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Torsten Schmidt
Simeon Vosen

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



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Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI)
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Prof. Dr. Thomas K. Bauer
RUB, Department of Economics, Empirical Economics
Phone: +49 (0) 234/3 22 83 41, e-mail: thomas.bauer@rub.de

Prof. Dr. Wolfgang Leininger
Technische Universität Dortmund, Department of Economic and Social Sciences
Economics – Microeconomics
Phone: +49 (0) 231/7 55-3297, email: W.Leininger@wiso.uni-dortmund.de

Prof. Dr. Volker Clausen
University of Duisburg-Essen, Department of Economics
International Economics
Phone: +49 (0) 201/1 83-3655, e-mail: vclausen@vwl.uni-due.de

Prof. Dr. Christoph M. Schmidt
RWI, Phone: +49 (0) 201/81 49-227, e-mail: christoph.schmidt@rwi-essen.de

Editorial Office

Joachim Schmidt
RWI, Phone: +49 (0) 201/81 49-292, e-mail: joachim.schmidt@rwi-essen.de

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Torsten Schmidt and Simeon Vosen¹

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

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.

JEL Classification: C53, E21, E27

Keywords: Google Trends, private consumption, forecasting, Consumer Sentiment Indicator

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1 Introduction

Since private consumption represents about 70 percent of US-GDP, timely information about private household spending is important to assess and predict overall economic activity. Data on private consumption for the US are published monthly and with a lag of one 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 psychological¹ 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 US. Indeed the co-movement of the most common survey-based consumption indicators – the Michigan University's 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 percent of the variation in the MCSI can be explained by other macroeconomic variables, suggesting that large part of sentiment might simply reflect respondents' knowledge of general economic conditions. A possible weakness of the survey-based

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

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 amount of people also use web search engines to collect information on goods they intend to buy. In 2008, U.S. 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 U.S. market research firm eMarketers estimates that 86% percent of the 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 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 and 2009b) 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 US. Askitas and Zimmermann (2009) found selected queries

² According to the Quarterly E-Commerce Report of the U.S. 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

associated with job search activity to be useful in forecasting the German unemployment rate. Suhoj (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. Section 3 presents the empirical approach to assess the forecasting performance of the Google indicator. Section 4 discusses the results. Section 5 concludes.

2 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

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

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 1).⁵ Google Trends data are provided on a weekly basis. We compute monthly averages since data on consumption are only available on 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 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 many 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 positive 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 to 13 factors which explain between 83 and 94 percent of the variance. The usual indices indicate that the resulting models fit the data quite well (Table 2). 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. In what follows we compare only these four factors with the other indicators.

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.

The survey-based indicators we employ as benchmark indicators are the University of Michigan’s Consumer Sentiment Index (MCSI) and 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 a current conditions and an expectations component. 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 displays also 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.

3 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:

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

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.

⁶ See e.g. Ludvigson (2004) for a more detailed description of the characteristics of these indexes.

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:

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

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 three-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 one month and can thus be used for nowcasting.⁷ For all macroeconomic variables we also use year-on-year growth rates.

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

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

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

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 sub-periods. 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

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.

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 one 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.

4 Empirical results

Table 3 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^2 s 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 one-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

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

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.

the relevant benchmark (table 4), 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 one-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. Forecasted values are compared with the actual 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 5, 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 one-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 6 and 7 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, Leybourne and Newbold (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 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 5 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 7) 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 one-month-ahead forecasts. The differences of both forecasting models are however no longer significant.

5 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 indicators' 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 indicators predictive power even further. Since 2008 Google also provides 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 data base this paper can thus only present first insights and there is certainly room for improvements, once longer time-series are available. The study nevertheless demonstrates the enormous potential that Google Trends data already offers today to forecasters of consumer spending.

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Appendix

Figure 1

Consumption and Survey-based Indicators (monthly YoY growth rates)

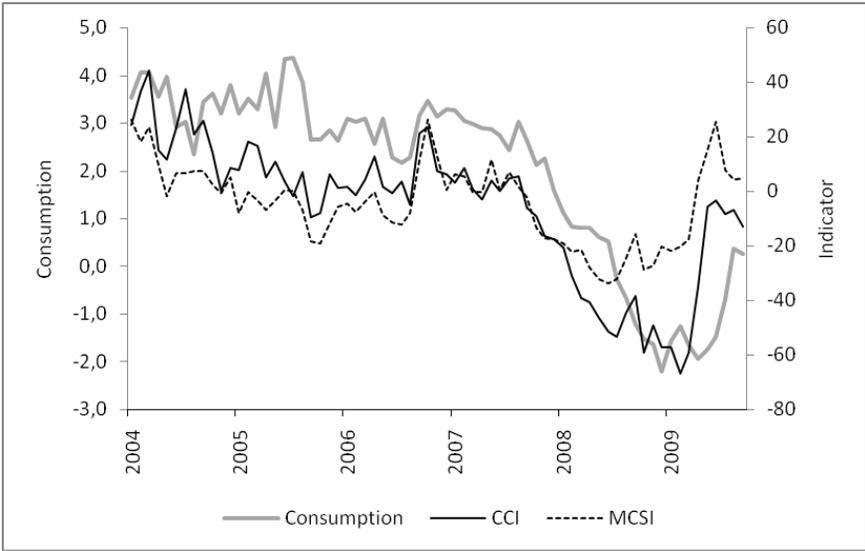


Figure 2
Out-of-sample Forecasts and Actual Levels (baseline model)
(in billions of USD)

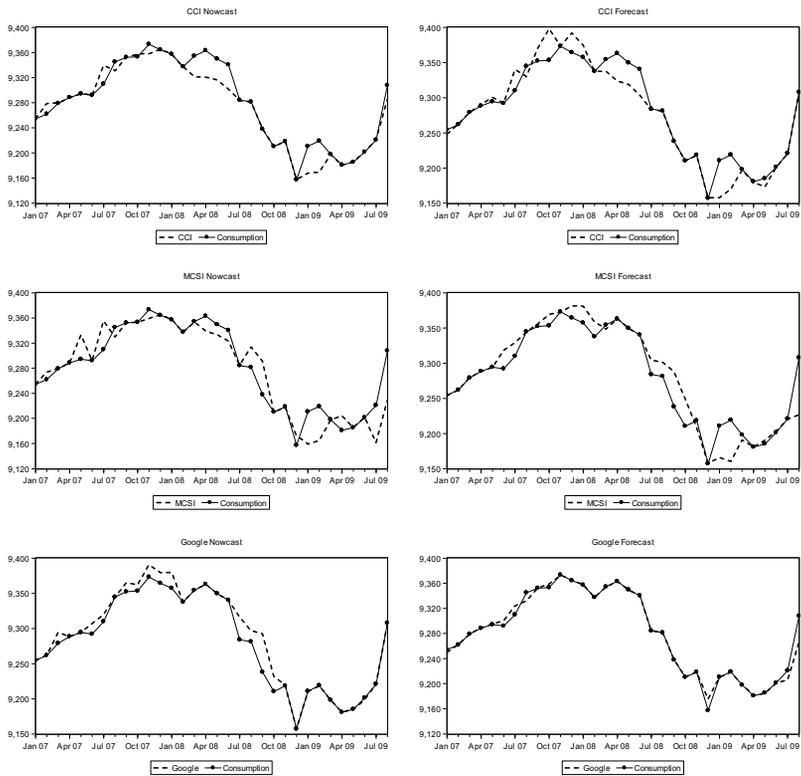


Figure 3

Out-of-sample Forecasts and Actual Levels (extended baseline model)

(in billions of USD)

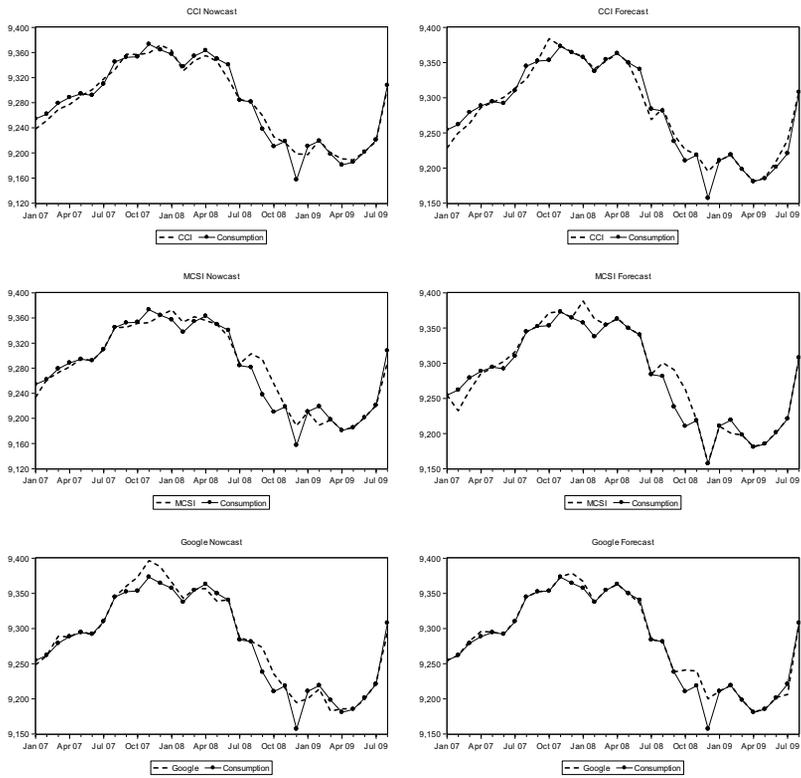


Table 1

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 & Electronics, Consumer Electronics, Home Appliances, Home Financing, Home Furnishings, Home & 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 & Wireless, Telecommunications
Nondurable goods	
Food and beverages purchased for off-premise consumption	Alcoholic Beverages, Food & Drink, Food Retailers, Nonalcoholic Beverages
Clothing and Footwear	Apparel, Clothing Labels & Designers, Clothing Retailers, Footwear, Lingerie & Undergarments, T-Shirts
Gasoline, and energy goods	Electricity, Energy & Utilities, Oil & Gas
Other nondurable goods	Beauty & Personal Care, Chemicals, Drugs & Medications, Face & Body Care, Hair Care & Products, Health, Newspapers, Tobacco Products
Services	
<i>Household consumption expenditures</i>	
Housing and utilities	Home Financing, Home Improvement, Home Insurance, , Homemaking and Interior Decoration, Interior Design, Real Estate, Real Estate Agencies
Health care	Drugs & Medications, Health, Health Insurance, Medical Facilities & Services, Mobile & Wireless
Transportation services	Auto Financing, Auto Insurance
Recreational services	Entertainment, Entertainment Industry, Movies, Ticket Sales, Video Games
Food services and accommodation	Food & Drink, Food Retailers, Hotels & Accommodation, Restaurant Supply, Restaurants
Financial services and insurance	Finance & Insurance, Home Financing, Home Insurance, Insurance
Other services	Retirement & Pensions, Social Services, Telecommunications, Waste Management
<i>Final consumption expenditures of nonprofit institutions serving households</i>	-

Table 2**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	

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

Table 3**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***

*, **, *** indicate significance at the 10 %, 5 %, 1 % significance level respectively. 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 4**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***

*, **, *** indicate significance at the 10 %, 5 %, 1 % significance level respectively. 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 5**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 6**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**

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

Table 7**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

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