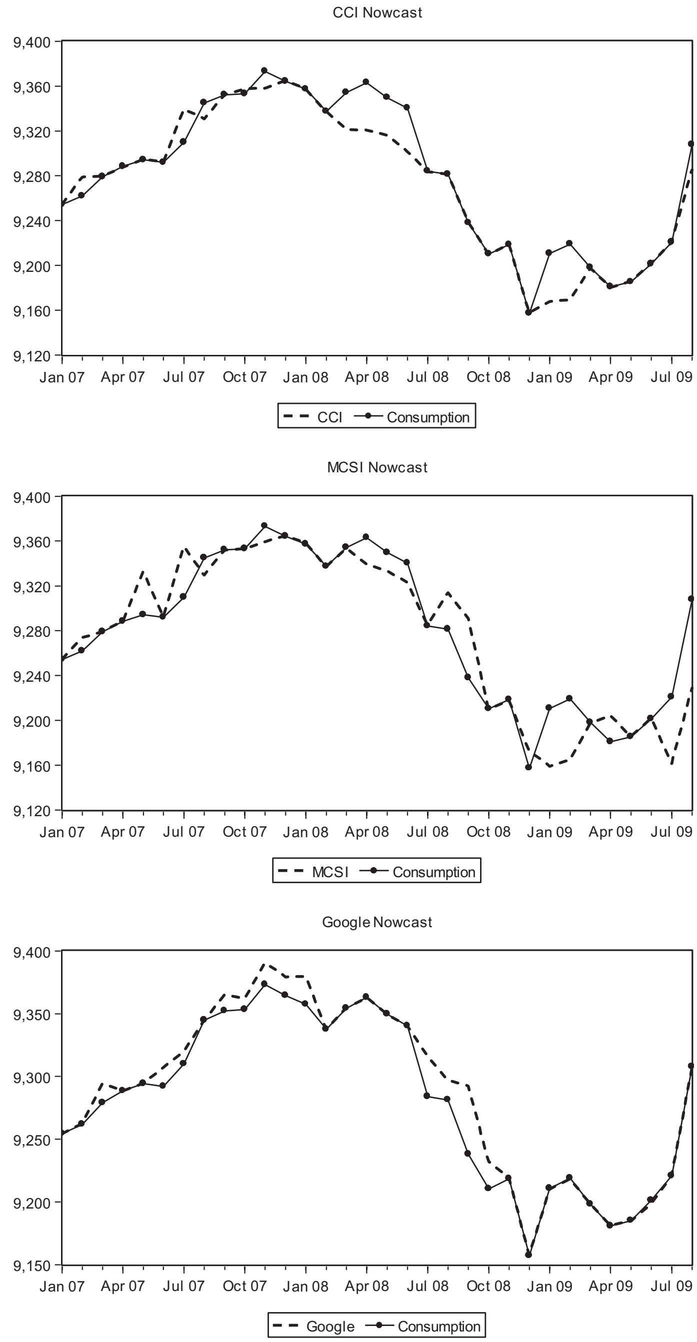

Figure 2. Out-of-sample forecasts and actual levels (baseline model) (in billions of US dollars)

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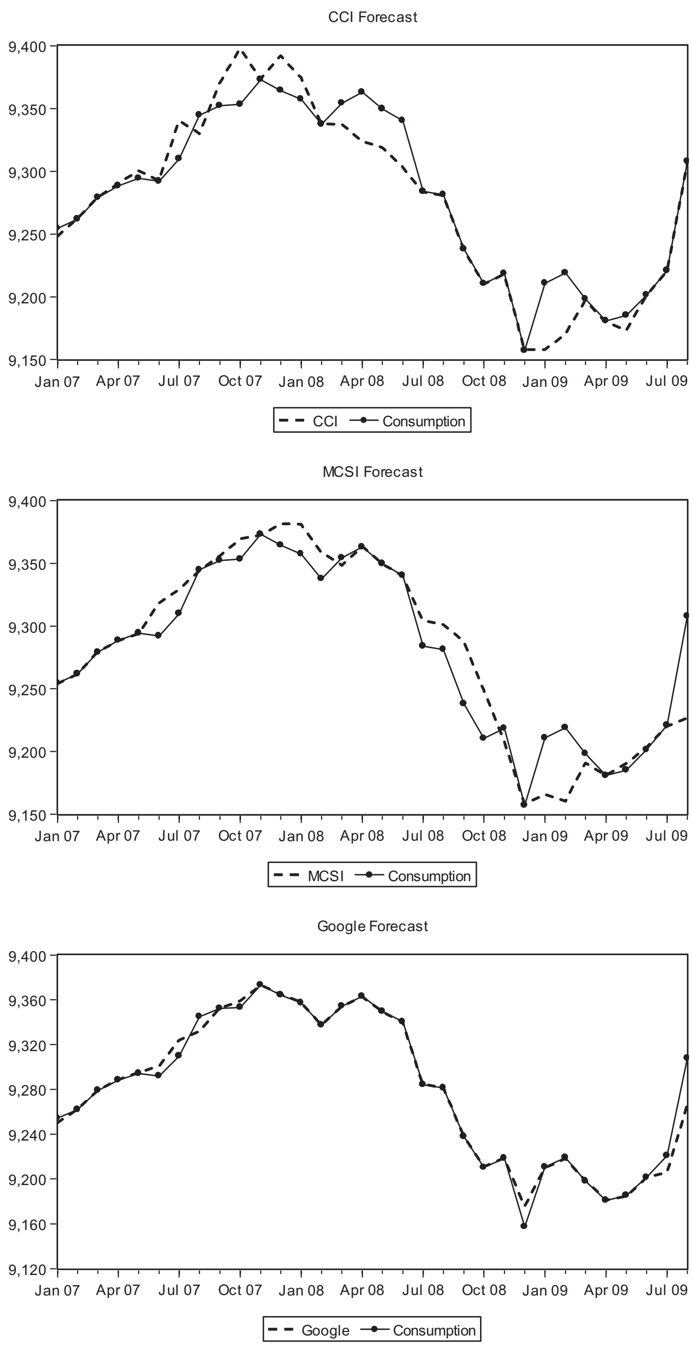

Figure 2. *Continued*

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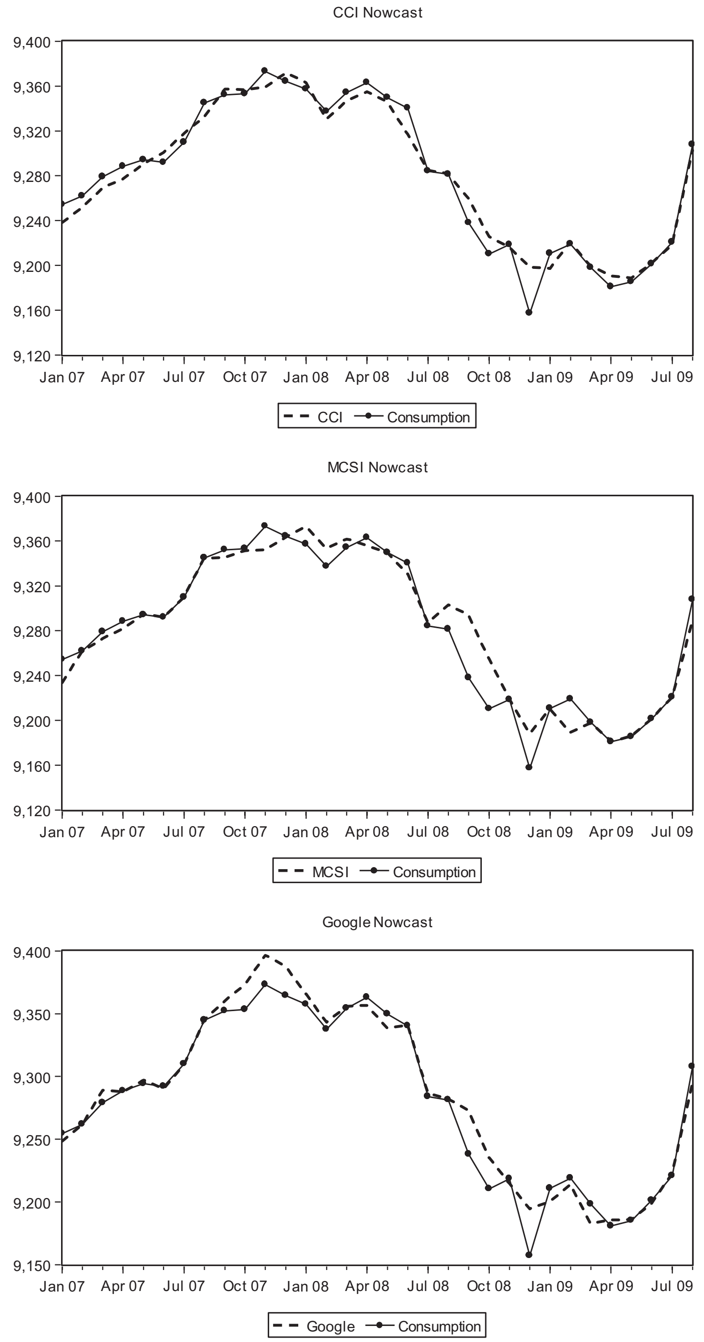

Figure 3. Out-of-sample forecasts and actual levels (extended baseline model) (in billions of US dollars)

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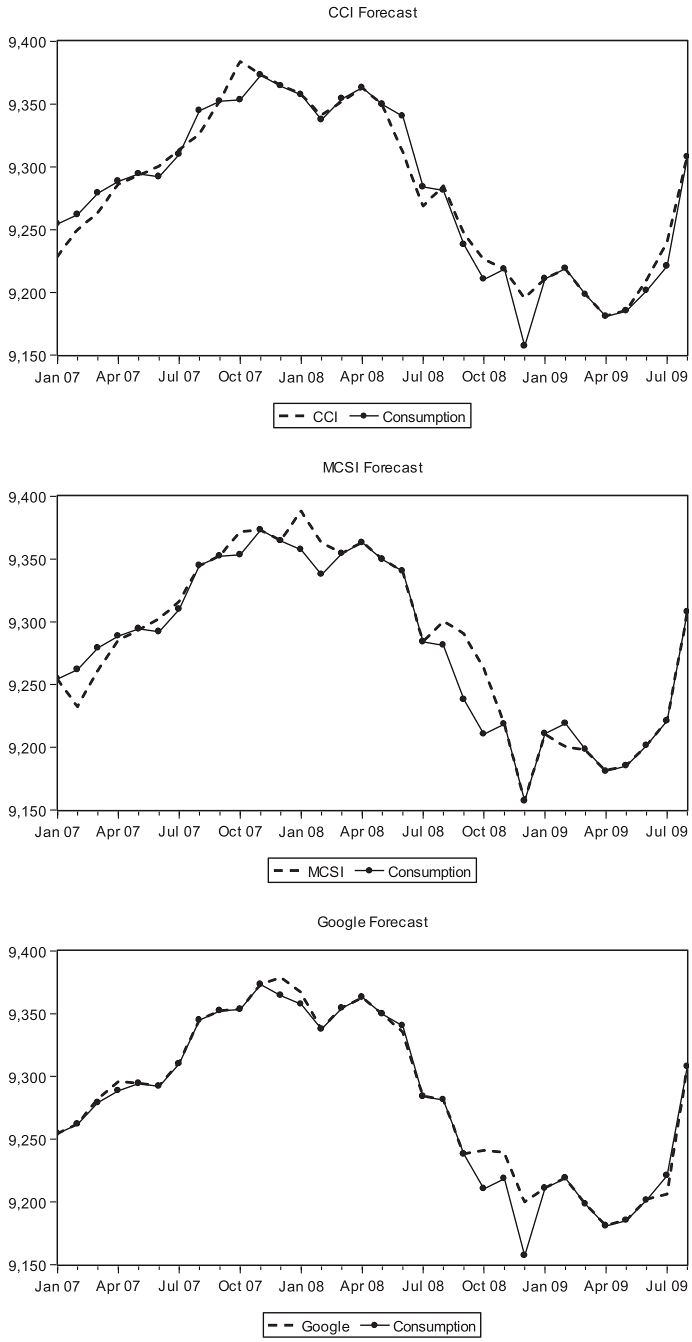

Figure 3. *Continued*

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levels of consumption. Figure 2 shows that the Google indicator is the only one to accurately indicate the turning point after consumption had reached its trough in December 2008. The forecasts of the other models perform particularly badly in the month following the trough. This underlines that forecasting models should not be based on survey-based indicators alone. The models augmented with the survey-based indicators obviously perform much better if macroeconomic variables are included in the baseline models (Figure 3). Table V, in which the RMSFEs for all indicator-augmented models are reported, supports these visual impressions. The RMSFEs of the survey-based indicators drop substantially once other macroeconomic variables are included in the model. For the Google indicator the picture is less clear. For the nowcasts, including macroeconomic variables slightly reduces the forecast error. For the 1-month-ahead forecasts, however, the reverse is the case. Interestingly, several models perform better in forecasting the next month than in nowcasting the current month.

Tables VI and VII compare the accuracy of the indicator-augmented models with that of the baseline models. Additionally, test statistics for equal forecasts accuracy of the indicator-augmented models are provided. The first entry reports the ratio of the RMSFE obtained for the MCSI to that for the respective baseline model. The second entry documents the ratio of the RMSFE for the CCI to that for the baseline model, and so on. The indicator-augmented models are also compared with one another. Entries lower than one indicate that the first model outperforms the second one. The Diebold–Mariano (1995) test statistic for equal forecast accuracy modified for small samples by Harvey *et al.* (1997) appears in the second column. The modified Diebold–Mariano statistics are provided only for the comparisons of the indicator-augmented models, since they are applicable only

Table V. Out-of-sample predictive power (RMSFEs)

	$h = 0$		$h = 1$	
	Baseline (2)	Baseline (4)	Baseline (2)	Baseline (4)
MCSI	28.1	17.2	24.8	17.3
CCI	19.3	12.1	21.0	13.4
Google	14.3	13.4	9.4	10.9

Table VI. Relative out-of-sample performance (baseline model)

	$h = 0$		$h = 1$	
	Rel. RMSFE	MDM statistic	Rel. RMSFE	MDM statistic
MCSI (2) / baseline (1)	0.71		0.62	
CCI (2) / baseline (1)	0.49		0.53	
Google (2) / baseline (1)	0.36		0.24	
Google (2) / MCSI (2)	0.51	−1.84**	0.38	−2.60***
Google (2) / CCI (2)	0.74	−0.78	0.45	−1.99**

Note: Asterisks indicate significance at the *10%, **5% and ***1% significance level. Hypothesis tests were conducted using a heteroskedasticity and serial correlation robust covariance matrix.

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Table VII. Relative out-of-sample performance (extended baseline model)

	$h = 0$		$h = 1$	
	Rel. RMSFE	MDM statistic	Rel. RMSFE	MDM statistic
MCSI (4) / baseline (2)	1.02		1.03	
CCI (4) / baseline (2)	0.71		0.80	
Google (4) / baseline (2)	0.79		0.65	
Google (4) / MCSI (4)	0.78	−1.11	0.63	−1.38*
Google (4) / CCI (4)	1.11	0.72	0.81	−0.88

Note: Asterisks indicate significance at the *10%, **5% and ***1% significance level. Hypothesis tests were conducted using a heteroskedasticity and serial correlation robust covariance matrix.

to non-nested models. The statistic has a Student's t-distribution and shows whether differences in RMSFEs are statistically significant. A negative sign indicates that the first model has a lower forecast error than the second.

Table V shows that if the baseline model is used the Google indicator significantly outperforms all other models. For the nowcast comparison with the CCI-augmented model, however, the modified Diebold–Mariano statistic is not significant. If macroeconomic variables are included (Table VII), the relative predictive power of all indicators deteriorates. For both forecast horizons the MCSI is now even inferior to the baseline model. For the MCSI our results thus support the findings of Croushore (2005) that this indicator is not of significant value in forecasting once other macroeconomic variables are included. The inclusion of the CCI and the Google factors, however, still reduce the RMSFE of the extended baseline model substantially, the CCI performing best for the nowcasts and the Google indicator for the 1-month-ahead forecasts. The differences of both forecasting models are, however, no longer significant.

CONCLUSIONS

This study shows that Google Trends is a very promising new source of data to forecast private consumption. In almost all experiments conducted the Google indicator's in-sample and out-of-sample predictive power proved to be better than that of the conventional survey-based indicators. Other methods of category selection might enhance the indicator's predictive power even further. Since 2008 Google has also provided data for product searches specifically and the respective categories should be even more suitable for consumption forecasts, as they are more related to purchases than the web search queries that were used here. However, at this point in time there are not even 2 years of data available, which forced us to refer to web search categories to obtain at least 2 years of data. Eventually, employing seasonally adjusted Google data might also be more appropriate than the usage of year-on-year growth rates. We refrained from seasonal adjustment in this paper, though, since accurate seasonal adjustment requires more time as well. Given the short time horizon of the database, this paper can thus only present first insights and there is certainly room for improvement once longer time series are available. The study nevertheless demonstrates the enormous potential that Google Trends data already offer today to forecasters of consumer spending.

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