Nowcasting of the U.S. unemployment rate using Google Trends

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ABSTRACT

This study examines whether and how the search intensity data obtained from Google Trends contributes to nowcasting of the U.S. unemployment rate compared to the conventional AR model. Our assessment is motivated by two issues that may affect the validity of the forecast model using the Google search intensity. The first issue is the change in Google Trends specification that limits the period during which the search intensity data can be retrieved on weekly basis. The second issue is the potential change in the endpoint value of seasonally-adjusted series based on the timing of seasonal adjustment, which may generate a problem when running a real-time forecast. Our results show that the usage of Google Trends doesn't necessarily contribute to improving the accuracy of forecasts under some preconditions, suggesting that there is a limit to the method of adding the search intensity of single keyword to the forecast model.

1. Introduction

Economic indicators such as GDP and labor statistics are used by investors to forecast economic trends and decide on the appropriate investment policy. In particular, the US unemployment rate is one of the most important economic indicators for financial market participants due to its correlation with the US business cycle and its influence on the Federal Open Market Committee (FOMC) members when they make monetary policy decisions.\textsuperscript{1}

However, the official release of economic indicators tends to generate an information time lag, because it takes time from the end of the reference period. To address this problem, nowcasting, which forecasts the movement of immediate economic indicators before their release, has been attempted through various approaches. Among them, the search intensity data obtained from Google Trends have been used to improve the accuracy of nowcasting diverse economic indicators. Many studies show the usefulness of Google Trends in various fields including not only economic forecasting and nowcasting (D’Amuri and Marcucci, 2017) but also epidemiology detecting influenza epidemics (Ginsberg et al., 2009), and predicting return on stocks and their transaction volume (Adachi et al., 2017; Da et al., 2011; Takeda and Wakao, 2014).

This study examines the applicability of Google Trends to nowcasting the US unemployment rate. D’Amuri and Marcucci (2017) report that adding an indicator based on Google job-search-related query data to the autoregressive (AR) model improves the predictive power. They also demonstrate the superiority of the model using Google Trends data by comparing it to the values forecasted

Abbreviations: GI, Google Index; IC, Initial claims
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\textsuperscript{1} According to the Federal Reserve Act, the three U.S. monetary policy objectives are maximum employment, stable prices, and moderate long-term interest rates. This means that labor market conditions are a part of monetary policy deliberations. The former FRB Chairman, Ben Bernanke, stated that FOMC members watched labor market indicators, such as labor force participation, non-farm payroll employment, and the unemployment rate (Dr. Econ, 2013).

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by models with other economic variables adopted as leading indicators, as well as to the predictions released by the Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia.

However, the past analysis cannot be replicated at present because Google Trends has changed its specifications several times since its release in 2008. The usefulness of Google Trends data to nowcasting of economic indicators may change by the specification of Google Trends in a period. In this study, therefore, we examine the applicability of Google Trends for running a real-time nowcasting under the specification as of November 2018. Furthermore, we discuss why the model that adds the search intensity of a single keyword as an explanatory variable is not effective under the current environment.

The structure of the paper is as follows. Section 2 provides background information on the US unemployment rate and Google Trends. Section 3 explains the data and methodology. Section 4 discusses the results. Section 5 provides implications for financial markets and Section 6 concludes.

2. Background

2.1. US unemployment rate

The monthly US unemployment rate is released on the first Friday of every subsequent month. At the time of announcement, they also retroactively adjust the indicator for the past two months. The period covered by the survey of employment statistics is defined as the week of the 12th day of the month. Measuring the job-search activities of those included in the definition of unemployed people from the perspective of online job search, and utilizing it for forecasting is the idea of nowcasting based on Google Trends.

The number of new unemployment insurance claims (initial claims, or IC) is known as a leading indicator of the unemployment rate. IC for the previous week is released every Thursday. Since this is a weekly indicator, the data for four weeks—the week of the 12th day to correspond to the period covered when calculating the unemployment rate and the preceding three weeks—are aggregated every month as monthly indicators. The weekly data on search intensity described in the next section is aggregated as well by averaging the data during the same period. Fig. 1 summarizes the day the unemployment rate is released and the corresponding period for the weekly data used for forecasting.

2.2. Google Trends

Google Trends is a service that outputs the time series data of search intensity to show the extent to which a particular keyword is searched for in a specified period and location. Search intensity is standardized in a way to turn the maximum value during the period into 100 based on the number of specific keyword searches relative to the number of all searches in a specified location. To speed up the computation, the figure is calculated based on a randomly selected part of the search data. Consequently, the figure varies based on the time when the search intensity is retrieved. \(^2\)

In many cases, previous studies that use Google Trends analyze the search intensity data retrieved weekly throughout the sample period. However, as of November 2018, the frequency of data output is set to monthly when retrieving the search intensity for a period exceeding five years. Furthermore, since search intensity is standardized based on the maximum value during the period of data retrieval as described above, it is difficult to join the search intensity data retrieved over multiple periods to create consistent data. Therefore, this study uses the data for both cases: the case of using the monthly data, and that of retrieving and using the weekly search intensity data only for the past five years when running a monthly forecast.

\(^2\) The correlation coefficients usually exceed 0.97 when they are calculated by retrieving the search intensity multiple times over different points of time (Da et al., 2011). Therefore, we can assume that the trending value of search intensity in a given period is stable regardless of when it is retrieved.
3. Data and methodology

3.1. Data

For the unemployment rate and the number of IC, the seasonally adjusted time series data are obtained from ALFRED, which is a website of the Federal Reserve Bank of St. Louis. While the economic indicators are revised over time after the initial release as more accurate data are obtained, ALFRED allows users to obtain all economic indicators released at the time of each official announcement, including the data before the revision. For running a real-time forecast, this study uses the unemployment rate and the number of IC that are initially released, considering reproducibility in terms of the timing for obtaining the data. Regarding the unemployment rate, this assumption should not much affect the forecasting of economic indicators since the revision occurs only once a year due to a seasonal adjustment during the sample period, as will be described later.

The search intensity data are obtained from Google Trends. We specify the region as the US and use two terms “jobs” and “job offer” as the search keywords following previous studies (Askitas and Zimmermann, 2009; D’Amuri and Marcucci, 2017).3 The seasonality with the search intensity in the US has been confirmed because Christmas-related searches predominantly increase toward the end of the year compared to other seasonal events, and the percentage of other keyword searches relatively decreases. We make seasonal adjustments to the search intensity data while considering the points described in the following subsection.

3.2. Seasonal adjustment

The X13-ARIMA-SEATS, a program developed by the US Census Bureau and the Bank of Spain, is used to make seasonal adjustments to the search intensity data. With this kind of seasonal adjustment method, smoothing is done using multiple centralized moving average filters. However, the moving average should be calculated by extrapolating the values forecasted by the time series model because the future values cannot be observed around the endpoint of the data. Many previous studies obtain the search intensity data for the sample period, process it into monthly data if necessary, make a seasonal adjustment, and use it for real-time forecast. We should note, however, that when we run a monthly forecast, the month in question becomes the endpoint of the data. Since the seasonally adjusted value based on the forecast for the future is different from that calculated with the actual data in the future, the accuracy might differ between the forecasts based on these two values. Therefore, this study examines both cases—the case in which the entire series of search intensity for the sample period is seasonally adjusted, and that in which the search intensity up to a given month is used for forecasting after it is seasonally adjusted each time the monthly forecast is performed.

In the case of the unemployment rate and the number of IC, the data are released after the difference caused by seasonal adjustment is revised once a year for a given period (unemployment rate: two years; number of IC: five years).

3.3. Forecasting method

Following D’Amuri and Marcucci (2017), we estimate an AR model and augment it with the search intensity or Google Index (GI) and the number of IC. The maximum lag is selected by the following method at the time of running a monthly forecast. We first estimate the AR model based on the following equation:

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \eta_t, \quad t = 1, 2, \ldots, T.$$  

where $y_t$ and $\eta_t$ denote the unemployment rate for the month $t$ (or the difference from the value of the month $t-1$) and the error term, respectively. Among the regression results for $1 \leq p \leq 4$, the best $p$ is chosen based on the Bayesian information criterion (BIC). Then by using the selected $p$, we estimate the following model:

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=1}^{q} \beta_2 x_{t-i} + \epsilon_t, \quad t = 1, 2, \ldots, T,$$  

where $x_t$ denotes the exogenous variable for the month $t$ while $\epsilon_t$ denotes the error term. Similar to $p$, the best $q$ is also chosen based on the BIC in the range of $1 \leq q \leq 4$ and used for prediction.

While D’Amuri and Marcucci (2017) employ the past 37 months for monthly forecasts using a rolling window, we use 57 months, the maximum available when the lags of explanatory variables are subtracted from the five years for which the weekly GI can be obtained. In addition, considering the possibility that the unemployment rate has a unit root, we use both the level of unemployment rate and the difference.4

As described earlier, GI has issues such as the relationship between the period and frequency of data as well as the timing of seasonality adjustment. To guarantee robustness, we employ the following three methods in obtaining the data and a seasonal

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3 Note that the search intensity of “jobs” is obtained by “jobs – steve” to exclude the influence of searches related to Steve Jobs (Steven Paul Jobs), the co-founder of Apple Inc. By doing so, we can exclude the search intensity outliers in October 2011 when Steve Jobs passed away (the trend of the search intensity remained consistent in other periods).

4 D’Amuri and Marcucci (2017) report that whether the unemployment rate has a unit root depends on the sample period, and use the level of unemployment rate because they are interested in the short sample.
(1) Obtain the monthly GI between January 2004 and June 2018 at once, seasonally adjust the entire data, and use it for a monthly forecast.
(2) Use the monthly GI between January 2004 and a given month that have been seasonally adjusted every time a monthly forecast is made.
(3) Obtain the weekly GI for the past five years and use the aggregated data to monthly frequency every time a monthly forecast is made.

It should be noted that method (1) cannot be executed when running a real-time forecast.

4. Results

We begin forecasting from March 2009 by setting the sample period from January 2004 to June 2018. The accuracy of the model is evaluated based on the root mean square error of the prediction. First, Table 1 shows the results for the case in which the period of data used for model estimation is set to 37 months. “Benchmark” on the second row represents the simple AR model without an exogenous variable while the other rows represent models with an exogenous variable. We also use the test proposed in Diebold and Mariano (1995) and compare the accuracy of each model’s prediction to that of the benchmark model.

Table 1 shows that when the level of unemployment rate is forecasted, the prediction accuracy improves relative to the benchmark AR model as it does in the previous studies. However, the degree of improvement is small compared to that made by adding IC. Furthermore, the degree of improvement varies across three models and the choice of search keyword. When predicting the difference in the unemployment rate, only one model outperformed the benchmark AR model in terms of prediction accuracy. Adding GI to the AR model shows almost no significant improvement in the prediction accuracy.

Next, Table 2 presents the results of the case in which the estimation period is set to 57 months. Table 2 shows that when forecasting the level of the unemployment rate, while the model with IC demonstrates a higher prediction accuracy than the benchmark, the model with GI shows no significant improvement. In the case of forecasting the difference in the unemployment rate, when the search keyword is set to “jobs” the prediction accuracy deteriorates for all three models. When the search keyword is set to “job offer,” no significant improvement in accuracy is observed.

Our results are not consistent with those of the previous study reporting that the model with GI consistently outperforms the benchmark in terms of prediction accuracy and also has an advantage over IC. To investigate what causes the difference between the
two results, we check how the correlation between the GI and the unemployment rate changes over time. Table 3 shows that GI(jobs) and GI(job offer) have a positive correlation between January 2004 and February 2014. However, the correlation coefficients decline in later periods, resulting in the negative correlation between March 2014 and June 2018. In contrast, IC has a positive correlation with the unemployment rate, which becomes larger in later periods.

Fig. 2 demonstrates the movements of GI(jobs), GI(job offer), and the unemployment rate. For clarifying the comovement of the unemployment rate and GI, we plot the series of “100–GI” as GI(job offer). The gap between GI(jobs) and the unemployment rate seems to increase since 2009. After the global financial crisis in 2008, the unemployment rate declines overtime, while GI(jobs) keeps moving between 80 and 90. Such a volatile correlation between internet search activities and economic variables may reduce the predictive power of the forecast model with GI. In contrast, Fig. 3 shows that IC seems to have a similar trend as the unemployment rate, indicating a more stable relationship between IC and the unemployment rate. These exercises indicate that internet search activities may fluctuate over time, reducing their correlation with economic variables and the predictive power of the forecast model incorporating search intensity. These insights are consistent with our results showing that the forecast model with additional economic variables (IC) is superior to the model with GI.

5. Implications for financial markets

Forecasting the US unemployment rate is very important for financial market participants. On the one hand, the unemployment rate is a reliable indicator of labor market conditions. Because personal consumption expenditures account for approximately 70% of US GDP, an increase (decrease) in income resulting from low (high) unemployment rate indicates expansion (decline) of consumption and thus aggregate demand. On the other hand, fluctuating unemployment rates can also affect asset prices via the change in monetary policy because full employment is one of the three monetary policy objectives. When making monetary policy decisions, the FOMC should mitigate deviations in the full employment level from its long-run goal by changing money supply and interest rates.

Although the release of monthly unemployment rate is one of the most important regular economic events for market participants, the effect of the unemployment news on stock returns is not so straightforward because the relative importance of information on labor market conditions and monetary policy changes overtime depending on the state of the economy; low (high) unemployment rate is not always positive (negative) news for the stock market. In fact, Boyd et al. (2005) find that a rising unemployment rate tends to increase average stock prices during economic expansion but decreases them during economic contraction.

Considering the difficulty in predicting market reactions, accurately forecasting the unemployment rate is useful for investors to hedge the market risk arising from the unexpected change in business conditions and monetary policy. Although our investigations
show that superiority of the forecast model with GI cannot be guaranteed when using the most recent data, we believe that our research provides useful suggestions for future research that should improve the prediction accuracy by methods such as using the GI of multiple keywords.

6. Concluding remarks

This study examines whether and how the search intensity data obtained from Google Trends contribute to nowcasting of the US unemployment rate compared to the conventional AR model. Our results show that while the frequency of GI and real-time seasonal adjustment affect the prediction, there is no consistent tendency regarding the direction, that is, whether the effect improved or reduced the prediction accuracy. The model with GI predicts the level of unemployment rate more accurately, on average, than the simple AR model by using a relatively short period of data. However, once these conditions are changed, robustness is not guaranteed. Furthermore, the degree of improvement to the accuracy made by using GI is smaller than that made by using IC. Thus, there is a limit to achieving a high level of prediction accuracy with the model using the GI of a single keyword. Therefore, future research should improve the prediction accuracy by methods such as using the GI of multiple keywords.

Declaration of interest

None.

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Supplementary materials

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