Forecasting Private Consumption with Google Trends Data

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Abstract

This paper examines the predictive relationship of consumption-related and news-related Google Trends data to changes in private consumption in the U.S. The results suggest that 1) Google Trends augmented models provide additional information about consumption over and above survey-based consumer sentiment indicators, 2) consumption-related Google Trends data provide information about pre-consumption research trends, 3) news-related Google Trends data provide information about changes in durable goods consumption, and 4) the combination of news and consumption-related data significantly improves forecasting models. We demonstrate that applying these insights improves forecasts of private consumption growth over forecasts that do not utilize Google Trends data and over forecasts that use Google Trends data, but do not take into account the specific ways in which it informs forecasts.

Key words: Google Trends; private consumption, forecasting; consumer sentiment indicators

JEL Codes: C53, E21, C55

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Introduction

Recent developments in the technology industry and the rapid increase in the availability of online data such as Google Trends (trends.google.com) provide researchers with new sets of data that can complement survey data like the Michigan Consumer Sentiment Index (MCSI) and the Conference Board Consumer Confidence Index (CCI) in economic forecasts. Some potential contributions of Google Trends data to consumption forecasts are a result of the transparent channels of influence, a large sample size, and its low cost. Unlike survey responses on consumer attitudes, Google Trends data measures the behavior of consumers such as their pre-purchase research activities and news readership. Google Trends' large quantity of individual level data supplements the small samples of consumer surveys. Moreover, Google Trends data are easily accessible with no cost and updated daily. This paper takes advantage of these benefits and extends the literature on consumption forecasting by introducing Google Trends News Search data in addition to using Google Trends consumption-related search data. We also examine how the predictive relationship of Google Trends data changes as we forecast different components of consumption (durables, nondurables, and services) over different time frames (one-month ahead forecasts and nowcasts). This helps us to gain more insight into the information content of Google Trends data. We demonstrate that these insights can be used to improve forecasts.

Our work is most similar to Vosen and Schmidt (2011) who show that consumption-related Google Trends search data outperforms the University of Michigan and the Conference Board's survey-based measures of consumer confidence in forecasts of private consumption. We extend these findings by treating the Google search data as complementary to the survey-based measures of consumer confidence rather than as substitutes and confirming that Google Trends augmented models provide additional information about current and future consumption over and above that provided by the survey-based measures of consumer confidence. We also employ a different approach by forecasting durable goods, nondurable goods, and services consumption separately to gain better insight into the ways in which the Google Trends data informs the forecast. Specifically, our findings suggest that consumption-related Google Trends data provides information about pre-consumption research for durable goods purchases and that news-related Google Trends data provides information about consumer sentiment related to durable goods consumption. We find that the combination of news and consumption-related search data improves forecasting models the most. These findings suggest how Google Trends data should be used in order to achieve the largest improvements in forecasts and we demonstrate that in an application that compares our best forecast to several different approaches.

Our work is related to two different strands of the literature. The first strand relates survey-based consumer sentiment indicators to changes in private consumption, and the second uses Google Trends data to improve a variety of economic forecasts. There is a general consensus in the extensive literature examining survey-based consumer sentiment indicators that they can predict changes in private consumption. (See, for example, Wilcox (2007) and Carroll et al. (1994).) Despite their predictive ability, MCSI and CCI are criticized for their opaque channels of influence on consumption and high correlation with other macroeconomic indicators. For instance, Carroll et al. (1994) conclude that the predictive power of MCSI comes from a complex mix of direct and indirect channels of influence that are unobservable. In a similar vein, Fuhrer (1993) finds that other macroeconomic indicators explain 70 percent of the variation in MCSI.

There is also an extensive literature on various applications of Google Trends data, which simply indicates a given search term or category's relative search popularity in a geographic region. For example, Chen et al. (2015) predict official recession dates with searches related to "recession," "foreclosure help" or "layoff," Preis et al. (2013) predict stock market movements with search terms related to finance, and Wu and Brynjolfsson

(2013) predict housing prices and sales with searches related to “real estate agencies” and “real estate listings.”[1] In theory, macroeconomic variables indicate a household’s *ability* to spend, survey data on sentiment reflect its *willingness* to spend, and Google Trends depict its *preparatory steps* toward spending.

To examine the relationship between consumption-related Google Trends data and personal consumption, Vosen and Schmidt (2011) compare the suitability of Google Trends and consumer sentiment indices (MCSI and CCI) as predictors of consumption and conclude that, albeit by small amount, Google Trends is a better predictor than MCSI and CCI. Penna and Huang (2009) find that the levels of MCSI, CCI and Google Trends are highly correlated (0.9 correlation coefficient). However, they also find that their month-to-month changes are only moderately correlated (0.4 correlation coefficient), and more importantly, that Google Trends can predict MCSI and CCI, and not the other way around. This leads us to believe that these three indicators are not substitutes, as in Vosen and Schmidt (2011), but rather complements. Survey-based consumer sentiment indicators still contain useful information about consumption behavior that is difficult to extract using Google Trends data. For these reasons, we focus on examining the marginal information that Google Trends data add to forecast models.

And, of course, there may be a relationship between consumer sentiment and the news media; Doms and Morin (2004) confirm that financial news can affect consumer sentiment. They directly count the number of articles that have the words “recession” or “layoff” in the title published by a sample of 70 news media agencies. We replicate their methodology but instead use news-related Google Trends data that measures the relative search frequencies of the words “recession” and “layoff” in “news.google.com.” Unlike Doms and Morin’s volume data, the Google Trends data will allow us to more directly and conveniently examine

[1] See also Bryer et al. (2011), Choi and Varian (2012), Drake et al (2012), D’Amuri and Marucci (2015), Ginsberg et al (2008), and Penna and Huang (2009).

households' interest in financial news articles. An increase in the search frequencies of the words "recession" and "layoff" should indicate a near-future decrease in consumer sentiment, and therefore consumption.

This study contributes to the existing literature in a few important ways. It examines how both consumption-related and news-related Google Trends can predict different components of consumption. To our knowledge, this study is the first to use the Google Trends' news search function, to examine Google Trends data's marginal information over and above survey-based measures of consumer sentiment, and to use components of consumption (durables, nondurables, and services) as dependent variables. Applying these contributions allows us to improve forecasts. In what follows, we explain in detail our data, methods, and results, starting with the data and methods in Section 3.

Data and Methods

For each of the three components of consumption, we observe whether or not recursive window OLS models augmented with three different specifications of Google Trends data can reduce the forecasting errors of baseline models for 1-month ahead forecasts and nowcasts.

The baseline model for 1-month ahead forecasts and nowcasts is:

$$C_{i,t+h} = \alpha * C_{i,t-2} + \beta * MCSI_{t-1} + \gamma * CCI_{t-1} + \theta * DI_{t-2} + \delta * VIX_{t-1} + \varphi * TBill_{t-1} + \varepsilon_{t+h}$$

C is the monthly 12-month growth rate of components of real private consumption. The subscript *i* refers to the different types of consumption (durable, nondurable and services), *t* is the month at the time of prediction, and *h* is 1 for 1-month ahead forecasts and 0 for nowcasts. We use 12-month growth rates of seasonally adjusted monthly real personal consumption expenditure of durable goods, nondurable goods and services released by the Bureau of Economic Analysis. While previous literature uses total personal consumption as the dependent variable, we use these three components and distinct models for each component because they react differently to economic events, as it can be seen in Figure 1. These three components are only moderately correlated; the 12-month growth rate of durable goods expenditure is far more volatile than that of nondurable goods and services as consumers faced with economic challenges during a downturn have greater flexibility to delay purchasing durable goods than some nondurable goods and services. Finally, studying the components of consumption allows us to examine Google Trends' forecasting abilities in detail.

In our main specification, we use 12-month growth rates rather than month-on-month growth rates because the Google Trends data are not seasonally adjusted. Furthermore, this specification allows the easiest comparison to the previous literature; Vosen and Schmidt (2011) also forecast 12-month growth rates. Reliable seasonal adjustment of the Google Trends data is difficult because the available time period is relatively short (from 2008 for Google Trends news data) and the time period contains a very unusual economic period, the Great Recession, followed by an uncharacteristic recovery. Nonetheless, in supplementary estimations, we do attempt to seasonally adjust the Google Trends data using the Census Bureau's X-13 ARIMA SEATS program and use that in forecasts of month-on-month growth rates for comparison.

In the baseline model, six independent variables are selected to account for the information already provided by other widely used macroeconomic indicators. We use both the University of Michigan Consumer Sentiment Index (MCSI) and the Conference Board Consumer Confidence Index (CCI). Although they measure similar things using similarly designed survey methodologies, CCI is believed to put heavier emphasis on the health of the labor market (Vosen and Schmidt 2011). Consequently, CCI's 12-month growth rates are more exaggerated than MCSI's. Nonetheless, the two indicators are highly linearly correlated at 0.805. We include both indicators, with the belief that the two indicators provide similar yet slightly different information.

The CBOE Volatility Index (VIX), which measures the expectation of 30-day volatility based on options-market data, controls for the changes in consumption due to unusual changes in the stock market. Similarly, real disposable income controls for the income effect on consumption. The secondary market rate of 3-month Treasury Bill controls for the effect of monetary policy on consumption. All of the independent variables are measured in 12-month growth rates, for easy comparison with the rest of the variables in the prediction models. In addition, all the variables are lagged to the latest monthly observation available at the time of each prediction.

In the augmented models, we add combinations of the Google Trends consumption data and Google Trends news data to the baseline specification. To create the Google Trends consumption data for each of the three components of personal consumption expenditure used as dependent variables, we follow Vosen and Schmidt's (2011) method and identify the Google Trends categories that are intuitively related to the Bureau of Economic Analysis' categorization. Since the 2011 study, Google has eliminated or updated some of its Trends categories. We are still able to identify and extract most of these Google Trends categories and find intuitively related replacements for the ones that are missing. Exhibit 1 shows the Google Trends categories used for each of the three components of consumption. Each of these Google Trends categories data depicts the overall relative popularity of all the Google searches that are related to the category. To measure the relative popularity, Google takes an unbiased sample from all the search queries in a given region over a given period. Then, Google divides the number of searches related to the given category by the sample size. Lastly, Google standardizes these numbers so that the highest proportion is equal to 100. We extract all Google Trends data at the monthly level and convert them to 12-month growth rates to account for seasonality. One of the shortfalls of using Google's predetermined categories is that the exact list of searches that are contained in each category is unknown.

Many of the categories that are in the same components of consumption are highly correlated. In order to mitigate the problem of multi-collinearity, we use principal components analysis. In the forecast equation, we use all the factors that are required to explain 90% of the variation in the Google Trends categories representing each component of consumption, which range from four factors for nondurable consumption to seven factors for services. (Results of the principal components analysis are available from the authors upon request.)

News-related Google Trends data are similar to the consumption-related Google Trends data discussed. The news-related data only goes as far back as January 2008 (January 2009 when converted to 12-month growth rates) and the sample search queries that are used to calculate the data are limited to ones submitted to "news.google.com" or the Google news search function under its search bar. These news-related Google Trends data allow one to measure the relative popularity of news articles with specific keywords. For this research, we extract the data for the keywords "recession" and "layoff."

The three augmented models include combinations of Google Trends data. Exhibit 2 shows the independent variables used in each model, where the "Baseline Variables" refer to all the independent variables used in the baseline model discussed above. "90% PCA" refer to all the principal components that are required to explain 90% of variation in the Google Trends categories related to the relevant component of consumption. The [News + 90% PCA] model includes both news-related Google Trends, "recession" and "layoff", and relevant principal components.

All Google Trends data are based on the U.S. only and were extracted on February 25th, 2017. For our main results, we rely on the Google Trends data from January 2009 to

November 2014 because that is the time period over which the annual growth rates of the Google Trends news data are available. Although Google Trends consumption data are available over a slightly longer time frame, the news data are what limit our sample.

Procedure

For each component of consumption and model specified in Exhibit 2, we conduct out-of-sample 1-month ahead forecasts and nowcasts using the recursive window method.[2] The out-of-sample prediction timeline is January 2015 to November 2016. Using the recursive window method, the forecast and nowcast models for January 2015 have the smallest training observations (January 2009 to November 2014 for nowcasts and January 2009 to October 2014 for forecasts) and the predictions should get more accurate over the course of the prediction timeline because the number of training observations increase.

For each component and model's forecasts and nowcasts, we calculate the root mean squared forecasting error (RMSFE).Then we compare the RMSFE of each augmented model to that of the relevant baseline model. A smaller RMSFE indicates more accurate predictions. In order to compare the magnitude of these errors to another benchmark, we also provide some error statistics from the Survey of Professional Forecasters of the Federal Reserve Bank of Philadelphia.

We also conduct other estimates to check for result robustness. First, to show that Google Trends augmented models can improve other baseline models, we use Vosen and Schmidt's baseline model. Their baseline includes 12-month growth rate of S&P 500, three-month treasury rate, real personal income and either MCSI or CCI. We include both MCSI and CCI for simplicity and to reduce the number of specifications. As mentioned above, we also forecast month-on-month growth rates after seasonally adjusting the Google Trends data.

[2] We also experimented with a 60-month rolling window sample, but found the recursive window procedure produced lower forecast errors, suggesting that the relationships estimated are relatively stable.

In addition, we use 60-month rolling window OLS models for the [90% PCA] models to estimate out-of-sample 1-month-ahead-forecasts and nowcasts and compare the errors to our baselines. We use these 60-month rolling window OLS [90% PCA] models and recession data to forecast the changes in components of consumption from 2010 to 2016. These estimates allow us to check for result robustness to changes in forecast method and training observation timeline. Finally, we estimate fixed sample OLS models where training observations are fixed over time. This allows us to examine the sign and significance of the coefficients.

Results

Our main results are the following: 1) Google Trends augmented models provide additional information about consumption over and above that provided by survey-based measures of consumer sentiment, 2) consumption-related Google Trends data provide information about pre-consumption research trends, 3) news-related Google Trends data provide information about changes in durable goods consumption, and 4) the combination of news and consumption-related data improves forecasting models at the one month-horizon the most. We discuss these results and their robustness in the subsequent sections. We conclude by applying these insights to demonstrate that they can improve forecasts.

Result 1: Google Trends augmented models provide additional information about changes in consumption

Exhibit 3 summarizes the results of 1-month-ahead root mean squared forecast errors (RMSFE) in 12-month percentage growth rates. In order to compare the forecast performance of the augmented models conveniently, we calculate the percentage of baseline errors that augmented models reduce (Exhibit 4). On average, augmented models reduce 1-month ahead baseline forecast errors by 11.15%. The 1-month ahead [News + 90% PCA] forecast models perform the best for all three components of consumption, reducing errors by 16.59% on average. This model was exceptionally effective in reducing errors in services consumption predictions (21.33% reduction).

Similarly, the augmented models reduce nowcast errors as well (Exhibit 4). On average, augmented models reduce nowcast errors by 7.14%. As it is the case for 1-month-ahead forecasts, the [News + 90% PCA] model continue to perform well for services consumption. The best models for durable and nondurable goods consumption are [News Only] and [90% PCA], respectively.

We also find improved forecasts with an alternative baseline model. Under the Vosen and Schmidt (2011) baseline model, the results are similar (Exhibits 5 and 6). On average, the augmented models reduced errors by 6.79% for forecasts and 4.30% for nowcasts. The augmented models' ability to reduce the average forecast and nowcast errors suggest that consumption-related and news-related Google Trends data contribute additional information about changes in consumption to baseline models.

Finally, in supplementary estimations, we find that the month-on-month forecasts for durable goods and services consumption as well as the nondurable goods nowcast are also improved with Google Trends data (Exhibits 7 and 8). Unlike with the 12-month forecast, we do not find improved forecasts for nondurable consumption or improved nowcasts for durable and services. These slightly weaker results for the usefulness of the Google Trends data could be due to the difficulty of seasonally adjusting the Google Trends data with our limited sample or because the baseline month-on-month forecasts are better (lower RMSFE), thus leaving less opportunity for improvement. Forecasting the longer-term 12-month growth rate is an inherently more difficult task and the additional information provided by Google Trends is more useful. The following sections discuss the nature of the contributions of Google Trends data to forecasts and the potential channels through which Google Trends can indicate changes in consumption.

Result 2: Consumption-related Google Trends data provide information about pre-consumption research

The characteristics of online pre-consumption research vary by the type of consumption. Durable goods, which are defined as goods that last more than three months, require more in-depth and extensive research than nondurable goods do because durable goods generally are larger investments with a longer lifetime.[3] In contrast, nondurable goods require relatively brief research, if any, because they usually are smaller investments. Services consumption, however, is not defined in terms of the lifetime of the products nor cost, and therefore, the characteristics of its online pre-consumption research are difficult to generalize. Following these ideas, consumption-related Google Trends data should be more effective as a leading indicator for durable goods than it is for nondurable goods or services.

Evidence from a comparison of the error reduction of 1-month ahead and nowcast [PCA 90%] models suggests that the pattern holds (Exhibit 9). In the table, a positive reduction difference means that the model was more effective in forecasting than nowcasting consumption. In other words, the Google Trends data in that model are more effective as leading indicators of consumption than as contemporaneous indicators. Conversely, negative difference means that the related Google Trends data are stronger contemporaneous indicators. Under our baseline model, the Google Trends models are more effective in forecasting than in nowcasting for all types of consumption, suggesting that Google Trends data provide information on pre-consumption research for all types. Of those models, however, especially effective is the durable goods model, which reduces forecast errors by 2.70% more than it reduces nowcast errors. This confirms our belief that Google Trends data are most effective in providing leading information about durable goods consumption due to nature of the products. The results are consistent under the alternative baseline model

[3] See, for example, Nelson (1970) for a discussion of the costs and benefits that consumers weigh when deciding to search for more information about purchases.

(Exhibit 9) and the 60-month rolling window method (Exhibits 10, 11, and 12). Under the 60-month rolling window models, the error reduction difference of durable goods forecasts is largest of the three. Under the alternative baseline, Google Trends models are more effective in nowcasting nondurable goods and services consumption than they are in forecasting them[4].

In summary, durable goods models augmented with consumption-related Google Trends data are more effective in forecasting than nowcasting consumption under all three different specifications. That is, durable goods Google Trends data provide more leading information about consumption than contemporaneous. For nondurable goods and services, the results are mixed, suggesting that Google Trends data contain similar magnitudes of leading and contemporaneous information. We believe the difference in the Google Trends' ability to lead components of consumption is due to the fact that generally durable goods pre-consumption research happens further out in advance than nondurable or services related ones do. Next, we discuss the nature of the information that news related Google Trends data provide.

Result 3: News related Google Trends data provide additional information about durable goods consumption.

News related Google Trends provide data on the relative popularity of news search queries. We use this data to see whether or not an increase in the search queries related to news articles that convey negative sentiments about the economy is followed by a reduction in consumption. If consumers have a precautionary savings motive, consumers who read about negative economic outlooks will be more likely to consume less to save more in preparation of an economic downturn or potential unemployment.[5] We extract data for the

[4] Durable goods Google Trends models performed worse than baseline models.
[5] See Browning and Lusardi (1996) for a discussion of savings motives.

search queries “recession” and “layoff” and find supporting evidence for their negative correlation to durable goods consumption.

Models augmented with news-related Google Trends reduce the baseline errors of durable consumption forecasts and nowcasts by 9.04% and 12.22% (Exhibit 4). Under the alternative baseline model, the results are similar (Exhibit 6). The [News Only] models reduce errors of durable goods consumption forecasts and nowcasts by 7.78% and 13.91%, respectively. This implies that the relative popularity of news articles with negative sentiments provide useful information on durable goods consumption, as expected.

The opposite is true for nondurable goods consumption. Under the standard baseline model, the [News Only] models actually increase the errors of both forecasts and nowcasts. Using the alternative baseline model, the same is true for nowcasts, but not forecasts. This relatively weak performance of the news-related Google Trends data suggests that nondurable goods consumption is not correlated to the popularity of the articles conveying negative images of the state of the economy.

The evidence is mixed also for services consumption. Using our baseline model, the [News Only] models decrease the baseline errors. Under the alternative baseline models, they increase errors. A potential explanation for this result is that it is difficult to generalize the effect of economic sentiment on services consumption because it includes a much larger variety of items.

Although we do not report the detailed results here, the regression outputs of fixed observation OLS models further strengthen the argument that durable goods consumption is negatively correlated with news-related Google Trends. The coefficients of lagged values of “Layoff” and “Recession” Google Trends in [News Only] and [News + 90% PCA] models are mostly negative for all three dependent variables and both forecast horizons. These coefficients are significant only when the dependent variable is durable goods consumption and 1-month ahead nondurable goods consumption.

The relatively strong performance of the [News Only] model for durable goods consumption suggest that changes in durable goods consumption is vulnerable to changes in the readership of news articles conveying pessimistic outlooks on the economy. A potential explanation for this result is that durable goods consumption is more responsive to changes in sentiment because the goods are usually larger investments. In fact, the 12-month growth rate of durable goods consumption is the most volatile and has the largest variability of the three components, with a standard deviation of over 5 compared to standard deviations less than 2 for the other two components of consumption. Furthermore, changes in durable goods are more strongly correlated to changes in CCI and MCSI than those of nondurable goods and services consumption are. This evidence implies that durable goods consumption is closely related to changes in sentiment, and that news-related Google Trends data provide marginal information to baseline models. This conclusion is supported in the month-on-month growth rate forecasts as well (Exhibits 7 and 8). In these results the News Only specification outperforms all others for durable goods consumption as well.

Result 4: Models augmented with both Google Trends news and consumption searches perform the best for 1-month ahead forecasts

The [News + 90% PCA] model reduces the average 1-month ahead baseline errors by 16.59% under our baseline model and 12.37% and the alternative baseline model (Exhibits 4 and 6). The [News + 90% PCA] model was also the best performing 1-month ahead forecast model for each component of consumption under both baseline models.

For nowcasts, however, the best performing models vary by components. For durable goods consumption, the [News Only] model reduces the most amount of error under both baseline models. For nondurable goods and services consumption [90% PCA] and [News + 90% PCA] respectively perform the best. This implies that consumption related Google Trends data disrupts durable nowcasts and news-related data disrupts nondurable nowcasts. For services consumption, both news related and consumption related data provide useful information, and therefore, reduce baseline errors.

Models augmented with both consumption-related and news-related Google Trends data reduce 1-month ahead forecast errors more than models augmented with only one type of Google Trends data do. The best models for nowcast predictions are mixed, since not all data provide information about contemporaneous change in components of consumption.

The results above indicate that Google Trends data can improve forecasts, but the best model to use depends on the type of consumption and the timeframe. For example, in Exhibit 4, we find that the best model for durable goods nowcast only incorporates news searches, indicating consumers are sensitive to negative news when deciding to purchase durable goods. However, we also show that if we are using that same information to predict current month's nondurable consumption, we actually make our forecast worse than if we did not use Google Trends data at all. These results suggest that we can improve our forecasts with a better understanding of how and why Google Trends data predicts consumption, using the Google search data only for the consumption types and timeframes for which it provides additional information about consumer behavior. We now demonstrate that by comparing a forecast that selects the best Google Trends information to include for each type of consumption and timeframe. We compare our best forecast to our baseline model that does not use Google Trends data, an alternative approach that uses Google Trends data in the same way for all types of consumption and time frames, and an alternative benchmark, the median forecast from the Survey of Professional Forecasters.

The Survey of Professional Forecasters provides quarterly annualized consumption growth forecasts so we adapt our methods to make quarterly forecasts. Specifically, we make out-of-sample forecasts for total private consumption growth for the current quarter using the information that would have been available to forecasters in the second month of the quarter. This includes using the initial releases for the different components of consumption and of lagged disposable income; we update the sample used for each quarter forecasted, simulating the process that forecasters would have used in real time. We forecast the three different components of private consumption for each month of the quarter using 1) the baseline model, 2) augmented models in which the same model is used across all timeframes and consumption types, and 3) the best model (augmented or baseline) for each specific time frame and type of consumption. In spite of the fact that we are using initial releases for the most recent data, in calculating the RMSFE for each forecast, we use the final revised values for each of the components of consumption. In other words, we judge how well the forecast predicts the change in sum of actual consumption components, even though some of the information forecasters have at the time is imperfect and will eventually be revised.[6]

For example, to forecast nondurable consumption, one month ahead, the best model is News + 90% PCA, but the lowest RMSFE for the previous month forecast is achieved with the baseline model. Therefore, we switch the model based on the different type of consumption and time frame being forecast. Once we estimate consumption growth for each type of consumption and timeframe, we calculate a weighted average growth rate, using the weights of each component in total consumption and then average the monthly estimates across the three months in a quarter. Then, we compare the forecasted weighted average for each quarter to the actual.

[6] Note that we must also "forecast" consumption growth for the previous month because that information would not be known at the time to the forecaster in the middle of the quarter.

The resulting RMSFEs for each forecast are shown in Exhibit 13. While all but one of our forecasts are significantly better than the median forecast of the Survey of Professional Forecasters, the approach of using different information to forecast different types of consumption and timeframes, the “Best Models” approach, results in a slightly lower RMSFE than the second best approach that uses the same model for all types and timeframes of consumption. Interestingly, the baseline model outperforms models that incorporate news searches uniformly across all types of estimations, in spite of the fact that the models with news searches are sometimes the best model (e.g., nondurable goods nowcast and forecast). The ultimate conclusion of this exercise is that Google Trends data has the potential to improve forecasts, however, it does not always do so. Care must be taken to consider the ways in which consumers are using Google searches to inform purchasing decisions.

Conclusion

This study shows the potential of Google Trends as a consumption indicator. Google Trends indicate changes in future and contemporaneous consumption components through providing information about pre-consumption research trends and popularity of economy-related news articles. Consumption forecast models augmented with Google Trends data reduce forecast errors of baseline models, and the results are nontrivial and robust to changes in baseline models, measurements of errors and statistical methods. That said, our results also suggest that the way that Google Trends data are added to forecast models should consider carefully the way in which search data is used by consumers and firms. Specifically, we demonstrate that different treatment of the Google Trends data for each of the components of consumption (durables, nondurables, and services) results in a better forecast. Furthermore, the optimal use of Google Trends data differs depending on whether or not the forecaster is attempting to predict future consumption or obtaining a nowcast. Therefore, a uniform approach to using Google Trends data for all economic series and time frames does not result in the best forecast.

The implications of this study are significant. Economists and policy makers can utilize daily and weekly Google Trends data to estimate high frequency changes in consumption. Because consumption is the largest part of the economy, unusual changes in consumption forecasts associated with changes in consumption-related and news-related Google Trends should be indicative of future economic events. Future research should investigate the potential of Google Trends data further, allowing its usefulness to vary with economic conditions. For example, the relationship between Google searches and consumption behavior may weaken in times of economic uncertainty. With further research and refinement, Google Trends data will allow policy makers to respond to economic events in a timelier and more appropriate manner.

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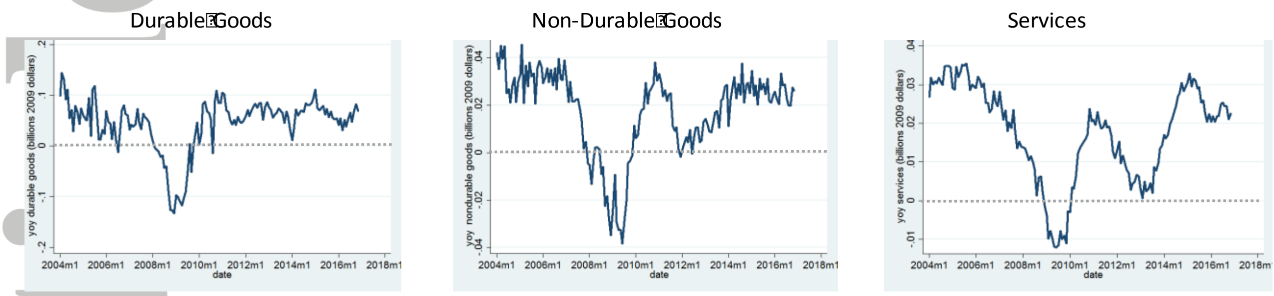
Figure 1

12 Month Growth Rates of Components of Consumption



Source: The Bureau of Economic Analysis

Exhibit 1

Components of Consumption and Matching Google Trends Categories

Google Trend Categories

Durable Consumption	Nondurable Consumption	Services Consumption
Auto Vehicles	Alcoholic Beverages	Home Financing
Auto Financing	Food & Drink	Home Improvement
Automotive Industry	Grocery & Food Retailers	Home Insurance
Auto Insurance	Non-alcoholic Beverages	Homemaking & Interior Décor
Vehicle Brands	Apparel	Drugs & Medications
Vehicle Shopping	Apparel Services	Health Insurance
Computer Electronics	Footwear	Medical Facilities & Services
Consumer Electronics	Undergarments	Auto Financing
Home Appliances	Athletic Apparel	Auto Insurance
Home Financing	Electricity	Entertainment Industry
Home Furnishing	Energy Utilities	Movies
Home Gardening	Oil & Gas	Computer & Video Games
Home Improvement	Beauty & Fitness	Ticket Sales
Home Insurance	Chemical Industry	Food & Drink
Homemaking and Interior Décor	Drugs & Medications	Grocery & Food Retailers
Book Retailers	Face & Body Care	Hotels & Accommodations
Arts & Entertainment	Hair Care	Restaurants
Entertainment Industry	Health	Home Financing
Movies	Newspapers	Home Insurance
Computer & Video Games	Tobacco Products	Insurance
Mobile Wireless		Internet & Telecom
Internet & Telecom		Retirement Pension
		Social Services
		Waste Management

Exhibit 2
Private Consumption Prediction Model Specifications

Variables	Baseline	News Only	90% PCA	News + 90% PCA
Baseline Variables	X	X	X	X
News Google Trends ("recession" & "layoff")		X		X
Consumption Google Trends (90% PCA)			X	X

Exhibit 3

RMSFE (12 Month % Growth) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	Statistics	Baseline	News Only	90% PCA	News + 90% PCA	Average
Forecast	Durable	RMSFE	1.836	1.670	1.703	1.610	1.705
	Nondurable	RMSFE	0.842	0.846	0.750	0.706	0.786
	Services	RMSFE	0.395	0.374	0.320	0.310	0.350
Nowcast	Durable	RMSFE	1.680	1.475	1.604	1.620	1.595
	Nondurable	RMSFE	0.670	0.723	0.612	0.624	0.657
	Services	RMSFE	0.289	0.282	0.241	0.239	0.263

Exhibit 4

RMSFE Reduction (% of Baseline Error) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	News Only	90% PCA	News + 90% PCA	Average	Best Model
Forecast	Durable	9.04	7.23	12.30	**9.52**	News + 90% PCA
	Nondurable	-0.51	10.82	16.15	**8.82**	News + 90% PCA
	Services	5.18	18.84	21.33	**15.12**	News + 90% PCA
	Average	**4.57**	**12.29**	**16.59**	**11.15**	
Nowcast	Durable	12.22	4.52	3.54	**6.76**	News Only
	Nondurable	-7.89	8.67	6.87	**2.55**	90% PCA
	Services	2.43	16.58	17.30	**12.10**	News + 90% PCA
	Average	**2.25**	**9.93**	**9.24**	**7.14**	

Note: Some models result in larger error.

Exhibit 5

Alternative Baseline Model RMSFE (12 Month % Growth) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	Statistics	Baseline	News Only	90% PCA	News + 90% PCA	Average
Forecast	Durable	RMSFE	1.831	1.688	1.870	1.614	1.751
	Nondurable	RMSFE	0.833	0.791	0.752	0.680	0.764
	Services	RMSFE	0.326	0.336	0.305	0.303	0.318
Nowcast	Durable	RMSFE	1.543	1.329	1.612	1.399	1.471
	Nondurable	RMSFE	0.628	0.696	0.560	0.593	0.619
	Services	RMSFE	0.254	0.258	0.235	0.233	0.245

Exhibit 6

Alternative Baseline Model RMSFE Reduction (% of Baseline Error) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	News Only	90% PCA	News + 90% PCA	Average	Best Model
Forecast	Durable	7.78	-2.17	11.83	**5.81**	News + 90% PCA
	Nondurable	5.10	9.81	18.38	**11.09**	News + 90% PCA
	Services	-3.02	6.46	6.92	**3.45**	News + 90% PCA
	Average	**3.29**	**4.70**	**12.37**	**6.79**	
Nowcast	Durable	13.91	-4.44	9.34	**6.27**	News Only
	Nondurable	-10.67	10.97	5.57	**1.95**	90% PCA
	Services	-1.59	7.43	8.19	**4.67**	News + 90% PCA
	Average	**0.55**	**4.65**	**7.70**	**4.30**	

Note: Some models result in larger error.

Exhibit 7

RMSFE of month-on-month forecasts (12 Month % Growth) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	Statistics	Baseline	News Only	90% PCA	News + 90% PCA
Forecast	Durable	RMSFE	1.094	1.078	1.093	1.078
	Nondurable	RMSFE	0.372	0.386	0.373	0.387
	Services	RMSFE	0.163	0.162	0.184	0.184
Nowcast	Durable	RMSFE	1.096	1.103	1.107	1.158
	Nondurable	RMSFE	0.318	0.332	0.317	0.331
	Services	RMSFE	0.157	0.157	0.161	0.162

Note: Sample starts in 2008. 90% PCA data are monthly growth rate of PCA's.

Exhibit 8

RMSFE Reduction of month-on-month forecasts (% of Baseline Error) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	News Only	90% PCA	News + 90% PCA	Average	Best Model
Forecast	Durable	1.52	0.07	1.45	**1.01**	News Only
	Nondurable	-3.85	-0.43	-4.09	**-2.79**	Baseline
	Services	1.03	-12.64	-12.65	**-8.09**	News Only
	Average	**-0.43**	**-4.33**	**-5.10**	**-3.29**	
Nowcast	Durable	-0.59	-0.94	-5.57	**-2.36**	Baseline
	Nondurable	-4.64	0.16	-4.11	**-2.87**	90% PCA
	Services	-0.06	-2.37	-3.14	**-1.86**	Baseline
	Average	**-1.76**	**-1.05**	**-4.27**	**-2.36**	

Note: Sample starts in 2008. 90% PCA data are monthly growth rate of PCA's.

Exhibit 9

Difference in Error Reductions (1-month ahead minus nowcast) - Forecast timeline: Jan 2015 - Nov 2016

Dependent Variable	Standard Baseline [PCA 90%]	Alternative Baseline [PCA 90%]
Durable	2.70	2.269*
Nondurable	2.15	-1.159
Services	2.25	-0.966

Note: negative number means nowcast error reduction is larger
*both models increased RMSFE

Exhibit 10

RMSFE using 60 Month Rolling Window Models (12 Month % Growth) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	Statistics	Baseline	90% PCA
Forecast	Durable	RMSFE	1.616	1.390
	Nondurable	RMSFE	0.636	0.573
	Services	RMSFE	0.305	0.276
Nowcast	Durable	RMSFE	1.698	1.527
	Nondurable	RMSFE	0.621	0.570
	Services	RMSFE	0.300	0.252

Exhibit 11

RMSFE Reduction using 60 Month Rolling Window Models (% of baseline error) - Forecast timeline: Jan 2015 - Nov 2016

	Dependent Variable	90% PCA
Forecast	Durable	14.00
	Nondurable	9.79
	Services	9.39
	Average	**11.06**
Nowcast	Durable	10.06
	Nondurable	8.22
	Services	15.94
	Average	**11.41**

Exhibit 12

Difference in Error Reduction using 60 Month Rolling Window Models (1-month ahead minus nowcast) – Forecast timeline: Jan 2015 – Nov 2016

Dependent Variable	Standard Baseline [PCA 90%]
Durable	3.95
Nondurable	1.57
Services	-6.55

Note: negative number means nowcast error reduction is larger

Exhibit 13

RMSFEs for Quarterly Consumption Growth Forecasts - Out of Sample Forecasts for Q1: 2015 - Q4: 2016

Model	RMSFE
Best Models Combined	0.4488
PCA 90 Model	0.4584
Baseline Model	0.5322
News + PCA 90 Model	0.5451
SPF Current Quarter Median Response	0.7760
Best Models Combined	3.7157