Nowcasting Building Permits with Google Trends

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Abstract

We propose a useful way to predict building permits in the US, exploiting rich real-time data from web search queries. The time series on building permits is usually considered as a leading indicator of economic activity in the construction sector. Nevertheless, new data on building permits are released with a lag close to two months. Therefore, an accurate now-cast of this leading indicator is desirable. We show that models including Google search queries nowcast and forecast better than our good, not naïve, univariate benchmarks both in-sample and out-of-sample. We also show that our results are robust to different specifications, the use of rolling or recursive windows and, in some cases, to the forecasting horizon. Since Google queries information is free, our approach is a simple and inexpensive way to predict building permits in the United States.

JEL Codes: C220, C530, E170, E270, E370, F370, L740, O180, R310.

Keywords: Online Search; Prediction; Forecasting; Time Series; Building Permits; Real Estate; Google Trends.

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I. Introduction

In this paper we provide strong evidence of the ability that some internet search queries have to generate accurate backcasts, nowcasts and forecasts of building permits in the U.S. (new private housing units authorized). In particular, search queries such as "new construction" and "new home construction" are shown to have significant predictive information.

The time series on building permits, which is released with a lag of almost two months, is the primary leading indicator of economic activity in the construction sector. Given this two-month lag, the current state of the business cycle in that sector cannot be known in real time. Consequently, strategies to build reliable backcasts, nowcasts and forecasts of building permits are desirable. In this paper, we fill this gap, by proposing methods to predict building permits in the US, exploiting rich real-time data from web search queries. Using Google Trends, we find some keywords with strong predictive information. In particular, we show that they predict better than our competing benchmark models in both in-sample and out-of-sample analyses.

Leading economic indicators are essential tools for macroeconomic forecasting. They are useful to evaluate where the economy is heading, and prepare investors, central banks and private parties to plan their decisions accordingly. Examples of leading indicators which have proven to be adequate predictors of real economic activity include money supply, jobless claims report, consumer confidence index and new orders of capital goods (Chen, 2009; Estrella & Mishkin, 1998.)

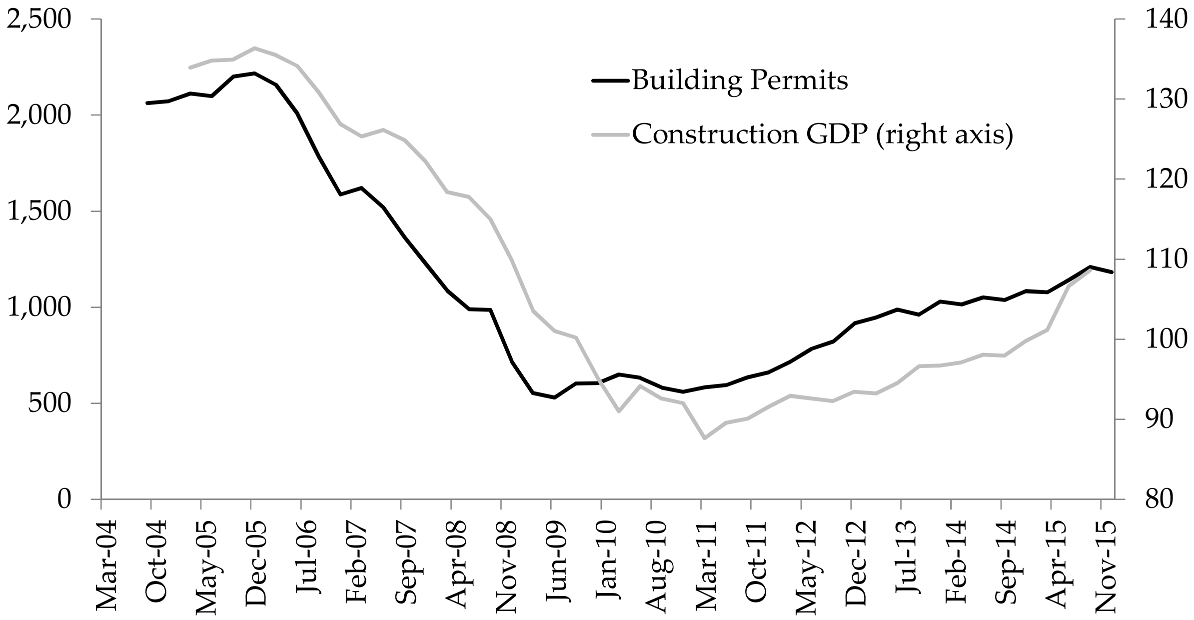
Building permits are another well-known leading indicator. A building permit is a written authorization that a government or official agency grants to people interested in starting a new construction. This index accurately predicts construction activity (Strauss, 2013).[1] Figure 1 depicts visually that building permits seem to predict changes in the construction business cycle. Furthermore, building permits are used as inputs to analyze the economy in many institutions. For example, they are used by the US Conference Board to construct its leading economic indicator index; by the Federal Reserve Board to analyze national and regional economic conditions such as employment and construction activity; by the Department of Housing and Urban Development to perform assessments on housing programs; by financial institutions to forecast the demand of mortgage-related products and by private parties for financial planning, investment analysis and risk evaluations.[2]

[1] In the US, the federal agency in charge of collecting these data from granting government agencies is the US Census Bureau, which provides a monthly estimate through the Building Permits Survey. See more information in the Data section.

[2] A non-comprehensive list of users of building permits statistics is available at the U.S. Census Bureau (https://www.census.gov/construction/bps/about_the_surveys/)

The rest of this paper is organized as follows: In section II we provide a brief literature review. Section III describes our dataset. In section IV we show our predictive evaluation strategy. Section V introduces our forecasting models. Empirical results are presented in section VI and, finally, in section VII we show conclusions and a summary of our findings.

Figure 1: New Private Housing Units Authorized by Building Permits and Construction Gross Domestic Product in the United States.



Source: US. Bureau of Economic Analysis and Census Bureau. Building permits are expressed in thousands of units, and are seasonally adjusted. Construction gross domestic product is expressed as a chain quantity index (2009=100), and is seasonally adjusted.

II. Literature Review

Google Trends started in 2009 when it publicly released information about intensity in search terms. Public data are available on a weekly basis, divided by geographic areas starting in 2004.[3] Since then, it has opened a new and fertile ground for research, as it can monitor social interests on different topics at a very low cost. At the same time, some research has focused on the study of macroeconomic variables in real time. For example, the term *nowcasting*—which was coined by Giannone, Reichlin, & Small (2008)—was introduced in the literature to refer to their methodology to track real-time flow of information within a month. At about the same time,

[3] To see more information, visit the website https://www.google.com/trends/

Aruoba & Diebold (2010) stressed the importance of having higher frequency, real-time data to monitor macroeconomic variables.

Many articles have been written on the topic since then. A frequently cited paper is Choi & Varian (2012). They show how intensity on internet search terms helps to predict automobile sales, unemployment claims, travel destination planning and consumer confidence. In the same line, Askitas & Zimmermann (2009) use Google Trends to predict unemployment rates in Germany. D'Amuri & Marcucci (2012) propose a leading indicator based on internet job-search intensity to forecast the unemployment rate in the US. Their results indicate that models including their Google Index (GI) outperform the standard models that they use as benchmarks. Guzmán (2011) proposes a new index based on web search intensity measures to predict real-time inflation expectations in the United States. Vosen & Schmidt (2011) performs several forecasting exercises to predict private consumption, and finds that web search activity outperforms several indicators constructed from surveys, such as the Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index. In a short article, McLaren & Shanbhogue (2011) use internet search intensities to forecast labor and housing outcomes for the UK, and mention the importance of this newly available data source to perform economic analysis. Also in the UK, Smith (2016) exploits Google search intensity data to nowcast unemployment. The author shows that this information nicely complements survey-based indicators and substantially reduces nowcasting errors.

Web search intensities as predictors not only perform well in developed countries, but also in emerging countries. In particular, Carrière-Swallow & Labbé (2013), using data for Chile, show that Google search queries improve the prediction of car sales and their turning points. Another interesting article links business cycles and mental health, by using Google search entries –such as "depression", and "anxiety"—with the unemployment insurance claims and unemployment rates, finding a strong linkage between them (Tefft, 2011).[4]

Financial research on the topic also has flourished. One of the earliest articles linking web activity to forecast stock returns is Joseph et. al. (2011). The authors investigate tickers search terms as a proxy for investor sentiment, which in turn help predict trading volume and stock returns, finding that searching activity on the internet predict relatively well.[5] In the same line, Da, Engelberg, & Gao (2011) create an index of investor attention by using Google search activity. They find that web search intensity provides new information compared to the existing

[4] Outside the macroeconomic spectrum, there are papers on electoral outcomes (Ripberger 2011; Huberty 2015) and even a study using web search activity to corroborate adolescent sexual behavior (Kearney & Levine, 2015).

[5] Other articles also provide web activity as a useful source of information to predict stock market volumes. For example, see Bollen, Mao, & Zeng, 2011; Bordino et al., 2012; Preis, Reith, & Stanley, 2010; and Moat et al., 2013.

indices and it is "more up to date", making it more attractive to measure investor attention.[6] Other authors also investigate web search queries as predictors of volatility (Vlastakis & Markellos 2012; G. P. Smith 2012; Dimpfl & Jank, 2016), uncertainty (Dzielinski, 2012) and risk diversification (Kristoufek, 2013).

Perhaps, the most connected paper with ours is Wu & Brynjolfsson (2015) which uses Google Trends to predict variables such as home sales and housing prices in the United States. They find that web search activity contains information that helps predict housing market outcomes with higher precision than experts from the National Association of Realtors. In the same line of research, Beracha & Wintoki (2013) also use Google to forecast housing prices in different markets in the US, while Oestmann & Bennöhr (2015) study how search engine data helps predict housing prices in fourteen European countries. Askitas (2015) uses Google trends to create an index to predict the state of the housing market in the US, emulating the monthly and two-month lagged Case Shiller index. Chauvet, Gabriel, & Lutz (2016) also create an index to measure housing market distress in the US, using web search queries. In another related paper, Askitas & Zimmermann (2011) investigate the web search intensity of the term "*hardship letter*", a common way to request a loan modification through a letter which outlines issues and hardship conditions to explain their inability to pay their mortgage. The authors find evidence that this search term helps predict future mortgage delinquency. Similarly, Das, Ziobrowski, & Coulson (2015) use Google search data to predict several real state variables in the market of apartments, such as vacancy rates, rental rates and real estate asset price returns.

Interestingly, none of the aforementioned papers study building permits. To our knowledge, this is the first paper predicting building permits using web search activity. One important difference with the existing literature is that we focus on the leading indicator itself, not on the actual state of the housing market. Therefore, we will not attempt to show the most accurate forecasting model to predict current housing market activity. In addition, unlike other papers that only show interest in the demand side, we exploit terms that are associated with *both* sides of the market: supply and demand. For example, the search term "*real estate exam*" is arguably connected with the supply side, as prospective realtors must pass a test to obtain their state-granted real estate licenses.[7] We exploit the high correlation between the online interest in the real estate exam and building permits, and argue that intuition supports the idea that the former is economically connected with the latter. The other search queries we work with: "new construction", "new housing development" and "new home construction" are keywords associated with both sides of the market. This list of search terms is not intended to be

[6] In a related article, the same authors propose a new investor sentiment index (FEARS), by measuring the web search queries related to typical investor concerns, such as "*recession*" or "*bankruptcy*". They find that their index captures breakpoints well, predicts volatility and movements of mutual funds in and out of equity funds (Da, Engelberg, & Gao, 2015)

[7] See a complete list of requisites to become a realtor in https://www.kapre.com/resources/real-estate/how-to-become-a-real-estate-agent.

exhaustive, but only a sample of the many ways researchers can use these freely available data to create their own indicators.

III. Data

We use monthly data on building permits for the sample period January 2004-December 2015 (144 observations). The source is the Census Bureau Building Permits Survey. Our data is not seasonally adjusted. This information is collected monthly from a sample of local public permit-issuing agencies, which is representative at a national, state and city levels. Estimates represent all-permit-issuing locations in the nation. Missing data - for example in the case that a survey report is not responded- is imputed using standard statistical methodologies. Non-respondents are rare, though, as these agencies are enforced to compliance by their respective State Data Centers. Building Permits data are released to the public on the 18th working day of the *next* month of reference. This means that new releases of the time series on building permits are practically published with a two-month lag. For the purpose of this study, we are only interested in the aggregated number of building permits in the United States which present no missing data.

The second source of information is Google Trends. We consider four search queries: "*real estate exam*", "*new construction*", "*new housing development*" and "*new home construction*". Our database considers time series on these four search queries on a *weekly* basis from the period January 2004 -first week to February 2016-fourth week. This means a total of 634 observations on each search query. We transform these weekly series into monthly series by taking averages. Basically the corresponding monthly data of "*real estate exam*" for January 2004 is the simple average of the four weekly observations in January 2004 of the corresponding search query. This means that in total we have 146 monthly observations for each search query covering the period January 2004-February 2016[8]. As before, our time series on search queries are not seasonally adjusted.

Our choice of the search queries is not intended to be exhaustive, as many other terms could also be used for the analysis. We chose these terms based mainly on two criteria: (i) meaningful economic connection; and (ii) their high correlation with building permits.[9]

Google Trends data provide a measure of the volume of queries from internet users for a given geographical area, which in this case is the United States. It does not provide a measure of the absolute number of searches, but rather the intensity in search terms relative to the rest of the searches in a certain period of time. In this sense, Google Trends provides an index between 0

[8] In summary, we have 144 monthly observations for the time series on building permits and 146 observations for the time series on each search query. We explain in section 4 how we deal with this unbalanced database.

[9] For a better assessment of the correlation between a time series and web search queries, visit https://www.google.com/trends/correlate.

and 100 for each term, based on both intensity with respect to other searches, and degree of broadness. For example, if the search term is “apple” some of those searches are related to section Computers and Technology, while the rest are related to Food and Drinks. Google Trends assigns a probability that the web search term is related to each of those categories, and weights their intensity with respect to the rest of the categories. In addition, in order to ensure confidentiality and representativeness at the same time, Google Trends compute search intensities using sampling methods that change daily. All in all, this causes some difficulties in performing any empirical analysis, as the time series on Google Trends are not entirely stable over time. We tend to believe that this shortcoming is not very serious, however, as the computed correlations using a sample of five different draws of our search queries provide figures in the range of 0.95-0.99[10].

Figure 2: New Private Housing Units Authorized by Building Permits & Google Search Queries in the United States.

Source: US. Census and Google Trends. Building permits are depicted in the right axis and expressed in thousands of units. For easier visualization, Google search terms (left axis) “real estate exam”, “new housing development”, “new construction” and “new home construction” are standardized (mean zero and standard deviation equal to one).

The aforementioned time series are depicted in Figure 2. As mentioned before, our series are not seasonally adjusted. Instead, we consider models that take into account the potential seasonal

[10] In addition, preliminary out-of-sample evaluations using different draws point out in the same direction qualitatively speaking.

behavior of the series. Figure 2 shows that all our time series may be modeled as having a stochastic trend. While in the Appendix we show unit root tests with mixed results, our preferred specifications for the forecasting exercises are constructed in first log-differences, as we will see en Section 5. More descriptive statistics such as correlograms and the alike are also found in the Appendix.

IV. Predictive Evaluation Strategy

Our evaluation strategy considers two univariate specifications for US building permits that we call benchmark models, and that we describe in detail in section 5. We evaluate the predictive ability of these benchmark models against their augmented versions with variables related to specific search queries in Google Trends. We analyze this predictive ability both in-sample and out-of-sample. We notice here that we are using either the term "prediction" or "forecasting" to summarize the exercises to obtain forecasts, nowcasts and backcasts. Let us elaborate. In general terms monthly information on building permits is known with a lag of two months. In sharp contrast, information on Google Trends is available in almost real time. This means that search queries in Google Trends may be used to three objectives: 1) To generate a backcast of the figure on building permits of the past month, 2) to generate a "nowcast" of the figure on building permits of the current month, and 3) to generate multistep ahead forecasts of building permits many months ahead in the future. As mentioned before, and for the sake of simplicity, we will use the words "forecasts" or "predictions" as general terms to denote forecasts themselves as well as backcasts and nowcasts.

To describe the out-of-sample exercise, let us assume that we have a total of T+1 observations on building permits (bp_t) and T+3 observations on a given search query. We generate a sequence of P(h) h-step-ahead forecasts estimating the models in either rolling windows of fixed size R or expanding windows of size equal or greater than R. Here h=-1 denotes a backcast, h=0 denotes a nowcast and h>0 denotes a forecast h-periods ahead. The size R of the rolling window is determined by the available information on building permits. This means that when having R observations on building permits we have R+2 observations available from Google Trends. For estimation of our models we remove the extra two observations on Google Trends and we only use a total of R observations both for building permits and Google Trends. For instance, to generate the first h-step-ahead forecasts using rolling windows, we estimate our models with the first R observations on building permits and Google Trends. Then, forecasts are built with information available only at time R for building permits, but with information available up until time R+2 on Google Trends. These forecasts are compared to observation bp_{R+2+h}. So, the first backcast is constructed for bp_{R+1}, the first nowcast is constructed for the observation bp_{R+2} and the first forecast one-period ahead is constructed for the observation bp_{R+3}. Next, we estimate our models with the second rolling window of size R that includes observations on building permits and Google Trends through R+1. These h-step-ahead forecasts are compared to observation bp_{R+3+h}. We iterate until the last forecast is built using the last R available observations for estimation. This forecast is indeed the last backcast that is compared to observation bp_{T+1}. When recursive or expanding windows are used instead, the only difference with the procedure described in previous lines relies on the size of the estimation windows. In the recursive scheme, the size of the estimation window grows with the number of available observations for estimation. For instance, the first h-step ahead forecast is constructed estimating the models in a window with R observations on building permits and Google Trends, whereas the last h-step-ahead forecasts are constructed based on models estimated in a window with T-1 observations on building permits and Google Trends.

We generate a total of P(h) forecasts, with P(h) satisfying

P(h)=T-h-R

Being more specific, we have a total of 144 monthly observations on building permits and 146 on search queries, so we set T+1= 144. We also set R to 50, which means that the total number of backcasts is

P(h=-1)=T+1-R=144-50=94.

Similarly, the total number of nowcasts is given by

P(h=0)=T-R=143-50=93.

And the total number of one-step-ahead forecasts is given by

P(h=1)=T-1-R=142-50=92.

Forecast accuracy is measured in terms of RMSPE. Because this is a population moment, we estimate it using the following sample analog:

$$\mathrm{SRMSPE} = \sqrt{\frac{1}{\mathrm{P(h)}} \sum_{\mathrm{t=R}}^{\mathrm{T-h-1}} \left(\mathrm{bp}_{\mathrm{t+2+h}} - \widehat{\mathrm{bp}}_{\mathrm{t+2+h|t}}\right)^2}$$

where SRMSPE stands for "Sample Root Mean Squared Prediction Error" and $\widehat{bp}_{t+2+h|t}$ represents the forecast of bp_{t+2+h} made with information on building permits and search queries known up until time t.

We carry out inference about predictive ability by considering pairwise comparisons between each model and its augmented version. Inference is carried out within the frameworks developed by Giacomini & White (2006) (henceforth GW) and Clark & West (2006, 2007) (henceforth CW). We focus on the unconditional version of the t-type statistic proposed by GW which in practice coincides with the well-known test attributed to Diebold & Mariano (1995) and West (1996) (henceforth DMW). This test has the distinctive feature of allowing comparisons between two competing forecast methods instead of two competing models in a given sample[11].

According to the unconditional version of the test developed by GW, we test the following null hypothesis

$$H_0: E\left(\hat{d}_t(h)\right) \leq 0$$

against the alternative:

$$H_A = E(\hat{d}_t(h)) > 0$$

where

$$\hat{d}_t(h) = \left(bp_{t+2+h} - \widehat{bp}_{1,t+2+h|t}\right)^2 - \left(bp_{t+2+h} - \widehat{bp}_{2,t+2+h|t}\right)^2$$

and $\widehat{bp}_{1,t+h|t}$ and $\widehat{bp}_{2,t+h|t}$ denote the h-step ahead forecasts generated from the two models under consideration. Model 1 is the parsimonious or "small" model that is nested in the larger model 2. In other words, model 2 would become model 1 if some of its parameters would be set to zero.

We focus on one sided tests because we are interested in detecting forecast superiority. Our null hypothesis poses that forecasts generated from the nested model perform at least as well as forecasts generated from the larger model. Our alternative hypothesis claims superiority of the forecasts generated by the larger model.

The asymptotic theory behind the derivation of the GW test rules out the possibility of using recursive estimation windows. For that reason, when using recursive windows we will show the results of the GW test only for completion, but we will consider those results with caution.

We also carry out inference using the framework developed by CW. Their test statistic is mainly aimed at evaluating models in an out-of-sample fashion. With the CW test we evaluate whether our search queries provide additional information to that already contained in our benchmarks.

[11] As mentioned in GW, their test of unconditional equal predictive ability of two competing forecasts coincides with the widely known test attributed to Diebold & Mariano (1995) and West (1996). Nevertheless, the econometric environment under which both tests are derived is quite different. While Diebold & Mariano (1995) rely simply on the assumption of stationarity for the loss function differential $\hat{d}_t(h)$, Giacomini & White (2006) provide primitive assumptions that ensure asymptotic normality under certain conditions. Amongst other things, these primitive assumptions rule out the use of expanding windows in the out-of-sample analysis.

The CW test can be considered either as an encompassing test or as an adjusted comparison of Mean Squared Prediction Errors (MSPE). The adjustment is made in order to make a fair comparison between nested models. Intuitively, this test removes a term that introduces noise when a parameter, that should be zero under the null hypothesis of equal MSPE, is estimated.

The core statistic of the CW test is constructed as follows

$$\hat{z}_{t+2+h} = \left(\hat{e}_{1,t+2+h}\right)^2 - \left[\left(\hat{e}_{2,t+2+h}\right)^2 - \left(\widehat{bp}_{1,t+2+h|t} - \widehat{bp}_{2,t+2+h|t}\right)^2\right]$$

Where $\hat{e}_{1,t+2+h} = bp_{t+2+h} - \widehat{bp}_{1,t+2+h|t}$ and $\hat{e}_{2,t+h} = bp_{t+2+h} - \widehat{bp}_{2,t+2+h|t}$ represent the forecast errors from the two models under consideration.

With some algebra it is straightforward to show that $\hat{z}_{t+2+h}$ could also be expressed as follows

$$\text{SMSPE} - \text{Adjusted} = \frac{2}{P(h)} \sum_{t=R}^{T-1-h} \hat{e}_{1,t+2+h}\left(\hat{e}_{1,t+2+h} - \hat{e}_{2,t+2+h}\right) \qquad (1)$$

This statistic is used to test the following null hypothesis

$$H_0\text{: E(SMSPE} - \text{Adjusted)} = 0$$

against the alternative

$$H_A\text{: E(SMSPE} - \text{Adjusted)} > 0$$

CW suggest a one-sided test for a t-type statistic based upon the core statistic in (1). They recommend asymptotically normal critical values for their test.

Three points are worth mentioning. First, it is important to emphasize that the CW test is fairly different from either the test by GW or DMW. A key difference is that with the CW test we are testing equal population forecasting ability under quadratic loss. In other words we are evaluating the population difference in MSPE between two nested models. This is to be distinguished from tests that focus on comparing the expected value of Sample Mean Squared Prediction Errors between two forecasting methods. These tests, like GW, are not concerned about comparing models, they are concerned about comparing forecasting performance in a given sample.

Second, the CW test is not entirely new. In fact, the core statistic of the CW test is the same as the core statistic of the encompassing test proposed by Harvey, Leybourne, & Newbold, (1998). This implies that the CW test is also evaluating whether a particular combination between the null and alternative model generates a forecasting strategy with the lowest RMSPE. The novelty of CW compared to Harvey, Leybourne, & Newbold (1998) relies on the interpretation of the test as a method to evaluate the difference in population MSPE between two nested models, and on the fact that CW explicitly consider the role of parameter uncertainty.

Third, the asymptotic distribution of CW is analyzed in detail in Clark & McCracken (2001, 2005). In these papers the correct asymptotic distribution of the CW test is derived when one-step-ahead forecasts are used (Clark & McCracken, 2001) and when longer horizon forecasts are constructed via the direct method (Clark & McCracken, 2005). In the first paper it is shown that the resulting asymptotic distribution of the CW test in general is not standard. In fact it is a functional of Brownian motions depending on the number of excess parameters of the nesting model, the limit of the ratio P(h)/R and the scheme used to update the estimates of the parameters in the out-of-sample exercise. In the second paper Clark & McCracken (2005) provide a generalization of their results for multistep ahead forecasts. Unfortunately, the resulting asymptotic distribution of the CW statistic is again a functional of Brownian motions but now depending on nuisance parameters. Differing from the previous work of Clark & McCracken (2001, 2005), one of the key contributions of CW is to show via simulations that normal critical values are indeed adequate in a variety of settings. They show that the cost of approximating the correct critical values with standard normal critical values is in general low: it produces a little undersized test. Further work by Clark & McCracken (2013) and Pincheira & West (2016) show that normal critical values tend to work well when multistep ahead forecasts are constructed using the iterative method, at least when the data generating process is not very persistent. This is very important because in this paper we rely on the iterative method for the construction of multistep ahead forecasts. We rely then on the vast simulations provided by CW, Clark & McCracken (2013) and Pincheira & West (2016) to use standard normal critical values in our out-of-sample exercises.

V. Forecasting Models

Our basic approach considers the comparison of forecasts coming from a benchmark model with forecasts coming from the same benchmark but augmented with variables related to specific search queries in Google Trends. We consider two main specifications that we describe next:

$$\Delta\ln(\mathrm{bp_t}) = \alpha + \beta_1\Delta\ln(\mathrm{bp_{t-1}}) + \beta_2\Delta\ln(\mathrm{bp_{t-2}}) + \beta_{12}\Delta\ln(\mathrm{bp_{t-12}}) + \gamma(\mathrm{L})x_t + \varepsilon_t \quad \text{(A.1)}$$

$$x_t = \rho_1 x_{t-1} + \rho_{12} x_{t-12} + u_t \quad \text{(A.2)}$$

$$\Delta\ln(\mathrm{bp_t}) = \mathrm{a} + \gamma(\mathrm{L})x_t + v_t \quad \text{(B.1)}$$

$$(I - \vartheta L^{12})(I - \lambda_1 L - \lambda_2 L^2)v_t = \mu_t \quad \text{(B.2)}$$

$$(I - \theta L^{12})(I - \delta_1 L)x_t = d + \omega_t \qquad \text{(B.3)}$$

Where $\gamma(\mathrm{L}) = \gamma_0 \mathrm{I} + \gamma_1 L^1 + \gamma_2 L^2$ represents a lag polynomial, L represents the lag operator such that

$$L^j Z_t = Z_{t-j},$$

Δ represents the "difference operator" such that

$$\Delta Z_t = Z_t - Z_{t-1},$$

"I " represents the identity operator, ε_t, u_t, v_t, μ_t and ω_t correspond to white noise processes and

$$x_t = \Delta ln(z_t)$$

where z_t denotes a generic search query in Google Trends. In other words, z_t corresponds to either the monthly time series on "real estate exam", "new housing development", "new construction" or "new home construction".

Our first specification is labeled specification A. It comprises expressions A.1 and A.2. Our second specification is labeled B. It comprises expressions B.1, B.2 and B.3. We consider two different specifications for robustness. We notice that specification A is linear, whereas specification B is nonlinear.

For our in-sample analyses we consider both specifications (A and B). In these in-sample analyses we are evaluating a contemporaneous relationship between building permits at time t+1 and Google Trends search queries at time t+1 as well, so these in-sample analyses are not predictive exercises necessarily, they are exercises aimed at determining a relationship between building permits and Google Search queries that could potentially be used to obtained backcasts, nowcasts and forecasts.

VI. Empirical Results

In-sample analysis

Tables 2-3 show diagnostic statistics associated to univariate versions of our specifications A and B. Being more specific, Table 3 shows results of expression A.1 when γ(L) is set to zero, and estimates of expression A.2 for each particular Google Search query. Similarly, Table 2 shows results of expressions B.1 and B.2 when γ(L) is set to zero, and estimates of expression B.3 for each particular Google Search query. We notice that estimates of the drift terms are removed from Tables 2-3. A quick view of Tables 2-3 indicates that our specifications offer a decent representation of the data as they are able to explain an important share of the total variation of the respective dependent variable, most of the coefficients are statistically significant and the Durbin-Watson statistic is close to 2 in most of the expressions.

Table 2: In-Sample Analysis: Basic nonlinear specifications.

Dependent Variable	dlog(bp)	dlog(nc)	dlog(nhd)	dlog(nhc)	dlog(rex)
AR(1)	*-0.3366****	*-0.2611****	*-0.3208****	*-03959****	*-0.3574****
	(0.0766)	*(0.0951)*	*(0.0662)*	*(0.0634)*	*(0.0861)*
AR(2)	*-0.1277**				
	(0.0761)				
SAR(12)	*0.7150****	*0.8668****	*0.3950****	*0.7918****	*0.6370****
	(0.0793)	*(0.04623)*	*(0.1005)*	*(0.0523)*	*(0.0794)*
R-squared	0.4725	0.7806	0.2259	0.6132	0.4139
N	129	132	132	132	132
Durbin-Watson	1.9461	1.9336	2.1439	2.0376	2.0491
Schwarz criterion	-1.7201	-3.3696	-1.3236	-2.2780	-1.7690

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey & West (1987) in parentheses. The operator dlog() refers to first log-difference monthly changes. Variables *bp, nhc, nc, nhd, rex* refer to "building permits", "new home construction", "new construction","new housing development" and “real estate exam”.

Table 3: In-Sample Analysis: Basic linear specifications.

Dependent Variable	dlog(bp)	dlog(nc)	dlog(nhd)	dlog(nhc)	dlog(rex)
Lag 1	*-0.1896****	*-0.0362*	*-0.2740****	*-0.0857*	*-0.2017****
	(0.0512)	*(0.0459)*	*(0.0550)*	*(0.0528)*	*(0.0767)*
Lag 2	*0.1026*				
	(0.0657)				
Lag 12	*0.6796****	*0.8509****	*0.3482****	*0.7310****	*0.5854****
	(0.0653)	*(0.0511)*	*(0.0937)*	*(0.0689)*	*(0.0872)*
R-squared	0.4826	0.7591	0.2108	0.5534	0.3740
N	131	133	133	133	133
Durbin-Watson	2.1872	2.3913	2.1680	2.5718	2.2806
Schwarz criterion	-1.6904	-3.2444	-1.2753	-2.1055	-1.6743

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses. The operator ‘Lag’ refers to a lag in the dependent variable in months; dlog() refers to first log-difference monthly changes. Variables *bp, nhc, nc, nhd, rex* refer to "building permits", "new home construction", "new construction","new housing development" and “real estate exam”.

Table 4 is more enlightening and interesting than Tables 2-3. It shows in-sample estimates of our specifications A and B when $\gamma(L)$ is allowed to be different from zero. In the first panel in Table 4 we show the estimates of the three coefficients of $\gamma(L)$: $\gamma 0$, $\gamma 1$ and $\gamma 2$. In all our estimations at least one of these coefficients is statistically significant at usual confidence levels. Furthermore, Table 5 shows the F statistic associated to the null hypothesis that all three gamma coefficients are zero. This null hypothesis is almost always rejected at usual significance levels. We also observe that the Durbin-Watson statistic is still close to 2, and that the coefficients of determination are almost always higher in Table 4 than in Tables 2-3. Of course this last point must not be considered too seriously as it is a textbook fact that the addition of irrelevant variables may induce an increment in the R^2 diagnostic statistic.

All in all, our in-sample estimates provide evidence of a relationship between the time series on building permits and the time series on several Google Search queries. In-sample estimates, however, are usually criticized because they are relatively different from a real time forecasting exercise and also because they have shown a tendency to overfit the data. To mitigate these shortcomings, we move next to a multistep ahead out-of-sample analysis.

Table 4: In-Sample Analysis: Explaining Building Permits with Google Trends

Dep. Var.: dlog(bp)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dlog(nhc)	*0.0987*				*0.0562*			
	(0.0910)				*(0.0636)*			
dlog(nhc(-1))	*0.284****				*0.0824*			
	(0.1073)				*(0.0657)*			
dlog(nhc(-2))	*0.4088****				*0.2425***			
	(0.1197)				*(0.1066)*			
dlog(nc)		*0.2124*				*0.1361*		
		(0.1593)				*(0.0957)*		
dlog(nc(-1))		*0.2473*				*0.1139*		
		(0.1752)				*(0.0728)*		
dlog(nc(-2))		*0.7389****				*0.4520****		
		(0.1122)				*(0.0902)*		
dlog(nhd)			*0.0431*				*0.0817*	
			(0.0611)				*(0.0609)*	
dlog(nhd(-1))			*0.0556*				*0.1004*	
			(0.0573)				*(0.0628)*	
dlog(nhd(-2))			*0.1091**				*0.1609****	
			(0.0578)				*(0.0639)*	
dlog(rex)				*-0.0547*				*0.0248*
				(0.0977)				*(0.072)*
dlog(rex(-1))				*0.2400****				*0.1788***
				0.084539				*(0.0748)*
dlog(rex(-2))				*0.1866***				*0.2223****
				(0.0865)				*(0.0758)*
AR(1)	*-0.4898****	*-0.4625****	*-0.3497****	*-0.3701****				
	(0.0648)	*(0.0700)*	*(0.0806)*	*(0.0815)*				
AR(2)	*-0.2539****	*-0.1969***	*-0.1374**	*-0.1767***				
	(0.0851)	*(0.0787)*	*(0.0762)*	*(0.0747)*				
SAR(12)	*0.5746****	*0.4871****	*0.6669****	*0.6385****				
	(0.0897)	*(0.0824)*	*(0.0857)*	*(0.0679)*				
dlog(bp(-1))					*-0.2104****	*-0.2463****	*-0.2167****	*-0.2416***
					(0.0512)	*(0.0491)*	*(0.0515)*	*(0.0483)*
dlog(bp(-2))					*0.0964*	*0.0897*	*0.0905*	*0.0634*
					(0.063)	*(0.0645)*	*(0.0731)*	*(0.0618)*
dlog(bp(-12))					*0.5430****	*0.4901****	*0.6016****	*0.5655****
					(0.0648)	*(0.0619)*	*(0.0673)*	*(0.0629)*
R-squared	0.5483	0.557	0.482	0.511	0.518	0.552	0.504	0.527
N	127	127	127	127	131	131	131	131
Durbin-Watson	1.964	1.971	1.944	1.955	2.347	2.276	2.218	2.248
F-statistic	24.273	25.189	18.576	20.868	22.226	25.437	21.040	22.987
P-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Schwarz criterion	-1.706	-1.726	-1.568	-1.626	-1.650	-1.722	-1.622	-1.668

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses. The dependent variable is the monthly log-difference in building permits. The operator dlog() refers to log-difference monthly changes. Variables bp, nhc, nc, nhd and rex refer to "building permits", "new home construction", "new construction", "new housing development" and “real estate exam”.

Table 5: In-Sample Analysis: Joint significance of Google Search Queries

Model Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wald Test (Chi-square)	26.530	54.356	5.443	17.511	8.099	27.641	9.833	12.856
P-value	*0.000*	*0.000*	*0.142*	*0.001*	*0.044*	*0.000*	*0.020*	*0.005*
F- Test	8.843	18.119	1.814	5.837	2.700	9.214	3.278	4.285
P-value	*0.000*	*0.000*	*0.148*	*0.001*	*0.049*	*0.000*	*0.023*	*0.007*

Source: Own calculations based on US. Census and Google Trends data. HAC standard errors according to Newey and West (1987) are used in the construction of the tests. The null hypothesis is that the parameters associated to the search queries (contemporaneous and the first two lags) are all jointly equal to zero. For specifications (1) and (5) the search queries are "nhc"; for (2) and (6), "nc"; for (3) and (7), "nhd"; and for (4) and (8), "rex". Variables nhc, nc, nhd and rex refer to "new home construction", "new construction","new housing development" and "real estate exam", respectively.

Out-of-sample analysis

Table 6-13 show results of our out-of-sample exercises. In particular, Tables 6-9 show the CW core statistic, its standard errors and the corresponding t-statistics. Tables 10-13 show similar results but for the GW/DMW test.

Table 6-13 show strong evidence of predictability for two Google Search queries: “new home construction” and “new construction”. This predictability is robust to our model specifications (linear or nonlinear), to the use of expanding or rolling windows, and also to the forecasting horizon. In particular, our results indicate that these two search queries are useful for backcasting, nowcasting and forecasting building permits in the U.S. Furthermore, in most cases evidence of predictability is found at extremely tight significance levels: 5% or even 1% in many cases.

For the other two search queries under analysis, our results are slightly less compelling. We do find evidence of predictability, but this evidence is not always robust to different forecasting horizons, model specifications and to the use of expanding or rolling windows. Robust results are found for both search queries when predicting building permits two months ahead and also for the query “real state exam” when forecasting one month ahead. At other forecasting horizons we obtain mixed results. This means little evidence of predictability in our nonlinear specifications but stronger evidence when using our linear specifications. Interestingly, for the search query “real state exam” the general picture is a little better than in the case of “new housing development”.

Table 6: Clark –West Test: Forecasting Building Permits with Google Trends in Expanding Windows using nonlinear models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				MSPE-adjusted / CW				
	backcast	*nowcast*			*forecasts*			
Google Query	*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
	14.15	22.62	32.08	47.89	45.68	35.70	34.83	81.22
New home construction	(2.96)	(5.33)	(7.88)	(9.54)	(8.85)	(13.60)	(15.45)	(30.54)
	4.78***	4.24***	4.07***	5.02***	5.16***	2.63***	2.25**	2.66***
	14.45	26.80	35.68	59.51	54.13	57.04	54.46	139.57
New construction	(5.00)	(9.51)	(13.90)	(14.74)	(14.71)	(20.21)	(24.52)	(44.69)
	2.89***	2.82***	2.57***	4.04***	3.68***	2.82***	2.22**	3.12***
	-0.53	1.52	1.40	4.86	0.94	-8.85	-0.81	5.77
New housing development	(1.85)	(1.56)	(2.56)	(2.80)	(3.78)	(8.75)	(6.93)	(10.63)
	-0.29	0.97	0.55	1.73**	0.25	-1.01	-0.12	0.54
	2.77	5.61	8.84	14.67	12.54	-5.01	-9.72	4.81
Real estate exam	(2.67)	(4.85)	(6.87)	(8.82)	(10.95)	(15.65)	(17.54)	(27.64)
	1.04	1.16	1.29*	1.66**	1.15	-0.32	-0.55	0.17

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Table 7: Clark –West Test: Forecasting Building Permits with Google Trends in Rolling Windows using nonlinear models as benchmarks.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				MSPE-adjusted / CW				
	backcast	*nowcast*			*forecasts*			
Google Query	*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
	13.54	23.18	30.31	51.18	48.98	47.75	53.18	137.98
New home construction	(4.19)	(7.16)	(9.96)	(12.25)	(12.52)	(20.88)	(23.68)	(65.67)
	3.23***	3.24***	3.04***	4.18***	3.91***	2.29**	2.25**	2.10**
	11.32	23.60	30.17	53.31	51.15	66.05	63.01	162.53
New construction	(6.26)	(10.98)	(15.23)	(15.58)	(19.30)	(23.37)	(30.00)	(68.78)
	1.81**	2.15**	1.98**	3.42***	2.65***	2.83***	2.10**	2.36***
	-2.24	0.99	2.75	6.77	4.28	-0.34	14.47	38.49
New housing development	(2.12)	(2.10)	(3.27)	(4.33)	(6.38)	(12.10)	(18.83)	(35.04)
	-1.05	0.47	0.84	1.56*	0.67	-0.03	0.77	1.10
	3.34	6.88	10.17	17.96	22.41	11.88	11.63	47.39
Real estate exam	(3.59)	(5.73)	(7.30)	(10.35)	(13.11)	(16.18)	(20.37)	(44.35)
	0.93	1.20	1.39*	1.73**	1.71**	0.73	0.57	1.07

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Table 8: Clark –West Test: Forecasting Building Permits with Google Trends in Expanding Windows, using Linear Models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	MSPE-adjusted / CW							
	backcast	*nowcast*	*forecasts*					
Google Query	*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
	4.60	11.83	25.10	38.27	42.07	30.15	13.05	39.18
New home construction	(1.76)	(3.80)	(7.27)	(8.76)	(9.69)	(9.65)	(9.77)	(19.36)
	2.62***	3.12***	3.45***	4.37***	4.34***	3.13***	1.34**	2.02**
	11.96	21.02	29.71	53.80	49.66	41.51	28.10	96.26
New construction	(3.45)	(6.45)	(10.05)	(10.91)	(9.81)	(12.44)	(16.47)	(29.38)
	3.46***	3.26***	2.96***	4.93***	5.06***	3.34***	1.71**	3.28***
	2.78	7.94	12.68	23.57	17.87	-0.48	0.36	26.91
New housing development	(1.81)	(2.69)	(4.52)	(7.55)	(8.15)	(7.76)	(7.65)	(15.54)
	1.53*	2.96***	2.81***	3.12***	2.19**	-0.06	0.05	1.73**
	6.65	14.76	25.74	42.85	42.95	25.96	20.82	72.69
Real Estate Exam	(2.28)	(4.85)	(7.36)	(8.63)	(10.34)	(16.06)	(17.60)	(33.98)
	2.91***	3.04***	3.50***	4.97***	4.15***	1.62*	1.18	2.14**

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Table 9: Clark –West Test: Forecasting Building Permits with Google Trends in Rolling Windows, using Linear Models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	MSPE-adjusted / CW							
	backcast	*nowcast*	*forecasts*					
Google Query	*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
	4.35	12.02	23.02	36.69	41.02	29.15	7.14	32.10
New home construction	(2.37)	(4.18)	(7.70)	(8.79)	(9.17)	(12.40)	(14.51)	(34.83)
	1.83**	2.87***	2.99***	4.17***	4.47***	2.35***	0.49	0.92
	10.86	21.67	30.86	53.04	50.88	41.30	13.11	77.14
New construction	(3.66)	(7.33)	(10.66)	(10.82)	(9.09)	(15.29)	(21.73)	(48.19)
	2.97***	2.96***	2.90***	4.90***	5.60***	2.70***	0.60	1.60*
	2.22	8.21	17.23	30.69	24.07	-0.51	-4.26	38.48
New housing development	(2.68)	(3.89)	(5.42)	(9.31)	(9.82)	(9.78)	(15.72)	(34.84)
	0.83	2.11**	3.18***	3.30***	2.45***	-0.05	-0.27	1.10
	8.61	19.02	25.31	44.30	45.78	34.42	29.06	99.73
Real Estate Exam	(3.51)	(6.10)	(8.09)	(9.63)	(13.87)	(18.29)	(22.09)	(52.11)
	2.45***	3.12***	3.13***	4.60***	3.30***	1.88**	1.32*	1.91**

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Tables 10-13 show sample Root Mean Squared Prediction Errors (RMSPE) and the t-statistics of the GW/DMW test. We notice that we expect weaker results using the GW/DMW test because our analysis involves the forecasting ability of two models, one nested in the other. Let us recall that in nested environments the CW test removes a term that should be zero in population under the null hypothesis, but that is not zero in finite samples. Tables 10-13 corroborate this prior as the corresponding t-statistics of the GW/DMW test are always lower than the t-statistics of the CW test, comparing the same forecasting exercises, of course. Despite this regularity, Tables 10-13 still provide evidence of predictability in some cases. The most robust evidence is found for the query: "new home construction" for which we do find evidence of "nowcastability" in all our forecasting exercises, for instance. Evidence of predictability with the GW/DMW test may also be found for the rest of the queries under analysis, more so when forecasting at short horizons, although this evidence is not always robust across our different out-of-sample exercises.

It is also interesting to mention some results regarding forecast accuracy. In the last row of Tables 10-13 we show sample RMSPE of our benchmark models. This is a measure of forecast accuracy when our models generate forecasts without the information provided by Google Trends. It is straightforward to compare this baseline sample RMSPE with that reported for each search query. Simple algebra leads to show that the most important gains in forecast accuracy are obtained using the query "new home construction" and "new construction". These queries allow gains of more than 10% in sample RMSPE when forecasting two and three months ahead. Table 14 provides a summary of these sample RMSPE ratios.

It is also important to mention that the lowest sample RMSPE across all our forecasting exercises is achieved when using our nonlinear models with expanding estimation windows (see Table 10). At short horizons the lowest sample RMSPE is achieved when our nonlinear specification is augmented with "new home construction", and at longer horizons of 6, 9 and 12 months ahead, the lowest sample RMSPE is achieved when our nonlinear specification is augmented with the query "new construction".

In summary, we find relatively strong evidence of predictability for our supply side queries "new home construction" and "new construction", and slightly less compelling evidence for the queries "new housing development" and "real state exam".

Table 10: Diebold-Mariano-West Test: Forecasting Building Permits with Google Trends in Expanding Windows, using Nonlinear Models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	RMSPE and DMW test								
	RMSPE/DMW	*backcast*	*nowcast*	*forecasts*					
Google Query		*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
New home construction	RMSPE	7.74	8.74	9.37	10.31	10.46	12.62	14.53	18.05
	DMW	2.57***	2.23**	2.64***	3.91***	4.10***	1.42*	1.21	0.98
New construction	RMSPE	7.98	8.84	9.72	10.44	10.65	12.22	14.15	17.05
	DMW	0.60	0.91	0.77	2.14**	2.02**	1.51*	1.21	1.35*
New housing development	RMSPE	8.26	9.31	10.25	11.62	11.93	13.86	15.33	18.90
	DMW	-0.75	0.32	0.02	1.07	-0.37	-1.38	-0.77	-0.04
Real estate exam	RMSPE	8.24	9.41	10.28	11.58	11.82	14.06	15.92	19.47
	DMW	-0.45	-0.32	-0.09	0.54	0.13	-1.18	-1.34	-0.94
	RMSPE benchmark	8.17	9.33	10.25	11.75	11.88	13.39	15.16	18.89

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Table 11: Diebold-Mariano-West Test: Forecasting Building Permits with Google Trends in Rolling Windows, using Nonlinear Models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				RMSPE and DMW test					
	RMSPE/DMW	*backcast*	*nowcast*			*forecasts*			
Google Query		*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
New home construction	RMSPE	8.15	9.05	9.74	10.54	10.90	13.50	16.29	21.09
	DMW	0.67	1.33*	1.49*	2.97***	2.85***	1.18	1.18	0.89
New construction	RMSPE	8.68	9.41	10.38	11.17	11.49	13.30	16.34	21.05
	DMW	-0.66	0.13	-0.01	1.03	0.93	1.22	0.87	0.84
New housing development	RMSPE	8.59	9.60	10.40	11.77	12.25	14.68	17.02	21.97
	DMW	-1.99	-1.00	-0.18	0.61	-0.12	-0.78	0.26	0.63
Real estate exam	RMSPE	8.48	9.67	10.46	11.71	11.93	14.61	17.35	22.34
	DMW	-0.88	-0.74	-0.31	0.48	0.75	-0.49	-0.38	0.12
	RMSPE benchmark	8.31	9.49	10.37	11.87	12.22	14.37	17.15	22.43

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Table 12: Diebold-Mariano-West Test: Forecasting Building Permits with Google Trends in Expanding Windows, using Linear Models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				RMSPE and DMW test					
	RMSPE/DMW	*backcast*	*nowcast*			*forecasts*			
Google Query		*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
New home construction	RMSPE	8.24	9.47	10.29	11.69	11.32	13.01	14.75	18.57
	DMW	1.02	1.84**	2.58***	3.70***	3.86***	2.12**	0.49	0.46
New construction	RMSPE	8.05	9.16	10.35	11.30	11.21	12.81	14.46	17.48
	DMW	1.61*	2.04**	1.68**	3.92***	4.16***	2.29**	0.90	1.72**
New housing development	RMSPE	8.30	9.50	10.67	12.10	12.18	13.97	15.10	18.41
	DMW	0.45	2.35***	2.15**	2.78***	1.77**	-0.76	-0.73	1.05
Real Estate Exam	RMSPE	8.23	9.49	10.45	11.64	11.42	13.40	14.71	18.02
	DMW	0.91	1.19	1.73**	3.68***	3.45***	0.61	0.34	0.91
	RMSPE benchmark	8.35	9.81	11.05	12.86	12.71	13.76	14.92	18.83

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. HAC standard errors according to Newey and West (1987) in parentheses.

Table 13: Diebold-Mariano-West Test: Forecasting Building Permits with Google Trends in Rolling Windows, using Linear Models as benchmarks

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				RMSPE and DMW test					
	RMSPE/DMW	*backcast*	*nowcast*			*forecasts*			
Google Query		*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
New home construction	RMSPE	8.48	9.74	10.93	12.42	12.15	13.92	16.44	21.44
	DMW	-0.58	1.46*	1.71**	3.11***	3.76***	1.21	-0.39	-0.18
New construction	RMSPE	8.34	9.51	10.89	12.13	12.01	13.84	16.48	21.11
	DMW	0.22	1.55*	1.41*	3.40***	4.08***	1.08	-0.36	0.11
New housing development	RMSPE	8.51	9.88	11.08	12.53	12.76	14.95	16.79	21.15
	DMW	-0.74	0.74	2.03**	2.68***	1.71**	-1.33	-1.17	0.13
Real Estate Exam	RMSPE	8.34	9.70	11.09	12.38	12.24	14.12	15.96	20.35
	DMW	0.24	1.12	1.09	3.05***	2.46***	0.63	0.40	0.85
	RMSPE benchmark	8.38	10.02	11.47	13.39	13.34	14.50	16.23	21.26

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. DMW t statistic is calculated using HAC standard errors according to Newey and West (1987).

Table 14: Sample RMSPE ratios between models with and without internet search queries

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RMSPE ratios									
Expanding Windows									
	Linear/Non Linear	*backcast*	*nowcast*	*forecasts*					
Google Query		*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
New home construction	Linear	0.99	0.97	0.93	0.91	0.89	0.95	0.99	0.99
	Non Linear	0.95	0.94	0.91	0.88	0.88	0.94	0.96	0.96
New construction	Linear	0.96	0.93	0.94	0.88	0.88	0.93	0.97	0.93
	Non Linear	0.98	0.95	0.95	0.89	0.90	0.91	0.93	0.90
New housing development	Linear	0.99	0.97	0.97	0.94	0.96	1.02	1.01	0.98
	Non Linear	1.01	1.00	1.00	0.99	1.00	1.03	1.01	1.00
Real Estate Exam	Linear	0.99	0.97	0.95	0.90	0.90	0.97	0.99	0.96
	Non Linear	1.01	1.01	1.00	0.99	1.00	1.05	1.05	1.03
Rolling Windows									
Google Query		*h* =-1	*h* =0	*h* =1	*h* =2	*h* =3	*h* =6	*h* =9	*h* =12
New home construction	Linear	1.01	0.97	0.95	0.93	0.91	0.96	1.01	1.01
	Non Linear	0.98	0.95	0.94	0.89	0.89	0.94	0.95	0.94
New construction	Linear	0.99	0.95	0.95	0.91	0.90	0.95	1.02	0.99
	Non Linear	1.04	0.99	1.00	0.94	0.94	0.93	0.95	0.94
New housing development	Linear	1.01	0.99	0.97	0.94	0.96	1.03	1.03	0.99
	Non Linear	1.03	1.01	1.00	0.99	1.00	1.02	0.99	0.98
Real Estate Exam	Linear	0.99	0.97	0.97	0.92	0.92	0.97	0.98	0.96
	Non Linear	1.02	1.02	1.01	0.99	0.98	1.02	1.01	1.00

Source: Own calculations based on US. Census and Google Trends data. Figures below 1 favor the model that includes the internet search query.

VII. Concluding Remarks

In this paper we provide strong evidence of the ability that some internet search queries have to generate backcasts, nowcasts and forecasts of building permits in the U.S. In particular, search queries such as "new construction" and "new home construction" are shown to have relevant predictive information.

Our findings are significant. The time series on building permits is a leading indicator of economic activity in the construction sector, which is released with a lag of almost two months. This means that the current state of the business cycle in that sector cannot be known in a timely manner. Consequently, strategies to build reliable backcasts, nowcasts and forecasts of building permits are required. We show that this non-comprehensive list of internet search queries may help in this direction.

It is important to emphasize here that the contribution of our paper is to provide evidence of a predictive relationship between internet search queries and building permits. Yet, behind the curtains of a predictive linkage there can be either a causal economic relationship or a common factor the moves the relevant variables with different reaction speeds. It is not the objective of this paper to identify the true nature behind the relationship we have documented. We leave this task for further research.

Our paper is part of a large literature that in the recent years has evaluated the predictive usefulness of the information that is available on the web. This is an attractive line of research because of the large and increasing proportion of internet users, the high frequency of the data that is released by Google Trends and the relative speed with which this data is released to the public.

A natural avenue of future research considers the evaluation of the predictive ability of our preferred search queries when forecasting measures of economic activity in more complex economic models. Similarly, we only have explored the predictive ability of simple internet search queries, without considering forecast combinations or more advanced techniques of dimensionality reduction. This also seems to be another attractive line of future research.

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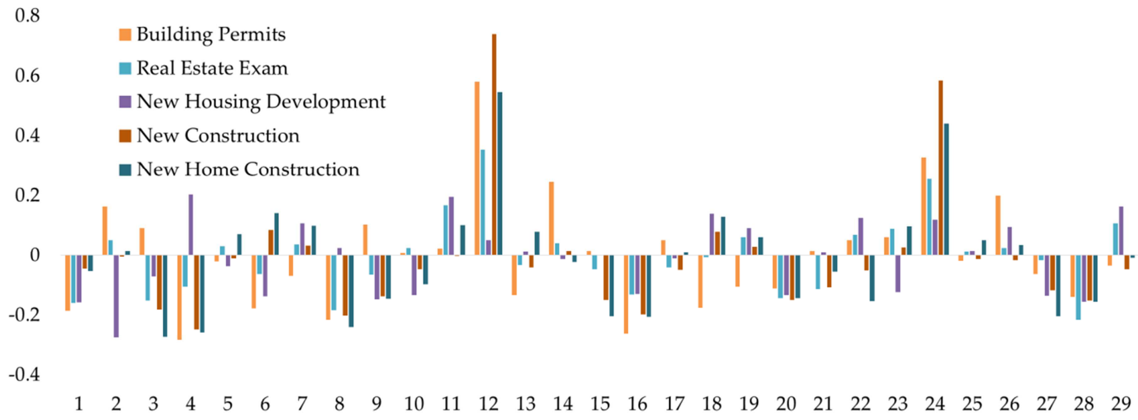
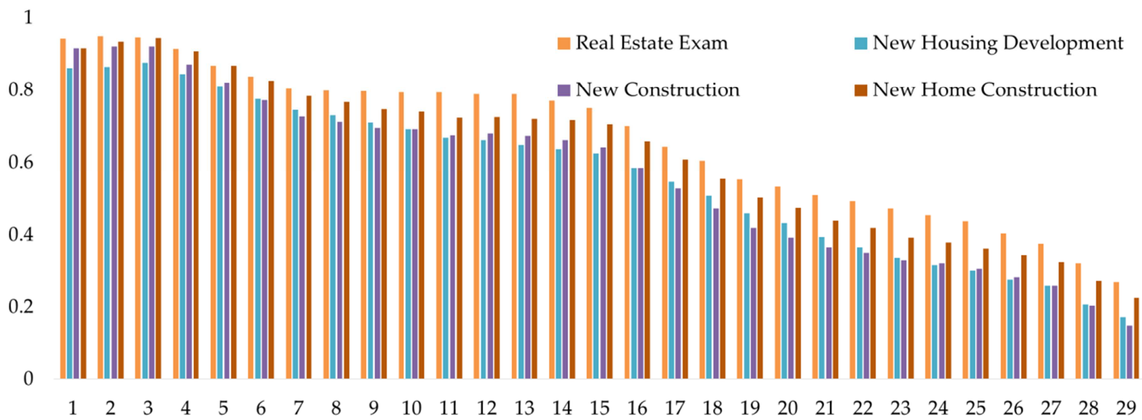
Appendix

Figure A1: Autocorrelograms in First Log-Differences.



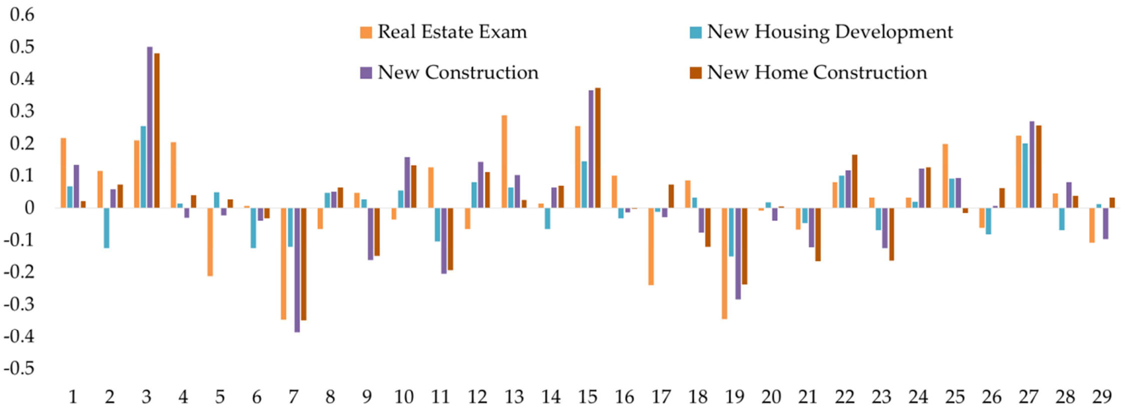
Source: Own calculations based on US. Census and Google Trends data.

Figure A2: Cross Correlograms of Building Permits and Google Search Queries (levels).



Source: Own calculations based on US. Census and Google Trends data.

Figure A3: Cross Correlograms of Building Permits and Google Search Queries (first differences).



Source: Own calculations based on US. Census and Google Trends data.

Table A1: Unit Root Tests

	Building Permits	Real Estate Exam	New Housing Development	New Construction	New Home Construction
			Augmented Dickey-Fuller Test		
	Levels				
Standard	-1.766	-1.924	-2.281	-2.169	-2.063
With trend	-1.736	-1.636	-3.288*	-2.476	-2.079
With drift	-1.766**	-1.924**	-2.281**	-2.169**	-2.063**
	First differences				
Standard	-13.895***	-13.611***	-15.483***	-12.682***	-12.073***
With trend	-13.884***	-13.678***	-15.491***	-12.676***	-12.105***
With drift	-13.895***	-13.611***	-15.483***	-12.682***	-12.073***
			Phillips-Perron Test		
	Levels				
Standard	-1.733	-1.779	-2.136	-1.976	-1.929
With trend	-1.713	-1.366	-2.817	-2.216	-1.794
	First differences				
Standard	-13.784***	-13.776***	-17.156***	-12.970***	-12.313***
With trend	-13.783***	-13.903***	-17.287***	-12.983***	-12.385***

Source: Own calculations based on US. Census and Google Trends data. * p<10%, ** p<5%, *** p<1%. The null hypotheses of both tests indicate the existence of a unit root. The levels are natural logarithms of the raw series, and the first difference is their monthly log-difference.