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NOWCASTING THE UNEMPLOYMENT RATE IN TURKEY: LET'S ASK GOOGLE

Meltem Gülenay Chadwick and Gönül Şengül*

ABSTRACT We investigate whether Google search query data can improve nowcasting performance of the monthly nonagricultural unemployment rate for Turkey, where monthly unemployment rate is revealed with a lag of three months. To do so, we employ linear regression models and Bayesian Model Averaging Procedure in our analysis and use data from January 2005 to October 2011. We show that Google search query data is successful at nowcasting nonagricultural unemployment rate both in-sample and out-of-sample. When compared with an autoregressive benchmark model, where we allow only the lag values of the monthly unemployment rate, the best model contains principal components of Google search query data and it is 47.7% more accurate in-sample and 38.4% more accurate out-of-sample in terms of relative root mean square errors (RMSE). The best model that does not include any Google data is 34.1% more accurate insample and 29.4% more accurate out-of-sample. We also show via Harvey et al (1997) modification of the Diebold-Mariano test that models with Google search query data indeed perform statistically better than the autoregressive benchmark model.
JEL E52, E58, F31, F32
Keywords Nowcasting, Nonagricultural unemployment rate, Bayesian model averaging, Google Trends, Linear models

ÖZ Bu çalışmada, Google tarama sonuçları verilerinin Türkiye'de üç aylık bir gecikme ile yayınlanan aylık tarım dışı işsizlik dönem içi tahminini geliştirip geliştirilmediği araştırılmaktadır. Bunun için yapılan analizde lineer tahmin modelleri ve Bayesgil Model Ortalaması yöntemi ve Ocak 2005 ve Kasım 2011 arası verisi kullanılmıştır. Sonuçlar, Google tarama sonuçları verilerinin hem örneklem içinde hem de örneklem dışında tarım dışı işsizlik oranı dönem içi tahminlerini iyileştirdiğini göstermektedir. Sadece tarım dışı işsizliğin gecikmeli değerlerinin kullanıldığı otoregresif baz modelle kök ortalma kare hatalarına (RMSE) göre kıyaslandığında en iyi performası gösteren model Google tarama sonuçları verilerinin ana bileşenlerini (principle components) içermekte ve baz modelden örneklem içinde %47,7, örneklem dışında ise %38,4 daha doğru tahminler vermektedir. Google tarama sonuçları verilerini içermeyen en iyi model örneklem içinde %34,1, örneklem dışında ise %29,4 daha doğru tahminler vermektedir. Çalışmada ayrıca Diebold-Mariano testinin Harvey vd. (1997) uyarlaması kullanılarak Google tarama sonuçları verilerini içeren modellerin perfromasının baz modelden istatistiki olarak anlamlı bir şekilde daha iyi oldugu gösterilmiştir.
TÜRKİYE'DE İŞSİZLİK ORANININ DÖNEMİÇİ TAHMİNİ: GOOGLE'A SORALIM
JEL E52, E58, F31, F32
Anahtar Kelimeler Dönem içi tahmin, Tarım-dışı işsizlik oranı, Bayesgil model ortalaması, Google Trends, Doğrusal modeller

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* Central Bank of the Republic of Turkey, Research and Monetary Policy Department, İstiklal Cad. 10, 06100-Ankara, Turkey ■ **CHADWICK:** meltem.chadwick@tcmb.gov.tr ■ **ŞENGÜL:** gonul.sengul@tcmb.gov.tr, Istanbul School of Central Banking, Fenerbahçe Mahallesi, Atlıhan Sokak, No:30/A, Kadıköy, 34726 İstanbul, Turkey ■ The views expressed in this paper belong to the authors only and do not represent those of the Central Bank of the Republic of Turkey or its staff.

1. Introduction

Timely information on the current situation of the economy is crucial for the economists, academicians and policy makers for variety of reasons. However, this information is usually released with a lag by the statistical offices. Hence, any means of getting timely information about the current state of the economy is highly valuable. Recently, data on internet based search is proven to carry valuable information about different economic indicators for different countries. This paper aims to provide more evidence on the predictive power of such internet search data by using Google search query data to nowcast[1] Turkish monthly nonagricultural unemployment rate, which is released with a lag of three months.

Using Google search activity to nowcast/forecast variables has been employed by many researches in different areas of life. Ginsberg et al. (2008) is the first paper, one of the most popular and commonly cited example in the literature, where authors use Google based search data for forecasting influenza epidemics. Kholodilin et al. (2010) nowcast year-on-year growth rate of monthly private consumption in the U.S. and find that Google search indicators improve the predictive power of a baseline benchmark autoregressive model. Choi and Varian (2009b) use Google data to nowcast retail sales, home sales and travel in the U.S.. Hand and Judge (2012) use Google Trends search information to forecast the cinema demand using monthly data for UK and find clear evidence that Google trends data improve the accuracy of cinema admissions forecasts. Wu and Brynjolfsson (2009) predict housing market trends using Google search data and they find that a housing search index is strongly predictive of the future housing market sales and prices for U.S.. Vosen and Schmidt (2012) develop a monthly consumption indicator for Germany based on Google Trends data. Vosen and Schmidt (2011) improve upon the survey based indicators that are commonly used in the U.S. to predict private consumption via using search query data. Carriere-Swallow and Labbe (2011) investigate whether internet search can be an indication of automobile purchases and therefore consumption patterns in Chile. Suhoy (2009) test the predictive ability of Israeli query indices using Google's Insights for Search application. Also in

[1] We define nowcasting as the prediction of the present and the term is named as 'present casting' by Choi and Varian (2009b). We nowcast unemployment rate from the month for which data is revealed to the present month.

another paper, Suhoy (2010) sets a framework for high-frequency nowcasts of private consumption for Israel, using consumption related query indices, available weekly from Google Insights for Search. Smith (2012) uses Google internet search activity to predict volatility in the market for foreign currency.

Studies for different developed countries confirm that the internet search index can be a good predictor of the unemployment rate. For instance, Choi and Varian (2009a) use the same methodology as in Choi and Varian (2009b) to nowcast the unemployment rate in the U.S. Askitas and Zimmermann (2009) use Google search data to establish a relationship between search activities for certain keywords and unemployment rate in Germany. To do so, they use data for search terms "unemployment office or agency", "unemployment rate", "Personnel Consultant", and "most popular search engines in Germany" and use error-correction model specification to analyse the predictive power of Google search activity data. They find that the search index is a good predictor of unemployment rate in Germany. McLaren and Shanbhogue (2011) use information on internet search behaviour and analyse UK housing and labour markets. They conclude that internet data provide some additional information relative to existing surveys. D'Amuri (2009) uses Google Index to predict unemployment in Italy, where data is available quarterly. He tests the empirical relevance of Google Index to forecast unemployment and shows that it has informational value. D'Amuri and Marcucci (2010) show that Google Index is the best leading indicator for the U.S. unemployment rate. Bughin (2011) nowcasts unemployment claims, among other macro-economic indicators, for Belgium using Google Insights for Search data while Moen et al. (2010) use Google data to nowcast Norwegian unemployment rate.

As the previous paragraphs state, almost all the inquiries as to whether Google Search data can help nowcast macro-economic indicators are done for developed countries. To our knowledge, Carriere-Swallow and Labbe (2011) provide the only evidence for an emerging economy. This paper provides more recent evidence for the predictive power of Google data in emerging economies as we use Google Search queries to nowcast the unemployment rate for Turkey. We expect the search queries to carry significant information regarding the present state of the economy in Turkey, as 45% of the population has internet access.[2]

[2] Data regarding internet use in Turkey comes from the Turkish Statistical Institute (TurkStat) Survey on Information and Communication Technology (ICT) Usage in Households. Percentage of the population with internet access was 30% for the whole country and 36.6% in urban areas for the year 2007. The data indicates

To our knowledge, this study is the first one that nowcasts unemployment rate in Turkey. Unemployment rate of each month is released with a lag of three months, on the 15th (or the first following business day) of the month in Turkey. Hence, our knowledge of the labour market conditions falls two and a half months behind the current conditions. This paper, using Google search index to nowcast seasonally unadjusted monthly nonagricultural unemployment rate, aims to provide a timely information. The focus of the study is on the nonagricultural unemployment rate as the agricultural labour market is mostly in the rural areas with very low internet usage rates, and it has its own dynamics. As independent variables, we use Google query data for different keyword searches that may contain information regarding the current unemployment rate in Turkey.[3] Additionally, we analyse the performance of models that include some macroeconomic fundamentals as independent variables, which can help predict the unemployment rate. These variables are industrial production and the initial unemployment claims. We estimate the predictive power of each model with different combinations of the explanatory variables mentioned, selected via Bayesian Model Averaging, and compare them to the benchmark where the unemployment rate is defined as an autoregressive process. We use root mean square error (RMSE) and modified Diebold-Mariano test results for comparison, and our results show that the model with the lowest root mean square error includes Google search query data. Hence, we conclude that using Google Insights improves the nowcast performance of the unemployment rate for Turkey.

The remainder of the paper is organized as follows: The following section describes the details of the dataset used to estimate all the nowcasting models. The third section gives an explanation on the econometric methodology and describes the models used in nowcasting. It is followed by the fourth section that discusses the results. The last section concludes.

2. Data

We collect data from different sources. The unemployment rate data is from the Turkish Statistical Institute (TurkStat). The TurkStat conducts Household Labour Survey and reports number of the labour force and the unemployed workers.[4] Our data is monthly and it covers the period between

that these numbers have been increasing since 2007, and 45% of the whole population and 53.2% of urban population had internet access for 2011.

[3] We look at both Google search query data and the principle components extracted from them, which is a very common usage in the literature (See Carriere-Swallow and Labbe (2011) and Kholodilin et al. (2010)) utilising Google search query data, to test whether Google search queries can help us nowcast unemployment rate.

[4] For more information, visit http://www.turkstat.gov.tr.

January 2005, and October, 2011. We also use data for industrial production and initial claims of unemployment. Industrial production data is from the Central Bank of Turkey while the Initial Claims of Unemployment data is collected by the Government Employment Agency (ISKUR). These data are monthly and they are released within the first half of the following month.

Google Insights for Search: To proxy for the internet based search, we use data from Google Insights for Search. Google Search analyses a portion of Google web searches from all Google domains of a specified geography to compute how many searches have been done for the terms entered, relative to the total number of searches done on Google over time in that region.[5] In other words, the data measure the likelihood that a random user searches for a particular search term from a certain location at a certain time. Data are delivered in weekly frequency, available from 2004 onward, normalized by the highest value observed and presented on a scale from 0-100. When there is not enough data, i.e., the traffic for the search term is below some threshold level, 0 is shown.

We select search terms that are either directly or indirectly related to unemployment.[6] As a natural start, we search over terms on the internet that one may use to search for a job using www, like “looking for a job” or “job announcements”. We also search for terms like “cv” and “career” along with the names of some popular career web sites, as these terms not only indicate job search of unemployed but also may signal whether employed people look for another job in anticipation of layoffs. Additionally, to get information from flows into unemployment and general state of the economy, we search over terms like “unemployment” and “unemployment insurance”.[7]

When a search inquiry is entered for a specific term, location, and time, Google Insights for Search examines a random fraction of all searches for that specific term within the same time and location parameters. Hence, if the traffic for a specific search term is not high enough, search results for the same term and parameters at different dates may give different results, which may introduce some noise to variables that we use to nowcast unemployment. For instance, Google search inquiry results for the key word “cv” today may not be the same as the inquiry results yesterday. To overcome possible noise introduced to the data, for each key word, we

[5] For more information visit: http://www.google.com/support/insights/.

[6] These search terms are in Turkish and the full list is provided in the Table A.2, as well as the English translations.

[7] D’Amuri (2009) uses queries for the term “job offers” (offerte di lavoroé) as a google indicator. Askitas and Zimmermann (2009) use “unemployment office or agency”, “unemployment rate”, “Personnel Consultant” and “most popular job search engines in Germany” as Google search queries.

collect data for 100 days and take their cross-sectional average to construct our series.[8] Also, Carriere-Swallow and Labbe (2011) use cross-sectional means for 50 days to get rid of the sampling noise. Recall that the data provided by Google Insights is weekly. We take averages of weekly data to convert them into monthly frequency. As such, we construct the monthly data that will be in line with the month for which the unemployment rate measured by the survey.[9]

We use difference of year-on-year growth rates (dyoy hereafter) of the monthly data for all the variables. Using year-on-year growth rate helps us to get rid of the seasonality. Turkish unemployment rate has a very clear deterministic pattern of seasonality, however this clear pattern is not very prominent in the most of the Google Search Inquiry data. Therefore, we take the year-on-year growth rates to smooth out the seasonal variation, instead of using statistical packages.[10] We work with the difference of year-on-year growth rates[11] as most of the variables we use have unit roots.[12]

Google Insights query data provides the most timely data to nowcast the unemployment rate for the Turkish economy. Figure 1 shows the structure of the data availability and the nowcasting period. For instance, in the middle of the month *t*, unemployment rate for month *t-3*, industrial production for month *t-2*, and initial unemployment claims for month *t-1* are announced. At the end of month *t*, we also have the Google Insights query data for that month.[13] Hence, at the end of the month *t*, we are able to give nowcast for unemployment rate in months *t-2*, *t-1*, and *t*.

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[8] Google Insights's different sampling for each day is a problem especially for the most recent data. We have 5 data points to average over the last week of the last month we have Google search data for.

[9] The reference week of the survey starts with the first monday of that month. A month for unemployment measures refers to the last 4 weeks ending with the reference week. Furthermore, in the calendar system used in Turkey, a week starts on mondays.

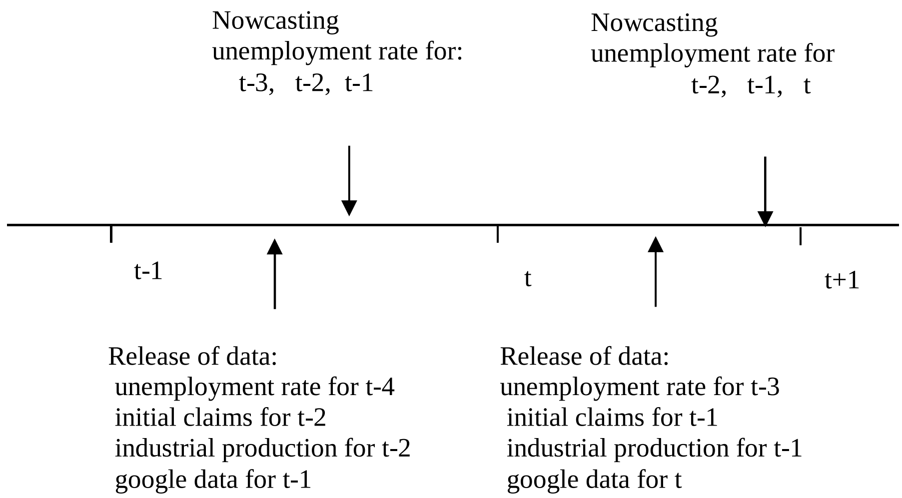
[10] Furthermore, since the unemployment rate has deterministic seasonal factors, they don't have much informational value, hence we don't employ them to nowcast.

[11] As we are interested in short-term nowcasts for the unemployment rate and not interested in the long-run dynamics we used differenced series similar to D'Amuri and Marcucci (2010).

[12] Descriptive statistics and unit root tests are illustrated at the appendix. Table A.1 and Table A.3 summarizes all the dataset used for the nowcasting exercise and gives the unit root test results, respectively.

[13] Notice that, based on the labour survey definition of a month, which unemployment rate data is based on, we could have Google Query data for month *t* in the middle of that month when unemployment rate for month *t-3* is announced. However, due to possible noise introduced by random sampling, we wait until the end of month *t* in order to increase our sample size regarding Google search observations for the month to be nowcasted.

Figure 1. Time Structure of Data Availability and Nowcasting



3. Econometric Methodology

We have a large group of potential explanatory variables to be used in the nowcasting models of the unemployment rate. We consider lags of unemployment rate, two other macroeconomic fundamentals and 20 additional Google variables as explanatory variables. Since we don't have any prior knowledge or theory of which ones of these models we should use, we need a model comparison procedure to deal with model uncertainty. Therefore, we start this section with giving a brief information regarding the Bayesian Model Averaging, the procedure we use to select our models.

We examine the predictive power of all the models within the framework of Bayesian Model Averaging (BMA), and BMA is very convenient under large number of variables when dealing with model uncertainty.[14] Since Leamer (1978), who introduced the basic paradigm of BMA, the methodology became one of the corner points of model comparison.[15] BMA procedure has been applied to many areas including cross-country growth regressions, predictability of stock returns and forecasting fundamentals like output growth, inflation and exchange rates.[16]

[14] Raftery et al. (1997) and Hoeting et al. (1999) are two invaluable resources that have some detailed analysis on BMA for linear regression models.
[15] See Hoeting et al. (1999) for a very detailed tutorial on BMA.
[16] We did not come across with any other article utilising BMA within the framework of using internet query data for nowcasting.

Bayesian Model Averaging and Occam's Window: We start the BMA procedure assuming we have a set of *n* possible models, where we parameterize the i^{th} model (M_i) by θ_i. We assume that the prior beliefs are such that every model has equal probability of being true. If we denote the prior beliefs by $P(M_i)$, assuming that all the models are equally likely will imply that $P(M_i)=1/n$. Observing the data (we denote as U), we update our prior beliefs according to a Bayesian formula to compute the posterior probability that the i^{th} model is the true model according to:

$$P(M_i|U) = \frac{P(U|M_i)P(M_i)}{\sum_{j=1}^{n} P\big(U\big|M_j\big)P(M_j)}$$

where $P(U|M_i)$ is the marginal likelihood of the i^{th} model that is given by:

$$P(U|M_i) = \int P(U|\theta_i, M_i)P(\theta_i|M_i)d\theta_i$$

and $P(\theta_i|M_i)$ is the prior density of the parameter vector θ_i associated with the i^{th} model. $P(U|\theta_i,M_i)$ is the likelihood function.[17]

We utilise an algorithm named "Occam's Window" besides BMA.[18] "Occam's Window" is a Bayesian model selection algorithm that involves averaging over a reduced set of models. Two basic principals underly the Occam's Window method. First, Madigan and Raftery (1994) argued that if a model predicts the data far less well than the model which provides the best predictions, then it has effectively been discredited and should no longer be considered. Second, complex models which receive less support from the data than their simple counterparts should be excluded. As we prefer to use very simple and parsimonious models to nowcast unemployment, Occam's Window supplies a favourable environment for model selection.

3.1. Nowcasting Models

Our first step is to choose a benchmark model that we think best represents the movement of the unemployment rate for the Turkish economy, where the unemployment rate is explained only by its own lags,

[17] We conducted BMA procedure using the R package "BMA" designed by Raftery and Painter (2005). This package provides ways of carrying out BMA for linear regression and we used the function bicreg, to account for uncertainty about the variables to be included in the model, using the simple BIC approximation to the posterior model probabilities via an exhaustive search over the model space using the fast leaps and bounds algorithm.

[18] See Madigan and Raftery (1994) for details. The writers compare Occam's Window and Markov Chain Monte Carlo method concluding that there are minor differences between the two procedure and both procedures provide better predictive performance than any single model which might reasonably have been selected. We also used Markov Chain Monte Carlo method to approximate for the exact solution and found very similar results so we are not reporting them in the paper.

and where maximum lag is 12, as we are using monthly data.[19] Our benchmark model for this nowcasting exercise is formalized in Equation 1 as:

$$U_{t+h} = \alpha(L)^{BM} U_{t-1} + \xi_{t+h}^{BM} \tag{1}$$

where U_{t+h} represents the difference of year-on-year growth rate of unemployment rate, h is the nowcast horizon, $\alpha(L)$ represents the autoregressive lag structure, *BM* stands for "Benchmark" and ξ_{t+h}^{BM} is the residual of the benchmark model. To choose the benchmark model, we incorporate BMA and start with possible number of models $n=2^{12}$, as we consider all variations of lag structure up to 12 lags.[20] We find that, from 2010m10 to 2011m10, there are 8 possible benchmark models. Among those, we pick the one with the best residual diagnostics and the smallest RMSE.[21] The residual diagnostics results and RMSE values are displayed in Table A.4.

After deciding on the benchmark model (Equation 1), we continue introducing group of nowcasting models that differ with respect to the independent regressor groups that we include in order to nowcast the unemployment rate. We proceed with different regressor groups separately, instead of pooling all explanatory variables together, to make sure that our nowcast models include different regressors.

In this respect, the first group is the one where the unemployment rate is explained by its own lags plus two fundamentals that are commonly used in the literature to forecast unemployment rate, i.e. industrial production (in_pr) and initial claims (in_clm).[22] The model is given by:

$$U_{t+h} = \alpha(L)^{FBM} U_{t-1} + \beta(L)^{FBM} F_t + \xi_{t+h}^{FBM} \tag{2}$$

where U_{t+h} represents the difference of year-on-year growth rate of unemployment and h is the nowcast horizon, as before, F_t is a vector that includes two variables in_pr and in_clm, $\alpha(L)$ and $\beta(L)$ represent the

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[19] Choi and Varian (2009a) use AR(1) as a baseline model when predicting initial claims for unemployment benefits. D'Amuri (2009) uses ARIMA(1,1,0) as the benchmark model. We do not use the most common benchmark models of the forecasting/nowcasting literature, i.e. AR(1) and random walk, as these commonly used models produce serially correlated residuals for Turkish unemployment data, which is not convenient for nowcasting.

[20] To choose the models, we apply BMA to 12 different sample periods where the last observation varies from 2010m10 to 2011m10, i.e. , we conduct the BMA for each of the 12 months of a year where for example, during the first month the sample ends at 2010m10. The models that should be included in the model set has been chosen by the Occam's Window and posterior probabilities are calculated through the procedure, after the selection process, to make sure that they add up to one among all the models considered for a specific sample.

[21] We want our models to give us unbiased parameter estimates and predictions, that is why we conduct such detailed diagnostic residuals. See George (1999).

[22] See Moore (1983), Choi and Varian (2009a), D'Amuri (2009), D'Amuri and Marcucci (2010) and Montgomery et al. (1998) for similar usage of these two fundamentals.

autoregressive lag structure of the related variables with $L=12$ lags, and *FBM* stands for "Fundamentals and Benchmark". We use BMA procedure to decide for the nowcasting models that have posterior probability that sum up to one for each month between 2010m10 and 2011m10, and we end up with 100 models. Among these 100 models, represented with Equation 2, we are left with 15 of them that passes all the residual diagnostic tests. Among these, 14 has smaller RMSE values than the benchmark model, and we include these models into the pool of nowcasting models.

Second group of our nowcasting models is an extension of the model represented by Equation 2 by including 20 google variables. The model is represented as:

$$U_{t+h} = \alpha(L)^{FGG} U_{t-1} + \beta(L)^{FGG} F_t + \gamma(L)^{FGG} G_t + \xi_{t+h}^{FGG} \quad (3)$$

where U_{t+h} is difference of year-on-year growth rate of unemployment, h is the nowcast horizon and FGG stands for "Fundamentals and Google Variables". We augment vector G_t to model 2, which includes 20 Google search variables, to the model represented by Equation 2.[23] We apply the same Bayesian model selection procedure as before between 2010m10 and 2011m10 for 12 months and end up with 101 models, 3 of which pass the residual diagnostic tests. However, none of these models have RMSE smaller than the benchmark, hence we don't include these 3 models in the nowcasting model pool.

Forecasting/Nowcasting using principal components extracted from google data is common in the related literature.[24] Main practicality of such an approach is to summarize all the information coming from various series with a few number of components. Using few variables that represent the information contained in the Google data is beneficial as it increases the degrees of freedom. Therefore, our third group of nowcasting models include principal components extracted from the 20 Google variables. The model is given by:

$$U_{t+h} = \alpha(L)^{PC} U_{t-1} + \delta(L)^{PC} PC_t + \xi_{t+h}^{PC} \quad (4)$$

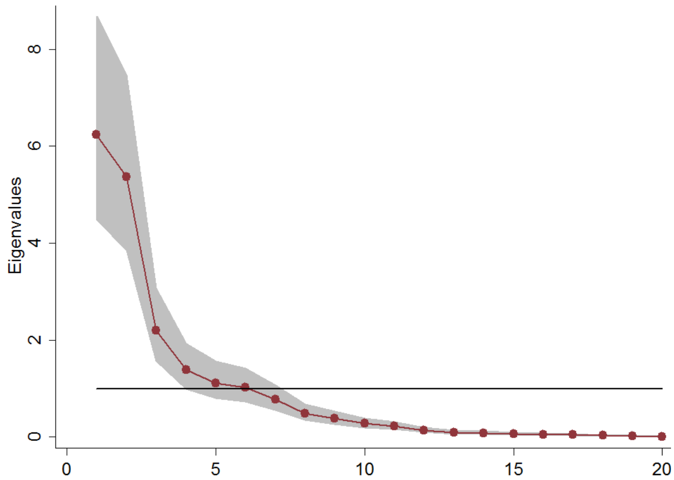
where *PC* stands for "Principle Components from Google Variables". In the model formalized by Equation 4, we include lags of unemployment up to 12 months and 6 principal components extracted from the Google data (PC_t). We use 6 principal components to feed into BMA procedure as suggested by the scree test to 20 Google variables (Figure 2). We also conduct a

[23] Note that we search over all possible combinations of these variables. Hence, we run into small sample size problem for a small subset of possible models. We do diagnostics tests on all the models selected by our procedure to eliminate the unreliable ones.

[24] See Carriere-Swallow and Labbe (2011) and Kholodilin (2010) for two examples using principal components extracted from Google Search items.

Likelihood Ratio test for selecting the number of principal components to include in model selection and the results point to 6 principal components. These 6 components account for 86.66% of the total variation of the 20 google variables. There are 6 models given by the BMA procedure between 2010m10 and 2011m10 for 12 months, and we end up with 4 models that pass the residual diagnostics. However, non can enter the nowcasting pool as they all have RMSE values bigger than that of the benchmark model.

Figure 2. Scree Test for the Principal Components



Note: Scree test is used to determine the number of factors extracted from Principle Components analysis to be used in regressions. We use the first six factors as additional factors bring relatively small changes in eigenvalues.

Next, we extend Equation 4 to include two fundamentals, i.e. in_pr and in_clm with 12 lags for each. This model, which is our fourth group of nowcasting models, is given by:

$$U_{t+h} = \alpha(L)^{FPC} U_{t-1} + \delta(L)^{FPC} PC_t + \beta(L)^{FPC} F_t + \xi_{t+h}^{FPC} \quad (5)$$

where *FPC* stands for “Principle Components from Google Variables and Fundamentals”. For this model we are left with only 24 models that passed the algorithm and residual diagnostics. 23 of these models have smaller RMSE values and are included in the nowcasting pool.

The last group of nowcasting model that we use for our nowcasting exercise is a model which includes only 20 google variables. This model is represented by Equation 6 that is represented as:

$$U_{t+h} = \alpha(L)^{GG} U_{t-1} + \gamma(L)^{GG} G_t + \xi_{t+h}^{GG} \quad (6)$$

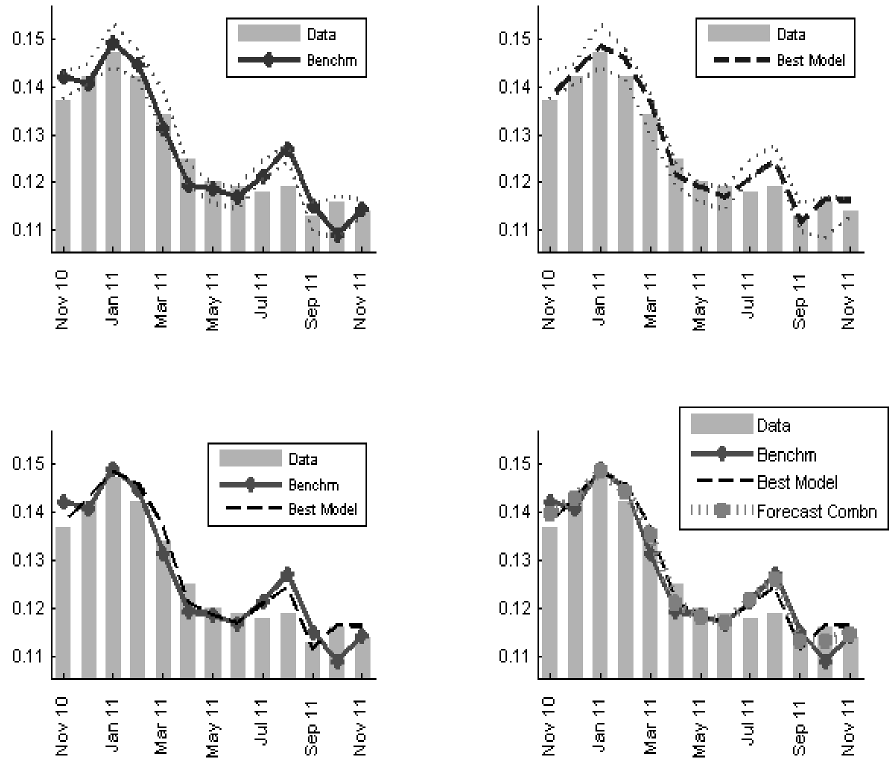
where *GG* stands for "Google Variables", and vector G_t in Equation 6 includes 20 variables collected using Google Insights. There are 60 such models and 9 of these models pass the diagnostic tests and have small enough RMSE values to be included among nowcasting models.

If we sum up this nowcasting methodology section, we can state that, in all the models given in this section we include lags of dyoy unemployment up to 12 lags, then we add fundamentals and their lags, and lastly we add either all google variables or principal components extracted from these google variables. We use BMA procedure where we utilise Occam's window algorithm to choose the best models, and we also require them to pass the residual diagnostic tests. We consider different groups of models separately, instead of putting all the models through BMA at once, so as the have models with different combinations of variable groups in our nowcast pool. Among these, we use all the models that have smaller RMSE values than the benchmark model for nowcasting the unemployment rate of following month, i.e, for nowcast horizon $h=1$. We also use these pool of models for nowcasting procedure over longer horizons, i.e., $h=2$ and $h=3$. We exclude models that include the fundamentals for nowcasting over longer horizons as these variables are announced with a lag.

4. Results

We select the benchmark model and other models to be used in the nowcasting via BMA and residual diagnostics as described in the previous session. The model with the lowest RMSE is called the best model and it includes fifth and sixth principle components of the Google variables, in addition to the fundementals. Table A.5 displays the varaibles included in those models that have lower RMSE than the bechmark. Note that 10 best models include principle compoments of the Google Search Quiry data. Moreover, majority of these models that outperform the benchmark include Google data.

Figure 3. 1 Month Ahead Nowcast Performances

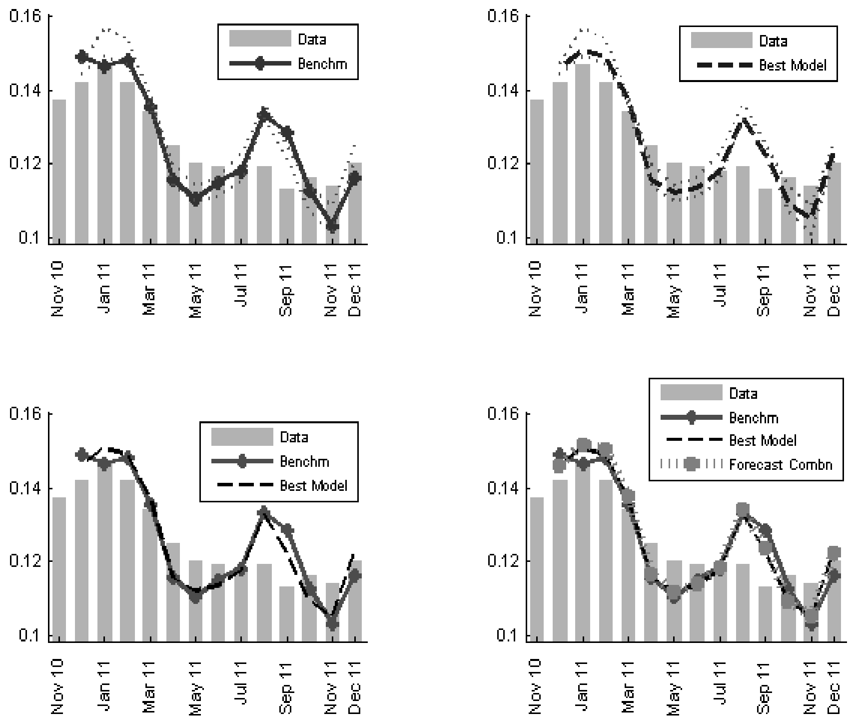


Note: Y-axis is the level of the unemployment rate. Dashed lines around the benchmark and the best model are minimum and the maximum nowcast values taken from all models that outperform the benchmark model. “Forecast Combn” is forecast combination series.

Figure 3 displays the 1 month ahead nowcast performance of the benchmark and the best models. Top-left panel of the figure compares the performance of the benchmark model to the actual data, whereas top-right panel compares best model's performance to the data. Dashed lines around the benchmark and the best model are minimum and the maximum nowcast values taken from all models that outperform the benchmark model.

By construction, the best model's unemployment rate nowcast will lie between these two dashed lines. However, the benchmark model needs not to be bounded by these values. As the top-left panel displays, the benchmark for 1 month ahead nowcast is between the minimum and the maximum nowcasts given by the better models. Bottom-left panel displays both the benchmark and the best model to compare their relative nowcast performances. As the figure displays, best model clearly outperforms the benchmark model. Bottom-right panel plots the forecast combination, calculated as the averages of forecasts weighted by the inverse of their RMSE, with the best model and the benchmark.[25]

Figure 4. 2 Month Ahead Nowcast Performances

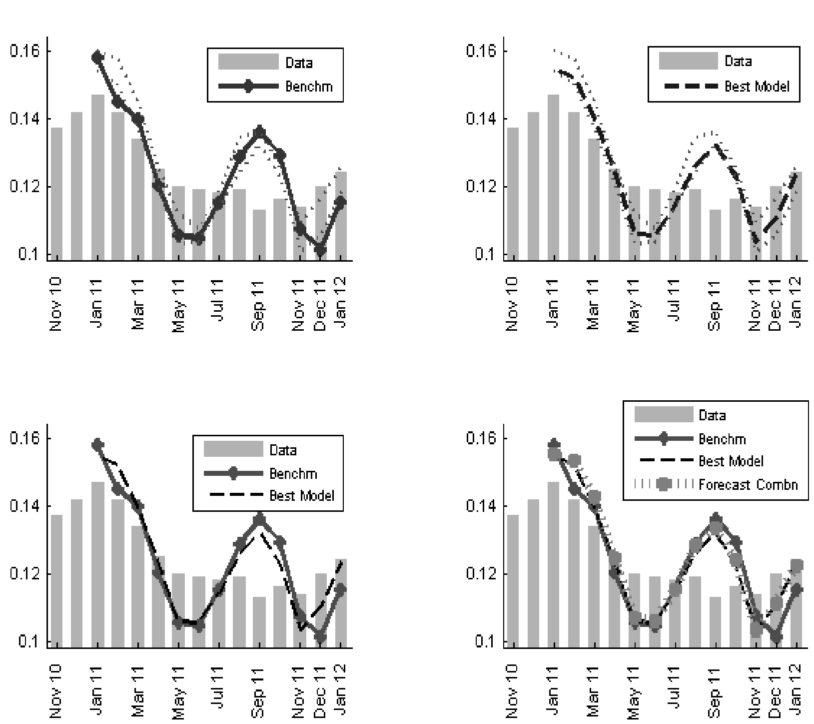


Note: Y-axis is the level of the unemployment rate. Dashed lines around the benchmark and the best model are minimum and the maximum nowcast values taken from all models that outperform the benchmark model. "Forecast Combn" is forecast combination series.

[25] Forecasting literature favors forecast combination against a forecast attained from a single model and usually simple average forecast combination gives better results than most techniques. See Clemen (1989), Diebold (1989), Granger (1989) and Timmermann (2006) that are excellent examples for this literature. We compared the RMSE weighted forecast combination results with forecast combination attained using simple averages and forecast combinations that use posterior model probabilities of unbiased models and found that the forecast combination results are very similar with different weights, so we decided to report the inverse RMSE weights results.

Figure 4 makes similar comparisons for model performances for 2 period ahead nowcasts. We observe that benchmark model's unemployment rate nowcast sometimes lies outside the minimum and the maximum nowcast values taken from models that outperform the benchmark model, contrary to its performance with 1 month ahead nowcast. Similarly, Figure 5 compares the performances of 3 months ahead nowcasts. We also observe nowcast results from the benchamrk model that is outside the range of nowcast values provided by the selected models. Figure 6 gives our projections for 1 month ahead, 2 months ahead and 3 months ahead unemployment rate nowcasts of Turkish economy as a fanchart.[26]

Figure 5. 3 Month Ahead Nowcast Performances



Note: Y-axis is the level of the unemployment rate. Dashed lines around the benchmark and the best model are minimum and the maximum nowcast values taken from all models that outperform the benchmark model. "Forecast Combn" is forecast combination series.

[26] We would like to thank Marco Buchmann making fanchart codes available on matlab, which can be downloaded at http://www.mathworks.com/matlabcentral/fileexchange/27702-fan-chart.

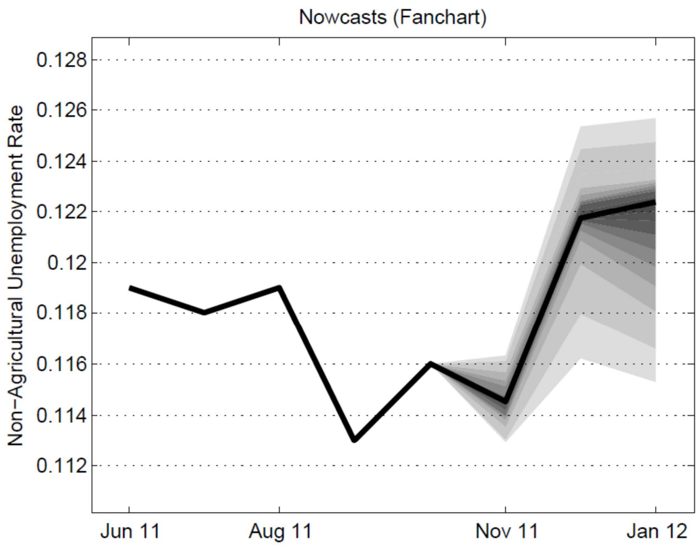
Table A.6 shows that best model at *h=1* improves the RMSE of our benchmark model by 47.7% in-sample and 38.4 out-of-sample. Table A.5 illustrates the variables augmented into our best model at *h=1*, where the best model at this horizon has fundamentals and principal components extracted from 20 Google Search variables. The models we use to nowcast horizon *h=2* and *h=3* include only Google variables, as fundamentals are announced with a lag. The best model for nowcast horizon *h=2* improves the RMSE of our benchmark model by 12.7%, while the best model for *h=3* improves the RMSE of our benchmark model by 11.9%. The last two columns of Table A.6 have MDM test results for all the non-nested models we have using Mean Squared Error (MSE) and Mean Absolute Error (MAE) and nearly all the models perform better than our benchmark model according to the test results.

We require these selected models to have normally distributed and serially independent and heteroscedasticity-free residuals. Since the period covers the global financial crises, which potentially has a serious effect on basic fundamentals, we also require the estimation coefficients to pass break point tests to make sure that the coefficients of our models do not suffer from the parameter instability problem.

Results of residual diagnostics are displayed in Table A.4, while the variables that are included in these selected models are summarized in Table A.5 in the appendix. Also, estimated coefficients of some of these models are given in Table A.7. Our benchmark model is the one with the lowest RMSE for the period between November 2010 and October 2011, among the possible benchmark equations that passes aforementioned diagnostics. Then, we pick all other models that pass the same diagnostics and have lower RMSE than the benchmark model for nowcasting the following month. The rankings of models' RMSE values relative to the benchmark for 1 period, 2 period, and 3 period ahead nowcasts are displayed in Table A.4 in the appendix. We also report in-sample and different horizon out-of sample RMSE values in Table A.6, as well as the results of modified Diebold-Mariano (MDM) tests for nonnested models.[27]

[27] See Harvey et al. (1997) for details of modified Diebold-Mariano test. We want to note that, as the Diebold-Mariano statistic has a non-standard distribution, it is only applicable to non-nested models.

Figure 6. Non-Agricultural Unemployment Rate Nowcast



5. Concluding Remarks

Especially after the global financial crisis, academicians, researchers from policy institutes and other policy makers follow all current information available very closely. Timely information on the current situation of the labour markets is highly essential, hence any means of getting timely information on the labour markets is highly valuable. Recent studies, mostly for developed countries, put forward evidence in favor of the nowcasting/forecasting performance of the internet based search query data. However, finding timely data that contains information regarding the current situation of the economy is especially valuable for developing countries, which generally experience bigger delays in term of data availability. This paper provides supporting evidence for using Google Insights Search data to nowcast unemployment rate in developing countries. We use Google data to gather the most recent information regarding the current situation in Turkish labour market as most of the macroeconomic data, as well as the unemployment rate, are announced with a lag for the Turkish economy.

We utilise Google Insights Query data to collect 20 variables that we think will proxy the job search of labour market in Turkey. Estimating linear models using Google Insights variables and principal components extracted from them, we show that the models with Google Search Indicators perform better in nowcasting the 1 period, 2 periods and 3 periods ahead unemployment rate than the benchmark where we use only the lag values of the unemployment rate. We use 45 models and a benchmark to illustrate this result, and all our models are selected with careful BMA procedure and detailed residual diagnostic tests. For comparison of nowcast performance, we use RMSE and Modified Diebold-Mariano test results, which clearly proves the better performance of the models including Google variables.

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Appendix.: Tables

Table A.1. Descriptive Statistics

	mean	median	max	min	std. dev.	correlation w/ u_rt
U_RT	-0.002	0.000	0.10	-0.13	0.04	1
IN_CLM	0.001	-0.012	0.27	-0.12	0.07	-0.22
IN_PR	0.003	-0.008	0.70	-0.63	0.22	0.41
V1	0.009	0.001	0.27	-0.14	0.08	0.21
V2	0.003	-0.006	0.52	-0.48	0.17	0.22
V3	0.001	-0.012	0.40	-0.34	0.13	0.26
V4	0.003	-0.002	0.13	-0.14	0.06	0.20
V5	0.001	-0.002	0.17	-0.17	0.07	0.28
V6	0.003	-0.001	0.36	-0.32	0.12	0.25
V7	-0.004	-0.014	0.23	-0.30	0.10	0.27
V8	0.002	0.002	0.37	-0.38	0.11	0.21
V9	0.001	0.001	0.67	-0.75	0.20	0.10
V10	0.000	-0.005	0.31	-0.23	0.10	0.09
V11	0.003	-0.010	0.28	-0.28	0.11	0.31
V12	0.008	-0.005	1.16	-0.75	0.25	0.19
V13	0.001	-0.004	0.63	-0.48	0.20	0.38
V14	-0.005	-0.004	0.44	-0.48	0.18	0.47
V15	0.002	-0.005	0.32	-0.32	0.09	0.26
V16	-0.002	0.000	0.85	-0.58	0.19	-0.15
V17	-0.001	-0.015	0.24	-0.23	0.09	0.00
V18	0.002	-0.002	0.40	-0.41	0.14	0.06
V19	-0.003	0.026	2.42	-4.15	0.80	-0.15
V20	-0.005	-0.034	0.53	-0.27	0.15	0.30

Note: “u_rt” is unemployment rate, “in_pr” is industrial production, and “in_clm” is initial unemployment claims. All variables are the monthly difference of year-on-year growth rate (dyoy). Number of observations is 69.

Table A.2. List of Keyword Terms Searched over at Google Insights

v1	cv	cv
v2	cv örnekleri	cv examples
v3	eleman aranıyor	looking for an employee
v4	iş	job
v5	iş arama	looking for a job
v6	iş arayanlar	people who look for a job
v7	iş arıyorum	I am looking for a job
v8	iş bulma	finding a job
v9	işçi bulma kurumu	employment placement agency
v10	iş ilanı	job ad
v11	iş ilanları	job ads
v12	işkur	abbrev. of the employment placement agency
v13	işsizlik	unemployment
v14	işsizlik sigortası	unemployment insurance
v15	kariyer	career
v16	kariyer.net	name of a career web site
v17	kariyer net	a different version of the name
v18	kariyernet	a different version of the name
v19	personel alımı	personnell hiring
v20	secretcv	another career web site

Table A.3. Unit Root Tests

	yoy PP	yoy ERS	dyoy PP	dyoy ERS
U_RT	-1.41	-3.20**	-4.47***	-2.79*
IN_CLM	-2.69*	-2.28	-13.39***	-1.98
IN_PR	-2.01	-1.81	-7.37***	-6.59***
V1	-1.24	-0.02	-11.65***	-1.58
V2	-2.34	-2.17	-10.06***	-8.28***
V3	-1.85	-1.62	-9.85***	-0.84
V4	-2.14	-1.34	-11.77***	-1.24
V5	-2.22	-2.04	-9.54***	-1.55
V6	-3.86***	-3.75***	-14.24***	-0.77
V7	-2.35	-2.58	-11.55***	-7.45***
V8	-4.23***	-4.23***	-19.04***	-0.75
V9	-5.78***	-5.21***	-32.82***	-8.13***
V10	-2.17	-1.48	-10.88***	-2.44
V11	-1.90	-1.48	-9.58***	-3.16**
V12	-2.64*	-2.27	-7.45***	-7.13***
V13	-2.29	-2.13	-8.49***	-1.88
V14	-2.03	-1.99	-8.40***	-1.31
V15	-2.11	-2.97**	-8.51***	-2.03
V16	-2.13	-1.49	-6.92***	-6.81***
V17	-1.64	-1.65	-8.49***	-6.24***
V18	-1.95	-1.58	-8.08***	-4.27***
V19	-4.01***	-3.92***	-13.98***	-11.15***
V20	-2.44	-1.96	-9.51***	-0.76

Note: "u_rt" is unemployment rate, "in_pr" is industrial production and "in_clm" is initial unemployment claims. All variables are the monthly difference of year-on-year growth rate (dyoy). + ERS is Elliot, Rothenberg, and Stock ADF-GLS test statistics and PP is Phillips-Perron test statistics respectively. ***, ** and * stand for 1%, 5% and 10% significance levels . yoy is year-on-year growth rate, dyoy is difference of yoy.

Table A.4. Diagnostics Test Results

	Rank Based on RMSE			Adjusted	Jarque-Bera	White Test	LM Test Result	
	h=1	h=2	h=3	R Square	P Val	Prob (F) Val	Prob (F) Val	Lag
Benchmark	46	46	9	0.52	0.19	0.25	0.21	4
Model 1	1	1		0.81	0.81	0.58	0.68	3
Model 2	2	5		0.81	0.60	0.86	0.72	1
Model 3	3	9		0.80	0.36	0.68	0.92	1
Model 4	4	3		0.79	0.88	0.90	0.50	1
Model 5	5	4		0.79	0.75	0.92	0.38	3
Model 6	6	18		0.79	0.55	0.92	0.53	3
Model 7	7	7		0.73	0.50	0.89	0.61	7
Model 8	8	8		0.78	0.88	0.99	0.32	3
Model 9	9	6		0.77	0.19	0.89	0.31	2
Model 10	10	12		0.79	0.97	0.93	0.45	2
Model 11	11	13		0.81	0.75	0.48	0.47	11
Model 12	12	20		0.78	0.86	0.74	0.65	2
Model 13	13	15		0.80	0.95	0.43	0.62	11
Model 14	14	11		0.80	0.94	0.56	0.64	12
Model 15	15	21		0.77	0.79	0.73	0.64	1
Model 16	16	2		0.82	0.99	0.94	0.21	2
Model 17	17	26		0.77	0.85	0.94	0.25	3
Model 18	18	17		0.79	0.43	0.56	0.41	2
Model 19	19	19		0.76	0.96	0.97	0.74	8
Model 20	20	16		0.77	0.83	0.60	0.58	4
Model 21	21	10		0.77	0.12	0.64	0.75	1
Model 22	22	27		0.74	0.71	0.95	0.48	3
Model 23	23	30		0.76	0.96	0.72	0.45	2
Model 24	24	22		0.76	0.59	0.93	0.51	2
Model 25	25	14		0.76	0.95	0.92	0.25	1
Model 26	26	23		0.77	0.98	0.65	0.45	2
Model 27	27	31		0.75	0.81	0.92	0.48	2
Model 28	28	24		0.75	0.41	0.98	0.45	2
Model 29	29	25		0.76	0.99	0.82	0.35	5
Model 30	30	43	7	0.65	1.00	0.95	0.20	12
Model 31	31	39	5	0.67	0.98	0.71	0.47	3
Model 32	32	38	2	0.70	0.82	0.82	0.31	3
Model 33	33	28		0.74	0.76	0.97	0.27	7
Model 34	34	33		0.74	0.45	0.78	0.37	12
Model 35	35	41	1	0.66	0.39	0.41	0.34	4
Model 36	36	29		0.76	0.98	0.91	0.28	4
Model 37	37	35		0.74	0.56	0.29	0.28	10
Model 38	38	40	3	0.69	0.81	0.88	0.32	3
Model 39	39	36		0.74	0.52	0.31	0.39	2
Model 40	40	32		0.75	0.86	0.92	0.33	4
Model 41	41	34		0.73	0.94	0.47	0.33	4
Model 42	42	37		0.71	0.14	0.95	0.35	3
Model 43	43	45	6	0.68	0.57	0.89	0.19	3
Model 44	44	44	8	0.65	0.37	0.73	0.25	3
Model 45	45	42	4	0.65	0.44	0.52	0.21	4

Note: First 3 columns states the model's rank based on RMSE results for each nowcast horizon h=1, h=2, h=3. LM Test reports the minimum probabilty value over 12 lags, and the lag that has the minimum test result.

Table A.5. Model Descriptions

	un_rt lags	in_pr lags	in_clm lags	google vars	pc vars
Benchmark	1, 3, 4, 6				
Model 1	1, 3, 4, 7	0, 1, 2, 10	0, 4, 6, 7, 10		5, 6
Model 2	1, 3, 4, 10	0, 1, 2, 10	0, 4, 6, 7, 10		5, 6
Model 3	1, 3, 4, 10	1, 2, 10	0, 4, 6, 7, 10		5, 6
Model 4	1, 3, 4, 10	0, 1, 2, 10	0, 4, 7, 10		5, 6
Model 5	1, 3, 4, 7	0, 1, 2, 10	0, 4, 7, 10		5, 6
Model 6	1, 3, 4	1, 2, 10	0, 4, 6, 7, 10		5, 6
Model 7	1, 3, 4	0, 1, 2, 10	4, 10		x
Model 8	1, 3, 4	0, 1, 2, 10	0, 4, 7, 10		5, 6
Model 9	1, 3, 4	0, 1, 2, 11	0, 4, 10		6
Model 10	1, 3, 4, 10	0, 1, 2, 10	0, 4, 6, 7, 10		5
Model 11	1, 3, 4, 6	1, 2, 10	0, 2, 4, 6, 10		
Model 12	1, 3, 4, 10	1, 2, 10	0, 4, 6, 7, 10		5
Model 13	1, 3, 4, 6	1, 2, 10	0, 4, 6, 10		
Model 14	1, 3, 4, 6	0, 1, 2, 10	0, 4, 6, 10		
Model 15	1, 3, 4	1, 2, 10	0, 4, 6, 10		5, 6
Model 16	3, 4, 6, 11, 12	0, 1, 2, 10	0, 4, 5, 6, 7, 10		
Model 17	1, 3, 4	1, 2, 10	0, 4, 6, 7, 10		5
Model 18	1, 3, 4, 6	2, 5, 10	0, 2, 4, 10		
Model 19	1, 3, 4	0, 1, 2, 10	0, 4, 10		6
Model 20	1, 3, 6	2, 5	0, 2, 4, 8, 10		
Model 21	3, 4, 6	0, 1, 2,10	0, 2, 4, 10		
Model 22	1, 3, 4	1, 2, 10	0, 4, 10		5
Model 23	1, 3, 4	1, 2, 10	0, 4, 6, 10		5
Model 24	1, 3, 4	0, 1, 2, 10	0, 4, 10		5
Model 25	3, 4, 6	0, 1, 2, 10	0, 4, 6, 10		
Model 26	1, 3, 4	2, 5	0, 2, 4, 8, 10		
Model 27	1, 3, 4	1, 2, 10	0, 4, 6, 10		x
Model 28	1, 3, 4	0, 1, 2, 10	0, 4, 10		x
Model 29	1, 3, 4	2, 5	0, 2, 4, 10		
Model 30	1, 3, 4, 6			1, 3, 6	
Model 31	1, 2, 3, 4, 6			3, 6, 20	
Model 32	1, 2, 3, 4, 6			3, 6, 14, 20	
Model 33	1, 3	2, 5	0, 2, 4, 8, 10		
Model 34	1, 3	2, 6	0, 4, 8, 10		3
Model 35	1, 3, 4, 6			1, 6, 14	
Model 36	1, 3	1, 2, 6	0, 2, 4, 8, 10		
Model 37	1, 3	2, 6	0, 4, 8, 10		3, 5
Model 38	1, 2, 3, 4, 6			3, 5, 6, 14, 20	
Model 39	1, 3, 4	2, 6	0, 4, 10		3, 5
Model 40	1, 3	2, 6	0, 2, 4, 8, 10		
Model 41	1, 3	1, 2, 6	0, 4, 8, 10		
Model 42	1, 4, 12	5, 11	0, 4, 10		x
Model 43	1, 2, 3, 4, 6			3, 5, 6, 13, 20	
Model 44	1, 4, 8			1, 3, 6, 14	
Model 45	1, 3, 4, 6			5, 6, 14	

Note: "un_rt" is unemployment rate, "in_pr" is industrial production and "in_clm" is initial unemployment claims. All variables are the monthly difference of year-on-year growth rate (dyoy). "pc vars" are principle componets of dyoy Google variables. Each row refers to a model. Numbers in the first 3 columns refer to the lags of the corresponding variables included in the model. The fourth column describes the Google variables included in the model, while the last column is the principle components of the Google variables included in the model. Cells with "x" means that principle components were originally included when Bayesina Model Averaging (BMA) was done, but these varaibles were not selected by the BMA.

Table A.6. In and Out of Sample Nowcast Performances and Modified Diebold-Mariano Tests

	In Sample	Out of Sample RMSE			Modified DM Results	
	RMSE	h=1	h=2	h=3	Modified DM-MSE	Modified DM-MAE
Benchmark	0.0270	0.0285	0.0356	0.0370		
Model 1	0.0141	0.0176	0.0204		0.0089	0.0029
Model 2	0.0145	0.0177	0.0211		0.0012	0.0000
Model 3	0.0151	0.0180	0.0230		0.0054	0.0001
Model 4	0.0146	0.0183	0.0209		0.0015	0.0001
Model 5	0.0147	0.0186	0.0209		0.0126	0.0046
Model 6	0.0157	0.0190	0.0248		0.0169	0.0131
Model 7	0.0182	0.0195	0.0227		0.0000	0.0000
Model 8	0.0156	0.0197	0.0228		0.0107	0.0089
Model 9	0.0150	0.0197	0.0220		0.0056	0.0013
Model 10	0.0179	0.0201	0.0236		0.0001	0.0000
Model 11	0.0178	0.0201	0.0237			
Model 12	0.0185	0.0204	0.0254		0.0007	0.0000
Model 13	0.0182	0.0205	0.0246			
Model 14	0.0180	0.0206	0.0234			
Model 15	0.0171	0.0207	0.0264		0.0123	0.0026
Model 16	0.0177	0.0208	0.0207		0.0128	0.0053
Model 17	0.0191	0.0216	0.0272		0.0022	0.0001
Model 18	0.0196	0.0217	0.0247			
Model 19	0.0178	0.0221	0.0251		0.0059	0.0007
Model 20	0.0202	0.0225	0.0247		0.1129	0.1026
Model 21	0.0203	0.0231	0.0232		0.0295	0.0238
Model 22	0.0206	0.0232	0.0274		0.0012	0.0000
Model 23	0.0207	0.0232	0.0285		0.0011	0.0000
Model 24	0.0206	0.0237	0.0265		0.0051	0.0005
Model 25	0.0211	0.0237	0.0240		0.1010	0.0764
Model 26	0.0212	0.0238	0.0266		0.0362	0.0089
Model 27	0.0214	0.0239	0.0269		0.0003	0.0001
Model 28	0.0213	0.0243	0.0288		0.0030	0.0001
Model 29	0.0221	0.0245	0.0272		0.0339	0.0022
Model 30	0.0228	0.0245	0.0342	0.0359		
Model 31	0.0221	0.0246	0.0317	0.0354		
Model 32	0.0217	0.0249	0.0311	0.0327		
Model 33	0.0231	0.0252	0.0280		0.1369	0.1329
Model 34	0.0232	0.0259	0.0298		0.2710	0.2650
Model 35	0.0232	0.0259	0.0329	0.0326		
Model 36	0.0230	0.0259	0.0284		0.0696	0.0072
Model 37	0.0235	0.0260	0.0302		0.3323	0.7083
Model 38	0.0220	0.0262	0.0319	0.0329		
Model 39	0.0233	0.0264	0.0305		0.4009	0.6566
Model 40	0.0238	0.0265	0.0294		0.2981	0.2639
Model 41	0.0249	0.0275	0.0301		0.1973	0.0031
Model 42	0.0253	0.0275	0.0308		0.2913	0.4315
Model 43	0.0233	0.0278	0.0354	0.0357		
Model 44	0.0259	0.0278	0.0351	0.0362	0.8312	0.7841
Model 45	0.0255	0.0280	0.0337	0.0334		

Note: The models which do not have Modified Diebold-Mariano test results are nested models.

Table A.7. Coefficients of Top 6 Models

	Benckmark	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
yoyd_un_rt(-1)	0.641	0.381	0.395	0.459	0.304	0.287	0.439
	0.082	0.068	0.066	0.052	0.076	0.079	0.057
yoyd_un_rt(-3)	-0.306	-0.614	-0.533	-0.512	-0.533	-0.597	-0.494
	0.126	0.107	0.097	0.097	0.101	0.111	0.107
yoyd_un_rt(-4)	0.605	0.525	0.522	0.513	0.498	0.500	0.520
	0.103	0.053	0.055	0.054	0.065	0.066	0.052
yoyd_un_rt(-6)	-0.307						
	0.122						
yoyd_un_rt(-7)		0.186				0.149	
		0.073				0.078	
yoyd_un_rt(-10)			0.150	0.147	0.132		
			0.080	0.077	0.083		
yoyd_in_pr		-0.104	-0.085		-0.121	-0.138	
		0.041	0.049		0.041	0.036	
yoyd_in_pr(-1)		-0.235	-0.228	-0.179	-0.239	-0.244	-0.169
		0.075	0.079	0.079	0.077	0.073	0.074
yoyd_in_pr(-2)		-0.271	-0.265	-0.264	-0.259	-0.263	-0.253
		0.055	0.060	0.059	0.064	0.060	0.055
yoyd_in_pr(-10)		0.147	0.163	0.164	0.161	0.146	0.141
		0.032	0.032	0.032	0.031	0.031	0.031
yoyd_in_clm		0.057	0.053	0.053	0.054	0.057	0.051
		0.010	0.011	0.011	0.012	0.012	0.011
yoyd_in_clm(-4)		0.055	0.048	0.047	0.056	0.061	0.044
		0.013	0.013	0.012	0.015	0.016	0.012
yoyd_in_clm(-6)		-0.030	-0.028	-0.035			-0.032
		0.011	0.013	0.012			0.012
yoyd_in_clm(-7)		0.030	0.042	0.040	0.040	0.029	0.030
		0.017	0.015	0.015	0.015	0.017	0.016
yoyd_in_clm(-10)		-0.055	-0.058	-0.059	-0.052	-0.049	-0.045
		0.015	0.015	0.015	0.016	0.015	0.014
pc_5		0.006	0.008	0.007	0.007	0.005	0.006
		0.002	0.002	0.002	0.003	0.003	0.002
pc_6		0.005	0.005	0.005	0.005	0.005	0.005
		0.002	0.002	0.002	0.002	0.002	0.002
AIC	-4.202	-4.924	-4.912	-4.882	-4.848	-4.846	-4.846
BIC	-4.032	-4.360	-4.349	-4.354	-4.319	-4.318	-4.353
N of Obs	63	59	59	59	59	59	59

Note: Numbers in parentheses are standard errors. “un_rt” refers to unemployment rate, “in_pr” refers to industrial production, “in_clm” refers to initial unemployment claims, “pc” refers to principle component, and yoyd refers to difference of year-on-year growth rate.