Campaign Rallies, Perceived Uncertainty, and Household Borrowing*

Shiwei Ye†

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Abstract

This paper examines how political compaigns during the 2016 U.S. presidential election influences perceptions of economic uncertainty and subsequent household financial behaviors. Using a difference-in-differences approach, I show that Clinton's rallies reduced perceived economic uncertainty, particularly macro uncertainty. Moreover, areas hosting rallies showed an increase in P2P and mortgage loan applications after Clinton's visits, aligning with life-cycle models with precautionary motives. Effects are stronger in areas having higher initial level of economic uncertainty. In contrast, Trump's rallies did not significantly influence uncertainty perceptions or borrowing decisions. These findings shed light on a novel channel through which campaign information shapes real financial decisions, with effects contingent on the candidate involved.

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†Rotterdam School of Management, Erasmus University. Email: ye@rsm.nl.

1 Introduction

This paper studies the relation between campaign information and perceived economic uncertainty as well as the real outcomes in the household sector. Elections raise uncertainty related to economic policies such as taxation, government spending, regulation, trade, and monetary policies, which can affect household financial decisions and consumer behavior. Previous studies show that political uncertainty seems to hinder stock market participation (Agarwal et al., 2022), restrict access to finance (Li et al., 2018; Kara and Yook, 2022), increase precautionary savings (Giavazzi and McMahon, 2012), and impact aggregate real economic fluctuations (Bloom, 2009; Basu and Bundick, 2017; Chatterjee and Milani, 2020). Yet, they do not address whether there are frictions that prevent individuals from better evaluating political uncertainty to make informed decisions.

Political campaigns have become the primary source of information about candidates (Galsgow and Alvarez, 2000; Vavreck, 2009; Wattenberg, 2013; Arbour, 2016). To influence voting decisions, the campaigning candidates have incentives to talk about the state of economy and their policy positions that effectively address these economic considerations (**?**). This information matters when voters face difficulties in understanding the economic effects of various policy options (Holbrook, 1996). As voters absorb campaign narratives, they may prospectively evaluate the potential implications and become more certain about economic prospects, such as future income growth and inflation rate. On the other hand, however, the spread of misinformation or conflicting information could increase uncertainty (Viscusi, 1997; Swire et al., 2017; Guess and Lyons, 2020). Hence, whether campaign information will reduces perceived economic uncertainty remains an empirical question.

This paper empirically tests the effect of campaign information in perceived uncertainty by leveraging the setting of candidate rallies in the 2016 presidential election cycle in the United States. This empirical setting is suitable for this study for several reasons. First, Baker et al. (2020) show that while national elections provide the most significant signal of future policy changes, election-related rise in economic policy uncertainty is driven by close elections in polarized periods. The 2016 U.S. presidential election, characterized by high polarization, closely contested races, and distinctive policy differences between the major candidates, is therefore pertinent to studying the impact of campaign information on uncertainty perceptions. Second, both candidates were non-incumbents, so that the interpretation of any observable effects is not skewed mainly due to incumbent advantage. Third, campaign rallies carry important information that addresses perceptions of economic uncertainties by providing a unique platform for candidates to communicate directly with hundreds or thousands of voters in-person and reinforce their issue positions and policy commitments. Beyond attracting direct attendance and generating free media coverage, these rallies can also spark discussions to reach individuals not much engaged in politics within communities, where social networks might amplify information dissemination (Foos and de Rooij, 2017).

Following Snyder and Yousaf (2020) and **?**, I obtain the travel schedules of candidates and event locations from the Democracy in Action project and from the video archive of Cable-Satellite Public Affairs Network (C-SPAN). Counties visited by both candidates are in battleground states, and the vote share differences between Democrats and Republicans in the 2012 presidential elections were smaller than in other counties. These counties have larger population and stronger economic performance before the election cycle. However, when demographic characteristics are controlled for, economic conditions no longer predict campaign visits.

The main outcomes of interest are perceived overall economic uncertainty and macro uncertainty. I use the Survey of Consumer Expectations (SCE) conducted by the Federal Reserve Bank of New York (FRBNY). In the core module of SCE, individuals are surveyed for 12 months consecutively, allowing tracking individuals over time. The core survey asks both the point estimates and subjective distributions of personal income growth, inflation rate, and home price growth over the next 12 months.

Following Ben-David et al. (2018), I calculate the individual-level uncertainty measure by averaging the standard deviations of subjective distributions for these three components. For the macro uncertainty measure, I focus solely on inflation and home price components. Additionally, I take the means of the subjective distributions as proxies for income and inflation expectations. Because SCE only provides location information at commune zone level, I aggregate the number of visits to commune zones. I then use the generalized difference-in-differences (DID) framework to exploit the staggered nature of the presidential rallies. Thus, the baseline specifications compare the self-reported economic uncertainty and macro uncertainty between individuals living in commune zones with and without a rally, and in the months before and after a rally.

I observe a significant reduction in perceived macro uncertainty following Clinton's rallies, while Trump's rallies have no discernible impact on either uncertainty measure. To be precise, each Clinton rally, on average, decreases perceived macro uncertainty by 0.1 standard deviation (SD), and this effect remains consistent across areas with different partisan preference, as proxied by the party vote share in the 2012 elections. The effects are stronger for individuals without college degree or renters, who are likely to be less informed or less politically engaged before the visits (Le Pennec and Pons, 2019; Hall and Yoder, 2022), and individuals living in areas with an initially higher uncertainty level. To put the estimated effect into perspective, Ben-David et al. (2018) use the same survey data and find an annual income growth by $10,000 is associated with a reduction of approximately 0.056 SD for macro uncertainty, controlling for location and time fixed effects and other demographic characteristics. The average effects of Clinton visits on perceived macro uncertainty are thus equivalent to an annual income increase by $17,850. Furthermore, dynamic event study analysis shows the immediate effect (0.2 SD) is similar to providing second-moment information, as documented in Coibion et al. (2021).

Campaign information can impact perceptions of uncertainty by affecting perceptions of two outcomes: election outcomes and policy outcomes. The election outcome channel posits that voters might already possess familiarity with candidates' policy stances. The campaign information helps them to gain increased certainty about future economic conditions because they have a better grasp of who will be elected. The policy outcome channel suggests that voters may already know the likelihood of each candidate to be elected, and they acquire information on the policy actions through campaigns. While both channels contribute, I argue that the election outcome channel does not dominate the policy outcome channel in my setting. First, prior research shows campaigns exert minimal persuasive effects on voting decisions and turnovers. Second, the election outcome set shrinks from a pool of numerous candidates to a binary choice after primary elections. If the election outcome channel dominates, one would expect post-primary campaigns to be less effective than pre-primary ones. However, I find the effects do not differ significantly before and after primaries. This is in line with Le Pennec and Pons (2019), who find that while voting consistency increases during the intensive campaign periods across multiple countries, the increase is substantially muted in the United States.

Because campaign rallies mainly target local voters, their effects on perceived uncertainty may translate to individual's economic decision making. Specifically, my last set of results focuses on the real effects of campaign information on household credit demand. If campaigns effectively reduce perceived uncertainty, it follows that households may exhibit less precautionary saving behavior and borrow more to finance current consumption (Carroll, 1997; Schooley and Worden, 2010; Chamon et al., 2013). To test this hypothesis, I examine changes in loan applications using P2P lending data from Lendingclub after rallies. Since P2P lending supply is plausibly elastic at the local level (Tang, 2019), any discernible changes are likely driven by shifts in demand. Consistent with the precautionary savings motive, ZIP3 areas visited by Clinton experience an increase of P2P loan applications after the rallies, particularly for consolidation, consumption, and undisclosed purposes. In addition, I do not find the likelihood of default increases. Instead, the increase is mainly driven by short-term loans, which on average perform better. The fact that default rate and the amount of non-performing loans remain unchanged alleviates the concerns that borrowers are driven by a misplaced optimistic sense of uncertainty stemming from misleading information and that the supply side shifts to be more risk-taking.

I extend the analysis on credit demand to the mortgage market. While marketplace lending offers the advantage of dissecting changes on the demand side from those on the supply side, it is a small segment characterized by highly indebted individuals, rendering it less representative for understanding the broader population's behaviors. Mortgages represent a substantial portion of the US credit market and are typically the largest financial commitment an individual can make. Home purchases, in particular, bear direct relevance to economic uncertainty, given the significant impact of real option value in decision-making related to irreversible investments.

Using mortgage data disclosed under the Home Mortgage Disclosure Act (HMDA), I find counties experiencing rallies have a 1.52% increase in number of mortgage applications one month after Clinton's visits, in comparison to counties not exposed to such events. Similarly, Trump's rallies continue to show no discernible impact. Exploiting monthly dynamics, I observe no immediate surge in loan origination following Clinton's visits. Instead, the increase in loan applications occurs only in the month after the visit, contrasting with the immediate effect observed for P2P lending market. This is likely, because it takes a substantial amount of time for households to search for properties and complete mortgage applications. The time discrepancy also partly alleviates the concern that households may anticipates changes in credit supply due to the rally events and act accordingly before the politicians actually visit. However, the overall effect, as estimated through the DID specification, is not statistically significant, partly due to spillover and limited geographic coverage of the monthly dataset. The effects are statistically significant, though, in counties located in states with an initially high economic uncertainty level.

The yearly panel of mortgage applications, which covers a broader range of areas and allows for controlling for lender-state-time fixed effects, yields consistent results regarding loan volume, with the overall effect estimated around 0.35%. Furthermore, I find nonlocal banks and national banks face an increase of applications of similar magnitude, alleviating the concerns related to supply-driven changes since nonlocal banks and national banks are less likely to be affected by local rally events. Overall, the evidence from the marketplace lending and mortgage lending markets is in line with life-cycle models with precautionary motives (Leland, 1968; Sandmo, 1970; Carroll, 1997), which argue that in times of uncertainty, individuals reduce consumption and investment to hedge against potential negative shocks.

Literature. This paper makes several contributions to the literature. First, this paper identifies a particular source of political uncertainty during elections: candidate-specific information frictions. While previous studies have extensively documented the adverse implications of political uncertainty across various economic sectors, including firms (Bittlingmayer, 1998; Julio and Yook, 2012; Nguyen and Phan, 2017; Bonaime et al., 2018; Datta et al., 2019), financial intermediaries (Bordo et al., 2016; Kara and Yook, 2022), financial markets (Goodell and Vhmaa, 2013), and households (Li et al., 2018; Agarwal et al., 2022; Maggio et al., 2022), none have distinctly examined the role of information gaps tied to individual candidates. This paper fills the gap by offering a more granular understanding of the dynamics and the components of political uncertainty during an election cycle.

The second contribution relates to the relationship between political uncertainty and household financial decisions. Households play a significant role in the macroeconomic landscape as their spending and saving decisions can directly influence macroeconomic indicators. Yet, the shifters of their beliefs and behaviors remain understudied (Reis, 2023). Indeed, most studies on the impact of political uncertainty weight on the big players such as firms and investors. This paper builds on the recent literature on the impact of political uncertainty on the household sector (Li et al., 2018; Agarwal et al., 2022) but takes one step back to investigate frictions contributing to election-related uncertainty perceptions and show households adjust their perceptions and financial behaviors in light of political information.

More broadly, this paper contributes to the extensive literature on the influence of public communication on individual judgments. Previous studies have generally taken two perspectives. One perspective examines how the communication of political candidates during elections affects political outcomes, namely persuasion and voter turnout (Galsgow and Alvarez, 2000; Vavreck, 2009; Sood and Iyengar, 2016; Le Pennec and Pons, 2019; Snyder and Yousaf, 2020; Broockman and Kalla, 2022). Another perspective focuses on the interaction of post-election public communication of incumbent politicians or regulators with socioeconomic outcomes, such as individuals' economic beliefs (Wood et al., 2005; Coibion et al., 2022; Bianchi et al., 2023, 2024). Since Trumps election, some researchers have combined these two perspectives to examine the potential harm of inflammatory rhetoric during election campaigns, through the lens of hatred and extremism (Abramowitz and McCoy, 2019; Newman et al., 2021; Feinberg et al., 2022; **?**). This paper adds to this combined perspective by studying the influence of political communication by candidates during election campaigns on individual perceptions of the economy in the future.

2 Institutional Background

2.1 US Presidential Election and Campaigns

The U.S. presidential election, occurring every four years, stands as one of the most significant national events, where both the President and Vice President are the only federal offices elected by the entire electorate. Research has shown the extensive economic impact of the U.S. presidential elections. For instance, economic uncertainty tends to rise leading up to Election Day (Baker et al., 2020), influencing a broad range of stakeholders from firms and financial intermediaries to investors and households. Following the declaration of election results, the policies implemented by the incoming administration can lead to significant shifts in policymaking (Goodell and Vhmaa, 2013; Wagner et al., 2018). And may extend to individual decision-making through partisan beliefs (Kempf and Tsoutsoura, 2021; Dahl et al., 2022; Meeuwis et al., 2022). Furthermore, such effects are not limited to national boundaries; rather, they also affect global asset markets (Brogaard et al., 2020).

Given its importance, the modern U.S. presidential election process spans approximately two years.[1] In the spring of the preceding year, candidates register with the Federal Election Commission and announce their campaigns. Qualified candidates might participate in primary and caucus debates. From January to June of the election year, state-level primaries and caucuses occur to select party presidential and vice-presidential candidates, critical for momentum and public support. Party conventions in July to early September formalize nominations, solidifying party support and rallying the electorate. In September and October, the presidential debates take center stage, providing a platform for candidates to communicate and differentiate themselves. The first Tuesday following the first Monday in November marks Election Day. The Electoral College vote follows, with the process culminating in the

[1] For details of the election process, see https://www.usa.gov/presidential-election-process.

Presidential Inauguration on January 20 of the next year, signaling the commencement of the new administration.

Since the decline of party power in 1976 and campaign finance reform, campaigns have become the primary communication platform for U.S. political candidates. The goal of campaigning is to maximize electoral gains within time and budget constraints. Candidates or their representatives typically use mass media (such as newspapers, radio, and TV advertising), public speaking (such as debates and rallies), and door-to-door visits to reach voters.

Because time and money are limited, presidential candidates need to be strategic in their campaigning activities, mainly considering timing, location, and message contents no matter which form of communication they use. Strategies vary by candidate and election cycle, but there are several general patterns (Denton et al., 2019). For example, rallies are often timed around milestones such as party conventions and the months leading up to Election Day (See Figure 1). Location choices may have symbolic or personal meaning, but the major objective is to reach the maximum number of persuadable or reinforceable voters. Therefore, most campaign efforts are concentrated in battleground states and populous areas within these states.[2] Message content is flexible and depends on the candidate's incumbency, ideology, beliefs, audience, and political environment. Messages are often adapted from stock speeches, speech modules that can be delivered as a short speech on certain issue. Campaign messages, whether positive or negative, can inform voters about policies. However, competitive campaign messages, such as those focused on horse race dynamics and attacks, are less policy-oriented.[3]

The party nomination after primaries and caucuses often marks a significant shift in campaign strategy due to a change in the voter base. Prior to primaries and caucuses, candidates appeal to partisan voters who cast votes at different times across states. This implies that candidates focus on more extreme issues, schedule visits based on state primary calendars, and invest in local interpersonal communication due to smaller voter numbers.[4] After securing the party nomination, candidates shift to attract a broader voter base, often

[2]For example, during the 2020 election cycle, seven out of eight dollars for TV ads of presidential candidates were spent in the following six states: Florida, Pennsylvania, Michigan, North Carolina, Wisconsin, and Arizona (Maisel, 2022).

[3]For example, in the 2016 presidential race, Trump had 87% more attacks than Clinton. See https://apps.bostonglobe.com/graphics/2016/07/convention-speeches.

[4]One extreme case is the "full Grassley" campaign strategy, where candidates visit all 99 counties in the state of Iowa. Recent adopters include Ted Cruz and Ron DeSantis in the 2016 and 2024 presidential election cycles, respectively.

compromising on polarized issues and participating in events that reach larger audiences.

2.2 Campaign Rallies During U.S. Presidential Election

Campaign rallies, public meeting events where political candidates deliver in-person speeches to sometimes large groups of people, have become an important part of U.S. campaign activity in recent years. For presidential elections, such events concentrate on major political milestones and need to be planned weeks or months in advance to secure permissions, security arrangements, and logistical arrangements. The event announcement date usually ranges from 7 to 14 days before the event date, though for very large events with more than 10,000 attendees, it can be announced one month prior to the event date. Campaigns announce rallies through press releases, social media, and other communication channels. The long preparation time and the fixed timing of election milestones make strategic timing on short-term economic fluctuations and economic perception less likely, and the short announcement period means the anticipation effect is limited.

For direct attendance, campaign rallies usually attract supporters. Attendees often have already made up their minds about who they are going to vote for, and they might be interested in seeing what the candidate might have to say. However, at the event, the main purpose of a rally is not to inform attendees but to energize the voter base. The real benefits outside the rally include free local TV and newspaper coverage and getting people talking about the candidate in the community, where less politically engaged swing voters might be reached and informed.

The strategies may vary among candidates. For instance, in the 2016 presidential election cycle, the Clinton campaign claimed to focus more on policy issues rather than on boosting excitement at rally events.[5] In contrast, Trump's nomination speech had 87% more attacks than Clinton's.[6] In addition, campaign events may backfire by motivating voters from the opposing party. For example, Heersink et al. (2021) document that while both Clinton's and Trump's campaign visits increased donations to their own campaigns, they also led to an increase in donations to their opponents. More strikingly, Trump's events spurred many more donations to Clinton than to himself.

[5]See https://www.nbcnews.com/politics/2016-election/hillary-clinton-gambles-choosing-small-events-over-huge-rallies-n575311.

[6]See an analysis on their convention speeches at https://apps.bostonglobe.com/graphics/2016/07/convention-speeches. Also, Figure IA1 provides word clouds based on Trump and Clinton's speeches in their 2016 campaigns.

3 Data and Methodology

In this section, I begin by presenting the data sources for the key variables in the paper, along with details of variable construction. A detailed list of variable description can be found in Table IA1. I then outline the event study and difference-in-differences frameworks used in the analysis.

3.1 Data

3.1.1 Rallies

I use rallies of Donald Trump and Hillary Clinton in the 2016 presidential election cycle to examine how the information provided during these political events affect household perceptions and borrowing decisions. The data comes from **?**, who sourced the original data from the Democracy in Action project and geocoded each event with date and county-level location. Because **?** only focused on counties with police stop data available, I further collect and geocode rally events to cover all counties in the United States through various sources, mainly the video archive of Cable-Satellite Public Affairs Network (C-SPAN)[7], which is a nonprofit organization created by the cable television industry to televize ideologically balanced and unmoderated political events. In total, there are 323 Trump events and 169 Clinton events in my sample[8].

Figure 1 plots frequency of campaign visits of Trump, Clinton, and Cruz each month from April 2015 to November 8th, 2016. While both Clinton and Cruz declared their candidacies earlier in the race, Trump swiftly closed the gap and held a notably higher number of campaign rallies. As the election day approached, both Trump and Clinton intensified their campaigning efforts, aligning with the widely acknowledged notion that the period around Labor Day marks the actual commencement of the presidential race, and returns to campaigns are higher as election day approaches due to their short-term effects on shaping voting behavior.

Figure 2 and Figure 3 visualize the geographic distribution of Trump and Clinton cam-

[7]Specifically, I search for "Rally" within "Speech" event type and "Campaign 2016" series for each candidate.

[8]As a comparison, there are 221 Trump events and 41 Clinton events in the replication files of **?**. I am grateful to the authors for generously providing their selection criteria and complete data sample for Clinton's events, which perfectly aligns with the data I collected.

paign rallies, both at the county and state levels. In addition, Table IA2 compares county-level socioeconomic characteristics in 2014 between counties visited by the presidential candidates and those unvisited. Several noteworthy patterns emerge from the table and figures. First, while the candidates appeared to target different counties, there were instances where they overlapped in their campaign visits. Second, both candidates strategically targeted key battleground states, such as Pennsylvania (PA), Florida (FL), Michigan (MI), North Carolina (NC), New Hampshire (NH), and Ohio (OH). Similarly, the counties being visited have a much lower vote share gap before the campaigns, defined as the absolute difference between the vote share secured by Democratic and Republican candidates in the 2012 presidential election cycle. Third, Trump's campaign exhibited a significantly broader geographic coverage compared to Clinton's, and he visited almost every state Clinton had ever visited. Fourth, rallies often took place in densely populated areas, consistent with the notion that reaching a larger electorate is crucial for presidential candidates (Snyder and Yousaf, 2020). While counties visited by either candidates have higher economic growth rate and lower unemployment rate in the raw data, they are not significant determinants of rally visit after controlling for other socioeconomic factors and state fixed effects in unreported regressions.

3.1.2 Household Expectations and Uncertainty

To examine individual-level economic expectations and perceived uncertainty, I use the core module of the Survey of Consumer Expectations (SCE), conducted by the Federal Reserve Bank of New York (FRBNY) between 2015 to 2017. Respondents are asked to provide a point estimate and density forecasts of future 12-month personal income growth, national home price growth, and inflation rates. Respondents' locations are recorded at the commuting zone level. To aggregate county-level data to commuting zones, I use a county-commuting zone crosswalk and require that the distance between the county centroid and commuting zone centroid is within 50 kilometers. This threshold is supported by previous research and further analysis on geographic spillovers in later sections.

Following the approach of Ben-David et al. (2018), I construct two uncertainty measures: overall uncertainty and macro uncertainty. The main uncertainty measure is calculated by averaging the standard deviations of the subjective distributions concerning future personal income growth, home price growth, and inflation rates. The macro uncertainty measure, on the other hand, considers only national home price and inflation components. Additionally, I use the means of the subjective distributions as measures for personal income growth and inflation expectations.

The SCE uses a rotating panel structure in which respondents are interviewed for up to 12 consecutive months. While participants could opt to drop out in any month, the majority tend to complete the full 12-month period. In 2014, for example, 58% of respondents successfully completed all 12 surveys (Armantier et al., 2016a). This feature provides a unique benefit as it allows me to control for time-invariant individual characteristics. As Giglio et al. (2019) point out, beliefs, portfolio choice, learning ability and past experience are highly individual-specific, with only a small portion of the heterogeneity attributable to demographic characteristics.

Two major concerns arise when working with SCE data. First, the survey questions directly ask about inflation, a concept that is often deemed to be complex for the average person. Some might argue that responses regarding inflation may not accurately reflect individuals' beliefs. However, evidence shows that the survey respondents do act on their inflation beliefs and make meaningful updates when provided with relevant information (Armantier et al., 2015, 2016a,b). Second, eliciting subjective distributions requires a relatively high level of numeracy. Comerford (2023) finds that SCE respondents identified as low in numeracy are are more prone to contradict themselves when asked about their inflation density forecasts compared to a simple directional question (inflation or deflation). To enhance data quality, I include only individuals identified as having high numeracy, meaning they correctly answer four out of five math questions, which excludes approximately 29% of observations.[9] Although the resulting sample is relatively signal-rich, it is worth noting that it may not represent the entire U.S. population. Table 1a reports the summary statistics of key variables related to self-reported expectation and uncertainty measures in the final sample.

3.1.3 Household Loan Application and Origination

To investigate whether the perceived uncertainty of households translates to their borrowing behavior, I analyze aggregate-level borrowing activities in two distinct sectors: the peer-to-peer (P2P) market and mortgages. For P2P lending, I aggregate the data on both rejected and accepted loans from Lendingclub, the largest P2P platform in the United States, in

[9] In Table IA7, I compare the campaign effects on perceived uncertainty of respondents with different numeracy levels and find that the effects, if they exist, are concentrated among those with higher numeracy. This can possibly be attributed to the fact that respondentsa with lower numeracy may provide random subjective distributions.

2015-2017. Specifically, I sum up the loan volume and number of loans for each area-month pair, with the area defined at the 3-digit ZIP code (ZIP3) level.

Lendingclub provides data of both accepted and rejected loans. A limited number of variables are available for rejected loans, including application date, loan title (which primarily describes the purpose of the loan), loan amount, employment length, FICO score, and ZIP3 code. Approved loans offer a more comprehensive range of information, such as funded amount, interest rate, maturity, financial characteristics of the applicant at the time of application, and loan status. Since Lendingclub has ceased to disclose its listed loans, I can only observe if a loan is default or not by the end of third quarter of 2020. However, given that 71% of loan approved in the sample has a three-year maturity and the sample period ends in the first quarter of 2017, the potential issue of not being able to observe loan default after the third quarter of 2020 may be less of concern. Table IA4a gives summary statistics of all P2P loans while Table IA4b summarizes characteristics specifically pertaining to approved loans on Lendingclub.

As for mortgages, I utilize the data publicly disclosed under the Home Mortgage Disclosure Act (HMDA) in 2014-2017. The HMDA data provides detailed information on individual mortgage applications, including the actions taken (accepted, rejected, or withdrawn), the size of the requested loan, the type of loan, and detailed demographics of the borrower, as well as the location (census tract) of the property. I supplement the yearly HDMA data with monthly aggregate lending activities of the top 500 counties in terms of mortgage application sourced from Neil Bhutta's website[10]. While the dataset does not have complete geographic coverage, its monthly frequency provides a dynamic perspective for analysis. Table IA5 reports the summary statistics of mortgage application and origination.

3.2 Empirical Strategy

To test the dynamic effect of campaign visits on individual-level economic perceptions, a generalized event study design with binned treatment adoption measure (Schmidheiny and Siegloch, 2020) is adopted to allow for multiple treatments and different treatment intensity:

$$Y_{i,c,s,t} = \sum_{p} \sum_{l=\underline{l}}^{\bar{l}} \beta_l^p D_{c,s,t}^{l,p} + \mu_i + \theta_{s,t} + u_{i,c,s,t} \tag{1}$$

[10] https://sites.google.com/site/neilbhutta/data.

Where

$$D_{c,s,t}^{l,p} = \begin{cases} \sum_{k=-\infty}^{\underline{l}} \Delta T_{c,s,t-k}^{p} & if \quad l = \underline{l} \\ \Delta T_{c,s,t-l}^{p} & if \quad \underline{l} < l < \bar{l} \\ \sum_{k=\bar{l}}^{\infty} \Delta T_{c,s,t-k}^{p} & if \quad l = \bar{l} \end{cases},$$

$\Delta T_{c,s,t}^{p} = T_{c,s,t}^{p} - T_{c,s,t-1}^{p}$, and $T_{c,s,t}^{p}$ increases accordingly by one unit with every visit of politician p to the commune zone c of state s where individual i lives in month t. μ_i and $\theta_{s,t}$ are individual and state-time fixed effects. $Y_{i,c,s,t}$ are dependent variables for individual-level perceived uncertainty and economic expectations. In the main regressions I set $\bar{l} = 3$ and $\underline{l} = 3$.

The model assumes that the effect of each event is linear. In other words, the impact of a politician's second visit to a particular location is equivalent to that of the initial visit. The assumption is plausible as politicians tend to vary their contents of speech in each event.[11] As reported in Table IA8, there are no statistically significant differences between the effects of the first and subsequent visits. Furthermore, conditional on being visited, 68.4% of these counties were only visited at most once by either candidate, and only 16 counties out of 244 received more than three visits from either candidate throughout the sample period. The specification can be easily simplified to a standard difference-in-differences model with staggered treatment by setting $\underline{l} = -1$ and $\bar{l} = 0$. Then I estimate the following equation

$$Y_{i,c,s,t} = \beta^T \times Post\_Trump_{c,s,t} + \beta^C \times Post\_Clinton_{c,s,t} + \mu_i + \theta_{s,t} + u_{i,c,s,t}, \tag{2}$$

where $Post\_Trump_{c,s,t}$ ($Post\_Clinton_{c,s,t}$) is the sum of Trump (Clinton) visits in or after month t in the commune zone c of state s where individual i lives.

I use similar identification strategy for aggregate-level household borrowing in the P2P and mortgage markets. Specifically, I estimate

$$Y_{r,s,t} = \sum_{p} \sum_{l=\underline{l}}^{\bar{l}} \beta_l^p D_{r,s,t}^{l,p} + \mu_r + \theta_{s,t} + \sigma_r \times t + u_{r,s,t} \tag{3}$$

[11] Anecdotal evidence shows that rally attendants had fresh experiences even if the messages had been said many times before. See https://www.nytimes.com/2019/07/05/podcasts/daily-newsletter-political-rallies-theo-balcomb-armchair-expert.html.

and

$$Y_{r,s,t} = \beta^T \times Post\_Trump_{r,s,t} + \beta^C \times Post\_Clinton_{r,s,t} + \mu_r + \theta_{s,t} + \sigma_r \times t + u_{r,s,t}, \qquad (4)$$

where the notations are generally the same with Equation 1 and Equation 2 except that loan application and origination are aggregated to area r.[12] In addition to area and state-time fixed effects, I also control for local linear time trend ($\sigma_r \times t$) to account for confounding factors such as local market expansion of lending platform services. $Y_{r,s,t}$ are dependent variables including loan number and loan volume applied or originated in area r of state s at time t.

4 Empirical Results

4.1 Rallies and Perceived Uncertainty of Households

Baseline results

I estimate equation (1) to analyze changes in individual-level perceptions of economic uncertainty and macroeconomic uncertainty before and after visits by both Trump and Clinton. The results are presented in Figure 4. Only Clinton's rallies lead to a reduction in macroeconomic uncertainty perceptions, while Trump's rallies do not appear to have any impact on uncertainty perceptions regarding the future performance of the macroeconomy. This suggests that Trump's rallies may not provide substantial information about future economic policies or that his speeches, characterized by inflammatory rhetoric, could actually increase perceived uncertainty for certain groups, as noted in **?**. Furthermore, there is no discernible effect from either candidate on overall uncertainty perceptions. This can be explained by the focus of presidential candidates on national policies rather than policies specific to the local economy, which are more relevant for the personal income component in the overall uncertainty measure.

One advantage of event study analysis is its ability to examine how and when effects change. Before the rally month, there is no evidence contradicting the parallel trend assumption for all uncertainty measures. After Clinton's rally events, the effect lasts for

[12] I use 3-digit ZIP code areas for P2P borrowing and census tracts for mortgage borrowing.

approximately two months, consistent with the findings of **?**, who observed an increase in policing behavior against Black people in the 60 days following Trump's rallies.

To assess the overall treatment effect of campaign rallies on perceived uncertainty, I aggregate the event study indicators into one DID treatment intensity and estimate equation (2). The results are presented in column (1) and column (4) in Table 2. As in the event study analysis, while the direction of the effects is similar, there is no statistically significant rally effect observed for either candidate on overall uncertainty perceptions. However, there is a noticeable decrease in perceived macroeconomic uncertainty of approximately 0.10 associated with Clinton's rallies.

To put the figure into perspective, the study by Ben-David et al. (2018) using the same survey data finds that an annual income growth of $10,000 corresponds to a reduction of approximately 0.056 standard deviation (SD) for macro uncertainty, after controlling for location and time fixed effects, as well as demographic characteristics. Therefore, the average effect of Clinton's visits on perceived macroeconomic uncertainty can be roughly equated to an annual income increase of $17,850. Additionally, Coibion et al. (2021) run randomized controlled trials (RCTs) involving information treatments for European households. They find that providing second-moment information on GDP growth forecasts reduces perceived uncertainty by 0.17 SD for an average person with mean prior uncertainty. This effect increases to 0.43 SD when first-moment information is also provided. Note that they measure the updated beliefs immediately after receiving the treatments. According to the event study analysis, the immediate effect in one month after Clinton's visits is estimated at around 0.2 SD.

Politicians may be able to shape expectations as some campaigns are fundamentally about persuasion. To explore the potential influence, I look at four economic expectation variables: personal income growth, inflation, tax growth, and credit access. The results for the DID specifications are presented in Table 3. The first-moment effects of rally speech appear to be minimal on all outcome variables. Event study dynamics depicted in Figure IA2 also indicate a lack of effect on expectation-related variables, and the point estimates of pre-treatment differences are close to zero.

Political affiliation often influences attendance at political events and media choices, leading individuals with varying political alignments to react differently to information conveyed during campaign rallies. However, since most campaign events target highly contested areas, treated individuals typically represent median voters. To examine the heterogeneous effects of campaign visits along the ideological spectrum, I split the sample based on commuting zone-level electoral outcomes from the 2012 presidential election. Specifically, I create a dummy variable, $Dem12$, which equals one if the Democrats secured a higher vote share than Republicans.

The results are reported in Columns (1)-(2) and (5)-(6) in Table IA6. I find no statistically significant difference between people living in areas with a higher Democratic vote share in 2012 and those dominated by Republicans. In particular, Clinton's rallies seem to be effective in influencing macro uncertainty perceptions in all areas, suggesting that her campaigns targeted less partisan individuals. Interestingly, while Trump's rallies do not have a significant impact in either case, the insignificant positive effect on uncertainty perceptions is primarily driven by individuals in areas with higher Democratic vote share, implying that Trump's rallies might indeed raise uncertainty perceptions for certain groups. Indeed, as reported in Table IA7, renters, who might lean more Democratic,[13] have significantly higher perceived uncertainty levels after Trump's visits. Similarly, Clinton's effects are stronger for renters and respondents without a college education, who are likely to have been less informed before the campaigns, as documented in prior studies (e.g., Le Pennec and Pons (2019) and Hall and Yoder (2022)).

If Clinton's campaign visits indeed reduce perceived economic uncertainty, one would expect the effects to be larger in areas initially with a higher uncertainty level. I consider commuting zones with average uncertainty levels in January 2015, the start of my sample period, in the fourth quartile as having a higher initial uncertainty level. I find that while respondents living in areas with relatively lower uncertainty levels lower their perceived macro uncertainty (-0.07 SD) insignificantly after Clinton's visits, the effect is much stronger (-0.28 SD, or about 4 times) and statistically significant for those living in areas with a higher initial uncertainty level. Table IA6 reports the results in Columns (3)-(4) and (7)-(8).

Channels

Rally visits can play a role in affecting individuals' perceived uncertainty through two channels: the prediction of election outcomes and the prediction of policy outcomes. To begin, consider a scenario where voters already possess a foundational understanding of the policy preferences of candidates. In such context, the dissemination of campaign information primarily serves as a tool to reinforce or clarify their beliefs, allowing them to anticipate

[13]For instance, according to a Pew Research Center's study, voters who rent favor Democrats by two-to-one in 2023. See https://www.pewresearch.org/politics/2024/04/09/partisanship-by-family-income-home-ownership-union-membership-and-veteran-status/.

future economic conditions more confidently based on their increased certainty about which candidate is more likely to secure an election victory. Conversely, in situations where the electorate is more informed about the potential electoral success of candidates but lacks clarity on their policy inclinations, campaigns become instrumental in bridging this information gap. In this case, voters gain insights into potential policy decisions and directions through the campaign rhetoric and promises.

While both channels could contribute, I argue that the policy outcome channel wields more influence in shaping voters' economic perceptions. The reasons are twofolds. Firstly, empirical studies have consistently highlighted that campaigns have limited impact on swaying voting choices or in creating significant turnovers. For example, Le Pennec and Pons (2019) find that vote choice consistency, defined based on whether a voter chooses the same candidate pre- and post-election, does not change much after campaign events in the U.S. Secondly, as the electoral process unfolds in the U.S., the election outcome set changes from a pool of candidates to a binary choice after primary elections. If the election outcome channel was the predominant force, one would expect that campaign events post the primary phase would hold smaller influence relative to pre-primary ones. Yet, I find consistent campaign effects both before and after the primaries. The results are shown in the column (2) and (4) of Table 2. The coefficients of the interaction terms are insignificant and close to zero, and the total effects on perceived macro uncertainty are significantly negative for Clinton, both before and after the primaries.

Spillovers

Campaign rallies may have spillover effects through media coverage within the same media market or social connections in communities. To investigate the geographic reach of rally effects on economic perceptions, I calculate the geographic distance between the centroid of the city holding rallies and the centroid of the commuting zone. Areas are considered treated if the distance is within l kilometers, where l is set to 50, 100, or 150 kilometers (31, 62, or 93 miles).

Table IA10 reports the results for both uncertainty and expectation measures. First, regarding uncertainty perceptions, the point estimates for Clinton's events consistently decrease as the distance increases and nearly reach zero when the distance threshold is set at 150 kilometers (93 miles). Second, the effect is only significant within 50 kilometers (31 miles), similar to **?**. Interestingly, the result for overall uncertainty is also significantly negative, indicating that the simple aggregation based on county-commuting zone crosswalk may introduce some noise and bias the baseline regression estimates toward zero.

In contrast, for income and inflation expectations, I do not observe any significant effects at any distance threshold, and the coefficients do not exhibit consistent monotonic patterns. This further confirms that rally events in my setting primarily influence second-moment perceptions rather than first-moment perceptions.

Alternative explanations

In staggered DID settings, the likelihood of results being influenced by simultaneous shocks is lower compared to settings with a single shock. Nonetheless, identification still hinges on the assumption that, in the absence of treatment, changes in perceived uncertainty from the pre- to post-treatment periods in visited areas mirror those in the untreated group.

An alternative explanation is that candidates might strategically visit areas anticipating better economic prospects or lenient economic policies, leveraging these improvements to enhance their campaign's appeal. Such visits could create a self-fulfilling prophecy, where economic conditions improve as anticipated post-visit, reducing perceived uncertainty. However, political motives predominantly drive campaign strategies, focusing more on reaching large, swing-voter populations rather than local economic variations. Indeed, county-level economic performance, after conditional on demographic characteristics, does not predict rally visit. Additionally, primary schedules heavily influence campaign itineraries, and I observe significant effects prior to primary election outcomes. Furthermore, state-time fixed effects are expected to account for state-level economic trends and policy changes.

Election campaigns for congressional candidates and state governors might also affect perceived uncertainty. For instance, down-ballot candidates often seek to align with more prominent figures to gain voter attention, as illustrated by some 2020 Republican candidates requesting President Trump's visit for this purpose (Maisel, 2022). Therefore, changes in uncertainty might be more linked to congressional and gubernatorial electoral prospects. However, state-time fixed effects should capture these effects, and presidential candidates are primarily concerned with their own elections rather than state-level races. Moreover, gubernatorial elections likely impact state-specific uncertainty rather than macro-level uncertainty, yet the data suggests uncertainty perceptions are largely driven by macro factors.

Voter anticipatory responses are an unlikely explanation for the findings. Voters might increase their attention to news in anticipation of candidate visits, and this heightened attention reverts to normal levels post-visit. If this is the case, the observed changes in perceptions are more likely attributed to information attention than the rally itself. However, rally announcements are often made on short notice, limiting the potential for long-term anticipatory effects. Furthermore, individual fixed effects control for inherent political news interests, and demographic differences between treated and untreated groups are minimal, as Table 1b demonstrates.

In summary, I find Clinton's rallies have an overall negative impact on perceived uncertainty, particularly in terms of macro-related uncertainty. These effects remain consistent before and after the primary elections. The influence generally extends to individuals residing across the ideological spectrum, although this may primarily result from campaign strategies targeting battleground areas. Clinton's effects are stronger for respondents without college education who are likely to be less informed before campaigns, for renters who lean more Democratic, and for those living in areas with an initially higher uncertainty level. On the contrary, there is no significant effect observed for Trump; if anything, he appears to increase perceived uncertainty for certain groups, such as renters. When comparing the effects on expectations to those on uncertainties, the rallies during the 2016 presidential election cycle seem to play a more substantial role in shaping second-moment rather than first-moment economic perceptions.

4.2 Household Borrowing

4.2.1 Peer-to-Peer Lending

In this section, I provide evidence of an increase in loan applications on the Lendingclub platform following rallies held by Hillary Clinton, while demand for P2P loans appears to remain stable following visits by Trump. The increase is driven by loan applications for consolidation, consumption and undisclosed purposes, along with loans with shorter maturities. Conditional on acceptance, I show that loan performance remains unchanged to rule out possibility of misbelief and supply-side changes.

Number and amount of P2P loan application

The decline in perceived uncertainty following campaign rallies can lead to increased borrowing, as there is a less extent of the precautionary saving motive. To test this hypothesis, I aggregate the number and amount of loan applications to the 3-digit ZIP code level for each month, the most granular location level that Lendingclub provides. The Lendingclub data presents another challange in identifying the month of application, as it offers issue month for accepted loans and application date for rejected loans. To overcome this inconsistency, I assume the accepted loans are applied in the same month of their issuance, as marketplace lenders typically approve loans within a few days. Nevertheless, I also conduct separate analyses for accepted loans and rejected loans and find robust results.

Table 4 reports the results. Column (1) and column (3) show that the number of application increases by around 3% following rallies of Clinton. There is a smaller increase for accepted loans, with the number of accepted loans increases by 1.56%. Similar to the effect on perceived uncertainty in Section 4.1, there is no significant difference in the impact of rallies on P2P loan applications before and after primary elections, though the effect appears slightly stronger after the primaries for accepted loans. In contrast, there is generally no effect of Trump's rallies on P2P borrowing. If anything, the number and amount of loan applications weakly decline by around 2.2%.

Figure 5 illustrates the dynamic effect on P2P loan applications. Following visits by Clinton, there is an increase in loan applications within two months. This pattern aligns with the observed changes in perceived uncertainty. Instead, there are no discernible changes in loan applications following Trump's visits. Additionally, there are no significant patterns in loan applications prior to the rallies of both candidates. The lack of pre-trend further alleviates the concern over the violation of identification assumptions in my empirical setting.

Loan purpose and maturity

The reduction of perceived economic uncertainty may decrease the precautionary saving motive and the value of real options. In addition, while the credit supply side tends to favor shorter loan maturities under uncertainty (Datta et al., 2019), the demand side has an incentive to seek long-term loans due to refinancing risk (Brick and Ravid, 1991). Hence, if political speeches by candidates decrease perceived uncertainty, households may borrow more for durable goods and are more willing to apply for loans with shorter maturity.

Lendingclub provides loan purposes either through the purpose of accepted loans or through the title of rejected loans. I map the titles of rejected loans to the loan purpose categories used for accepted loans. I then group credit card and debt consolidation purposes into "Consolidation". The category "Consumption" encompasses car, major purchase, medical, vacation, wedding, and moving purposes. "Home-related" includes home improvement and house. "Business" refers to loans for small business purpose. Finally, I classify other purposes as "Non-disclosure". In summary, based on loan purposes, Lendingclub loans are categorized as Consolidation, Consumption, Home-related, Business, and Non-disclosure. As for maturity, Lendingclub only has 3-year or 5-year loans during the sample period.

Table IA4a and Table IA4b give summary statistics of the ratio of loans in each purpose category for all loans and approved loans, respectively. On average, more than 60% P2P loans are applied for the Consolidation purpose. The second largest category is Consumption (13.78%), followed by Other (14.1%). The ratio of loans with Consolidation purpose increases to 79% for approved loans, suggesting that P2P investors are more willing to fund this type of loans. Regarding maturity, 3-year loans make up an average of 71% of accepted loans. I then take the log of the total number and total amount of loans for each purpose category and maturity. As there is a limited amount of data available for accepted loans (with a mean acceptance rate of 8%), for the loan maturity analysis, I use $log(1+\text{number of loans})$ as the outcome variable. Table IA4a presents the summary statistics for these log-transformed dependent variables.

Table 5a and Table 5b present the impact of campaign rallies by Trump and Clinton on P2P borrowing for various purposes. loan applications for Consolidation purpose, which represents the primary category of loans on Lendingclub, increases for Clinton and weakly decreases for Trump. Furthermore, borrowing for consumption also shows an increase following Clinton's visits, in line with the precautionary saving motive. In contrast, there is no significant change for these purposes after Trump's visits.

An increase in credit demand for durable goods and investment would be expected if the real option channel played a significant role. However, I do not observe any significant changes in loan applications for Home-related or Business purposes following Clinton's visits. Several factors could explain this phenomenon. First, it is possible that the P2P platform does not serve as the primary source for lending for durable goods, and households targeted by Clinton seek alternative borrowing options. Alternatively, the increase in lending for undisclosed purposes may provide an explanation. Borrowing for undisclosed purposes increases by 2.67% in terms of number of applications and 3.27% in terms of loan volume after Clinton's visits. Given that loan purpose is self-reported and not obligatory, borrowers have the discretion to disclose or withhold non-verifiable information. It is likely that individuals borrowing for durable goods or small businesses after Clinton's visits prefer to do so without disclosing the purpose of the loan.

Borrowers with a higher degree of certainty regarding their ability to repay tend to opt for shorter-term loans and default less. This is because they have less incentive to pay for insurance against repricing risk (Hertzberg et al., 2018). Therefore, if borrowers perceive reduced economic uncertainty following campaign visits, they are more inclined to select short-term loans. In line with this hypothesis, I find the increase in accepted P2P loans after Clinton's rallies is primarily driven by short-term loans (3-year loans) and performing loans. Table 6 reports results for accepted loans categorized by maturity and performing status.

The choice of loan term can also be linked to the non-disclosure of loan purpose.Caldieraro et al. (2018) suggest that a countersignaling theory can explain the nonmonotonic relationships between disclosure of non-verifiable information (i.e., loan purpose), loan funding, and loan performance in the P2P lending market. In particular, their findings indicate that shorter loan lengths are associated with non-disclosure across all loan grades and better loan performance. It is plausible that the preference for shorter loan terms observed in my data corresponds to borrowing without disclosing loan purposes.

In summary, I find individuals increase borrowing in the P2P market for consumption and consolidation subsequent to Clinton's rallies, consistent with the precautionary saving motive. This increase in borrowing is accompanied by a rise in non-disclosed loan purposes and a preference for shorter loan maturities. These trends are consistent with the impact of uncertainty on shaping preferences for debt maturity and are aligned with the countersignaling theory, which relates shorter loan durations with less disclosure of non-verifiable information. In contrast, there are no notable changes across these dimensions following Trump's events.

Non-performing rate

Even if the reduced perceived uncertainty increases credit demand, it may not imply a welfare gain for borrowers due to misperception and behavioral biases. For example, inflammatory political rhetorics could contribute to overconfidence which ultimately leads to extremeness and polarization (Ortoleva and Snowberg, 2015). If individuals borrow more and the supply side increases lending because they are certain about mistaken information, it will likely result in poorer loan performance for accepted loans. Column (5)-(7) in Table 6 presents the effect of campaign visits on nonperforming loans, performing loans, and average non-performing rate (NPR). For both candidates, I do not find political information disseminated during the rallies affects NPR or the origination of nonperforming loans. Instead, the observed increase in approved loans after Clinton's visits is driven by loans that are fully paid or have not defaulted by the third quarter of 2020. This suggests that loans originated after campaign visits are of higher quality and that individuals are not borrowing excessively due to misbelief.

An alternative explanation for the aggregate-level observation is that the composition of borrowers changes towards individuals with better financial conditions but they still hold misbelief after rallies. To rule out the explanation, I examine whether campaign visits affect performance at the loan level. Table 7 presents the results. I find that Trump's rallies have a negative impact on default rate. However, after controlling for loan characteristics and fixed effects, there is no effect on default rates for either candidate. The estimates are not significant and close to zero. This provides further evidence against the hypotheses that individuals' borrowing behavior is driven by a misplaced sense of uncertainty stemming from misleading information propagated during campaign rallies and that the observed pattern is driven by more risk-taking of the supply side.

Geographic spillovers

I conduct a similar robustness check on geographic spillovers, as detailed in Section 4.1. The assignment of treatment status is based on the distance between the centroid of the city hosting the event and the centroid of the ZIP3 area, with distance thresholds of l being 50, 100, and 150 kilometers (31, 62, and 93 miles). Table IA11 reports the results. Once again, I observe a consistently decreasing effect for Clinton's events as the distance increases, although the effect does not completely vanish beyond 50 kilometers. Conversely, the impact of Trump Rallies is generally insignificant, and the coefficients do not demonstrate consistent monotonic patterns.

4.2.2 Mortgages

While P2P lending allows for a clearer analysis of shifts in demand compared to those in supply, its small scale, dominated by highly leveraged individuals, may not be sufficiently representative for the wide population. In contrast, mortgages make up a significant part of the US credit landscape and often constitute an individual's most significant financial decision. In this section, I turn to examine the changes of the activity level in the mortgage market to see if similar trends hold.

Mortgage borrowing can be particularly sensitive to political uncertainty as the investment is perhaps the most important decision to be made by households and difficult to reverse. Uncertainty level could increase the real option value of waiting for irreversible investment such that households have incentives to delay their decision making when their perceived uncertainty is high. Consequently, if campaign visits by presidential candidates disseminate information that helps to reduce perceived uncertainty over labor income and policies, an increase in mortgage application is expected.

County-month panel

I start with the county-month data on mortgage applications and originations from 2015 to 2017, obtained from Neil Bhutta's website[14]. This data covers the top 500 counties with the highest mortgage applications in a given year. I focus only on loans for home purchase and therefore exclude refinancing and home improvement loans. The event study coefficients from equation 1 are presented in Figure 6 and Figure 7. In line with the real option channel, following Clinton's visits, there is an increase in mortgage loan applications, particularly one month after the events. Short-term reactions to Trump's visits appear minimal. The figures also show that a pre-treatment trend is less likely a concern. Table 8 reports the DID results. The overall average effect is not significant and nearly zero. There are at least two potential explanations. First, if Clinton's visits have an effect on perceived uncertainty and thus borrowing demand, the effect should reverse after the election outcome. Second, as shown above for uncertainty and P2P lending, there can be positive spillover effects in neighboring counties such that the estimated effect is a lower bound of the true effect. Since the dataset only covers 500 counties, the spillover effect is more likely to dominate. Table IA13 shows some evidence consistent with these explanations.

If households increase borrowing after campaign visits because they have lower perceived uncertainty, one would expect the effects would be larger for counties with higher uncertainty levels in the beginning. In Table 8, Columns (2)-(3), (5)-(6), and (8)-(9) exploit the heterogeneity of initial economic uncertainty. Specifically, I define states with a state-level Economic Policy Uncertainty (EPU) Index in the fourth quartile in the beginning of the sample period (January 2015), built by Baker et al. (2022), as having high initial uncertainty levels. I assign $High\ EPU = 1$ for counties located in such states. By splitting the sample based on $High\ EPU$, I show that the effects of campaign visits on mortgage applications concentrate on counties with high initial uncertainty levels, implying that changes in perceived uncertainty may explain the increase in mortgage borrowing.

Theories of opportunistic political cycles suggest that politicians may strategically time their policy decisions to maximize their chance of winning. Mller (2023), for example, shows that macroprudential regulations are less restrictive before elections, especially during pe-

[14] https://sites.google.com/site/neilbhutta/data.

riods with high election-related uncertainty. Therefore, the observed increases in loan applications and originations are likely driven by changes in credit supply. Comparing loan application and origination dynamics sheds light on this explanation. Since home purchase decisions take time, and mortgage arrangements require a thorough assessment of a borrower's financial situation, creditworthiness, and property evaluation, the increase in loan applications is less likely to be observed immediately after the events, and banks' decisions on loan acceptance or denial occur even later. However, if banks also adjust credit supply due to belief changes, regulations, or political motivations, an immediate increase in loan originations should be observed. While I observe an increase in loan applications mainly one month after Clinton's events, there are no immediate significant changes in loan originations by action date. In fact, any immediate effect, if anything, tends to be negative, as Figure 7 shows. Interestingly, loan originations jump one month after Trump's events. The evidence suggests that supply-side changes are less likely to explain my results for Clinton's rallies, but Trump's visits may influence mortgage loan origination decisions.

Finally, I examine the geographic spillovers in mortgage borrowing by using the distance between the city hosting the event and the county's centroid. I set the distance thresholds for treatment status l to be 50, 100, and 150 kilometers (31, 62, and 93 miles). The results are presented in Table IA12. For Clinton's events, the effect is only significant within a 50km (31 miles) radius. However, no significant or consistent patterns are observed after Trump's visits. These findings align with the geographic spillovers seen in uncertainty perceptions and P2P borrowing, reinforcing the idea that geographic distance plays a crucial role in my analysis, and the effect is mainly concentrated within a relatively short distance.

One potential concern is that campaign rallies follow the seasonality of the housing market. As documented by Ngai and Tenreyro (2014), the volume of housing transactions increases in the "hot season," i.e., the spring and summer. Also, people may be more likely to move during warmer weather. To eliminate this possibility of seasonal effects influencing both rally attendance and housing decisions, I conduct a placebo test where the date of each rally is moved to two years earlier. This test assumes that the weather and temperature, along with other factors that may explain the seasonality of the housing market, are approximately the same on the same dates across different years. Figure IA4 illustrates the event study plots. and I do not find significant changes in mortgage applications after the shifted rallies for either Clinton or Trump. Similarly, Table IA14 reports insignificant coefficients from DID specifications. These results indicate that rally visits do not show the same seasonality as the housing market.

Yearly mortgage applications

Despite the granularity offered by the county-month data, the sample only covers the top 500 counties in terms of mortgage activities. An analysis covering the whole US market helps to give a broader view. In addition, using purely aggregate data might also mask heterogeneity among borrowers and lenders. To address these limitations, I turn to the loan-level data with year-level timestamp from HMDA for 2014-2017, constructing a tract-bank-year panel to investigate if households alter their borrowing behavior over a longer time horizon.

Table 9 presents results derived from tract-bank-year mortgage data. With higher dimension available, I include census tract fixed effects and bank-state-year fixed effects. The latter allows me to not only control for state-level time-varying variables like regulations and economic conditions but also account for banks' potential strategic behavior to support some states during election years based on their ideological preferences.

The findings mirror those from the monthly data analysis mentioned above. Specifically, I find that the dollar amount of loan applications and originations at the census-tract level, on average, remains relatively unchanged after Trump's rallies but increases by 0.35% after Clinton's rallies. Notably, this effect appears smaller compared to the previous county-month panel analysis. One explanation is that since the monthly data only includes the top 500 counties in terms of mortgage applications, the two samples may not be directly comparable.

Local and nonlocal banks

As previously mentioned, unlike the P2P lending market, local changes in mortgage applications and originations are typically influenced by both supply and demand factors. For instance, lenders in treated areas may benefit from the information disseminated during rallies, reducing their uncertainty and potentially increasing credit supply. Alternatively, they may strategically support candidates by offering easier credit access to influence voting decisions. These factors are largely controlled by the fixed effects included. In this section, I provide additional evidence by comparing local and nonlocal lenders and comparing national and state banks. Nonlocal lenders and national banks are less likely to be affected by events in local areas, and if they also experience an increase in loan applications from focal areas, it is more likely to be driven by increased demand.

To test if my results hold for nonlocal lenders, I divide the sample based on the headquarters location of banks and whether a bank operates nationally or locally. I classify banks as having nonlocal headquarters (HQ) if their headquarters are located in another state. The underlying assumption is that banks primarily make mortgage lending decisions at their headquarters.

I find consistent results for nonlocal banks. There is a significant increase in loan applications and originations for both local and nonlocal banks after Clinton's rallies, as presented in Table 10. The coefficients are nearly identical, although the increase is slightly larger for banks with local headquarters. Results are similar for the comparison between national and state banks. These consistent results for nonlocal banks and national banks strengthen the argument that the observed increase in loan applications is not solely driven by changes in credit supply.

In summary, the empirical evidence from both marketplace and mortgage lending markets corresponds well with life-cycle models that emphasize precautionary saving motives. These models (Leland, 1968; Sandmo, 1970; Carroll, 1997) argue that in times of uncertainty, individuals might change their consumption and investment behaviors to hedge against potential negative shocks. The spike in P2P loans and mortgage applications after rallies could be indicative of such behaviors, where individuals become more certain about future policy outcomes and economic conditions by prospectively evaluating information disseminated in rally events.

5 Conclusion

In this paper, I explore the interplay between campaign information and perceived political uncertainty during elections, and extend its implications to household financial decisions. By leveraging the unique empirical setting of the 2016 U.S. presidential election, I provide detailed evidence on how campaign rallies, beyond their impact on political outcomes, influence both economic perceptions and behaviors in the household sector.

The core results show that campaign rallies could lead to a reduction in perceived uncertainty, but this is contingent to the candidate involved. Specifically, I find Clinton's rallies have an overall negative impact on perceived macro uncertainty. Effects are similar before and after primaries, suggesting that individuals prospectively evaluate not only election outcomes but also policy outcomes. In addition, the effects are stronger for respondents without college education who are likely to be less informed before campaigns, for renters who lean more Democratic, and for those living in areas with an initially higher uncertainty level.

Test on geographic spillovers shows that the effect drops down monotonically and is mainly confined within 50 kilometers (31 miles) of the rallies.

The second set of findings bridges the perception of uncertainty with actual financial decisions. Using loan application data in the P2P and mortgage lending markets, I find areas that host Clinton's rallies see an increase in loan applications. Notably, the changes observed in the credit market do not merely reflect supply-side shifts. The feature of elastic local supply in the P2P setting, the timing difference between mortgage application and origination, and the consistent evidence focusing on nonlocal and national banks in the mortgage lending market, corroborate that these shifts are likely demand-driven. In addition, the effects on mortgage borrowing are stronger in counties with higher initial economic uncertainty levels. This aligns with life-cycle models with precautionary saving motives and underscores the real effects of campaign narratives on household financial behaviors.

The study could have policy implications at mitigating the negative effects of uncertainty on household finance. Compared with firms, households are found to have higher information acquiring costs and lower information demand when facing uncertainty (Mikosch et al., 2021). In particular, it is precisely those who are more likely to be affected by uncertainty (e.g., households that are in financial distress and highly leveraged) participate less in the political process (McCartney, 2020). A voter education initiatives that provides information about the candidates and their policy positions may alleviate perceived uncertainty regarding the election's potential economic impact, enabling households to make more informed decisions.

For future research, given that firms also suffer from the negative effects of political uncertainty, a related question is whether firms exhibit higher sophistication in evaluating political uncertainty by leveraging related information, including candidate-specific information during campaign events, and shed light on the strategies employed by firms to cope with election cycles.

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A Appendix

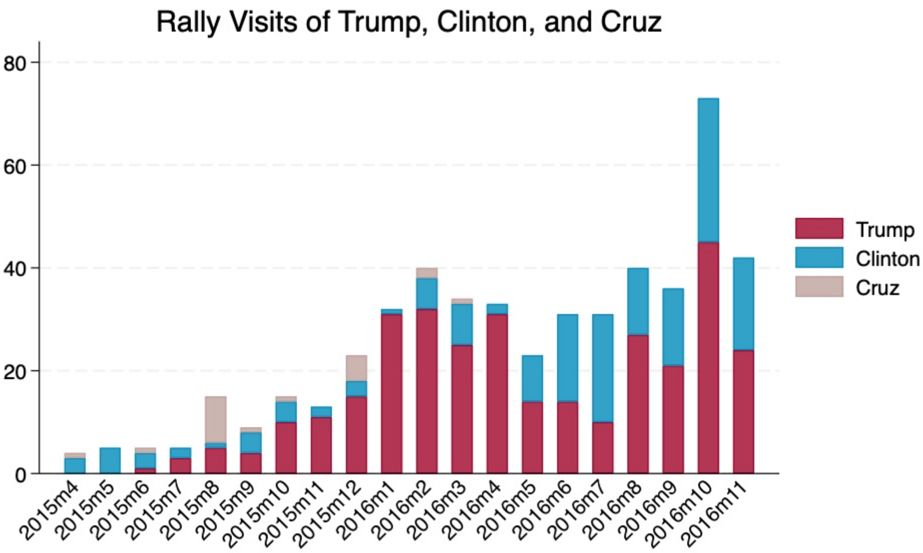


Figure 1. Rally Visits by Candidates Each Month in the 2016 Election Cycle

This figure plots the monthly number of rally visits by Clinton, Cruz, and Trump during the 2016 presidential election cycle, from April 2015 to November 8th, 2016.

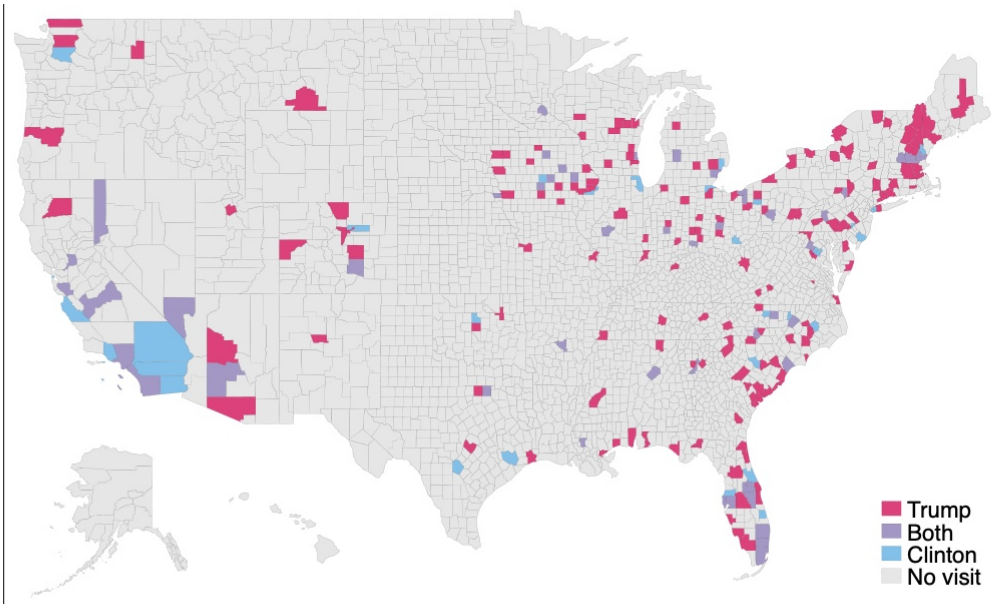


Figure 2. Counties with Rallies by Trump and Clinton

This figure shows the geographic distribution of rally visits by Clinton and Trump in the 2016 presidential election cycle at the county level. Red areas represent counties visited by Trump but not Clinton, blue areas represent counties visited by Clinton but not Trump, purple areas represent counties visited by both candidates, and grey areas represent counties that neither candidate visited.

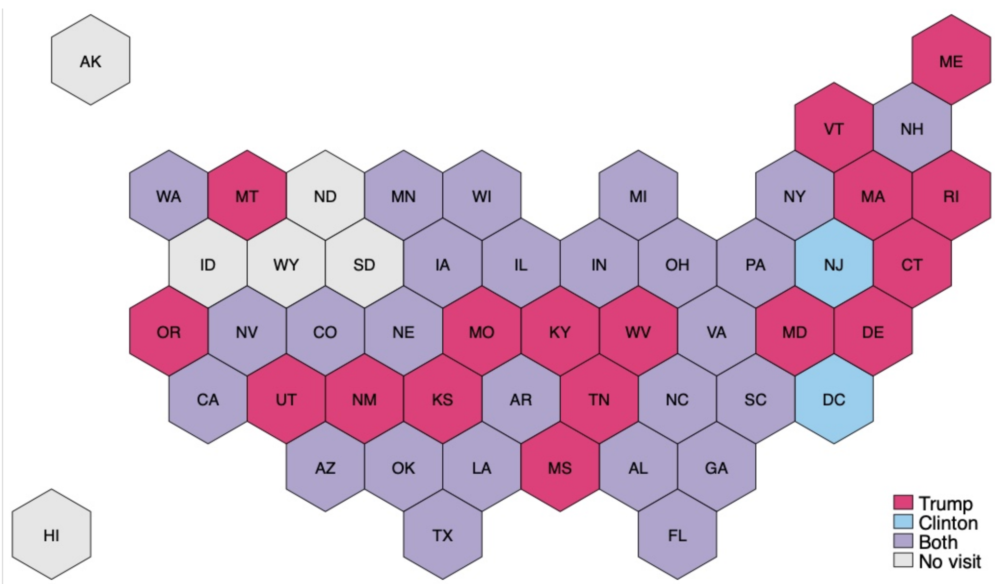
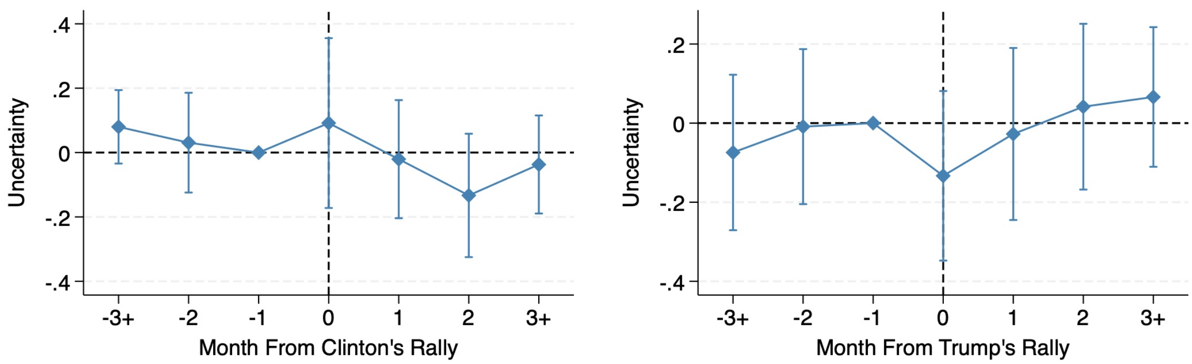
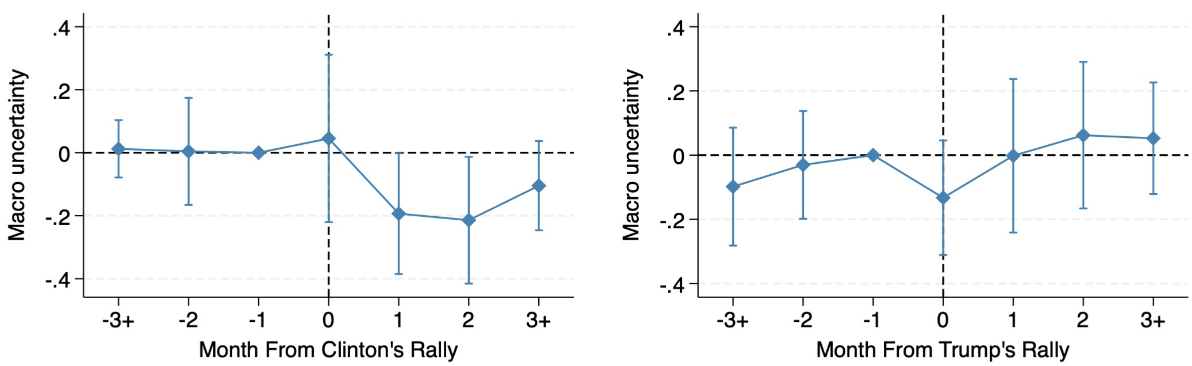


Figure 3. States with Rallies by Trump and Clinton

This figure shows the geographic distribution of rally visits by Clinton and Trump in the 2016 presidential election cycle at the state level. Red areas represent states visited by Trump but not Clinton, blue areas represent states visited by Clinton but not Trump, purple areas represent states visited by both candidates, and grey areas represent states that neither candidate visited.



(a) Uncertainty



(b) Macro Uncertainty

Figure 4. Perceived Economic Uncertainty After Rallies

This figure plots coefficients of the generalized event study specification described in equation 1 with 95% confidence intervals. The outcome variables are perceived overall uncertainty (in (a)) and macro uncertainty (in (b)). The left graphs present coefficients for Clinton's rallies, while the right graphs show coefficients for Trump's rallies. Standard errors are clustered at both the commuting zone and year-month levels.

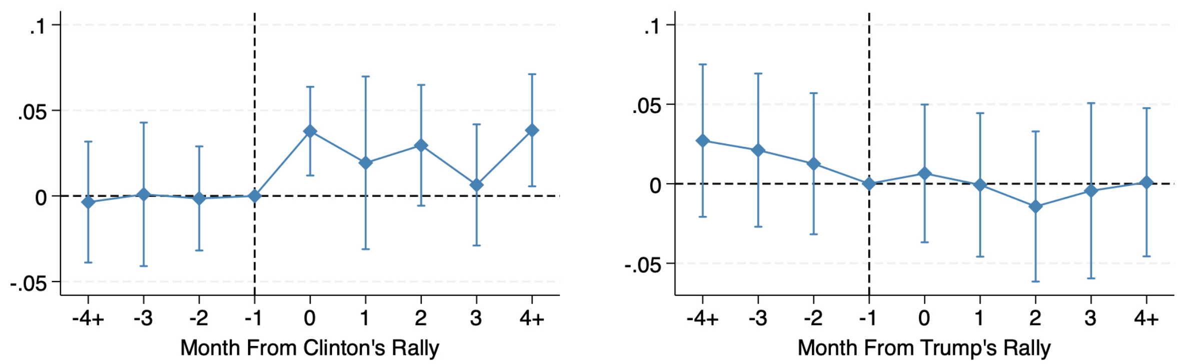


Figure 5. Number of Peer-to-Peer (P2P) Applications After Rallies

This figure plots coefficients of the generalized event study specification described in equation 3 with 95% confidence intervals. The outcome variable is natural log of number of loan applications on the Lendingclub platform. The left graph presents coefficients for Clinton's rallies, while the right graph shows coefficients for Trump's rallies. Standard errors are double clustered at ZIP3 and year-month level.

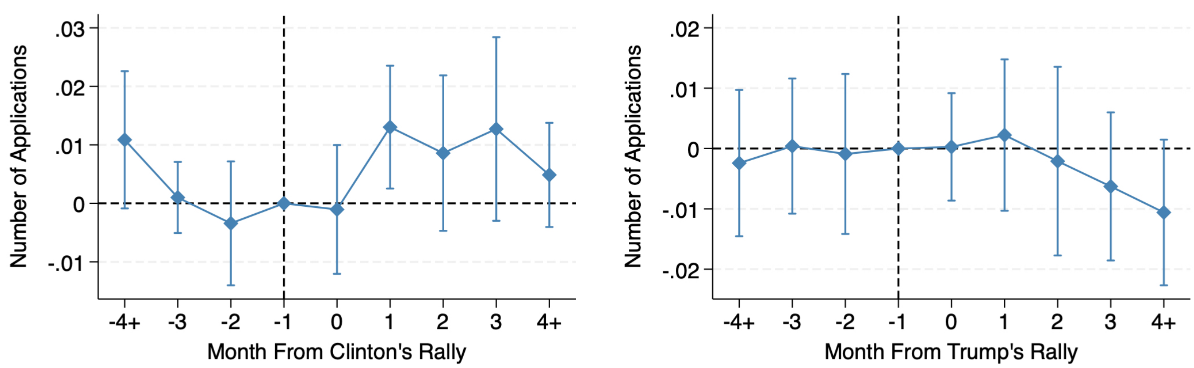


Figure 6. Mortgage Applications After Rallies by Application Date

This figure plots coefficients of the generalized event study specification described in equation 3 with 95% confidence intervals. The outcome variables are natural log of number of mortgage application for home purchase based on *application* date. The left graph presents coefficients for Clinton's rallies, while the right graph shows coefficients for Trump's rallies. Standard errors are double clustered at county and year-month level.

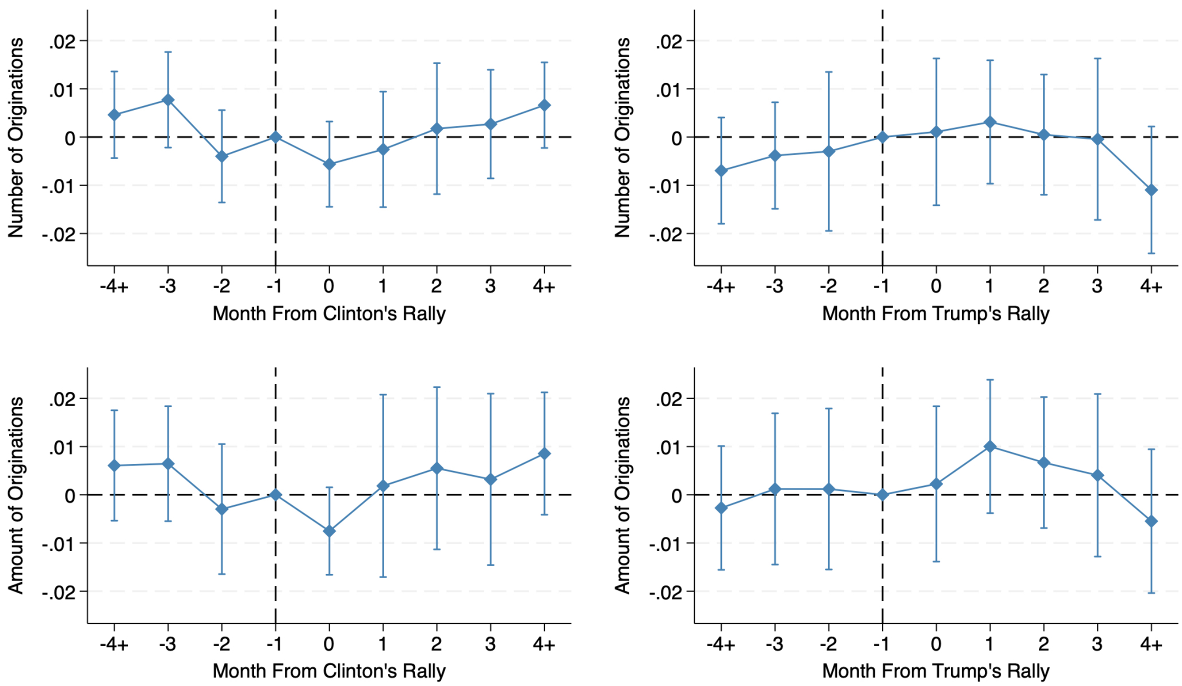


Figure 7. Mortgage Applications After Rallies by Action Date

This figure plots coefficients of the generalized event study specification described in equation 3 with 95% confidence intervals. The outcome variables are natural log of number of mortgage origination (upper) and natural log of dollar amount of mortgage origination (lower), for home purchase based on *action* date. The left graphs present coefficients for Clinton's rallies, while the right graphs show coefficients for Trump's rallies. Standard errors are double clustered at county and year-month level.

Table 1. Summary Statistics of SCE Respondents

This table presents summary statistics of the Survey of Consumer Expectations (SCE) data. Panel (a) summarizes key outcome variables used in the regression analysis. Uncertainty measures are based on standard deviations for income, inflation, and home prices, as computed by FRBNY from respondents' subjective distributions. As per Ben-David et al. (2018), *Uncertainty* accounts for all three components, while *Macro Uncertainty* includes only inflation and home price components. $Uncertainty(IQR)$ is the averaged interquartile range of individual means at the commuting-zone level across the three components. Income and inflation expectation measures are calculated from respondents' distribution means. Tax expectations are taken directly from respondents' point estimates. *Better credit access* is a dummy that equals one if the respondent believes that obtaining credit or loans will be the same or easier over the next 12 months. Panel (b) presents demographic characteristics grouped by respondents' treatment status.

(a) Main outcome variables of SCE respondents

	Mean	SD	P10	P50	P90	N
Uncertainty	2.24	1.95	0.71	1.61	4.36	33,055
Macro uncertainty	2.36	2.10	0.71	1.69	4.70	32,762
Uncertainty (IQR)	3.30	2.96	1.06	2.37	6.51	33,290
Macro uncertainty (IQR)	3.47	3.21	1.04	2.46	7.00	33,213
Income Expectation	3.19	4.48	0.19	2.54	7.41	23,435
Inflation Expectation	3.22	3.93	0.35	2.62	6.51	33,058
Tax Expectation	3.41	11.17	-2.00	3.00	10.00	33,438
Better Credit Access	0.73	0.44	0.00	1.00	1.00	33,488

(b) Demographic characteristics of SCE respondents by treatment status

	All		Treated: Clinton		Treated: Trump		Never Treated	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	0.41	0.49	0.42	0.49	0.42	0.49	0.41	0.49
Married	0.68	0.47	0.66	0.47	0.68	0.47	0.69	0.46
Age								
Under 40	0.29	0.45	0.33	0.47	0.30	0.46	0.27	0.45
40 to 60	0.38	0.49	0.38	0.49	0.39	0.49	0.37	0.48
Over 60	0.33	0.47	0.29	0.45	0.31	0.46	0.35	0.48
Race								
White	0.80	0.40	0.78	0.42	0.82	0.39	0.78	0.41
Black	0.05	0.22	0.07	0.25	0.06	0.24	0.04	0.19
Hispanic	0.05	0.22	0.06	0.24	0.04	0.21	0.05	0.22
Asian/Pacific Islander	0.05	0.22	0.05	0.22	0.04	0.18	0.06	0.25
American Indian or Alaska Native	0.02	0.14	0.01	0.09	0.01	0.12	0.03	0.16
Other	0.03	0.18	0.03	0.18	0.03	0.17	0.04	0.19
Education								
No HS	0.00	0.06	0.00	0.07	0.00	0.05	0.01	0.07
High school graduate	0.07	0.25	0.06	0.23	0.07	0.25	0.07	0.26
Some college	0.17	0.38	0.17	0.38	0.17	0.38	0.18	0.39
2-year	0.12	0.33	0.10	0.30	0.11	0.32	0.13	0.34
4-year	0.35	0.48	0.38	0.49	0.37	0.48	0.33	0.47
Post-grad	0.28	0.45	0.28	0.45	0.28	0.45	0.27	0.45
Family income								
Less than 10,000	0.02	0.14	0.02	0.14	0.02	0.14	0.02	0.15
10,000 - 19,999	0.05	0.22	0.04	0.20	0.04	0.20	0.06	0.23
20,000 - 29,999	0.07	0.25	0.07	0.26	0.07	0.25	0.07	0.26
30,000 - 39,999	0.07	0.26	0.06	0.24	0.07	0.26	0.07	0.26
40,000 - 49,999	0.08	0.28	0.09	0.28	0.08	0.27	0.09	0.29
50,000 - 59,999	0.09	0.29	0.09	0.28	0.09	0.29	0.09	0.28
60,000 - 79,999	0.13	0.33	0.12	0.33	0.12	0.33	0.13	0.34
80,000 - 99,999	0.16	0.36	0.17	0.37	0.16	0.37	0.15	0.36
100,000 - 149,999	0.18	0.39	0.18	0.39	0.20	0.40	0.17	0.38
150,000 or more	0.15	0.36	0.16	0.37	0.15	0.35	0.15	0.35
Home ownership								
Own	0.75	0.43	0.73	0.44	0.76	0.43	0.75	0.43
Rent	0.23	0.42	0.25	0.43	0.22	0.42	0.24	0.43
Other	0.01	0.11	0.02	0.13	0.01	0.11	0.01	0.10
Employment status								
Full-time	0.55	0.50	0.60	0.49	0.58	0.49	0.52	0.50
Part-time	0.10	0.30	0.10	0.30	0.10	0.30	0.10	0.30
Temporarily laid off	0.01	0.08	0.01	0.09	0.01	0.08	0.01	0.08
Unemployed	0.02	0.15	0.02	0.15	0.02	0.15	0.02	0.16
Retired	0.21	0.41	0.16	0.37	0.19	0.40	0.24	0.43
Permanently disabled	0.03	0.17	0.02	0.15	0.03	0.16	0.04	0.19
Homemaker	0.03	0.17	0.03	0.18	0.03	0.17	0.03	0.16
Student	0.03	0.17	0.03	0.18	0.03	0.17	0.03	0.17
Other	0.02	0.13	0.01	0.12	0.01	0.12	0.02	0.14

Table 2. Perceived Economic Uncertainty

This table reports weighted regression results of equation 2. *Uncertainty* accounts for income, inflation, and home price uncertainties, while *Macro Uncertainty* includes only inflation and home price components. Columns (2) and (4) add interaction terms between the post treatment indicator and *Primary*. *Primary* is a dummy for periods post primaries, i.e., after June 2016. The total effects (sum of the coefficients of the post treatment indicator and the interaction term) are reported underneath. Standard errors are double clustered at the commuting zone and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	Uncertainty		Macro Uncertainty	
	(1)	(2)	(3)	(4)
Post_Clinton	-0.0669	-0.0636	-0.0993**	-0.1023*
	(-1.26)	(-1.14)	(-2.21)	(-2.00)
Post_Trump	0.0323	0.0330	0.0530	0.0572
	(0.51)	(0.51)	(0.96)	(1.00)
Post_Clinton×Primary		-0.0067		0.0079
		(-0.26)		(0.27)
Post_Trump×Primary		-0.0007		-0.0106
		(-0.02)		(-0.31)
Post_Clinton & Primary		-0.0703		-0.0944**
		(-1.32)		(-2.27)
Post_Trump & Primary		0.0324		0.0466
		(0.50)		(0.81)
N	32,095	32,095	31,815	31,815
Adj. R2	0.7357	0.7357	0.7088	0.7088
Respondent FE	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES

Table 3. Expectations Over Income, Inflation, Tax, and Credit Access

This table reports weighted regression results of equation 2. Income and inflation expectation measures are calculated from respondents' distribution means. Tax expectations are taken directly from respondents' point estimates. *Credit Access* is a dummy that equals one if the respondent believes that obtaining credit or loans will be the same or easier over the next 12 months. Columns (2), (4), (6), and (8) add interaction terms between the post treatment indicator and *Primary*. *Primary* is a dummy for periods post primaries, i.e., after June 2016. The total effects (sum of the coefficients of the post treatment indicator and the interaction term) are reported underneath. Standard errors are double clustered at the commuting zone and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	Income Expectation		Inflation Expectation		Tax Expectation		Credit Access	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post_Clinton	0.1434	0.1128	0.1716	0.2058	-0.4580	-0.4265	0.0028	0.0011
	(0.98)	(0.87)	(1.41)	(1.64)	(-1.47)	(-1.35)	(0.25)	(0.10)
Post_Trump	0.0048	0.0226	-0.1619	-0.1739	0.2637	0.3137	-0.0076	-0.0044
	(0.03)	(0.15)	(-0.96)	(-0.98)	(0.73)	(0.79)	(-0.51)	(-0.29)
Post_Clinton×Primary		0.0722		-0.0760		-0.0506		0.0045
		(1.11)		(-1.32)		(-0.37)		(1.00)
Post_Trump×Primary		-0.0490		0.0366		-0.1038		-0.0077
		(-0.54)		(0.57)		(-0.41)		(-0.82)
Post_Clinton & Primary		0.1850		0.1298		-0.4771		0.0057
		(1.07)		(1.05)		(-1.56)		(0.52)
Post_Trump & Primary		-0.0263		-0.1373		0.2099		-0.0121
		(-0.13)		(-0.85)		(0.60)		(-0.79)
N	22,545	22,545	32,096	32,096	32,464	32,464	32,512	32,512
Adj. R2	0.5400	0.5400	0.4901	0.4901	0.2792	0.2792	0.4821	0.4821
Respondent FE	YES	YES	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 4. Peer-to-Peer Loan Application

This table reports regression results of equation 4, with added interaction term between the post treatment indicator and the dummy for months after the primaries. The outcome variables are the natural logarithms of the number of P2P loan applications, the amount of loan applications, the number of accepted loans, and the amount of accepted loans. The total effects (sum of the coefficients of the post treatment indicator and the interaction term) are reported underneath. The specification includes a ZIP3 local linear trend. Standard errors are double clustered at the ZIP3 and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	Number of Application		Amount of Application		Number of Accepted		Amount of Accepted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post_Clinton	0.0301***	0.0286***	0.0196	0.0179	0.0156**	0.0134**	0.0157*	0.0141*
	(3.38)	(3.17)	(1.42)	(1.30)	(2.48)	(2.28)	(2.03)	(1.89)
Post_Trump	-0.0229*	-0.0230**	-0.0217*	-0.0220*	0.0027	0.0032	0.0016	0.0017
	(-2.02)	(-2.03)	(-1.86)	(-1.88)	(0.51)	(0.61)	(0.29)	(0.33)
Post_Clinton×Primary		0.0041		0.0044		0.0070**		0.0048
		(1.27)		(1.08)		(2.04)		(1.19)
Post_Trump×Primary		0.0040		0.0081		-0.0007		0.0017
		(0.85)		(1.34)		(-0.30)		(0.62)
Post_Clinton & Primary		0.0328***		0.0223		0.0204***		0.0189**
		(3.38)		(1.57)		(2.84)		(2.11)
Post_Trump & Primary		-0.0190*		-0.0140		0.0025		0.0035
		(-1.73)		(-1.21)		(0.45)		(0.56)
N	31,956	31,956	31,956	31,956	30,082	30,082	30,082	30,082
Adj. R2	0.9608	0.9608	0.9349	0.9349	0.9345	0.9345	0.9117	0.9117
ZIP3 FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
ZIP3 Trend	YES	YES	YES	YES	YES	YES	YES	YES

Table 5. Peer-to-Peer Loan Application by Loan Purpose

This table reports regression results of equation 4. The dependent variables are the natural logarithms of number of loan application (Panel (a)) and natural log of dollar amount of loan application (Panel (b)) by different purposes. Credit card and debt consolidation purposes are grouped into "Consolidation". The category "Consumption" encompasses car, major purchase, medical, vacation, wedding, and moving purposes. "Home-related" includes home improvement and house. "Business" refers to loans for small business purpose. Other purposes are classified as "Non-disclosure". The specification includes a ZIP3 local linear trend. Standard errors are double clustered at ZIP3 and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Number of P2P Loans by Loan Purpose

	(1) Total	(2) Consolidation	(3) Consumption	(4) Home-related	(5) Business	(6) Non-disclosure
Post_Clinton	0.0301***	0.0353***	0.0122*	-0.0032	-0.0038	0.0266***
	(3.38)	(4.60)	(1.96)	(-0.41)	(-0.50)	(3.73)
Post_Trump	-0.0229*	-0.0183*	0.0008	0.0091	-0.0070	-0.0026
	(-2.02)	(-1.89)	(0.10)	(1.36)	(-0.79)	(-0.33)
N	31,956	31,521	31,026	30,488	29,749	30,809
Adj. R2	0.9608	0.9577	0.9514	0.9247	0.8839	0.9533
ZIP3 FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
ZIP3 Trend	YES	YES	YES	YES	YES	YES

(b) P2P Loan Volume by Loan Purpose

	(1) Total	(2) Consolidation	(3) Consumption	(4) Home-related	(5) Business	(6) Non-disclosure
Post_Clinton	0.0196	0.0429***	0.0193*	-0.0036	-0.0205	0.0327***
	(1.42)	(4.12)	(1.98)	(-0.33)	(-1.25)	(2.94)
Post_Trump	-0.0217*	-0.0170	0.0000	0.0098	-0.0051	-0.0057
	(-1.86)	(-1.49)	(0.00)	(1.28)	(-0.37)	(-0.51)
N	31,956	31,521	31,026	30,488	29,749	30,809
Adj. R2	0.9349	0.9377	0.8983	0.8626	0.7264	0.8982
ZIP3 FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
ZIP3 Trend	YES	YES	YES	YES	YES	YES

Table 6. Number of Peer-to-Peer Accepted Loans by Maturity and Loan Status

This table reports regression results of equation 4. The dependent variables are the natural log of number of accepted Lendingclub loans plus one by maturity and loan performance until the third quarter of 2020. The specification includes a ZIP3 local linear trend. Standard errors are double clustered at ZIP3 and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	(1) Total	(2) Accepted	(3) 3 Year	(4) 5 Year	(5) Nonperforming	(6) Performing	(7) NPR
Post_Clinton	0.0301***	0.0273***	0.0220***	0.0133	0.0077	0.0246***	0.0001
	(3.38)	(3.40)	(3.10)	(1.44)	(1.14)	(3.24)	(0.07)
Post_Trump	-0.0229*	-0.0043	-0.0057	-0.0089	-0.0108	-0.0043	-0.0000
	(-2.02)	(-0.50)	(-0.73)	(-0.99)	(-1.33)	(-0.52)	(-0.00)
N	31,956	31,956	31,956	31,956	31,956	31,956	30,082
Adj. R2	0.9608	0.9435	0.9334	0.8828	0.8461	0.9381	0.0917
ZIP3 FE	YES	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES	YES
ZIP3 Trend	YES	YES	YES	YES	YES	YES	YES

Table 7. P2P Loan Performance After Rallies

This table reports regression results of equation 4. The dependent variable is a non-performing dummy that equals one if the borrower has defaulted by the third quarter of 2020. The specification includes a ZIP3 local linear trend and a variety of loan characteristics, including interest rates. Standard errors are double clustered at ZIP3 and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	(1)	(2)	(3)	(4)
Post_Clinton	0.0009	0.0004	-0.0001	-0.0002
	(1.34)	(0.99)	(-0.13)	(-0.30)
Post_Trump	-0.0049***	0.0006	0.0006	-0.0002
	(-5.90)	(1.31)	(0.67)	(-0.21)
N	1,298,719	1,298,711	1,298,711	1,209,694
Adj. R2	0.0004	0.0052	0.0054	0.0767
ZIP3 FE	NO	YES	YES	YES
Year-Month FE	NO	YES	YES	YES
ZIP3 Trend	NO	NO	YES	YES
Loan Characteristics	NO	NO	NO	YES

Table 8. Monthly Mortgage Application and Origination

This table reports regression results of equation 4 for county-month mortgage application and origination activities. The dependent variables are the natural logarithm of the monthly count of mortgage applications, the count of originated mortgages, and the total value of originated mortgages in the top 500 counties with the highest number of mortgage applications during 2015-2017. Columns (2)-(3), (5)-(6), and (8)-(9) are for subsamples based on the county's initial uncertainty level. Specifically, *High Init EPU* is a dummy variable that equals one if the county is located in a state where the initial economic policy uncertainty (EPU) index was in the fourth quartile in January 2015. The p-values for the coefficient differences across subsample regressions are reported underneath. Control variables include log of county-level population, employment, and personal income in year $t-1$.The model incorporates a local linear trend specific to each county. Standard errors are clustered at both the county and year-month levels. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	Number of Application			Number of Origination			Amount of Origination		
By Categories	All	High Init EPU		All	High Init EPU		All	High Init EPU	
Group		Yes	No		Yes	No		Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post_Clinton	0.0009	0.0150**	-0.0021	-0.0012	0.0121	-0.0040	0.0004	0.0131	-0.0022
	(0.19)	(2.33)	(-0.45)	(-0.29)	(1.67)	(-0.99)	(0.10)	(1.62)	(-0.46)
Post_Trump	-0.0033	-0.0084	-0.0026	-0.0027	-0.0061	-0.0025	-0.0011	-0.0041	-0.0010
	(-0.99)	(-1.01)	(-0.67)	(-0.82)	(-0.75)	(-0.65)	(-0.29)	(-0.47)	(-0.22)
Diff. P-Value Clinton			0.022			0.024			0.089
Diff. P-Value Trump			0.552			0.714			0.767
N	16,999	3,602	13,397	16,999	3,602	13,397	16,999	3,602	13,397
Adj. R2	0.9915	0.9923	0.9912	0.9906	0.9910	0.9904	0.9893	0.9898	0.9889
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County Trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 9. Tract-Bank-Year Mortgage Application and Origination

This table reports regression results of equation 4 for tract-bank-year mortgage application and origination activities. The dependent variables are the natural logarithm of the yearly count of mortgage applications, the total value of mortgage applications, the count of originated mortgages, and the total value of originated mortgages in census tracts covered by HMDA data during 2014-2017. Standard errors are clustered at census tract level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	(1) Number of Application	(2) Amount of Application	(3) Number of Origination	(4) Amount of Origination
Post_Clinton	-0.0009	0.0035***	-0.0009	0.0035**
	(-1.02)	(2.64)	(-1.09)	(2.48)
Post_Trump	-0.0002	0.0022	-0.0002	0.0025
	(-0.22)	(1.11)	(-0.20)	(1.25)
N	8,473,732	8,473,450	7,136,027	7,135,813
Adj. R2	0.3049	0.4588	0.2974	0.4635
Census Tract FE	YES	YES	YES	YES
Bank×State×Year FE	YES	YES	YES	YES

Table 10. Mortgage Application by Headquarters and National/Local Operations

This table reports regression results of equation 4 for tract-bank-year mortgage application and origination activities. Sample is split based on the headquarters location (panel (a)) and whether the bank operates nationally or locally (panel (b)). The dependent variables are the natural logarithm of the yearly count of mortgage applications, the total value of mortgage applications, the count of originated mortgages, and the total value of originated mortgages in census tracts covered by HMDA data during 2014-2017. Standard errors are clustered at census tract level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Banks With Local and Nonlocal Headquarters

	Local HQ				Nonlocal HQ			
	(1) Number of Application	(2) Amount of Application	(3) Number of Origination	(4) Amount of Origination	(5) Number of Application	(6) Amount of Application	(7) Number of Origination	(8) Amount of Origination
Post_Clinton	-0.0008	0.0042	-0.0008	0.0052*	-0.0012	0.0032**	-0.0011	0.0031**
	(-0.45)	(1.62)	(-0.43)	(1.77)	(-1.12)	(2.31)	(-1.15)	(2.15)
Post_Trump	-0.0024	0.0008	-0.0029	0.0011	-0.0001	0.0023	0.0001	0.0027
	(-1.03)	(0.26)	(-1.23)	(0.33)	(-0.08)	(1.10)	(0.05)	(1.26)
N	1,495,241	1,495,212	1,299,760	1,299,737	6,977,157	6,976,904	5,834,394	5,834,203
Adj. R2	0.3062	0.4377	0.3075	0.4430	0.3143	0.4713	0.3049	0.4768
Census Tract FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank×State×Year FE	YES	YES	YES	YES	YES	YES	YES	YES

(b) National and State Banks

	National				State			
	(1) Number of Application	(2) Amount of Application	(3) Number of Origination	(4) Amount of Origination	(5) Number of Application	(6) Amount of Application	(7) Number of Origination	(8) Amount of Origination
Post_Clinton	-0.0011	0.0040***	-0.0008	0.0041**	-0.0004	0.0039*	-0.0006	0.0045*
	(-0.80)	(2.64)	(-0.57)	(2.40)	(-0.29)	(1.72)	(-0.44)	(1.87)
Post_Trump	0.0002	0.0024	0.0008	0.0050*	-0.0029	-0.0014	-0.0028	-0.0018
	(0.12)	(0.92)	(0.44)	(1.86)	(-1.63)	(-0.54)	(-1.52)	(-0.69)
N	1,653,379	1,653,352	1,376,781	1,376,760	1,901,466	1,901,464	1,629,750	1,629,748
Adj. R2	0.3737	0.5347	0.3579	0.5323	0.3057	0.4328	0.3063	0.4367
Census Tract FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank×State×Year FE	YES	YES	YES	YES	YES	YES	YES	YES

B Internet Appendix

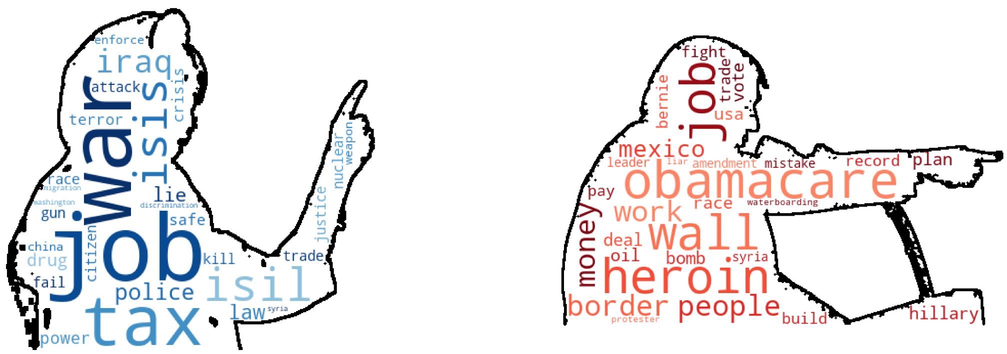


Figure IA1. Word Clouds Based on Clinton and Trump's Speeches

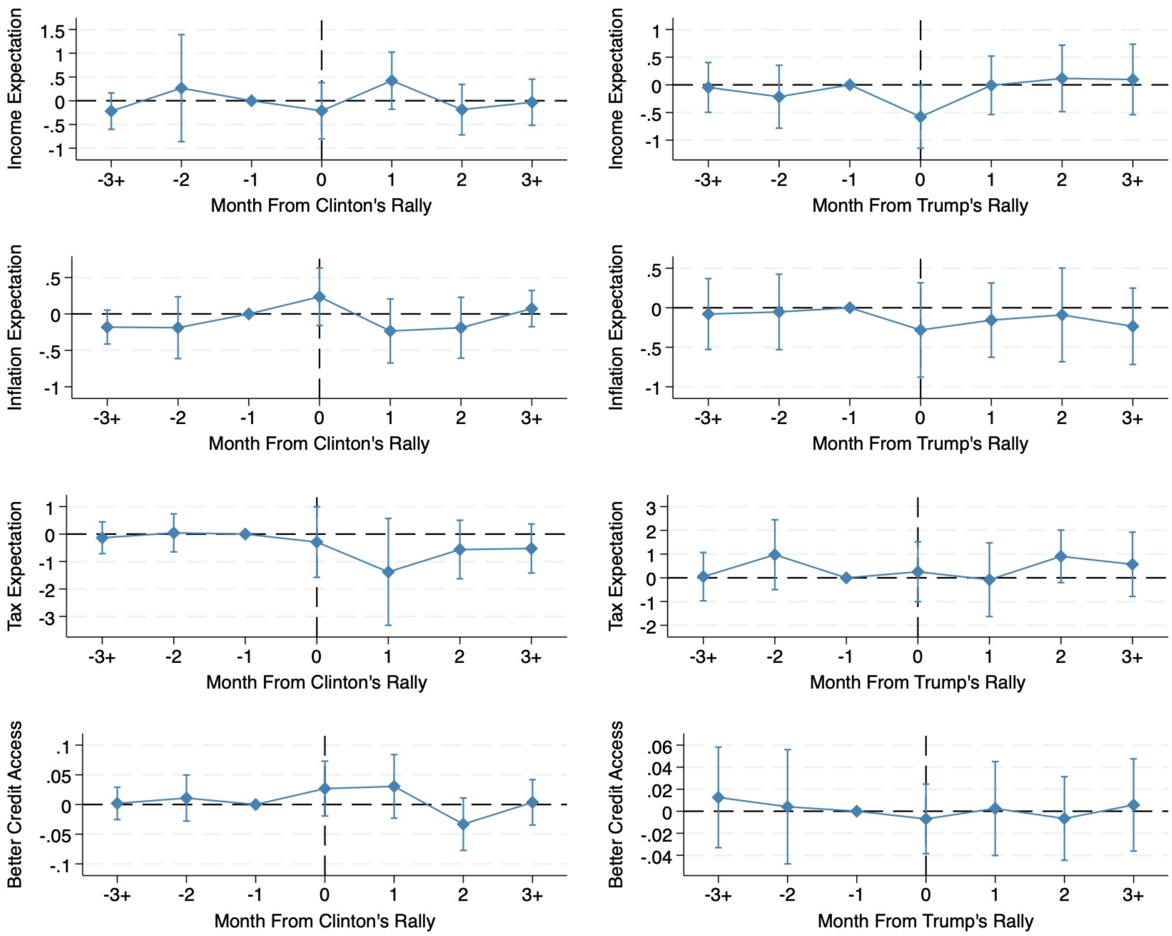


Figure IA2. Economic Expectations After Rallies

This figure plots coefficients of the generalized event study specification described in equation 1 with 95% confidence intervals. The outcome variables are self-reported expected personal income growth, inflation rate, tax growth, and credit access condition. The left graphs present coefficients for Clintons rallies, while the right graphs show coefficients for Trumps rallies. Standard errors are double clustered at commuting zone and year-month levels.

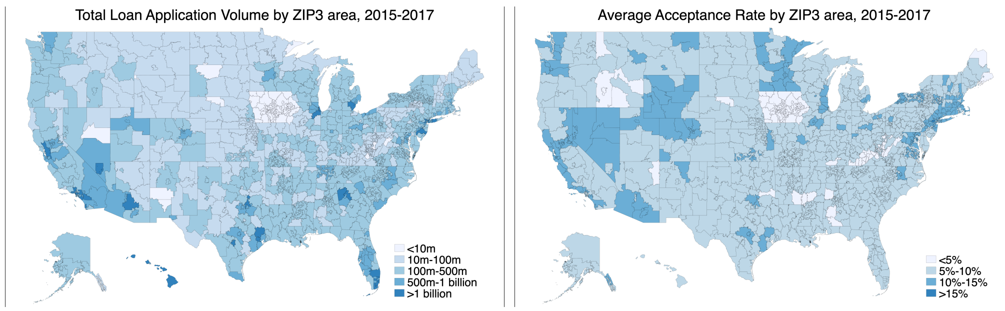


Figure IA3. P2P Loan Activity by ZIP3 Area, 2015-2017

This figure plots geographic distribution of total P2P loan applications and acceptance in 2015-2017. The left graph shows the dollar amount of loan applications aggregated at 3-digit ZIP code level, and the right graph shows the average acceptance rate, in terms of number of loans, at 3-digit ZIP code level.

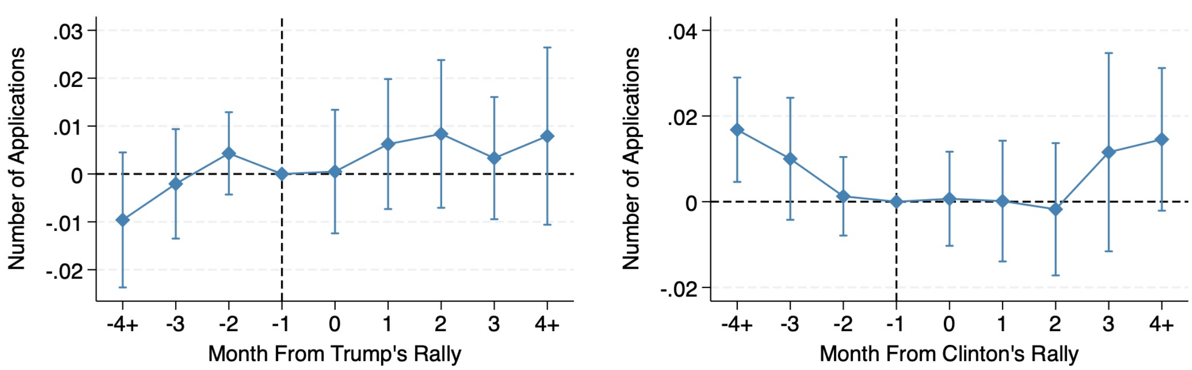


Figure IA4. Placebo Test: Mortgage Applications After Rallies That Are Shifted to the Same Dates Two Years Earlier

This figure plots coefficients of the generalized event study specification described in equation 3 with 95% confidence intervals. The outcome variables include the natural logarithm of the number of mortgage applications, specifically for home purchases based on the *application* date. The actual rally dates are shifted to the same day but two years earlier. The left graphs present coefficients for Clinton's rallies, while the right graphs show coefficients for Trump's rallies. Standard errors are double clustered at county and year-month levels.

Table IA1. Variable Description

This table provides descriptions and sources of key variables used in the empirical analysis section. SCE stands for Survey of Consumer Expectations, HMDA stands for Home Mortgage Disclosure Act data, and BEA stands for U.S. Bureau of Economic Analysis.

Variable	Description	Source
Uncertainty	Overall uncertainty calculated by taking the average of the standard deviation of the subjective distributions over personal income growth, inflation rate and national home price growth	SCE
Macro Uncertainty	Macro uncertainty calculated by taking the average of the standard deviation of the subjective distributions over inflation rate and national home price growth	SCE
Income Expectation	Mean of the subjective distribution over personal income growth in the next 12 months	SCE
Inflation Expectation	Mean of the subjective distribution over inflation rate in the next 12 months	SCE
Tax Expectation	Direct point estimate over tax growth rate in the next 12 months	SCE
Better Credit Access	Dummy that equals one if the respondent believes that obtaining credit or loans will be the same or easier over the next 12 months	SCE
Dem12	Dummy that equals one if the vote share of the Democratic Party in 2012 is higher than the Republican Party	MIT Election Data and Science Lab
Number of Application	Number of applications for P2P loans	Lendingclub
Amount of Application	Amount of applications for P2P loans	Lendingclub
Number of Accepted	Number of accepted P2P loans	Lendingclub
Amount of Accepted	Amount of accepted P2P loans	Lendingclub
Number of Application	Number of applications for mortgage loans	HMDA
Amount of Application	Amount of applications for mortgage loans	HMDA
Number of Origination	Number of originated mortgage loans	HMDA
Amount of Origination	Amount of originated mortgage loans	HMDA
EPU	State-level Economic Policy Uncertainty Index	Baker et al. (2022)
Bank Charter	Bank charter level (state/national/other)	HMDA
Bank Headquarter	Bank headquarter location (state)	HMDA
Population	County-level population	BEA
Unemployment Rate	County-level unemployment rate	BEA
Personal Income	County-level personal income in thousands	BEA
Centroid	U.S. geographical centroid location	U.S. Census Bureau

Table IA2. County-Level Socioeconomic Characteristics in 2014

This table compares county-level socioeconomic characteristics in 2014 between counties visited by Clinton or Trump and counties unvisited during the 2016 election cycle. GDP and personal income data are sourced from the U.S. Bureau of Economic Analysis, with GDP values expressed in real 2017 dollars, while personal income per capita is in nominal terms. Labor force-related statistics are obtained from U.S. Bureau of Labor Statistics. Demographic data, including age, race, and education, come from the 2014 American Community Survey. The "Higher education" category pertains to individuals with a bachelor's degree or higher. County-level vote shares are acquired from MIT Election Lab's dataset on presidential returns in 2012. The "Democrats majority" variable is a dummy variable which equals one if the Democratic candidate secured over 50% votes in the 2012 election cycle. The "Democrat-Republican gap" represents the absolute difference between Democratic and Republican vote shares.

	All		Treated: Clinton		Treated: Trump		Never Treated	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Economic								
Real GDP growth (%)	1.53	10.45	2.85	3.24	2.25	4.37	1.47	10.81
Per capita income growth (%)	3.02	6.19	4.39	1.91	3.72	2.35	2.96	6.41
Per capita income	39799.87	11,527.66	46350.21	11,735.47	44615.08	10,463.92	39386.98	11,473.07
Labor								
Labor force ratio	0.47	0.08	0.51	0.05	0.50	0.05	0.47	0.08
Unemployment rate (%)	6.48	2.86	6.35	2.54	5.89	1.47	6.51	2.93
Population (000)	98.68	316.23	1104.17	1,420.43	521.96	877.94	58.70	119.81
Demographic								
Median age	40.64	5.20	36.84	3.88	38.66	4.21	40.83	5.22
White ratio	0.76	0.23	0.58	0.20	0.71	0.19	0.76	0.23
Black ratio	0.09	0.14	0.15	0.13	0.13	0.14	0.08	0.14
Higher education ratio	0.14	0.06	0.21	0.07	0.20	0.06	0.13	0.06
Voting age ratio	0.77	0.03	0.77	0.03	0.77	0.03	0.77	0.03
Political								
Democratic vote share	0.38	0.15	0.58	0.11	0.50	0.11	0.37	0.14
Republican vote share	0.60	0.15	0.40	0.11	0.48	0.11	0.61	0.15
Democrats majority	0.20	0.40	0.82	0.39	0.53	0.50	0.17	0.38
Democrat-Republican gap	0.30	0.20	0.21	0.18	0.18	0.13	0.31	0.20

Table IA3. Demographic Characteristics of SCE Respondents by Democratic Party's Vote Share in the 2012 Election Cycle

This table compares demographic characteristics of SCE respondents by vote share in the 2012 election cycle. *Dem*12 is a dummy that equals one if the vote share of the Democratic Party in 2012's presidential election in a given commuting zone is higher than the Republican Party.

	Dem12=0		Dem12=1		All	
	Mean	SD	Mean	SD	Mean	SD
Female	0.42	0.49	0.41	0.49	0.41	0.49
Married	0.71	0.45	0.66	0.47	0.68	0.47
Age						
Under 40	0.29	0.45	0.29	0.46	0.29	0.45
40 to 60	0.38	0.49	0.38	0.49	0.38	0.49
Over 60	0.33	0.47	0.32	0.47	0.33	0.47
Race						
White	0.83	0.37	0.77	0.42	0.80	0.40
Black	0.05	0.22	0.05	0.22	0.05	0.22
Hispanic	0.04	0.20	0.05	0.23	0.05	0.22
Asian/Pacific Islander	0.02	0.15	0.07	0.26	0.05	0.22
American Indian or Alaska Native	0.03	0.16	0.01	0.11	0.02	0.14
Other	0.03	0.16	0.04	0.19	0.03	0.18
Education						
No HS	0.00	0.05	0.00	0.07	0.00	0.06
High school graduate	0.09	0.29	0.05	0.22	0.07	0.25
Some college	0.20	0.40	0.15	0.36	0.17	0.38
2-year	0.13	0.34	0.11	0.32	0.12	0.33
4-year	0.34	0.47	0.36	0.48	0.35	0.48
Post-grad	0.23	0.42	0.31	0.46	0.28	0.45
Family income						
Less than 10,000	0.02	0.14	0.02	0.14	0.02	0.14
10,000 - 19,999	0.05	0.22	0.05	0.21	0.05	0.22
20,000 - 29,999	0.08	0.27	0.06	0.24	0.07	0.25
30,000 - 39,999	0.09	0.28	0.06	0.24	0.07	0.26
40,000 - 49,999	0.10	0.29	0.08	0.27	0.08	0.28
50,000 - 59,999	0.11	0.31	0.08	0.27	0.09	0.29
60,000 - 79,999	0.14	0.35	0.11	0.31	0.13	0.33
80,000 - 99,999	0.16	0.36	0.16	0.36	0.16	0.36
100,000 - 149,999	0.16	0.37	0.20	0.40	0.18	0.39
150,000 or more	0.10	0.30	0.19	0.39	0.15	0.36
Home ownership						
Own	0.78	0.41	0.73	0.44	0.75	0.43
Rent	0.21	0.40	0.26	0.44	0.23	0.42
Other	0.01	0.12	0.01	0.11	0.01	0.11
Employment status						
Full-time	0.53	0.50	0.57	0.50	0.55	0.50
Part-time	0.09	0.29	0.10	0.30	0.10	0.30
Temporarily laid off	0.01	0.09	0.01	0.08	0.01	0.08
Unemployed	0.02	0.14	0.03	0.16	0.02	0.15
Retired	0.23	0.42	0.20	0.40	0.21	0.41
Permanently disabled	0.04	0.19	0.02	0.15	0.03	0.17
Homemaker	0.04	0.19	0.02	0.15	0.03	0.17
Student	0.03	0.17	0.03	0.17	0.03	0.17
Other	0.02	0.13	0.02	0.13	0.02	0.13

Table IA4. Summary Statistics of P2P Loans

This table presents summary statistics of the Lendingclub loan data. Panel (a) summarizes key variables used in the regression analysis at both aggregate level and loan level. Panel (b) summarizes loan characteristics of approved loans. *FICO score* is calculated as the mean of the lower and higher bounds of the raw FICO range.

(a) All P2P Loans

	Mean	SD	p10	p50	p90	N
Zip3 aggregate level						
Log of number of loan application	5.42	1.51	3.71	5.60	7.09	31,956
Debt consolidation	4.99	1.43	3.37	5.13	6.60	31,521
Consumption	3.54	1.31	1.79	3.64	5.14	31,026
Home-related	3.00	1.18	1.39	3.09	4.43	30,490
Small business	2.22	1.19	0.69	2.20	3.78	29,750
Nondisclosure	3.59	1.34	1.79	3.66	5.24	30,809
Log of total loan application volume	14.92	1.54	13.24	15.10	16.60	31,956
Debt consolidation	14.55	1.46	12.95	14.69	16.16	31,521
Consumption	12.54	1.43	10.79	12.65	14.23	31,026
Home-related	12.56	1.27	10.96	12.67	14.06	30,490
Small business	12.56	1.55	10.51	12.73	14.43	29,750
Nondisclosure	12.48	1.44	10.71	12.59	14.18	30,809
Log of (1+number of accepted loans)	3.00	1.32	1.10	3.04	4.64	31,956
3-year term	2.69	1.27	1.10	2.71	4.32	31,956
5-year term	1.93	1.13	0.00	1.95	3.43	31,956
Non-performing loans	1.55	1.04	0.00	1.61	2.94	31,956
Performing loans	2.82	1.29	1.10	2.89	4.45	31,956
Loan level						
Loan purpose (Y/N)						
Consolidation	0.61	0.49	0.00	1.00	1.00	16,000,907
Consumption	0.14	0.35	0.00	0.00	1.00	16,000,907
Durable	0.07	0.26	0.00	0.00	0.00	16,000,907
Business	0.03	0.18	0.00	0.00	0.00	16,000,907
Nondisclosure	0.15	0.36	0.00	0.00	1.00	16,000,907
Loan amount by purpose						
Consolidation	14197.07	10404.01	3000.00	10000.00	30,000.00	9,684,905
Consumption	8831.09	9422.59	1000.00	5000.00	23,000.00	2,218,097
Durable	14895.17	12016.02	2000.00	10000.00	35,000.00	1,125,202
Business	40143.92	59496.18	4000.00	20000.00	100,000.00	545,323
Nondisclosure	7682.93	8796.34	1000.00	5000.00	20,000.00	2,427,380

(b) Characteristics of P2P Approved Loans

	Mean	SD	P10	P90	N
Non-performing loan (Y/N)	0.18	0.39	0.00	1.00	951,999
Loan amount	14970.10	8,854.06	5000.00	28,000.00	951,999
Monthly payment	443.76	260.97	162.49	812.45	951,999
Interest rate (%)	12.88	4.69	7.39	18.99	951,999
Initial listing is whole loan market (Y/N)	0.70	0.46	0.00	1.00	951,999
Loan term (months, Y/N)					
36	0.71	0.45	0.00	1.00	951,999
60	0.29	0.45	0.00	1.00	951,999
Grade (Y/N)					
A	0.17	0.37	0.00	1.00	951,999
B	0.29	0.46	0.00	1.00	951,999
C	0.30	0.46	0.00	1.00	951,999
D	0.14	0.35	0.00	1.00	951,999
E	0.07	0.25	0.00	0.00	951,999
F	0.02	0.15	0.00	0.00	951,999
G	0.01	0.07	0.00	0.00	951,999
Purpose (Y/N)					
Car	0.01	0.10	0.00	0.00	951,999
Credit card	0.23	0.42	0.00	1.00	951,999
Debt consolidation	0.58	0.49	0.00	1.00	951,999
Educational	0.00	0.00	0.00	0.00	951,999
Home improvement	0.07	0.25	0.00	0.00	951,999
House	0.00	0.06	0.00	0.00	951,999
Major purchase	0.02	0.14	0.00	0.00	951,999
Medical	0.01	0.11	0.00	0.00	951,999
Moving	0.01	0.08	0.00	0.00	951,999
Other	0.06	0.23	0.00	0.00	951,999
Renewable energy	0.00	0.03	0.00	0.00	951,999
Small business	0.01	0.10	0.00	0.00	951,999
Vacation	0.01	0.08	0.00	0.00	951,999
Wedding	0.00	0.00	0.00	0.00	951,999
Home ownership (Y/N)					
Any	0.00	0.02	0.00	0.00	951,999
Mortgage	0.49	0.50	0.00	1.00	951,999
None	0.00	0.00	0.00	0.00	951,999
Own	0.12	0.32	0.00	1.00	951,999
Rent	0.39	0.49	0.00	1.00	951,999
Employment length (Y/N)					
1 year	0.07	0.26	0.00	0.00	893,188
10+ years	0.36	0.48	0.00	1.00	893,188
2 years	0.10	0.30	0.00	0.00	893,188
3 years	0.09	0.28	0.00	0.00	893,188
4 years	0.06	0.24	0.00	0.00	893,188
5 years	0.06	0.25	0.00	0.00	893,188
6 years	0.04	0.21	0.00	0.00	893,188
7 years	0.04	0.20	0.00	0.00	893,188
8 years	0.05	0.22	0.00	0.00	893,188
9 years	0.04	0.20	0.00	0.00	893,188
< 1 year	0.08	0.27	0.00	0.00	893,188
Annual income	78708.17	99,208.75	35000.00	130,000.00	951,999
Income verified (Y/N)	0.72	0.45	0.00	1.00	951,999
Debt-to-income ratio (%)	18.97	10.03	7.83	30.81	951,901
FICO score	696.74	30.94	667.00	737.00	951,999
Delinquency in the past 2 years (Y/N)	0.21	0.41	0.00	1.00	951,999
Number of derogatory public records	0.25	0.67	0.00	1.00	951,999
Number of inquiries in the past 6 months	0.56	0.86	0.00	2.00	951,998
Number of open credit lines	11.90	5.70	6.00	19.00	951,999
Total number of credit lines	24.89	12.05	11.00	41.00	951,999
Number of collections in 12 months excl. medical collections	0.02	0.16	0.00	0.00	951,999
Log of loan amount	9.41	0.69	8.52	10.24	951,999
Log of monthly payment	5.91	0.65	5.09	6.70	951,999
Log of annual income	11.11	0.54	10.46	11.78	951,909
Log of total credit revolving balance	9.29	1.03	8.11	10.45	948,793

Table IA5. Summary Statistics of Mortgages

This table presents summary statistics of the HMDA mortgage loan data. Panel (a) summarizes home-purchase mortgage data at the county-month level during 2015-2017. It only includes the top 500 counties by mortgage applications. Panel (b) summarizes mortgage data at the census tract-lender-year level during 2014-2017. State and national banks are categorized by the lender's charter, while local and nonlocal banks are categorized based on whether the bank's headquarter is located in the same state as the applicant. County-level socioeconomic controls in panel (a) (population, employment and personal income) are obtained from U.S. Bureau of Economic Analysis.

(a) County-Month Level Home-Purchase Mortgages

	Mean	SD	p10	p50	p90	N
Number of applications	673.82	831.17	179.00	412.00	1364.00	18,000
Number of originations	530.46	630.49	149.00	327.00	1076.00	18,000
Amount of originations (millions)	144.46	234.42	26.70	70.51	327.14	18,000
Number of applications (action date)	664.63	828.23	173.00	404.00	1357.00	18,000
Number of originations (action date)	527.13	631.09	146.00	325.00	1083.00	18,000
Amount of originations (millions, action date)	143.03	234.07	25.97	69.33	320.81	18,000
Log of population	12.68	0.82	11.77	12.51	13.77	17,856
Log of total employment	12.12	0.92	11.05	11.97	13.40	17,856
Log of personal income (thousands)	16.55	0.91	15.55	16.33	17.83	17,856

(b) Census Tract-Bank-Year Level Home-Purchase Mortgages

	Mean	SD	p10	p50	p90	N
All						
Number of applications	2.45	4.21	1.00	1.00	5.00	8,517,509
Amount of applications (millions)	630.53	2032.38	97.00	297.00	1209.00	8,517,509
Number of originations	1.88	3.40	0.00	1.00	4.00	8,517,509
Amount of originations (millions)	492.54	1539.36	0.00	234.00	990.00	8,517,509
State						
Number of applications	2.43	3.80	1.00	1.00	5.00	1,917,883
Amount of applications (millions)	578.71	1525.37	84.00	277.00	1174.00	1,917,883
Number of originations	1.95	3.33	0.00	1.00	4.00	1,917,883
Amount of originations (millions)	466.04	1283.08	0.00	221.00	979.00	1,917,883
National						
Number of applications	2.51	3.65	1.00	1.00	5.00	1,662,244
Amount of applications (millions)	806.76	2613.27	92.00	325.00	1547.00	1,662,244
Number of originations	1.90	2.98	0.00	1.00	4.00	1,662,244
Amount of originations (millions)	620.89	2067.48	0.00	248.00	1239.00	1,662,244
Local headquarters						
Number of applications	2.69	4.23	1.00	1.00	6.00	1,499,278
Amount of applications (millions)	620.42	1619.11	78.00	285.00	1304.00	1,499,278
Number of originations	2.17	3.68	0.00	1.00	5.00	1,499,278
Amount of originations (millions)	507.64	1351.85	0.00	228.00	1100.00	1,499,278
Nonlocal headquarters						
Number of applications	2.40	4.21	1.00	1.00	5.00	7,018,231
Amount of applications (millions)	632.68	2110.20	101.00	300.00	1190.00	7,018,231
Number of originations	1.82	3.33	0.00	1.00	4.00	7,018,231
Amount of originations (millions)	489.31	1576.51	0.00	235.00	967.00	7,018,231

Table IA6. Heterogeneous Effects on Perceived Economic Uncertainty Based on Commuting Zone Characteristics

This table reports weighted regression results of equation 2. *Uncertainty* accounts for income, inflation, and home price uncertainties, while *Macro Uncertainty* includes only inflation and home price components. The sample is split based on commuting zone characteristics, *Dem*12 and *High Init Uncertainty*. *Dem*12 is a dummy that equals one if the vote share of the Democratic Party in 2012's presidential election in a given commuting zone is higher than the Republican Party. *High Init Uncertainty* is a dummy that equals one if the respondent lives in a commuting zone with an initial average uncertainty level in January 2015 in the fourth quartile. The p-values for the coefficient differences across subsample regressions are reported underneath. Standard errors are double clustered at the commuting zone and year-month level. Significance: *, p < 0.1; **, p < 0.05; ***, p < 0.01.

	Uncertainty				Macro Uncertainty			
By Categories	Dem12		High Init Uncertainty		Dem12		High Init Uncertainty	
Group	Yes (1)	No (2)	Yes (3)	No (4)	Yes (5)	No (6)	Yes (7)	No (8)
Post_Clinton	-0.0518	-0.0596	-0.2501***	-0.0445	-0.1116	-0.1264*	-0.2761***	-0.0683
	(-0.82)	(-0.72)	(-4.12)	(-0.82)	(-1.63)	(-1.79)	(-4.47)	(-1.46)
Post_Trump	0.0685	-0.0480	0.1232	0.0118	0.1061	-0.0148	0.1218	0.0343
	(0.57)	(-0.62)	(0.40)	(0.13)	(1.07)	(-0.24)	(0.37)	(0.43)
Diff. P-Value Clinton		0.943		0.029		0.891		0.010
Diff. P-Value Trump		0.400		0.732		0.221		0.796
N	18,601	13,247	3,050	25,702	18,442	13,127	3,022	25,482
Adj. R2	0.7122	0.7643	0.7166	0.7009	0.6856	0.7384	0.6904	0.6740
Respondent FE	YES	YES	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Table IA7. Perceived Economic Uncertainty of Respondents With Different Characteristics

This table reports weighted regression results of equation 2. In Panel (a), the dependent variable is *Uncertainty*, which accounts for income, inflation, and home price uncertainties. In Panel (b), the dependent variable is *Macro Uncertainty*, which includes only inflation and home price components. The sample is split based on respondent characteristics. *High Numeracy* is a dummy that equals one if the respondent answers at least four out of five numerical questions in the survey correctly. *Higher Education* is a dummy that equals one if the respondent has a college or postgraduate degree. *Home Ownership* is a dummy that equals one if the respondent is a homeowner. The p-values for the coefficient differences across subsample regressions are reported underneath. Standard errors are double clustered at the commuting zone and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Dependent Variable: Uncertainty

By Categories	High Numeracy		Higher Education		Home Ownership	
Group	Yes (1)	No (2)	Yes (3)	No (4)	Yes (5)	No (6)
Post_Clinton	-0.0669	0.1230	-0.0144	-0.1398	-0.0343	-0.1364
	(-1.26)	(1.34)	(-0.66)	(-1.50)	(-0.76)	(-1.54)
Post_Trump	0.0323	-0.0227	-0.0003	0.0306	-0.0806	0.2565*
	(0.51)	(-0.10)	(-0.01)	(0.33)	(-1.38)	(1.85)
Diff. P-Value Clinton		0.101		0.129		0.199
Diff. P-Value Trump		0.816		0.759		0.037
N	32,095	11,657	20,389	11,424	24,066	7,687
Adj. R2	0.7357	0.7897	0.6220	0.7607	0.7481	0.7402
Respondent FE	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES

(b) Dependent Variable: Macro Uncertainty

By Categories	High Numeracy		Higher Education		Home Ownership	
Group	Yes (1)	No (2)	Yes (3)	No (4)	Yes (5)	No (6)
Post_Clinton	-0.0993**	0.1135	-0.0580**	-0.1690*	-0.0474	-0.2484***
	(-2.21)	(1.05)	(-2.07)	(-2.01)	(-1.67)	(-2.80)
Post_Trump	0.0530	-0.0254	-0.0101	0.0726	-0.0563	0.2825*
	(0.96)	(-0.11)	(-0.16)	(0.88)	(-1.01)	(1.83)
Diff. P-Value Clinton		0.085		0.210		0.004
Diff. P-Value Trump		0.756		0.439		0.055
N	31,815	11,427	20,246	11,284	23,881	7,588
Adj. R2	0.7088	0.7728	0.5918	0.7353	0.7172	0.7156
Respondent FE	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES

Table IA8. Heterogeneous Effects on Perceived Economic Uncertainty Based on Treatment Characteristics

This table reports weighted regression results of equation 2. *Uncertainty* accounts for income, inflation, and home price uncertainties, while *Macro Uncertainty* includes only inflation and home price components. All Columns add interaction terms between the post treatment indicator and *Repeat* or *Both*. *Repeat* is a dummy that equals one if the candidate has visited the same place before. *Both* is a dummy that equals one if the place visited has been visited by another candidate before. The total effects (sum of the coefficients of the post treatment indicator and the interaction term) are reported underneath. Standard errors are double clustered at the commuting zone and year-month level. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	Uncertainty		Macro Uncertainty	
	(1)	(2)	(3)	(4)
Post_Clinton	-0.1423	-0.1050	-0.2786**	-0.1346*
	(-1.16)	(-1.25)	(-2.24)	(-1.99)
Post_Trump	-0.0027	0.0486	0.0344	0.0349
	(-0.02)	(0.55)	(0.33)	(0.44)
Post_Clinton×Repeat	0.0982		0.1707	
	(0.76)		(1.20)	
Post_Trump×Repeat	0.1107		0.1549	
	(0.93)		(1.28)	
Post_Clinton×Both		0.0563		0.0375
		(0.92)		(0.64)
Post_Trump×Both		-0.0206		0.0778
		(-0.27)		(0.93)
Post_Clinton&Repeat	-0.0441		-0.1078*	
	(-0.72)		(-1.85)	
Post_Trump&Repeat	0.1081**		0.1892***	
	(2.05)		(2.78)	
Post_Clinton&Both		-0.0486		-0.0972*
		(-0.90)		(-2.00)
Post_Trump&Both		0.0281		0.1127**
		(0.54)		(2.20)
N	32,095	32,095	31,815	31,815
Adj. R2	0.7358	0.7357	0.7090	0.7089
Main Effects Included	YES	YES	YES	YES
Respondent FE	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES

Table IA9. Total Visits by Trump and Clinton in Areas With High vs. Low Initial Uncertainty

This table compares campaign visits by Trump and Clinton during 2015-2016 across areas with different levels of initial uncertainty as of January 2015. Panel (a) uses commuting zones with respondent data from the Survey of Consumer Expectations in January 2015. Panel (b) uses the top 500 counties based on mortgage applications, with monthly data disclosed under HMDA. The initial uncertainty level is calculated using the average uncertainty level of respondents in a given commuting zone in panel (a) and the state-level economic policy uncertainty (EPU) index where the county is located in panel (b). An area is classified as having a high initial uncertainty level if it falls in the fourth quartile, which is included in Column (2), while other areas are included in Column (1). The last column presents the t-test results of the mean difference between the two groups. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

(a) Commuting Zones

	(1) Low Initial Uncertainty		(2) High Initial Uncertainty		(1)-(2) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Total Visit Trump	202	0.876 (0.104)	54	0.352 (0.130)	256	0.524**
Total Visit Clinton	202	0.545 (0.110)	54	0.185 (0.167)	256	0.359
Has Trump Visit (1/0)	202	0.406 (0.035)	54	0.148 (0.049)	256	0.258***
Has Clinton Visit (1/0)	202	0.208 (0.029)	54	0.037 (0.026)	256	0.171***

(b) Top 500 Counties by Mortgage Applications

	(1) Low Initial EPU		(2) High Initial EPU		(1)-(2) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Total Visit Trump	390	0.521 (0.055)	103	0.466 (0.086)	493	0.054
Total Visit Clinton	390	0.344 (0.057)	103	0.233 (0.082)	493	0.111
Has Trump Visit (1/0)	390	0.313 (0.024)	103	0.262 (0.044)	493	0.051
Has Clinton Visit (1/0)	390	0.162 (0.019)	103	0.126 (0.033)	493	0.035

Table IA10. Geographic Spillover Effects on Economic Uncertainty and Expectations

This table reports weighted regression results of equation 2. *Uncertainty* accounts for income, inflation, and home price uncertainties, while *Macro Uncertainty* includes only inflation and home price components. Income and inflation expectation measures are calculated from respondents' distribution means. Treatment status is assigned based on the geographic distance between the centroid of the city holding rallies and the centroid of the commuting zone. Areas are considered treated if the distance is within l kilometers, where l is set to 50, 100, or 150 kilometers (31, 62, or 93 miles). Standard errors are double clustered at the commuting zone and year-month level. Significance: *, p < 0.1; **, p < 0.05; ***, p < 0.01.

	Uncertainty			Macro Uncertainty			Income Expectation			Inflation Expectation		
	(1) 50km	(2) 100km	(3) 150km	(4) 50km	(5) 100km	(6) 150km	(7) 50km	(8) 100km	(9) 150km	(10) 50km	(11) 100km	(12) 150km
Post_Clinton	-0.1049**	-0.0479	0.0084	-0.1172***	-0.0569	-0.0034	0.0613	0.1084	0.1129	0.0438	0.0657	-0.0523
	(-2.53)	(-1.06)	(0.31)	(-2.92)	(-1.45)	(-0.12)	(0.56)	(1.03)	(1.47)	(0.50)	(0.80)	(-0.71)
Post_Trump	0.0819	0.0060	-0.0172	0.0623	-0.0060	-0.0150	0.0609	-0.0801	-0.0273	0.0143	-0.0703	-0.0480
	(1.56)	(0.15)	(-0.69)	(1.03)	(-0.18)	(-0.51)	(0.32)	(-0.89)	(-0.29)	(0.10)	(-0.94)	(-0.61)
N	32,095	32,095	32,095	31,815	31,815	31,815	22,545	22,545	22,545	32,096	32,096	32,096
Adj. R2	0.7359	0.7357	0.7357	0.7090	0.7088	0.7087	0.5399	0.5399	0.5401	0.4899	0.4900	0.4900
Respondent FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table IA11. Geographic Spillover Effects on P2P Borrowing

This table reports regression results of equation 4. Outcome variables are natural log of number and dollar amount of P2P loan applications. Treatment status is assigned based on the geographic distance between the centroid of the city holding rallies and the centroid of the commuting zone. Areas are considered treated if the distance is within l kilometers, where l is set to 50, 100, or 150 kilometers (31, 62, or 93 miles). The specifications include a ZIP3-specific linear trend. Standard errors are double clustered at the ZIP3 and year-month level. Significance: *, p < 0.1; **, p < 0.05; ***, p < 0.01.

	Number of Application			Amount of Application		
	(1) 50km	(2) 100km	(3) 150km	(4) 50km	(5) 100km	(6) 150km
Post_Clinton	0.0242***	0.0172***	0.0109**	0.0149	0.0137**	0.0092*
	(3.60)	(3.66)	(2.45)	(1.61)	(2.27)	(1.72)
Post_Trump	-0.0210*	-0.0064	-0.0051	-0.0158	-0.0055	-0.0045
	(-1.83)	(-1.10)	(-1.21)	(-1.36)	(-1.02)	(-1.08)
N	31,956	31,956	31,956	31,956	31,956	31,956
Adj. R2	0.9608	0.9608	0.9607	0.9349	0.9349	0.9349
ZIP3 FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
ZIP3 Trend	YES	YES	YES	YES	YES	YES

Table IA12. Geographic Spillover Effects on Mortgage Borrowing

This table reports regression results of equation 4. Outcome variables are natural log of number of mortgage applications and originations, and natural log of dollar amount of mortgage originations, in the top 500 counties in terms of number of mortgage applications in 2015-2017. Treatment status is assigned based on the geographic distance between the centroid of the city holding rallies and the centroid of the commuting zone. Areas are considered treated if the distance is within l kilometers, where l is set to 50, 100, or 150 kilometers (31, 62, or 93 miles). Control variables include log of county-level population, employment, and personal income in year $t-1$. The specifications include a county-specific linear trend. Standard errors are double clustered at the county and year-month level. Significance: *, p < 0.1; **, p < 0.05; ***, p < 0.01.

	Number of Application			Number of Origination			Amount of Origination		
	(1) 50km	(2) 100km	(3) 150km	(4) 50km	(5) 100km	(6) 150km	(7) 50km	(8) 100km	(9) 150km
Post_Clinton	0.0066**	0.0025	0.0037	0.0028	0.0006	0.0032	0.0023	-0.0012	0.0007
	(2.57)	(1.21)	(1.56)	(1.14)	(0.30)	(1.39)	(0.95)	(-0.55)	(0.24)
Post_Trump	-0.0052*	-0.0017	-0.0037**	-0.0027	-0.0022	-0.0035**	-0.0011	-0.0048**	-0.0043*
	(-2.00)	(-0.84)	(-2.39)	(-0.94)	(-1.09)	(-2.25)	(-0.34)	(-2.13)	(-1.93)
N	16,999	16,999	16,999	16,999	16,999	16,999	16,999	16,999	16,999
Adj. R2	0.9915	0.9915	0.9915	0.9906	0.9906	0.9906	0.9893	0.9893	0.9893
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County Trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table IA13. Monthly Mortgage Application

This table reports regression results of equation 4 for county-month mortgage application for purchase purpose. The dependent variables are the natural logarithm of the monthly count of mortgage applications in the top 500 counties with the highest number of mortgage applications during 2015-2017. Column (2)-(3) and Column (5)-(6) add interaction terms between the post treatment indicator and *Primary* or *yr*17. *Primary* is a dummy for periods post primaries, i.e., after June 2016. *yr*17 is a dummy for periods in 2017, i.e., after the election result was known. The total effects (sum of the coefficients of the post treatment indicator and the interaction term) are reported underneath. Control variables include log of county-level population, employment, and personal income in year $t-1$. The model incorporates a local linear trend specific to each county. Standard errors are clustered at both the county and year-month levels. Significance: *, p < 0.1; **, p < 0.05; ***, p < 0.01.

	Mortgage Application			Mortgage Application (50km)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Clinton	0.0009	-0.0004	0.0016	0.0066**	0.0119*	0.0066***
	(0.19)	(-0.09)	(0.40)	(2.57)	(1.84)	(2.77)
Post_Trump	-0.0033	-0.0008	-0.0031	-0.0052*	-0.0078**	-0.0048*
	(-0.99)	(-0.21)	(-0.92)	(-2.00)	(-2.05)	(-1.81)
Post_Clinton×Primary		0.0022			-0.0016	
		(0.51)			(-0.25)	
Post_Trump×Primary		-0.0044			0.0051	
		(-1.59)			(0.72)	
Post_Clinton×yr17			-0.0059			-0.0031
			(-1.44)			(-1.52)
Post_Trump×yr17			0.0036			0.0018
			(1.03)			(0.93)
Post_Clinton & Primary		0.0018			0.0103**	
		(0.36)			(2.67)	
Post_Trump & Primary		-0.0052			-0.0027	
		(-1.55)			(-0.44)	
Post_Clinton & yr17			-0.0043			0.0034
			(-0.82)			(1.15)
Post_Trump & yr17			0.0005			-0.0030
			(0.09)			(-0.85)
N	16,999	16,999	16,999	16,999	16,999	16,999
Adj. R2	0.9915	0.9915	0.9915	0.9915	0.9912	0.9915
County FE	YES	YES	YES	YES	YES	YES
State × Time FE	YES	YES	YES	YES	YES	YES
County Trend	YES	YES	YES	YES	YES	YES

Table IA14. Placebo Test: Monthly Mortgage Application With Rally Dates Shifted to Two Years Earlier

This table reports regression results of equation 4 for county-month mortgage application for purchase purpose. In this placebo test, the actual rally dates are shifted to the same day but two years earlier. The dependent variables include the natural logarithm of the monthly count of mortgage applications, originations, and the amount of originations in the top 500 counties with the highest number of mortgage applications during 2013-2014. Control variables include log of county-level population, employment, and personal income in year $t-1$. The model incorporates a local linear trend specific to each county. Standard errors are clustered at both the county and year-month levels. Significance: *, $p < 0.1$; **, $p < 0.05$; ***, $p < 0.01$.

	(1) Number of Application	(2) Number of Origination	(3) Amount of Origination
Post_Trump	0.0064	0.0074	0.0076
	(1.10)	(1.20)	(1.23)
Post_Clinton	-0.0047	-0.0006	-0.0001
	(-1.00)	(-0.13)	(-0.02)
N	10,925	10,925	10,925
Adj. R2	0.9901	0.9890	0.9903
County FE	YES	YES	YES
Year-month FE	YES	YES	YES
County trend	YES	YES	YES