Do Partisans Make Different Investment Decisions When Their Party is in Power?

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Abstract

Partisans' stated beliefs about the economy vary dramatically depending on the party that holds the presidency. Do these responses represent genuine differences in beliefs about the economy, or do they reflect partisans' expressive reporting on surveys? To answer this question, we rely on a novel dataset of Bing searches related to housing, automobiles, and stock market purchases by partisans from February 2016 to July 2017, as well as a dataset of personal vehicle registrations from the Department of Motor Vehicles (DMV) in New York State. We find that in the aftermath of the 2016 election, Democrats, as members of the losing party, were less likely to search for both house and car purchase terms. Furthermore, we find that Republican ZIP codes experienced a greater increase in car registrations in 2017 than Democratic ZIP codes. This statistically significant and meaningful shift in investment behavior suggests that partisans' survey responses are actually due to different beliefs about the economy, rather than just expressive reporting.

With the rise of political polarization (Iyengar et al. 2012), partisanship has become a more visible and salient part of Americans' lives. Partisans discriminate against outparty members in a variety of domains, including dating (Nicholson et al. 2016; Iyengar et al. 2017; Huber and Malhotra 2017), employment (Gift and Gift 2015; McConnell et al. 2018), and education (Iyengar and Westwood 2015). However, the effects of partisanship on Americans' economic behaviors remain unclear (McGrath et al. 2017; Gerber and Huber 2009). On surveys, partisans are loath to acknowledge positive economic outcomes under an outparty president (Bartels 2002), but these differences dramatically diminish when partisans are paid for correct responses (Prior et al. 2013; Bullock et al. 2013). Do partisans change their investment patterns when the presidency switches parties? In this article, we examine this question and its implications for the economy.

Are partisans more likely to change their investment patterns after their party wins the presidency? Conversely, do "losing" partisans scale back their durable goods purchases in fear of a dimmer economic future? To answer these questions, we combine survey data with a novel dataset of individual-level searches for cars, houses, and stock purchase terms, with their partisan affiliation and key demographics, as well as a separate dataset zip code level new car registration data in 2016 and 2017. This strategy allows us to measure partisans' individual level purchasing behaviors, free of the limitations of surveys such as non-attitudes, expressive reporting, or social desirability effects.

We find that Democrats, as members of the losing party, were less likely to search for cars and houses after the 2016 election. This effect is sizable and significant - for housing, the decrease is equivalent to 48% of the seasonal change in housing searches between the first week of January and the last week of July, and for cars, it is equivalent to 30% of the same seasonal change. Republicans showed no change in their search patterns. These effects cannot be explained by income differences between Democrats and Republicans - richer Democrats were no less likely to decrease their house and car-related searches than poorer ones, despite Republican promises to cut taxes on the wealthy. We find a similar effect for car purchasing behavior - Republican zip codes had a larger increase in new car registrations in 2017 than did Democratic ones.

This article is structured as follows. In the next section, we present the theoretical debates that motivate this project. In the third section, we discuss the data and methodology used to test the effect of partisanship on purchasing decisions. In the fourth section, we compare searches during the same months in 2016 and 2017 to examine the longer-term effects of Trump's victory on partisan web searches and determines the relative strength of the effect for both Democrats and Republicans. In the fifth section, we compare short term changes in survey responses with short term changes in behavior immediately following the 2016 election. The sixth section examines the effect of the election on real-world car purchasing behavior in 2016 and 2017. In the seventh section, we consider possible alternative explanations for our results, including the role of partisans' differing economic situations. Finally, we conclude by discussing the ramifications of these findings.

Theoretical Perspectives

Partisan affective polarization has increased significantly since the 1980's (Iyengar et al. 2012). This rise has heralded a slew of consequences among partisans in the US, from their willingness to discriminate against members of the opposing party (Iyengar and Westwood 2015), to a disinclination to co-operate with government regulations when their party is out of power (Krupenkin 2020; Lerman et al. 2017), to non-compliance with public health recommendations during the COVID-19 pandemic (Allcott et al. 2020). However, to fully understand the consequences of partisan polarization on American democracy, it is critical to understand the ways in which partisanship influences perceptions of objective facts.

The classical Michigan model of partisan identification (Converse et al. 1960) argues for the existence of a 'partisan screen', a form of motivated reasoning (Kunda 1990) which prevents partisans from accepting information that is critical of their own party. However, more modern models (Fiorina 1981; Green et al. 2004) argue that there is no partisan screen and that partisans are able to accurately appreciate unflattering information about their own party. This distinction has serious consequences for democratic accountability. If partisans cannot accurately incorporate new information about a party's electoral performance due to motivated reasoning, they cannot punish or reward incumbents based on their performance. In turn, this diminishes incentives for elected officials to invest in policy, and encourages them to pander to partisans.

Scholars have found ample survey support for partisan motivated reasoning effects. For example, partisans are likely to uncritically accept arguments that support their own perspective, while arguing against those that do not (Taber and Lodge 2006). Further, providing negative information about an in-party candidate may have no effect or may actually increase partisans' support for that candidate (Redlawsk 2002; Nyhan and Reifler 2010).

However, more recent literature has suggested that partisan survey differences may be the result of expressive reporting, not motivated reasoning or actual differing impact. Partisan expressive reporting occurs when survey respondents give an answer that they know to be incorrect but that makes their party look good. For example, Republicans with a college degree were significantly more likely to say that Trump's inauguration photo had more people than Obama's than were Democrats or Republicans without a college degree (Schaffner and Luks 2018). Expressive reporting has been found in a number of domains, including economic (Prior et al. 2013; Bullock et al. 2013) and health (Krupenkin et al. 2018) attitudes. However, Berinsky (2018) has found little evidence of expressive reporting on the topic of conspiracy theories.

Partisan expressive reporting effects pose a significant threat not only to the literature on partisan motivated reasoning, but to the survey literature on partisanship more broadly. If partisans' survey responses do not represent their true beliefs, then they are an unreliable tool for the study of partisanship.

Considering the effect of partisanship on perceptions of objective facts is important to understand partisanship, but it is especially critical in how it relates to the decision to invest in durable goods, such as cars and houses. Democrats and Republicans differ on many characteristics, including race and income. Consequently, they tend to live in different types of neighborhoods (Mummolo and Nall 2017), and in different parts of the country. If a large segment of American society experiences irrationally depressed consumption during an economically prosperous period, this is bad news for the economy. The negative impact is even greater if partisans decrease the money they spend on investments.

Partisanship is important for evaluations of the economy (Bartels 2002), and especially prospective predictions about economic performance. These evaluations are made with fairly little information and thus must rely more heavily on partisan heuristics (Popkin 1994)[1]. This, in turn, is likely to affect their purchasing patterns, especially for durable goods such as cars and houses.

While prior research has shown some partisan effects on post-election consumption patterns (Gerber and Huber 2009), McGrath et al. (2017) find that the effects measured in Gerber and Huber (2009) have substantial robustness issues, as the "finding of a relationship between partisanship and economic behavior does not hold when observations from a single state-year (Texas in 1996) are excluded from their analysis". Given these concerns, as well as the multiple studies that do show expressive reporting effects in the domain of economic perceptions (Prior 2013; Bullock et al. 2013), the effect of partisanship on investment behavior is still an open question.

[1]Selective media exposure could also influence presidential in partisans to engage in different consumption behavior than out partisans. Republicans who consume Breitbart and Fox News may be treated to non-stop coverage of the Trump administration's economic successes, while Democrats who consume HuffPost and Daily Kos may receive the opposite message. However, selective exposure to partisan news coverage has shown at best only modest effects on political polarization (Peterson et al. 2017; Prior 2013)

Furthermore, consumers' prospective perceptions of the economy have an especially pronounced influence on their investment in durable goods specifically (Mishkin et al. 1978; Dunn 1998), rather than just on their raw consumption. A person might increase their consumption for a wide variety of reasons unrelated to their perceptions of the economy. For example, during the early weeks of the 2020 COVID-19 pandemic, consumption went up dramatically, as people rushed to purchase food and household necessities in bulk, even as economic confidence went down significantly. On the other hand, a purchase of a house or car requires is a significant, long-term investment that requires one to take on a long-term financial obligation, an obligation one may be less likely to undertake if one has little confidence in one's economic future.

Political polarization is likely to further exaggerate the effects of partisanship on their investment decisions. Partisans' distrust of the opposing party can further feed motivated reasoning about economic performance. If partisans do not think that members of the opposing party make good mates (Huber and Malhotra 2017) or employees (Gift and Gift 2015; McConnell et al. 2018), they should be especially loath to put their economic future in the hands of an out-of-party president. Accordingly, partisans, especially members of the "losing" party, should significantly modify their economic expectations when control of the presidency switches parties.

In this paper, we tackle two closely related questions. First, when partisans express pessimism about the economy under an opposing party president (and vice versa), are they engaging in expressive reporting, or do their survey responses reflect sincere beliefs? Second, if partisans' responses to surveys are sincere, are partisan differences in economic evaluations the result of their partisanship (motivated reasoning), or of their different economic situations?

It is possible that partisans have truly held different economic beliefs that are not due to motivated reasoning, but due to actual differing economic outcomes that are correlated with partisanship. Partisans may also experience different economic outcomes and pressures depending on which party is in power. For example, lower-income individuals, who are more likely to be Democrats, experience less income growth under Republican presidents than under Democratic ones (Bartels 2016). Similarly, the Trump tax plan was more beneficial to higher-income households (who were more likely to be Republican) than lower-income households (Nunns et al. 2016).

Data and Methods

This study draws on a number of different data sources in order to illustrate the relationship between presidential co-partisanship and investment decisions. Table 1 provides a summary of the different data sources used, as well as their temporal availability. We used search data to examine individual-level search responses to a change in the party of the presidency, and NY State car registration data in order to measure actual car purchase behavior. The Gallup survey data economic confidence time series is more broadly explored in the appendix.

Web Search Data Measures Purchasing Behavior

Search data is a powerful predictor of economic activity: to measure partisan investment behavior, we use a unique, individual-level search dataset from Bing. Google Trends data has

Table 1: Data Summary

Dataset	**Measures**	**Availability**
Gallup Survey	Partisan Survey Response	10/91 - 12/17
MSN Survey	Party ID and covariates	09/16 - 06/17
Bing Search	House, Car, and Stock Purchase	02/16 - 07/17
NY State DMV Data	New Car Purchases	01/16 - 11/17

been shown to be a significantly better predictor of consumption than consumer confidence indices (Kholodilin et al. 2010). Search data has been used to accurately predict the stock market (Bordino et al. 2012), automobile sales (Choi and Varian 2012; Kinski 2016), and housing prices (Wu and Brynjolfsson 2015). Beyond economics, search data has provided valuable insights into suicide (Gunn III and Lester 2013), the COVID-19 pandemic (Lampos et al. 2020), and state ballot initiative roll-off rates (Reilly et al. 2012). Time and time again, search data has been shown to be strongly associated with real-world behavior, making it a valuable metric for testing our hypothesis.

Beyond its strong correlation with multiple forms of behavior, search data also has several useful properties that distinguishes it from survey data. First, unlike survey data, search data is free from non-attitudes (Converse et al. 1960). Searching is motivated behavior - a user who types "zillow" into their search engine is looking for information on real estate prices. On the other hand, an on-the-spot answer to a survey question may be the product of random top of the head considerations (Zaller et al. 1992) or mere satisficing (Kramer 1983). Second, because there is no "audience" for a user's search queries, search data is free from social desirability (Fisher 1993) and expressive reporting effects. Search queries represent a user's revealed preferences, rather than their stated preferences.

To examine investment behaviors, we created a novel dataset of relevant Bing searches for house, car, or stock purchases. Using a seed term and the "related searches" function on Google Trends, we generated a list of searches for house purchases, school quality, car purchases, truck purchases, and stock market investment. Table 2 shows the topics, seed terms, and generated terms. All searches that subsumed these searches were also counted (e.g., "buy house florida"). Results were robust to the inclusion or exclusion of specific search terms.

To ensure that our search measures accurately represent partisans' perceptions of economic expectations, we used a survey of 8,200 MSN users to show that house, car, and stock searches were correlated with perceptions of the economy. We asked respondents: "Do you

Table 2: Search Terms

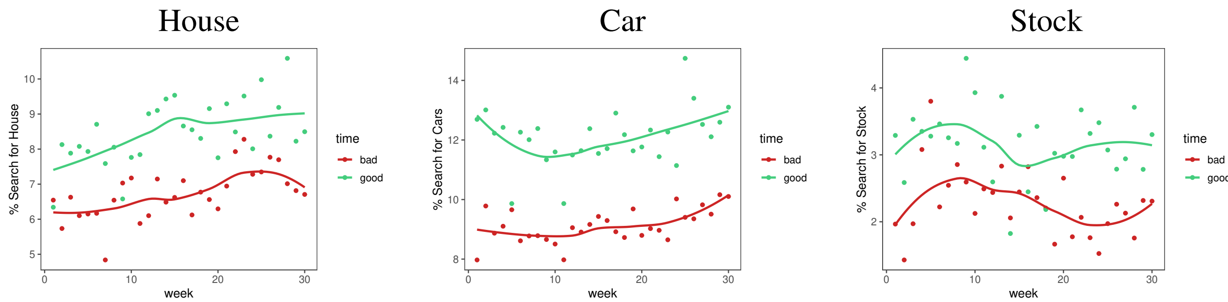
Category	Seed Term	All Search Terms
House	buy house	buy house, buying house, buy home, home buying, homes, real estate, fha loan, mortgage calculator, loan calculator, home loan, zillow, realtor, trulia, realty, remax, century 21, coldwell banker, va loan, mortgage, conventional loan, nationstar, amortization, payment calculator, pmi
House	school district ratings	school district ratings, great school ratings, greatschools, redfin, schooldigger
Car	buy truck	buy truck, trucks
Car	buy car	buy car, honda, toyota, car insurance, carmax, autotrader, auto insurance, insurance quote, geico, state farm, allstate, ford, nissan, hyundai, acura, chevy, cheap insurance, general insurance, dodge, jeep, chevrolet, blue book, bmw, kia, lexus, kbb, audi, state auto, usaa, gtr, mazda, infiniti, mercedes, camaro, gmc, the general, national general, challenger, chrysler, cherokee, wrangler, kelley blue, kelley book, nada, cars, brz, r34, g35, q50, mustang, yukon, buick, denali
Stock Market[a]	invest in stock	invest in stock, how to invest, stock, dow, aapl, tsla, amzn, nflx, msft, finance, twtr, nasdaq, nyse, s&p, etf, vanguard, fidelity, mutual fund, index funds, lnkd, gpro, scty, intc, csco

[a]We removed "goog" from the terms because in addition to being the ticker symbol for Google, it is also the first few letters of a the navigational search to the Google search engine, which is a popular search on Bing

think now is a good time to buy a new car/buy a new house/invest in the stock market?". Figure 1 shows the percentage of survey respondents from January 2017 through July 2017 (the survey was conducted in November 2017) who searched for one of the terms. Respondents who answered that now was a good time to buy a car/house/stocks were much more likely to search for these terms, which shows that our search terms do indeed reflect people's interest in purchasing these goods.

We extract two measures from this data. Our first measure counts each searcher per day who searched for houses, cars, or the stock market that day as 1, and any searcher who did not as a 0. This measure is labelled in the tables and figures as users. The second measure looks at the total number of daily *searches* for our terms (irrespective of whether they came from one or many searchers) as a proportion of total Bing searches on that date. This analysis is labelled as searches. In both instances, we use a logistic model to model the data, and standard errors were clustered by User ID. We also replicate the analysis using OLS, available in the

Figure 1: Validating Searches (Users)

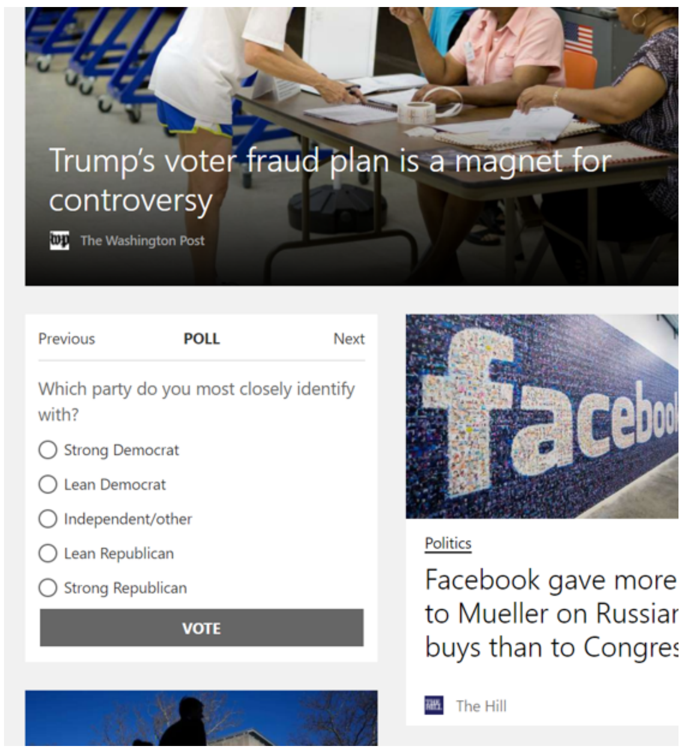


Notes: In all three cases, people who believe that it is a "good time" to invest in one of the following goods are more likely to search for it than people who believe it is a "bad time". Survey was fielded in Nov 2017. Data displayed in the plot is from Jan-July 2017, prior to the survey administration. Each point represents one week of searches.

appendix. These two analyses complement one another, and if our hypothesis is correct we expect that both will show similar responses based on partisanship.

We also included two tests to measure more closely general partisan search patterns. First, we examined the mean and median number of searches for any topic per user based on party. If Democrats were so depressed and demoralized that they stopped searching after the election, this would pose a significant challenge to our results. Second, we examined changes in searches for “adult” content[2] over the same period. This specific placebo was chosen because it comprises a significant volume of internet searches (Ogas and Gaddam 2011), while having no connection to perceptions of the economy. If there were changes in partisans’ searches for pornography in addition to changes in searches for cars, houses, and the stock market, this would suggest that something other than changes in perceptions of the economy were driving these differences in search behavior.

Figure 2: Partisanship Question



Notes: Partisanship information was gathered through a question on both the MSN.com/news/politics page and the MSN.com front page from 09/19/2016 to 06/12/2017. The party ID question was measured on a 5-point scale.

Table 3: User Information

Party	Number Users	Trump Vote (Search Data)	Trump Vote (ANES)
Strong Dem	53,913	4.2%	2.4%
Lean Dem	28,584	12.5%	7.3%
Independent/Other	59,808	70.3%	55.8%
Lean Rep	40,648	94.5%	92.3%
Strong Rep	39,504	90.4%	97.5%
Total	222,457	58.1%	46.3%

Notes: This table provides statistics about the users in our search dataset. For the partisans and leaners, the proportion of the Trump vote in the web searchers is similar to the proportion among the ANES respondents. Pure Independents in our sample were substantially more likely to vote for Trump than were ANES Independents. For more comparisons of our sample with the ANES, please see the appendix. Due to survey rolloff and some surveys asking only the Party ID question, only 60% of search users have a recorded vote preference

Polling Links Search to Party ID

In order to measure the partisanship of MSN survey respondents, along with the age, gender, and vote preference, we relied on a web survey of respondents to the MSN homepage or MSN/news/politics page polls who provided their partisan identification along with their age and gender. Figure 2 provides an example of the environment within which our users encountered the survey question. For respondents who searched on Bing, we then recorded how many relevant searches they conducted, by day, on the days in our study. Accordingly, a unique record includes: age, gender, partisan identification, vote choice, and number of searches for any category/day in the study. The final dataset included 222,457 unique records.

In order to determine how demographically representative the users in our dataset were, we compared their demographic distribution to the distribution of respondents to the ANES. While our searchers did differ from ANES respondents in meaningful ways (the full analysis is

[2] Content automatically labelled by Bing as adult

presented in the appendix), their vote preferences matched up to their partisanship in a similar way to ANES respondents', as displayed in Table 3. While overall, the Bing users did tend to skew substantially more pro-Trump than ANES respondents, partisans and leaners had similar Trump vote frequencies in both the search and ANES datasets. Pure Independents, on the other hand, did tend to skew in a much more pro-Trump direction in the search dataset, suggesting that we should expect their search patterns to look more likely those of Republicans than like those of Democrats.

Estimation Strategy: Comparing Searches 2016 and 2017 Searches

We undertake two main analyses using the search data. The first looks at searches on the same date in 2016 and 2017, in order to examine partisan differences before and after the 2016 election. Housing (Ngai and Tenreyro 2014; Rosenthal 2006; Mille et al. 2013), automobile (Tian et al. 2012), and stock (Gultekin and Gultekin 1983; Ritter 1988) markets exhibit strong seasonality effects. Each of these three markets has "hot" and "cool" periods[3]. Therefore, in order to fully understand the effects of the 2016 election on investment searches, we need to compare them with searches in 2016.

In our first analysis, we estimate equations of the form:

$$Y_i = \beta_0 + \beta_1 PID_i + \beta_2 Year\ 2017_i + \beta_3 PID_i \times Year\ 2017_i + \beta X_i + State\ FE + Seasonality\ FE + \varepsilon_i$$

PID_i is a variable capturing partisanship (Baseline is Republican), and $Year\ 2017_i$ is the post-election indicator (0 if 2016). Thus, the quantities of interest are β_2, which represents the post-election effect for Republicans, and β_2 + β_3, the post-election effect for other partisans. X_i represents the vector of the individual level (age, gender) and county/zip level (income, education, race, population density) covariates[4]. We also include state-level fixed effects to account for geo-

[3]These periods are generally reflected in web searches - for example, see `https://trends.google.com/trends/explore?date=today%205-y&geo=US&q=zillow`

[4]County level covariates come from the 2016 ACS

graphic variation in search and purchasing behavior.

To understand the effects of the Trump presidency on purchasing behavior, we compared house/car/stock searches and car registrations on the same day in 2016 and 2017. Our regression specified two types of time fixed effects - month of the year (seasonality) and day of the week (searches tend to differ dramatically on weekdays versus weekends CITE). Due to 2016 search data availability, we looked at results from February 15 to July 31 in 2016 and 2017[5].

The second analysis looks more explicitly at the effects of the Trump victory on searches in the short term. Given the gradual shift in partisan economic perceptions as described by survey responses[6] about economic confidence during this time period, we do not expect to find a sharp discontinuity at election day. Partisan shifts in economic confidence occur over the few months between the election and the inauguration, not immediately after election day. As a result, we expect to see partisan search gaps temporally mirror partisan survey gaps, instead of generating a sudden discontinuity at election day.

To look at immediate post election effects, we compared the gap in cars, house, and stock searches between Democrats and Republicans between October 2016 and March 2017. Democrats and Republicans should be similarly affected by seasonality, so an increase in the gap means that at members of least one of the parties are changing their search behaviors.

Car Registration Measures New Car Purchase

To test the effects of partisanship on actual purchase behavior, we examined DMV vehicle registration records for January through October of 2016 and 2017. These files contained informa-

[5]For example, a user who uses Bing only in October of 2016 will make it into the dataset as described in Table 3 and the post-election analysis, but not into the main seasonality analysis. The 176,010 searchers in the seasonality analysis were demographically similar to the full sample - please see appendix for a modified version of Table 3 that describes these searchers only

[6]Surveys from Gallup. For more information on how we compiled the Gallup survey time series, please see appendix

tion on all 11 million vehicles registered by the 19.75 million residents of New York State[7]. New York State requires vehicle owners to register their vehicle every 12 months, or upon transfer of ownership (such as when selling a used car). Therefore, any increase in the number of vehicle registrations is due to either the purchase of a car or a vehicle owner moving to New York State. We use increases in the number of vehicle registrations as a proxy for new car purchases.

Since individual-level partisanship data was not available, we instead compared the 2008 ZIP-code-level presidential vote to vehicle registration data aggregated to the ZIP-code level.[8] To analyze this data, we used a binomial logit model where the number of car registrations per day per ZIP code was counted as the number of successes, and the ZIP code population minus the number of daily registrations was considered the number of failures.[9]

Results: Democrats Were Less likely to Search for Houses, Cars After the 2016 Election

The top panel of Figure 3 plots the weekly proportion of partisan users who searched for cars, houses, and stock in 2016 and 2017. As expected, Democrats were substantially less likely to make a search for cars or houses in any given week in 2017 as compared to the same week in 2016. Republicans showed no substantial changes in their investment search patterns. The bottom panel of Figure 3 shows the proportion of total searches done by Democrats and Republicans that were for one of the three categories. The results of this figure are similar to the top panel of Figure 3, with the exception that Republicans seemed more likely to make more stock related searches in 2016 than in 2017.

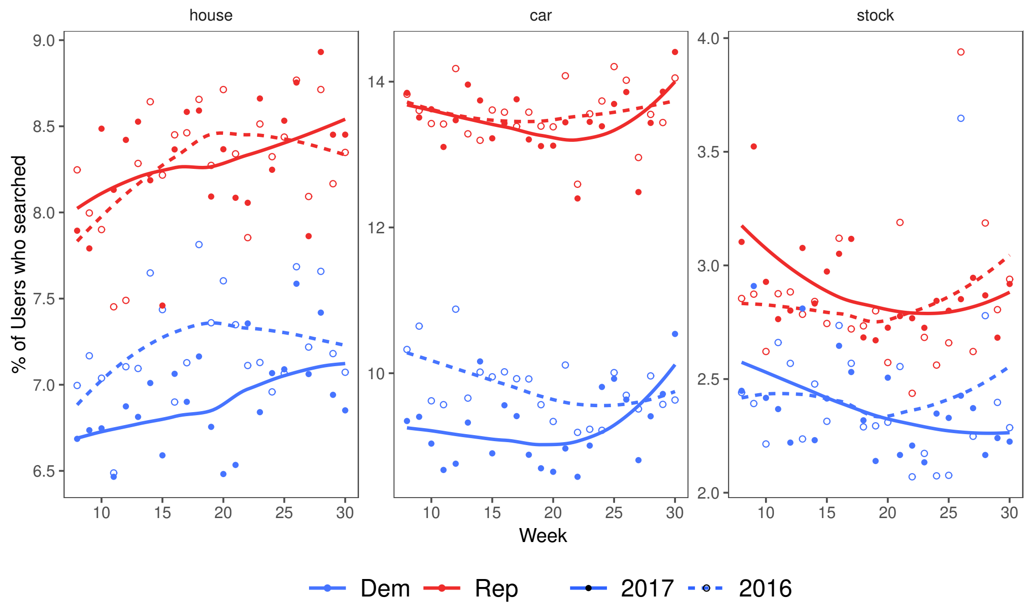
[7] New York is the only state that makes these records publicly available online

[8] We used 2008 data due to availability. If anything, this would add noise versus 2016 data and downwardly bias our results.

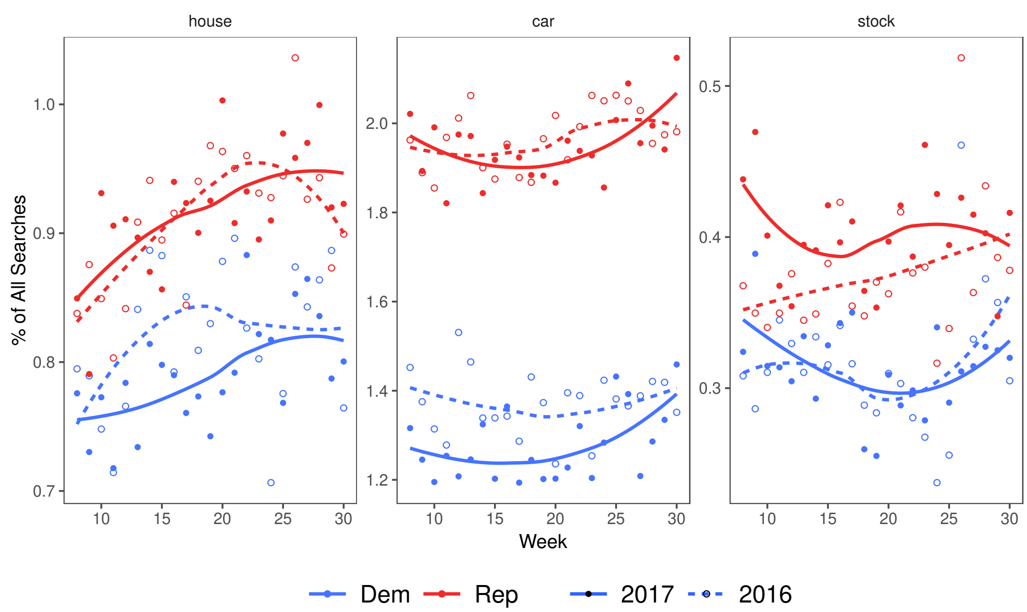
[9] Unfortunately, we are unable to accurately match searchers to zip codes, so we cannot link searches to car registrations

Figure 3: Change in Partisan Search Behavior (2016-2017)

Users



Searches



Notes: Plot shows the changes in the search behavior of partisans using both the User and Search measures. The top panel shows the overall proportion of Republicans and Democrats who made at least one search for house, car, or stock purchase related terms during weeks 8-30 in 2016 and 2017 (leaners counted as partisans), and the bottom panel shows house, car, and stock searches as a proportion of all partisans' Bing searches. We see that Democrats were consistently less likely to make house or car related searches in 2017 than in 2016. Republicans held largely constant. There was no significant difference among Democrats or Republicans in their stock market searches.

Table 4: Partisan Change in Search Behavior (3 Point PID)

	House		Car	
	Users	Searches	Users	Searches
2017	0.027 (0.022)	−0.005 (0.029)	−0.020 (0.014)	−0.042* (0.023)
Dem	−0.151*** (0.034)	−0.114** (0.046)	−0.244*** (0.023)	−0.260*** (0.033)
2017 x Dem	−0.065* (0.034)	−0.076 (0.049)	−0.040* (0.024)	−0.080** (0.036)
Ind	−0.010 (0.034)	−0.029 (0.047)	−0.173*** (0.023)	−0.208*** (0.033)
2017 x Ind	0.026 (0.037)	0.068 (0.056)	0.009 (0.024)	0.059 (0.037)
Age 30 - 44	0.150** (0.059)	0.120 (0.080)	−0.002 (0.035)	−0.039 (0.052)
Age 45 - 64	0.291*** (0.055)	0.333*** (0.075)	−0.072** (0.032)	−0.104** (0.047)
Age 65+	0.240*** (0.058)	0.381*** (0.078)	−0.231*** (0.035)	−0.212*** (0.051)
Female	0.268*** (0.023)	0.443*** (0.033)	−0.599*** (0.016)	−0.626*** (0.021)
County % Black	−0.196 (0.159)	−0.303 (0.206)	−0.059 (0.112)	0.023 (0.145)
County % Hisp	−0.096 (0.134)	−0.344* (0.189)	−0.001 (0.086)	0.089 (0.134)
County % College	−0.065 (0.626)	−0.522 (0.883)	−0.287 (0.376)	−1.012* (0.560)
County Log Med HH Inc	0.183* (0.101)	0.239* (0.133)	−0.046 (0.064)	0.012 (0.089)
County Log Pop Density	−0.010 (0.014)	−0.020 (0.018)	−0.022** (0.009)	−0.037*** (0.012)
Month FE	X	X	X	X
Day of Week FE	X	X	X	X
State FE	X	X	X	X
Constant	−5.705*** (1.052)	−7.723*** (1.395)	−1.783*** (0.669)	−3.334*** (0.938)
Observations	8132422	8129054	8132422	8125751
Unique Users	151995	151995	151995	151995

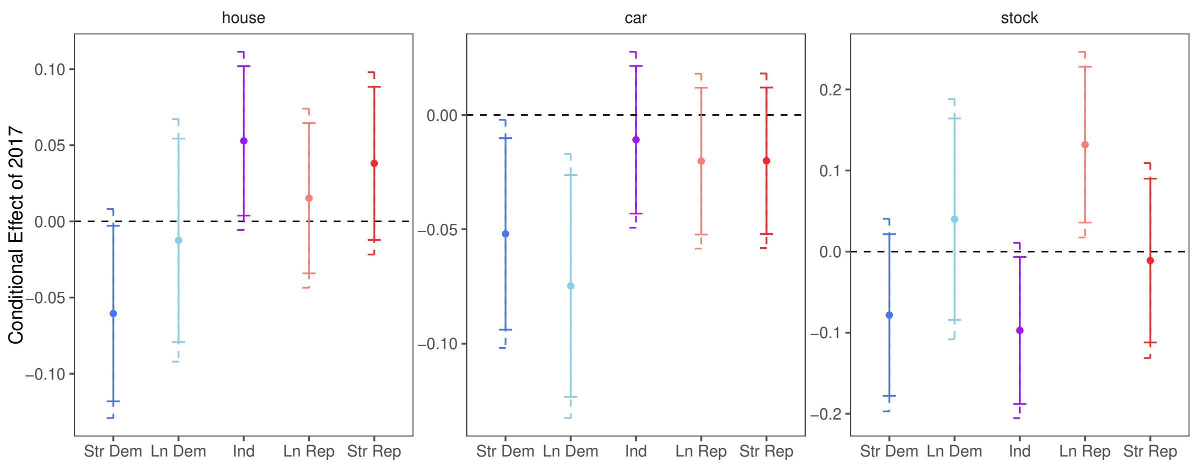
	Stock	
	Users	Searches
2017	0.063 (0.043)	0.029 (0.095)
Dem	−0.065 (0.068)	−0.117 (0.133)
2017 x Dem	−0.099 (0.063)	−0.152 (0.142)
Ind	−0.017 (0.071)	−0.030 (0.124)
2017 x Ind	−0.160** (0.069)	−0.185 (0.133)
Age 30 - 44	−0.271*** (0.103)	−0.484*** (0.178)
Age 45 - 64	−0.154* (0.091)	−0.462*** (0.159)
Age 65+	0.210** (0.097)	0.089 (0.171)
Female	−0.499*** (0.049)	−0.405*** (0.086)
County % Black	−0.094 (0.351)	−0.402 (0.449)
County % Hisp	−0.178 (0.308)	−0.424 (0.533)
County % College	−0.626 (1.160)	−2.323 (1.743)
County Log Med HH Inc	0.355* (0.198)	0.397 (0.258)
County Log Pop Density	0.024 (0.030)	0.060 (0.042)
Month FE	X	X
State FE	X	X
Day of Week FE	X	X
Constant	−7.797*** (2.098)	−9.607*** (2.691)
Observations	8132422	8131650
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

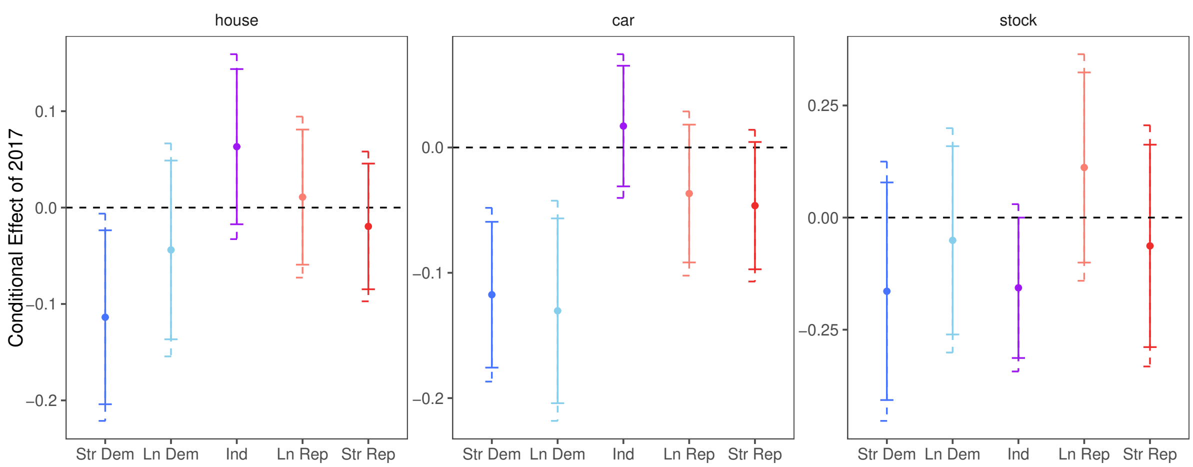
Notes: Democrats were significantly less likely to search for houses and cars in 2017 than were Republicans. In this regression, leaners are counted as partisans. Regression is binomial logit with standard errors clustered by user. For regression table with basic model (no covariates or FEs), please see appendix.

Figure 4: Year 2017 x Party ID Conditional Coefficient Plot (5 Point PID)

Users



Searches



Notes: These plots show the magnitude of the 2017 year coefficient conditional on partisanship. Solid lines represent 90% confidence intervals, and dashed lines represent 95% confidence intervals. Strong Democrats were significantly less likely to search for houses and cars in 2017 than in 2016, according to both the user and search measures. Independent-leaning Democrat were significantly less likely to search for cars in 2017 according to both the user and search measures. Independents, Republican leaners, and Strong Republicans were equally likely to search in 2016 as in 2017.

Table 4 presents the results of the seasonality model, and confirms that Democratic users were significantly less likely to search for cars or houses after Trump became president than they were before, as the interaction on the 2017 x Dem coefficient is negative and statistically significant. In Table 4, leaners are counted as partisans[10]. These results hold for both the basic model, as well as the model that includes covariates. In the appendix we demonstrate that these patterns are robust to multiple measurements of partisanship, including 5-point party ID (Tables A4-A5) and 2016 vote choice (Tables A6-A7).

When we further break down the analysis into 5-point party ID and plot the size of the year coefficient conditional on partisanship, plotted in Figure 4, we find that the post-election effect in Table 4 is driven by strong Democrats[11]. Strong Democrats consistently show significant drops in their car and house search behavior, followed by Democratic Leaners, who show significant drops for car searches, and non-significant drops for house searches. Independents, Republican Leaners, and Strong Republicans show no effect. The Independents in our sample were unusually pro-Trump, which explains why they were more similar to Republicans than to Democrats in their behavior.

In order to ensure that the results presented in Figure 4 are robust to model specification, we utilize a methodology described in Young and Holsteen (2017) to further test the significance of the results under a wide variety of possible specifications. This methodology involves estimating models containing all possible combinations of a set of relevant covariates, and determining what proportion of these models yields coefficients of interest that are statistically significant according to traditional significance thresholds. We estimate 2^8 (or 256 different models[12]) each for the user

[10] Counting partisan leaners as Independents under a 3-point model of party ID does not meaningfully change the results

[11] The regressions upon which these plots are based, available in Tables A4-A5 in the appendix, are identical to the regressions in Table 4 in all but their party ID measure

[12] To arrive at this number, we looked at combinations of the following covariates: age, gender, county racial composition, county education, county income, county density, day of the week fixed effects, and month fixed effects. We did not include state fixed effects in this robustness check, as including them would increase the necessary computation time by a factor of 8x. However, given the results of the 256 models we did estimate, as well as the inclusion of the state fixed effects in the final model, it is unlikely that their inclusion would substantially change the results.

house measure, the user car measure, the search house measure, and the search car measure, for a total of 1024 different models.

The results were highly robust to model specification. In the case of the user house measure, 100% of the 256 models yielded a conditional coefficient on 2017 for strong Democrats that was negative and had a p-value <0.1, with 41% of models yielding a p-value <0.05. The other three measures were even more robust, with 100% of the models for car users, house searches, and car searches yielding a negative and significant conditional coefficient at $p<0.05$ for strong Democrats[13].

The change in Democrats' search patterns post-Trump is not only statistically significant but also substantively significant. Housing markets exhibit strong and well-documented seasonality effects–people are significantly more likely to buy houses in June than in January (Ngai and Tenreyro 2014). The year-over-year decrease in housing searches among Strong Democrats after Trump's election is equivalent to approximately 48% of the annual seasonal difference between the first week of January and the last week of July. For cars, the effect is approximately 30% of the annual seasonal decrease for that same time period.

In general, Republicans and Independents were about equally likely to search for cars and houses in 2016 and 2017. For the same period, Republicans were slightly more likely to search for houses, and slightly less likely to search for cars, but the difference was not significant. Neither party showed any consistent change in searches for stock market-related terms[14]. The base-rate is much lower for searches for stocks, as trading is confined to a small, sophisticated group of people. Therefore, ex-post, it is unsurprising that there is no significant shift in behavior between parties.

The covariate coefficients on the regression estimate in Table 4 provide an additional validation of our search measures. People who lived in wealthier counties were more likely to search

[13] For a more detailed breakdown by partisanship, please see appendix

[14] Republican leaners were significantly more likely to search for stocks in 2017 than 2016

for houses and stock than those in poorer counties. Similarly, people who lived in denser (more urban) areas were less likely to search for cars than people who lived in areas more sparsely populated.

This section has established the effect of the Trump presidency on Democrats' car, house, and stock searches. This effect is substantively significant, as it is a significant fraction of the seasonal change in searches between January and July.

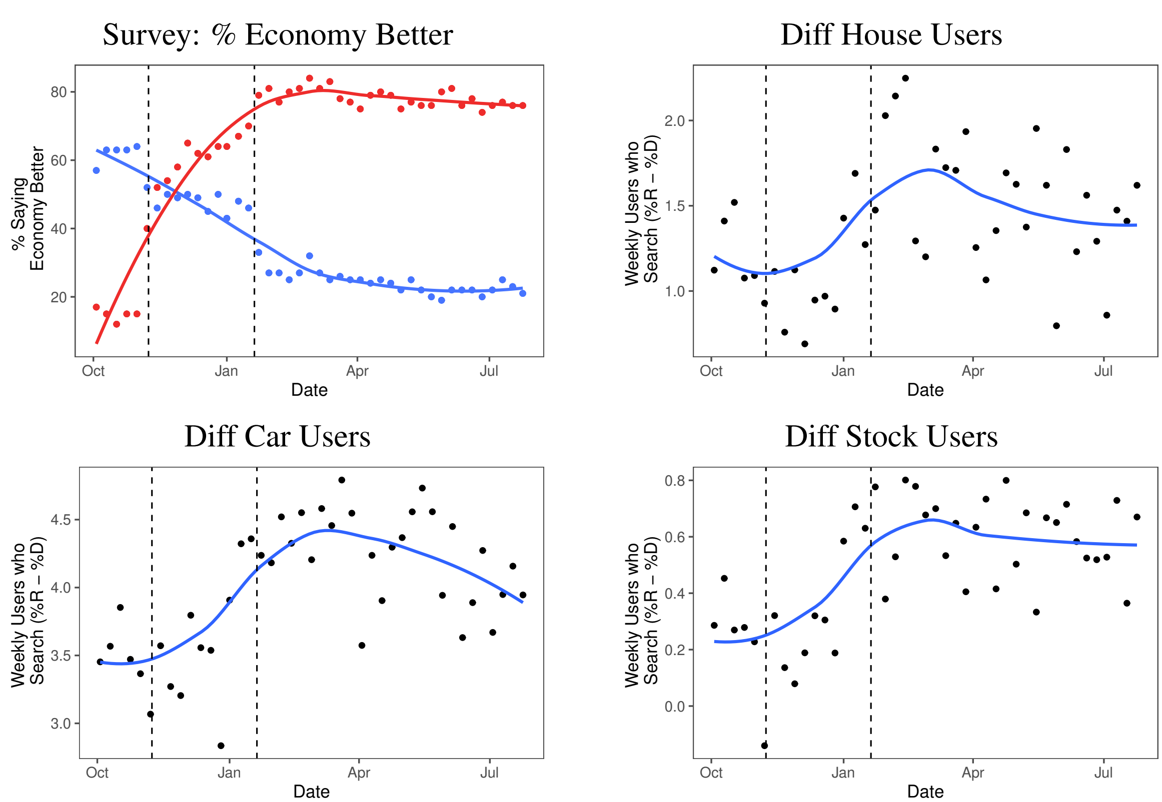
Post-Election Changes in Partisan Investment Mirror Polling

In the previous section, we examined the effect of a switch in presidential administrations on car and house searches over the long term. In this section, we look more closely at partisan search gaps in the few months before and after the election. While the strong seasonality effects on these specific terms preclude us from being able to tell whether investment searches increased or decreased relative to the baseline, we are able to determine whether gaps between partisans increase or decrease during this time period. For example, searches for houses decrease significantly throughout the fall for both Democrats and Republicans [15], so a post-election decline in searches does not necessarily mean a decrease in economic confidence. However, if Democrats' searches decline more quickly than Republicans' (or increase more slowly in the first quarter of the new year), this does suggest a partisan economic effect, especially if it is coupled with a decrease in survey responses to questions about economic confidence during the same time period and evidence of longer term search effects.

Most partisans do not change their economic beliefs the day after a presidential victory or loss. Instead, this process occurs over the course of the months between election day and the new president's inauguration, as shown in the upper left hand panel of figure 5 for the 2016 election. For Republicans, about 1/3 of the total effect occurs immediately after election day, with the

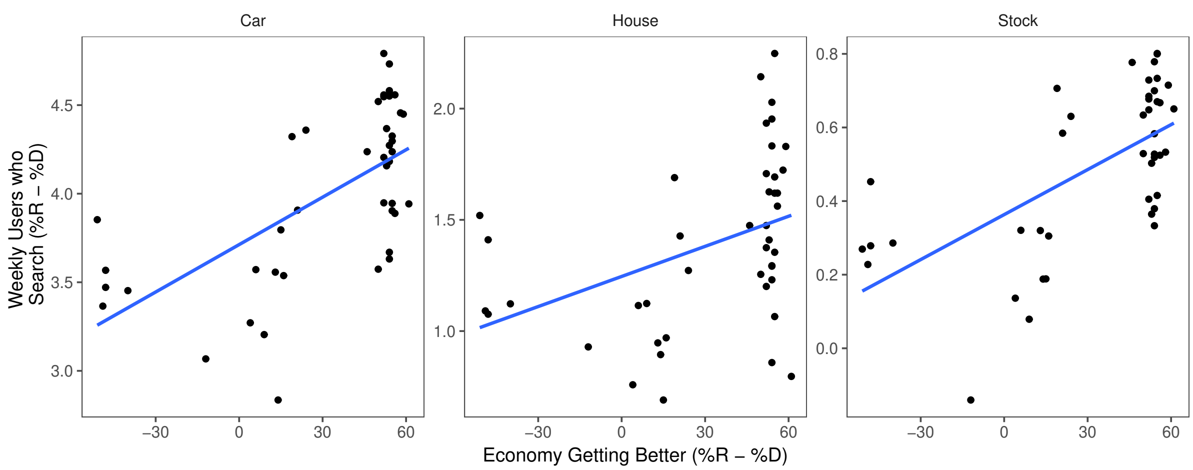
[15] To see the raw proportions of Dems and Reps who search for the three categories of terms, please see appendix

Figure 5: Partisan Differences in Searches and Polling (2016 Election)



Notes: The gap between the % of Democrat users and the % Republican users who searched for cars, houses, and stock mirrored the shift in Gallup polling responses. Partisan gaps increased gradually over time, rather than as a single discontinuity at election day. Dashed lines represent the 2016 election and the inauguration of President Trump. Top left-hand panel represents partisan gaps in survey responses around the 2016 election. Other three panels represent the weekly difference between the % of Republicans and the % of Democrats who searched for the specific search terms. Plot of short term proportions of users who searched for terms for both Democrats and Republicans individually available in the appendix.

Figure 6: Partisan Gap in Polling vs Partisan Gap in Search



Notes: The partisan gap in survey answers to the economic perception question closely tracks the partisan gap in car, house, and stock searches. Dates when the Democrats are more optimistic about the economy have a smaller search gap than dates when they are pessimistic. Each dot represents searches and polling results on a specific date between Oct 1, 2016 and Jul 31, 2017.

other 2/3 gradually increasing over the course of months. For Democrats, the effect is even more gradual, with a small drop after election day and a consistent decline thereafter.

Investment search gaps between Democrats and Republicans increased substantially during this time period, as shown in the other three panels in Figure 5. As described in the previous section, Republicans make more searches for houses, cars, and stock than do Democrats, so an increase in the partisan gap between the two signals an increase in investment searches by Republicans and/or a decline in investment searches by Democrats. Given the results of the previous section, it is most likely that this represents shifts in Democrats' search behaviors. This increase is strongly correlated with partisan differences in survey responses about perceptions of the economy. Figure 6 plots the size of the partisan survey gap versus the size of the partisan search gap by survey. As expected, dates where Democrats were more confident in the economy also had a smaller partisan gap in house, car, and stock searches. For all three categories of search, this relationship was highly statistically significant at $p<0.01$.

This section demonstrates an increase in short-term partisan gaps in search in the months following the 2016 election. Partisan search gaps mirror changes in partisan survey response. Partisans gradually shift their perceptions of the economy over the course of the few months between the election and the inauguration, and they modify their search behavior accordingly. Taken in tandem with the findings of the previous section, this finding strongly suggests that Democrats decreased their purchase searches for houses and cars after the 2016 election. In the next section, we go beyond the search data to examine changes in vehicle registrations after the 2016 election.

Car Registration Data Shows Decreased Purchase Behavior Among Democrats

The results presented thus far focus on the effect of the 2016 election on changes in house, car, and stock searches. In this section, we use car registration data from the New York State DMV to look at the effect of the election on car purchases.

New York residents who own or lease a vehicle are required to submit or renew their vehicle registration every 12 months, or upon transfer of vehicle ownership. If residents do not purchase additional cars, there will be no increase in vehicle registration from year to year, because each owner will register their car once a year. However, if a current vehicle owner purchases a new car, they will have had two car registrations in the previous 12 months—a registration for the old car and one for the new car. As a result, the number of per capita car registrations in that ZIP code will increase.

In the search data, we found that Democrats searched for car-purchase-related terms at a lower rate in 2017 than in 2016. This means that a larger proportion of Democratic households in New York State should have renewed their car registration but not made any new car purchases during that period. The percentage of Democrats who searched for cars did not drop to zero, so they should have made some new car purchases, just fewer than Republicans. Therefore, we expect that while both Democratic and Republican ZIP codes would have new car registrations, there would be significantly less growth in Democratic ZIP codes than in Republican ones.

Table 5: Partisanship and Car Registrations (2016-2017)

	Dependent variable:	
	(1)	(2)
2017	-0.077^{***} (0.005)	0.046^{***} (0.004)
Zip 2008 Dem Vote	-2.145^{***} (0.167)	-1.465^{***} (0.178)
2017 x Zip 2008 Dem Vote	-0.020^{**} (0.008)	-0.043^{***} (0.008)
Zip Log Pop Density		-0.134^{***} (0.010)
Zip % College		-0.331^{*} (0.177)
Zip Log Per Cap Inc		0.497^{***} (0.075)
Zip % Black		0.608^{***} (0.126)
Zip % Hisp		0.123 (0.152)
Day of Week FE		X
Month FE		X
Constant	-5.845^{***} (0.111)	-10.401^{***} (0.772)
Observations	630905	630905
Unique Zips	1377	1377
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: Negative and significant coefficient on the Democrat x 2017 interaction shows that Democrats had a statistically significant post-election effect. Standard Errors clustered by zip code.

We find that growth in car registrations was indeed lesser for Democratic ZIP codes than for Republican ones. Table 5 shows vehicle registrations in New York State. Republican ZIP codes had a larger increase in vehicle registrations in 2017 than Democratic ZIP codes, even after controlling for covariates that influence car registration, such as population density. Similarly to the search data, the vehicle registration data showed similar and expected patterns for other covariates such as household income (more cars in wealthier areas) and population density (fewer cars in cities), further validating the connection between car search data and car purchase data.

These results show that real-world car purchase patterns did change in the aftermath of the 2016 election. Not only did Democrats perform fewer searches for cars after Trump was elected, but patterns for actual car purchases and registrations also followed the expected partisan pat-

Table 6: Number of Daily Bing Searches Per User By Partisanship

Party	Mean Daily Searches (2016)	Mean Daily Searches (2017)	Median Daily Searches (2016)	Median Daily Searches (2017)
Strong Dem	10.289	10.357	5	5
Lean Dem	9.963	10.428	5	5
Independent/Other	10.895	10.750	5	5
Lean Rep	10.534	10.724	5	5
Strong Rep	10.987	11.179	5	5

Notes: This table measures the mean and median number of daily Bing searches per user, conditional on using Bing that day. In general, there were no large shifts in search patterns between 2016 and 2017 for any of the partisan groups. Strong Democrats had slightly more average daily searches in 2017 than in 2016. The median number of searches did not change for any partisan group.

tern. Democratic areas purchased fewer cars per capita than Republican areas, consistent with the smaller proportion of car searches among Democrats in 2017 than in 2016.

Alternative Explanations Do Not Diminish Effects of Partisanship

How do we explain these effects? In this section, we examine possible threats to the finding that partisans are less likely to invest in durable goods because their party has lost the presidency. First, we will show that the shift in partisan searches for cars and houses was not the result of a larger shift in search patterns. Second, we will examine the effect of income on partisans' economic searches.

To ensure that partisan differences in house and car search patterns were not the result of overall changes in search patterns, we performed two tests. First, we looked at the overall number of Bing searches (for any topic) done by each partisan group in 2016 and 2017. If Democrats were less likely to search in general, we could not attribute the changes in house and car purchase searches to shifts in economic perceptions. Table 6 shows that none of the partisan groups exhibited a substantial shift in their mean or median number of daily Bing searches. In fact, the mean number of searches among most groups increased slightly, while the median number stayed the same for all groups. This suggests that the drop in house and car searches for Democrats was not the result of less search activity in general.

Table 7: Porn Searches By Partisanship (3 point PID)

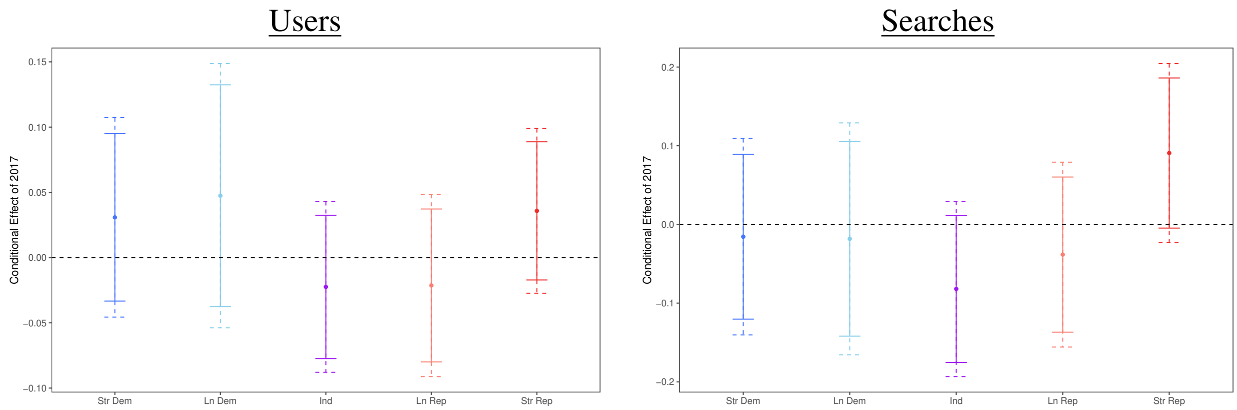
	Users		Searches	
	(1a)	(1b)	(2a)	(2b)
2017	0.010 (0.024)	0.009 (0.024)	0.006 (0.043)	0.032 (0.042)
Dem	-0.084^{**} (0.043)	0.133^{***} (0.043)	0.102 (0.072)	0.269^{***} (0.069)
2017 x Dem	0.026 (0.039)	0.026 (0.039)	-0.058 (0.068)	-0.054 (0.064)
Ind	0.084^{*} (0.045)	0.139^{***} (0.045)	0.101 (0.072)	0.156^{**} (0.070)
2017 x Ind	-0.017 (0.041)	-0.031 (0.041)	-0.107 (0.072)	-0.114 (0.070)
Age 30 - 44		0.037 (0.092)		-0.055 (0.175)
Age 45 - 64		0.467^{***} (0.079)		0.450^{***} (0.161)
Age 65+		0.572^{***} (0.082)		0.725^{***} (0.162)
Female		-1.916^{***} (0.044)		-1.972^{***} (0.085)
County % Black		-0.667^{***} (0.222)		-0.018 (0.348)
County % Hisp		-0.445^{**} (0.176)		-0.441^{*} (0.260)
County % College		-1.095 (0.747)		-0.491 (1.237)
County Log Med HH Inc		-0.135 (0.123)		-0.037 (0.177)
County Log Pop Density		0.005 (0.018)		-0.040 (0.026)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	-2.925^{***} (0.026)	-1.279 (1.293)	-3.196^{***} (0.041)	-2.633 (1.870)
Observations	7413153	7413153	7413153	7413153
Unique Users	148277	148277	148277	148277
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Neither Democrats nor Republicans showed any change in their adult searches after the 2016 election.

Our second test examines whether Democrats were also less likely to search for non-economic searches. If they were, partisan motivated reasoning would not be a viable explanation for the drop in Democrats' car and house searches. To test this, we looked at our users' searches for adult content. We chose this particular topic because it both represents a significant portion of internet traffic and because Bing automatically labels certain searches as "adult". More crucially, porn consumption does not have anything to do with partisans' economic perceptions.

Table 7 confirms that there was no statistically significant change in porn searching habits for Democrats or Republicans after the 2016 election. Figure 7 plots the conditional coefficients for

Figure 7: Porn Placebo Conditional Coefficient Plot (5 Point PID)



Notes: Effect of year on Porn searches is insignificant for all groups of partisans, on both the search and user measures.

5-point Party ID, and further shows that no partisan groups changed their adult search behavior. This means that Democrats' post-election drop in searches for cars and houses was not the result of a broader change in partisan post-election search patterns.

Our second set of tests examines whether the partisan effects we find are attributable to different economic circumstances. On average, Democrats tend to be poorer than Republicans (Gelman 2009). Republican economic policies are more likely to benefit wealthier Americans (Bartels 2016). Was Democrats' drop in searches for houses and cars, as well as car registrations, the result of rational expectations about an incoming Republican president's economic policies? Put another way, did Democrats expect tougher days ahead because of policies that disadvantaged them specifically, rather than their partisan motivated belief that a Republican president was mismanaging the economy?

To investigate this hypothesis, we ran two tests. First, we looked at the effect of interacting income with the 2017 year variable. If income, rather than partisanship, was the driving force behind Democrats' decrease in searches, then this interaction should render the year 2017 x Dem interaction insignificant. Table 8 shows the effect of including the interaction term on car, house, and stock searches - the interaction is not significant, nor does it reduce the significance of the post-election effect for Democrats. In the case of the car searches, the interaction is not even positive. The first two columns of table 8 shows the effect of this interaction for car registrations. In this case, while the income interaction is significant (but negative!) in the first column, the partisan post-election effect for Democrats also remains significant.

The second test looks at behavior of people living in the 10% richest counties or zip codes in the US. If poorer people (not partisan Democrats) are driving the results, we should see no partisan difference in searches or registrations among the wealthiest set of geographies. However, by discarding consumers living in 90% of the country, we are significantly limiting our power, especially to test the significance of an interaction term. Table 10 shows the result of this test. While the effect of 2017 x Dem is positive and insignificant for the users measure, it is still negative and sizable for the searches measure, although insignificant. For cars, the effect is negative and sizable for both the users and searches measures. The last two columns of Table 8 show that the negative effect of the election of Democratic zip codes persists even when we limit our results to the top 10% of wealthiest zip codes in New York state.

Taken together, these results suggest that partisanship, not income, is the driving force behind Democrats' drop in car searches, house searches, and car registrations. Including a year x income interaction does not change the effect of partisanship, nor does limiting the results to the richest searchers who would most likely benefit from Republican economic policy.

Table 8: Partisanship and Car Registrations (2016-2017)

	Wealth Interaction		Top 10% Wealthiest	
	(1a)	(1b)	(2a)	(2b)
2017	0.026 (0.031)	0.058^{**} (0.028)	-0.084^{***} (0.012)	0.059^{***} (0.014)
Zip 2008 Dem Vote	-2.059^{***} (0.164)	-1.465^{***} (0.178)	-3.091^{***} (0.394)	-1.475^{***} (0.301)
2017 x Zip 2008 Dem Vote	-0.023^{***} (0.008)	-0.044^{***} (0.008)	-0.025 (0.018)	-0.069^{***} (0.022)
Zip Log Per Cap Inc	0.234^{***} (0.065)	0.497^{***} (0.075)	-0.555^{***} (0.184)	-0.235^{*} (0.120)
2017 x Zip Log Per Cap Inc	-0.010^{***} (0.003)	-0.001 (0.003)		
Zip Log Pop Density		-0.134^{***} (0.010)		-0.251^{***} (0.019)
Zip % College		-0.331^{*} (0.177)		0.165 (0.375)
Zip % Black		0.608^{***} (0.126)		0.493 (0.918)
Zip % Hisp		0.123 (0.152)		-0.324 (0.540)
Day of Week FE		X		X
Month FE		X		X
Constant	-8.315^{***} (0.752)	-10.406^{***} (0.770)	0.991 (1.945)	-1.710 (1.222)
Observations	630905	630905	77457	77457
Unique Zips	1377	1377	122	122
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: This table summarizes the wealth tests for the car registration data. Adding a zip code wealth interaction and looking at the top 10% wealthiest zip codes in New York State did not remove the significance of the 2017 x Dem interaction.

Table 9: Interaction with County Economic Status

	House		Car	
	Users	Searches	Users	Searches
2017	−0.853 (0.652)	−0.687 (1.018)	0.176 (0.431)	0.197 (0.689)
Dem	-0.150^{***} (0.034)	-0.114^{**} (0.046)	-0.244^{***} (0.023)	-0.260^{***} (0.033)
2017 x Dem	-0.067^{**} (0.034)	−0.078 (0.049)	-0.040^{*} (0.024)	-0.079^{**} (0.036)
Ind	−0.009 (0.034)	−0.029 (0.047)	-0.174^{***} (0.023)	-0.208^{***} (0.033)
2017 x Ind	0.024 (0.037)	0.067 (0.056)	0.010 (0.024)	0.059 (0.037)
County Log Med HH Inc	0.139 (0.106)	0.206 (0.138)	−0.036 (0.068)	0.023 (0.098)
2017 x County Log Med HH Inc	0.080 (0.059)	0.062 (0.093)	−0.018 (0.039)	−0.022 (0.063)
Age 30 - 44	0.150^{**} (0.059)	0.120 (0.080)	−0.002 (0.035)	−0.039 (0.052)
Age 45 - 64	0.291^{***} (0.055)	0.333^{***} (0.075)	-0.072^{**} (0.032)	-0.104^{**} (0.047)
Age 65+	0.240^{***} (0.058)	0.380^{***} (0.078)	-0.231^{***} (0.035)	-0.212^{***} (0.051)
Female	0.268^{***} (0.023)	0.443^{***} (0.033)	-0.599^{***} (0.016)	-0.626^{***} (0.021)
County % Black	−0.196 (0.159)	−0.302 (0.206)	−0.059 (0.112)	0.023 (0.145)
County % Hisp	−0.095 (0.134)	-0.344^{*} (0.189)	−0.001 (0.086)	0.089 (0.134)
County % College	−0.066 (0.626)	−0.523 (0.883)	−0.287 (0.376)	-1.011^{*} (0.560)
County Log Pop Density	−0.010 (0.014)	−0.020 (0.018)	-0.022^{**} (0.009)	-0.037^{***} (0.012)
Month FE	X	X	X	X
Day of Week FE	X	X	X	X
State FE	X	X	X	X
Constant	-5.229^{***} (1.113)	-7.357^{***} (1.446)	-1.887^{***} (0.724)	-3.458^{***} (1.042)
Observations	8132422	8129054	8132422	8125751
Unique Users	151995	151995	151995	151995

	Stock	
	Users	Searches
2017	−0.563 (1.199)	1.509 (2.611)
Dem	−0.064 (0.069)	−0.118 (0.135)
2017 x Dem	−0.100 (0.064)	−0.150 (0.144)
Ind	−0.016 (0.071)	−0.032 (0.124)
2017 x Ind	-0.162^{**} (0.069)	−0.182 (0.134)
County Log Med HH Inc	0.325 (0.210)	0.467 (0.289)
2017 x County Log Med HH Inc	0.057 (0.109)	−0.135 (0.240)
Age 30 - 44	-0.271^{***} (0.103)	-0.484^{***} (0.179)
Age 45 - 64	-0.154^{*} (0.091)	-0.462^{***} (0.159)
Age 65+	0.210^{**} (0.097)	0.089 (0.171)
Female	-0.499^{***} (0.049)	-0.405^{***} (0.086)
County % Black	−0.094 (0.351)	−0.404 (0.449)
County % Hisp	−0.177 (0.308)	−0.424 (0.533)
County % College	−0.627 (1.160)	−2.320 (1.744)
County Log Pop Density	0.024 (0.030)	0.060 (0.042)
Month FE	X	X
State FE	X	X
Day of Week FE	X	X
Constant	-7.461^{***} (2.230)	-10.376^{***} (3.044)
Observations	8132422	8131650
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Interacting 2017 and wealth does not remove the significance of partisanship. Regressions are identical to the regressions presented in Table 4, except for the addition of an interaction term between county wealth and 2017.

Table 10: Top 10% Wealthiest Counties

	House		Car	
	Users	Searches	Users	Searches
2017	0.044 (0.060)	0.099 (0.085)	−0.029 (0.041)	−0.036 (0.070)
Dem	−0.226** (0.101)	−0.123 (0.121)	−0.175** (0.074)	−0.209** (0.099)
2017 x Dem	0.029 (0.093)	−0.082 (0.134)	−0.097 (0.075)	−0.160 (0.111)
Ind	0.090 (0.115)	0.238* (0.144)	−0.249*** (0.071)	−0.360*** (0.101)
2017 x Ind	−0.107 (0.116)	−0.126 (0.186)	0.058 (0.069)	0.080 (0.110)
Age 30 - 44	0.313 (0.192)	0.277 (0.274)	0.100 (0.112)	−0.055 (0.134)
Age 45 - 64	0.449** (0.184)	0.476* (0.264)	−0.093 (0.104)	−0.206* (0.121)
Age 65+	0.406** (0.198)	0.489* (0.272)	−0.156 (0.118)	−0.247* (0.144)
Female	0.155** (0.073)	0.340*** (0.097)	−0.466*** (0.050)	−0.548*** (0.071)
County % Black	−0.989 (1.052)	−0.589 (1.407)	−0.912 (0.719)	−0.676 (0.923)
County % Hisp	0.193 (1.030)	−1.337 (1.467)	−0.003 (0.711)	−0.135 (0.947)
County % College	3.474 (2.813)	3.237 (3.642)	0.985 (1.757)	−1.476 (2.412)
County Log Med HH Inc	0.528 (0.618)	0.652 (0.768)	0.403 (0.447)	0.420 (0.563)
County Log Pop Density	−0.018 (0.081)	−0.096 (0.106)	−0.021 (0.050)	−0.017 (0.072)
Month FE	X	X	X	X
Day of Week FE	X	X	X	X
State FE	X	X	X	X
Constant	−9.829 (6.874)	−12.912 (8.570)	−7.539 (5.004)	−8.373 (6.285)
Observations	857033	856672	857033	856439
Unique Users	16464	16464	16464	16464

	Stock	
	Users	Searches
2017	0.127 (0.121)	0.152 (0.149)
Dem	0.049 (0.177)	0.289 (0.229)
2017 x Dem	0.022 (0.165)	−0.064 (0.217)
Ind	0.337 (0.208)	0.546** (0.260)
2017 x Ind	−0.263 (0.184)	−0.389 (0.252)
Age 30 - 44	−0.111 (0.272)	−0.287 (0.319)
Age 45 - 64	−0.308 (0.233)	−0.557** (0.243)
Age 65+	0.309 (0.259)	0.174 (0.281)
Female	−0.569*** (0.127)	−0.496** (0.199)
County % Black	−1.242 (1.552)	−0.749 (1.580)
County % Hisp	0.579 (2.515)	0.782 (2.717)
County % College	−8.263 (5.609)	−7.181 (5.704)
County Log Med HH Inc	2.337* (1.327)	1.911 (1.271)
County Log Pop Density	0.203 (0.166)	0.315* (0.163)
Month FE	X	X
State FE	X	X
Day of Week FE	X	X
Constant	−30.119** (14.621)	−27.527** (13.992)
Observations	857033	856943
Unique Users	16464	16464

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Democrats in the top 10% wealthiest counties were still less likely to search for cars and houses in 2017 than 2016.

Conclusion

Do partisans change their purchasing patterns when the presidency switches parties? Americans' large increase in affective partisan polarization over the past few decades as well as their increased willingness to discriminate against out partisans suggests that their party preferences increasingly spill over into their everyday life, including on life-and-death matters such as social distancing and mask wearing. However, partisans' tendency to engage in expressive reporting on surveys has made it difficult to accurately measure their economic preferences. We address this issue by using web search data, a data source that is free from non-attitudes, expressive reporting, and social desirability bias. Using this data, we show that Democrats were significantly less likely to search for cars and houses after Trump was elected. Searches for cars and houses are strongly related to purchases of these goods (Choi and Varian 2012; Kinski 2016; Wu and Brynjolfsson 2015). Furthermore, using car registration data, we found that they are also less likely to purchase new cars relative to Republicans. These effects are non-trivial - the decrease in housing searches among Democrats is equivalent to 48% of the seasonal difference between January and July.

We also find that these effects are likely the result of partisan motivated reasoning. Democrats' decline in car and house searches was not the result of a broader shift in non-economic search patterns, as their searches for adult content did not change after the election. Furthermore, differences in income between Democrats and Republicans did not explain the partisan effect. Democrats who lived in the richest parts of the country were still less likely to search for cars and houses and register cars after the 2016 election.

Partisan polarization continues to rise. Politics continues to seep into our everyday lives, often in unexpected ways. Partisan differences in purchasing and investment behaviors can become a serious problem if this trend continues. If America wants a strong economy, entire segments of the country cannot opt out of socially beneficial economic behaviors because the opposing party holds the presidency.

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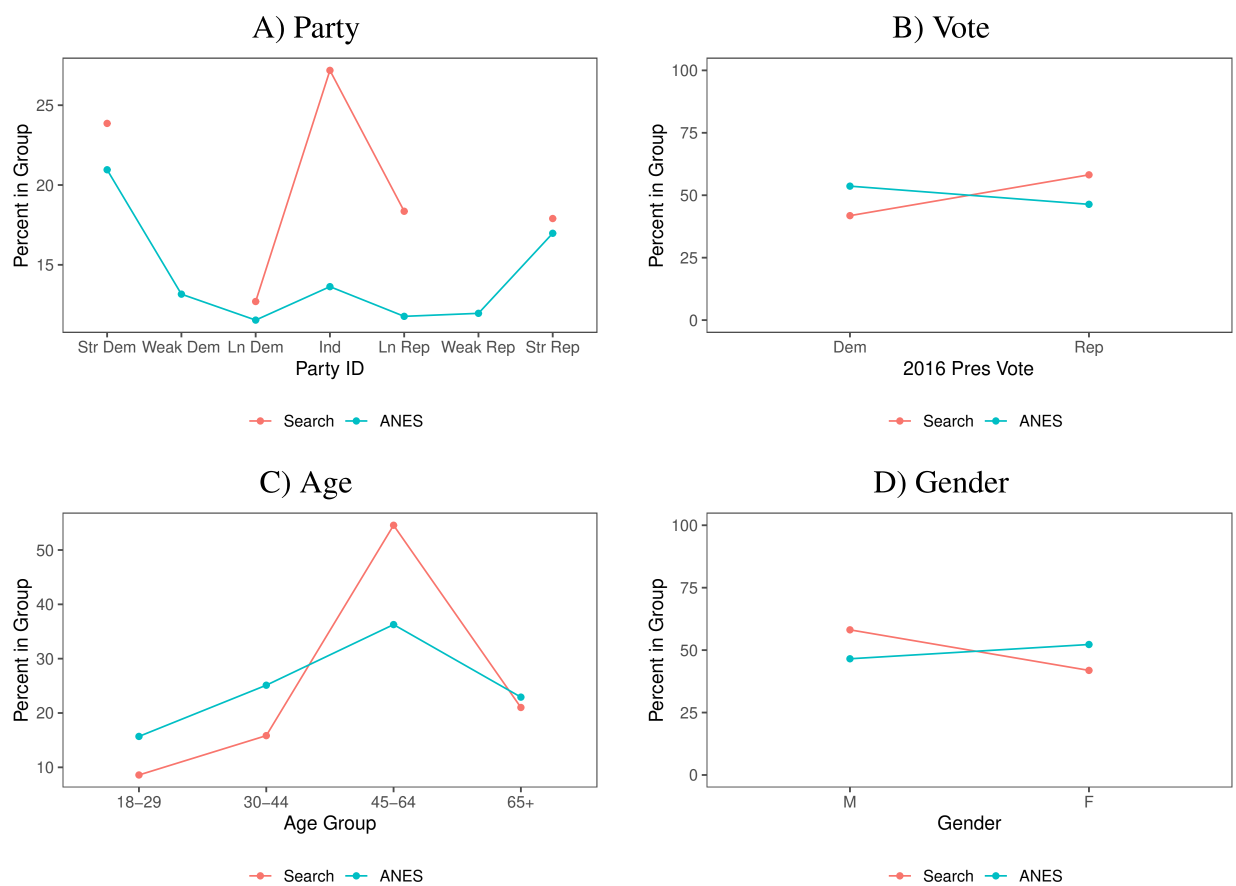
Appendix

Contents

A.1 Additional Data

A.1.1 Additional User Information

Figure A1: Search vs ANES Demographics



Notes: These plots show the demographic distribution of the users in our sample as compared to the 2016 ANES. In general, the Bing users in our sample were relatively similar to the ANES respondents.

In this section, we examine the differences between the demographics of our sample, as compared to the 2016 American National Election Studies pre-election survey. We use this survey as a comparison point, as it is a commonly used dataset to understand the 2016 election. In general, while there were some differences between our dataset and the ANES, these differences were not overwhelming.

Politically, our dataset contained user who were substantially more likely to be Pure Independents, and somewhat more likely to vote for Trump in 2016. Our dataset contained similar proportions of strong Dems, Dem leaners, and str Republicans to the ANES, and more Republican leaners and Independents.

With respect to age and gender, our dataset contained slightly more men than the 2016 ANES, and substantially more people in the 45-64 age group. Relative to the ANES, it contained fewer people from the 18-29 and 30-44 age groups.

A.1.2 Main Analysis Demographics

Table A1: Searchers 2/15 - 7/31

Party	Number Users	Trump Vote (Search Data)[a]	Trump Vote (ANES)
Strong Dem	40,194	3.4%	2.4%
Lean Dem	23,569	12.3%	7.3%
Independent/Other	48,593	70.3%	55.8%
Lean Rep	31,545	94.8%	92.3%
Strong Rep	32,109	93.4%	97.5%
Total	176,010	60.8%	46.3%

[a]Due to survey rolloff and some surveys asking only the Party ID question, only 60% of search users have a recorded vote preference

This section contains a replication of Table 3 in the main body of the paper that looks at the partisanship of users who made it into our main analysis. This table shows that the same pattern as described in Table 3 holds for this subset of searchers as well - Democrats are more likely to vote for Clinton and Republicans more likely to vote for Trump. Again, pure Independents were more likely to vote for Trump than in the ANES.

A.1.3 Gallup Time Series

This section further elaborates on the Gallup data we used to describe the stated shifts in partisan economic perception.

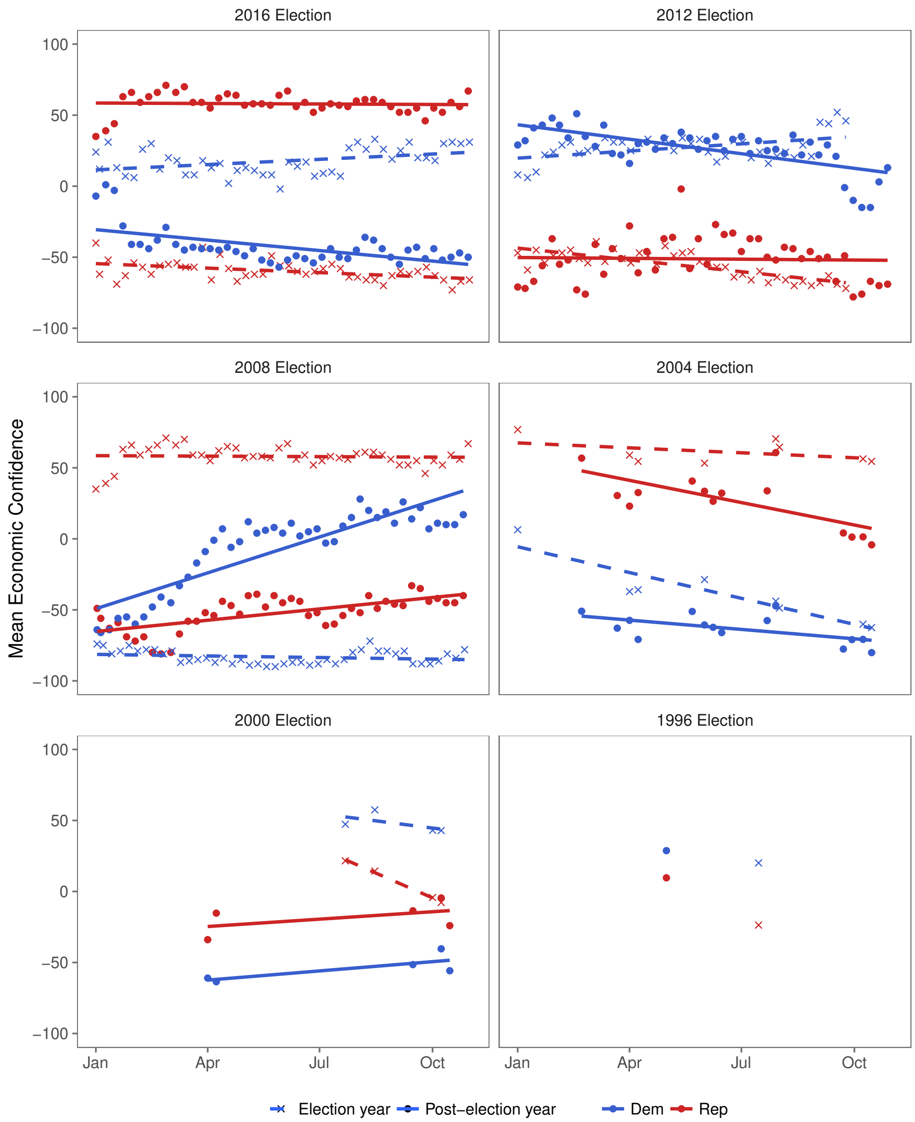
To test partisans' stated perceptions about the economy, we compiled 704 Gallup surveys from 1996 to 2017 to create a time series of partisans' economic perceptions. This time series contains partisans' answers to the question *"Right now, do you think that economic conditions in the country as a whole are getting better or getting worse?"* from July 1996 to December 2017. An answer of "getting better" was coded as 1, "getting worse" was coded as -1, and "same" was coded as 0.[16] This 20-year time series allows us to measure the effects of three elections that resulted in the presidency switching parties on partisans' economic perceptions. The time series itself is valuable because it holds the question wording and survey methodology constant, allowing comparison of partisans' post-election perceptual shifts to non-election shifts in economic beliefs. plot data

Figure A2 plots the changes in reported economic confidence among partisans before and after 6 presidential elections. On average, partisans whose party lost the presidency reported a -85 point decrease in their economic confidence. Similarly, partisans whose party won the presidency reported a +85 point increase. On the other hand, partisans whose party failed to beat an incumbent reported a +2 increase, while partisans whose incumbent won re-election reported a -9 decrease.

In all three cases, partisans whose party lost the presidency were extremely pessimistic about the economy, regardless of the actual economic conditions. In 2009, the US was in the depths of recession, while in 2017, the economy was doing well. However, Democrats' economic confidence in 2017 was comparable to Republicans' in 2009, and comparable to Democrats' in 2001. Regardless of how the economy is actually doing, the losing party reports very low confidence.

[16] Nearly 10% of respondents overall volunteered "same" as the answer to this question.

Figure A2: Changes in Economic Perceptions (Gallup Survey)



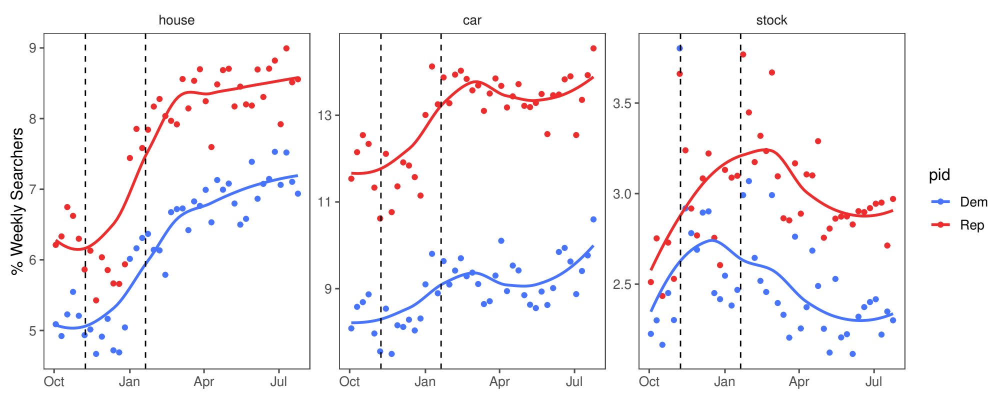
*Notes:*Partisans' economic confidence changes significantly after an election where the presidency switches parties, but does not appreciably shift after an incumbent is re-elected. Each dot represents one survey (x-axis is survey start date). The dashed line represents partisans' reported economic confidence during the presidential election year, and the solid line represents their confidence in the year immediately following the election. Lines are OLS fit. X-axis goes from January 1 to Nov 1.

This low confidence continues throughout the outparty president's term - Republicans had similarly dim views of the economy in 2009 and in 2016.

On the other hand, winning partisans levels of confidence more accurately reflect the state of the economy. In both 2001 and 2009, when the US was experiencing a recession, the winning party was relatively neutral on the state of the economy, while in 2017, Republicans were very positive.

A.1.4 Raw Short Term Difference in Purchase Searches

Figure A3: Short Term Search Changes



Notes: This plot shows short term changes after the 2016 election. Due to the sharp seasonal changes, coupled with pre-existing partisan differences, it is difficult to see the changes in the partisan gap in this plot. Dashed lines represent the 2016 election on 11/8/2016 and inauguration on 1/20/2017. Leaners counted as partisans.

This section shows the raw short-term changes in house, car, and stock searches over the post-election time period. Unfortunately, due to the strong seasonality effects and the large gap between Democrats and Republicans, it is difficult to observe the effect presented in Figure 5 in this format.

A.2 Additional Analysis

In this section, we perform four additional robustness checks on our data:

First, we present regression tables for both the basic models (no additional covariates/FEs) and the full models for the main analysis.

Second, we vary our measure of partisanship, and find that the results still hold when we measure partisanship as 5 point party ID or 2016 vote choice, in addition to the 3 point PID results presented in the body of the paper.

Second, we present our results in OLS, to demonstrate that this model specification does not generate different results from the logistic model presented in the body of the paper.

Finally, we present the results of the model robustness tests described by Young and Holsteen (2017) and presented in Table A8, and show that inclusion or exclusion of any combination of covariates does not dramatically affect the results. We provide this data for both the logistic and OLS specifications.

A.2.1 Basic Model Results

Table A2: Partisan Change in House, Car, and Stock Search Behavior (Users)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	0.018 (0.021)	0.027 (0.022)	−0.018 (0.014)	−0.020 (0.014)
Dem	-0.095^{***} (0.033)	-0.151^{***} (0.034)	-0.369^{***} (0.023)	-0.244^{***} (0.023)
2017 x Dem	-0.063^{*} (0.034)	-0.065^{*} (0.034)	-0.045^{*} (0.024)	-0.040^{*} (0.024)
Ind	−0.002 (0.034)	−0.010 (0.034)	-0.199^{***} (0.023)	-0.173^{***} (0.023)
2017 x Ind	0.030 (0.037)	0.026 (0.037)	0.003 (0.024)	0.009 (0.024)
Age 30 - 44		0.150^{**} (0.059)		−0.002 (0.035)
Age 45 - 64		0.291^{***} (0.055)		-0.072^{**} (0.032)
Age 65+		0.240^{***} (0.058)		-0.231^{***} (0.035)
Female		0.268^{***} (0.023)		-0.599^{***} (0.016)
County % Black		−0.196 (0.159)		−0.059 (0.112)
County % Hisp		−0.096 (0.134)		−0.001 (0.086)
County % College		−0.065 (0.626)		−0.287 (0.376)
County Log Med HH Inc		0.183^{*} (0.101)		−0.046 (0.064)
County Log Pop Density		−0.010 (0.014)		-0.022^{**} (0.009)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	-3.300^{***} (0.020)	-5.705^{***} (1.052)	-2.806^{***} (0.013)	-1.783^{***} (0.669)
Observations	8132422	8132422	8132422	8132422
Unique Users	151995	151995	151995	151995

	Stock	
	(3a)	(3b)
2017	0.061 (0.042)	0.063 (0.043)
Dem	-0.142^{**} (0.068)	−0.065 (0.068)
2017 x Dem	−0.096 (0.063)	−0.099 (0.063)
Ind	−0.028 (0.071)	−0.017 (0.071)
2017 x Ind	-0.158^{**} (0.069)	-0.160^{**} (0.069)
Age 30 - 44		-0.271^{***} (0.103)
Age 45 - 64		-0.154^{*} (0.091)
Age 65+		0.210^{**} (0.097)
Female		-0.499^{***} (0.049)
County % Black		−0.094 (0.351)
County % Hisp		−0.178 (0.308)
County % College		−0.626 (1.160)
County Log Med HH Inc		0.355^{*} (0.198)
County Log Pop Density		0.024 (0.030)
Month FE		X
State FE		X
Day of Week FE		X
Constant	-4.242^{***} (0.042)	-7.797^{***} (2.098)
Observations	8132422	8132422
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

Table A3: Partisan Change in House, Car, and Stock Search Behavior (Searches)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	−0.011 (0.029)	−0.005 (0.029)	−0.042* (0.023)	−0.042* (0.023)
Dem	−0.040 (0.045)	−0.114** (0.046)	−0.369*** (0.032)	−0.260*** (0.033)
2017 x Dem	−0.070 (0.050)	−0.076 (0.049)	−0.085** (0.036)	−0.080** (0.036)
Ind	−0.026 (0.047)	−0.029 (0.047)	−0.232*** (0.032)	−0.208*** (0.033)
2017 x Ind	0.081 (0.057)	0.068 (0.056)	0.052 (0.037)	0.059 (0.037)
Age 30 - 44		0.120 (0.080)		−0.039 (0.052)
Age 45 - 64		0.333*** (0.075)		−0.104** (0.047)
Age 65+		0.381*** (0.078)		−0.212*** (0.051)
Female		0.443*** (0.033)		−0.626*** (0.021)
County % Black		−0.303 (0.206)		0.023 (0.145)
County % Hisp		−0.344* (0.189)		0.089 (0.134)
County % College		−0.522 (0.883)		−1.012* (0.560)
County Log Med HH Inc		0.239* (0.133)		0.012 (0.089)
County Log Pop Density		−0.020 (0.018)		−0.037*** (0.012)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	−4.735*** (0.029)	−7.723*** (1.395)	−3.881*** (0.019)	−3.334*** (0.938)
Observations	8129054	8129054	8125751	8125751
Unique Users	151995	151995	151995	151995

	Stock	
	(3a)	(3b)
2017	0.033 (0.095)	0.029 (0.095)
Dem	−0.179 (0.137)	−0.117 (0.133)
2017 x Dem	−0.151 (0.142)	−0.152 (0.142)
Ind	−0.040 (0.126)	−0.030 (0.124)
2017 x Ind	−0.182 (0.134)	−0.185 (0.133)
Age 30 - 44		−0.484*** (0.178)
Age 45 - 64		−0.462*** (0.159)
Age 65+		0.089 (0.171)
Female		−0.405*** (0.086)
County % Black		−0.402 (0.449)
County % Hisp		−0.424 (0.533)
County % College		−2.323 (1.743)
County Log Med HH Inc		0.397 (0.258)
County Log Pop Density		0.060 (0.042)
Month FE		X
State FE		X
Day of Week FE		X
Constant	−5.662*** (0.084)	−9.607*** (2.691)
Observations	8131650	8131650
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

A.2.2 Results by 5 point PID

Table A4: Partisan Change in House, Car, and Stock Search Behavior (Users)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	−0.069** (0.035)	−0.060* (0.035)	−0.054** (0.025)	−0.052** (0.025)
Lean Dem	0.134** (0.055)	0.156*** (0.055)	0.081** (0.037)	0.034 (0.037)
2017 x Lean Dem	0.051 (0.054)	0.048 (0.053)	−0.027 (0.039)	−0.023 (0.039)
Ind	0.144*** (0.044)	0.201*** (0.045)	0.200*** (0.030)	0.084*** (0.030)
2017 x Ind	0.116** (0.046)	0.113** (0.046)	0.039 (0.032)	0.041 (0.032)
Lean Rep	0.129*** (0.043)	0.196*** (0.044)	0.395*** (0.030)	0.249*** (0.030)
2017 x Lean Rep	0.074 (0.046)	0.076* (0.046)	0.038 (0.032)	0.032 (0.032)
Str Rep	0.162*** (0.045)	0.225*** (0.045)	0.403*** (0.030)	0.265*** (0.030)
2017 x Str Rep	0.099** (0.046)	0.099** (0.046)	0.034 (0.032)	0.032 (0.032)
Age 30 - 44		0.151** (0.059)		−0.002 (0.035)
Age 45 - 64		0.295*** (0.055)		−0.072** (0.032)
Age 65+		0.246*** (0.058)		−0.230*** (0.035)
Female		0.271*** (0.023)		−0.599*** (0.016)
County % Black		−0.185 (0.159)		−0.058 (0.112)
County % Hisp		−0.091 (0.134)		−0.001 (0.086)
County % College		−0.058 (0.625)		−0.288 (0.376)
County Log Med HH Inc		0.181* (0.101)		−0.046 (0.064)
County Log Pop Density		−0.010 (0.014)		−0.022** (0.009)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	−3.446*** (0.034)	−5.908*** (1.053)	−3.205*** (0.023)	−2.040*** (0.668)
Observations	8132422	8132422	8132422	8132422
Unique Users	151995	151995	151995	151995

	Stock	
	(3a)	(3b)
2017	−0.076 (0.060)	−0.078 (0.061)
Lean Dem	−0.092 (0.108)	−0.118 (0.108)
2017 x Lean Dem	0.114 (0.097)	0.118 (0.097)
Ind	0.081 (0.090)	0.006 (0.090)
2017 x Ind	−0.020 (0.082)	−0.019 (0.082)
Lean Rep	0.122 (0.091)	0.038 (0.092)
2017 x Lean Rep	0.207** (0.084)	0.210** (0.084)
Str Rep	0.095 (0.090)	0.007 (0.090)
2017 x Str Rep	0.063 (0.086)	0.067 (0.086)
Age 30 - 44		−0.271*** (0.103)
Age 45 - 64		−0.154* (0.091)
Age 65+		0.211** (0.097)
Female		−0.499*** (0.049)
County % Black		−0.096 (0.352)
County % Hisp		−0.176 (0.309)
County % College		−0.614 (1.160)
County Log Med HH Inc		0.354* (0.198)
County Log Pop Density		0.024 (0.030)
Month FE		X
State FE		X
Day of Week FE		X
Constant	−4.351*** (0.069)	−7.808*** (2.094)
Observations	8132422	8132422
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

Table A5: Partisan Change in House, Car, and Stock Search Behavior (Searches)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	-0.116^{**} (0.055)	-0.114^{**} (0.055)	-0.121^{***} (0.035)	-0.117^{***} (0.035)
Lean Dem	0.090 (0.070)	0.129^{*} (0.069)	0.090^{*} (0.053)	0.044 (0.053)
2017 x Lean Dem	0.080 (0.079)	0.070 (0.078)	-0.020 (0.057)	-0.013 (0.057)
Ind	0.047 (0.060)	0.133^{**} (0.060)	0.170^{***} (0.042)	0.069 (0.042)
2017 x Ind	0.186^{**} (0.073)	0.177^{**} (0.073)	0.131^{***} (0.046)	0.135^{***} (0.046)
Lean Rep	0.038 (0.057)	0.133^{**} (0.057)	0.407^{***} (0.042)	0.278^{***} (0.043)
2017 x Lean Rep	0.117^{*} (0.070)	0.125^{*} (0.069)	0.088^{*} (0.049)	0.081^{*} (0.049)
Str Rep	0.106 (0.065)	0.188^{***} (0.066)	0.398^{***} (0.042)	0.274^{***} (0.043)
2017 x Str Rep	0.094 (0.068)	0.094 (0.067)	0.071 (0.047)	0.071 (0.047)
Age 30 - 44		0.121 (0.080)		-0.038 (0.052)
Age 45 - 64		0.335^{***} (0.075)		-0.103^{**} (0.047)
Age 65+		0.385^{***} (0.078)		-0.210^{***} (0.051)
Female		0.445^{***} (0.033)		-0.625^{***} (0.021)
County % Black		-0.296 (0.205)		0.024 (0.145)
County % Hisp		-0.338^{*} (0.190)		0.090 (0.134)
County % College		-0.521 (0.884)		-1.010^{*} (0.560)
County Log Med HH Inc		0.238^{*} (0.133)		0.012 (0.089)
County Log Pop Density		-0.020 (0.018)		-0.037^{***} (0.012)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	-4.808^{***} (0.047)	-7.871^{***} (1.404)	-4.283^{***} (0.032)	-3.606^{***} (0.934)
Observations	8129054	8129054	8125751	8125751
Unique Users	151995	151995	151995	151995

	Stock	
	(3a)	(3b)
2017	-0.155 (0.147)	-0.164 (0.148)
Lean Dem	-0.067 (0.207)	-0.099 (0.204)
2017 x Lean Dem	0.103 (0.195)	0.114 (0.194)
Ind	0.115 (0.173)	0.052 (0.169)
2017 x Ind	0.006 (0.175)	0.008 (0.174)
Lean Rep	0.200 (0.184)	0.130 (0.180)
2017 x Lean Rep	0.269 (0.197)	0.276 (0.196)
Str Rep	0.111 (0.192)	0.035 (0.187)
2017 x Str Rep	0.098 (0.202)	0.101 (0.201)
Age 30 - 44		-0.483^{***} (0.178)
Age 45 - 64		-0.458^{***} (0.159)
Age 65+		0.097 (0.170)
Female		-0.404^{***} (0.085)
County % Black		-0.395 (0.451)
County % Hisp		-0.416 (0.533)
County % College		-2.285 (1.736)
County Log Med HH Inc		0.394 (0.258)
County Log Pop Density		0.059 (0.042)
Month FE		X
State FE		X
Day of Week FE		X
Constant	-5.818^{***} (0.146)	-9.663^{***} (2.719)
Observations	8131650	8131650
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

A.2.3 Results by 2016 Vote

Table A6: Partisan Change in House, Car, and Stock Search Behavior (Users)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	0.055*** (0.021)	0.063*** (0.021)	0.004 (0.013)	0.003 (0.013)
Clinton Vote	−0.114*** (0.033)	−0.177*** (0.033)	−0.396*** (0.023)	−0.276*** (0.023)
2017 x Clinton Vote	−0.042 (0.036)	−0.045 (0.036)	−0.045* (0.025)	−0.041 (0.025)
Age 30 - 44		0.108 (0.076)		−0.017 (0.046)
Age 45 - 64		0.228*** (0.070)		−0.110*** (0.041)
Age 65+		0.203*** (0.075)		−0.243*** (0.045)
Female		0.313*** (0.028)		−0.608*** (0.019)
County % Black		−0.290 (0.192)		−0.170 (0.137)
County % Hisp		−0.022 (0.159)		−0.076 (0.104)
County % College		−0.129 (0.763)		−0.147 (0.460)
County Log Med HH Inc		0.198 (0.123)		−0.071 (0.078)
County Log Pop Density		0.0001 (0.017)		−0.018 (0.011)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	−3.271*** (0.019)	−5.761*** (1.278)	−2.789*** (0.013)	−1.502* (0.821)
Observations	5619856	5619856	5619856	5619856
Unique Users	78295	78295	78295	78295

	Stock			
	(3a)	(3b)		
2017	−0.025 (0.041)	−0.020 (0.041)		
Clinton Vote	−0.079 (0.068)	−0.017 (0.069)		
2017 x Clinton Vote	0.012 (0.067)	0.007 (0.067)		
Age 30 - 44		−0.414*** (0.136)		
Age 45 - 64		−0.222* (0.123)		
Age 65+		0.131 (0.131)		
Female		−0.477*** (0.062)		
County % Black		−0.017 (0.435)		
County % Hisp		−0.048 (0.381)		
County % College		−1.281 (1.448)		
County Log Med HH Inc		0.437* (0.246)		
County Log Pop Density		0.017 (0.037)		
Month FE		X		
State FE		X		
Day of Week FE		X		
Constant	−4.252*** (0.040)	−8.617*** (2.597)		
Observations	5619856	5619856		
Unique Users	78295	78295	78295	78295

Note: *p<0.1; **p<0.05; ***p<0.01

Table A7: Partisan Change in House, Car, and Stock Search Behavior (Searches)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	0.029 (0.028)	0.029 (0.029)	−0.010 (0.022)	−0.009 (0.022)
Clinton Vote	−0.076* (0.044)	−0.159*** (0.045)	−0.447*** (0.031)	−0.348*** (0.032)
2017 x Clinton Vote	−0.041 (0.054)	−0.048 (0.053)	−0.077** (0.037)	−0.071* (0.037)
Age 30 - 44		0.093 (0.095)		−0.036 (0.068)
Age 45 - 64		0.272*** (0.088)		−0.141** (0.061)
Age 65+		0.362*** (0.091)		−0.218*** (0.066)
Female		0.494*** (0.040)		−0.628*** (0.026)
County % Black		−0.393 (0.240)		−0.102 (0.177)
County % Hisp		−0.212 (0.232)		0.022 (0.159)
County % College		−0.566 (1.090)		−0.470 (0.677)
County Log Med HH Inc		0.255 (0.159)		−0.029 (0.109)
County Log Pop Density		−0.011 (0.021)		−0.034** (0.015)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	−4.712*** (0.027)	−7.774*** (1.671)	−3.861*** (0.018)	−3.001*** (1.146)
Observations	5617455	5617455	5614993	5614993
Unique Users	78295	78295	78295	78295

	Stock	
	(3a)	(3b)
2017	−0.041 (0.089)	−0.039 (0.089)
Clinton Vote	−0.125 (0.135)	−0.091 (0.132)
2017 x Clinton Vote	−0.113 (0.144)	−0.120 (0.146)
Age 30 - 44		−0.651*** (0.228)
Age 45 - 64		−0.485** (0.211)
Age 65+		0.105 (0.229)
Female		−0.370*** (0.108)
County % Black		−0.588 (0.523)
County % Hisp		−0.241 (0.697)
County % College		−2.798 (2.364)
County Log Med HH Inc		0.541* (0.323)
County Log Pop Density		0.055 (0.055)
Month FE		X
State FE		X
Day of Week FE		X
Constant	−5.666*** (0.079)	−11.281*** (3.317)
Observations	5619319	5619319
Unique Users	78295	78295

Note: *p<0.1; **p<0.05; ***p<0.01

A.2.4 Model Robustness to Specification

Logit Models Robustness checks Here, we present the model robustness checks described in the body of the paper. We ran 256 different models per regression, containing every possible combination of covariates. Table A8 shows that virtually all models yielded statistically significant negative coefficients for Strong Democrats - that is, Strong Dems were less likely to purchase houses and cars after the 2016 election than they had been before.

Table A8: Logit Robustness Checks

	House Users					Car Users				
	Str Dem	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**	**Str Dem**	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**
Mean Coefficient	−0.065	−0.015	0.051	0.01	0.034	−0.055	−0.08	−0.015	−0.018	−0.021
Max Coefficient	−0.059	−0.0089	0.058	0.016	0.04	−0.053	−0.078	−0.011	−0.016	−0.019
Min Coefficient	−0.07	−0.02	0.045	0.0042	0.029	−0.057	−0.082	−0.018	−0.021	−0.024
Mean p-val	0.066	0.72	0.09	0.74	0.26	0.031	0.007	0.46	0.35	0.27
Max p-val	0.09	0.83	0.13	0.89	0.34	0.037	0.009	0.57	0.43	0.32
Min p-val	0.045	0.62	0.052	0.6	0.19	0.026	0.0053	0.35	0.28	0.22
% p-val < 0.05	41.0	0	0	0	0	100	100	0	0	0
0.05 < % p-val < 0.1	59.0	0	52.7	0	0	0	0	0	0	0
	House Searches					Car Searches				
	Str Dem	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**	**Str Dem**	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**
Mean Coefficient	−0.11	−0.038	0.068	0.0057	−0.02	−0.12	−0.14	0.012	−0.035	−0.051
Max Coefficient	−0.11	−0.03	0.075	0.011	−0.015	−0.12	−0.13	0.016	−0.032	−0.049
Min Coefficient	−0.12	−0.045	0.061	0.001	−0.023	−0.12	−0.14	0.0086	−0.038	−0.053
Mean p-val	0.038	0.51	0.16	0.89	0.63	0.00067	0.0022	0.68	0.3	0.097
Max p-val	0.046	0.6	0.21	0.98	0.7	0.00082	0.0034	0.77	0.34	0.11
Min p-val	0.03	0.42	0.12	0.8	0.56	0.00055	0.0014	0.58	0.27	0.085
% p-val < 0.05	100	0	0	0	0	100	100	0	0	0
0.05 < % p-val< 0.1	0	0	0	0	0	0	0	0	0	67.0

OLS Models Here, we use an OLS model to ensure that the results presented in the body of the paper are robust to that particular model specification. We find that they are. Furthermore, in Table A12 we repeat the analysis from Table A8 on the OLS regressions, and find that the OLS models are similarly robust to the inclusion or exclusion of a variety of covariate combinations.

Table A9: Partisanship and Purchase Searches (OLS)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	-0.001^{**} (0.0003)	-0.001^{**} (0.0003)	-0.001^{**} (0.0004)	-0.001^{**} (0.0004)
Lean Dem	-2.076^{*} (1.160)	-2.021^{*} (1.158)	0.792 (1.181)	0.695 (1.173)
2017 x Lean Dem	0.001^{*} (0.001)	0.001^{*} (0.001)	-0.0004 (0.001)	-0.0003 (0.001)
Ind	-3.107^{***} (1.005)	-3.031^{***} (1.002)	-0.846 (1.046)	-0.868 (1.041)
2017 x Ind	0.002^{***} (0.0005)	0.002^{***} (0.0005)	0.0004 (0.001)	0.0004 (0.001)
Lean Rep	-1.610 (1.054)	-1.684 (1.055)	-0.730 (1.113)	-0.551 (1.105)
2017 x Lean Rep	0.001 (0.001)	0.001 (0.001)	0.0004 (0.001)	0.0003 (0.001)
Str Rep	-1.761^{*} (0.991)	-1.806^{*} (0.989)	-0.630 (1.123)	-0.607 (1.116)
2017 x Str Rep	0.001^{*} (0.0005)	0.001^{*} (0.0005)	0.0003 (0.001)	0.0003 (0.001)
Age 30 - 44		0.001^{**} (0.001)		0.0003 (0.001)
Age 45 - 64		0.003^{***} (0.001)		-0.001 (0.0005)
Age 65+		0.003^{***} (0.001)		-0.002^{***} (0.001)
Female		0.002^{***} (0.0003)		-0.010^{***} (0.0002)
County % Black		-0.002 (0.002)		-0.0001 (0.002)
County % Hisp		-0.001 (0.001)		0.001 (0.001)
County % College		0.004 (0.007)		-0.003 (0.006)
County Log Med HH Inc		0.001 (0.001)		-0.001 (0.001)
County Log Pop Density		-0.0002 (0.0002)		-0.0004^{***} (0.0002)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	1.582^{**} (0.695)	1.462^{**} (0.697)	1.754^{**} (0.760)	1.743^{**} (0.761)
Observations	8129054	8129054	8125751	8125751
Unique Users	151995	151995	151995	151995

	Stock	
	(3a)	(3b)
2017	-0.0001 (0.0003)	-0.0001 (0.0003)
Lean Dem	-0.270 (0.947)	-0.334 (0.948)
2017 x Lean Dem	0.0001 (0.0005)	0.0002 (0.0005)
Ind	0.669 (0.886)	0.650 (0.886)
2017 x Ind	-0.0003 (0.0004)	-0.0003 (0.0004)
Lean Rep	-1.197 (1.069)	-1.245 (1.069)
2017 x Lean Rep	0.001 (0.001)	0.001 (0.001)
Str Rep	-0.433 (0.982)	-0.511 (0.981)
2017 x Str Rep	0.0002 (0.0005)	0.0003 (0.0005)
Age 30 - 44		-0.001^{*} (0.0005)
Age 45 - 64		-0.0002 (0.0005)
Age 65+		0.002^{***} (0.001)
Female		-0.002^{***} (0.0002)
County % Black		-0.002 (0.002)
County % Hisp		-0.0002 (0.002)
County % College		-0.005 (0.006)
County Log Med HH Inc		0.001 (0.001)
County Log Pop Density		0.0002 (0.0001)
Month FE		X
State FE		X
Day of Week FE		X
Constant	0.163 (0.614)	0.198 (0.617)
Observations	8131650	8131650
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

Table A10: Partisanship and Purchase Users (OLS)

	House		Car	
	(1a)	(1b)	(2a)	(2b)
2017	−0.002* (0.001)	−0.002* (0.001)	−0.002** (0.001)	−0.002** (0.001)
Lean Dem	−2.829 (3.445)	−2.638 (3.432)	2.350 (3.021)	1.978 (2.986)
2017 x Lean Dem	0.001 (0.002)	0.001 (0.002)	−0.001 (0.001)	−0.001 (0.001)
Ind	−7.377** (2.942)	−7.171** (2.933)	−2.637 (2.582)	−2.780 (2.561)
2017 x Ind	0.004** (0.001)	0.004** (0.001)	0.001 (0.001)	0.001 (0.001)
Lean Rep	−4.346 (2.904)	−4.505 (2.900)	−2.238 (2.815)	−1.683 (2.789)
2017 x Lean Rep	0.002 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
Str Rep	−6.149** (2.995)	−6.155** (2.988)	−1.767 (2.821)	−1.570 (2.797)
2017 x Str Rep	0.003** (0.001)	0.003** (0.001)	0.001 (0.001)	0.001 (0.001)
Age 30 - 44		0.004*** (0.002)		0.00002 (0.002)
Age 45 - 64		0.009*** (0.002)		−0.003** (0.002)
Age 65+		0.007*** (0.002)		−0.010*** (0.002)
Female		0.009*** (0.001)		−0.026*** (0.001)
County % Black		−0.006 (0.005)		−0.003 (0.005)
County % Hisp		−0.003 (0.004)		−0.0003 (0.004)
County % College		−0.002 (0.021)		−0.013 (0.017)
County Log Med HH Inc		0.006* (0.003)		−0.002 (0.003)
County Log Pop Density		−0.0003 (0.0005)		−0.001** (0.0004)
Month FE		X		X
Day of Week FE		X		X
State FE		X		X
Constant	4.064** (2.063)	3.407* (2.067)	4.038** (1.883)	3.872** (1.874)
Observations	8132422	8132422	8132422	8132422
Unique Users	151995	151995	151995	151995

	Stock	
	(3a)	(3b)
2017	−0.001 (0.001)	−0.001 (0.001)
Lean Dem	−2.748 (2.317)	−2.905 (2.309)
2017 x Lean Dem	0.001 (0.001)	0.001 (0.001)
Ind	0.665 (2.091)	0.593 (2.087)
2017 x Ind	−0.0003 (0.001)	−0.0003 (0.001)
Lean Rep	−5.832** (2.322)	−5.924** (2.319)
2017 x Lean Rep	0.003** (0.001)	0.003** (0.001)
Str Rep	−1.491 (2.256)	−1.637 (2.251)
2017 x Str Rep	0.001 (0.001)	0.001 (0.001)
Age 30 - 44		−0.003** (0.001)
Age 45 - 64		−0.002 (0.001)
Age 65+		0.003** (0.001)
Female		−0.006*** (0.001)
County % Black		−0.001 (0.004)
County % Hisp		−0.002 (0.004)
County % College		−0.008 (0.015)
County Log Med HH Inc		0.005* (0.003)
County Log Pop Density		0.0003 (0.0004)
Month FE		X
State FE		X
Day of Week FE		X
Constant	1.876 (1.495)	1.917 (1.500)
Observations	8132422	8132422
Unique Users	151995	151995

Note: *p<0.1; **p<0.05; ***p<0.01

Table A11: Registrations by Partisanship (OLS)

	Dependent variable:	
	(1)	(2)
2017	-0.0001^{***} (0.00001)	0.00005^{***} (0.00001)
Zip 2008 Dem Vote	-0.002^{***} (0.0001)	-0.001^{***} (0.0001)
2017 x Zip 2008 Dem Vote	0.0001^{***} (0.00001)	-0.00005^{***} (0.00001)
Zip Log Pop Density		-0.0001^{***} (0.00001)
Zip % College		-0.00003 (0.0001)
Zip Log Per Cap Inc		0.0003^{***} (0.00005)
Zip % Black		0.0003^{***} (0.0001)
Zip % Hisp		0.0002^{**} (0.0001)
Month FE		X
Day of Week FE		X
Constant	0.002^{***} (0.00004)	-0.001^{**} (0.0005)

Note: *p<0.1; **p<0.05; ***p<0.01

Table A12: OLS Robustness Checks

	House Users					Car Users				
	Str Dem	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**	**Str Dem**	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**
Mean Coefficient	−0.0019	−0.00049	0.0018	0.00034	0.0012	−0.002	−0.0031	−0.00065	−0.00096	−0.0011
Max Coefficient	−0.0017	−0.0003	0.002	0.00053	0.0014	−0.0019	−0.003	−0.00049	−0.00083	−0.001
Min Coefficient	−0.002	−0.00068	0.0016	0.00014	0.001	−0.0021	−0.0032	−0.00083	−0.0011	−0.0012
Mean p-val	0.072	0.72	0.09	0.74	0.27	0.032	0.0081	0.46	0.35	0.28
Max p-val	0.1	0.83	0.13	0.89	0.34	0.039	0.011	0.58	0.42	0.32
Min p-val	0.046	0.62	0.055	0.6	0.19	0.025	0.0057	0.34	0.3	0.23
% p-val < 0.05	26	0	0	0	0	100	100	0	0	0
0.05 < % p-val< 0.1	71	0	52	0	0	0	0	0	0	0

	House Searches					Car Searches				
	Str Dem	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**	**Str Dem**	**Ln Dem**	**Ind**	**Ln Rep**	**Str Rep**
Mean Coefficient	−0.00075	0.00027	0.00078	0.000064	0.00014	−0.00087	−0.0012	−0.00045	−0.00054	−0.00056
Max Coefficient	−0.00069	0.00034	0.00086	0.00012	0.0002	−0.00085	−0.0012	−0.00041	−0.00049	−0.00053
Min Coefficient	−0.0008	0.0002	0.00071	0.0000054	0.000077	−0.0009	−0.0013	−0.0005	−0.00058	−0.00059
Mean p-val	0.032	0.56	0.031	0.87	0.7	0.021	0.0052	0.21	0.18	0.17
Max p-val	0.046	0.66	0.049	0.99	0.83	0.025	0.0063	0.26	0.22	0.2
Min p-val	0.02	0.47	0.017	0.76	0.58	0.017	0.0041	0.16	0.15	0.14
% p-val < 0.05	100	0	100	0	0	100	100	0	0	0
0.05 < % p-val< 0.1	0	0	0	0	0	0	0	0	0	0