# Polarized Expectations, Polarized Consumption*

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**Abstract**

This paper argues that political polarization plays a key role in shaping the economic expectations and consumption behavior of households. Using a combination of survey and consumption data of U.S. households, we document five facts. First, household beliefs are well-described by a single factor, which behaves like sentiment. Second, at any given time there is wide dispersion in household sentiment, largely driven by political affiliation. Third, household sentiment is highly persistent, with one exception: following elections when the White House switches parties, optimistic households become pessimistic and vice versa. Fourth, the magnitude of this switching behavior has increased over time. Fifth, consumption responds differentially along party lines following changes in the White House. We show that standard theories of expectation formation struggle to simultaneously rationalize these facts.

**Keywords:** expectations, voting, consumption

**JEL Classification:** E7, D72, D83

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# 1 Introduction

Political polarization is rising.[1] Although this fact has been discussed at length in the political sphere, this paper empirically explores how the economic beliefs and actions of households interact with political polarization.

We show that political polarization is an extremely strong driver of both U.S. household beliefs and actions. Our results can be organized around the following five facts. First, household beliefs are well-described by a single factor in a component analysis. This component behaves like traditional concepts of "sentiment," and households fall on a spectrum of optimism to pessimism at any given point in time. A household's sentiment describes a shockingly large fraction of their answers to a wide range of forward- and backward-looking questions, as well as their forecasts of both aggregate and personal economic conditions. Second, at any given time there is wide dispersion across households in optimism and pessimism regarding economic outcomes. This dispersion appears to be largely driven by political affiliation: Democratic households tend to be optimistic at the same time as Republican households are pessimistic, and vice versa. Third, household sentiment is highly persistent during almost all periods. However, there are large breakdowns of sentiment persistence following presidential elections when the White House switches parties (but not during other presidential elections, or midterm elections). At these times, optimistic households become pessimistic and vice versa. Fourth, the magnitude of this switching behavior has increased over time. Fifth, consumption responds differentially along party lines following changes in the White House: households affiliated with the winning party strongly and immediately increase consumption.

In Section 2, we utilize survey data of U.S. consumers to show that political affiliation affects macroeconomic beliefs. We begin by showing that households' beliefs and forecasts about macroeconomic conditions as well as their own financial situation are almost entirely determined by a single component from a factor analysis. We argue that this component is a measure of economic sentiment. There is widespread

[1]Among others, Pew Research Center (2014) has documented a long-term increase in negative views of the opposing party or ideology within the U.S.

dispersion of sentiment across individuals at any point, but for a given individual we show that sentiment is highly persistent. Since 1980, the only exceptions are following presidential elections when the White House changed parties. During these periods, previously optimistic individuals are more likely to become pessimistic, and similarly pessimistic individuals are more likely to become optimistic. Moreover, this decline in persistence following elections has grown over time, with the most striking change in persistence coming after the 2016 and 2020 presidential elections.

The typical persistence in sentiment followed by strong switching behavior when the White House switches party also holds for any given economic expectation. For instance, people who think unemployment will fall tend to feel the same way when asked again in the future. A striking exception is following presidential elections when the White House switches party, this pattern reverses. Individuals who believed unemployment would fall before the election become more likely to say that unemployment will rise following the election. We observe an identical switch in beliefs for individuals who believed unemployment would rise before the election; after the election, these individuals believe that unemployment will fall. Similar patterns hold for other macroeconomic beliefs.

There is a strong theoretical link between beliefs and economic actions, but how strong this connection is in reality is an open question. Section 3 demonstrates empirically that political polarization does lead to differential consumption responses. To do this, we conduct event studies around the 2016 and 2020 presidential elections. For 2016, we combine disaggregated consumption data with voting data from 47 states and the District of Columbia at the zip code level to study consumption responses in the weeks surrounding the 2016 election. Our results show that areas with a higher Republican vote share exhibited substantially higher consumption in the weeks following the 2016 election of Donald Trump (R). We next utilize high-frequency, individual-level survey responses and actual consumption measures from Democratic and Republican households during the days before and after the 2020 election. The results corroborate the evidence from the 2016 election: relative to Democratic households, Republican households became more pessimistic about unemployment, expected higher inflation, and became less enthusiastic about purchasing consumption goods following the 2020 election of Joe Biden (D). Finally, we show that actual consumption of Republican households relative to Democratic households fell immediately following the 2020 election. The 2016 and 2020 election case studies highlight that not only do expectations change when the White House switches party, but also actual consumption follows suit. Moreover, the response is economically meaningful: our results show that the consumption of individuals of the winning party is roughly 5% higher than that of households in the losing party immediately following the outcome of the election. Finally, these effects persist in the weeks following the election.

After empirically documenting our five facts about polarized expectations and consumption, Section 4 discusses their implications for theoretical models of expectation formation. We first show that, unsurprisingly, our results are not consistent with full-information rational expectations (FIRE), the canonical model of expectations formation in macroeconomics. Next, we discuss a range of commonly used belief formation models which depart in various ways from FIRE (e.g., robustness, rational inattention, learning, diagnostic expectations). All of these models can partially explain some of the facts. However, we show that none of these models can fully explain all of these facts simultaneously. Therefore, rationalizing the facts presented in this paper requires either combining these approaches or developing new theoretical tools. Section 5 concludes and discusses avenues for future work.

This paper contributes to three strands of literature: (i) survey-based empirical investigations of economic expectations, (ii) empirical analyses of how the decisions of consumers are affected by their economic beliefs, and (iii) the rise of polarization. First, there is a growing literature that uses survey data to better understand the economic beliefs of individuals. Coibion et al. (2018) provide a summary of recent papers that demonstrate deviations from FIRE. For instance, Malmendier and Nagel (2016) and Kuchler and Zafar (2015) propose that individuals overweight their own personal experiences in developing their expectations. Additionally, Bryan and Venkatu (2001) find that women tend to have higher inflation expectations even after controlling for demographic factors. Bruine de Bruin et al. (2012) find that individuals with lower financial literacy have higher inflation expectations. The literature on heterogeneity in survey-based beliefs has recently incorporated political affiliations as an important factor in economic expectations. For example, Mian et al. (2018) and Coibion et al. (2020) find that households are more optimistic about the economy when their preferred party has political power. Our results support their findings, and further show that individuals' economic expectations are largely stable over time but change dramatically after the election where the White House switches parties.

Second, there is limited work in macroeconomics on how consumer beliefs are tied to actions. Theoretical models in macroeconomics suggest economic expectations (e.g., inflation and income expectations) should affect today's actions (e.g., consumption and savings decisions). However, there is little empirical work establishing this relationship. Furthermore, this empirical work has yielded mixed results. For example, survey-based confidence indices contain significant, but very small, predictive power for future aggregate consumer expenditure (e.g., Carroll et al. 1994, Bram and Ludvigson 1998, and Ludvigson 2004). Additionally, inflation expectations have been shown to affect household spending decisions, but the direction of the relationship has varied across environments and individuals studied (e.g., Bachmann et al. 2015, D'Acunto et al. 2016, and D'Acunto et al. 2018). In a political context (and empirically most similar to this paper) Benhabib and Spiegel (2019), Mian et al. (2018), and Gerber and Huber (2009) studying the U.S. and Gillitzer and Prasad (2018) studying Australia show that economic sentiments can change in the wake of elections. However, they have different results when it comes to the consumption response to a positive political shock. Mian et al. (2018) find no effects on household spending, whereas Benhabib and Spiegel (2019), Gerber and Huber (2009), and Gillitzer and Prasad (2018) find a positive response in consumption or planned consumption. Our results support the view that households' macroeconomic expectations do play a role in actions; namely, their actual consumption decisions.

In contrast to the macroeconomics literature, a recent finance literature has found strong evidence that political affiliation plays an important role in both the expectations and the actions of individuals and firms. Bonaparte et al. (2017) and Meeuwis et al. (2018) find that political beliefs influence individual portfolio choices. For example, following the 2016 presidential election, Republicans increased their equity share and market betas of their portfolios relative to Democrats. Cassidy and Vorsatz (2021) find this effect is even larger for institutional investors. Furthermore, bankers and credit rating analysts affiliated with the party in control of the White House have been shown to give cheaper loans and higher ratings, respectively (Dagostino et al. 2020 and Kempf and Tsoutsoura 2021). Similarly, managers have been shown to be more optimistic about earnings forecasts when their preferred party holds the presidency (Stuart et al. 2021) and accordingly invest more (Rice 2020). Our results on partisan bias in household beliefs and consumption are complementary to the work on partisan bias in financial settings.

Third, there has been much discussion over the secular rise in polarization of the political discourse. Bartels (2002) demonstrates that party identification affects voter's interpretation of objective events. In addition to voters, this polarization exists amongst lawmakers. Andris et al. (2015) document a steady decline in co-operation and increase in partisanship amongst U.S. legislators in the post-war era. We add to this literature by demonstrating that both economic beliefs and actual consumption decisions are sensitive to the rise in political polarization.

# 2 Expectations and Polarization

This section uses survey data to provide empirical evidence that political affiliation plays an important and increasingly influential role in how individuals form their economic beliefs.

## 2.1 Data

We use the Michigan Survey of Consumers (MSC) to measure consumer beliefs. The MSC is a rotating panel survey of approximately 500 consumers per month. The survey began in 1978 and is still running today, which provides us with a long time series dimension to utilize. Historically, respondents were surveyed at most twice, six months apart. In recent years, some respondents are surveyed a third time. The MSC asks a variety of questions about consumer beliefs. Some of these questions are backwards-looking, while others are forwards-looking; some are about personal conditions, while others are about aggregate variables. For instance, there are questions that solicit beliefs about current economic policy, expectations about future personal financial conditions, perceptions about past personal financial conditions, and inflation expectations.

The questions about beliefs in the MSC typically solicit a categorical response from the consumer. The consumer frequently is given a range of possible responses, which fall broadly into an "optimistic" response, a "stay the same/neutral" response, and a "pessimistic" response. For instance, the MSC obtains beliefs regarding government policy by asking the question "As to the economic policy of the government – I mean steps taken to fight inflation or unemployment – would you say the government is doing a good job, only fair, or a poor job?" Similarly, for the question on 12 month unemployment expectations relative to today, the consumer chooses if they believe unemployment will "rise," "stay about the same," or "fall." While many of the MSC questions follow the same categorical pattern above, there are a handful of questions which ask for quantitative responses. In particular, households are asked to report their price expectations and personal income expectations in terms of percentage point changes.

In addition to questions about perceptions and expectations, the MSC collects demographic information such as income and education from the survey respondents. Furthermore, the MSC has infrequently (albeit more consistently in recent years) solicited respondents' political leaning as well as the strength of that affiliation. Most recently the political affiliation question has been framed as "Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent or what?" If the respondent says "Democrat" or "Republican", they are then asked if their affiliation is strong or not so strong, whereas if the respondent says "Independent" or something else, they are then asked if they think of themselves as being closer to the Republican or Democratic party.

## 2.2 Beliefs and Political Shocks

To explore the behavior of expectations over time and for an array of questions, we first conduct a range of components analyses using a broad set of questions in the MSC. We conduct a multiple correspondence analysis (MCA), the categorical analog to a principal components analysis, with questions that are forward-looking as well as backward-looking, and questions that are related to personal as well as aggregate conditions. We also include quantitative questions regarding price and income expectations; in order to include these in the MCA, we bin the responses into quintiles.

Table 1: MCA Loadings, First Component

| | Responses | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Unemployment Up/Down (Next Year) | -1.50 | | 0.38 | | 1.49 |
| Prices Up/Down (Next Year) | -1.06 | -0.36 | 0.12 | 0.62 | 0.63 |
| Interest Rates Up/Down (Next Year) | -0.17 | | 0.25 | | 0.05 |
| Economy Better/Worse (Last Year) | 1.17 | | 0.09 | | -1.17 |
| Economy Better/Worse (Next Year) | 1.34 | | -0.01 | | -2.03 |
| Economy Good/Bad (Next Year) | 1.31 | 0.73 | 0.10 | -0.74 | -1.47 |
| Economy Good/Bad (Next 5 Years) | 1.39 | 1.00 | 0.17 | -0.77 | -1.41 |
| Government Policy Good/Bad | 1.48 | | 0.20 | | -1.47 |
| Family Income Up/Down (Next Year) | 0.84 | 0.61 | 0.16 | -0.65 | -1.51 |
| Personal Finances Better/Worse (Last Year) | 0.84 | | -0.17 | | -1.14 |
| Personal Finances Better/Worse (Next Year) | 0.98 | | -0.22 | | -2.16 |
| Real Income Up/Down (Next Year) | 1.33 | | 0.35 | | -1.18 |

Notes: each row corresponds to a question included in the MCA. Column (1) reports the MCA loadings for responses associated with "up", "better", or "good"; column (5) reports the loadings for responses associated with "down", "worse", or "bad"; columns (2) through (4) are intermediate or neutral responses. The first component explains 81% of the response inertia.

Table 1 reports the set of questions included in our baseline specification, and the loadings associated with the first factor of the MCA. The first component alone explains over 81% of the inertia in the responses, while the second component explains only an additional 6%.

What is economic interpretation of the first component? Although the MCA factors (like those from any components analysis) are purely statistical in nature, examining the estimated loadings can shed light on the economic drivers of these factors. Based on the estimated loadings reported in Table 1, we argue that the first component appears to be a measure of sentiment. Our argument is based on the following observations. Note that the loadings are monotonically increasing as one moves from the pessimistic responses to the more optimistic responses for all questions. For example, take the question on unemployment expectations over the next year. Respondents can answer that unemployment will go up (pessimistic), stay the same (neutral), or go down (optimistic). The pessimistic response that unemployment will increase has a coefficient of -1.50. The neutral response that unemployment will stay the same has a loading of 0.38. Lastly, the optimistic response of unemployment falling enters the first component with a loading of 1.49. This pattern is repeated for nearly every question (including inflation, to the extent that consumers view rising prices as a negative outcome). The only slight exception is the question regarding interest rates. However, while the other responses can be unambiguously mapped to optimistic, neutral, and pessimistic responses, the change in interest rates is ambiguous. Therefore, we interpret the first component as a general measure of the sentiment of the consumer (see Kamdar (2019) for additional component analyses and robustness exercises).

The fact that the first component in the MCA explains the majority of the variation in beliefs is robust to using different sets of questions in the MCA, as shown in Table 2. That is, even if we only include aggregate questions (columns 2 to 4), or only include questions about personal conditions (columns 5 and 6), or only use backwards looking questions (column 7), the first component explains the majority of the variation in beliefs. Furthermore, the fitted first components are highly correlated across specifications.

**Fact 1: Consumer beliefs follow a single factor (sentiment) model**

The results from Tables 1 and 2 document our first fact: household beliefs are well-described by a single factor in a component analysis, and this important first

Table 2: MCA Fraction Explained

| | Baseline | | Aggregate | | Personal | | Backward |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| % Explained (1) | 80.97 | 87.13 | 94.24 | 75.96 | 80.68 | 77.20 | 85.07 |
| % Explained (2) | 6.29 | 3.52 | 2.76 | 4.52 | 14.21 | 14.36 | 14.93 |
| Baseline Corr. | | 0.923 | 0.916 | 0.916 | 0.657 | 0.695 | 0.673 |
| Observations | 207,327 | 233,678 | 254,685 | 129,906 | 260,460 | 130,321 | 297,967 |
| Start Date | 1978 | 1978 | 1978 | 1990 | 1978 | 1990 | 1978 |

Notes: column (1) is the baseline MCA for which the coordinates were described in Table 1; column (2) includes aggregate questions only; (3) does not include price and interest rate questions; (4) includes price and interest rate as well as 5-year price/gas price questions; (5) uses personal questions only; (6) adds home price expectations; (7) includes backward-looking questions only. Columns (4) and (6) are based on data from 1990 due to gas and home price questions. The baseline correlation is the correlation of fitted first components of the baseline and the given column.

component appears to be a measure of sentiment. A households sentiment describes a shockingly large fraction of their answers to a wide range of forward- and backward-looking questions, as well as their forecasts of both aggregate and personal economic conditions. In Appendix Table A1, we show that unlike households, professional forecasters have a higher dimension factor structure to their beliefs.

Next, we use the baseline MCA to construct the fitted first component (a measure economic sentiment), $f_{i,t}$, for each individual across time. From the results in Table 1, we see that consumers who respond positively to any of the questions end up with a higher level of the first component. We now use this sentiment measure to study how beliefs react over time to political shocks.

Figure 1 shows how the distribution of sentiment across individuals has evolved over time. The solid line is the median economic sentiment across individuals in a given month. As expected, this measure is related to the business cycle, falling during recessions and increasing during booms. However, the dotted lines (plotting the 90-10 percent distribution) show that there is substantial variation in sentiment across individuals at any given time, and even during large booms and busts. For instance, during the 2009 recession, more than 10% of individuals exhibited positive economic

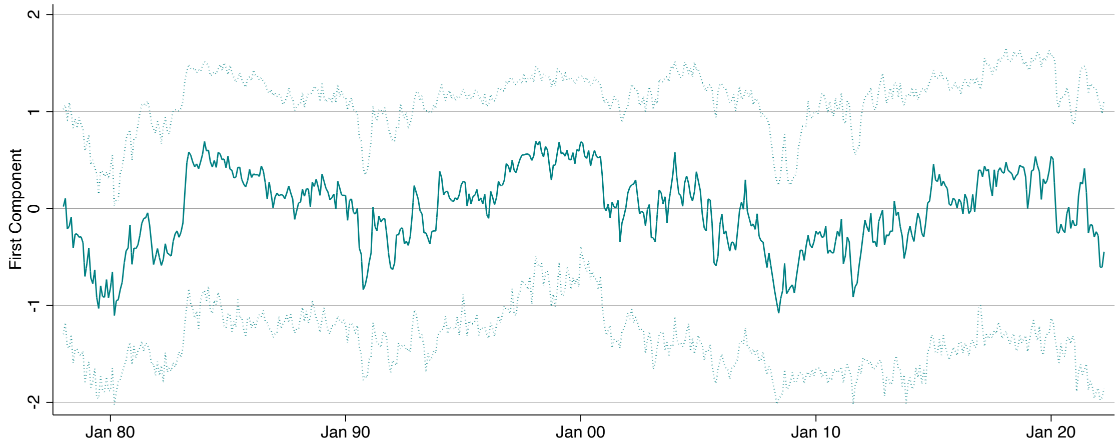


Figure 1: Sentiment Distribution Across Time

Notes: time series of the first component $f_{i,t}$ from an MCA analysis. The solid line is the median value of sentiment, while the dotted lines are the 90-10 percent distribution.

sentiment. To get a sense of the magnitude of the heterogeneity in sentiment at any given point in time, notice that the difference between the 90-10 percentiles is larger than movements in median sentiment around booms and busts. In Appendix Figure A1, we show that there is substantially less heterogeneity in beliefs in the first component of professional forecasters' beliefs, and movements in the median around booms and busts are much larger than the difference in the 90-10 percentiles at any time.

What could account for the large heterogeneity in consumer sentiment at any given point in time? Using the MSC question on political affiliation (available with sufficient frequency since 2006), we show that a respondent's political affiliation is strongly related to their economic beliefs and overall sentiment. Figure 2 plots the estimated coefficients of a month-by-month regression of sentiment on political affiliation dummy variables. As is apparent in the figure, Republican households frequently are optimistic at precisely the times in which Democratic households are pessimistic (and vice versa) There are times in which the sentiment of Republican households and Democratic households move in the same direction (such as during

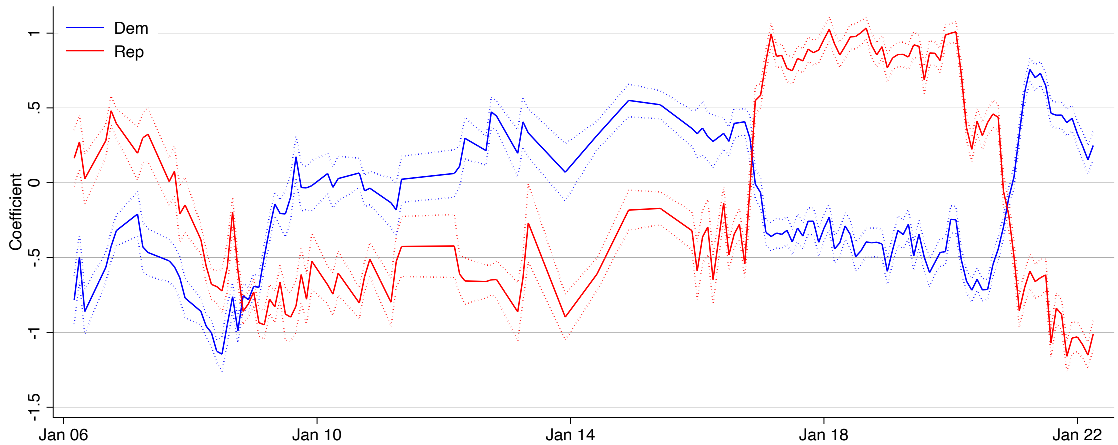


Figure 2: Sentiment by Political Affiliation

Notes: plots the estimated coefficients of a month-by-month regression of $f_{i,t}$ on political affiliation dummy variables, where $f_{i,t}$ is the first component from the baseline MCA. Dotted lines represent 90% confidence intervals. An individual is counted as a Republican (Democratic) voter if they self-report they are Republican (Democratic) or are independent but closer to the Republican (Democratic) party.

the Great Recession, when both Democratic and Republican households were pessimistic). However, virtually without exception, Republican households are more positive than Democratic households during periods in which a Republican occupies the White House, while the opposite is true when a Democratic president is in power.

Sentiment tends to switch from pessimistic (optimistic) to optimistic (pessimistic) when the occupant of the White House switches towards (away from) an individual's preferred party. Democratic households were relatively less optimistic when Bush Jr. (R) was in the White House, became more optimistic when Obama (D) was elected in 2008, became more pessimistic when Trump (R) was elected in 2016, and became more optimistic when Biden (D) was elected in 2020. Republicans, on the other hand, were relatively optimistic with Bush Jr. more pessimistic when Obama was elected, more optimistic when Trump was elected, and more pessimistic when Biden was elected. Not only do we find this party-based switching behavior in our measure of economic sentiment, but also in individual questions (see Appendix Figure A2).

Furthermore, political affiliation explains a large fraction of the variation in economic sentiment. Appendix Figure A3 shows that regressing individual sentiment on simple dummy variables of Republican and Democratic households results an R-squared of 0.3 in recent months.

Table 3: MCA by Subgroups

| | Baseline | By Income | | By Education | | By Pol. Affil. | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| % Explained (1) | 80.97 | 79.16 | 79.74 | 81.64 | 79.25 | 76.09 | 87.59 |
| % Explained (2) | 6.29 | 7.78 | 6.34 | 6.09 | 6.92 | 6.85 | 4.05 |
| Baseline Corr. | | 0.999 | 0.999 | 1.000 | 1.000 | 0.998 | 0.999 |
| Observations | 207,327 | 24,182 | 49,764 | 123,304 | 84,023 | 21,679 | 20,287 |
| Start Date | 1978 | 1979 | 1979 | 1978 | 1978 | 2006 | 2006 |

Notes: the MCA results in columns (2) through (6) are based on MCAs that use the same questions as the baseline but are conducted using a subset of individuals. Column (2) uses only consumers in the bottom quintile income; (3) the top quintile income; (4) without a college education; (5) with a college education; (6) Democratic households; (7) Republican households.

Moreover, conditional on sentiment, both Republican and Democratic households have similar beliefs. Table 3 conducts the baseline MCA on different subgroups based on political affiliation (as well as by income and by education). First, notice that regardless of the subgroup used, the first component explains the majority of the variation in beliefs. Second, the fitted first component is extremely correlated with our baseline estimate. This suggests that conditional on sentiment, individuals have similar beliefs regardless of their demographic group. It is not that Republican and Democratic households have different economic models of the world, but rather at any given time they have a different sentiment. Conditional on sentiment, the mapping of sentiment to beliefs is similar for individuals in both parties.

**Fact 2: Large sentiment heterogeneity explained by political affiliation**

We have now demonstrated our second fact: at any given time there is wide dispersion across households in optimism and pessimism, and the dispersion is strongly correlated with political affiliation. Put another way, Democratic households tend to be optimistic at the same time as Republican households are pessimistic, and vice versa. While the sentiment of Republican and Democratic households may substantially differ at a given point in time, conditional on sentiment, individuals of both parties have similar beliefs.

Next, we explore how sentiment varies over time for consumers by estimating the regression,

$$f_{i,t} = \alpha_t + \beta_t f_{i,t-6} + \varepsilon_{i,t}. \tag{1}$$

The variable $f_{i,t}$ is the first component from the MCA for an individual $i$ at month $t$. We regress this on the individual's previous response 6 months prior, $f_{i,t-6}$. Hence, the coefficient $\beta_t$ in Eq. (1) measures how persistent is an individuals' sentiment measure over time. We estimate Eq. (1) period by period, pooling over individuals.

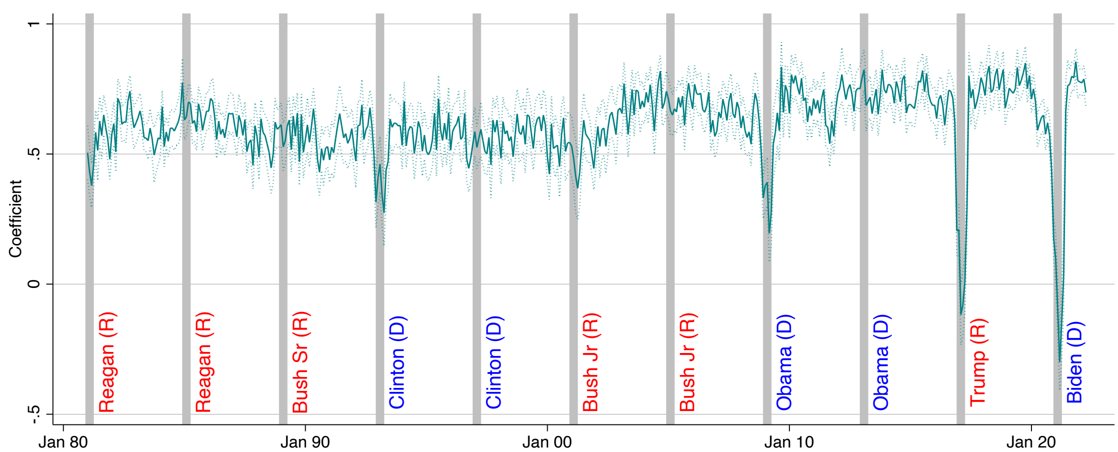


Figure 3: Sentiment Autocorrelation

Notes: coefficient from period-by-period regressions pooled across respondents $f_{i,t} = \alpha_t + \beta_t f_{i,t-6} + \varepsilon_{i,t}$. $f_{i,t}$ is the first component from an MCA analysis. Shaded regions correspond to six-month periods following presidential elections. Dotted lines represent 90% confidence intervals.

Figure 3 plots the estimated coefficients $\hat{\beta}_t$. The shaded regions correspond to the six month period following the outcome of presidential elections. In these periods, $f_{i,t}$ is determined by responses given after the outcome of the election, while $f_{i,t-6}$ is determined by responses from before the election. Hence, in the shaded regions Eq.

(1) regresses responses following an election on the same individual's responses that were given before the election.

In general, sentiment is highly persistent: individuals who were optimistic 6 months prior tend to be optimistic today; similarly, pessimistic individuals remain pessimistic. The only exception to this is during certain presidential elections. Moreover, these elections where the persistence falls are exactly the elections where the White House changed party: 1980, when Reagan (R) replaced Carter (D); 1992, when Clinton (D) replaced Bush Sr. (R); 2000, when Bush Jr. (R) replaced Clinton; 2008, when Obama (D) replaced Bush Jr., 2016, when Trump (R) replaced Obama; and 2020, when Biden (D) replaced Trump (R). Notice that the switching behavior of beliefs does not occur when the same party stays in the White House (for example, the 1988 election where the White House when from Reagan (R) to Bush Sr. (R) or the 2012 re-election of Obama (D)).

**Fact 3: Sentiment persistence falls when the White House changes party**

We have now documented our third fact: household sentiment is highly persistent during almost all periods; however, there are large breakdowns of sentiment persistence following presidential elections when the White House switches parties (but not during other presidential elections, or midterm elections).[2]

**Fact 4: Sentiment-switching has increased over time**

Furthermore, these results also demonstrate our fourth fact: the magnitude of the fall in persistence has increased over time. The drop in sentiment persistence in the 2016 and 2020 elections are the most striking, with an estimated negative coefficient.

Our results regarding the persistence of household sentiment and the breakdowns following changes in the White House are extremely robust. We report some of these

[2] Appendix Figures A4 and A5 show the same pattern for three individual questions in the MSC. We estimate the probability that individuals answer optimistically or pessimistically conditional on the response that they gave when they were surveyed six months prior using a multinomial logit model around the 2016 and 2020 elections. The results show that usually beliefs tend to be unchanged. However, following the elections where the White House switches party, beliefs are most likely to switch.

robustness exercises in the Appendix. Appendix Figure A6 Panel A repeats the sentiment autocorrelation exercise, but estimates the first component of an MCA using only questions about aggregate outcomes. Similarly, Panel B is based on an MCA estimated only from questions regarding beliefs about personal financial conditions. When using only beliefs about aggregate outcomes, the results are highly similar to Figure 3. But even when focusing on sentiment measures based on entirely on beliefs regarding personal financial conditions, the qualitative results are the same. Optimistic individuals typically remain optimistic over short periods; the only exception is following presidential elections when the White House switches parties. While the magnitude of this switching behavior is smaller for personal sentiment than aggregate sentiment, in both cases the switching behavior has increased over time.

# 3 Consumption and Polarization

Macroeconomic models typically imply a tight connection between agents' beliefs and actions. Hence, the results in the previous section suggest that political shocks should lead to large changes in consumption. However, there is surprisingly little empirical evidence documenting tight connections between expectations and actions. In this section, we explore whether political affiliation does indeed play a crucial role in how individuals make spending decisions.

As a first step, we continue to utilize survey responses in the MSC. We assess how Republican and Democratic households differ in their attitudes towards purchases over time. Figure 4 plots the estimated coefficients from a regression of purchase attitudes on political affiliation. The dependent variable is an indicator of whether an individual said it was a good time (top row) or bad time (bottom row) to buy durable goods, a home, or a car. The independent variable is a dummy for whether the household reports they are a Republican (or lean more towards the Republican party). The estimated coefficient reports how much more optimistic or pessimistic Republican households are relative to Democratic households towards purchasing different goods.

While the results are not as stark as for economic expectations, the same pattern

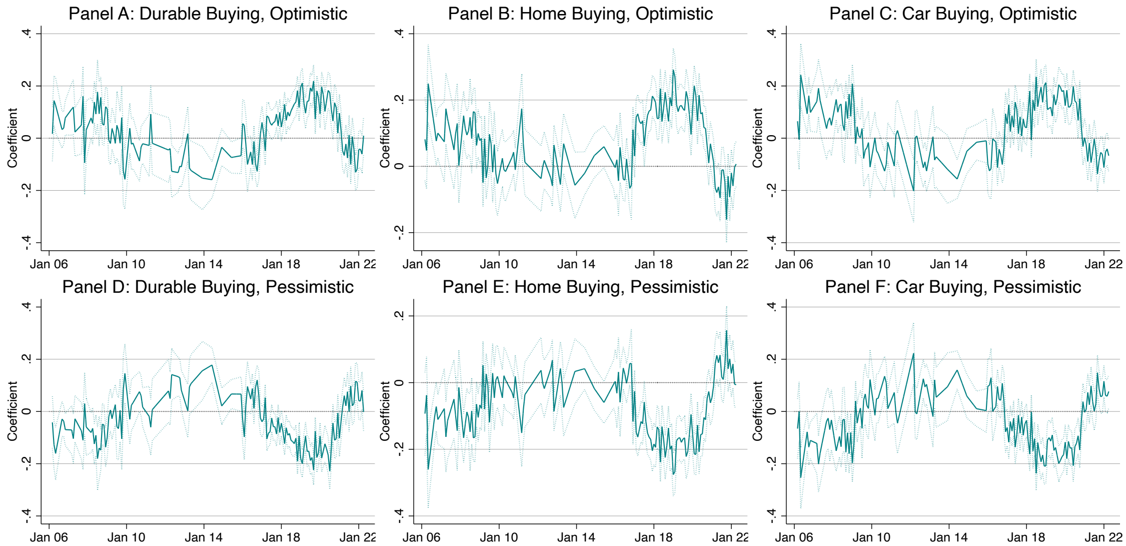


Figure 4: Consumption Beliefs by Political Affiliation

Notes: plots the estimated coefficients of a month-by-month regression of a dummy variable for if a consumer says it is a good time (top row) or bad time (bottom row) to buy on a dummy variable for Republican. The first column plots the results for questions regarding attitudes towards durable consumption; the second for automobile purchases; and the third for home purchases. Dotted lines represent 90% confidence intervals. Only Republican and Democratic voters are included in the regression. An individual is counted as a Republican (Democratic) voter if they self-report they are Republican (Democratic) or are independent but closer to the Republican (Democratic) party.

emerges yet again. During periods in which a Republican is in the White House, Republican voters tend to feel that it is a better time to purchase durables, cars, and homes, compared to Democratic consumers. This pattern flips during periods in which a Democrat occupies the White House. That is, Republican households were more likely to say it was a good time to buy durables, homes, and cars relative to Democratic households during the presidencies of Bush Jr. (2000-2008) and Donald Trump (2016-2020). In contrast, Republican households were less likely to say it was a good time to make purchases relative to Democratic households during the presidencies of Obama (2008-2016) and Biden (2020-).

However, the Michigan Survey is an imperfect tool for studying the behavior of consumption: it does not include a direct measure of consumption, and the monthly frequency does not allow us to focus precisely on small windows around an election. Instead, we now use the 2016 and 2020 elections as case studies. For the 2016 election, we utilize high frequency spending data combined with voting data *at the zip code level* to examine how political affiliation affects spending decisions. For the 2020 election, we again utilize high frequency spending data but are able to match this spending data to *individual-level* measures of political affiliation. Our results provide novel insights into how changes in economic expectations affect actual consumption and interact with political affiliation.

## 3.1 Consumption Data

We use the Nielsen Homescan data to study the response of consumption and spending to the outcome of the 2016 and 2020 presidential elections.[3] Nielsen Homescan is a panel dataset which measures U.S. consumer behavior. Panelists use scanners to record all purchases of products tracked by Nielsen in food and non-food categories. The dataset tracks when, where, and how much of each product a given panelist purchases across time. Nielsen also records demographic and geographical information on the panelists. Since 2007, the Homescan data includes roughly 60,000 households.

## 3.2 2016 Case Study: Data

Using the Nielsen Homescan data, we construct a weekly measure of consumption spending at the (five-digit) zip code level around the 2016 presidential election. We aggregate daily consumption over the course of a week because spending tends to be concentrated on weekends. Additionally, since presidential elections fall on Tuesdays, our weekly measure starts on Wednesday and runs through the following Tuesday.

[3] Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

We merge our consumption data with voting data at the zip code level. Voting data is recorded at the precinct level, which is not observed in the Homescan dataset (and in general is not a common regional measure outside of elections). Instead, we use geographical shape data to allocate precinct-level voting data to zip codes. Precincts are smaller geographical areas than zip codes, and most precincts fall entirely within zip codes. For precincts that fall within multiple zip codes, we allocate votes proportionally to each zip code based on geographical size overlap.

Our voting and geographical precinct data is from the United States Election Project at the University of Florida. The data includes 47 states and the District of Columbia.[4] We define the Trump margin of victory as the percentage point difference between the vote share for Trump and Clinton (third party votes are excluded from the vote share calculations).

Figure 5 Panel A plots a histogram of the Trump margin in all U.S. zip codes. The distribution is skewed to the right as there were many small zip codes that voted in favor of Trump, despite Clinton winning the popular vote. As a precise example of our zip code voting data, Figure 5 Panel B plots the vote shares by zip code in Orange County, California. Orange County voted for Clinton by a margin of 8.6 percentage points, but as the Figure shows this does not imply that votes were uniformly distributed across zip codes. Indeed, there are some zip codes that voted strongly in favor of Trump even though the county as a whole voted for Clinton. This highlights the high degree of heterogeneity of political affiliation, even within relatively small geographical units like counties, and emphasizes the importance of using as small a geographic area as possible.

Our analyses focus on zip codes with at least 100 recorded votes. This leaves us with about 16,000 zip codes. The median number of votes across zip codes in our sample is roughly 5,000, with the largest made up of about 42,000 votes. The median Republican margin across zip codes in our sample was roughly 22% in favor of Trump. The largest and smallest zip code margins in our sample are 93% in favor

[4]The states that are not included are: Mississippi, New York, and West Virginia. The United States Election Project is still in the process of collecting voting data and geographic boundary data for these states.

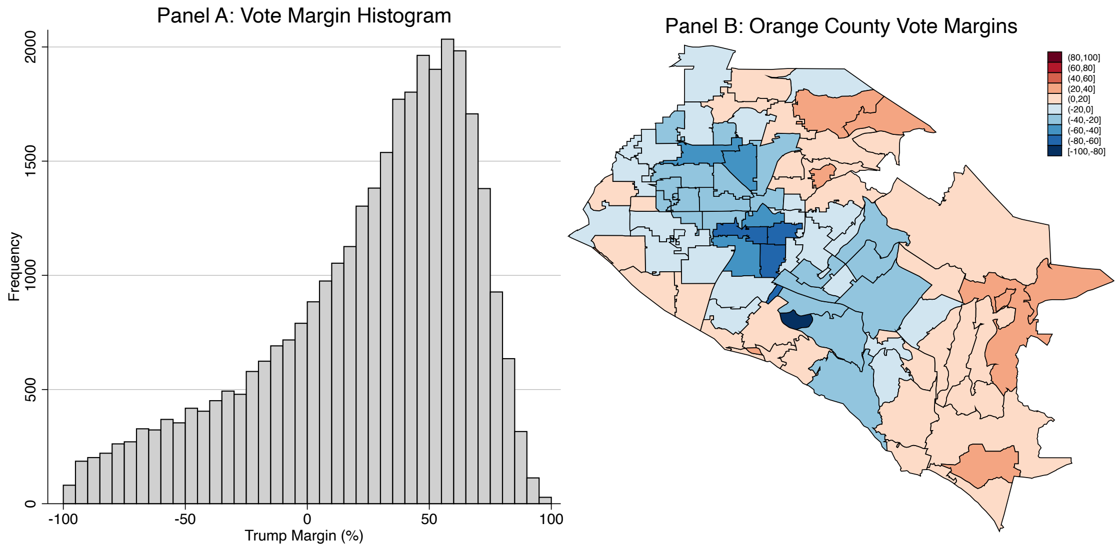


Figure 5: Vote Margins by Zip Codes

Notes: Panel A is is the histogram of all zip code Trump vote margins in the 2016 presidential election. Panel B depicts the vote shares in the 2016 presidential election in Orange County, California, at the zip code level. Blue indicates zip codes in which Clinton received more votes than Trump; and vice versa for red. Dark shades indicate a larger margin.

of Trump, to -97% in favor of Clinton.

### 3.3 2016 Case Study: Event Study Results

In order to assess how spending reacted to the 2016 election, we estimate the following event study regression:

$$c_{z,t,y} = \alpha_{z,t} + \gamma_{t,y} + \sum_{k=-\underline{T}}^{\overline{T}} \beta_{k,y} \cdot v_z^{16} \cdot \mathbf{I}_{t=k} + \varepsilon_{z,t,y}. \tag{2}$$

The variable $v_z^{16}$ measures the Trump margin in zip code $z$ in the 2016 election. The outcome variable $c_{z,t,y}$ is (log) consumption in zip code $z$ at week $t$ and year $y$. In order to control for potentially different time trends in consumption across zip codes, we not only include consumption data from 2016, but also from 2014 and

2015 (results are robust to including different years). We normalize the event time $t$ such that $t = 0$ is the week in which the 2016 presidential election took place; we set $\underline{T} = 4$ and $\overline{T} = 8$ in order to study consumption patterns one month before and two months after the election. For years without a presidential election, we set $t = 0$ to correspond to the week in which a hypothetical election would have taken place. The regression equation Eq. (2) also includes zip code and time fixed effects. Hence, the coefficient $\beta_{k,2016}$ represents the predicted percentage increase in consumption in a zip code with 1 percentage point higher Trump margin in the 2016 election.

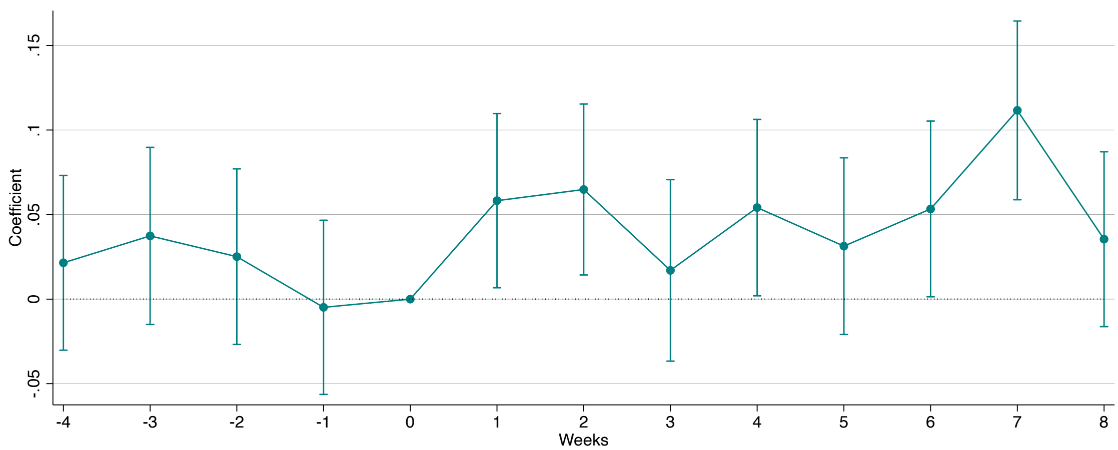


Figure 6: 2016 Event Study of Consumption Responses

Notes: $\hat{\beta}_{k,2016}$ from event study described in Eq. (2) in the weeks preceding and following the 2016 presidential election. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

Figure 6 plots the estimated $\hat{\beta}_{k,2016}$ from the event study in Eq. (2). The increase in consumption is large and statistically significant in the weeks immediately following the election. In contrast, the estimates for the weeks preceding the election are small and not significantly different from zero; this shows there was no differential time variation in consumption patterns related to voting propensities in the lead-up to the election. The lack of pre-trends is reassuring that the change in consumption is in fact a response to the election.

Further, although the standard errors are large, the point estimate remains above zero for all of the weeks in the sample period following the election. Economically, our estimates are large: a zip code with 1 percentage point higher Republican margin is associated with about a 0.05 percent increase in consumption over the weeks following the election.[5] To put this in perspective, consider two hypothetical zip codes: in the first, the margin was -100% in favor of Clinton, while the second was 100% for Trump. Then the fully Trump zip code is predicted to have 10% higher consumption relative to the fully Clinton zip code in response to the election outcome.

Note that our specification controls for the possibility of predictable time variation in consumption for zip codes that tended to favor Trump relative to Clinton. This is not outside the realm of possibility; we might expect consumption behavior to differ around the holidays given the demographic differences across the zip codes. To assess this further, Appendix Figure A8 plots the same event study but only using specific years (2013 through 2018). Besides 2016, no presidential election took place during these years, and moreover no midterm elections took place during 2013, 2015, and 2017. The results show that there is no differential consumption pattern during the weeks of October and November; however, there does appear to be some seasonal differences at the end of the year. However, if anything these patterns suggest that Trump zip codes reduce consumption relative to Clinton zip codes. Finally, focusing on the results using only 2016 data (Panel D), we see that the results are highly similar to our baseline regression. None of the other years exhibit the same pattern as those observed around the 2016 election. Further, the point estimates are never as large as the estimates we find following the 2016 election. This allows us to rule out that our results are driven by differential consumption patterns over time in zip codes that have a higher propensity to vote Republican for reasons unrelated to political shocks (e.g. different seasonal patterns in consumption).

These findings are highly robust to many other alternative specifications. For instance, our results are also robust to different choices of vote cutoffs and hold across different regions. For instance, Appendix Figure A9 conducts the same analysis using only zip codes from California and Texas. We further run our analysis using a more

[5] The point estimate remains high, and at times significant, well into 2017. See Appendix Figure A7 for a longer time frame.

restrictive cutoff for inclusion in our analysis, and only include zip codes with at least 1,000 votes. Although the estimates are slightly noisier than our baseline estimates, in general we find similar patterns when focusing on two specific states. This shows that the results are not driven by differential responses in "red" vs. "blue" states *per se*. That is, even within states that voted heavily for Clinton, zip codes with higher Trump voters increased consumption. Finally, Appendix Figure A10 shows that our results still hold when we focus only on zip codes in which the margin of victory was large. In particular, we only include zip codes where the margin of victory was greater than 25% for Trump or Clinton (that is, Republican margins above 25% or less than -25%).

**Fact 5: Partisan consumption response to White House elections**

The case study of the 2016 presidential election documents our fifth empirical fact. We show that after an election where the White House changes party, individuals of the winning party increase their consumption relative to those of the losing party. Our empirical consumption results are in line with the results from a similar empirical design in Australia, as shown in Gillitzer and Prasad (2018). In the context of the U.S., our results contrast with the findings in Mian et al. (2018), who find no evidence that political shocks lead to differential consumption responses. This is likely due to two factors. First, we use voting data at the zip code level, rather than at the county level or survey-based measures of geographical partisanship, which allows for a much tighter link between voting propensity of a given region and the consumption responses.[6] Second, we use a higher-frequency measure of consumption. This allows us to pick out more immediate consumption responses. However, a downside is the Nielsen consumption data is largely composed of nondurable consumption.

[6] Appendix Figure A11 reports the results of our event study if we instead conduct our analysis at the 3-digit zip code (which roughly corresponds to counties). Although the results are qualitatively similar, the estimates are significantly noisier (and statistically indistinguishable from zero).

### 3.4 2020 Case Study: Data

We next turn to the recent 2020 presidential election to shed further light on how expectations, consumption plans, and actual consumption react to changes in control of the White House. We utilize a survey of the respondents in the Nielsen Homescan undertaken by Coibion et al. (2020). The survey was conducted in the days before and after the 2020 presidential election, and solicited responses regarding respondents macroeconomic forecasts (such as inflation and unemployment), as well as attitudes towards consumption decisions (such as buying durables). Importantly, respondents also were asked their political affiliation. Individuals are only surveyed once, and hence we cannot track the beliefs of the same individual before and after the election. However, by comparing the responses of Democratic and Republican individuals over the days preceding and following the election, we can trace out how beliefs and consumption attitudes changed in a high-frequency manner following the results of the election. Furthermore, by linking these responses with the Homescan consumption data, we can compare the actual consumption of Democratic and Republican individuals in the days before and after the election.

Note that unlike most previous presidential elections, the outcome of the 2020 election was not known immediately. The major media organizations did not declare Biden the winner until the weekend following the election.

### 3.5 2020 Case Study: Event Study Results

In order to assess how expectations and consumption plans reacted to the 2020 election, we estimate the following event study regression:

$$y_{i,t} = \gamma_t + \sum_{\kappa=-\underline{T}}^{\overline{T}} \beta_\kappa \cdot \mathbf{I}_{i \in R} \cdot \mathbf{I}_{t=\kappa} + \varepsilon_{i,t}. \tag{3}$$

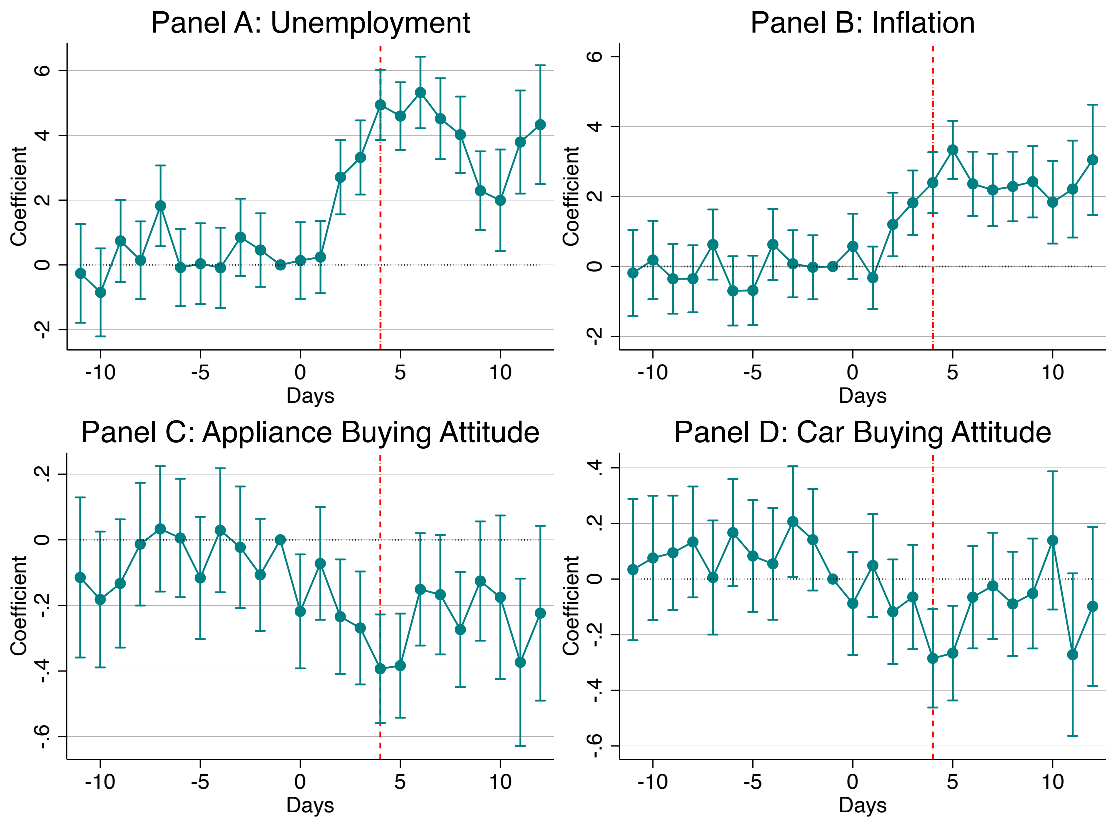


Figure 7: 2020 Event Study of Expectations and Consumption Attitudes

Notes: $\hat{\beta}_\kappa$ from event study described in Eq. (3) in the days preceding and following the 2020 presidential election. Vertical lines represent 90% confidence intervals. The outcome variables are the respondent's unemployment expectations and inflation expectations in panels (A) and (B), respectively. The outcome variables in panels (C) and (D) are the respondent's attitudes to purchasing large appliances and cars, where responses range from 1 (very good time to buy) to 5 (very bad time to buy). The vertical line corresponds to the date at which major news agencies called the race for Biden.

The outcome variable $y_{i,t}$ is the response to different questions in the survey (discussed below) for individual $i$ on day $t$. $\mathbf{I}_{i \in R}$ is an indicator which measures whether respondent $i$ is a Republican. As before, we normalize the event time $t$ such that $t = 0$ corresponds to the day in which the 2020 presidential election took place; $\underline{T} = \overline{T} = 12$ captures the full wave of respondents in the 12 days before and after the election. The regression equation Eq. (3) also includes time fixed effects. Hence, the coefficient $\beta_\kappa$ represents the predicted differential response to a given question for a Republican respondent during the lead up and aftermath of the 2020 election. Note that unlike Eq. (2), we only observe these responses in the two weeks before and after the 2020 election and hence cannot include data from other years.

Panels A and B of Figure 7 plot the event study for 12-month unemployment expectations and 12-month inflation expectations, respectively. The results show that before the 2020 election, there was no differential movement in macroeconomic expectations across Republican and Democratic individuals. However, in the days following the 2020 election, Republican respondents began increasing their forecasts of both unemployment and inflation relative to Democratic respondents. Note that the estimates begin increasing the day after the election, and continue increasing until four days following the election, when major media organizations called the election for Biden. The differential increase in Republicans expectations was roughly 5 percentage points for unemployment expectations and 3 percentage points for inflation expectations. These results are consistent with our findings in the previous section, but additionally show that the response of expectations occur within days following the outcome of the presidential election.

Next, Panels C and D of Figure 7 plot the results regarding attitudes towards consumption decisions. In particular, these questions solicit respondents' attitudes towards buying large appliances (Panel C) or cars (Panel D). For each question, responses range from 1 (very good time to buy) to 5 (very bad time to buy). The results mimic our findings for macroeconomic expectations: in the days following the 2020 election, Republican respondents became more pessimistic about purchasing appliances and cars. Again, the response peaks near the day in which major media organizations called the election for Biden. Although survey responses regarding attitudes towards consumption decisions are not the same as directly observing consumption patterns, these results confirm our findings from the 2016 election.

In order to assess in more detail how spending reacted to the 2020 election, we link respondents' affiliation with their actual consumption as measured in the Homescan data. We estimate the following event study regression:

$$c_{i,t,y} = \alpha_{i,t} + \gamma_{t,y} + \sum_{k=-\underline{T}}^{\overline{T}} \beta_{k,y} \cdot \mathbf{I}_{i \in R} \cdot \mathbf{I}_{t=k} + \varepsilon_{i,t,y}. \tag{4}$$

Our specification is the same as in Eq. (2), with a few differences. First, we observe an individual $i$'s stated political affiliation. Second, we utilize individual-level consumption, $c_{i,t,y}$. Finally, in order to control for potentially different time trends in consumption across Republican and Democratic households, we not only include consumption data from 2020, but also from 2019 (note that we cannot include data from years further in the past as the sample of households in the Homescan data changes). Finally, we normalize the event time $t$ such that $t = 0$ corresponds to the week in which the 2020 presidential election was called, rather than the day of the election (however, results are robust to defining the start of the week on different dates) The coefficient $\beta_{k,2020}$ represents the predicted percentage increase in consumption for a Republican household relative to a Democratic household before and after the 2020 election.

Figure 8 plots the event study results of realized consumption based on the Nielsen Homescan data from Eq. (4).[7] Prior to the election, there is no significant difference between Democratic and Republican individuals in consumption. Following the election of Biden, Republican individuals immediately decrease their consumption relative to Democratic individuals. The effect is large and at times significant. The differential consumption response is roughly 5% in the weeks after the election. Moreover, the magnitude of the differential consumption in the 2020 individual-level event study is similar to that of the 2016 zip code-level event study (although our point estimates are somewhat smaller).

[7] Appendix Figure A12 plots the same event study using only 2020 data and finds similar results.

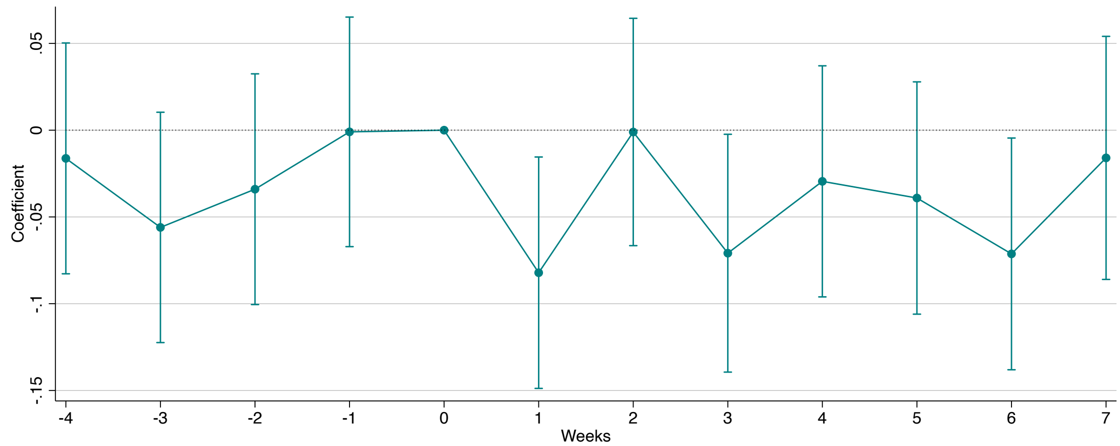


Figure 8: 2020 Event Study of Consumption

Notes: $\hat{\beta}_{\kappa,2020}$ from event study described in Eq. (4) in the weeks preceding and following the 2020 presidential election. The outcome variable is the respondent's actual weekly consumption as measured by Nielsen Homescan. Vertical lines represent 90% confidence intervals.

# 4 Implications for Theory

Our five facts about polarized expectations and consumption have implications for the validity of standard theoretical models of expectation formation. To discuss these implications, we propose a notation to describe our five facts and demonstrate that commonly used models of expectations struggle to simultaneously explain all of the empirical facts. However, some models can account for some of the existing facts.

## 4.1 Formalizing the Facts

In order to discuss the theoretical implications of our findings, it is useful to briefly formalize our results. We use the following notation: a household denoted by $i$ has subjective beliefs $E_t^i$. These beliefs may differ from full-information rational expectations, $E_t$.

Let $\mathbf{X}_t$ be a vector of aggregate and idiosyncratic variables such as output, inflation, household consumption, or economic policy at time $t$. The (linearized) dynamics of the economy are summarized by the following equation

$$\mathbf{X}_{t+1} = \mathbf{A}\mathbf{X}_t + \boldsymbol{\varepsilon}_{t+1},$$

where the matrix $\mathbf{A}$ governs the transition from period $t$ to $t+1$, and $\boldsymbol{\varepsilon}_{t+1}$ are shocks to aggregate and idiosyncratic variables. Then the FIRE expectation of the dynamics of this system is simply $E_t\mathbf{X}_{t+1} = \mathbf{A}\mathbf{X}_t$. However, household $i$'s perceived dynamics may differ from FIRE, as summarized by the following

$$E_t^i\mathbf{X}_{t+1} = \mathbf{A}^i E_t^i\mathbf{X}_t + E_t^i\boldsymbol{\varepsilon}_{t+1},$$

where $\mathbf{A}^i$ are household $i$'s subjective beliefs about the transition matrix $\mathbf{A}$. Hence, households may differ from FIRE along multiple dimensions: beliefs about dynamics ($\mathbf{A}^i \neq \mathbf{A}$); beliefs about the distribution of shocks ($E_t^i\boldsymbol{\varepsilon}_{t+1} \neq \mathbf{0}$); beliefs about the current state of the economy ($E_t^i\mathbf{X}_t \neq \mathbf{X}_t$); and beliefs about the future state of the economy ($E_t^i\mathbf{X}_{t+1} \neq E_t\mathbf{X}_{t+1}$). Many theoretical models of belief formation can be formalized as restrictions on how these objects may differ from FIRE. Using this stylized framework, we discuss each of our five facts in turn.

**Fact 1:** the variance-covariance matrix of a household $i$'s beliefs has a rank of approximately one: $\text{rank}(\text{Var}^i\,\mathbf{X}_t) \approx 1$. Equivalently, household $i$'s beliefs can be approximated by a single "sentiment" factor $s_t^i$ with an associated vector of loadings: $E_t^i\mathbf{X}_t \approx \boldsymbol{\lambda}^i \cdot s_t^i$.

**Fact 2:** for any two households $i$ and $j$, sentiment $s_t^i$ and $s_t^j$ are correlated across political ideology:

$$\rho(s_t^i, s_t^j) = \begin{cases} > 0 & \text{if } i,\ j \text{ share party affiliation} \\ < 0 & \text{if } i,\ j \text{ do not share party affiliation} \end{cases}$$

Furthermore, dispersion in beliefs is driven by dispersion in $s_t^i$, not by dispersion regarding $\boldsymbol{\lambda}^i$. Formally, we have that $\boldsymbol{\lambda}^i \approx \boldsymbol{\lambda}^j$.

**Fact 3:** household beliefs exhibit a muted reaction to all innovations, except a presidential election where the White House switches party. Relative to full-information rational expectations, households under-react to nearly all innovations, but over-react to a change in the presidential party. For any outcome variable $x_t \in \mathbf{X}_t$, we have

$$\left|\frac{\partial E_t^i x_t}{\partial \varepsilon_t}\right| < \left|\frac{\partial E_t x_t}{\partial \varepsilon_t}\right|, \quad \left|\frac{\partial E_t^i x_t}{\partial w_t}\right| > \left|\frac{\partial E_t x_t}{\partial w_t}\right|,$$

where $w_t$ is an innovation to the White House and $\varepsilon_t$ are all other innovations (including other political shocks).

**Fact 4:** the switching magnitude in beliefs to changes in the White House has increased over time: $\left|\frac{\partial E_t^i x_t}{\partial w_t}\right| > \left|\frac{\partial E_t^i x_\tau}{\partial w_\tau}\right|$ where $t > \tau$.

**Fact 5:** the consumption decisions $c_t^i$ for household $i$ respond to changes in the White House: $\frac{\partial c_t^i}{\partial w_t} \neq 0$. Moreover, $\frac{\partial c_t^i}{\partial w_t} > 0$ if and only if household $i$ shares the political affiliation of the party taking control of the White House.

## 4.2 Inconsistencies with Existing Theory

**Full-Information Rational Expectations:** the workhorse approach to modelling expectations in macroeconomics has been FIRE since the rational expectations revolution of the 1970s (e.g., Muth 1961, Lucas Jr 1972, Lucas 1976, Lucas and Sargent 1979). However, ensuing work using survey-based measures of expectations has consistently documented deviations from FIRE such as forecast error predictability and persistent biases (see Coibion et al. 2018 for a summary of the literature).

Unsurprisingly, our five empirical facts also clearly contradict the assumption that household beliefs are full-information and rational. The key failures of FIRE with respect to our facts are two-fold. First, rational agents fully understand the dynamics of the model, and so the only difference between forecasts and outcomes are due to unpredictable shocks. However, Fact 1 implies that consumer beliefs have a lower dimension than FIRE expectations. Second, FIRE implies that beliefs are the same across all agents. Even if this assumption is slightly relaxed, belief dispersion is not predictable under FIRE. Fact 2 shows that dispersion in expectations is large, and moreover this dispersion is predictable by political affiliation.

**Models of Under/Over-Reaction:** there is a large class of models that depart from FIRE and imply that agents will either under-react or over-react to shocks relative to FIRE. For example, under-reaction of beliefs due to incomplete information is a feature of models such as rational inattention (Sims 2003), sticky information (Mankiw and Reis 2007), adaptive learning (Evans and Honkapohja 2012), and sparsity (Gabaix 2014). On the other hand, diagnostic expectations may suggest an over-reaction to incoming news (Bordalo et al. 2018).

Our findings strongly suggest that household beliefs over-react to changes in the White House, but under-react to other news. Hence, theories which attempt to rationalize this behavior clearly must feature different types of under- and over-reaction. However, standard formulations of the models discussed above typically result in agents reacting the same way to all shocks. That is, agents either always under-reaction or always over-react:

$$\left|\frac{\partial E_t^i x_t}{\partial \varepsilon_t}\right| < \left|\frac{\partial E_t x_t}{\partial \varepsilon_t}\right| \qquad \text{(under-reaction)}$$
$$\left|\frac{\partial E_t^i x_t}{\partial \varepsilon_t}\right| > \left|\frac{\partial E_t x_t}{\partial \varepsilon_t}\right| \qquad \text{(over-reaction)}$$

where $\varepsilon_t$ represents all innovations. This is inconsistent with Fact 3: households under-react to many shocks, while simultaneously over-reacting to changes in the White House.

**Robustness/Ambiguity Models:** robustness-based models (e.g., Hansen and Sargent 2001b, Hansen and Sargent 2001a, Bhandari et al. 2019) imply that agents act as if the worst states of the world are more likely to occur than in reality, and this may be reflected in survey responses.[8] Then a robustness-based explanation could explain the large reaction to changes in the White House if agents believe the worst

[8] Note that formally, robust agents recognize this, so it is unclear what a robust agent is reporting when answering surveys. In principle, a robust agent with full information would still report their true expectations, not their worst-outcome-skewed beliefs.

possible states of the world have changed following the election. However, these models would imply that agents would react to the outcome of presidential elections where the party did not change. For example, suppose an individual prefers the party currently in power. The "worst-case" outcomes for this agent are more likely to occur if the challenging party were to win. Hence, following the realization of the election wherein the current party retains power, the worst-case states of the world have improved and the agent would become more optimistic. In contrast, we find that empirically beliefs are stable around elections where the party in the White House remains unchanged. Moreover, to the extent worst-case outcomes are related to economic policy, these models would also imply reactions to non-presidential elections (such as midterm Congressional elections). Hence, models of robustness with respect to political outcomes are not fully consistent with Fact 3.

**Agree-to-Disagree Models**: clearly, our results show that there is a huge range of disagreement across individuals. Moreover, it is common knowledge that the Democratic and Republican parties disagree strongly across a wide range of issues. However, our results are not necessarily consistent with the "agree-to-disagree" models in the literature. These models feature agents who "disagree" about the model of the world or the parameters that govern it, but these agents also "agree" to not learn from others' behavior (e.g., Dumas et al. (2009), David (2008)).[9]

Generally, these models feature agents who have potentially misspecified models. In our stylized framework, this implies $\mathbf{A}^i \neq \mathbf{A}^j$. Moreover, "full-information" agree-to-disagree models further imply that while agents disagree about future outcomes, they do not disagree about the current state of the economy: $E_t^i \mathbf{X}_t = E_t^j \mathbf{X}_t = \mathbf{X}_t$. Hence, these models are inconsistent with the implications of Facts 1 and 2.

Finally, in our context an "agree-to-disagree" model would likely feature disagreement about government policy. This would imply that beliefs would respond to changes in the political landscape beyond only the outcome of the presidential

[9] Agree-to-disagree models are commonly used in finance, but to the best of our knowledge, there is no textbook implementation in macroeconomics.

election. For instance,

$$\frac{\partial E_t^i x_t}{\partial m_t} \neq 0, \quad \frac{\partial E_t^i x_t}{\partial p_t} \neq 0,$$

where $m_t$ are innovations to Congressional and other non-presidential elections, and $p_t$ are innovations to the probability of the outcome of any election (presidential or otherwise). Hence, agree-to-disagree models of this type would be inconsistent with Fact 3: beliefs are persistent outside of presidential elections.

**Cheerleading Models:** in models of "cheerleading", agents do not report their true beliefs, but instead report optimistic beliefs when their preferred party is in power and vice versa (e.g., Bullock et al. 2015, Prior et al. 2015, Peterson and Iyengar 2021). Our results certainly do not rule out some degree of "cheerleading" in survey responses. However, a pure cheerleading model is inconsistent with actual changes in consumption (Fact 5). Note that while we can rule out pure cheerleading models, we are silent on whether consumption responds by as much as it would if surveys fully reflected true beliefs.

# 5 Concluding Remarks

This paper argues that political polarization plays a large and growing role in how individuals form their beliefs, and these polarized expectations lead to polarized consumption decisions. First, we show that household beliefs are well-described by a single factor, which we argue behaves like traditional concepts of sentiment. Second, there is wide dispersion across households in optimism and pessimism regarding economic outcomes, but this dispersion is largely driven by political affiliation. Third, household sentiment is highly persistent during almost all periods, except following presidential elections when the White House switches parties. At these times, optimistic households become pessimistic and vice versa. Fourth, the magnitude of this switching behavior has increased over time. Fifth, consumption responds differentially along party lines following changes in the White House.

Standard theoretical models of expectation formation struggle to simultaneously explain all five of our empirical facts. We show that commonly-used models such as FIRE, models of consistent under- or overreaction to news, models of robustness, agree-to-disagree models, and cheerleading models can only explain some of the facts. This suggests that to model expectations in a way that accurately reflects the beliefs of households would require combining some of these approaches or developing entirely new models of expectation formation.

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# Appendix A Additional Tables and Figures

Table A1: Survey of Professional Forecasters Principal Components Analysis Loadings and Fraction Explained

| | Dim 1 | Dim 2 | Dim 3 | Dim 4 |
|---|---|---|---|---|
| Nominal Growth (Current Quarter) | 0.398 | 0.019 | 0.105 | -0.257 |
| Nominal Growth (Next Year) | 0.325 | 0.338 | 0.138 | 0.039 |
| Inflation (Current Quarter) | 0.134 | 0.498 | 0.187 | -0.143 |
| Inflation (Next Year) | 0.148 | 0.512 | 0.193 | -0.100 |
| Corporate Profit Growth (Current Quarter) | 0.247 | -0.082 | 0.031 | 0.457 |
| Corporate Profit Growth (Next Year) | 0.205 | 0.127 | -0.089 | 0.671 |
| Unemployment Change (Current Quarter) | -0.358 | 0.157 | 0.022 | 0.322 |
| Unemployment Change (Next Year) | -0.368 | 0.119 | 0.083 | 0.047 |
| Industrial Production Growth (Current Quarter) | 0.369 | -0.179 | 0.073 | -0.116 |
| Industrial Production Growth (Next Year) | 0.332 | -0.016 | -0.062 | 0.272 |
| Housing Starts Growth (Current Quarter) | 0.242 | -0.109 | -0.480 | -0.200 |
| Housing Starts Growth (Next Year) | 0.070 | 0.069 | -0.658 | -0.014 |
| T-Bill Rate Change (Current Quarter) | 0.102 | -0.371 | 0.348 | -0.017 |
| T-Bill Rate Change (Next Year) | 0.098 | -0.356 | 0.298 | 0.094 |
| % Explained | 34.113 | 18.979 | 11.494 | 9.618 |

Notes: each column reports the loadings for a principal components analysis on the SPF.

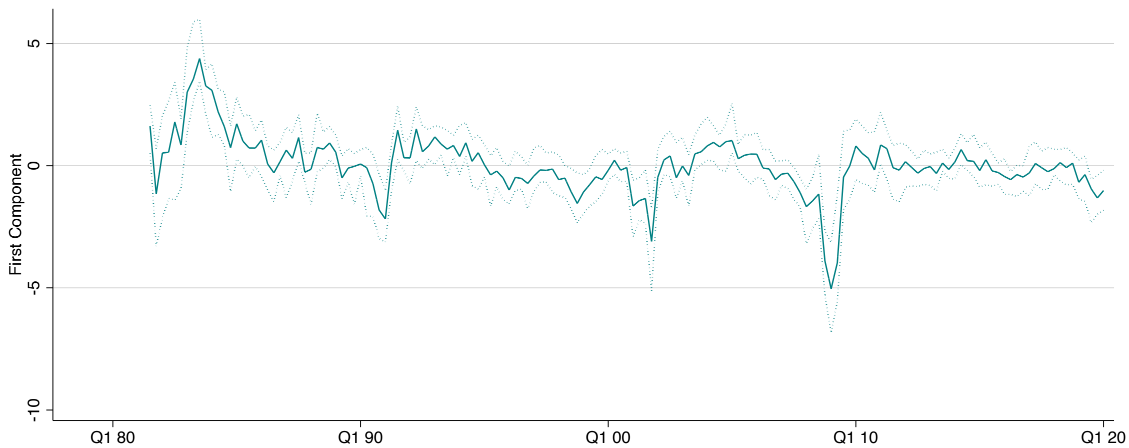


Figure A1: SPF First Component Distribution Across Time

Notes: time series of the first component $f_{i,t}$ from the SPF PCA. The solid line is the median value, while the dotted lines are the 90-10 percent distribution.

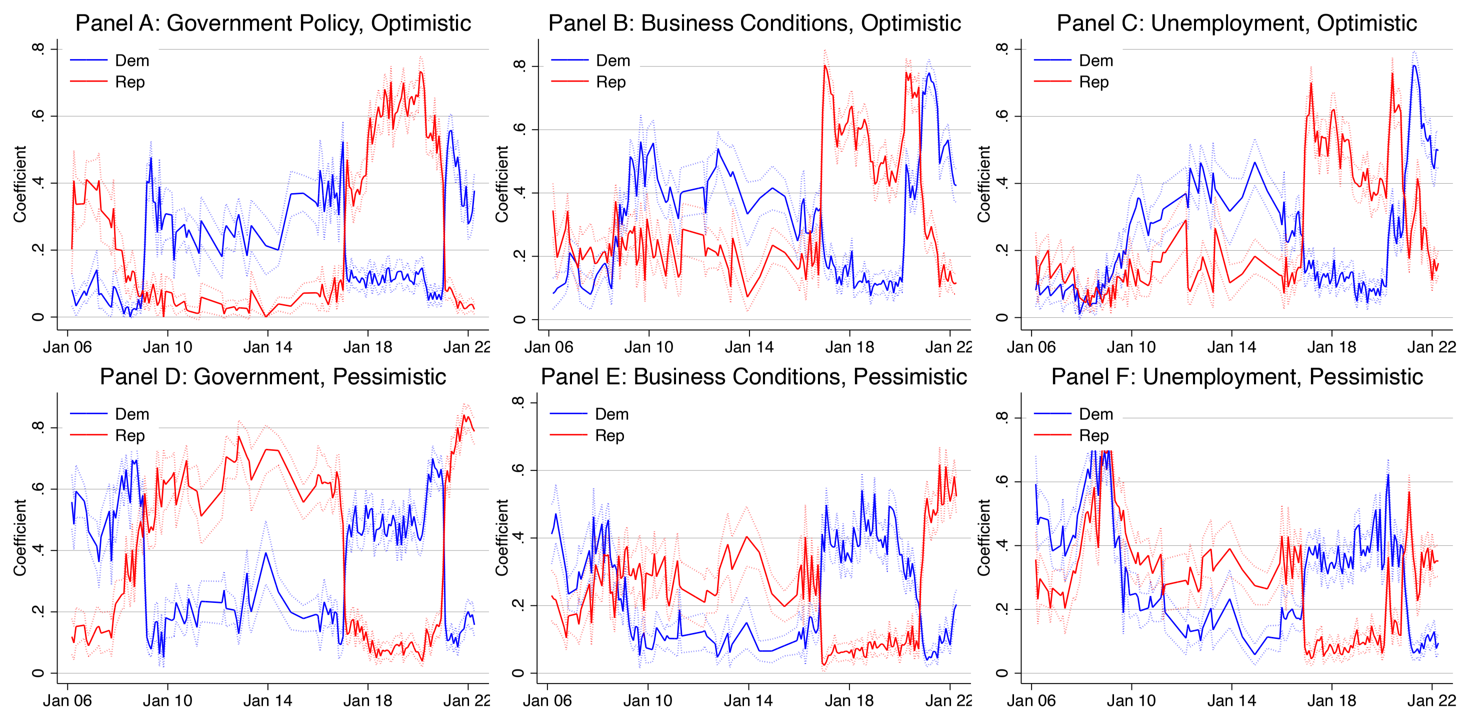


Figure A2: Economic Beliefs by Political Affiliation

Notes: plots the estimated coefficients of a month-by-month regression. The independent variable is an indicator for if a consumer gives an optimistic (top row) or pessimistic (bottom row) response to a specific MSC question, and the dependent variables are dummies for if an individual is a Republican or Democratic voter. The first column plots the results for questions regarding government policy; the second for future business conditions; and the third for unemployment forecasts. Dotted lines represent 90% confidence intervals. An individual is counted as a Republican (Democrat) if they self-report they are a Republican (Democrat) or are independent but closer to a Republican (Democrat).

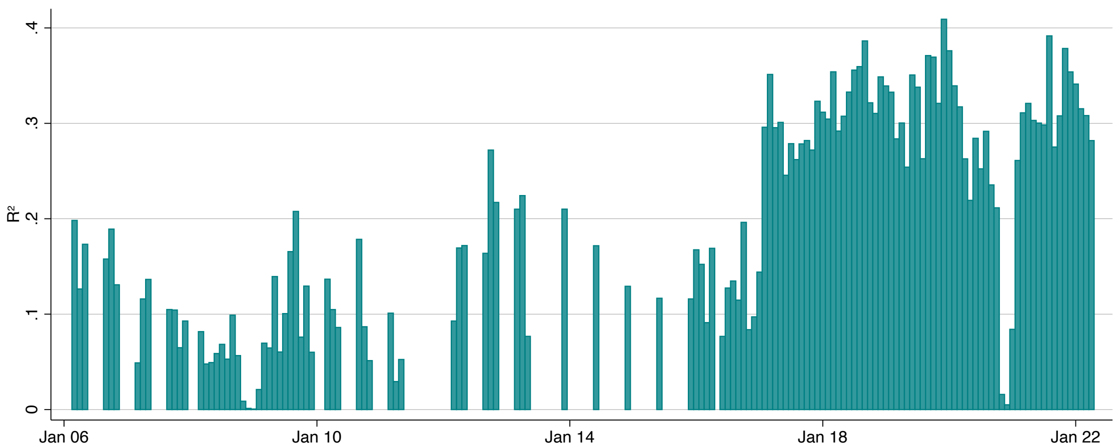


Figure A3: Sentiment and Political Affiliation Explanatory Power

Notes: $R^2$ from a rolling regression of $f_{i,t}$ on political affiliation dummy variables, where $f_{i,t}$ is the first component from the baseline MSC MCA.

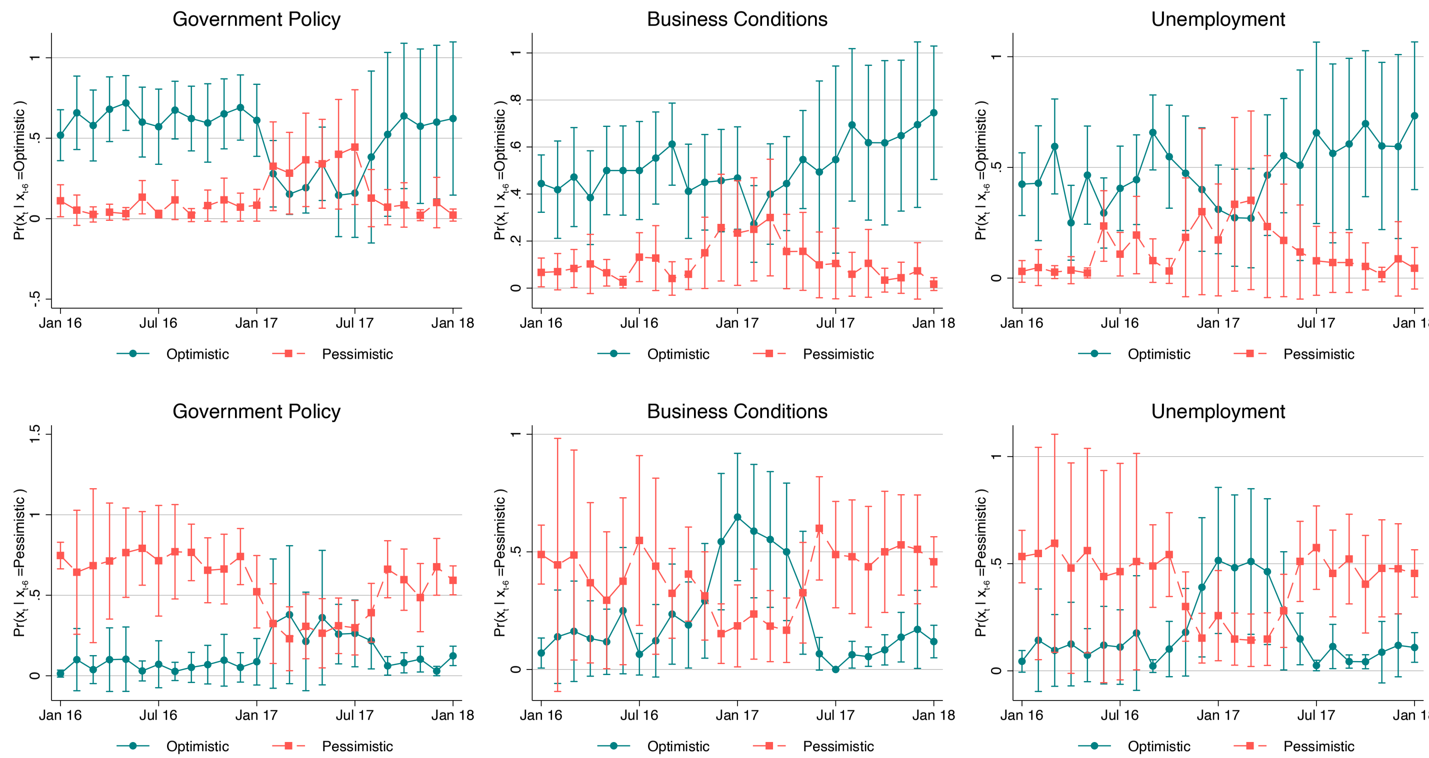


Figure A4: Switching Probabilities, 2016-2018

Notes: probability of an optimistic or pessimistic response conditional on an individual giving an optimistic response (top panels) or pessimistic response (bottom panels) in the previous survey 6 months ago. Survey questions are from the MSC regarding Government Policy (first column panels), Business Conditions (second column panels), or Unemployment (third column panels). The green circles represent the conditional probability of an optimistic response, while the blue squares represent the conditional probability of a pessimistic response. Estimates from a period-by-period multinomial logit model; vertical lines represent 90% confidence intervals.

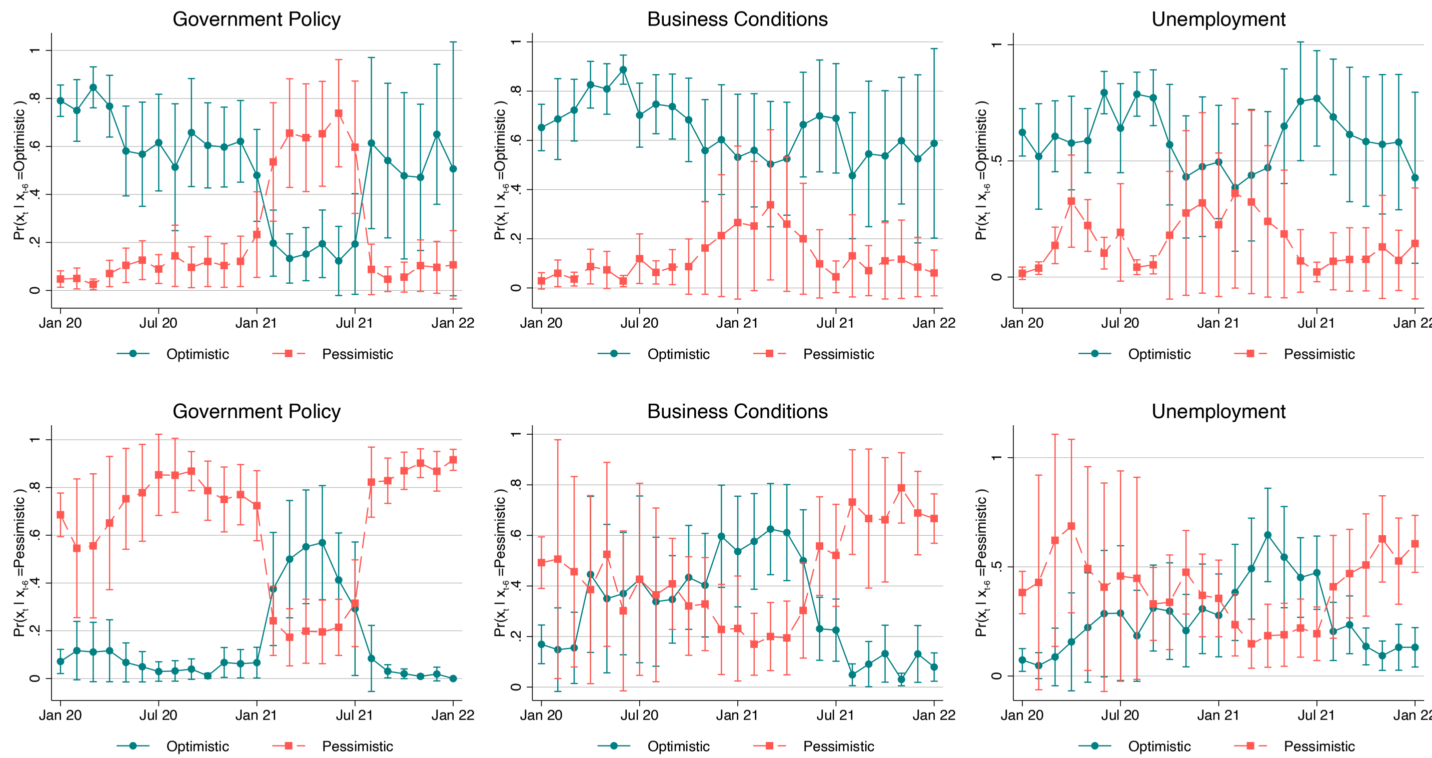


Figure A5: Switching Probabilities, 2020-2022

Notes: probability of an optimistic or pessimistic response conditional on an individual giving an optimistic response (top panels) or pessimistic response (bottom panels) in the previous survey 6 months ago. Survey questions are from the MSC regarding Government Policy (first column panels), Business Conditions (second column panels), or Unemployment (third column panels). The green circles represent the conditional probability of an optimistic response, while the blue squares represent the conditional probability of a pessimistic response. Estimates from a period-by-period multinomial logit model; vertical lines represent 90% confidence intervals.

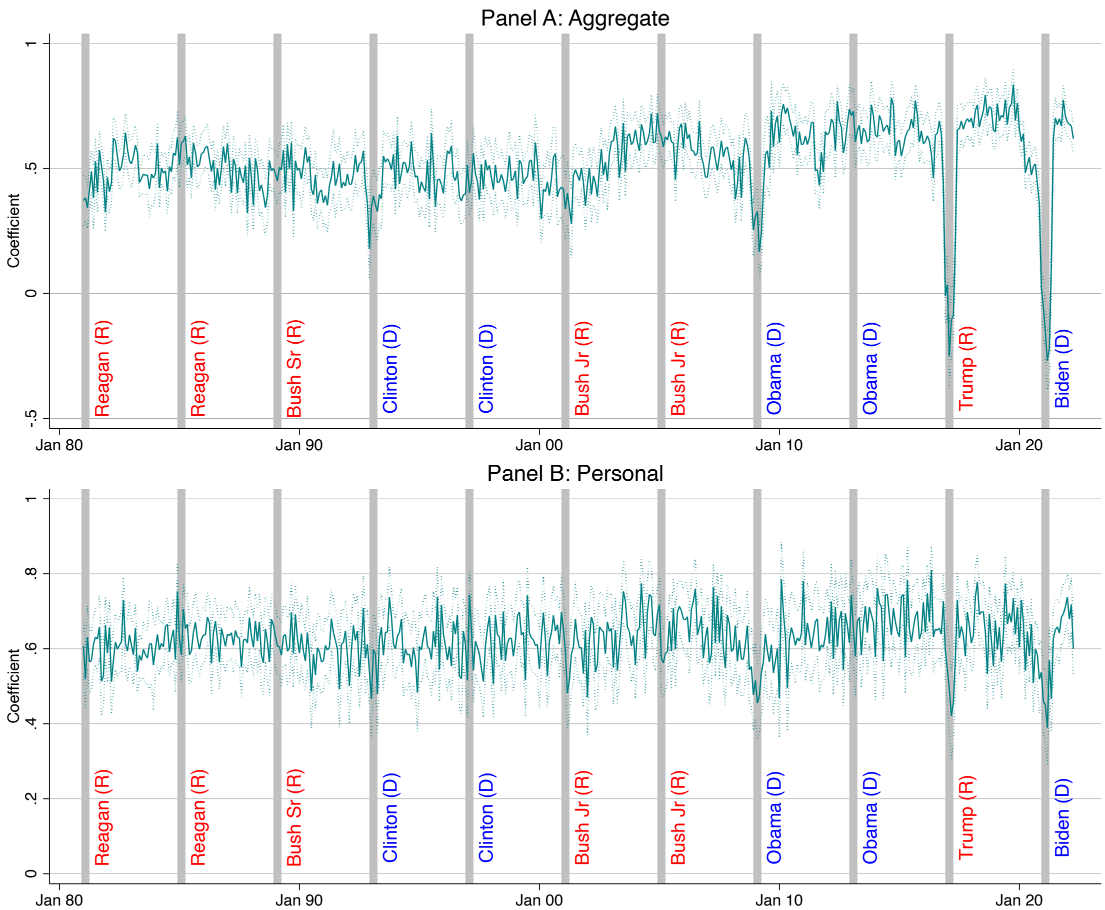


Figure A6: Sentiment Autocorrelation, Aggregate/Personal Beliefs Only

Notes: Panel A plots the coefficient from period-by-period regressions pooled across respondents: $f_{i,t}^{AGG} = \alpha_t + \beta_t f_{i,t-6}^{AGG} + \varepsilon_{i,t}$, where $f_{i,t}^{AGG}$ is the first component from an MCA analysis with aggregate belief questions only. Panel B plots the coefficient from period-by-period regressions pooled across respondents $f_{i,t}^{PER} = \alpha_t + \beta_t f_{i,t-6}^{PER} + \varepsilon_{i,t}$, where $f_{i,t}^{PER}$ is the first component from an MCA analysis with personal belief questions only. Shaded regions correspond to 6-month periods following presidential elections. Dotted lines represent 90% confidence intervals.

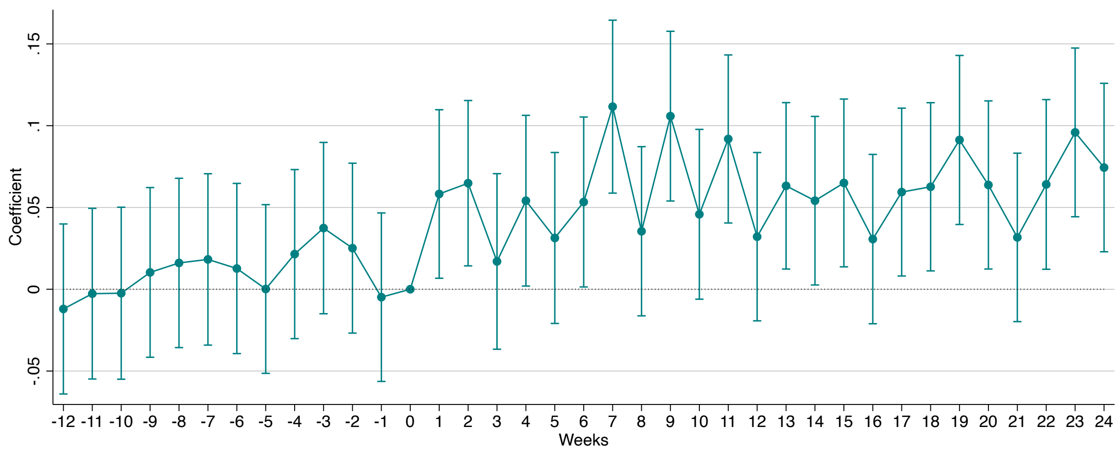


Figure A7: Long Window Event Study of Consumption Responses

Notes: a longer window of the event study presented in Figure 6.

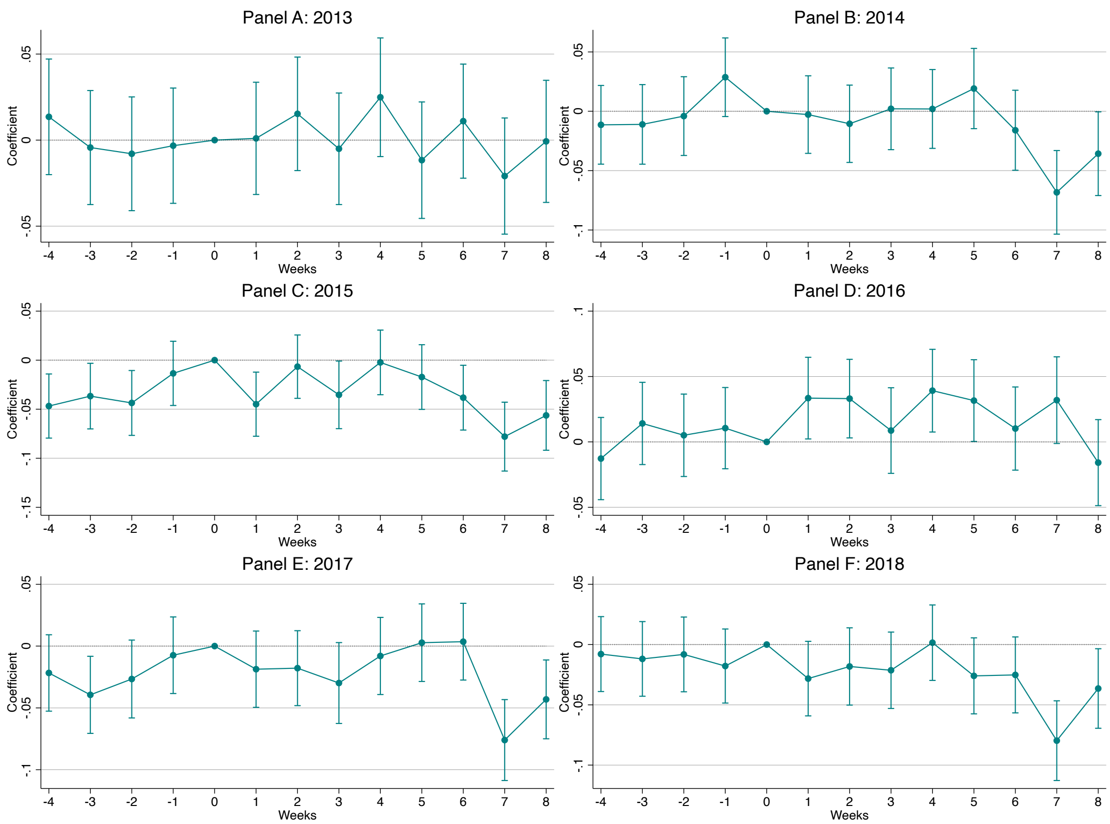


Figure A8: Placebo Event Study of Consumption Responses

Notes: $\hat{\beta}_{k,2016}$ from event study described in Eq. (2), estimated separately by year. For non-election years, "week zero" corresponds to the week in which a hypothetical presidential election would have taken place during these years. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

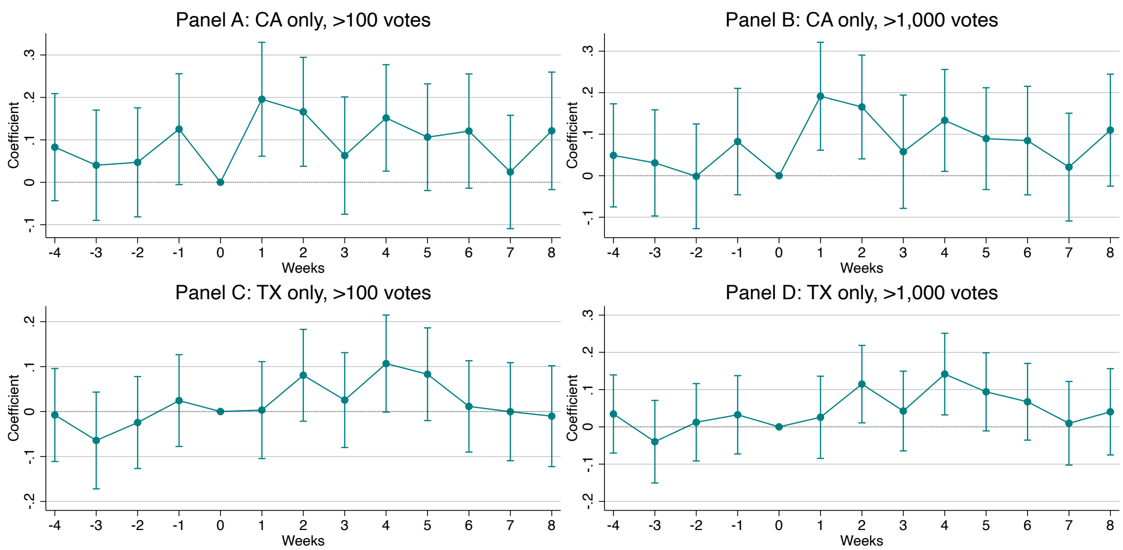


Figure A9: 2016 Event Study of Consumption Responses: CA and TX

Notes: $\hat{\beta}_{k_2 016}$ from event study described in Eq. (2), using only zip codes from California (top row) and Texas (bottom row). The first column corresponds to our baseline where we include zip codes with at least 100 votes. The second column instead only includes zip codes with at least 1,000 votes. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

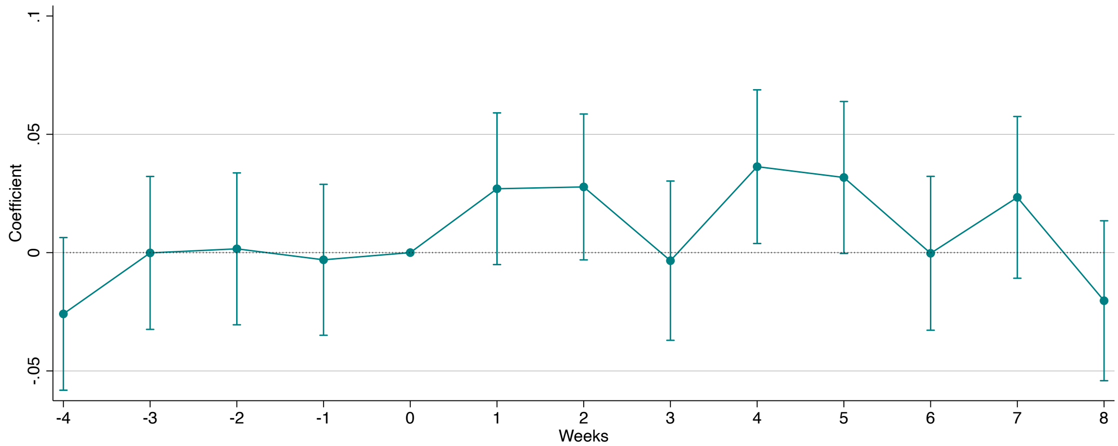


Figure A10: 2016 Event Study of Consumption Responses, Large Margin of Victory

Notes: $\hat{\beta}_{k,2016}$ from event study described in Eq. (2) in the weeks preceding and following the 2016 presidential election, only including zip codes with a vote margin above 25% (for either Trump or Clinton). Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

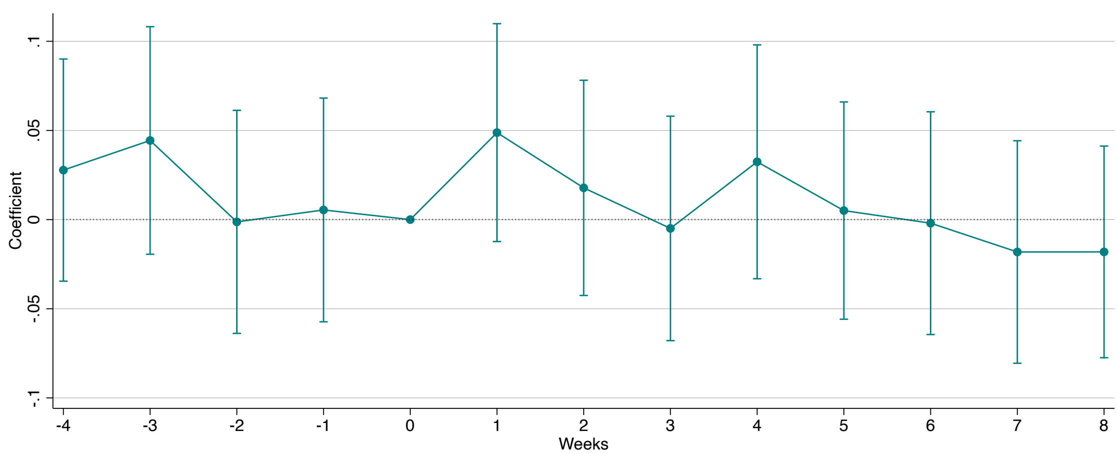


Figure A11: 2016 Event Study of Consumption Responses, 3-Digit Zip Codes

Notes: $\hat{\beta}_{k,2016}$ from event study described in Eq. (2) in the weeks preceding and following the 2016 presidential election, aggregated to 3-digit zip codes. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

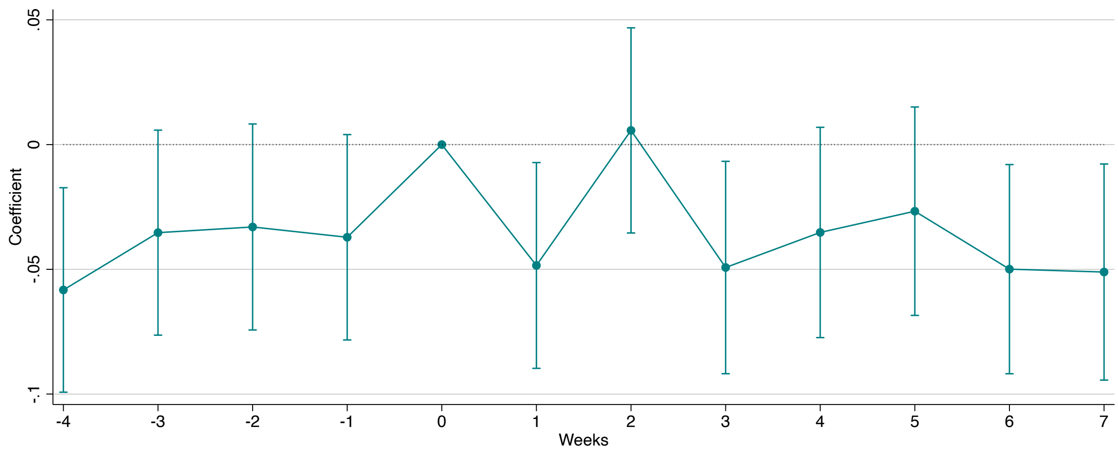


Figure A12: 2020 Event Study of Consumption Responses, No Control Years

Notes: $\hat{\beta}_{k,2020}$ from event study described in Eq. (4), estimated separately for 2020. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.