Trendy Election Forecasting:
Using Google Search Trends as a Proxy for Perceptions of Economic Performance

Abinav Nanda Kumar

HMN 679H
Special Honors in the Department of Humanities
The University of Texas at Austin

May 2018

Brian Roberts
Department of Government
Supervising Professor

Christopher Wlezien
Department of Government
Second Reader

Trendy Election Forecasting:
Using Google Search Trends as a Proxy for Perceptions of Economic Performance

Abinav Nanda Kumar, HMN

The University of Texas at Austin, 2019

Supervisor: Brian Roberts

Abstract

This paper aims to answer two questions: Do measures of economic perception outperform objective economic measures in economic election forecasting models? Can Google search trend data serve as a proxy for perceptions of economic performance and outperform survey data? These questions were addressed by creating a baseline election forecasting model using objective economic measures, and then replacing the data with survey data and Google search trend data. The tests found that measures of economic perception do outperform objective economic measures. Even though Google search trends did not outperform survey data in this paper, there is potential for search trend data to be supplemented or filtered to improve its performance.

Table of Contents

List of Tables

Introduction

Prevalent political science literature maintains that voters vote primarily based on economic performance under incumbent governments, rewarding their governments for good economic performance and punishing for bad. This model is referred to as the *Retrospective Economic Evaluations Voter Model (REEVM)*. These models use objective economic measures as an explanatory variable, stating voters vote by taking economic performance into account. Although these models once performed well, the evolution of America's political landscape caused the models to wane in performance. Many of the available works bring up a similar concern: do voters *perceive* economic performance accurately? This paper aims to answer that question by deconstructing the REEVM's reliance on objective economic measures and patching it back up using data from Google search trends as a proxy for perceptions of economic performance. This generates a couple of questions: Do measures of perceptions of economic performance outperform objective economic performance measures in forecasting models? Can Google search trends serve as a better proxy for perceptions of economic performance than the traditional method of surveying? Currently, many models of human behavior rely heavily on data from surveys, which often do not prove accurate for many reasons including bias, shame, and flawed methodologies. If Google search trends can serve as a proxy for perceptions then this could spill over to many different aspects of political science and move the literature away from relying solely on survey data.

Brief Overview of Economic Evaluation Voter Models

The political science literature finds that voters do not look exclusively at economic issues, but they are generally weighted more than any other issue, regardless of the democracy they are in (Lewis-Beck & Stegmaier 2000). This realization spurred the publication of hundreds of articles analyzing the interaction between economic performance and the success of political candidates. The most common explanation for aggregate voter behavior is the retrospective economic evaluation hypothesis. The hypothesis states that voters punish poor performing incumbents by voting them out of office, and reward incumbents that perform well by voting them in office. According to V.O. Key's seminal work, *The Responsible Electorate*, the theoretical definition of retrospective voters defines them as agents who place greater focus on policy outcomes rather than how they are achieved, consider only the performance of the incumbent largely ignoring the opposition, and evaluate what has been done and not what is promised to be done (1966). Since the publication of V.O. Key's book, many empirical presidential election models using objective economic variables have proven successful at the aggregate voter level and support the notion that voters, en masse, vote based on retrospective economic evaluations (Fair 1978; Abramowitz 1988; Lewis-Beck & Stegmaier 2000; Erikson & Wlezien 2008).

In addition to retrospective economic evaluations, the literature explores prospective, sociotropic, and egocentric economic evaluations. Table 1 below lays out the four types of economic evaluations. The literature addresses each of these evaluation methodologies in-depth, but models assuming retrospective sociotropic evaluations appear to the most consistent results backed by empirical evidence. This paper assumes that voters are sociotropic retrospective economic evaluators for two reasons. First, voters do not appear to vote based on personal economic circumstances, but rather seem to vote based on perceptions of macroeconomic performance (Fiorina 1978; Kramer 1983). Both individual-level survey-based studies and aggregate-level studies find this to be true (Stein 1990). This is key to the retrospective evaluation hypothesis because it means voters conceptualize a standardized source of information to base their decisions on instead of chance events. Second, the literature available on prospective economic voting conveys inconsistent results. A potential explanation for the variance in results is the prospective economic evaluation school of thought's reliance on questions asking voters to prospectively evaluate the economy unconditional on which candidate wins the election (Tucker et al. 2010). This explanation requires that prospective evaluation studies be consistent with the definition of prospective economic evaluations, as originally formulated by Anthony Downs, that prospective evaluations ought to be conditional on which party wins the election (1957). Because of these inconsistencies in available data and the complexity involved in incorporating trend data into a model with both prospective and retrospective evaluation terms, this paper will focus solely on retrospective economic evaluations. Additionally, this paper will not address the distinction between simple and mediated retrospective evaluations because the model will not be able to accommodate Google trend data well.

Table 1: Types of Economic Voter Evaluations

	Prospective	**Retrospective**
Sociotropic	Will the economy perform better?	Has the economy been performing well?
Egocentric	Will my personal economic condition be better?	Has my been personal economic condition been doing well?

Although voters are deemed to behave in a manner consistent with the REEVM, they demonstrate a short-term memory, holding candidates responsible for the performance of the economy in a more recent time period (Fair 1978). Because older literature relies primarily on objective economic measures of the second quarter, the models cannot be used to forecast elections well in advance. In order for these models to have practical applications in election forecasting, there must be a methodology that can capture perceptions of economic performance well before an election. A partial solution to this problem is to use leading economic indicators (LEI) to estimate economic performance closer to the election dates (Erikson & Wlezien 2008). LEI growth demonstrates a strong correlation with future economic performance and the models that use them perform well in the months leading up to an election, but the variable likely does not capture how voters will perceive future economic performance.

This paper draws from gubernatorial elections because Google's search data only goes back to the beginning of 2004 and four presidential elections is too small a sample size to come to any meaningful conclusions. For gubernatorial elections, at the aggregate level, voters seem to still vote using retrospective economic evaluations, but, according to the literature, they follow a couple of corollaries. First, voters seem to hold governors that are of the same party as the president hostage for national economic performance and do not hold governors responsible for their own state's economic performance (Peltzman 1987). Because most gubernatorial elections take place during midterms, this is likely an intentional choice by voters instead of a result of misinformed straight-ticket voting where voters cast their ballots in a manner that holds the president's party accountable. Second, voters supposedly only hold governors responsible for the state's economy if the governor's party commands a unified government – control of all three branches of their state's government (Leyden & Borelli 1995). This conclusion was reached using an older dataset, so it is possible that voter behavior has evolved, for better or worse, since the release of that study. These corollaries allow, and even encourage, the use of Google search trend data because of its ability to accommodate national level economic performance data in state-level elections.

As discussed earlier, in general, aggregate-level studies tend to support the idea that voters are well-informed about the economy and act in a rational manner consistent with the retrospective economic evaluations hypothesis. In contrast, individual-level research finds that voters are largely misinformed and apathetic (Neuman 1986). This does not have major implications for the retrospective economic evaluations model because if en masse, voters are still voting in accordance with the hypothesis there is still a relationship worth exploring, and it is highly likely that these voters are making decisions based on economic performance whether cognizant or not. Survey-based studies utilizing self-reported data from individuals find varied results inconsistent with aggregate-level results regarding who should be held accountable for economic performance (Stein 1990; Atkenson & Partin 1995; Svoboda 1995; Niemi et al. 1995; Hansen 1999; Orth 2001). Most studies find that voters overwhelmingly hold the president accountable for macroeconomic performance, even though the actual end of the responsibility falls on Congress, but the studies also find that voters do believe that governors are partially responsible for the condition of the state's economy. While voters respond to the surveys in a manner which makes them seem likely to hold the governor accountable for the state's economic condition, in the aggregate, voter cast ballots in a manner inconsistent with the survey responses, holding solely the president responsible. Simple explanations for the inconsistencies are potential over-confidence of voters in their ability to reason towards their vote choice and potential inconsistencies in survey methodology.

Perceptions of Economic Performance and Vote Choice

According to economic voting models, it is voters' perceptions of the economy that is the keystone for vote choice. Early findings argue vote choice is formulated from a combination of retrospective evaluations of parties, prospective evaluations of parties, and party identification (Fiorina 1978, 1981). This perspective paints a picture of a semi-intelligent voter subject to a type of bounded-rationality, with the voter attempting to base decisions on objective evaluations through prospective and retrospective evaluations, but also accounting for their partisan biases. This painted voter is likely a small minority of voters; as mentioned before, individual-level survey data finds that voters are grossly misinformed and apathetic. This model intuitively may hold up but does not remain steadfast when put up against micro- and macro-level economic voting studies. The assumption that perceptions of economic performance are even partially exogenous at both the individual- and aggregate-level ought to be evaluated thoroughly.

The opposing view to this bounded-rationality model suggests that economic perceptions are primarily endogenous, based almost exclusively on political orientation or identity. This view grounds itself in a critique of causality, instead of assuming that political orientation is derived from economic perception, it proposes that economic perceptions come primarily from political identification. Voters perceive the economy in varied ways depending on many factors, in this case, encompassed by the term party identification

(Anderson 2007). At the national level, media consumption and prior political partisanship are partial explanations for altered perceptions of economic performance (Hetherington 1996; Evans & Anderson 2006). The same results are found at the state level (Brown 2010). Behavioral economics refers to this inability to comprehend the objective truth as confirmation bias – when given information objectively in direct opposition to pre-existing beliefs and preferences an agent will become *more* steadfast in their beliefs by spinning their reality to conform with their beliefs (Nickerson 1998). Reliance on an identity or influences that are already conditioned within the voter would ease the cognitive load required to decide. For example, income, employment status, and social class likely shape an agent's economic perceptions regarding their vote choice (Duch, Palmer, & Anderson 2000). Improving models relying on economic indicators would require removing the models' reliance on these indicators into a more encompassing proxy for economic perceptions.

Ideally, voter models' error terms would account for misperceptions and biases, operating under the assumption that all distortions are randomly distributed and thus do not affect the accuracy of the forecasts, but as the political landscape evolves – and the literature along with it – it has become increasingly clear that objective economic performance measures no longer capture how citizens view the economy. In the case of the 1992 election – the election attributed with Carville's coining of the slogan "It's the economy stupid!" – economic growth was positive, but Democrats still managed to unseat the Republican incumbent largely due to the excessively negative media coverage of Bush's performance (Hetherington 1996). Because early studies argue that citizens vote based on the economic performance of a party, it follows that if voters have a distorted perception of economic performance, their votes will reflect that. At the state level, the literature finds that economic perceptions do have an impact on gubernatorial voting, but as mentioned before the question of who voters hold responsible is still under contestation (Niemi et al. 1999; Cohen & King 2004). This paper attempts to explore a potential option to measure perceptions of economic performance.

National Economic Performance Model (The Baseline Model)

To effectively determine whether measures of economic perception can outperform objective measures of economic performance, there must be a standard of comparison. Pulling from models in the literature this paper uses a compiled set of variables to construct a baseline model. The election data comes from United States gubernatorial elections that took place between January 2005 and December 2016, where the two major United States political parties – Republicans and Democrats – received more than ninety-five percent of the vote together. The dependent variable is the share of votes won by the incumbent party (IPS – Incumbent Party Share) for that election. Note that this is not the share of votes won by the incumbent. This allows for a larger sample size and exploration of the notion – the party as a filter. The operationalization of the independent variables is as described below:

1. *Incumbent Party Share Lagged t-1* this is the result of the previous election for the incumbent party. It will serve as an unbiased control for every election in the sample size. As previously mentioned, voters appear to have a short-term memory regarding party performance, so no more than one lag is required (Fair 1978). Additionally, including multiple lags could result in an increase in outliers that require removal.

2. *National Economic Performance* is the annual percent change of national Real GDP from the second quarter of the election year. The second quarter data is released around election time, meaning if voters do base their votes on macroeconomic performance it would be centered around this figure. Additionally, this is the highest performing quarter within the model. This variable will later be replaced with measures of perception of national economic performance.
3. *State Economic Performance* is the annual percent change of state Real GDP from the first quarter of the election year. State GDP is only released on an annual basis, so this is the latest number of economic performance available.
4. *Incumbent Running* is a dummy variable, coded as 1 if the incumbent governor is running for reelection and 0 if not. Ceteris paribus, incumbents should experience advantage over non-incumbents.
5. *Incumbency Length* is the number of months the incumbent party has held office. In presidential elections, if a party holds office for more than two terms they face a severe disadvantage, controlling for all else (Abramowitz 1988).
6. *Unified Government* is a dummy variable, coded as 1 if the incumbent governor and both houses of the state legislature are the same, and 0 if not. The literature states that voters cast ballots in opposition to unified government regardless of their performance (Leyden & Borelli 1995). This variable is expected to be negative.
7. *Presidential Party Dummy* is a dummy variable, coded as 1 if the incumbent governor is the same party as the president, and 0 if not. This relationship is expected to be negative.

8. *Unified Government x State Economic Performance* is an interaction variable that examines the relationship between the economic performance of the incumbent party on both incumbent and non-incumbent candidates in the incumbent party. This relationship is expected to be positive.
9. *Unified Government x Incumbent Running* is an interaction variable that tracks the impact of a unified government on the incumbent party candidate. This relationship is expected to be negative.
10. *President Party Dummy x National Economic Performance* is an interaction variable that tracks the extent at which candidates are held accountable for the national economy when they share the same party as the president. This relationship is expected to be positive.

Table 2 contains the results of an OLS regression. Figure (1) is the instance of the model using all previously listed dependent variables. Figure (2) is the instance of the model that accounts for the most variation for while removing all insignificant variables, and therefore increasing the adjusted R^2. The baseline model will consist of the remaining dependent variables in Figure (2).

Table 2: Baseline Model

	Dependent variable:	
	Incumbent Party Share	
	(1)	(2)
Incumbent Party Share Lagged	0.336***	0.345***
	(0.110)	(0.105)
National Economic Performance	−2.314	
	(1.646)	
State Economic Performance	0.113	
	(0.496)	
Incumbent Running	12.486***	12.520***
	(2.375)	(2.315)
Incumbency Length	0.025	
	(0.113)	
Unified Government	4.513*	4.890**
	(2.524)	(2.300)
Presidential Party Dummy	−9.390*	
	(4.883)	
Unified Government x State Economic Performance	0.033	
	(0.596)	
Unified Government x Incumbent Running	−8.260**	−8.073**
	(3.178)	(3.129)
President Party Dummy x National Economic Performance	1.606	−1.848***
	(1.907)	(0.546)
Constant	35.860***	29.398***
	(7.311)	(6.199)
Observations	126	126
R^2	0.336	0.312
Adjusted R^2	0.278	0.284
Note:	*p<0.1; **p<0.05; ***p<0.01	

Although many implications of these regressions are not key to this papers focus, it is interesting to note that there are some inconsistencies with this dataset and the datasets used in previous research. Voters do not appear to consider the following when voting for their governors: how long a party has controlled the governor's mansion, and their state's economic condition *avec-ou-sans* unified government. The former indicates that voter's, en masse, do not mind having a singular party control the governor's mansion for an extended period of time unlike party control of the White House. The latter could potentially be an indicator of decreasing political awareness at the local level and a large shift in attention towards the federal-level or it could be a side effect of using IPS_{t-1} instead of using measures of state partisanship like the original work which inspired the use of these variables (Leyden & Borelli 1995).

An item of concern is the negative coefficient of the interaction variable in question: *President Party Dummy × National Economic Performance*. This does not mean that the theoretical framework of this paper is flawed, but it does mean that voters do not vote with a reward/punish system but still vote in a manner related to economic performance. There are many potential explanations for this result, but no conclusions can be reached without individual-level studies being conducted and a deeper analysis of aggregate-level implications.

Model Using Survey Data

The survey data comes from the University of Michigan's Survey of Consumers. The question asked was: "Would you say that at the present time business conditions are better or worse than they were a year ago?" The survey also has an option for "same." The data used in the regression below is the percentage of respondents that said "better." This had the best results of any combination of responses. Table 3 below displays three models: the first, the baseline model mentioned earlier; the second, the baseline model with the economic variable removed; the third, the baseline model with GDP growth replaced with the survey response rate of the option, "better."

Table 3: Survey Data Regression Comparison

	Dependent variable:		
	Incumbent Party Share		
	(1)	(2)	(3)
Incumbent Party Share Lagged	0.345***	0.356***	0.322***
	(0.105)	(0.109)	(0.104)
Incumbent Running	12.520***	12.396***	12.188***
	(2.315)	(2.413)	(2.292)
Unified Government	4.890**	4.727*	4.577**
	(2.300)	(2.397)	(2.276)
Unified Government x Incumbent Running	−8.073**	−7.534**	−7.761**
	(3.129)	(3.258)	(3.094)
President Party Dummy x National Economic Performance	−1.848***		
	(0.546)		
President Party Dummy x Survey Data			−0.121***
			(0.032)
Constant	29.398***	26.516***	31.388***
	(6.199)	(6.400)	(6.212)
Observations	126	126	126
R^2	0.312	0.247	0.327
Adjusted R^2	0.284	0.222	0.299
Note:	*p<0.1; **p<0.05; ***p<0.01		

As expected, the model created using survey data outperformed the baseline model by a sizeable amount. Again, it is worth mentioning how the coefficient in question, *Presidential Party Dummy x Survey Data*, is negative.

Brief Overview of Data from Search Trends

> "The everyday act of typing a word or phrase into a compact, rectangular white box leaves a small trace of truth that, when multiplied by millions, eventually reveals profound realities." - Seth Stephens-Davidowitz, *Everybody Lies*.

The uniqueness of this dataset appeals for three reasons: First, humans appear to be much more revealing with a search box than any survey method. Second, Google search trend data exists in a relative frequency format, meaning that data must be used in context for any conclusions to be reached. Third, the correlation between certain terms and certain events appear to be random at first, but likely have an explanation that does not need to be known to initially improve models.

In the last 14 years, the span of Google's lifetime, search trend dataset was used to detect influenza epidemics, capture racism missed by surveys, and outperform a multitude of models in different fields and industries (Ginsberg et al. 2005; Choi & Varian 2011; Stephens-Davidowitz 2012). The tech giant controls the largest, most intimate, brutally honest dataset available on human behavior. The fluctuations in the frequency of certain term searches indicate a shift in public behavior. Based on its proven track record in many academic papers, Google search trends should be a legitimate source of data for public perceptions.

To limit the scope of this paper no terms directly related to the political sphere (e.g. "Democrat", "Republican", etc.) will be used in this paper because those terms would likely capture sentiments related to the election and likelihood of voting, but unrelated to economic performance. Because there will always an infinite number of terms to test. This paper uses the top twenty terms from another paper using Google search trends to develop a successful financial trading strategy[1] (Preis et al. 2013). The paper uses terms related to economic performance to determine whether they should buy or sell their holdings. Because stocks are largely based on public perception, the search trend data worked quite effectively. Additionally, as a set of control terms, the top fifteen most searched keywords that are

[1] Refer to these terms as the *Preis et al. terms* from here forward.

common nouns on the Open Source Shakespeare database[2]. These were arbitrarily chosen to capture both terms related to economics and "random" terms that are commonly searched on the web. The search trends are not meant to completely fill the void for an accurate representation of public perceptions, but instead, demonstrate that search trend data can be a foundation to gauge the public's thoughts and feelings. Google search trend data uses a relative frequency measure on a scale from zero to one-hundred; one-hundred indicating the most searched time-period and zero indicating the least searched time-period. Needless to say, trend data will be localized to the United States.

The search trends are not meant to, nor able to, replace all independent variables in the model because they only reflect perceptions of the economy. An increased frequency in searches may indicate an increase or a decrease in favorable perceptions of economic performance. Each aggregate behavior is unique for each term, and testing a composite term is not possible due to the relative frequency format of the data.

The data is filtered from cyclical trends using the Christiano-Fitzgerald filter[3], the parameters were all set to their defaults. Filtering the data for any cyclical trends by smoothening regular spikes in the data – for example, an increase in the search term "dow jones" towards the end of the year when people are looking to dump their bad investments for tax benefits – will ensure that search trends are a more accurate representation of economic perceptions at any point in time.

---

[2] Refer to these terms as the *Shakespeare terms* from here forward.

[3] See appendix.

Table 4 below shows the correlation between each search trend of the Preis et al. search terms and economic performance:

Table 4: Correlation between Preis et al. Search Trends and GDP Growth

Terms	Estimate	Std. Error	t value	Pr(>|t|)
debt	−0.0516	0.0373	−1.3833	0.1728
color	0.1244	0.0672	1.8500	0.0703
stocks	−0.0924	0.0360	−2.5705	0.0132
restaurant	−0.0324	0.0570	−0.5672	0.5732
portfolio	−0.0072	0.0570	−0.1260	0.9003
inflation	−0.0163	0.0295	−0.5531	0.5827
housing	−0.0119	0.0360	−0.3307	0.7422
dow jones	−0.0516	0.0193	−2.6691	0.0103
revenue	0.0063	0.0233	0.2699	0.7884
economics	0.0090	0.0272	0.3316	0.7416
credit	−0.1347	0.0992	−1.3573	0.1809
markets	−0.1078	0.0413	−2.6113	0.0119
return	0.0332	0.0275	1.2100	0.2321
unemployment	−0.0193	0.0180	−1.0692	0.2902
money	−0.2178	0.0769	−2.8346	0.0066
religion	0.0244	0.0286	0.8541	0.3972
cancer	0.0344	0.0417	0.8259	0.4129
growth	0.0392	0.0383	1.0250	0.3104
investment	0.0258	0.0478	0.5396	0.5919
hedge	−0.0531	0.0476	−1.1157	0.2700

While only four of the terms are correlated and statistically significant, when the trend data is used alongside GDP growth, both variables become insignificant. The remaining terms may not be heavily correlated with economic performance, but there is some relationship causing multicollinearity in a combined model. Additionally, it is worth noting that the terms that have negative and statistically significant coefficients are terms associated closely with the stock market. It is likely that as the economy is doing worse there is an increase in people's interest in the stock market as they check up on their investments.

Table 5 below shows the correlation between each search trend of the Shakespeare search terms and GDP growth:

Table 5: Relationship between Shakespeare Search Trends and GDP Growth

Terms	Estimate	Std. Error	t value	Pr(>|t|)
love	−0.0232	0.0459	−0.5052	0.6157
hate	0.0589	0.0483	1.2191	0.2286
blood	−0.0138	0.0542	−0.2539	0.8006
night	−0.0506	0.0448	−1.1294	0.2642
death	−0.0264	0.0585	−0.4513	0.6538
sleep	0.1213	0.0622	1.9512	0.0568
time	0.0768	0.0616	1.2480	0.2180
hand	0.1025	0.0618	1.6585	0.1036
man	0.0828	0.0554	1.4953	0.1412
honest	0.0648	0.0237	2.7383	0.0086
kind	0.0857	0.0473	1.8114	0.0762
dream	−0.0220	0.0351	−0.6252	0.5347
heart	0.0112	0.0739	0.1512	0.8804
nature	0.0847	0.0481	1.7628	0.0842
poison	0.0265	0.0188	1.4068	0.1658

There is only one term with a strong correlation with GDP growth in this dataset, and it is most probably a spurious correlation. There is no strong correlation between any of the other search trends, but again, when the data is used alongside GDP growth, both variables lose significance.

Model Using Google Search Trends Data

The model using Google search trends replaces the national economic performance data from the baseline model with the query results for each term. The trend data I use comes from the 1st of November ahead of every election.

Table 6 below displays the results of the four models. Figure (1) is the base model. Figure (2) is the base model with the economy variable removed. Figure (3) is the model for the trend data of the term *return*, the best performing model of the Preis et al. terms. Figure (4) is the model for the trend data of the term *hedge*, the worst performing model of the Preis et al. terms.

Table 6: Trend Data Regression Comparison

	Dependent variable:			
	Incumbent Party Share			
	(1)	(2)	(3)	(4)
Incumbent Party Share Lagged	0.345***	0.356***	0.331***	0.336***
	(0.105)	(0.109)	(0.104)	(0.106)
Incumbent Running	12.520***	12.396***	12.076***	12.814***
	(2.315)	(2.413)	(2.299)	(2.343)
Unified Government	4.890**	4.727*	4.558**	4.870**
	(2.300)	(2.397)	(2.283)	(2.324)
Unified Government x Incumbent Running	−8.073**	−7.534**	−7.706**	−8.511***
	(3.129)	(3.258)	(3.102)	(3.174)
President Party Dummy x National Economic Performance	−1.848***			
	(0.546)			
President Party Dummy x Search Trend Data			−0.137***	−0.141***
			(0.037)	(0.047)
Constant	29.398***	26.516***	30.999***	29.926***
	(6.199)	(6.400)	(6.215)	(6.309)
Observations	126	126	126	126
R^2	0.312	0.247	0.323	0.298
Adjusted R^2	0.284	0.222	0.295	0.269
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 7 and 8 below display the adjusted R^2 of each term's respective model:

Table 7: Adjusted R^2's of Preis et al. Term Models

Terms	Unfiltered Trends	CF Filtered Trends	Difference
debt	0.278	0.286	0.008
color	0.290	0.289	−0.0004
stocks	0.268	0.281	0.013
restaurant	0.289	0.283	−0.006
portfolio	0.284	0.290	0.006
inflation	0.293	0.294	0.001
housing	0.282	0.284	0.002
dow jones	0.234	0.285	0.051
revenue	0.285	0.292	0.007
economics	0.283	0.293	0.011
credit	0.292	0.291	−0.001
markets	0.273	0.280	0.006
return	0.293	0.295	0.002
unemployment	0.279	0.287	0.008
money	0.289	0.289	−0.001
religion	0.283	0.289	0.005
cancer	0.288	0.289	0.001
growth	0.287	0.288	0.001
investment	0.274	0.289	0.015
hedge	0.263	0.269	0.006
Mean	0.280	0.287	0.007
St. Dev.	0.014	0.006	0.012
Min	0.234	0.269	−0.006
Max	0.293	0.295	0.051

Table 8: Adjusted R^2's of Shakespeare Term Models

Terms	Unfiltered Trends	Filtered Trends	Difference
love	0.297	0.293	−0.003
hate	0.287	0.291	0.004
blood	0.289	0.278	−0.011
night	0.294	0.293	−0.0002
death	0.288	0.287	−0.001
sleep	0.292	0.289	−0.003
time	0.294	0.294	−0.001
hand	0.292	0.290	−0.002
man	0.294	0.294	0.001
honest	0.272	0.251	−0.021
kind	0.294	0.296	0.002
dream	0.301	0.299	−0.001
heart	0.294	0.291	−0.004
nature	0.288	0.289	0.002
poison	0.293	0.287	−0.007
Mean	0.291	0.288	−0.003
St. Dev.	0.0065	0.0115	0.006
Min	0.272	0.251	−0.021
Max	0.301	0.299	0.004

Table 9 and 10 below display the differences between trend models and the baseline model:

Table 9: Differences between R^2's of Preis et al. Term Models and Baseline Model

Terms	Unfiltered Trend Difference	Outperform?	CF Filtered Trend Difference	Outperform?
debt	−0.006	No	0.002	Yes
color	0.006	Yes	0.005	Yes
stocks	−0.016	No	−0.003	No
restaurant	0.005	Yes	−0.001	No
portfolio	0.0003	Yes	0.006	Yes
inflation	0.009	Yes	0.010	Yes
housing	−0.002	No	−0.00005	No
dow jones	−0.050	No	0.001	Yes
revenue	0.001	Yes	0.008	Yes
economics	−0.001	No	0.009	Yes
credit	0.008	Yes	0.007	Yes
markets	−0.011	No	−0.004	No
return	0.009	Yes	0.011	Yes
unemployment	−0.005	No	0.003	Yes
money	0.005	Yes	0.005	Yes
religion	−0.001	No	0.005	Yes
cancer	0.004	Yes	0.005	Yes
growth	0.003	Yes	0.004	Yes
investment	−0.010	No	0.005	Yes
hedge	−0.021	No	−0.015	No
Mean	−0.004		0.003	
St. Dev.	0.014		0.006	
Total Yes		10		15

Table 10: Differences between R^2's of Shakespeare Term Models and Baseline Model

Terms	Unfiltered Trend Difference	Outperform?	CF Filtered Trend Difference	Outperform?
love	0.013	Yes	0.009	Yes
hate	0.003	Yes	0.007	Yes
blood	0.005	Yes	−0.006	No
night	0.010	Yes	0.009	Yes
death	0.004	Yes	0.003	Yes
sleep	0.008	Yes	0.005	Yes
time	0.010	Yes	0.010	Yes
hand	0.008	Yes	0.006	Yes
man	0.010	Yes	0.010	Yes
honest	−0.012	No	−0.033	No
kind	0.010	Yes	0.012	Yes
dream	0.017	Yes	0.015	Yes
heart	0.010	Yes	0.007	Yes
nature	0.004	Yes	0.005	Yes
poison	0.009	Yes	0.003	Yes
Mean	0.007		0.004	
St. Dev.	0.006		0.011	
Total Yes		14		13

The original expectation was the Preis et al. search trend data would outperform the controls, but all the terms appeared to perform similarly to each other. It is likely that Google search trends reflect perceptions of economic performance across the board, and until more data is available – which they will be in a few more election cycles – it will not be possible to determine which terms are the key terms. In all models, the coefficient of the term, *Presidential Party Dummy x Search Term Data*, is negative. Additionally, all trend-based models had a statistically significant (alpha = .01) negative coefficient for the previously mentioned term. There are two potential conclusions, assuming causation. First, a shift in trend frequency could result in corresponding distorted perceptions of the economy, as voters, in aggregate, consume more information they somehow skew their perceptions of the economy – unlikely, but a potential explanation. Second, a decrease in economic performance could be perceived by voters and this causes them to search more on Google – the more likely option.

The filtration of the Shakespeare trend data decreased the performance of the majority of its models, unlike the filtration of the Preis et al. data. This implies that the Shakespeare benefitted from cyclical trends, improving its relationship to perceptions of economic performance, while the Preis et al. data was punished for cyclical trends. The corresponding means of both the term sets Adjusted R^2's reached a similar level.

Results and Model Comparison

Table 11 below shows the three main regressions of this papers: Figure (1) is the baseline model; Figure (2) is baseline model with the economic performance variable replaced with Michigan consumer survey data; Figure (3) is the baseline model with the economic performance variable replaced with the trend data for the term "investment." The model for Figure (3) was chosen because it was a median performing model.

Table 11: Final Regression Comparison

	Dependent variable:		
	Incumbent Party Share		
	(1)	(2)	(3)
Incumbent Party Share Lagged	0.345***	0.322***	0.339***
	(0.105)	(0.104)	(0.104)
Incumbent Running	12.520***	12.188***	12.319***
	(2.315)	(2.292)	(2.307)
Unified Government	4.890**	4.577**	4.618**
	(2.300)	(2.276)	(2.292)
Unified Government x Incumbent Running	−8.073**	−7.761**	−8.029**
	(3.129)	(3.094)	(3.118)
President Party Dummy x National Economic Performance	−1.848***		
	(0.546)		
President Party Dummy x Survey Data		−0.121***	
		(0.032)	
President Party Dummy x Search Trend Data			−0.098***
			(0.028)
Constant	29.398***	31.388***	30.506***
	(6.199)	(6.212)	(6.223)
Observations	126	126	126
R^2	0.312	0.327	0.317
Adjusted R^2	0.284	0.299	0.289
Note:	*p<0.1; **p<0.05; ***p<0.01		

The survey model was the top performing model, accounting for fifteen percent more variation than the baseline model and eleven percent more variation than the average of all the trend models. In between baseline model performance and survey model performance lay the majority of the Preis et al. search trend models and Shakespeare search trend models. All models have the interaction variable in question as negative.

Conclusion

To answer the first question posed at the beginning of this paper: Do measures of perceptions of economic performance outperform objective economic performance measures in forecasting models? It is clear that measures of economic perception do outperform objective economic figures. The performance of the trend data and the survey data were positive overall. There is enough evidence to warrant further research into the relationship between Google search trends and election forecasting. Whether or not Google search trends are a way to measure perceptions of the economy or could be used as another tool to gauge real-time economic performance is a topic that needs more focus. A qualitative analysis of the relationship between Google search trends and perceptions of economic performance must be conducted before reaching any conclusions about the influence of search trends over election forecasting models.

To answer the second question at the beginning of the paper: Can Google search trends serve as a better proxy for perceptions of economic performance than the traditional method of surveying? It is still plausible. Considering that this paper tested only one cyclical filtration process and thirty-five terms trends, it would be short-sighted to claim that search trend data cannot measure perceptions of economic performance better than surveys. As the sample size of gubernatorial, and potentially senatorial elections, increases, more grounded conclusions will be reached as it will be possible to test for the difference in terms performance.

Potential avenues for future research include: First, conducting qualitative or experimental research on the relationship between search trends and perceptions of economic performance. Second, the relative frequency format of the data makes trend data from different state impossible to compare. Testing a methodology to standardize the search trends across the states to test if accounting for localized perceptions would improve models. This was not done in this paper because of the uneven and limited cross-section sample sizes, which only time can do at this point. Third, testing the viability of Google search trends when predicting senatorial elections. The literature on senatorial forecasting agrees that perceptions of national economic performance are a significant factor of senatorial election outcomes. Fourth, revisiting the relationship between economic performance and the incumbent vote share with updated data to verify the interaction variable in question in this paper.

Works Cited

Abramowitz, Alan I. "An improved model for predicting presidential election outcomes." PS: Political Science & Politics 21.4 (1988): 843-847.

Alesina, Alberto, John Londregan, and Howard Rosenthal. "A Model of the Political Economy of the United States." American Political Science Review (1993): 87:12-3

Anderson, Christopher J. "The end of economic voting? Contingency dilemmas and the limits of democratic accountability." Annu. Rev. Polit. Sci. 10 (2007): 271-296.

Atkeson, Lonna Rae, and Randall W. Partin. "Economic and referendum voting: A comparison of gubernatorial and senatorial elections." American Political Science Review 89.1 (1995): 99 107.

Brown, Adam R. "Are governors responsible for the state economy? Partisanship, blame, and divided federalism. "The Journal of Politics 72.3 (2010): 605-615.

Choi, Hyunyoung, and Hal Varian. "Predicting the Present with Google Trends." Google (2009): Technical Report.

Cohen, Jeffrey E., and James D. King. "Relative unemployment and gubernatorial popularity." Journal of Politics 66.4 (2004): 1267-1282.

Downs, Anthony. *An Economic Theory of Democracy*. Harper and Row (1957).

Ebeid, Michael, and Jonathan Rodden. "Economic geography and economic voting: Evidence from the US states. "British Journal of Political Science 36.3 (2006): 527-547.

Erikson, Robert S., and Christopher Wlezien. "Leading economic indicators, the polls, and the presidential vote." PS: Political Science & Politics 41.4 (2008): 703-707.

Evans, Geoffrey, and Robert Andersen. "The political conditioning of economic perceptions." Journal of Politics 68.1 (2006): 194-207.

Fair, Ray C. "The effect of economic events on votes for president." The Review of Economics and Statistics (1978): 159-173.

Fiorina, Morris. "Economic Retrospective Voting in American National Elections: A Micro-analysis." (1978): 22:426-443.

Fiorina, Morris. "Retrospective Voting in American National Elections." New Haven, CT: Yale University Press (1981).

Gelman, Andrew, and Gary King. "Why are American presidential election campaign polls so variable when votes are so predictable?." British Journal of Political Science 23.4 (1993): 409 451.

Ginsberg, Jeremy, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant. "Detecting Influenza Epidemics Using Search Engine Query Data. Nature 457 (2009): 1012-1014.

Hansen, Susan B. ""Life Is Not Fair": Governors' Job Performance Ratings and State Economies." Political Research Quarterly 52.1 (1999): 167-188.

Hetherington, Marc J. "The media's role in forming voters' national economic evaluations in 1992." American Journal of Political Science (1996): 372-395.

Key, V.O.. The Responsible Electorate. Belknap Press (1966).

Lewis-Beck, Michael S., and Mary Stegmaier. "Economic determinants of electoral outcomes." Annual Review of Political Science 3.1 (2000): 183-219.

Leyden, Kevin M., and Stephen A. Borrelli. "The effect of state economic conditions on gubernatorial elections: Does unified government make a difference?." Political Research Quarterly 48.2 (1995): 275-290.

MacKuen, Michael B., Robert S. Erikson, and James A. Stimson. "Peasants or Bankers? The American Electorate and the U.S. Economy." American Political Science Review (1992): 86:597- 611.

Neuman, W. Russell. *The Paradox of Mass Politics: Knowledge and Opinion in the American Electorate*. Harvard University Press (1986).

Nickerson, Raymond S. 1998. "Confirmation Bias: A Ubiquitous Phenomenon in Many Guises." Review of General Psychology 2(2): 175–220.

Niemi, Richard G., Harold W. Stanley, and Ronald J. Vogel. "State economies and state taxes: Do voters hold governors accountable?." American Journal of Political Science (1995): 936-957.

Niemi, Richard G., John Bremer, and Michael Heel. "Determinants of state economic perceptions." Political Behavior21.2 (1999): 175-193.

Orth, Deborah A. "Accountability in a federal system: the governor, the president, and economic expectations." State Politics & Policy Quarterly 1.4 (2001): 412-432.

Peltzman, Sam. "Economic conditions and gubernatorial elections." The American Economic Review 77.2 (1987): 293-297.

Preis, Tobias, Helen Susannah Moat, and H. Eugene Stanley. "Quantifying Trading Behavior in Financial Markets Using Google Trends." Scientific Reports (2013): 1684.

Stephens-Davidowitz, Seth I., The Effects of Racial Animus on a Black Presidential Candidate: Using Google Search Data to Find What Surveys Miss (June 9, 2012). Available at SSRN: https://ssrn.com/abstract=2050673.

Stein, Robert M. "Economic voting for governor and US senator: the electoral consequences of federalism." The Journal of Politics 52.1 (1990): 29-53.

Svoboda, Craig J. "Retrospective voting in gubernatorial elections: 1982 and 1986." Political Research Quarterly 48.1 (1995): 135-150.

Tucker, Joshua A., Kristin Michelitch, Marco Morales-Barba, Andrew Owen. "Looking to the future: a better way to study prospective economic voting." Manuscript (2010).

Appendix

Data Sources:

Election Data – Wikipedia

Google Search Trends – https://trends.google.com/trends/

Economic Performance (State and National) – Federal Reserve Economic Database (FRED)

Unified Government – https://www.ballotpedia.org

R Packages:

gtrendsR, mFilter, tidyr, dplyr, Quandl, stargazer

Unfiltered trend results:

Table 12: Relationship between Unfiltered Preis et al. Trends and GDP Growth

Terms	Estimate	Std. Error	t value	Pr(>|t|)
debt	−0.0548	0.0315	−1.7364	0.0888
color	0.0565	0.0329	1.7181	0.0921
stocks	−0.1101	0.0276	−3.9869	0.0002
restaurant	0.0461	0.0452	1.0195	0.3130
portfolio	−0.0406	0.0361	−1.1254	0.2659
inflation	−0.0415	0.0275	−1.5057	0.1386
housing	−0.0254	0.0354	−0.7196	0.4752
dow jones	−0.1125	0.0298	−3.7685	0.0004
revenue	−0.0017	0.0202	−0.0834	0.9339
economics	−0.0267	0.0237	−1.1263	0.2655
credit	0.0283	0.0350	0.8088	0.4225
markets	−0.1140	0.0308	−3.6986	0.0005
return	0.0232	0.0220	1.0550	0.2966
unemployment	−0.0144	0.0162	−0.8912	0.3772
money	−0.0261	0.0343	−0.7627	0.4493
religion	−0.0042	0.0276	−0.1525	0.8795
cancer	0.0366	0.0411	0.8906	0.3775
growth	0.0507	0.0383	1.3240	0.1917
investment	−0.0213	0.0229	−0.9292	0.3574
hedge	−0.0552	0.0458	−1.2042	0.2343

Table 13: Relationship between Unfiltered Shakespeare Trends and GDP Growth

Terms	Estimate	Std. Error	t value	Pr(>|t|)
love	−0.0144	0.0432	−0.3338	0.7399
hate	0.0610	0.0450	1.3573	0.1809
blood	0.0385	0.0308	1.2490	0.2176
night	−0.0025	0.0293	−0.0864	0.9315
death	0.0302	0.0409	0.7383	0.4638
sleep	0.0362	0.0199	1.8162	0.0755
time	0.0358	0.0274	1.3052	0.1979
hand	0.0464	0.0327	1.4173	0.1627
man	0.0300	0.0248	1.2086	0.2326
honest	0.0280	0.0136	2.0557	0.0452
kind	0.0265	0.0150	1.7660	0.0836
dream	−0.0375	0.0337	−1.1135	0.2709
heart	0.0924	0.0485	1.9047	0.0627
nature	0.0579	0.0478	1.2107	0.2318
poison	0.0317	0.0184	1.7236	0.0911

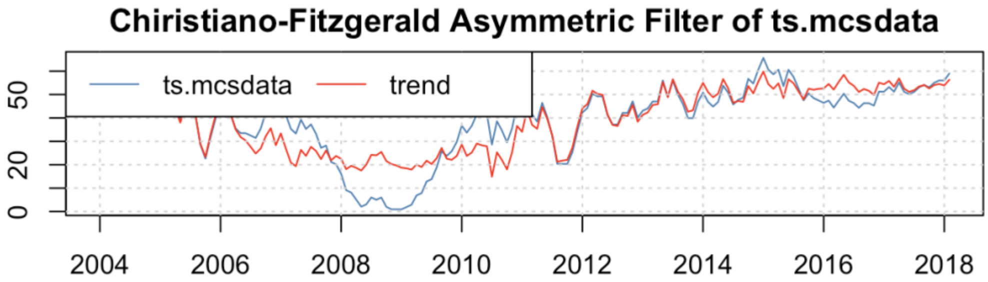
Table 14: Unfiltered Regression Comparison

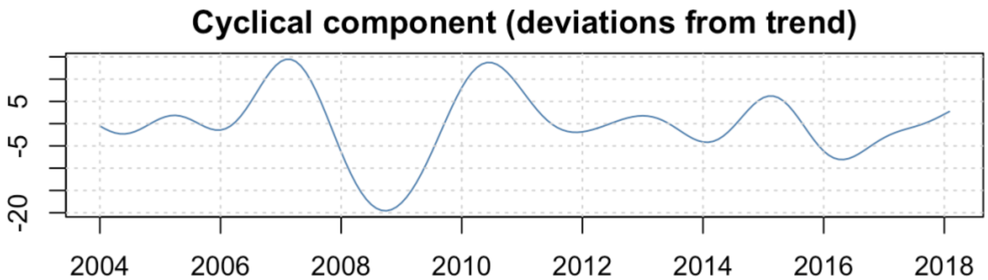
	Dependent variable:			
	Incumbent Party Share			
	(1)	(2)	(3)	(4)
Incumbent Running	0.345***	0.356***	0.341***	0.351***
	(0.105)	(0.109)	(0.104)	(0.108)
Incumbent Running	12.520***	12.396***	12.277***	12.371***
	(2.315)	(2.413)	(2.301)	(2.394)
Unified Government	4.890**	4.727*	4.658**	4.803**
	(2.300)	(2.397)	(2.285)	(2.379)
Unified Government x Incumbent Running	−8.073**	−7.534**	−8.080**	−7.766**
	(3.129)	(3.258)	(3.109)	(3.236)
President Party Dummy x National Economic Performance	−1.848***			
	(0.546)			
President Party Dummy x Search Trend Data			−0.073***	−0.138*
			(0.020)	(0.082)
Constant	29.398***	26.516***	30.452***	27.857***
	(6.199)	(6.400)	(6.197)	(6.400)
Observations	126	126	126	126
R^2	0.312	0.247	0.321	0.264
Adjusted R^2	0.284	0.222	0.293	0.234
Note:				*p<0.1; **p<0.05; ***p<0.01

Christiano-Fitzgerald Filter:

This paper uses the Christiano-Fitzgerald filter from the mFilter package in R.

https://cran.r-project.org/web/packages/mFilter/mFilter.pdf





Selection from the R Package documentation, explaining the filter, link of which is above:

The finite sample approximation to the ideal bandpass filter uses the alternative filter

$$y_t = \hat{B}(L)x_t = \sum_{j=-n_1}^{n_2} \hat{B}_{t,j} x_{t+j}$$

Here the weights, $\hat{B}_{t,j}$, of the approximation is a solution to

$$\hat{B}_{t,j} = \arg\min E\{(y_t - \hat{y}_t)^2\}$$

The Christiano-Fitzgerald filter is a finite data approximation to the ideal bandpass filter and minimizes the mean squared error defined in the above equation.

Several band-pass approximation strategies can be selected in the function `cffilter`. The default setting of `cffilter` returns the filtered data $\hat{y}_t$ associated with the unrestricted optimal filter assuming no unit root, no drift and an iid filter.

If `theta` is not equal to 1 the series is assumed to follow a moving average process. The moving average weights are given by `theta`. The default is `theta=1` (iid series). If `theta=` $(\theta_1, \theta_2, \ldots)$ then the series is assumed to be

$$x_t = \mu + 1_{root} x_{t-1} + \theta_1 e_t + \theta_2 e_{t-1} + \ldots$$

where $1_{root} = 1$ if the option `root=1` and $1_{root} = 0$ if the option `root=0`, and e_t is a white noise.

If `drift=TRUE` the drift adjusted series is obtained as

$$\tilde{x}_t = x_t - t\left(\frac{x_T - x_1}{T-1}\right), \quad t = 0, 1, \ldots, T-1$$

where $\tilde{x}_t$ is the undrifted series.