Partisan Bias, Economic Expectations, and Household Spending

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Abstract

Individuals who support the winning candidate in U.S. Presidential elections become significantly more optimistic about the economy after the election, a phenomenon we utilize to measure the effect of partisan bias on economic expectations. The well-documented rise in political polarization among the electorate over the past 20 years has been accompanied by a substantial increase in the effect of partisan bias on economic expectations. The culmination of this trend is the unprecedented 1.8 standard deviation increase in relative economic optimism for those supporting the candidacy of Donald Trump after November 2016. The Trump effect is six times larger than the increase in relative economic optimism for those supporting George W. Bush in 2000. We investigate spending behavior using a variety of measures, and we are unable to find evidence that those most likely to support the winning candidate increased spending after any of the elections. For example, despite the substantial rise in economic expectations among those most likely to support Donald Trump since November 2016, we are unable to detect higher actual spending among this group after the election. Partisan bias is exerting a stronger influence on economic expectations over time, but shifts in economic expectations driven by partisan bias do not appear to affect household spending.

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How do individuals develop expectations about future economic activity, and how do those expectations affect economic behavior? Economists have long believed that household expectations are crucial to understanding economic activity and the effect of government economic policy. One line of research on economic expectations examines responses to survey questions. For example, the University of Michigan Survey of Consumers asks individuals the following question: "Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression or what?" What determines how an individual responds to such a question, and how might their answer be related to their future spending behavior?

Economists typically treat an individual's answers to these questions as a reflection of the individual's expectations of future income growth. The evolution of such expectations could reflect information the household receives on fundamental changes in the economy. Alternatively, household beliefs about future income growth may reflect sentiment, or changes in expectations that are orthogonal to future economic conditions. A large body of research in economics has focused on these issues (e.g., Barsky and Sims (2012), Azariadis (1981), Benhabib and Farmer (1994), Lorenzoni (2009), and Angeletos and La'O (2013)).

Political scientists have taken a complementary approach by showing that partisan identity may shape views on the state of the economy. For example, research shows that individuals have a more positive assessment of the economy when the White House is occupied by the party they support (e.g, Bartels (2002)). The idea of a "partisan perceptual screen" has been present in the literature since the seminal work by Campbell et al. (1960); Gerber and Huber (2009) summarize the idea succinctly by writing: "In short, this evidence portrays partisan voters as individuals who tend to see what they want to see." A further question in the political science literature is whether survey answers about economic activity driven by political partisanship affect the partisan's actual spending behavior (Palmer and Duch (2001), Gerber and Huber (2009), and McGrath (2016)).

A separate but related line of research in political science documents a large increase in social and affective polarization across political parties (e.g., Iyengar et al. (2012); Mason (2013); Mason (2015); Gentzkow (2016); Boxell et al. (2017)). Political parties are increasingly homogeneous in the ideology of their members, and partisans show increasing hostility toward members of the opposite political party. A natural question emerging from this literature is whether the rise in political polarization has been accompanied by increasing partisan bias in the formation of economic expectations.

In this study, we estimate the effect of partisan bias on the formation of economic expectations by focusing on the evolution of economic optimism for those most likely to support the winning candidate after U.S. Presidential elections from 2000 to 2016. We then evaluate whether the shift in economic expectations due to partisan bias affects household spending.

Individuals more likely to support the winning presidential candidate witness a substantial relative rise in optimism about the economy and their personal financial situation immediately after the election. Further, the strength of this partisan effect on economic expectations has been increasing over time. The culmination of this increasing trend is the unprecedented relative increase in optimism for individuals most likely to support Donald Trump after the 2016 election. The relative increase in optimism of supporters of Donald Trump after the 2016 election is approximately three to four times larger than that of Barack Obama's supporters after the 2008 and 2012 elections. It is six times larger than the relative increase in optimism of supporters of George W. Bush in the 2000 election.

One hypothesis is that economic expectations of partisans react to the presidential election outcome because the actual economic condition improves for partisans if their preferred candidate wins the election. Using county-level data, we do not find much support for this view. It is difficult to detect differential personal income growth for Republican voting counties and Democratic voting counties after the 2000 or 2008 election. Further, we find only limited evidence of relative changes in federal transfers to the counties. Using state-level data, we find little evidence of differential changes in federal tax rates based on whether the state voted for the Republican or Democratic candidate. It is difficult to find evidence that the sharp changes in economic expectations of partisans following Presidential elections are due to changes in the actual economic condition of partisans.

We then move to an examination of household spending. We find little evidence that these dramatic changes in economic expectations driven by presidential election outcomes affect actual household spending. We explore a number of measures of consumption, including individual-level answers to questions in a survey on whether it is a good time to buy durable goods or a car; and administrative data on county-level credit card spending, county-level new auto purchases, and state-level total consumption.

The evidence for the 2016 election is most striking. For example, despite reporting an unprecedented increase in optimism on the economy after the 2016 election, supporters of Donald Trump in the same survey do not report that it is a better time to buy durable goods. Further, through April 2017, there is no relative increase in auto purchases in U.S. counties where individuals voted in the highest proportion for the Republican candidate, even though the increase in optimism on the economy in these counties is large.

Perhaps cross-sectional variation in economic expectations as measured in the Michigan survey never correlate with household spending? To explore this issue, we focus on an alternative shock: cross-sectional variation across U.S. counties in the decline in house prices from 2006 to 2007. There is an established body of research showing that counties seeing a bigger decline in house prices during the housing bust witnessed a substantial relative drop in employment and income that lasted several years (e.g., Mian and Sufi (2014), Yagan (2016)). As a result, we view the decline in house prices from 2006 to 2007 in a county as a fundamental shock to future income for those living in the county.

Using this alternative source of variation, we find that the decline in house prices in a county is correlated with the decline in economic expectations of survey respondents living in the county and the decline in all of our measures of consumption. This benchmark exercise shows that it is possible to measure a change in economic expectations driven by fundamentals in the cross-section of respondents in the Michigan survey that is correlated with changes in spending. Consumer expectations correlate with spending when they are driven by fundamental shocks, but they do not correlate with spending when they are driven by partisan bias.

Our findings complement the growing body of research in political science showing that partisan bias and affective polarization have been increasing over time. Partisan bias is also exerting an increasingly powerful influence on the formation of economic expectations. Using the entire sample from 2000 to 2017, we show that the party an individual supports in the nearest Presidential election has become increasingly powerful in shaping economic expectations. There was a noticeable increase during the second Obama term from 2012 to 2016, but the election of Donald Trump boosted this effect well beyond anything seen in the recent past. Yet despite the fact that individuals increasingly form their economic expectations with significant partisan bias, there is little evidence of an effect on actual household spending.

There is a large body of research in political science evaluating the effect of partisan bias on views on the economy (e.g., Wlezien et al. (1997); Duch et al. (2000); Bartels (2002); Evans and Andersen (2006); Stanig (2013)). Our research is most closely related to three studies in particular. Gerber and Huber (2010) examine changes in evaluations of the economy among partisans before and after the 2006 mid-term election, and they find large differences across partisans in how economic assessments are revised immediately after the election. Gerber and Huber (2009) evaluate a longer time series of county-level spending responses to Presidential elections based on the partisan leaning of the county, and they find evidence that counties leaning to the winning Presidential candidate experience a boost in spending after the election. However, McGrath (2016) extends the sample in Gerber and Huber (2009) and examines the previous evidence in more detail, and concludes that there is no evidence of a differential partisan effect of Presidential election outcomes on spending.

To the best of our knowledge, this study is the first to show both the dramatic rise in the effect of partisan bias on economic expectations over time, and that this rise does not appear to affect household spending. In addition, to the best of our knowledge, this is the first study to evaluate the election of Donald Trump in this context. Much of the political science literature has focused on assessments of current economic conditions, whereas our study focuses on expectations of future conditions. Further, we use a variety of data sources on household spending that we believe are new to the literature. Two closely related studies were written either contemporaneously or subsequent to the original version of this study (Gillitzer and Prasad (2016) and Benhabib and Spiegel (2016)). We will discuss these two studies in more detail in Section 4 below.

The rest of this study proceeds as follows. In the next section, we present the data, our methodology for estimating voting propensity in Presidential elections, and summary statistics. Section 2 shows the shift in economic expectations among partisans following each Presidential election from 2000 to 2016. Section 3 examines whether spending changes differentially for partisans after elections. Section 4 compares our results to other research, and Section 5 concludes.

1 Data, Vote Prediction, Measurement, and Summary Statistics

We use data sets at the individual, county, and state level, focusing on the 2000 to 2017 period in the United States. In each of these data sets, we estimate a propensity to vote for the Republican candidate of the unit of observation in question. We explain the data sets and the methodology for estimating the vote propensity in the following sections.

1.1 Data

The primary individual-level data set we use in this study is from Thomson Reuters University of Michigan Survey of Consumers. This survey is a nationally representative survey of about 500 individuals every month. On average two-thirds of the individuals surveyed in a month are interviewed a second time after six months. The remaining third are only surveyed once. We do not utilize the panel structure of the data, and so the sample is a repeated cross-section in each month. An important advantage of the Michigan survey is that we can match individuals to the counties they live in. The county match is possible in the survey for data after the year 2000 and as such we focus on the period 2000 to 2017 in this study. There are 103,350 individual survey responses in the Michigan Survey of Consumers data between January 2000 and April 2017 that we can match to county-level data.

The Michigan survey does not contain information on the presidential candidate an individual supports in any given election. As a result, we rely on two other data sets with voting information available. The first is the Cooperative Congressional Election Study (CCES), which is a sample survey of more than 50,000 people conducted almost every year since 2005. This survey is administered by YouGov/Polimetrix, and has been widely used in the political science literature (see Gerber and Huber (2010) for an early example). It surveys individuals both before and after Presidential elections. Most important for our research, the CCES survey asks individuals after each Presidential election the candidate for which they voted.

The other data set with voting information is exit poll data distributed to academics by the Roper Center for Public Opinion Research. These exit poll data contain approximately 15,000 individuals after each Presidential election from 1992 to 2012. As of the time of this writing, the 2016 individual level exit poll data were not available from Roper. Both the CCES and exit poll data contain the state in which the individual lives, and demographic information on race, age, education, income, marital status, and whether an individual has children. As we explain below, we will use the predictive effect of demographics in the CCES and Roper data on voting to estimate a Republican voting propensity in the Michigan data.

We also use a number of data sets at the county level. The first is the share of individuals in the county voting for the Republican candidate in each presidential election, which we purchased from David Leip's Atlas of U.S. Presidential Elections website. We also use income and transfers data from the Bureau of Economic Analysis. To measure spending at the county-level, we utilize two data sets. First, we use new auto purchases from R.L. Polk. These data are derived from new car registrations and are based on the county where the buyer lives. The data are described in detail in Mian and Sufi (2012), and are available over our entire sample period. Second, we use a previously unused data set on credit card spending from Argus Information and Advisory Services, a Verisk Analytics company. Argus specializes in credit card and deposit benchmarking. The benchmarking data is collected from individual issuers at the account and transaction level, and then aggregated at the county level to construct an annual measure of spending through credit cards. The Argus spending data is available from 2006 through 2013. Both the Argus and Polk data are available at the monthly frequency, which allows us to examine at a relatively high frequency whether spending tracks changes in economic expectations around Presidential elections. Finally, we use state-level data on tax rates and per capita consumption from the Bureau of Economic Analysis. These data are available through 2015 at the annual frequency.

1.2 Predicting vote propensity in the Michigan survey

In this section, we describe the methodology we utilize to predict the probability an individual in the Michigan survey votes for the Republican candidate in Presidential elections from 2000 to 2016. The first step in this methodology is to standardize the available demographic information in the Michigan survey, the CCES, and the Roper exit poll data. There are eight characteristics contained in all three data sets that we utilize: the state in which the individual lives, race, age, marital status, education level, gender, income, and whether the individual has children. There are some slight differences in categorization of some of the variables across the three data sets. For example, income categories are finer in the CCES and Michigan data relative to the Roper exit poll data. We standardize all variables to have the same categorization across all three data sets.

We then estimate the effect of these demographics on Republican vote propensity in the CCES and exit poll data using a maximum likelihood Probit estimation. More specifically, we estimate the following likelihood function for voting for a Republican:

$$L = \prod_{i=1}^{n} [\Phi(\beta'\mathbf{x})]^{y_i} * [1 - \Phi(\beta'\mathbf{x})]^{1-y_i}$$

where the probability of voting for the Republican candidate ($Y = 1$) follows the normal distribution:

$$Prob(Y = 1) = \Phi(\beta'\mathbf{x})$$

The set of covariates $\mathbf{x}$ include the state in which the individual lives, race, age, marital status, education level, gender, income, and whether the individual has children. In the estimation, we include only individuals voting for either the Republican or Democratic candidate, and we conduct the estimation for each election separately. We have data from the CCES for 2008, 2012, and 2016; we have data from the exit poll data for 2000, 2004, 2008, and 2012.

The results are reported in Table 2. The coefficients we report are marginal effects of the covariates on the probability of voting for the Republican candidate. State indicator variables are included in the estimation, but they are not reported. Relative to blacks, Hispanics and others are more likely to vote for the Republican candidate, and whites are much more likely to vote for the Republican. This ranking is present in both data sets and across all elections. Older individuals are more likely to vote Republican, but this result is weaker in the exit poll data. Married individuals are much more likely to vote Republican, and this result holds across both data sets and in all the elections.

In Appendix Table 1 in the online appendix, we show the univariate pseudo-R^2 for each of the eight characteristics in explaining the probability of voting Republican. Race is the most powerful predictor, followed by either the state indicator variables, marital status, or age depending on the exact election and data set.

Our methodology uses estimates of the coefficient vector β from the Probit estimation to project Republican voting propensity for individuals in the Michigan survey. This is possible because the Michigan data set contains the exact same covariates $\mathbf{x}$ used in the Probit estimation conducted with CCES and exit poll data. This produces a Republican voting propensity for each individual in the Michigan survey, and for each election.

An alternative approach is to assign each individual in the Michigan survey the vote fraction for the Republican of the county in which they live. We view this as an inferior method, as it ignores valuable information on race, marital status, and age, all of which are powerful predictors of vote propensity. However, the county-level approach is useful because we must switch to county-level data when measuring consumption.

In Appendix Table 2 in the online appendix, we present the correlations across individuals in the Michigan survey of the different republican vote propensities using different data sets and methodologies. Overall, the propensities using the CCES and the exit poll data are strongly correlated across years and across data sets, with pairwise correlation coefficients ranging between 0.75 to 0.9. For the 2008 and 2012 elections, we have both CCES and exit poll data. The Republican voting propensities using the CCES and exit poll data for the 2008 election have a correlation of 0.83. They have a correlation of 0.93 for the 2012 election. Further, the correlation across elections is strong. For example the 2008 and 2016 Republican vote propensities calculated from the CCES data have a correlation of 0.92.

Overall, the strong correlations across elections and across data sets suggest that we have isolated a "fixed effect" in Republican voting propensity based on demographics. This is not too surprising, given the course measure of demographics we have to predict votes. The strong correlations across data sets for the same election suggest that demographics have relatively stable effects on voting propensities even with different samples and different sampling methodologies.

The final Republican vote propensity variable we use in the Michigan data is based on the 2000 exit poll projection for individuals from 2000 to 2002, the 2004 exit poll projection for individuals from 2003 to 2006, the 2008 CCES projection for individuals from 2007 to 2010, the 2012 CCES projection for individuals from 2011 to 2014, and the 2016 CCES projection for individuals from 2015 to 2017.

1.3 Measuring economic expectations in the Michigan Survey

The Michigan Survey is widely cited in the financial press as a measure of consumer economic expectations. The main reported results from the Michigan Survey are the index of consumer sentiment (ICS), the index of consumer expectations (ICE), and index of current economic conditions

(CEC). The first is a slightly adjusted average of the latter two.

Our main measure of consumer expectations is the ICE. The ICE is a slightly adjusted average of answers to the following three questions:

First, “Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?” The answers are coded in the data as 1 for better off, 3 for the same, and 5 for worse off. We refer to this as the “my financial situation, 1 year” question, which is coded in the Michigan survey as PEXP.

The second question is: “Now turning to business conditions in the country as a whole–do you think that during the next twelve months we’ll have good times financially, or bad times, or what?” The answers are coded as 1 for good times, 2 for good times with qualifications, 3 for no opinion, 4 for bad with qualifications, and 5 for bad times. We refer to this question as the “Country business conditions, 12 months” question, which is coded in the Michigan Survey as BUS12.

The third question is the one mentioned in the introduction: ‘Looking ahead, which would you say is more likely that in the country as a whole well have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression or what?” The answers are coded exactly the same as the 12 months question. We refer to this question as the “Country business conditions, 5 years” question, which is coded in the Michigan Survey as BUS5.

The ICE is the following average of these three questions:

$$ICE = \frac{PEXP + BUS12 + BUS5}{4.1134} + 2.0$$

For ease of interpretation, we re-scale all four of these variables to be mean zero and standard deviation one for the entire 2000 to 2017 sample. We also invert the ordering so that higher numbers are associated with more optimistic assessments.

There are four other questions from the Michigan Survey we utilize in the analysis below. The Current Economic Conditions index is a slightly adjusted average of the answer to two different questions meant to capture how people feel about the current economy. The first is: “We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?” The second is: “About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good time or a bad time for people to buy major household items?" The latter question is a component of the CEC, and it also serves as an independent measure of household spending views which we refer to as the "household items" question.

The other household spending question relates to car purchases. It is: "Speaking now of the automobile market – do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van, or sport utility vehicle?" We refer to this as the "car" question.

Finally, there is a question regarding views on government economic policy. This specific question is: "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?" We refer to this as the "government economic policy" question. As with the expectations variables, all four of these measures are re-scaled to be mean zero and standard deviation one for the entire sample. We also invert the ordering so that higher numbers are associated with more positive assessments.

1.4 Summary statistics

Table 1 presents summary statistics. We utilize individual-level data, county-month-level data, county-year-level data, and state-year level data. All variables from the Michigan survey are standardized to be mean zero and standard deviation one over the entire sample period from January 2000 to April 2017. Auto sales data are available over this entire time frame. Credit card spending data are available from 2006 to 2013. The BEA data sets are available from 2000 to 2015. For the county-level data sets, we provide summary statistics weighting by the population in the county as of 2008. We do so because there are many counties in the United States with small populations.

For all data sets, the final Republican vote propensity or vote share variable we utilize is based on the 2000 election for 2000 to 2002, the 2004 election for 2003 to 2006, the 2008 election for 2007 to 2010, the 2012 election for 2011 to 2014, and the 2016 election for 2015 to 2017. Across all data sets, the average propensity to vote for the Republican candidate (or the vote share for county and state level data) is between 0.48 to 0.50. In the Michigan individual-level data, this propensity should be interpreted as the propensity to vote for the Republican over the Democrat.

For county-level and state-level vote shares, we utilize the total votes for the Republican divided by the total votes for the Republican or Democrat, which we refer to as the two-party vote share.

2 Partisan Bias and Economic Expectations

2.1 Economic expectations around elections

Figure 1 presents the index of consumer expectations for individuals that either vote for Donald Trump and Hillary Clinton in the 2016 election. Recall that our data set is a repeated cross-section that includes a propensity to vote for the Republican candidate for each individual around the nearest election. To construct the ICE for those voting with probability 1 and 0 for Donald Trump in the 2016 election, we first estimate the following cross-sectional regression for every month m from November 2015 to April 2017:

$$ICE_{im} = \alpha^m + \gamma^m * RepVote_{im} + \nu_{im} \tag{1}$$

We then use the predicted value at $RepVote_{im} = 1$ and $RepVote_{im} = 0$ to estimate the ICE for those voting for Donald Trump and Hillary Clinton, respectively.

As Figure 1 shows, there is a dramatic relative change in consumer expectations around the election. Prior to September 2016, individuals most and least likely to vote for Donald Trump see no relative shift in expectations. There is some evidence that Clinton supporters begin to become slightly less optimistic in October 2016. However, expectations abruptly change in November and December 2016. The magnitude is large. Trump voters see an increase in economic expectations of 1.5 standard deviations, while Clinton supporters see a decline of almost 1 standard deviation.

Figure 2 shows the results for prior elections. For the 2000 and 2008 elections, there are changes in economic expectations based on the candidate supported in the election, but both the timing and size of the changes are less stark than in the 2016 election. It is difficult to see any effect in the 2004 election, whereas the 2012 election evidence is more ambiguous. For 2012, there is a sharp immediate decline in the expectations of Republican voters in December, but it rebounds partially.

Just how statistically robust are these relative shifts in expectations around Presidential elections? To answer this question, we estimate regressions for each year, where the year is centered on November. We call these "pseudo-years" as they run from June of one calendar year to May of the next calendar year (November being the sixth month of a "pseudo-year"). For example, the 2008 pseudo-year runs from June of 2008 to May of 2009. For each pseudo-year y, we estimate the following regression (where we exclude the subscript y for ease of exposition):

$$X_{im} = \sum_{m=June}^{m=May} \alpha^m * d_m + \gamma^0 * RepVote_i + \sum_{m=June, m \neq Oct}^{m=May} \gamma^m * (d_m * RepVote_i) + \nu_{im} \qquad (2)$$

where d_m is an indicator variable for month m, $m = 0$ is the "omitted" month which is October, α^m represents month fixed effects, and γ^m are the coefficients of interest that measure the relative shift in economic expectations X around the election for those individuals most likely to vote for the Republican candidate. We have a set of coefficients γ^m for each pseudo-year in the sample.

Figure 3 shows estimates of these γ^m coefficients for each pseudo-year. The election pseudo-year coefficients are shown with a bold line with a different pattern and different markers. To help illustrate statistical significance, we also plot the coefficients of γ^m for the non-election years, which we keep in gray thin lines with no markers. The coefficients γ^m should be interpreted as the relative shift in consumer expectations among individuals most likely to vote for the Republican candidate around October of each year. The gray lines can be thought of as "placebo" tests; they reflect the relative change in economic expectations among individuals most likely to vote for a Republican candidate but in non-election years.

As the figure shows, the size of the relative shift in economic expectations among those most likely to vote for the Republican candidate in 2016 is unprecedented. In terms of magnitude, going from a 0 likelihood of voting for Donald Trump to a likelihood of 1 leads to a two standard deviation increase in economic expectations from October to December 2016. There is no evidence of a pre-trend, and the relative optimism endures to the end of our sample period in April 2017.

The 2000, 2008, and 2012 elections also appear to have an effect on relative shifts in economic expectations, but it is not obvious from Figure 3 whether they are statistically significant. Regardless of statistical significance, the shifts are significantly smaller in magnitude than that of the 2016 election. The 2008 election effect appears to be the second largest.

In Figure 4 we present coefficient estimates of γ_m from estimation of equation 2 using an alternative left hand side variable measuring confidence in government economic policy. As Figure

4 shows, there are large relative shifts in the answers to these questions, but the shifts tend to be concentrated around the inauguration of the winner in January. The 2016 election effect is larger than all the other elections. But interestingly, the effect size is almost as large (in absolute value) in 2000 and 2008.

To test statistical significance in a regression framework, we estimate the following specification on the full Michigan sample of individuals from 2000 to 2017:

$$X_{iym} = \alpha_m + \alpha_m * RepVote_i + \alpha_y + \alpha_y * RepVote_i + \sum_{y=00,04,08,12,16} [\beta^y * Post_y] \\ + \sum_{y=00,04,08,12,16} [\gamma^y * Post_y * RepVote_i] + \epsilon_{iym} \quad (3)$$

where X_{iym} is the outcome of interest in the Michigan survey, α_m are month of year indicator variables, α_y are pseudo-year indicators (i.e., June to May), and $Post_y$ is an indicator variable for November to May of pseudo year y. The coefficients of interest are the γ^y for each election year. The coefficients γ^y measure the differential change in outcome X during pseudo-year y for individuals more likely to vote for the Republican candidate in the six months after each election. We interact the Republican vote propensity with both year indicator variables and month of year indicator variables to control for any relative patterns in seasonality or annual trends.

The coefficient estimates of β^y and γ^y are reported in Table 3. Economic magnitudes are easy to interpret as the left hand side variables all have a mean of zero and a standard deviation of one, and the Republican vote propensity varies from zero to one. In column 1, we examine the index of consumer expectations. Consistent with the pattern shown in Figure 3, the estimate of γ^{2016} is significantly larger than the estimates of any of the other election years. The estimate is six times as large as the γ^{2000} estimate, and between three and four times larger (in absolute magnitude) than the estimates of γ^{2008} and γ^{2012}.

As mentioned above, the index of consumer expectations is a weighted average of three survey questions regarding expectations of an individual's personal financial situation over the next year, expectations of business conditions in the country over the next 12 months, and expectations of business conditions in the country over the next five years. In columns 2 through 4 of Table 3, we examine the answers to each of these questions separately.[1]

The relative optimism for the individual's personal financial situation is smaller in magnitude and not statistically significant at the five percent confidence level for any of the elections prior to 2016. However, the effect is large and statistically significant for the 2016 election. This suggests that Republican voters expect more personal gain from the Trump election relative to previous elections.

The relative pessimism for Republican voters after the 2008 election is concentrated in expectations about national business conditions over the subsequent 12 months. In contrast, the relative optimism of Republicans after the 2000 election is concentrated in expectations about national business conditions over the subsequent 5 years. The relative pessimism of Republicans after the 2012 election is spread evenly over the three questions. Finally, the positive reaction among Republicans in response to the 2016 election is present for all three expectations-related questions. The 2016 effect is not only larger for the overall index of consumer expectations, but it is also more robust in the sense that the effect is there for all three components of the index.

While we focus primarily on the effect of partisan bias on expectations of future economic activity, political scientists have typically focused on the effect of partisan bias on assessments of the current economy. As mentioned above, the Michigan survey also has an index of current economic conditions, which is a weighted average of questions related to whether an individuals is better off financially today relative to a year ago, and whether now is a good or bad time to buy major household items. We examine the index of current economic conditions in column 5 of Table 3.[2]

As the coefficient estimates show, there is no statistically reliable response of the index of current economic conditions for Republican-leaning individuals after elections prior to 2016. In the Michigan survey, partisan bias appears to act more through expectations than through current assessments, at least in the six months after the election. However, we estimate a positive effect on the index of current economic conditions for those most likely to vote for Donald Trump after the November 2016 election. While the estimate is marginally statistically significantly distinct from zero, it is smaller in magnitude relative to the effect on the index of consumer expectations.

[1] Appendix Figure 1 presents a graph similar to Figure 3 for each of the three sub-components of the index of consumer expectations.

[2] Appendix Figure 2 presents a graph similar to Figure 3 for the index of current economic conditions.

The final column of Table 3 examines confidence in government economic policy. Consistent with the patterns shown in Figure 4, individuals most likely to vote for the Republican candidate in 2000 and 2008 see a large relative increase and decrease, respectively, in confidence in government economic policy. The effect after the 2016 election is two to three times as large as the 2000 and 2008 effects.

2.2 Partisan bias and economic expectations over time

The response of economic expectations around election outcomes is shaped by partisan bias, and this effect appears to be increasing over time. But is this stronger effect of partisan bias on economic expectations just about immediate election outcomes? In Figure 5, we examine the longer run trends to examine this question.

To produce Figure 5, we estimate a cross-sectional specification identical to the one shown in equation 1 for every month of the sample.[3] We then plot the absolute value of these estimates of γ_m over time. Recall from Figure 3 that γ_m tends to shift from being negative to positive after a Republican victory, and from positive to negative after a Democratic victory.

The blue line with circle markers is the absolute value of γ_m over time, and the red solid line is the average of the absolute value of γ_m for each Presidential term.[4] The absolute value of γ_m can be interpreted as the predictive power of partisan bias on economic expectations. Partisan bias exerted a powerful effect on economic expectations during the first term of George W. Bush, but it diminished significantly in the second Bush term. It increased again in the first Obama term, but then jumped significantly in the second Obama term. The increase since the election of Trump is unprecedented in our sample period. Overall, the power of partisan bias in shaping economic expectations has increased substantially since 2012.

2.3 Actual economic conditions?

Why are partisans experiencing such dramatic changes in economic expectations around elections? One starting hypothesis is that a partisan truly is better off economically when the White House

[3] In Figure 5, the $RepVote_{im}$ variable is based on the nearest Presidential election, but the results are similar if we fix the $RepVote_{im}$ to be the same for individuals in the sample based on one election. In other words, differential sorting into who votes in each Presidential election is not responsible for the pattern shown in Figure 5.

[4] We exclude November of each Presidential election year.

is controlled by the party she favors. We explore this idea in Figures 6 and 7. In these figures, we examine longer run trends in transfers, federal tax rates, and personal income for Republican-leaning counties and states around the 2000 and 2008 election. We focus on these two elections because the White House changed parties in both of them, and it is too early to examine longer run outcomes after the 2016 election.

More specifically, for a given outcome X and for the 2000 election, we estimate the following regression for each year 1997 through 2008:

$$ln(X_{gy}) - ln(X_{g,1997}) = \alpha^y + \beta^y * RepShare_{g,2000} + \epsilon_{gy} \tag{4}$$

where g indexes a geographical area (either a county or a state), and $RepShare_{g,2000}$ is the number of votes in a state or county for the Republican candidate, scaled by the total number of votes for either the Republican or Democrat. The analagous regression for the 2008 election is estimated for the 2005 to 2015 period:

$$ln(X_{gy}) - ln(X_{g,2005}) = \alpha^y + \beta^y * RepShare_{g,2008} + \epsilon_{gy} \tag{5}$$

We utilize cumulative growth specifications to see if there is a sharp break in any outcomes after the election year.

The top two panels of Figure 6 utilize county-level BEA data on transfers from the Federal government. The bottom two panels utilize state-level data on taxes and income from the BEA to construct the state-level average tax rate. All four panels plot the estimates and standard errors for β^y for the years around each election for the outcome in question.

As the top left panel shows, transfers toward Republican-leaning counties began to rise in 1999 and accelerated in 2000. While this relative increase in transfers to Republican areas continued throughout the Bush presidency, there is not a sharp break at the time of the election. In the bottom left panel, we examine tax rates. The evidence suggests that tax rates were declining in Republican-leaning counties from 1996 to 2000, but then leveled off after 2000 and even began to rise in 2006 and 2007. For tax rates, the evidence suggests Republican-leaning counties experienced higher tax rates relative to Democrat-leaning counties under Bush.

There is evidence of a short-lived relative decline in transfers to Republican-leaning counties immediately after the election of Barack Obama that lasts until 2010. However, the pattern reverses after 2010 when Republican leaning-counties see strong growth in transfers. The tax rate evidence suggests that tax rates actually declined in relative terms for Republican-leaning counties in 2009 and 2010. Given the mixed evidence, it is hard to see a sharp break in relative transfers or relative tax rates when the White House changes hands that would justify the dramatic relative changes in economic expectations after the election.

Figure 7 examines per capita income growth at the county level. Republican-leaning counties experienced a sharp relative decline in personal income from 1996 to 2000 that was reversed during the early Bush years. However, Republican-leaning counties saw another sharp relative decline from 2005 to 2007. Republican-leaning counties saw their relative income growth improve substantially in 2008, and it continued to improve in relative terms through 2013. From 2013 to 2015, there is evidence of a relative decline in income in Republican leaning counties. Our reading of the personal income patterns is that the evidence does not support the view that there was a sharp break in relative personal income growth that would justify the dramatic relative changes in economic expectations after the elections of 2000 and 2008.

3 Does Partisan Bias Affect Household Spending?

3.1 Individual and county-level evidence

We begin our investigation of the effect of partisan bias on household spending by exploring answers to questions in the Michigan survey. As mentioned in Section 1, the Michigan survey asks individuals questions about whether now is a good time to buy a car or household items. Figure 8 examines the answers to these questions by presenting coefficient estimates from equation 2, where we use the spending questions in the Michigan survey as the left hand side variable.

In stark contrast to the evidence on economic expectations, we see little evidence to support the view that individuals more likely to vote for the Republican candidate see a relative change in answers to spending questions after Presidential elections. This is particularly surprising given that these questions are in the same survey in which those more likely to vote for the Republican express optimism on future economic conditions. For example, Table 3 shows evidence that individuals more likely to vote for President Trump see a sharp increase in optimism concerning their personal financial situation after November 2016; however, there is little evidence of a change in their views on whether it is a good time to buy a car or household items.

A drawback to these survey questions is that they do not capture actual household spending. To measure the response of actual spending, we turn to data on auto purchases and credit card spending at the county level. Moving to the county level requires us to construct county-level measures of the propensity to vote for the Republican candidate in each election. To measure this propensity, we use the total votes for the Republican candidate in the county divided by the total votes for either the Republican or Democrat, which we refer to as the two-party vote share for the Republican.

We focus on new auto purchases around the Trump election in Figure 9. To create this figure, we utilize a methodology similar to the methodology used to create Figure 1. For each county, we index auto sales to be 100 in October of the Presidential election year. We then estimate for each month the following county-level cross-sectional regression:

$$autosalesindexed_{cm} = \alpha^m + \gamma^m * RepShare_{cm} + \nu_{cm}$$

Using the estimates from this specification, we predict auto sales in each month around the election for $RepShare_{cm} = 0$ and $RepShare_{cm} = 1$. In this manner, we estimate the evolution of auto sales in a county where all voters vote for Hillary Clinton in 2016 ("Democratic counties") and where all voters vote for Donald Trump in 2016 ("Republican counties").

As Figure 9 shows, there is little evidence of a larger rise in auto purchases in counties that voted for Donald Trump in 2016. This null result on auto purchases is in stark contrast to the strong rise in optimism on the economy among those most likely to vote for Donald Trump, which is shown above in Figure 1 in Section 2. The strong relative rise in optimism among Trump voters does not appear to translate into higher auto purchases.[5]

In Figure 10, we estimate the county-level version of equation 2 from Section 2 above. More

[5]In Appendix Figure 3 contains a similar graph for each of the previous four elections. As with 2016, there is no evidence of a relative change in auto purchases in Republican-voting counties around the previous four elections. The only exception is the 2012 election in which counties voting for Barack Obama see some evidence of a relative rise in auto sales. As we show below, this relative rise in Democratic counties after the 2012 election is not statistically significant at a reasonable confidence level.

specifically, for each pseudo-year y, we estimate the following regression:

$$Ln(S_{cm}) = \sum_{m=June}^{m=May} \alpha^m * d_m + \gamma^0 * RepShare_c + \sum_{m=June, m \neq Oct}^{m=May} \gamma^m * (d_m * RepShare_c) + \nu_{cm} \quad (6)$$

where d_m is an indicator variable for month m, $m = 0$ is the "omitted" month which is October, α^m represents month fixed effects, and γ^m are the coefficients of interest that measure the relative shift in log spending ($Ln(S)$) around the election for counties with a higher vote share for the Republican candidate ($RepShare$). We estimate equation 6 for both auto purchases and credit card spending. We only have data for credit card spending from 2006 to 2013, and so the analysis for credit card spending is focused only on the 2008 and 2012 elections.

There is little evidence in Figure 10 of a sharp change in spending patterns for Republican-leaning counties around any of the elections. If anything, there may be some evidence that auto spending actually rose more for Republican-leaning counties after the 2008 election. For credit card spending, Republican-leaning counties tend to see a stronger spike in spending every December, but there is no evidence that 2008 or 2012 were special relative to the non-election years.

In Table 4 we formally test the statistical significance of the patterns shown in Figures 8 and 10. In columns 1 and 2, we estimate a regression specification that is identical to equation 3 shown in Section 2, but we replace the left hand side variable with the spending measures from the Michigan survey on whether an individual believes it is a good time to buy household durables or a car, respectively.

For both measures, none of the 10 coefficients on the Republican vote propensity interacted with the post election indicator are statistically significantly different than zero at the five percent confidence level. This is despite the fact that Republicans see large shifts in economic expectations after four of these elections, as shown above in Table 3. There is some evidence that individuals more likely to vote Republican in 2008 see a relative decline in the household items measure after the 2008 election. There is also some evidence that individuals more likely to vote for the Republican see a relative rise in the car measure after the 2016 election. But these coefficients are only marginally statistically significant.

In columns 3 and 4 of Table 4, we estimate a similar specification using the county-month level data on new auto purchases and credit card spending. More specifically, we estimate the following specification:

$$Ln(S_{cym}) = \alpha_m + \alpha_m * RepShare_c + \alpha_y + \alpha_y * RepShare_c + \sum_{y=00,04,08,12,16} [\beta^y * Post_y] + \sum_{y=00,04,08,12,16} [\gamma^y * Post_y * RepShare_c] + \epsilon_{cym} \quad (7)$$

where S_{cym} is either new auto purchases or credit card spending, α_m are month of year indicator variables, α_y are pseudo-year indicators (i.e., June to May), and $Post_y$ is an indicator variable for November to May of pseudo year y. As before, the coefficients of interest are the γ^y for each election year. The coefficients γ^y measure the differential change in log spending after the election for counties that more heavily favored the Republican candidate in the election in question.

As the coefficient estimates on the interaction terms show, there is no evidence of a relative change in auto purchases or credit card spending among those supporting the Republican candidate in any of the elections. The evidence does not support the view that changes in expectations driven by who wins the White House affects actual spending.

One potential explanation for the lack of an effect on actual spending is borrowing constraints. Perhaps those supporting the winner of the Presidential election want to increase consumption, but they cannot obtain financing. While this is a possibility, recall that there is a decline in economic expectations for those supporting the losing candidate in Presidential elections, and we do not see a relative decline in spending for this group. It is difficult for borrowing constraints to explain why those become more pessimistic do not decrease spending–borrowing constraints do not prevent an individual from reducing purchases.

3.2 State-level evidence

A concern with the results above is that we do not have a comprehensive measure of total consumption. In this section, we examine state-level consumption data from the Bureau of Economic Analysis. The advantage of this data set is that it contains comprehensive measures of consumption in a state. But a disadvantage is that it is only available at the annual frequency. As a result, we cannot do a monthly analysis right around the election. Furthermore, these data are only available through 2015 at the time of this writing.

Our approach is to measure annual per-capita consumption growth rates for each state, and then see if these annual growth rates exhibit a sharp relative change in the years after a Presidential election for states that have a larger vote share for the Republican candidate. More specifically, for each year t, we estimate the following cross-sectional regression:

$$\Delta Ln(C_{st}) = \alpha^t + \beta^t * RepShare_{st} + \epsilon_{st} \quad (8)$$

where C_{st} is per-capita consumption in state s in year t, and $RepShare_{st}$ is the Republican vote share for state s in year t. As above, for non-election years, we assign a state its Republican vote share in the nearest election: 2000 for 2001 and 2002; 2004 for 2003, 2005, and 2006; 2008 for 2007, 2009, and 2010; 2012 for 2011, 2013, and 2014; and 2016 for 2015.

The regressions above in equation 8 yield a β for each year. We plot these coefficients in Figure 11. In the left panel, we plot coefficients using total per-capita consumption growth as the left hand side variable. In the right panel, we exclude spending on gas in our measure of consumption growth. We show results excluding gas spending because there is a strong correlation between the gas share of total consumption in a state and whether the state tends to lean Republican. For example, a regression of the average gas share in a state during the 2000 to 2015 period on the average Republican vote share yields an R^2 of 0.45. As a result, a large change in gas prices may lead to large changes in consumption growth across states that are correlated with the political leaning of states. These changes in consumption driven by gas price fluctuations are unlikely to be driven by to partisan-related economic expectations.

In both panels, the estimate of β^{2013} and β^{2001} are opposite to what we would expect if changes in economic expectations driven by Presidential elections affected consumption growth. Republican-leaning states saw a relative decline in consumption growth after the Bush 2000 victory, and they witnessed a relative increase in consumption growth after the Obama 2012 victory. In the left panel, β^{2009} is the third most negative estimate in the distribution, which is supportive of the idea that Republican-leaning states witnessed a relative decline in consumption growth after the Obama 2008 election. However, as shown in the right panel, the negative value of β^{2009} appears to be related to the sharp drop in gas prices that began in late 2008 and continued into 2009. When we exclude gas expenditures, Republican-leaning states did not experience a relative decline in consumption in 2009.

3.3 The 2006 to 2007 decline in house prices

The analysis above suggests that shifts in economic expectations driven by Presidential election outcomes do not have strong effects on consumption. But this raises a concern. Do shifts in economic expectations as measured in the Michigan survey ever correlate with actual household spending? Perhaps these shifts in expectations are always random noise with little relevance for actual economic outcomes?

We already have evidence from Barsky and Sims (2012) that "unexplained movements in the responses to forward-looking questions from the Michigan Survey of Consumers have powerful predictive implications for the future paths of macroeconomic variables." In aggregate analysis, movements in economic expectations as measured in the Michigan survey are related to future income and consumption growth. But perhaps the cross-sectional variation in survey responses is rarely if ever correlated with cross-sectional changes in household spending?

To examine this question, we focus on an alternative economic shock: the initial decline in aggregate house prices from 2006 to 2007 in the United States. This shock offers a promising source of cross-sectional variation across U.S. counties in exposure to a fundamental shock, and it therefore serves as a useful counter-example where we should expect to find an effect on both economic expectations and household spending. More specifically, there is a great deal of variation across U.S. counties in the degree to which house prices fell during the 2006 to 2009 period (e.g., Mian et al. (2013)). Also, total employment declined more in counties seeing a sharper decline in house prices (e.g., Mian and Sufi (2014)), and there are long-lasting effects on income for the individuals living in these counties (Yagan (2016)). Finally, there is a strong positive correlation across counties between house price growth from 2006 to 2007 and house price growth from 2007 to 2008. In hindsight, we know individuals living in counties where house prices began to fall in 2007 experienced a sharp decline in subsequent income and employment growth.

So how did their expectations react? We cannot measure the decline in house prices for a given individual in the Michigan survey, and so we conduct all of the analysis in this section at the county level. For the sake of comparability, we first show our findings for the Trump 2016 election at the county level. More specifically, the top left panel of Figure 12 shows the county-level correlation between the change in the index of consumer expectations around the 2016 election and the Republican vote share of the county in the 2016 election. As above, we measure the change in expectations from the June to October 2016 period to the November 2016 to April 2017 period.

One issue in such a county-level analysis is that the Michigan survey only surveys approximately 500 people a month, which means only the more populated counties have sufficient pre- and post-election survey respondents to obtain an accurate measure of the change in the index of consumer expectations. For the top two panels of Figure 12 we limit the sample to the 111 counties that have at least five Michigan survey respondents in both the pre- and post-election periods. We also weight each county by the number of survey respondents.

The top two panels of Figure 12 show the same pattern for the 2016 election as already shown above. Counties that voted more heavily in favor of Donald Trump see a relative rise in economic expectations (left panel). But there does not appear to be any effect on auto purchases (right panel).

For the house price shock, we measure economic expectations in the pre-period from 2004 to 2006. This was a period of economic expansion when house prices rose nationally. Beginning in 2007, house prices began to fall in the United States. Further, they began to fall quite dramatically in some counties. We measure economic expectations in the post period using survey responses of a county in 2007. We purposefully do not include 2008 because it was a year of dramatic national economic events and it was the year that Barack Obama became President. Both of these factors would likely affect economic expectations for reasons unrelated to house price growth. As a result, 2007 is a clean year for measuring cross-sectional variation across counties in exposure to house price declines during the Great Recession. As before, we only keep counties that have at least five individuals surveyed both in the pre- and post-period.

As the bottom left panel shows, counties seeing a relative decline in house prices also report a relative decline in the index of consumer expectations. There is substantial variation across counties in house price growth from 2006 to 2007, with some counties seeing declines of 20 to 30 percent. Individuals living in those counties report a more pessimistic economic outlook. As already mentioned, these individuals did in fact experience a relatively worse recession after 2007. In this case, survey respondents changed their economic expectations in a predictable way given the fundamental shock they received.

Further, as the bottom right panel shows, auto purchase growth from 2006 to 2007 in a county is strongly correlated with house price growth from 2006 to 2007 in a county. So in the case of the house price growth shock, we see that variation across counties in a fundemental shock to economic prospects is correlated with the change in economic expectations in the county. And this variation is also correlated with actual spending.

In Table 5, we show coefficients from univariate county-level regressions to confirm the robustness of the patterns shown in the bottom two panels of Figure 12. In the regressions, we keep all counties where we have at least one survey respondent in the pre- and post-periods. We weight each county in all regressions with the number of survey respondents to the Michigan survey in the county.

As column 1, the change in economic expectations and house price growth in a county from 2006 to 2007 are positively correlated. Columns 2, 4, 6, and 8 show that all of our measures of household spending are also correlated with the underlying house price growth shock. Columns 3, 5, 7 and 9 show that these reduced form correlations are strong enough to generate a correlation between our spending growth measures from 2006 to 2007 and the change in economic expectations as recorded in the Michigan survey. When there is a true shock to economic fundamentals, economic expectations and actual household spending react as would be predicted in most economic models.

4 Comparison with Recent Research

In a study made public subsequent to the original version of this study, Benhabib and Spiegel (2016) use an alternative political measure to capture changes in economic expectations related to political events. In particular, their study utilizes state-level data from 2006 to 2013, and it constructs a variable for each state-quarter which is the fraction of U.S. Congressional delegates from the state that is from the same party as the sitting President, which the authors call *congpres*. The primary measure of economic expectations in their study is the country business conditions in 5 years question from the Michigan survey (*BUS5*).

The study by Benhabib and Spiegel (2016) employs a two-stage least squares framework in a state-quarter panel in which they first regress *BUS5* on *congpres*, where the specification includes state fixed effects.[6] The framework then regresses year over year GDP growth in a state on the predicted value of *BUS5*, again including state fixed effects. In the specification with year indicator variables and where standard errors are clustered by state, the methodology does not find a positive effect of instrumented changes in expectations on a state's GDP that is statistically distinct from zero at a reasonable confidence level.[7]

In Appendix Tables 3 and 4, we replicate the analysis in Benhabib and Spiegel (2016). We also replace the left hand side variable of the second stage with state personal consumption expenditures annual growth instead of state GDP growth.[8] We show that there is no statistically reliable effect of instrumented *BUS5* on consumption growth in a state using the methdology in Benhabib and Spiegel (2016). We conclude based on these findings that the specification proposed in Benhabib and Spiegel (2016) does not yield a statistically reliable positive effect of changes in expectations driven by political considerations on household spending or GDP growth.

A contemporaneous study by Gillitzer and Prasad (2016) examines how shifts in economic expectations due to Federal elections in Australia affect household spending.[9] They examine four elections in Australia that led to a change of government in 1983, 1996, 2007, and 2013. They also find large shifts in economic expectations around these elections based on the party supported by the individual in the survey (see in particular their Figure 4). However, they find different results when it comes to other survey questions on the intention to spend on automobiles or major household items (see in particular their Figure 7 and Figure 8). Whereas we find at most a small effect, they find large effects for the 1996, 2007, and 2013 Australian elections.[10]

What might explain this difference? One advantage of the Gillitzer and Prasad (2016) data set is that it includes a direct measure of the party supported by the survey respondent. We do not have such a variable in the Michigan survey; instead, we estimate the propensity to vote for a given candidate based on the methodology described in Section 1. Gillitzer and Prasad (2016) suggest the difference in their results with ours may be due to better measurement of party affiliation in their data set relative to the Michigan data set used here. While this may be true, recall that we

[6] More specifically, Benhabib and Spiegel (2016) use the share of respondents answering 1 or 2 to the *BUS5* question.

[7] More specifically, in the specification reported in Table 8, column 6 of the working paper dated December 20, 2016, the coefficient estimate on instrumented *BUS5* is 0.104 with a standard error of 0.995.

[8] State personal consumption data from the BEA is available only at the annual frequency.

[9] We refer specifically to the August 2016 version of this study.

[10] They do not have data on intention to spend for the 1983 election.

find large and statistically precise effects of elections on changes in economic expectations among partisans (see our Figure 3). Measurement error of our partisan variable is difficult to explain why we are able to detect these large relative changes in economic expectations based on voting propensity, but not for relative changes in the intention to spend. An alternative reason for the difference in results is that we focus on two different countries.

To measure actual spending, Gillitzer and Prasad (2016) use postcode-quarterly level auto purchases for the 2007 and 2013 elections in Australia. The short-run evidence they find using actual auto purchase data is similar to the findings presented in this study. In particular, for both Australian elections, there is no relative difference in the evolution of auto sales from the two quarters before the election to two quarters after the election based on the vote share of the postal code.[11] As in our analysis, Gillitzer and Prasad (2016) find a large and immediate effect of elections on economic expectations, but no effect on actual auto purchases in the six months following the election.

For both the 2007 and 2013 election, Gillitzer and Prasad (2016) find longer run effects that begin three quarters after the election. For the 2007 election, they find the strongest relative growth in auto sales among those supporting the Australian Liberal Party in the 2010 to 2012 period. Individuals supporting the ALP see a sharp rise in economic expectations immediately after the election in 2007 and the strongest effect on auto purchases is from 2010 to 2012. One concern is that such longer run effects shown in Gillitzer and Prasad (2016) could be driven by alternative factors rather than a reaction to the Federal election outcome. In Appendix Figure 5, we do not find evidence of a relative change in auto sales for those more likely to support the winning candidate one year after each presidential election for which we have data. For the 2016 election, we do not see evidence of a relative shift in auto purchases through April 2017 for counties most heavily voting for Donald Trump in November 2016, but only time will tell if an effect on auto purchases materializes in the longer run.

One other difference between our analysis of auto purchases and the analysis in Gillitzer and Prasad (2016) is the level of aggregation. Their analysis is conducted at the Australian post code level, which is similar to the U.S. zip code level. For the 2008 presidential election, we have vote

[11] See in particular their Figure 10. Gillitzer and Prasad (2016) do not present regression estimates and statistical significance for the estimates in their Figure 10, but based on the figure there does not appear to be a short-run effect from two quarters before the election to two quarters after the election.

shares available at the zip code level. We also have both auto spending and credit card spending at the zip code level. In Appendix Figure 4, we replicate Figure 10 around the 2008 election using zip code level data, and we find no relative decline in auto purchases in zip codes most heavily supporting the Republican candidate. In Appendix Table 5, we show there that zip codes more likely to vote for the Republican in the 2008 election actually see higher auto spending in the six months after the election. We conclude based on these robustness test that the higher level of aggregation is unlikely to explain the null spending result we find in county-level data.

5 Conclusion

Individuals form economic expectations through a partisan perceptual screen, and this tendency is increasing over time. The election of Donald Trump boosted this phenomenon beyond any effect seen since 2000. The well-documented rise in political polarization among the U.S. electorate has been accompanied by a substantial increase in the effect of partisan bias on the formation of economic expectations. However, the shift in economic expectations induced by partisan bias does not appear to affect household spending. For example, despite the enormous relative increase in economic optimism among Trump supporters after November 2016, there is little evidence of a relative increase in spending patterns since the election.

We have purposely kept our analysis mostly descriptive, because we view these results as surprising and puzzling. Our view is that these results are most consistent with the lessons from political science and social psychology as illustrated by Iyengar et al. (2012), Mason (2013), and Mason (2015). For example, Mason (2015) writes, "... a partisan behaves more like a sports fan than like a banker choosing an investment ... the connection between partisan and party is an emotional and social one, as well as a logical one." Individuals feel elation after their "team" wins the White House. They feel the economy will improve. But their spending does not respond. One interesting avenue for future research would be to explore whether the same phenomenon applies to sports. When an individual's favorite sports team wins a championship, does she expect the economy to improve while keeping spending unchanged?

Our findings raise a number of additional questions. For example, why is partisan bias exerting a larger effect on economic expectations over time? The answer to this question is likely related to reasons for the well-documented rise in social and affective polarization (e.g., Gentzkow (2016), Boxell et al. (2017)). Could it be television media? Could it be racial tension? We speculate that the underlying causes of the rise in polarization also explain the increasing partisanship in economic expectations formation.

Second, does reported partisan bias in economic expectations matter if it does not affect actual household spending? McGrath (2016) writes, "... although partisans report biased perceptions of the economy, their economic behavior reflects an unbiased perception of the state of the world." Although the increasing partisan bias in economic expectations may not affect spending, this increased partisan bias may be correlated with other important outcomes, such as voting. For example, it could be that a rise in pessimism about the overall economy in survey questions predicts who an individual votes for in the next Presidential election, despite the fact that such pessimism does not affect the individual's actual spending. More broadly, we may be able to predict voting patterns or other behavior based on how individuals answer survey questions better than using economic measures such as income growth or employment status. We look forward to future research exploring this idea.

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Table 1
Summary Statistics

This table presents summary statistics for the individual-level, county-month-level, county-year-level, and state-year-level data sets used in the analysis. The sample is from 2000 to 2017. For the county-level data sets, we weight summary statistics by the population in the county as of 2008.

	Obs	Mean	SD	P10	P90
Individual level					
Index of consumer expectations	103,350	0.00	1.00	-1.06	1.53
My financial situation, 1 year	100,690	-0.00	1.00	-1.83	1.23
Country business conditions, 5 years	99,181	0.00	1.00	-1.05	1.19
Country business conditions, 12 months	94,428	0.00	1.00	-0.97	1.12
Government economic policy	101,645	-0.00	1.00	-1.17	1.59
Index of current economic conditions	103,350	-0.00	1.00	-1.92	1.19
Good time to buy durables	98,488	0.00	1.00	-1.72	0.62
Good time to buy car	98,366	-0.00	1.00	-1.53	0.68
Individual republican vote propensity	93,332	0.48	0.19	0.21	0.71
County republican vote share	103,347	0.49	0.15	0.29	0.68
County-month level (weighted by population)					
Auto sales	644,527	4940.08	9382.06	102.00	12600.00
Credit card spending (Argus) (millions USD)	298,463	335.37	585.95	5.31	913.41
Republican vote share	645,605	0.49	0.15	0.29	0.68
County-year level (weighted by population)					
Per capita personal income (thousands USD)	48,926	38.69	12.97	25.84	53.22
Per capita transfers (thousands USD)	48,926	5.97	2.03	3.49	8.75
State-year level					
Tax rate	800	0.08	0.02	0.06	0.11
Per capita consumption (thousands USD)	800	31.36	6.34	23.53	39.84
Per capita consumption, excluding gas (thousands USD)	800	30.20	6.16	22.67	38.51
Republican vote share	800	0.50	0.11	0.37	0.64

Table 2
Predicting Republican Vote Propensity

This table presents marginal effects of demographics on the probability an individual votes for the Republican candidate in a given election in a given survey. The estimates come from a maximum likelihood Probit estimation. All estimations also include state indicator variables, which are not reported. The sample is limited to those that vote for either the Republican or Democrat.

	EXIT Survey				CCES Survey		
	2000	2004	2008	2012	2008	2012	2016
Ethnicity (Black omitted)							
Hispanic	0.414***	0.401***	0.436***	0.399***	0.439***	0.425***	0.392***
	(0.026)	(0.021)	(0.046)	(0.022)	(0.012)	(0.013)	(0.013)
Non-Hispanic white	0.522***	0.507***	0.482***	0.560***	0.564***	0.538***	0.490***
	(0.016)	(0.013)	(0.018)	(0.010)	(0.009)	(0.007)	(0.007)
Other	0.422***	0.397***	0.542***	0.481***	0.500***	0.524***	0.479***
	(0.027)	(0.025)	(0.038)	(0.019)	(0.008)	(0.008)	(0.010)
Age ($<$ 25 omitted)							
25 to 29	-0.072*	0.066*	-0.056	-0.050*	0.022	0.003	0.019
	(0.035)	(0.027)	(0.037)	(0.023)	(0.017)	(0.020)	(0.019)
30 to 39	-0.065*	0.032	-0.038	-0.036	0.068***	-0.010	0.055**
	(0.030)	(0.024)	(0.035)	(0.021)	(0.015)	(0.019)	(0.017)
40 to 44	-0.058	0.066*	0.042	0.004	0.100***	0.048*	0.102***
	(0.033)	(0.026)	(0.040)	(0.023)	(0.016)	(0.021)	(0.019)
45 to 49	-0.065	0.015	0.009	0.033	0.127***	0.087***	0.153***
	(0.033)	(0.025)	(0.038)	(0.023)	(0.015)	(0.018)	(0.018)
50 to 59	-0.084**	0.003	0.009	0.021	0.159***	0.090***	0.192***
	(0.032)	(0.023)	(0.035)	(0.020)	(0.014)	(0.016)	(0.016)
60 to 64	-0.051	0.068*	0.007	-0.028	0.196***	0.102***	0.179***
	(0.040)	(0.031)	(0.043)	(0.023)	(0.015)	(0.017)	(0.017)
Over 64	-0.039	0.017	0.045	0.068**	0.237***	0.164***	0.192***
	(0.035)	(0.026)	(0.040)	(0.022)	(0.013)	(0.016)	(0.016)
Demographics							
Male (=1)	0.151***	0.072***	0.048**	0.077***	0.098***	0.110***	0.093***
	(0.014)	(0.011)	(0.017)	(0.009)	(0.007)	(0.006)	(0.006)
Married (=1)	0.091***	0.104***	0.110***	0.121***	0.066***	0.095***	0.075***
	(0.017)	(0.013)	(0.020)	(0.011)	(0.008)	(0.007)	(0.006)
Dependent children (=1)	0.057**	0.035*	0.022	0.016	0.089***	0.072***	0.083***
	(0.017)	(0.014)	(0.020)	(0.012)	(0.008)	(0.009)	(0.008)
Education ($<$ HS omitted)							
High school diploma	0.133***	-0.019	0.036	0.074*	0.070***	0.031	0.019
	(0.039)	(0.033)	(0.051)	(0.029)	(0.019)	(0.023)	(0.024)
Some college	0.148***	-0.037	0.011	0.051	0.051**	0.028	-0.052*
	(0.038)	(0.033)	(0.049)	(0.029)	(0.020)	(0.023)	(0.023)
College degree	0.128**	-0.083*	-0.034	0.022	-0.019	-0.041	-0.149***
	(0.040)	(0.033)	(0.049)	(0.029)	(0.020)	(0.023)	(0.022)
Post college	0.034	-0.201***	-0.089	-0.114***	-0.149***	-0.146***	-0.239***
	(0.042)	(0.031)	(0.048)	(0.028)	(0.020)	(0.022)	(0.020)
HH income ($<$ \$30,000 omitted)							
\$30,000 to \$50,000	0.010	0.074***	0.052	0.013	0.044**	0.026**	0.018*
	(0.022)	(0.018)	(0.030)	(0.015)	(0.016)	(0.009)	(0.009)
\$50,000 to \$100,000	0.055*	0.126***	0.097***	0.094***	0.104***	0.040***	0.031***
	(0.022)	(0.017)	(0.028)	(0.015)	(0.013)	(0.009)	(0.008)
Over \$100,000	0.090**	0.159***	0.111***	0.099***	0.144***	0.029**	0.010
	(0.028)	(0.020)	(0.033)	(0.017)	(0.013)	(0.011)	(0.010)
Observations	5420	8905	3700	13351	26140	33084	36479
Pseudo R^2	0.134	0.142	0.171	0.191	0.118	0.128	0.128
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports marginal effects for discrete change of dummy variables.
p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Standard errors in parentheses.

Table 3
Economic Expectations and Republican Vote Propensity

This table presents estimates of how answers to the Michigan survey change differentially for individuals most likely to vote for the Republican candidate in Presidential elections. We report β^y and γ^y from the following specification:

$$X_{iym} = \alpha_m + \alpha_m * RepVote_i + \alpha_y + \alpha_y * RepVote_i + \sum_{y=00,04,08,12,16} [\beta^y * Post_y] + \sum_{y=00,04,08,12,16} [\gamma^y * Post_y * RepVote_i] + \epsilon_{iym}$$

$Post_y$ is an indicator variable for a given pseudo-year y that is one for November through May (i.e., the six months following the Presidential election).

	(1) Index of consumer expectation	(2) My financial situation, 1 year	(3) Country business conditions, 12 months	(4) Country business conditions, 5 years	(5) Index of current economic conditions	(6) Government economic policy
Post 2000 election	-0.478***	-0.198*	-0.480***	-0.433***	-0.132	-0.197*
	(0.079)	(0.081)	(0.082)	(0.083)	(0.079)	(0.078)
Post 2004 election	-0.120	-0.047	-0.113	-0.110	-0.019	0.080
	(0.073)	(0.075)	(0.075)	(0.076)	(0.073)	(0.072)
Post 2008 election	0.124	0.139	0.159*	0.001	-0.013	0.404***
	(0.073)	(0.076)	(0.076)	(0.076)	(0.074)	(0.072)
Post 2012 election	0.165*	0.045	0.147	0.167*	-0.061	0.065
	(0.073)	(0.075)	(0.077)	(0.075)	(0.073)	(0.072)
Post 2016 election	-0.672***	-0.310***	-0.585***	-0.631***	-0.075	-0.255***
	(0.070)	(0.072)	(0.073)	(0.072)	(0.070)	(0.069)
Republican vote propensity						
× Post 2000 election	0.326*	0.247	0.169	0.417**	-0.034	0.311*
	(0.148)	(0.152)	(0.153)	(0.155)	(0.148)	(0.147)
× Post 2004 election	0.096	0.004	0.129	0.092	0.008	-0.190
	(0.137)	(0.140)	(0.140)	(0.141)	(0.137)	(0.134)
× Post 2008 election	-0.507***	-0.267	-0.635***	-0.225	-0.239	-0.715***
	(0.142)	(0.147)	(0.148)	(0.147)	(0.143)	(0.140)
× Post 2012 election	-0.521***	-0.290	-0.381*	-0.497***	0.132	-0.173
	(0.145)	(0.150)	(0.153)	(0.149)	(0.145)	(0.143)
× Post 2016 election	1.844***	0.813***	1.744***	1.619***	0.299*	0.948***
	(0.143)	(0.149)	(0.150)	(0.147)	(0.143)	(0.141)
Observations	92455	90422	84902	89092	92455	91118
R^2	0.074	0.037	0.075	0.046	0.075	0.103

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 4
Household Spending and Republican Vote Propensity

This table presents estimates of the differential response of household spending for those most likely to vote for the Republican candidate in Presidential elections. In columns 1 and 2, we use answers to the Michigan survey using a specification identical to the one described in Table 3. For columns 3 and 4, we use the county-level analogous specification:

$$Ln(S_{cym}) = \alpha_m + \alpha_m * RepShare_c + \alpha_y + \alpha_y * RepShare_c + \sum_{y=00,04,08,12,16} [\beta^y * Post_y] + \sum_{y=00,04,08,12,16} [\gamma^y * Post_y * RepShare_c] + \epsilon_{cym}$$

$Post_y$ is an indicator variable for a given pseudo-year y that is one for November through May (i.e., the six months following the Presidential election).

	(1) Good time to buy durables	(2) Good time to buy a car	(3) Log auto sales	(4) Log credit card spending
Post 2000 election	-0.092	-0.033	-0.103	
	(0.082)	(0.084)	(0.063)	
Post 2004 election	-0.004	-0.104	-0.039	
	(0.076)	(0.077)	(0.064)	
Post 2008 election	0.058	0.108	-0.240***	-0.063
	(0.076)	(0.076)	(0.056)	(0.060)
Post 2012 election	-0.014	0.016	0.081	0.017
	(0.075)	(0.076)	(0.054)	(0.058)
Post 2016 election	-0.038	-0.092	0.015	
	(0.072)	(0.073)	(0.051)	
Republican vote propensity				
× Post 2000 election	-0.138	-0.009	0.102	
	(0.153)	(0.157)	(0.123)	
× Post 2004 election	-0.016	0.081	0.023	
	(0.141)	(0.143)	(0.120)	
× Post 2008 election	-0.283	0.166	0.023	0.013
	(0.147)	(0.147)	(0.114)	(0.123)
× Post 2012 election	0.084	-0.124	-0.015	0.006
	(0.149)	(0.151)	(0.106)	(0.115)
× Post 2016 election	0.119	0.289	0.006	
	(0.147)	(0.149)	(0.098)	
Observations	88536	88498	626917	298459
R^2	0.044	0.021	0.274	0.304

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 5
An Alternative Shock: House Price Growth from 2006 to 2007

This table presents county-level regressions relating house price growth from 2006 to 2007 to the change in economic expectations and spending. In columns 2 and 3, we focus on responses in the Michigan survey to the question of whether now is a good time to buy a major household item, and in columns 4 and 5 we focus on the question of whether now is a good time to buy a car. All specifications are weighted by the number of respondents to the Michigan survey in the county, which is highly correlated with the total population of the county.

	Δ ICE 04-06 to 07	Δ Major HH items 04-06 to 07		Δ Car 04-06 to 07		Auto sales growth, 06-07		Credit card spending growth, 06-07	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
House price growth, 06-07	1.068***	0.991***		0.427		0.593***		0.190***	
	(0.252)	(0.218)		(0.269)		(0.045)		(0.039)	
Δ ICE, 04-06 to 07			0.215***		0.206***		0.010*		0.007*
			(0.029)		(0.029)		(0.004)		(0.003)
Constant	-0.036	-0.035	-0.061***	-0.057*	-0.066***	0.005	-0.028***	0.049***	0.043***
	(0.022)	(0.022)	(0.016)	(0.022)	(0.017)	(0.004)	(0.004)	(0.004)	(0.003)
Observations	714	703	1201	708	1218	714	1236	714	1237
R^2	0.025	0.025	0.051	0.004	0.040	0.360	0.006	0.060	0.004

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Figure 1

Economic Expectations around the 2016 Presidential Election by Vote Propensity

This figure presents the index of consumer expectations for individuals who vote for the Republican candidate and the Democratic candidate in the 2016 Presidential election. To construct the plots below, we first estimate the following regression for each month around the election:

$$ICE_{im} = \alpha^m + \gamma^m * RepVote_{im} + \nu_{im}$$

Where $RepVoteim$ is the propensity to vote for the Republican candidate. The plotted lines below represent predicted values for $RepVote_{im} = 0$ (Democratic voter) and $RepVote_{im} = 1$ (Republican voter) given this estimation.

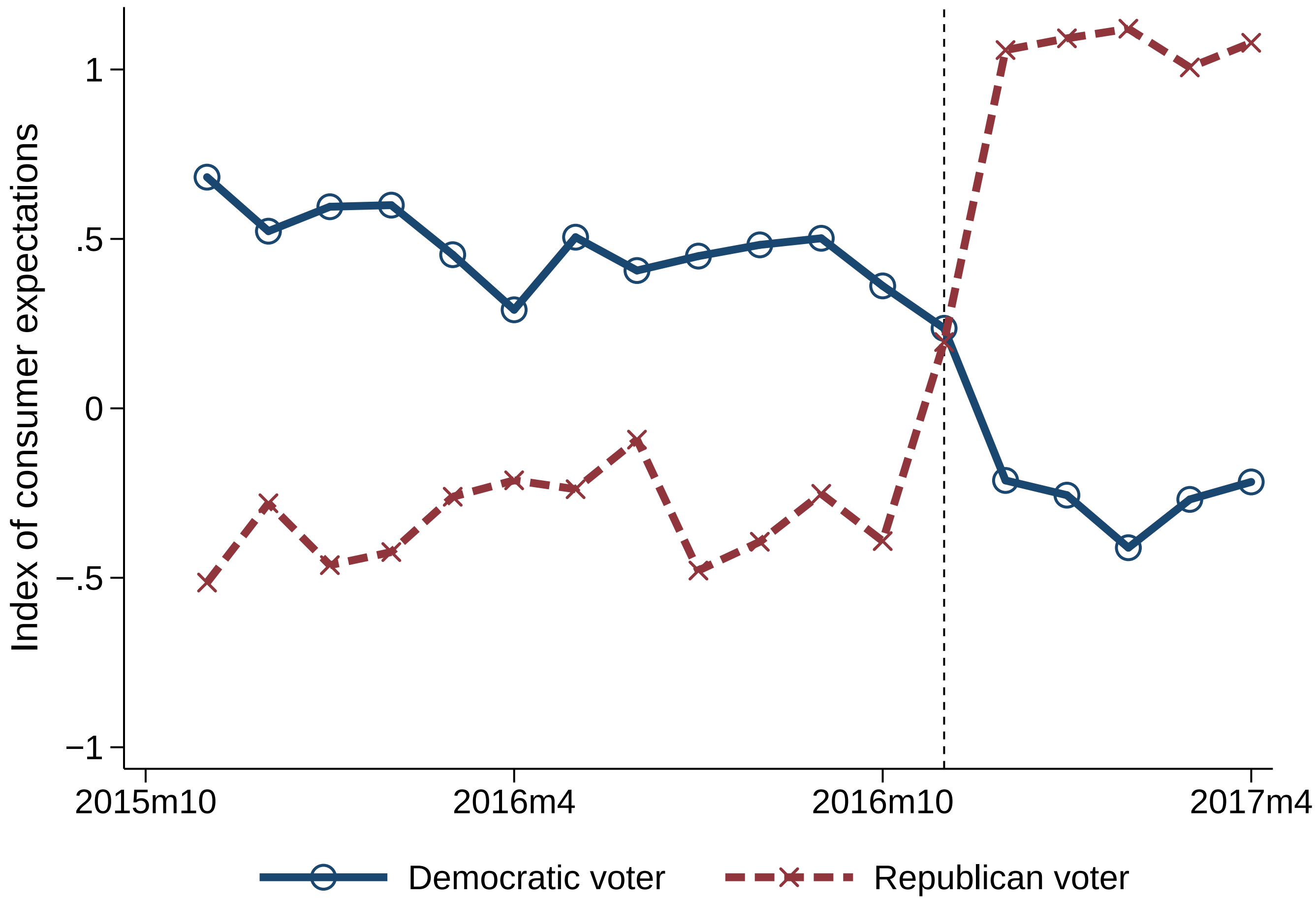

Figure 2
Economic Expectations around Previous Presidential Elections by Vote Propensity

This figure presents the index of consumer expectations for individuals who vote for the Republican candidate and the Democratic candidate in previous Presidential elections. These plots are created using the same technique as described in Figure 1.

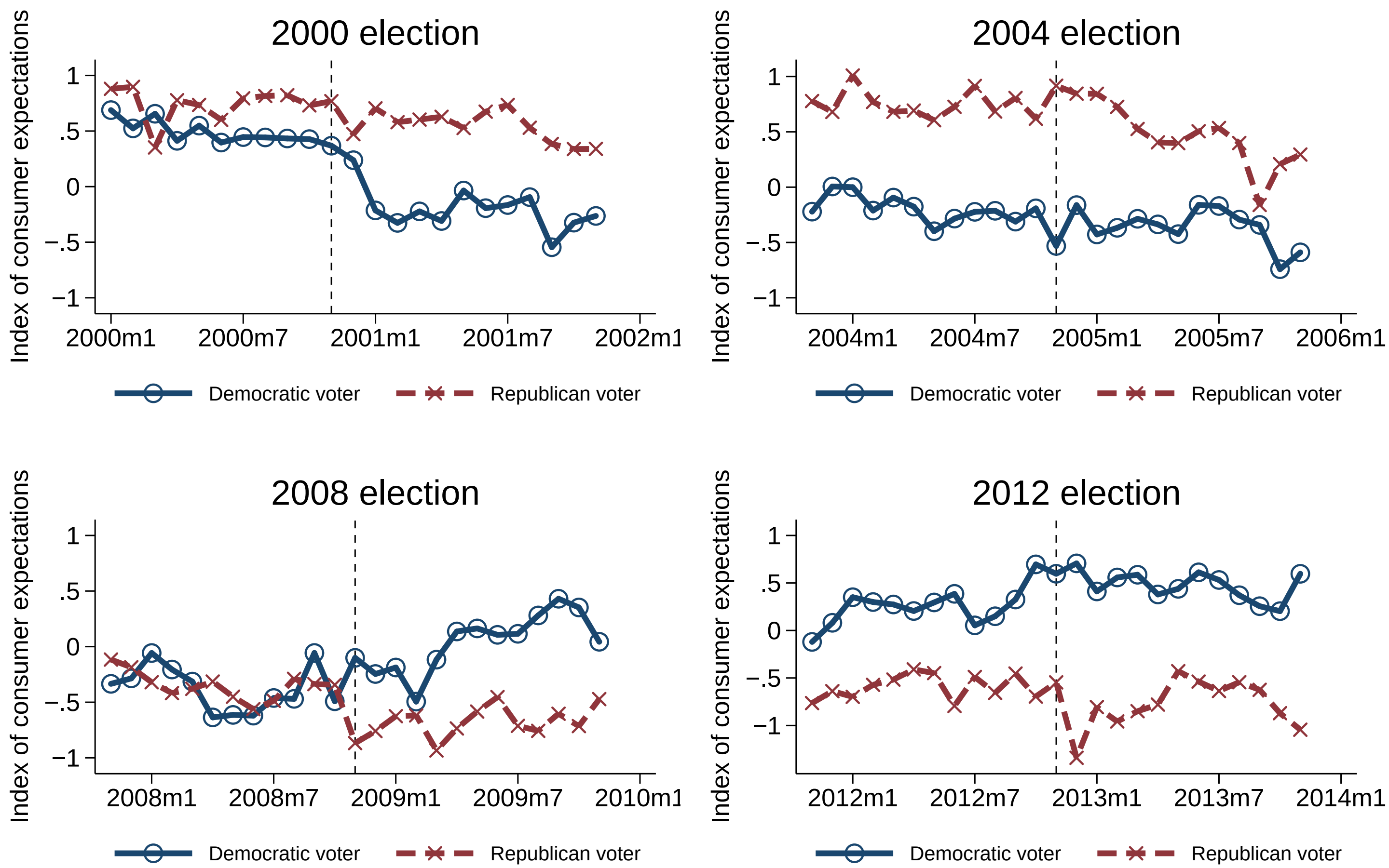

Figure 3
Republican Vote Propensity and the Index of Consumer Expectations

This figure presents coefficient estimates of γ^m for each pseudo year y (June to May) from the following specification:

$$X_{im} = \sum_{m=June}^{m=May} \alpha^m * d_m + \gamma^0 * RepVote_i + \sum_{m=June, m \neq Oct}^{m=May} \gamma^m * (d_m * RepVote_i) + \nu_{im}$$

The coefficients plotted can be interpreted as the relative change in economic expectations for those most likely to vote for the Republican candidate around each Presidential election. The thin gray lines plot γ^m for non-election years, where $RepVote_i$ is based on nearest election year.

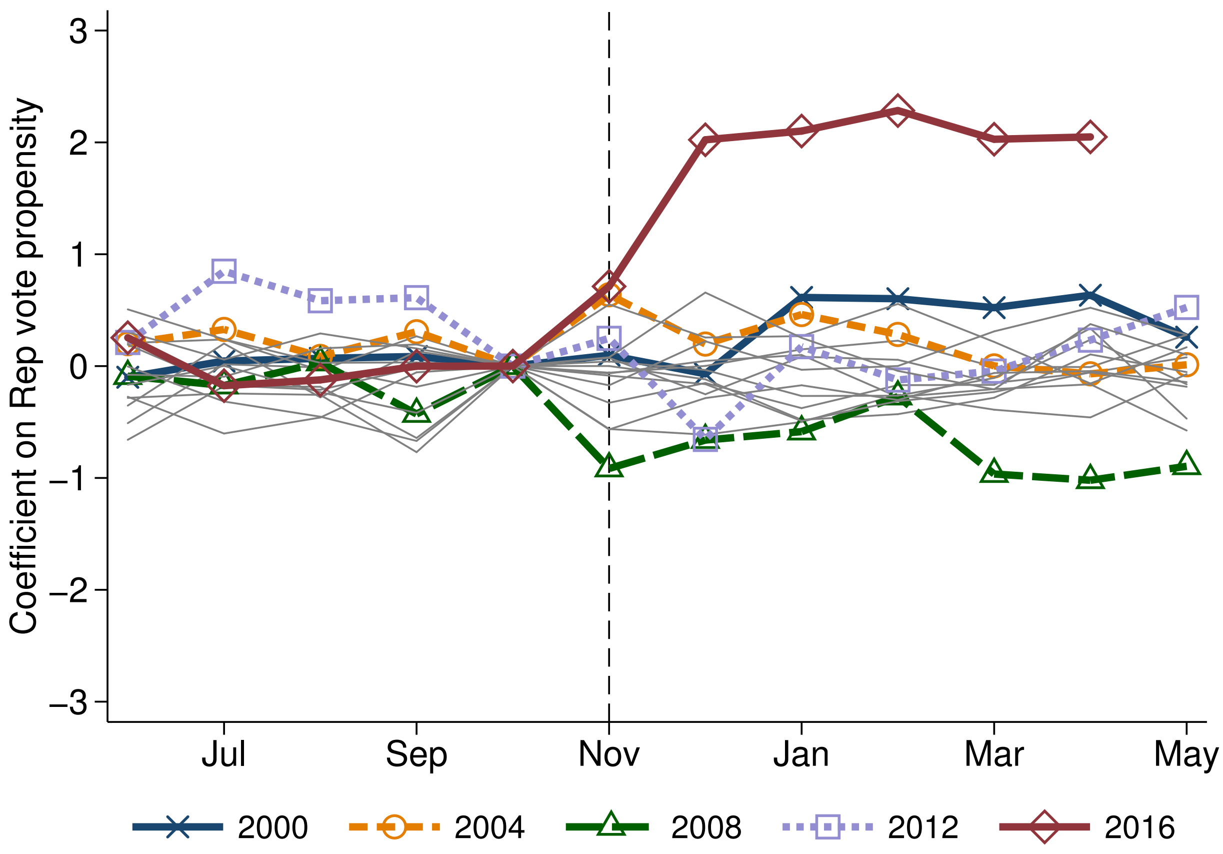

Figure 4

Republican Vote Propensity and Views on Government Economic Policy

This figure presents coefficient estimates of γ^m for each pseudo year y (June to May) for the exact same specification described in Figure 3, but replacing the left hand side variable with views on government economic policy. The coefficients plotted can be interpreted as the relative change in views on government economic policy for those most likely to vote for the Republican candidate around each Presidential election. The thin gray lines plot γ^m for non-election years, where $RepVote_i$ is based on nearest election year.

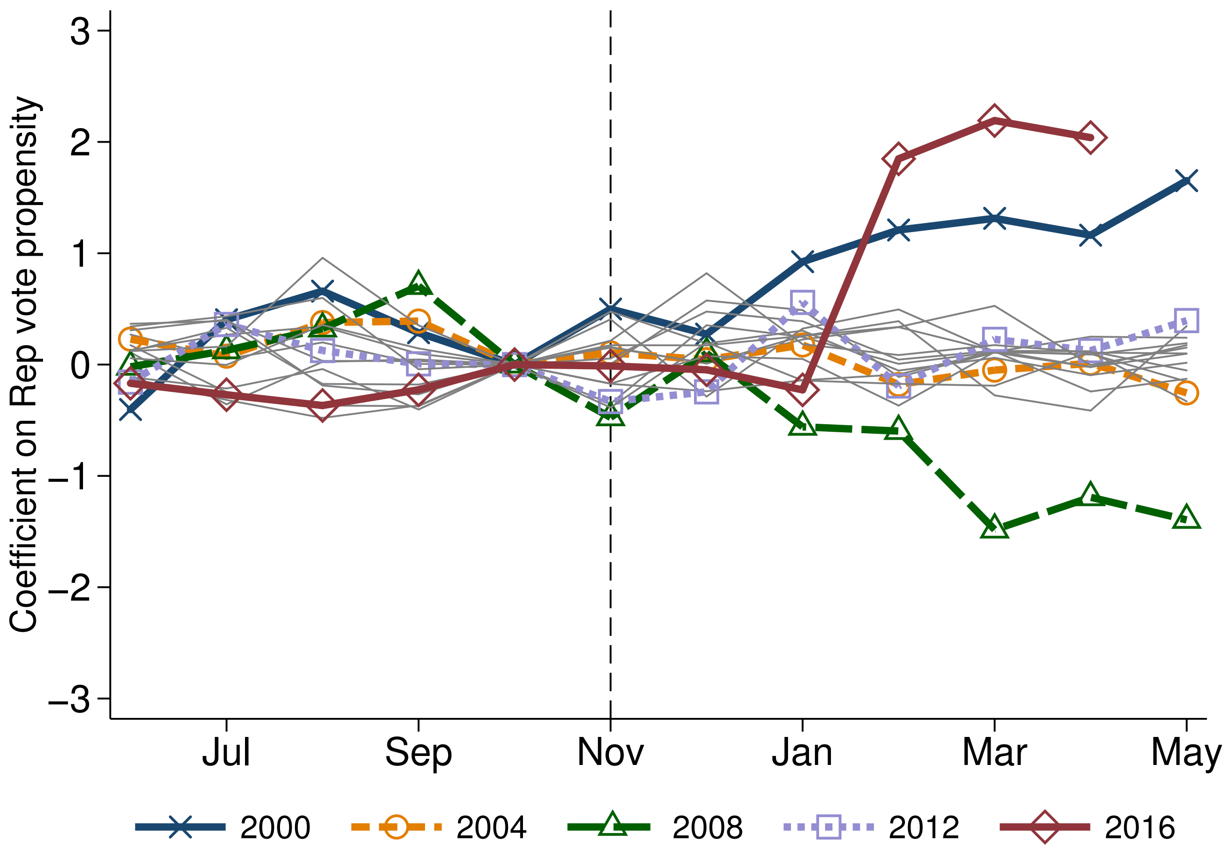

Figure 5
Partisan Bias and Economic Expectations over Time

This figure presents the absolute value of the coefficients γ^m from the following cross-sectional regression run for each month m from January 2000 to April 2017:

$$ICE_{im} = \alpha^m + \gamma^m * RepVote_{im} + \nu_{im}$$

We also plot the averages of these coefficient for each Presidential term. We exclude November of the election years 2000, 2004, 2008, 2012, and 2016.

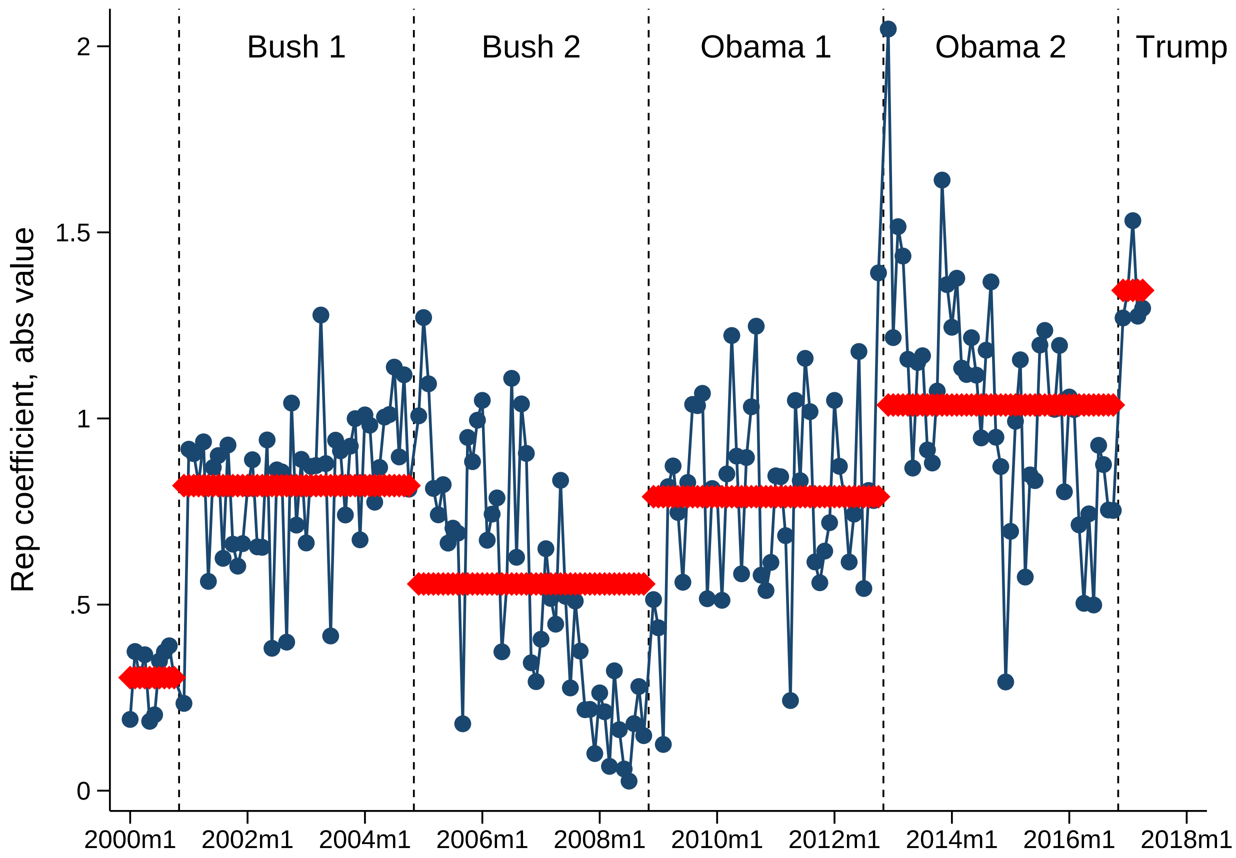

Figure 6
Republican Vote Propensity, Transfers, and Tax Rates

This figure presents coefficient estimates of β^y from the following specification:

$$ln(X_{gy}) - ln(X_{g,baseyear}) = \alpha^y + \beta^y * RepShare_{g,baseyear} + \epsilon_{gy}$$

The base year for the Bush years is 1997, and the base year for the Obama years is 2005. The coefficients in the left and right panels can be interpreted as the relative change in transfers and tax rates for geographical areas most likely to vote for the Republican candidate in the 2000 and 2008 Presidential election, respectively. The transfer specification uses county-year-level data, whereas the tax rate specification uses state-year-level data.

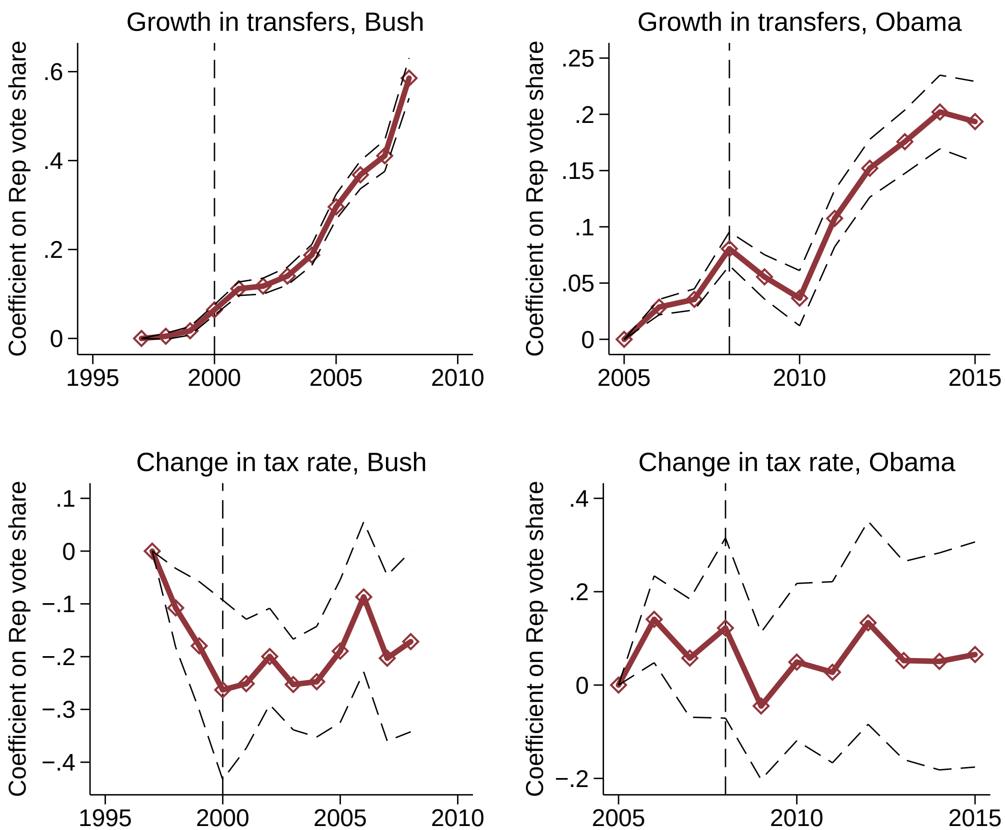

Figure 7
Republican Vote Propensity and Personal Income Growth

This figure presents coefficient estimates of β^y from the exact same specification as Figure 6 but replacing the left hand side variable with per-capita personal income growth from the base year. The coefficients in the left and right panel can be interpreted as the relative change in per capita personal income for counties most likely to vote for the Republican candidate in the 2000 and 2008 Presidential election, respectively. This specification is based on county-year-level data.

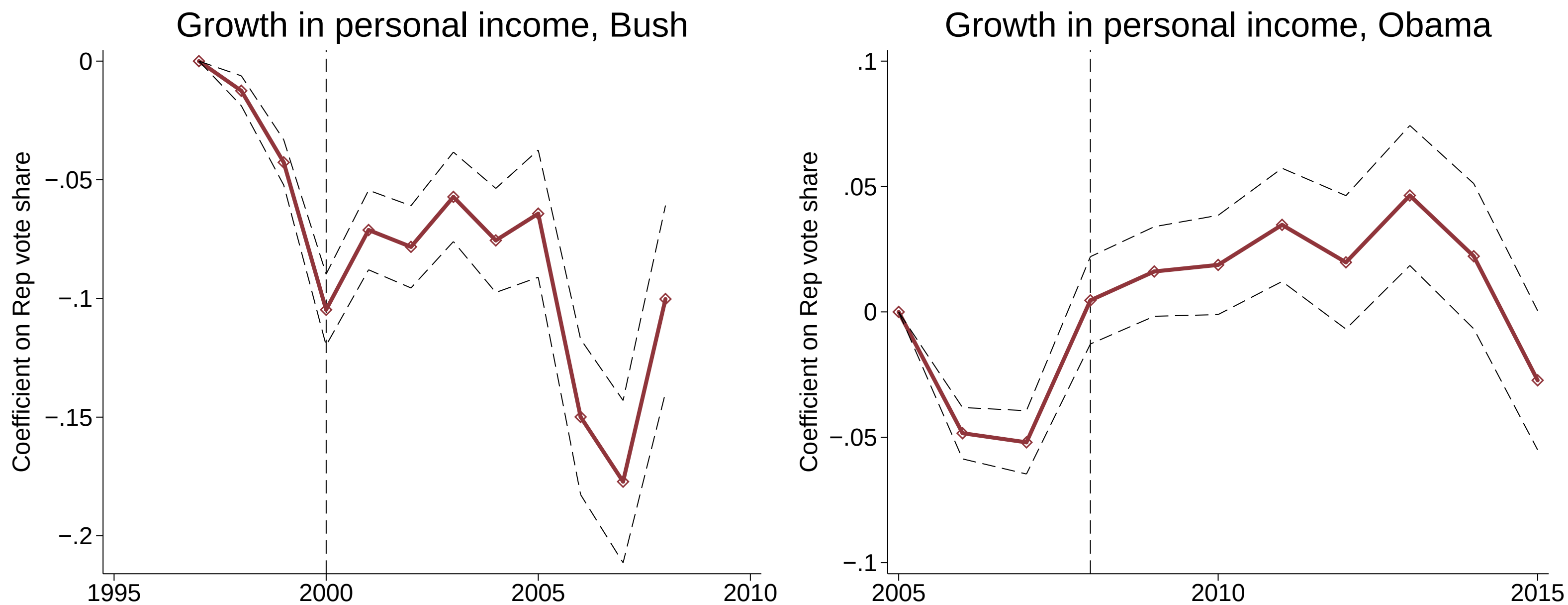

Figure 8
Republican Vote Propensity and "Is It a Good Time to Buy?"

This figure presents coefficient estimates of γ^m for each pseudo year y (June to May) for the exact same specification described in Figure 3, but replacing the left hand side variable with answers to questions on whether it a good time to buy major household items (left panel) or a car (right panel). The coefficients plotted can be interpreted as the relative change in views on whether it is a good time to buy these items for individuals most likely to vote for the Republican candidate around each Presidential election. The thin gray lines plot γ^m for non-election years, where $RepVote_i$ is based on nearest election year.

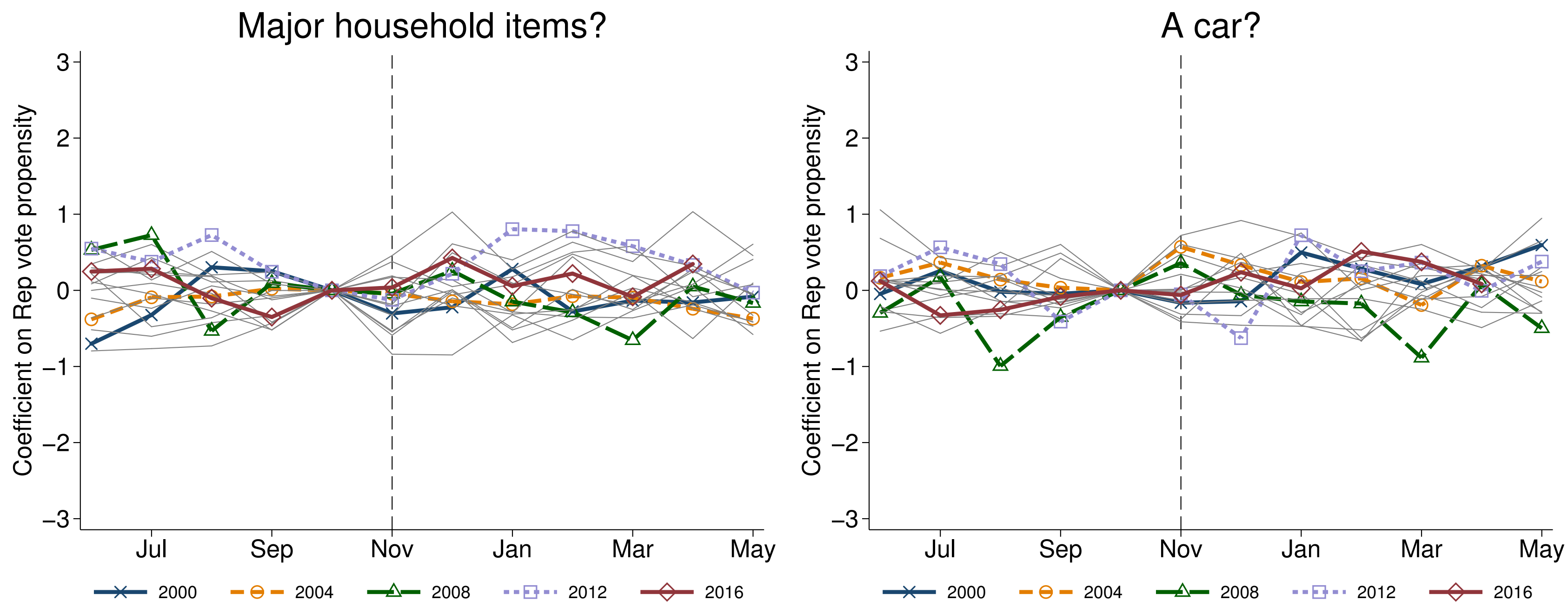

Figure 9

Republican Vote Propensity and Auto Purchases around the 2016 Election

This figure presents auto sales for a county where all voters vote for the Republican candidate and for a county where all voters vote for the Democratic candidate in the 2016 Presidential election. To construct the plots below, we first index auto sales in a county to be 100 in October prior to the election, and then estimate the following regression for each month around the election:

$$autosalesindexed_{cm} = \alpha^m + \gamma^m * RepShare_{cm} + \nu_{cm}$$

Where $RepShare_{cm}$ is the two-party share voting for the Republican candidate in the county. The plotted lines below represent predicted values for $RepShare_{cm} = 0$ (Democratic county) and $RepVote_{cm} = 1$ (Republican county) given this estimation.

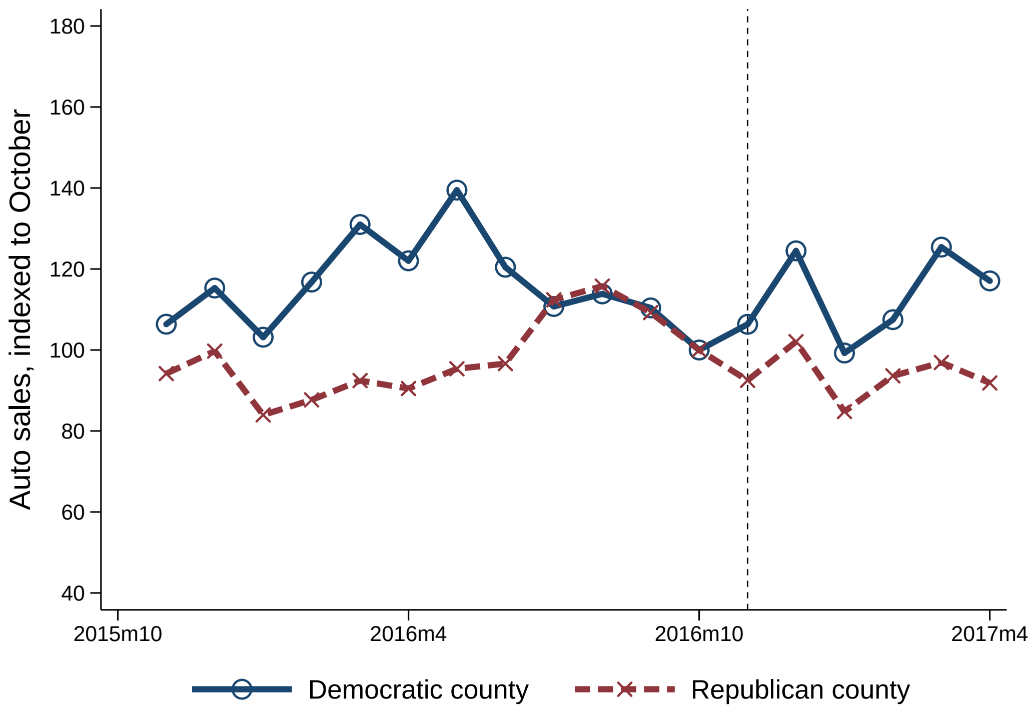

Figure 10
Republican Vote Propensity, Auto Purchases, and Credit Card Spending

This figure presents coefficient estimates of γ^m for each pseudo year y (June to May) from the following specification:

$$Ln(S_{cm}) = \sum_{m=June}^{m=May} \alpha^m * d_m + \gamma^0 * RepShare_c + \sum_{m=June,m\neq Oct}^{m=May} \gamma^m * (d_m * RepShare_c) + \nu_{cm}$$

The coefficients plotted can be interpreted as the relative change in spending for those counties most strongly supporting the Republican candidate around each Presidential election. The thin gray lines plot γ^m for non-election years, where $RepShare_c$ is based on nearest election year.

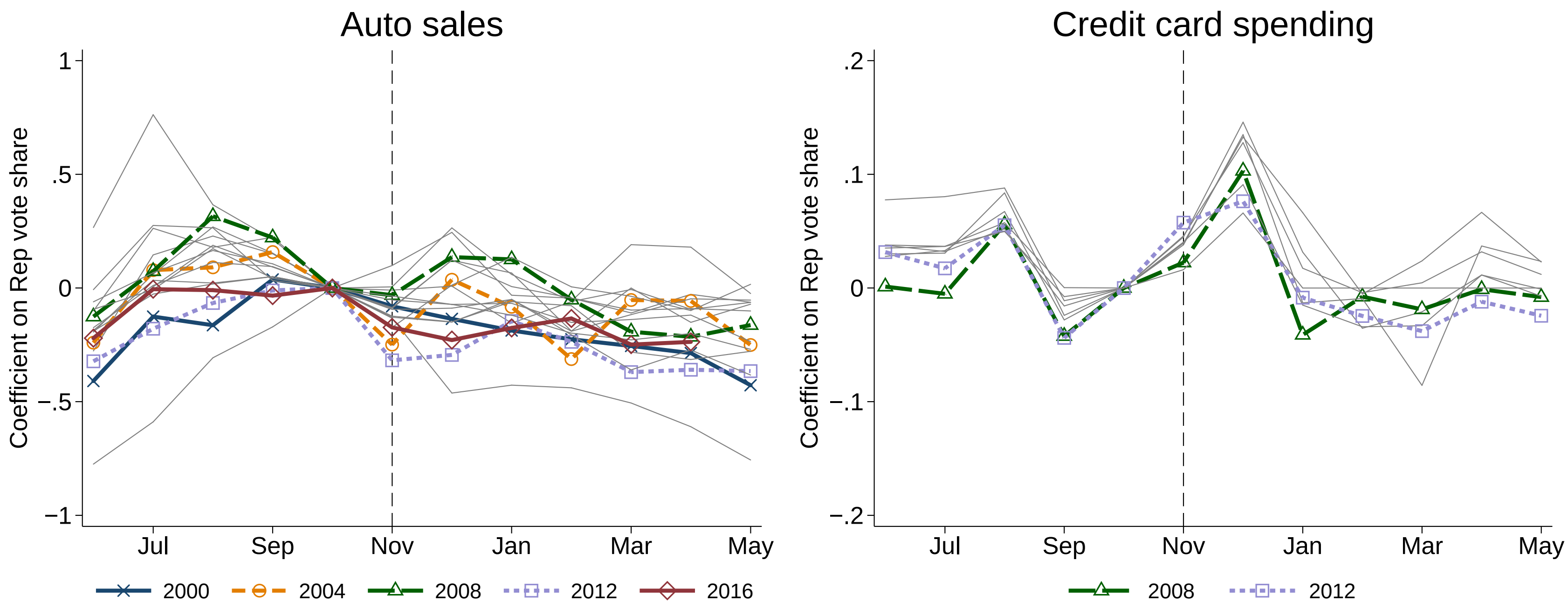

Figure 11
Republican Vote Propensity and State-Level Growth in Consumption

This figure presents coefficient estimates of β^t from the following specification:

$$\Delta Ln(C_{st}) = \alpha^t + \beta^t * RepShare_{st} + \epsilon_{st}$$

where $RepShare_{st}$ is the two-party share of votes in the state for the Republican candidate in the nearest Presidential election. The coefficients can be interpreted as the relative growth in consumption for states most likely to vote for the Republican candidate. The left panel examines total consumption, and the right panel excludes expenditures on gas.

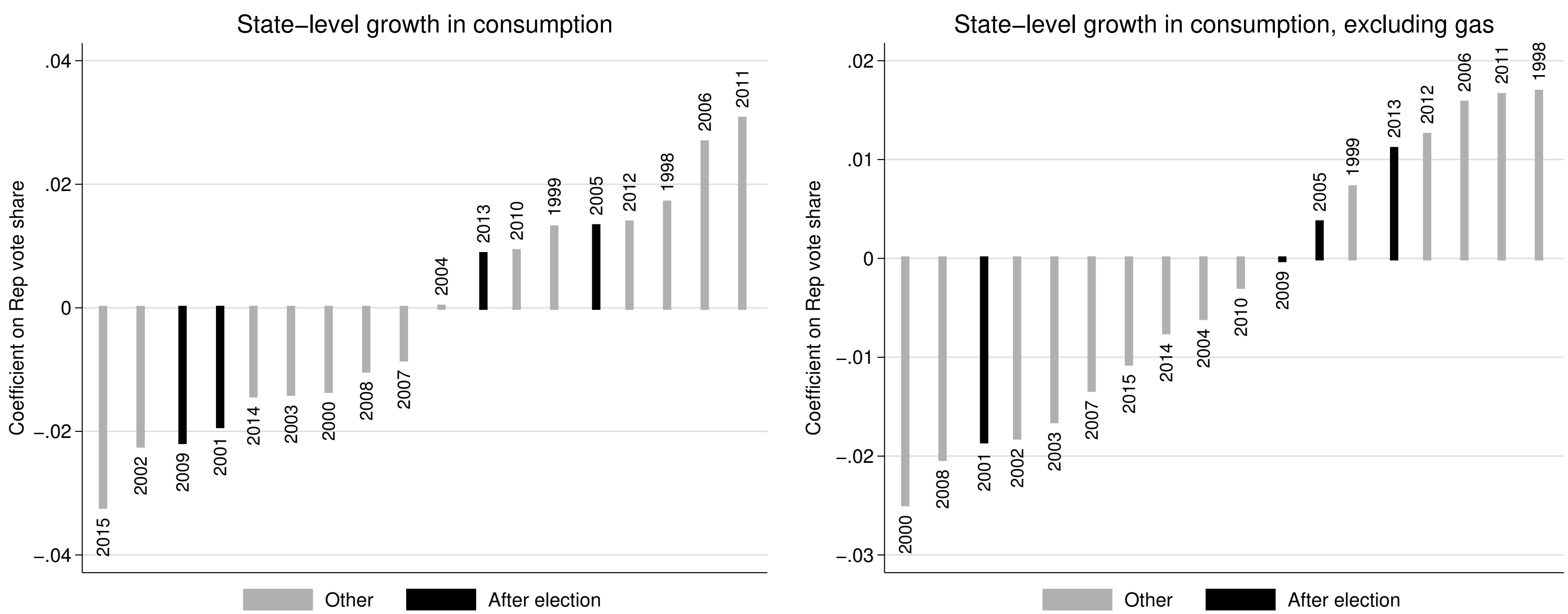

Figure 12

Comparing 2016 Election to 2007 Decline in House Prices

This figure presents scatter-plots of county-level data relating the change in economic expectations and auto sales to an underlying shock. The underlying shock in the top two panels is the election of Donald Trump in 2016, and the underlying shock in the bottom two panels is the decline in house prices from 2006 to 2007. Only counties with at least 5 surveyed respondents in the pre- and post-shock period are included, and counties are weighted by the total number of individuals surveyed.