Partisan Entrepreneurship

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July 2023

Abstract

Republicans start more firms than Democrats. In a sample of 40 million party-identified Americans between 2005 and 2017, we find that 5.5% of Republicans and 3.7% of Democrats become entrepreneurs. This partisan entrepreneurship gap is time-varying: Republicans increase their relative entrepreneurship during Republican administrations and decrease it during Democratic administrations, amounting to a partisan reallocation of 170,000 new firms over our 13-year sample. We find sharp changes in partisan entrepreneurship around the elections of President Obama and President Trump, and the strongest effects among the most politically active partisans: those that donate and vote.

Keywords: Entrepreneurship, Politics, Partisanship

JEL Classification Numbers: L26, G41, G51, M13

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1. Introduction

In the United States, political identity is central to economic expectations: Americans are much more optimistic about the economy when their political party is in power. Republicans were markedly more optimistic than Democrats during the administrations of George W. Bush and Donald Trump – by almost two standard deviations (Figure 1) – but this difference disappeared during the Democratic administrations of Bill Clinton and Barack Obama.

This paper examines whether changes in political regime and the corresponding shifts in partisan beliefs translate into a critical economic behavior: entrepreneurship. To do this, we consider a sample of approximately 40 million Americans for whom we have political party identification and who live in the 33 states for which we have complete data on firm registrations from the Startup Cartography Project (Andrews et al., 2020).[1] We find that Republicans are more likely to be entrepreneurs than Democrats: over our 13-year sample, 5.5% of Republicans started a business, compared to 3.7% of Democrats. Even after controlling for age, gender, race, education, income and county-year fixed effects, Republicans are 26% more likely than Democrats to start a business in a given year, relative to the mean.

To examine the effects of political regime changes on entrepreneurship among Republicans and Democrats, we perform individual-level difference-in-differences (DID) event studies around two presidential elections. These compare individual Republicans and Democrats in the same county before vs. after the party-changing presidential elections of 2008 and 2016. We find that Republicans decrease their likelihood of starting a business in the year following Obama's election by 3.4% of the mean relative to Democrats and increase their relative entrepreneurship after Trump's election by 2.4%.

Our DID event studies focus on the years immediately surrounding party-changing elections and thus use less than half of the sample years. When we consider the entire sample

[1]These 33 states cover 69% of U.S. GDP as of 2016.

(2005 - 2017), we find that politically mismatched individuals — that is, voters whose party did not control the presidency — have a probability of starting a business that is 3.3% of the mean lower than those whose party is in power. Our effect size corresponds to an annual difference of 13,000 new firms between politically matched versus mismatched individuals.[2]

Moreover, the largest estimated effects occur among the most *politically active* individuals. We estimate an effect size for partisans with a below-median voting propensity of 2.4% of the mean, but for those with an above-median voting propensity the effect expands to 4.3%. Using FEC-reported donations to a political party as an alternative measure of political engagement, the effect among politically active individuals jumps to 10%.

We also examine the types of firms founded in our sample, because firm characteristics at founding have been shown to capture growth potential and thus economic impact (Schoar, 2010, Guzman and Stern, 2020, Sterk et al., 2021). We find that corporations are much more responsive than LLCs (an effect size of 10.7% versus 0.7% of the mean).[3] Our main result is also present across the full range of the firm quality distribution of Guzman and Stern (2020), and high quality startups appear to be especially sensitive to political regime change. Our mismatch estimate for firms in the top 5% of the quality distribution, which captures over half of high growth firms, is nearly seven times as large as that of LLCs (4.8% versus 0.7% of the mean).

Next, we turn to founder characteristics, where we find partisan differences by gender, age, and income. For example, we find the well-known gender gap in our data: 6.6% of men and 3.2% of women started a business in our 13-year sample. After controlling for individual characteristics and county-year fixed effects, men are about 0.4 percentage points (pp) per year more likely to start a business than women, a difference of approximately

[2]We find that being mismatched to the state Governor also affects the likelihood of entrepreneurship and that this effect is additive. In other words, an individual is most likely to start a business when their party matches the party of both the president and the governor.

[3]Corporations are better suited to having investors, are more likely to be employer firms, and are less likely to be used as pass-through entities than LLCs.

90% of the annual mean. This gender gap varies by political party. Among Democrats this gap is 14% smaller than the gap among independents, while among Republicans it is 24% larger. Moreover, male entrepreneurs are more sensitive to political regime changes than female entrepreneurs, consistent with the pattern in economic expectations from survey data. Relative to their respective means, men are 3.8% less likely to engage in entrepreneurship when politically mismatched with the president, but for women this likelihood is only 1.5% lower.

While the evidence thus far compares individual Democrats to Republicans within the same county, we can also compare Republican-leaning *counties* to Democratic-leaning counties under changing presidential regimes. By comparing counties we lose the precise identification we have at the individual level, but there are advantages. First, county level data are available for almost all states. Second, more economic data exist at the county level, such as job creation and firm closures, allowing us to explore how the startup decisions of partisans aggregate up at the level of local economies following elections.

Figure 5 compares Republican to Democratic counties before vs. after the 2008 and 2016 presidential elections in a DID framework. The same pattern emerges: start-up rates in Democratic counties rise (relative to Republican ones) after the election of Barack Obama and fall after the election of Donald Trump. Specifically, following the 2008 election the startup rate in Democratic (relative to Republican) counties rose by 2.3% of the mean over the year; for the 2016 election, the corresponding increase was 3.5% for Republican counties. Extrapolating across all counties, this change corresponds to a partisan shift of approximately 40,000 new firms in the year following the 2016 election and 21,000 firms after the 2008 election.

We also examine *existing* firms using the Business Dynamics Statistics data from the U.S. Census Bureau. These data exist only at the county level. Despite using a different data source and focusing on a different firm population, we continue to find partisan effects.

Existing firms in mismatched counties are less likely to open new establishments, more likely to close existing ones, and more likely to shut down the entire business, resulting in a net loss of jobs. For example, the net job creation rate of existing firms in counties mismatched with the party of the president is 6% of a standard deviation lower than in matched counties.

Finally, the entrepreneurial response we document in our event studies begins within 1-2 quarters of the election outcome, likely before any substantive changes from the new administration can take place. This suggests that partisan entrepreneurship begins as a response to changing *expectations*, with politically matched entrepreneurs expecting an increased return to entrepreneurship relative to mismatched ones. In our final section we examine whether these beliefs are correct, i.e., whether the return to entrepreneurship is consistent with the expectations. Using data on the number of employees and the sales of firms founded before elections, as well as entrepreneurs' personal income, we find no evidence that the return to entrepreneurship for Democrats vs. Republicans differentially changes around party-changing elections.

In addition, we find that the entrepreneurial response is stronger among industries that are most sensitive to policy and in counties where the local economy co-moves most with the national economy. This suggests that the partisan entrepreneurship effect we document likely stems from differential expectations about both policy treatment and the economy, with entrepreneurs on the winning side expecting both more favorable policies as well as more economic growth relative to those on the losing side.

Overall, the effects we find aggregate up into a substantial component of economic activity. Between 2005 and 2017, we estimate a partisan shift of around 170,000 new firms, which is approximately the total number of firms created in the state of Mississippi over the same period. These new firms also contribute to local employment growth, consistent with the evidence in Adelino et al. (2017) and Glaeser et al. (2015). We estimate a shift of around 2.4 million jobs across Republican and Democratic counties, or 2% of average annual employment over the sample period. Critically, these economic changes are not evenly distributed: some states and counties see entrepreneurship spike, along with the associated job creation and investment flows, while others experience a decline. In short, we document a shifting of economic dynamism across political geographies in the wake of major elections, with downstream implications for labor markets, productivity dynamics, and regional inequality (Haltiwanger et al., 2013, Decker et al., 2014, Clementi and Palazzo, 2016). Understanding and anticipating these effects could improve place-based policies (Kline and Moretti, 2014), which are of increasing interest given the declining trend in US business dynamism and job reallocation since the 1980s (Decker et al., 2016).

Contribution to the literature. Our findings relate to several strands of the literature in entrepreneurship and political economy. In entrepreneurship, many have explored the links between the decision to start a firm and founder characteristics such as age, race, wealth, and gender (e.g., Evans and Jovanovic, 1989, Holtz-Eakin et al., 1994, Hurst and Lusardi, 2004, Guzman and Kacperczyk, 2019, Azoulay et al., 2020, Fairlie et al., 2021, Bellon et al., 2021, Bernstein et al., 2022b). Our paper shows that political affiliation is an important characteristic, representing 38% of the size of the well-known gender gap in entrepreneurship even after controlling for founder age, gender, race, geography and time.

A related line of inquiry examines how entrepreneurship relates to founder psychological characteristics such as cognitive skills, individualism, risk-tolerance and optimism (e.g., Puri and Robinson, 2013, Levine and Rubinstein, 2017, Kerr et al., 2019, Pástor and Veronesi, 2020, Barrios et al., 2021). These characteristics are generally viewed as static throughout adulthood (e.g., Astebro et al., 2014). We provide evidence of *time-varying* economic optimism among business owners induced by partisan sentiment.

We also contribute to the literature exploring determinants of the entrepreneurship decision. Existing work has focused on the impacts of financial constraints, risk-reduction policies, training, and entrepreneurial peers.[4] We uncover a new driver of entrepreneurial entry – political sentiment – of comparable magnitude to existing shock-based estimates. For example, our political mismatch effects on entrepreneurship are similar to estimated effects of unemployment insurance reform (Hombert et al., 2020), access to reproductive healthcare (Zandberg, 2021), and the introduction of ride-sharing (Barrios et al., 2022).[5] Critically, our shock is correlated across founders and time, thus contributing to the business cycle.

Finally, our paper contributes to a new literature on the economic consequences of partisanship. At the corporate level, several papers have found evidence of partisan effects on credit ratings, syndicated lending, and the composition of employees (Kempf and Tsoutsoura, 2021, Dagostino et al., 2020, Fos et al., 2023, Colonnelli et al., 2022). At the household level there is strong evidence from surveys that partisanship affects economic optimism around elections (e.g., (Bartels, 2002, Evans and Andersen, 2006)). However, there is mixed evidence that such optimism matters for important economic outcomes. Some papers report a link between spending on consumer goods and political alignment (Gerber and Huber, 2009, Gillitzer and Prasad, 2018, Benhabib and Spiegel, 2019), while others argue against this connection (McGrath et al., 2017, Mian et al., 2021).[6] We provide evidence that a key driver of economic activity – new firm formation – changes in response to partisan sentiment.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 provides evidence from individual data; Section 4 examines evidence at the county level; and Section

[4]For financial constraints see, for example, Bertrand et al. (2007), Kerr and Nanda (2009), Chatterji and Seamans (2012), Robb and Robinson (2014), Kerr et al. (2015), Adelino et al. (2015), Schmalz et al. (2017). For risk reduction, training and peers see Gottlieb et al. (2022), Karlan and Valdivia (2011), Drexler et al. (2014), Fairlie et al. (2015), Fehder and Hochberg (2019) and Lerner and Malmendier (2013), Nanda and Sørensen (2010).

[5]Our estimated political mismatch effects range from 3 to 10%. Zandberg (2021) shows that a one standard deviation increase in access to abortion predicts a 5.9% increase (relative to the mean) in the probability a woman becomes an entrepreneur. Hombert et al. (2020) shows that following pro-entrepreneurship unemployment insurance reform in France, new firm creation increased by around 10% relative to the pre-period. Finally, Barrios et al. (2022) shows that the introduction of ride-sharing, by providing a fallback option in case of failure, increased entrepreneurship by 3 to 6%.

[6]Recent papers link partisanship with household decisions such as tax evasion, stock market trading, retirement investing, fertility, and residential sorting (Cullen et al., 2021, Cookson et al., 2020, Addoum and Kumar, 2016, Meeuwis et al., 2022, Dahl et al., 2022, Bernstein et al., 2022a, McCartney et al., 2021).

5 explores the expectations of partisan entrepreneurs. Section 6 concludes.

2. Data

2.1 Entrepreneurship data from business registrations

We measure new firm formation using business registration records, the legal filings required to establish a new corporation, partnership, or limited liability company in the United States. Firms register in the jurisdiction of their choice, a sort of statutory domicile, as well as in states in which they engage in meaningful business activity. In practice, firms tend to choose either the state of their headquarters or Delaware as their jurisdiction, with the latter favored by growth-oriented firms because of its corporation law and court system.

We use data from the Startup Cartography Project (Andrews et al., 2020), which contains business registration records across 49 U.S. states and Washington D.C. from 2005 to 2017. Since the data are business registrations, sole proprietorships and self-employed individuals without formal registration are not in our sample. The data includes the name of the firm, the firm type (corporation, LLC, or partnership), the address of record, and the jurisdiction (Delaware or local). We focus on for-profit firms and assign them to the state of their headquarters, independent of their state of jurisdiction. 33 states also include information on the names and titles of firm directors and detailed firm location; we focus on these states for our individual-level analysis. To ensure individuals are startup founders, we exclude personnel whose titles imply that they play only an administrative role.[7] Nonetheless, some

[7]The titles we exclude are: incorporator, applicant, secretary, clerk, treasurer, director, and general partner. We also exclude lawyers and other forms of registered agents. We further exclude names that appear in more than five different firm registrations in a year, as they are unlikely to have an operational role. Our results remain quantitatively similar when we do not impose these restrictions. 79% of our founders have the following titles: President, Manager (of LLCs), CEO, CFO, Managing Director, Vice-President, Owner, Organizer, and Member. The remaining titles are idiosyncratic and state-specific; for example, Agent is the only title registered in Colorado and Montana. In addition, we took a random sample of 100 firms founded in 2017 for which we could identify an online presence and manually verified founder status. We confirmed that the individual we code as founder was indeed the founder in 87 cases, was likely to be the founder in 10 cases, and was not the founder in 3 cases.

individuals we identify as founders may in fact be early employees. To address this, in the Appendix we consider only solo-founder firms, for which we do not need to distinguish between a founder and an early employee in business registration records. We find similar patterns and magnitudes.

2.2 Voter and donor data

We use data on registered voters from L2, a leading non-partisan data vendor used by political campaigns and the academic literature (e.g., Brown and Enos, 2021, Billings et al., 2021, Bernstein et al., 2022a, Spenkuch et al., 2021), for the 33 states for which we have sufficient information on firm founders to permit accurate matching.[8] For 21 of these states, L2 assigns political affiliation using self-reported voter registration. For the remaining states, L2 infers party identification using a variety of data sources, including voter participation in primaries, demographics, exit polling, and commercial lifestyle data.[9][10] For most analyses we compare Republicans to Democrats because they have clear directional sentiment. However, in Table 2 and Figure 3 we compare both groups to registered Independents.

L2 has complete coverage of the U.S. voter population starting in 2014. To minimize concerns over survivorship bias and reverse causality, we use the 2014 voter roll to assign voter partisanship. This strategy resolves such concerns for the 2016 election, and mitigates

[8]These states are: Alabama, Alaska, Arizona, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Hawaii, Idaho, Indiana, Iowa, Kentucky, Louisiana, Massachusetts, Minnesota, Mississippi, Missouri, Montana, New Mexico, Ohio, Oregon, Pennsylvania, Rhode Island, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wyoming.

[9]These states are: Alabama, Georgia, Hawaii, Indiana, Minnesota, Missouri, Montana, Ohio, Texas, Vermont, Virginia, Washington. 43% of entrepreneurs in our sample are in these states. L2's party inference varies according to features in each state. For example, in states like Georgia, Indiana and Texas, where the state provides voter participation in party primaries, L2 uses participation in these primaries to infer political party. However, in states like Minnesota, Missouri and Montana, where states provide no information that indicates likely party affiliation, L2 models each voter's party based on characteristics it collects independently.

[10]L2 data is subject to repeated testing by political campaigns in the field. In addition, academic papers have also verified the accuracy of voter file partisanship measures: Bernstein et al. (2022a) validates the accuracy of L2 partisanship by comparing partisanship in state files to L2 data; Brown and Enos (2021) runs a survey to verify L2 partisanship; Pew (2018a) compares voter file data to Pew national survey microdata.

them for the 2008 election to the extent possible with L2 data. Party status is largely stable: the annual probability of changing from Republican to Democrat or vice versa is 1.8%. We add individuals' voting histories, which we need to construct political activeness measures, from the most recent L2 voter file we have (October 2020) to the 2014 voter population, dropping those without this data.[11] Baseline results are similar if we keep such voters.

We use L2 data on voting history and political donations to identify more politically-active individuals. We define individuals as *active voters* if the share of even-year general and primary elections they have voted in by 2020 (out of elections they were eligible for) exceeds their party's sample median, which is about half of elections. L2 has two variables which describe political donation behavior. The first is a variable identifying donations recorded by the Federal Election Commission (FEC). Using the L2-linked FEC data, we call individuals *active FEC donors* if they have made a political donation by 2020 (2.3% of the sample). L2 also identifies individuals whose household members have made a contribution to any political cause as of 2020, which we call *active household donors* (40% of our voters).

L2 provides a suite of demographic variables, such as registered state and county, age, gender, and race/ethnicity, which we use as controls in the main specifications.[12]

We obtain county-level vote share in presidential elections from the MIT Election Data and Science Lab (MIT, 2018).

2.3 Sample of registered voters

We begin by keeping all voter-year observations in which individuals are between 18 and 70. We then match voters to firm founders in the business registration database by name and county. To perform this match we further focus on voters whose combination of first and

[11] Voting history is only attached to the data starting with the 2018 voter file, but is comprehensive for each voter.

[12] In some states voters report their race as part of voter registration, but in others L2 infers race data; race is missing for 15% of the regression sample. Bernstein et al. (2022a) validates L2's race data using HMDA; Pew (2018a) finds high levels of accuracy for commercial voter registration data on race by matching to their national panel survey microdata.

last names is unique in the L2 data among all voters in a county.[13] We use unique names because no other common identifier (e.g., home address or social security number) exists in both the voter and founder datasets to enable matching. However, name uniqueness within the voter database does not guarantee uniqueness among all county residents, because some people are non-registrants. Therefore, we further require the probability of a first and last name combination appearing among non-voters in a county to be below 0.1 pp.[14] In the Appendix we consider more stringent cutoffs, which increase the uniqueness of names and thus the precision of our matches. Our results are unchanged.

A sample of names that are unique at the county level will oversample women, because American women have a considerably wider range of first names than men (Wilson, 2016). It may also over or undersample other population sub-groups. To mitigate this concern, we show results that weight individuals in our sample so as to match observable characteristics of the full U.S. voter population (political party, education, race/ethnicity, and birth cohorts within each party). We also present our main analysis separately for men and women. In Section 3.3.2 we discuss the representativeness of the sample and compare its characteristics to those of all US voters and to voters in sample states (see Table A1).

L2 has 140 million registered voters in the 33 states for which we have data on firm founders and addresses. After restricting the sample to unique names within a county as described above we have around 40 million voters. Of these, 1.9 million (4.6%) started a company during our sample period. Conditional on both voter and founder having middle initials (M.I.), the matched individuals have the same M.I. 90% of the time, indicating a high

[13]We do not use middle initials in sample construction because, unlike for voter registration, only 45% of individuals in our 33 SCP states have a recorded M.I., and this fraction varies from 10% to 60% across states. Were we to use M.I. for matching we would be applying a higher bar to individuals in states that record M.I. diligently compared to those in states that do not (and similarly within states, to people with middle names vs. those without).

[14]Estimating this likelihood requires assumptions about unregistered individuals. First, we assume the probabilities of first and last name combinations are the same across registered and non-registered individuals. Second, we assume those probabilities are the same across geographies. With these assumptions we calculate the probability of each first and last name combination in each county among non-registered individuals using the binomial formula.

match quality between voter and founder databases.[15] Using M.I. as an additional matching criterion does not meaningfully affect our estimates (see Appendix Table A5), and matching errors, if anything, are likely to cause attenuation bias in our setting.[16]

A voter is coded as starting a business in a period if they register at least one firm in that period. The resulting sample is a voter-time panel with approximately 40 million observations at any point in time. For computational tractability we collapse the regression sample to a set of fully saturated county-party-characteristic-time cells, where each cell is a combination of county, party identification (Democrat, Republican, other), gender (male, female), age (18-29, 30-29, 40-29, 50-29, 60-70), race/ethnicity (white, Black, Hispanic, Asian, or missing), and time (either calendar year or year-month). Because all variables are categorical indicators, this approach generates identical regression estimates and standard errors to those obtained from regressions using individual data (Theil, 1954).

2.4 Descriptive statistics

Table 1 reports summary statistics on the *annual likelihood* of starting a business and the probability of *ever* starting a business during our sample period. It also reports the distribution of the sample across political parties and demographics, as well as the likelihood of starting a business in these subgroups. The political demographics of our sample appear broadly consistent with those of voters in general and by party. For example, female voters are more likely to be Democrats, as are younger individuals and minorities (Pew, 2018b). We further discuss the representativeness of our sample in Section 3.3.2.

Out of over 40 million voters in our sample, around 4.6% started a business at some point between 2005 and 2017. The likelihood of starting a business in a given year is approximately

[15]The individuals with M.I. in both datasets whose M.I. do not match may in fact be the same person. For example, marriage sometimes triggers name changes that are recorded as middle names.

[16]To cause estimates to be biased away from zero we would need matching errors to be correlated with partisanship, with the probability of starting a firm, and election outcomes. Moreover, we also estimate county-level results which do not require any matching.

0.5 pp.[17] When we split the data by political party, a consistent theme emerges: Republicans are more likely to start a business than Democrats. For example, while 5.5% of Republicans ever start a firm in our data, only 3.7% of Democrats do. In a given year, the probability that a Republican starts a business is 0.6%, while for a Democrat this is 0.4%.

When we examine the entrepreneurship rate across demographic characteristics, we note a few differences. First, consistent with prior results in Fairlie et al. (2021), whites are more likely to start a business in a year than Blacks and Hispanics, as are college graduates (Hurst and Lusardi, 2004). Second, the entrepreneurship rate is the highest in the middle of our age distribution (between 30 and 49 years old), with a 0.7% chance of starting a business in a year, consistent with the pattern described in Azoulay et al. (2020) using U.S. Census Bureau data. As expected, higher income individuals are more likely to start a firm (Evans and Jovanovic, 1989). Finally, men are more than twice as likely to start a firm in a year than women, an estimate similar to previous work on the gender gap in entrepreneurship (e.g., Guzman and Kacperczyk, 2019).

To move beyond summary statistics, in Table 2 we estimate regressions of the likelihood of starting a business as a function of party affiliation and demographic characteristics. All regressions include county-year fixed effects. Column (1) estimates that Democrats are 0.08 pp *less* likely to start a business in a year, relative to political independents, while Republicans are 0.16 pp *more* likely. This Republican-Democrat spread in startup likelihood is substantial, amounting to 49% of the outcome mean.

Column (2) adds age controls and confirms the evidence that individuals are most likely to start firms between the age of 30 and 49. However, adding age controls does little to change the partisan entrepreneurship gap. Column (3) supports previously-established patterns in gender and entrepreneurship: men are over 0.4 pp more likely to start a business in

[17]The fraction of voters ever founding a firm (4.6%) is smaller than the annual startup rate multiplied by the number of sample years (0.5% x 13) because serial entrepreneurs start firms in more than one year. They make up 18.4% of all entrepreneurs in our sample (similar to Lafontaine and Shaw, 2016).

a year than women, all else equal, which is nearly 90% of the mean likelihood. After controlling for gender, the partisan entrepreneurship gap shrinks from 49 to 39% of the mean, reflecting that men are disproportionately entrepreneurs and Republicans. Column (4) adds controls for race and shows that Asian voters are 90% of the mean more likely to start a business than whites. Column (5) further adds controls for education – college graduates are substantially more likely to start new firms – and column (6) shows that this is true also for those in the highest income bracket. After controlling for all of these covariates – which correlate with political party and so may partially absorb the differences of interest – the partisan entrepreneurship gap remains large (at 26% of the mean) and statistically significant. Finally, column (7) explores how political party interacts with gender and shows that the entrepreneurship gender gap among Independents is similar to the mean, while Democrats have a 14% smaller gap and Republicans a 24% larger one.

Overall, our sample appears to map well to general patterns of entrepreneurship in the U.S. while providing new facts about the relationship between entrepreneurship and political identity. Republicans are more likely to start firms than Democrats, even after controlling for individual characteristics and county-year fixed effects. Moreover, the well-known gender gap in entrepreneurship differs between Republicans and Democrats.

3. Evidence from Individual Data

3.1 Elections and optimism

To motivate our analysis, consider Figure 1 panel (a) which plots the difference in economic views of Republicans and Democrats via Bloomberg's Consumer Comfort Index (CCI). The index is constructed from a telephone survey of 1,000 individuals (250 individuals per week for 4 weeks) and reported as a four-week rolling average. Respondents are asked to rate the national economy, their personal finances, and the buying climate on a scale from

Excellent to Poor. Bloomberg aggregates their answers into a 0-100 point index. As the figure demonstrates, the difference in CCI between Republicans and Democrats varies significantly across political regimes. For example, the average CCI of Republicans was almost two standard deviations higher than that of Democrats during the Republican administrations of George W. Bush and Donald Trump, but it was lower than the CCI of Democrats during the administration of Barack Obama.

In addition, there are sharp swings in the views of Republicans and Democrats after party-changing presidential elections, especially after those of Obama (2008), Trump (2016) and Biden (2020).[18] Non-party-changing elections and midterms appear to have little to no effect on economic optimism.

Entrepreneurship is a future-oriented activity, so an entrepreneur's decision to start a business is likely tied to their belief about the current and future economic climate (e.g., Bengtsson and Ekeblom 2014). In fact, in panels (b) and (c) we show similar patterns for business owners between 2008 and 2016 from the Gallup survey — we discuss this evidence in detail in Section 5.3. Given the survey evidence of stark differences in beliefs between Republicans and Democrats across political regimes, especially around party-changing elections, we examine whether entrepreneurship follows these same patterns.

3.2 Individual-level event-study evidence

We begin by comparing the changes in Republican individuals' likelihood of starting a firm relative to that of Democrats in an event study DID framework. In what follows, we contrast individuals of different political parties *within the same county* around presidential elections. This allows us to avoid confounding factors that may differentially affect Republican or Democratic areas. Moreover, we can control for founder characteristics associated with

[18] There is a decline in relative Republican optimism in the 12 months before the 2008 election, suggesting some anticipation of candidate Obama's victory. This is consistent with his lead in prediction markets prior to the 2008 election.

entrepreneurship, such as gender, age, and race.

We then estimate the following OLS regression:

$$\mathrm{Y}_{it} = \sum_{t=-8}^{7} \beta_t \times Dem_i + \gamma' \mathbf{X_{it}} + \alpha_{c(i),t} + \epsilon_{it} \tag{1}$$

Y_{it} is the excess likelihood of individual i starting a business in time t, the number of time periods relative to the presidential election.[19] We define $t = 0$ as the three-month period following an election month and omit $t = -2$ as the base period. Our treatment variable is Dem_i, which equals one if individual i is a Democrat and zero if they are Republican. We include county $\times$ time fixed effects $\alpha_{c(i),t}$ to control for county-specific time-varying startup likelihood. $\mathbf{X_{it}}$ is a vector of gender, race, and age group bins.[20]

Our coefficients of interest are β_t, which identify the impact of presidential elections on the likelihood of starting a business among Democrats (relative to Republicans) living in the same county and time around party-changing elections.

Our results indicate that individuals adjust their propensity to start firms along party lines in response to political regime changes. Figure 2 plots the β_t coefficients, comparing the likelihood of starting a business among Republicans to the likelihood among Democrats with the same demographics living in the same county, before vs. after the 2008 and 2016 presidential elections. Appendix Table A2 reports regression coefficients.

Following the election of President Obama in late 2008, Democrats immediately increase their startup likelihood relative to Republicans, an increase of 3.4% of the mean over 12

[19]Because we are estimating within-year (quarterly) coefficients, seasonality is an important confounder. To address this we deseasonalize the likelihood of starting a firm by subtracting the party-specific county $\times$ month-of-year average, and county annual trend using data starting from 2004 (for the 2008 election) or 2012 (for the 2016 election). We also produce an annual event study in Appendix Figure A2 and Table A3 so that within-year seasonalities are not a concern. The patterns are consistent with the quarterly event study.

[20]Among our individual characteristics only the age group is potentially time varying. For computational tractability, we collapse the regression sample to fully saturated county-party-characteristic-month cells, weighting each cell by the number of individuals in it (see Section 2.3 for details).

months. Extrapolating across the U.S., this represents a narrowing of the Republican-Democrat entrepreneurship gap by around 13,000 entrepreneurs.[21] There is no indication of a differential pre-trend. For the 2016 presidential election the estimates for the pre-period in Figure 2 also support the assumption of parallel trends. Following the election, Republicans' startup probability rose by 2.4% of the mean relative to Democrats over 12 months, increasing the entrepreneurship gap by around 11,000 founders.

The entrepreneurship response we document is almost immediate, appearing in the same quarter of the Donald Trump election and in the quarter following the Barack Obama election. The speed of the reaction is consistent with other work documenting new firm starts following shocks. For example, both Fazio et al. (2021) and Haltiwanger (2021) document large changes in firm formation that begin in the month following the onset of the COVID-19 pandemic in the U.S.

To understand the relative contributions of Republicans and Democrats to changes in the partisan entrepreneurship gap following presidential elections, we include Independents as the control group. Figure 3 plots the β_t estimates for each party. The figure indicates that the decrease in the partisan entrepreneurship gap following the 2008 election is attributable to Republicans decreasing their rate of entrepreneurship relative to independents. By contrast, around 40 percent of the increase in the gap after the 2016 election comes from Republicans increasing their startup rate, and 60 percent comes from Democrats decreasing their rate.

3.3 Partisanship and startups over the full sample

Our DID event studies focus on the years immediately surrounding party-changing presidential elections and use less than half of the sample years as a result. In this section, we use

[21]This calculation is obtained by multiplying the sum of coefficients in quarters 1 to 4 by three (to translate the monthly average to a quarterly total), multiplying by one-third of the U.S. population (assuming an equal share of Democrats, Republicans, and Independents), and dividing by 100 (to adjust the outcome unit from percentage point to one).

the entire sample (2005-2017) to estimate the average relationship between entrepreneurship and being politically mismatched with the sitting president. To do so, we exploit the panel structure of our individual-level data and estimate the following:

$$\mathrm{Y}_{it} = \beta\, Mismatch_{it} + \gamma_D\, Dem_i + \gamma_{\mathbf{x}}' \mathbf{X_i} + \alpha_{c(i),t} + \epsilon_{it} \tag{2}$$

where Y_{it} is an indicator equal to one if individual i starts a business in year t. Dem_i is an indicator equal to one for Democrats and zero for Republicans. $Mismatch_{it}$ is an indicator equal to one when individual i's party identification *differs* from the party of the president in year t, namely one for Republicans during 2009-2016 and for Democrats during 2005-2008 and 2017. $\alpha_{c(i),t}$ denotes county $\times$ year fixed effects. We additionally control for $\mathbf{X_i}$, a vector of demographic characteristics (gender, age, and race). Standard errors are clustered by county.[22]

The coefficient of interest is β, which estimates the average difference in the probability of starting a business when an individual's party affiliation is mismatched with that of the sitting president, relative to when their party is matched.

3.3.1 Main estimates

Table 3 reports the estimates from Equation 2. Column (1) uses all registered Republican and Democrat voters. The coefficient on *Mismatch* is negative and significant: individuals whose party is not in power are 0.017 pp less likely than politically aligned individuals to start a business in a given year. This is a sizeable effect, equal to 3.3% of the sample mean. Extrapolating across the U.S., this amounts to an annual change in the partisan gap of around 13,000 founders, or approximately 170,000 over our 13-year sample.

To support the idea that it is political sentiment that drives differential entrepreneurship,

[22]For computational tractability we run the regression at the county-party-characteristic-year cell level. We weight each cell by the number of observations.

we compare regular partisans to more *active* ones, i.e., those who vote more often or donate (see Section 2.2 for definitions). Since active partisans are more invested in politics, we hypothesize that shifts in political power will have a stronger impact on their optimism and startup decisions. We add an indicator for active partisans (and interactions) to Equation 2 and re-estimate the model. The negative and significant coefficient on $Mismatch \times Active$ in column (2) means that active voters are 0.01 pp (2% of the mean) less likely to found a company than their less active counterparts in the same county and year when their party is not in power. In other words, the relationship between active voters' startup decision and political mismatch is 82% stronger than that of less active partisans.[23]

Turning to active *donors*, columns (3) and (4) indicate that household and FEC donor voters, respectively, are 0.007 and 0.04 pp less likely to start a company when mismatched, relative to their non-active counterparts. This represents an additional 1.4% and 7.3% of the average annual probability of starting new firms. While the effect for FEC donors is much larger, they are a much smaller subset of registered voters: 2.3% of individuals are FEC donors while 50% are active voters and 40% are in donor households.

We view individuals who make an effort to donate to a political campaign as more likely to be actively involved in partisanship. A natural concern is that wealth and the propensity to donate are correlated, and the mismatch effect among wealthy people may be larger. In Appendix Table A4 we find no evidence for this concern when we re-run the specifications in Table 3 separately for individuals in above- and below-median income households. The mismatch effect and its interaction with all of our activeness measures in both income groups is similar to the full-sample estimates. If anything, we find stronger mismatch effects for below-median income households.

Taken together, the larger effects we find for active voters point towards partisanship

[23]Appendix Figure A1 plots the event study by election for *active* Republicans and Democrats. Effects for the 2008 election are stronger for active voters and somewhat stronger for the 2016 election.

driving the time-varying gap in entrepreneurship between Republicans and Democrats.

3.3.2 Robustness

Sample construction

Next, we consider the representativeness of our sample. Recall that we focus on voters with unique names in a county to ensure an accurate match between the voter file and the business registration data. To examine how this unique-named sample compares to the full voter file, Appendix Table A1 reports individual characteristics for the full 2014 U.S. voter population (panel A - 160 million voters), for the 33 states which we can match to the SCP data (panel B - 108 million voters), and for voters in our regression sample (panel C - 40 million voters). Panels A and B are very similar, suggesting that the states in our sample are representative in terms of the voter characteristics we can measure. However, panel C displays some differences from the other two panels. This is likely the result of the unique name filter we use to generate our sample. For example, female and Black individuals are more likely to have unique names, while this is less likely for Hispanics.

To ensure that the differences between our sample and the U.S. voter population are not driving our reported results, in columns (5)-(8) of Table 3 we re-estimate the specifications in the first four columns using individual-level data and an entropy-balance method (Hainmueller, 2012) that weights each observation so that the means of covariates in the re-weighted sample match those in the U.S. voter population.[24] For example, since our regression sample under-represents men, this procedure will give more weight to male observations to correct for this. Estimates in columns (5)-(8) are very similar to the unweighted ones, providing support to the view that our estimates are representative of the underlying dynamics of partisan entrepreneurship. We report unweighted results in the remainder of the

[24]The characteristics we match are share of Democrats and, within each party, the shares of men, Hispanics, Blacks, Asians, whites, and birth cohorts.

paper. Note also that we find consistent results at the county level (Section 4.1) and when using the Census Bureau's Business Dynamics Statistics (Section 4.3), both of which do not impose any name uniqueness constraints and cover 45 and 50 states plus DC, respectively.

We also perform several robustness checks relating to our matching procedure in Table A5. The first five columns present estimates using progressively more stringent name rarity requirements i.e., replacing the baseline 0.1 pp threshold (column 1) with 0.05 pp, 0.01 pp, 0.001 pp and 0.0001 pp in columns (2)-(5). To address any concern that our match process operates more effectively in sparsely populated counties, we replicate our baseline specification using only counties with at least 300,000 registered voters in the voter file (approximately the 95th percentile of U.S. counties). In our main analysis we do not use middle initials (M.I.) in selecting unique-name voters or matching voters to founders because the missing rates of M.I. in SCP data vary substantially across states (e.g., 10% in Arizona but 60% in Colorado). However, in this table we use M.I. to define unique-name voters and match voters to founders in states whose M.I. non-missing rate is at least 50% (column 7), at least 40% (column 8), and in all states (column 9); in the remaining states, we match individuals without using M.I. In the final column we drop individuals who start a firm with more than one founder. Focusing on solo-founders mitigates the possibility that the individuals listed in the SCP data are early employees, rather than founders.[25] Across all specifications, the results are similar.

State-level elections

Party-changing elections often happen in waves. When there is a change in the executive branch at the federal level, there are often corresponding changes at the state level. To disentangle whether our results are driven by party-changing presidents or party-changing governors, we consider the 19 states which had at least one change in the party of the

[25] Additionally, in Figure A2 we show event study estimates excluding multi-founder firms.

governor (from Democratic to Republican or vice versa) from 2005 through 2017. We create an indicator for a mismatch between a voter's party and that of their state governor, called *Governor mismatch*. Table 4 column (1) reproduces our baseline result for presidential mismatch among the 19 states. Here, the mismatch effect is 4.4% of the mean, which is higher than the 3.3% effect size in our main sample. Column (2) considers the effect of governor mismatch alone and finds a 5% effect. When we include both the presidential and governor mismatch variables in column (3) the effect sizes (and coefficients) are largely unchanged, suggesting these are additive effects. In other words, an individual whose party matches both the governor and the president is twice as likely to start a business than if they match only one of the two.[26]

Table 4 not only shows robustness of our main result to state-level elections, but also provides evidence of an additional dimension along which political misalignment affects entrepreneurship.

3.3.3 Heterogeneity by gender, age, and income

In Table 5 we begin by considering how partisan effects vary across gender because there is evidence that women's economic expectations react differently to those of men (e.g., Meeuwis et al. 2022, D'Acunto et al. 2020). Columns (1) and (2) of Table 5 replicate Table 3 column (1) for men and women separately. Men appear more sensitive to political power shifts than women. Relative to their respective means, men are 3.8% less likely to engage in entrepreneurship when politically mismatched with the presidential regime, but for women the effect is only 1.5%.

In columns (3) to (5) we explore heterogeneity by age (Azoulay et al. 2020). Individuals between 18 and 29 years old show the largest effect relative to their mean (7.4%), followed by

[26]In Appendix Table A6 we show that the founding of *corporations* (vs. other legal vehicles for startups) responds to presidential mismatch but not to governor mismatch. This may be because corporations are larger and more growth-oriented, and thus more sensitive to the national economy than to the local economy.

those between 30 and 49 (3.4%), while those between 50 and 70 respond the least (2%). This monotonic decrease across age is consistent with partisanship-induced economic optimism: as entrepreneurs age they discount expected cash flows over shorter horizons.

Because wealth is correlated with the ability to start a business (e.g., Evans and Jovanovic, 1989, Fairlie, 1999, Hurst and Lusardi, 2004), Appendix Table A4 separately considers individuals with annual household incomes above and below $100,000, respectively. While the mismatch coefficient is larger among high-income individuals, the relative effect is actually larger among low-income individuals (4.2 vs. 3.9%).

3.3.4 Heterogeneity by firm type

We next consider the *types* of firms founded in our sample. Firm characteristics at founding predict firms' growth potential, survival, and contribution to employment, reflecting heterogeneity in founder ambitions and project potential (Schoar, 2010, Sterk et al., 2021). Guzman and Stern (2020) shows that firms founded as corporations instead of LLCs are three times more likely to go public or be acquired within six years of registration. For firms that file for a patent in their first year, this number jumps to 49 times. Guzman and Stern (2020) combines founding characteristics into a measure of "entrepreneurial quality" which we use to examine the ex-ante quality of the entrepreneurship induced by partisan sentiment.[27]

We begin by plotting firm quality as a function of party and gender in Figure 4. The figure shows that Democrats are more likely than Republicans to start firms in the highest quality quintile. Moreover, men are more likely to start top-quality firms and less likely to start bottom-quality firms than women. In untabulated results, we find that these quality

[27] In essence, this measure – also called the entrepreneurial quality index in Guzman and Stern (2020) – uses the founding characteristics of startups available in the business registration records, such as corporate form, jurisdiction, name, and intellectual property to create out of sample estimates of the probability of achieving an equity outcome (i.e., IPO or acquisition). These estimates have a high predictive power: startups in the top 1% of the quality distribution account for 36% of the equity outcomes and the top 5% accounts for 53% of all equity outcomes, out of sample.

differences across gender and party persist even after we control for demographics and county $\times$ year fixed effects.

Next, we reconsider our main specification among firms of different ex-ante quality. Specifically, Table 6 replaces the outcome variable of Table 3 with indicators for firm type. Column (1) examines LLCs, while column (2) focuses on corporations. We observe a larger effect size on *Mismatch* for corporations: politically mismatched individuals are only 0.7% of the mean less likely to start an LLC compared to 10.7% for corporations.

Columns (3) to (5) focus on firm types that have high ex-ante growth potential: VC backed, firms that filed for a patent, and firms in the top five percent of the Guzman and Stern (2020) quality distribution. Despite finding large economic magnitudes for the effect size (15.9% of the mean for VC-backed and 4.7% for patent firms), the rarity of these firm types limits power and hence the statistical significance of these estimates. However, firms in the top 5 percent by ex-ante quality show a mismatch effect of 4.8% of the mean that is statistically significant.

Columns (6)-(10) consider quintiles of the quality distribution and show a near-monotonic decrease in the estimated sensitivity to mismatch as firm quality declines. For example, firms in the top quintile have a mismatch coefficient of -0.004 (6.4% of the mean), while coefficients for firms in the fourth, third, second and first quintiles are -0.003, -0.002, -0.001 and -0.003, respectively.

In Appendix Table A7 we examine whether the average ex-ante quality of businesses started by politically aligned versus misaligned entrepreneurs. Conditional on having started a firm, mismatched entrepreneurs start higher quality firms, potentially because pessimistic entrepreneurs will only start firms of sufficiently high ex-ante quality that overcome their pessimism.

In summary, when looking across various measures, we find partisan entrepreneurship across the entire distribution of firm quality, with stronger effects among higher-quality firms.[28]

4. Evidence from County-level Data

All the non-survey evidence thus far compares Republican vs. Democrat *individuals* within the same county across changing political regimes. In this section, we compare Republican vs. Democratic *counties*. There are both advantages and disadvantages with this level of analysis. The main disadvantage at the county level is that we lose the precise identification we have at the individual level, where we can compare the behavior of Republicans and Democrats within the same county when the party of the presidency changes. However, there are three advantages. First, county-level data are available for almost all states, so we are not restricted to the 33 states for which we have firm founder data that we can match to voter rolls. Second, with county data we do not need to impose the unique name constraint that was required to match founder and voter data. Third, more economic data exist at the county level – such as job creation and firm closures – so that we can better understand how partisans' startup choices aggregate up to impact local economies, and whether there are effects on existing firms.

4.1 County-level evidence from the Startup Cartography Project

Similar to our event study DID analysis at the individual level, in this subsection we compare Democratic versus Republican *counties* across 45 states, before vs. after the 2008 and 2016 elections.[29]

We classify a county as Democratic-leaning (and refer to it as a "Democratic county" for brevity) if its vote share for the Democratic party is above the sample median in the

[28] The large effects we find for high-quality firms may be related to the pro-cyclicality of growth entrepreneurship (Nanda and Rhodes-Kropf, 2013, Howell et al., 2020). If political mismatch reduces founders' expectations of the availability of future capital, it could lead to reduced entry among growth-oriented firms.

[29] We drop MI, NV, ME, AL and DC (leaving us with 45 states) because we are unable to assign more than 50% of firms to counties in these states.

preceding presidential election, and Republican-leaning otherwise.[30] The outcome of interest is the startup rate: the total number of new firms registered in a month per 100,000 county residents. If there are no new firms in a county × month, we code it as a zero. Because we are estimating quarterly coefficients seasonality is an important confounder, so we de-seasonalize the startup rate by regressing it on county × month-of-year indicators and county annual linear trends using data starting from 2004 (for the 2008 election) and 2012 (for the 2016 election).[31] We refer to the resulting variable as the *excess* startup rate.

We use the following OLS specification:

$$\mathrm{Y}_{ct} = \sum_{t=-8}^{7} \beta_t \times Dem_c + \gamma' X_{ct} + \alpha_c + \alpha_t + \epsilon_{ct} \tag{3}$$

Y_{ct} is the excess startup rate in county c in time t, the number of time periods relative to when each presidential election was decided, i.e., November 2008 and November 2016. Our treatment variable is Dem_c, which equals one if county c is classified as Democrat-leaning, and zero otherwise. X_{ct} includes the county annual unemployment rate, per-capita income, and the employment share in each two-digit NAICS industry (excluding non-classifiable establishments) as controls for contemporaneous economic conditions and industry importance in each county. We include county fixed effects α_c and event time fixed effects α_t to absorb the average startup rate in a county and national registration trends. We cluster standard errors by county. While the data is monthly, for precision and clarity we estimate quarterly averages, and report the monthly version in the Appendix. We define $t = 0$ as the three-month period following an election month. For example, November 2016 through January 2017 constitute $t = 0$ for the 2016 election. We omit the indicator for $t = -2$ to form our base period. Similar to the individual-level DID we interpret the β_t coefficients as the causal

[30] Results are unaffected if we define county partisanship using the Republican vote share instead.

[31] In Figure A3 we also consider an alternative approach to addressing the seasonality issue by computing the change in the startup rate relative to the same period in the preceding year. The results are very similar.

effect of presidential elections on startups, assuming that Republican and Democrat-leaning counties would have moved in parallel in the absence of elections. As we will show, there are no differential pre-trends.

Figure 5 panels (a) and (b) plot the estimated β_t coefficients. Mirroring our results in Figure 2, Democratic counties increase their startup rate relative to Republican counties following the election of President Obama, and Republican counties increase their relative rate after the election of President Trump. Specifically, Democratic counties on average see 18 more firms per 100,000 residents (2.3% of the mean) relative to Republican counties in the year following the 2008 election. Republican counties experience a relative increase of 35 firms per 100,000 residents (3.5% of the mean) in the year following the 2016 election. The timing of the election effects generally mirror the individual-level analysis, except for a slight anticipation effect in the county level data in quarter -1.[32] This could be due to perceptions of Trump's likelihood of winning being different *across* geographic areas but not *within* areas.

Panels (c) and (d) repeat the previous analysis, except now we compare clearly Democratic and clearly Republican-leaning counties to more politically divided ones (so-called "purple counties") rather than to each other, in order to examine which areas are driving the election effects. We define purple counties as those with a victory margin of less than 10 percentage points in the preceding election. Both panels indicate that the county-level election effects are driven by *Republican* counties: they experience a sharp increase in their entrepreneurship around the 2016 election and a sharp decrease around the 2008 election. These results generally mirror what we found when comparing individual Republican and

[32]Appendix Figure A4 shows the same regression at a *monthly* frequency and provides strong support for the parallel trend assumption. In fact, we see that the slightly negative coefficient in quarter -1 for the 2016 election in Figure 5 is entirely driven by the month before the election (October 2016), a period of political turbulence which included FBI director Comey's letter to Congress about candidate Clinton's emails. In another robustness test, we drop contemporaneous economic controls from Equation 3 and find quantitatively similar estimates (Figure A5).

Democrat voters to Independents within the same county in Figure 3, especially around the 2008 election.

4.2 County-level evidence from BLS data

We next evaluate the impact of party-changing elections at the county level using the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics (BLS). This provides quarterly data on employment and establishments for all firms (i.e., *both* new and existing firms) within narrow (6-digit NAICS) industries, which allows us to absorb industry-quarter variation for a more precise identification at the county level.

In Figure A6, we report event study DID coefficients for the change in the number of establishments per capita and the employment growth rate around the 2016 and 2008 elections. To account for the significant seasonality in quarterly data, we focus on the year-over-year change in the dependent variable rather than on levels. While some coefficients are significant in the second year before the election (in some panels), the overall pattern of results is similar to the other county analyses. In panels (a) and (b) we focus on the number of establishments per capita. By the second year after the Obama election, relative to the mean number of establishments per capita, Republican counties report 8.1% fewer than Democratic ones. In contrast, in the seven quarters following the Trump election, Republican counties see a 5% of the mean increase in establishments per capita.

We observe a similar pattern when we instead consider employment growth, which on average drops by 0.25 pp per quarter for Republican counties after the Obama election, and increases by 0.25 pp in the two years following the Trump election. This analysis provides supporting evidence of partisan election effects manifesting across political geographies and even within narrowly-defined industries.

4.3 County-level evidence from Census

Our main analysis focuses on new startups, i.e., the extensive margin of entrepreneurship. The preceding analysis using QCEW data explores both new and existing firms together. The Census Bureau's Business Dynamics Statistics (BDS) data allow us to *separately* analyze new and existing firms for all 50 states plus DC at the county level. Specifically, the data allow us to explore how the expansion, contraction, and death of existing firms co-varies with counties' political alignment around elections.

BDS reports the number of new and existing *employer* firms, the number of newly opened and closed establishments of existing firms, and the job creation rate by firm age bins, for every county. We run the following regression:

$$\mathrm{Y}_{ct} = \beta \; Mismatch_{ct} + \gamma' \mathbf{X_{ct}} + \alpha_c + \alpha_t + \epsilon_{ct} \tag{4}$$

where Y_{ct} is a variable of interest from BDS in county c in year t. $Mismatch_{it}$ is an indicator equal to one when the partisanship of county c differs from the party of the sitting president in year t. We include a vector of county-level, time-varying variables X_{ct}, i.e., annual unemployment rate, annual per-capita income, and the employment share of each two-digit NAICS industry (excluding NAICS=99) to control for economic conditions and industry presence in the county. When the outcomes are for existing firms, we include firm age bin fixed effects.[33] We also include county fixed effects α_c and year fixed effects α_t to absorb any persistent difference across counties and a national trend in business dynamics.

The coefficient of interest is β, which estimates the average difference in business dynamics in counties that are mismatched with the party of the sitting president, relative to those in aligned counties.

[33] Because the BDS data are provided at the county-year level, we cannot include firm-level controls. However, we do include county-level controls, as described in the text. Note that our results are robust to excluding contemporaneous economic controls: see Table A9.

Table 7 reports the estimates from Equation 4. Column (1) confirms our earlier results for startups in a different dataset. It shows that there are around five fewer *new* firms per 100,000 county residents in politically mismatched counties relative to matched ones, amounting to 2.9% of the outcome mean. In terms of economic magnitude, the relationship between a county's political misalignment and new firm creation is roughly equivalent to a 2.2 pp increase in the local unemployment rate, using the coefficient on *Unemp(%)* from the table. Column (2) indicates that there is no economic or statistical difference in the job creation rate of new firms between matched and mismatched counties, implying that new firms that are born during aligned periods have, on average, the same number of employees as firms that begin during times of mismatch.

Turning to intensive margin effects, columns (3) through (5) show that firms in politically mismatched counties open fewer establishments (1% of the mean), close more establishments (1.1% of the mean), and experience more firm death (1.4% of the mean), relative to those in matched counties. These business dynamics have implications for the labor market, as the net job creation rate (job creation minus destruction) in column (6) among existing firms in mismatched counties is 0.33 pp of annual employment lower than in matched counties, amounting to 6% of the standard deviation (5.2).[34] Summing across new and existing firms (column 7), politically mismatched counties experience a relative fall in their net job creation rate of 0.32 pp of annual employment.

Aggregating up, we find that the extensive margin effects from columns (1) and (5) translate to approximately 82,000 new employer firms in politically matched counties (relative to mismatched ones), and the death of over 10,000 employer firms in mismatched counties over 13 years.[35] The intensive margin effects in columns (3), (4) and (6) indicate a broader impact

[34] Note that because the net job creation rate is a net variable it has a near-zero mean, making the mean a poor benchmark – this is why we compare our estimate to the standard deviation.

[35] Even though the estimated effect (relative to the mean) of partisanship on entry using BDS data is similar to the main effect in Table 3, these aggregate estimates of the number of firms are substantially smaller because BDS data captures only *employer* firms.

on business dynamism, amounting to 4,000 new establishments and 2.4 million net jobs in matched counties (relative to mismatched ones) over our sample period.[36]

5. The Expectations of Partisan Entrepreneurs

Figure 2 shows that the entrepreneurial response in our event studies is almost immediate, likely before any actual policy or economic changes can take place. This immediacy suggests that the effect we document is a response to changing *expectations*, with politically matched entrepreneurs expecting an increased return to entrepreneurship relative to mismatched ones, leading them to start new firms.

In this section, we explore these expectations further. In Section 5.1, we examine whether these beliefs are correct, i.e., does the true return to entrepreneurship match these expectations? In the remaining subsections we look for evidence that the expectations are about policy changes (Section 5.2) and economic growth (Section 5.3).

5.1 Expectation vs. reality: The return to entrepreneurship around elections

Our evidence demonstrates Republican entrepreneurship increases relative to that of Democrats when an election results in a newly-elected Republican president (and vice versa). This increase occurs at both the extensive margin via new firms (Table 3) and at the intensive margin via the expansion of existing firms (Table 7). In this section we ask whether these investments reflect a change in the relative *return* to entrepreneurship. In other words, we know that Republicans invest more (relative to Democrats) when a Republican president comes to power. This could be because the expectations of Republicans are rational and the return to Republican entrepreneurship has increased, relative to Democrats. However,

[36] We calculate these numbers making the simplifying assumption that Republican and Democrat counties have the same average population and/or employment.

it could also be the case that partisan expectations are biased, and there is little change in the relative return to entrepreneurship following elections.

To test whether Republican or Democratic firms perform differently following party-changing elections, we would like to have a dataset analogous to Compustat for the firms in our sample, almost all of which are private. Unfortunately such a dataset does not exist. As an alternative, we use (i) private firm sales and employment data from Reference USA (Infogroup), a comprehensive dataset of firms similar to Dunn & Bradstreet, and (ii) individual income data from Experian matched to L2 data. Before proceeding, we note that firms born soon after an election are unlikely to be random. With this in mind, we focus on *existing* firms, founded before the party-changing election, to determine whether the return to Democrat vs. Republican investment changes after the election.[37]

Figure 6 reports evidence from Reference USA that Republican and Democratic firms founded before the 2008 and 2016 elections appear to hire more workers post election if they are on the winning side, but do not appear to have differential productivity. Panels (a) and (c) show that the number of employees at Democratic (relative to Republican) firms increases after Obama's election and decreases after Trump's election. Increased hiring is consistent with our findings using Census BDS data (Section 4.3): founders of the winning party grow their firms after the election, thus increasing investment. Panels (b) and (d) instead consider the productivity of this investment using the only measure available in the Reference USA dataset: sales per employee. Consistent with the hypothesis that the true return to entrepreneurship is unchanged, there are no discernible differences in sales per employee between pre-existing Republican and Democratic firms for at least three years

[37] We define "existing" SCP businesses as those founded before the pre-period, i.e., between 2001 and 2004 for the 2008 election, and between 2009 and 2012 for the 2016 election. We match them to Reference USA by firm name, address, and year of incorporation where available, resulting in a sample of 57,000 and 51,000 firms for the 2008 and 2016 elections, respectively.

following each election.[38] Table A10 reports the corresponding estimates.

A more direct test of our question would consider the profitability of the investment (rather than productivity per worker). Because we cannot construct profitability from the Reference USA data we use the income of the founding entrepreneur from Experian. L2 provides the Experian data starting in 2015, so we examine entrepreneurs' income around the 2016 election. If the true return on investment increased for Republican-founded (relative to Democrat-founded) businesses after Trump's election, we would expect this higher return to flow through to the income of the business founder, on average. We restrict the sample to entrepreneurs with pass-through entities, (i.e., entities which are not corporations), to maximize the likelihood that the yearly income from the business flows to the entrepreneur. Column (5) in Table A10 shows no evidence of decreasing income from Democrat (relative to Republican) entrepreneurs around Trump's election. If anything, the income of Democrat entrepreneurs is slightly higher after 2016, although the magnitudes are small.

There are differences in the benefits provided by each of these analyses. The advantage of Reference USA is that it provides business employee and sales data, but not costs, and so we cannot calculate business income. The advantage of the Experian data is that we have income (rather than sales), but it is the founder's income and so may include non-business income. Nevertheless, both data sources point to a similar conclusion: we find no difference in the true return to entrepreneurship between parties following the election outcomes.

5.2 Policy Expectations

One reason why an entrepreneur might start a business immediately after their party wins an election is that they expect the new president to implement policies that disproportionately favor members of their party. For example, President Trump's 2017 Tax Cuts

[38]Increased hiring would not increase profits under standard competitive market assumptions absent a change in the true return to entrepreneurship. However, productivity is directly related to profitability if a startup's pre-election marginal revenues equal marginal costs and it faces an upward sloping cost curve.

and Jobs Act included a state and local tax cap of $10,000 which disproportionately hurt taxpayers in Blue States, while the 2010 Affordable Care Act may have benefited Democratic areas more than Republican ones.

We investigate whether entrepreneurs' expectations anticipate future policy by conducting tests in two domains that policy often targets: geography and industry. Mian et al. (2021) finds little evidence of changes in tax rates, personal income growth, and transfers at the county and state levels around U.S. presidential elections. In addition, to examine whether partisans' economic situation differentially improves, they use zip code-by-month fixed effects, assuming that people within zip codes are subject to the same government policies. Similarly, we re-estimate Equation 2 but add fine-unit geography-time fixed effects so that identification comes, for example, via differences between Democrats and Republicans who live in the same census block group at the same time. If policy is targeted to geography, we would expect our main result to disappear as we include these fixed effects. However, we find little evidence that this is the case. In Table 8 we progressively include finer geography-by-year fixed effects, from state-level (column 1) to census block group-level (column 5).[39] The point estimates under these alternative geography $\times$ year fixed effects are all similar to the estimates under the main specification shown in column (2). Appendix Table A11 repeats the exercise for politically active and donor voters, with similar results. Moreover, to the extent that policies are different by income group (e.g., tax policies), geography-by-year fixed effects for zip, census tract, or block group would also absorb such targeting.

Turning to industry, we categorize companies into two-digit NAICS industries using a word-tagging approach based on company names – see Appendix A for details. We identify the industry of 55% of firms in our sample in this way, and group industries into terciles of policy sensitivity following Hassan et al. (2019). We then re-estimate Equation 2 but

[39] There are 10,000 people per zip code, 4,000 per census tract, and 1,500 per census block group, on average.

change the dependent variable to be an indicator for whether an individual starts a firm in an industry in a certain tercile of policy sensitivity. Table 9 columns (1) to (3) show that the political mismatch effect is generally higher for firms in industries with higher policy sensitivity, suggesting that expectations regarding future policy may contribute to the partisan entrepreneurship we document. However, policy expectations cannot be the sole driver, as the industry groups with low and middle sensitivity have mismatch effects that are economically and statistically significant. Additionally, in Appendix Table A8 we show estimates for the 12 most populated industries in the sample. We observe effects for mismatched entrepreneurs across almost all industries including retail, the industry with the lowest policy sensitivity according to Hassan et al. (2019). The robustness of our result across industries is also consistent with the fact that our $Mismatch$ estimates are quantitatively similar when we include census block group $\times$ year fixed effects (in Table 8). The latter can be seen as capturing some of the variation in industry $\times$ year fixed effects, because in our data the firms started by two randomly chosen founders in the same census block group and year on average have a 25 percent chance of being in the same industry.

Columns (4) to (6) of Table 9 show an alternate measure of firms' exposure to policy that does not require each firm to be classified into an industry, allowing us to use the entire sample. We group *counties* into terciles by their policy sensitivity (using their employment exposure to each industry), and then estimate Equation 2 in each county subsample. We find that low and middle-sensitivity counties also have meaningful mismatch responses, and middle-sensitivity counties' response is indistinguishable from that of high-sensitivity ones.

5.3 Economic Expectations

Another potential reason for partisan differences in entrepreneurship following elections is a partisan divergence in beliefs about future economic conditions. For example, an entrepreneur who is optimistic about the future economy might expect stronger demand and might be more likely to start a new business. Similarly, optimistic entrepreneurs may believe they will have a better safety net: if their business fails they may believe that they have a healthier labor market as a fallback option (e.g., Barrios et al., 2022, Gottlieb et al., 2022).

Recall that Figure 1 panel (a) demonstrates sharp partisan swings in economic expectations following party-switching presidential elections. To show that similar patterns also exist *among entrepreneurs*, we utilize the Gallup U.S. Daily Survey of 1,000 adults daily from 2008 to 2016. We focus on the 2008 presidential election because the number of respondents falls sharply after 2016 to only 30 per day. Importantly, respondents identify their political party (38% are Democrats, 37% are Republicans) and whether they are a business owner (2%).[40]

In Figure 1 panels (b) and (c), we show respondents' expectations about the economy and their standard of living, separately for business owners and non-owners. Panel (b) plots the average response to the question *"How would you rate economic conditions in this country today?"* Panel (c) plots the share of respondents choosing *"Getting better"* to the question *"Right now, do you feel your standard of living is getting better or getting worse?"* Both panels show that the optimism of Democratic business owners (relative to that of Republican ones) rises after the 2008 presidential election and stays stronger in subsequent years. Moreover, business owners appear to respond at least as much, or even more, to the 2008 election as non-business owners do.

Recall from Table 5 that the political mismatch effect we document was twice as large for men than women. Examining economic expectations, we also find larger partisan swings for men. Specifically, Figure 7 plots the quarterly partisan difference in responses to the Gallup U.S. Daily Survey separately for men and women around the election of Barack Obama. While the Republican-minus-Democrat difference for men was above that of women before

[40]Business owners need not be business founders, but this is the closest population to entrepreneurs that is identifiable in the Gallup survey.

Obama's 2008 victory, it fell below, and stayed below, throughout his presidency.

Finally, while Figure 1 shows partisan swings in optimism at the *national* level, most entrepreneurship depends on the local economy (e.g., Schoar, 2010). Thus, if economic expectations drive partisan entrepreneurship, we would expect the localities whose economic growth is most connected to the national economy to be most affected by party-changing elections, and partisan entrepreneurs in these areas to be most responsive to these elections.

This is precisely what we find in Table 10 when we sort individuals by their counties' GDP growth correlation with national GDP growth and rerun Equation 2. Effect sizes monotonically increase with the local-to-national correlation. For example, the estimated political mismatch effect goes from 1.6% of the mean in the lowest quartile of correlation to 3.7% in the highest.

Overall, we find two kinds of evidence supporting the hypothesis that party-specific economic expectations drive the entrepreneurship differences among partisans that we observe. In surveys, the economic expectations of business owners follow our partisan entrepreneurship result, with more optimistic expectations among owners when their party is in power. We also find stronger survey evidence among men, which aligns with our empirical evidence on partisan entrepreneurship. In addition, we find the strongest partisan entrepreneurship effect among counties that are most sensitive to national economic growth.

6. Conclusion

This paper documents a relationship between political identity and entrepreneurship, with Republicans over 26% more likely to start a firm in a given year than Democrats, after controlling for a range of other characteristics. This partisan entrepreneurship gap is time-varying, widening when Republicans take control of the presidency and shrinking when Democrats do.

Our paper highlights that supporters of a political party exhibit consequential changes in economic behavior when their preferred regime comes to power. Thus, it has potentially different policy implications compared to prior work. Most of the existing literature focuses on political connections and allocation of government resources (e.g., Fisman, 2001, Faccio, 2006, Robinson and Verdier, 2013), with policy prescriptions aimed at reducing clientelism and regulatory capture. In contrast, the effect we document on political supporters appears to arise organically via partisan expectations. It is not clear which policy actions would best mitigate the dampening economic effect on regions supporting the losing side, or whether such policies would be welfare-improving.

Finally, US political polarization is growing along many dimensions (e.g., Abramowitz and Saunders, 2008, Gentzkow et al., 2019, Alesina et al., 2020). If polarization continues to rise, will the role of political identity become more central to entrepreneurial decisions? We leave these questions to future research.

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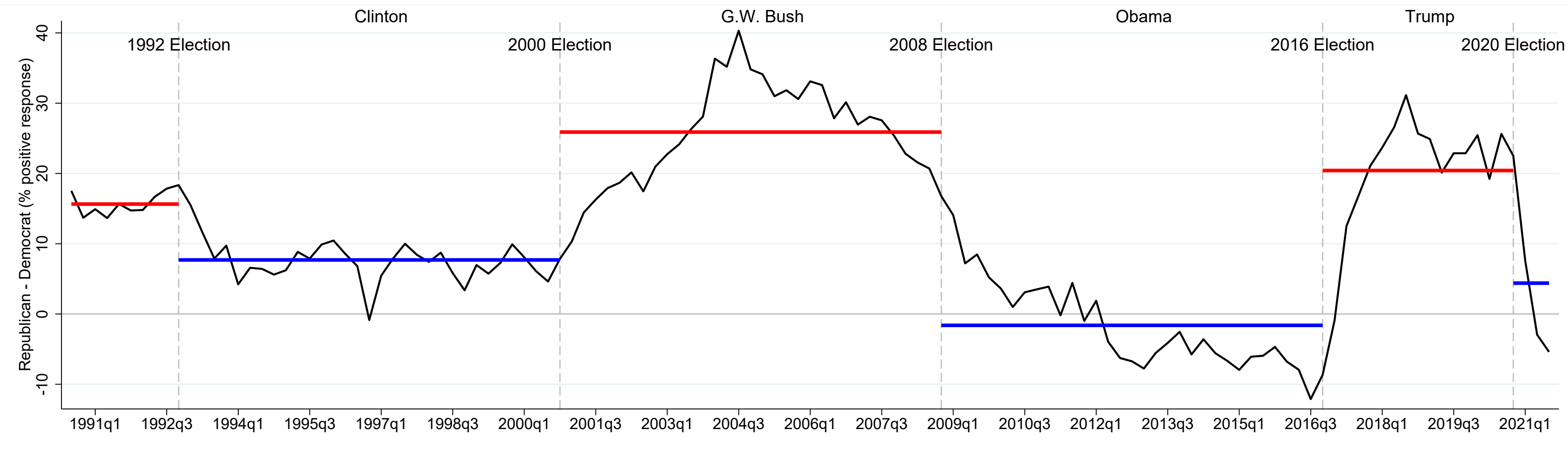
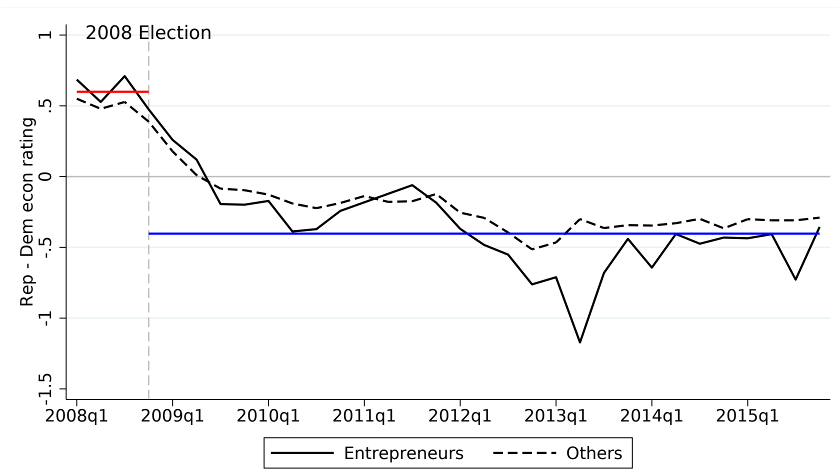
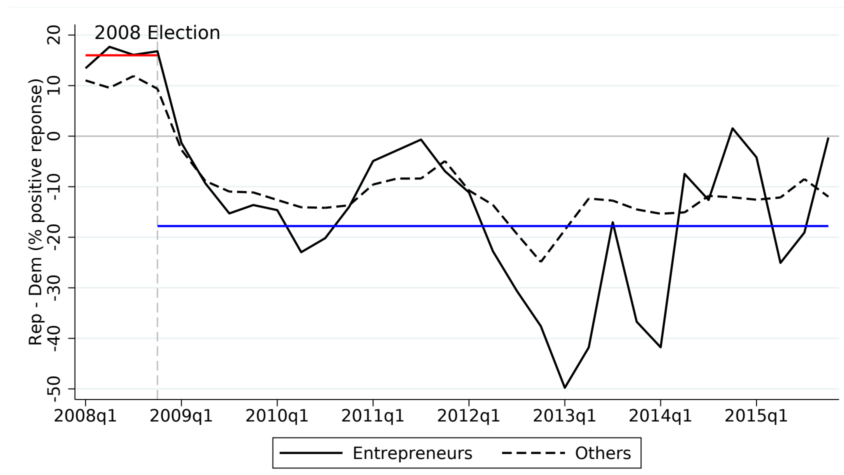


(a) Bloomberg Consumer Comfort Index: national average



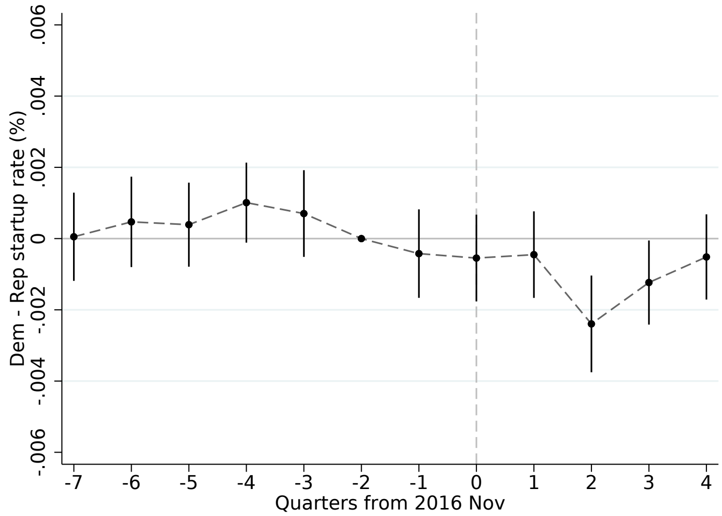
(b) Gallup question: *Economic conditions in the country today*



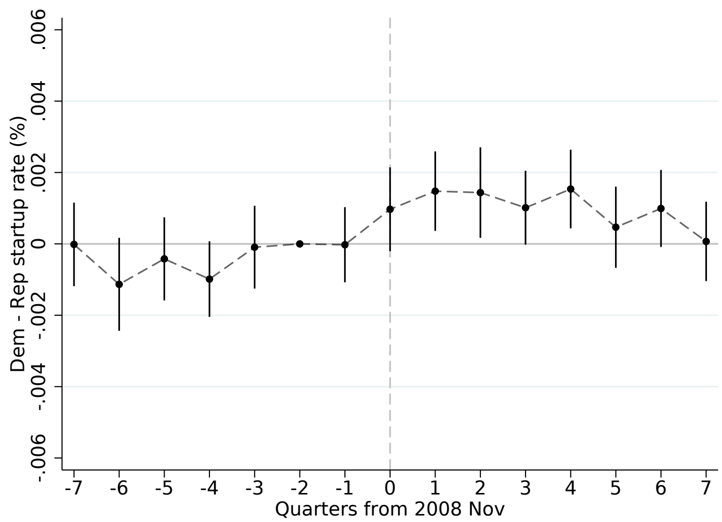
(c) Gallup question: *Standard of living*

Figure 1. Optimism by party

Note: The black line in panel (a) plots the quarterly difference in The Bloomberg Consumer Comfort Index between Republicans and Democrats. Survey respondents are asked to rate (i) the national economy, (ii) their personal finances, and (iii) the buying climate as "Excellent," "Good," "Not so Good," or "Poor." The Index is calculated as the quarterly average fraction of positive responses ("Good" or "Excellent") across the three questions. Panels (b) and (c) plot the quarterly difference in responses to the Gallup U.S. Daily Survey between Republicans and Democrats among entrepreneurs (black line) and others (dashed black line). Panel (b) uses respondents' average rating ("Poor", "Only fair", "Good", and "Excellent", translated into a 1-4 range) to the question "How would you rate economic conditions in this country today?" and panel (c) the fraction of respondents choosing "Getting better" to the question "Right now, do you feel your standard of living is getting better or getting worse?" "Entrepreneurs" are self-identified business owners, while "others" refers to all other respondents. The horizontal lines plot the average of the difference between each party-switching presidential election (for all respondents in panel a and for entrepreneurs in panels b and c).



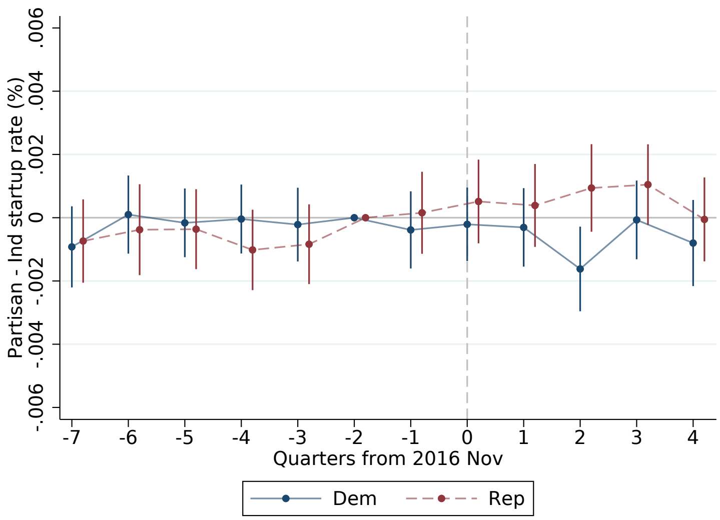
(a) 2016 election



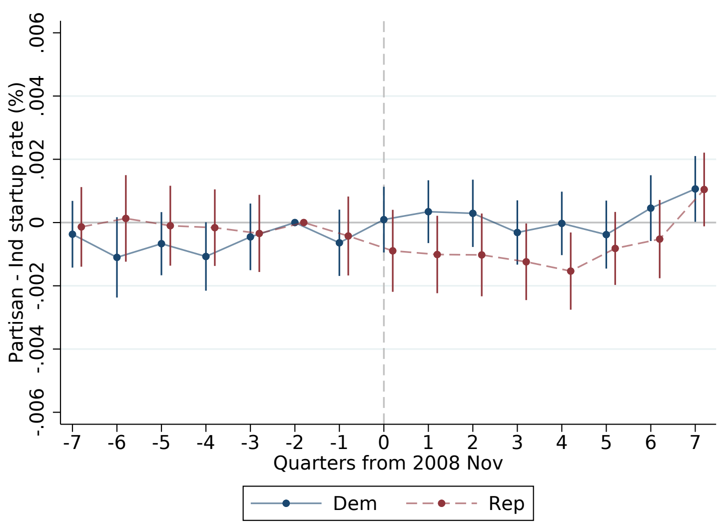
(b) 2008 election

Figure 2. Political mismatch and the probability of starting a business Democratic vs. Republican *individuals*

Note: This figure plots the coefficients on the interactions between Democrat and event time indicators from Equation 1, capturing Democrats' time-varying excess probability of starting a business relative to Republican voters (omitted group). Units are in percentage points. Event time 0 denotes the month of a presidential election and the two subsequent months. For example, for the 2016 election, event time 0 is November 2016 through January 2017. Event time -2 is the omitted period. All regressions control for county×event fixed effects and voter characteristics (gender, age groups, race). Regressions are run at the county-party-characteristic-month cell and are weighted by the number of observations in each cell. Standard errors are clustered by county. Regression coefficients are reported in Table A2.



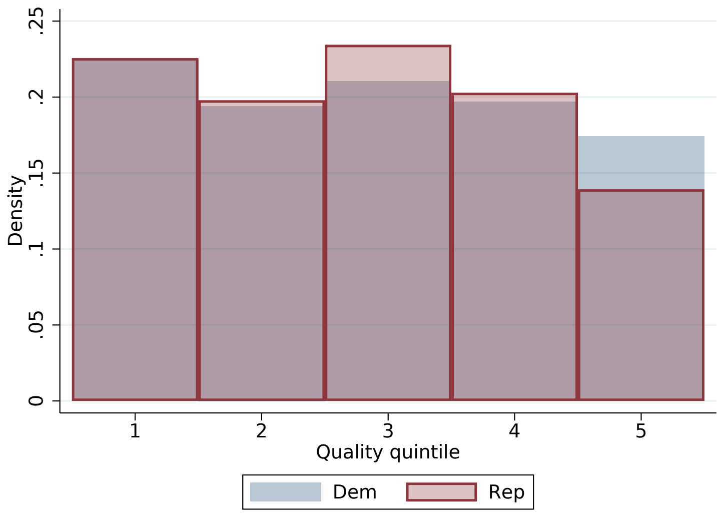
(a) 2016 election



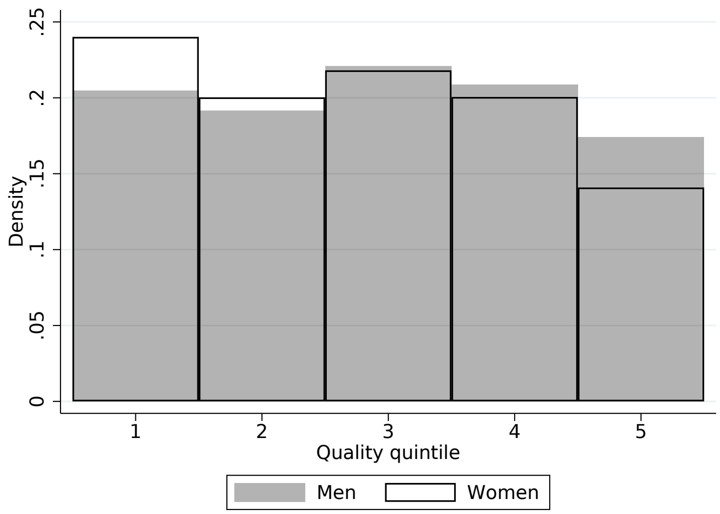
(b) 2008 election

Figure 3. Political mismatch and the probability of starting a business Democratic and Republican individuals vs. *Independents*

Note: This figure plots the coefficients on the interactions between Democrat and event time indicators from a modified version of Equation 1, capturing Democrats' (blue solid line) and Republicans' (red dashed line) time-varying excess probability of starting a business relative to Independents' (omitted group). Units are in percentage points. Event time 0 denotes the month of a presidential election and the two subsequent months. For example, for the 2016 election, event time 0 is November 2016 through January 2017. Event time -2 is the omitted period. All regressions control for county×event fixed effects and voter characteristics (gender, age groups, race). Regressions are run at the county-party-characteristic-month cell and are weighted by the number of observations in each cell. Standard errors are clustered by county. Regression coefficients are reported in Appendix Table A13.



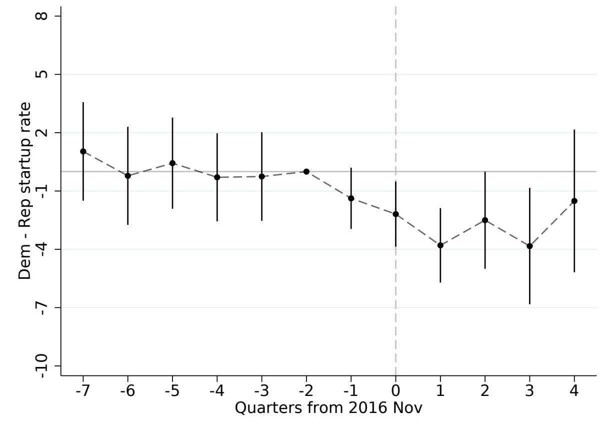
(a) By party



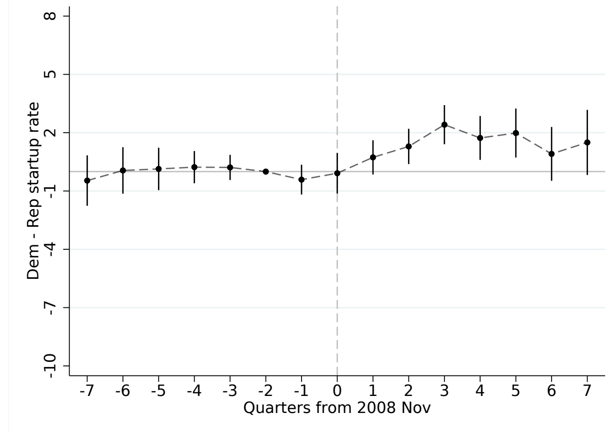
(b) By gender

Figure 4. Firm quality distribution by party and by gender

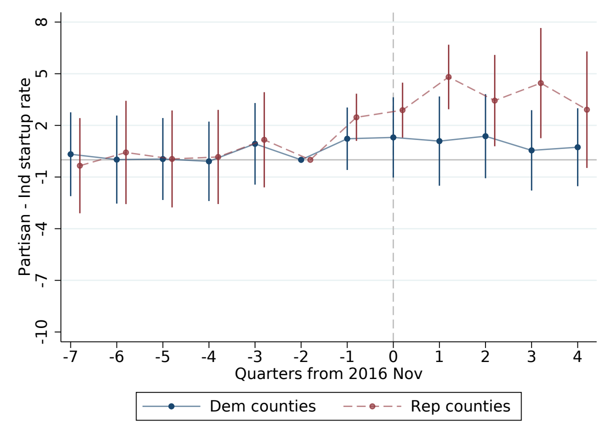
Note: This figure plots the quintile of firm entrepreneurial quality (using the entrepreneurial quality index from Guzman and Stern (2020)) by founder party and gender. Quintile 1 corresponds to the lowest quality.



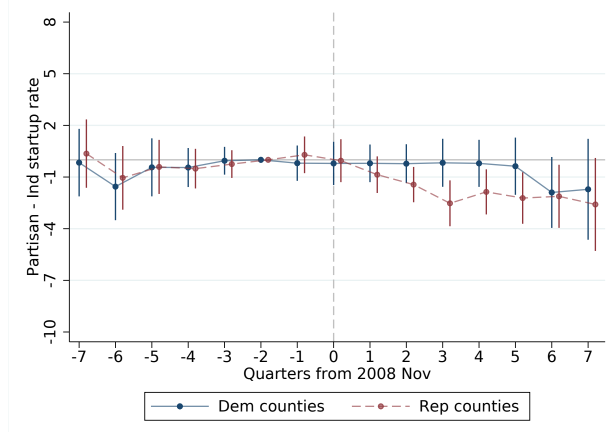
(a) 2016 election



(b) 2008 election



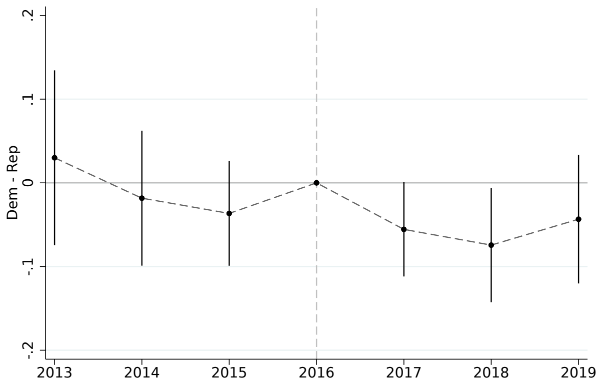
(c) 2016 election



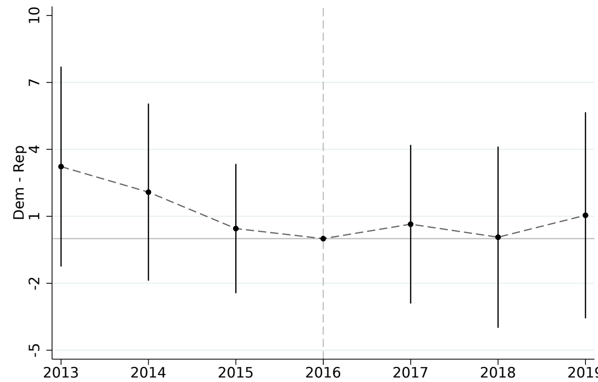
(d) 2008 election

Figure 5. Political mismatch and new firms: Democratic and Republican *counties*

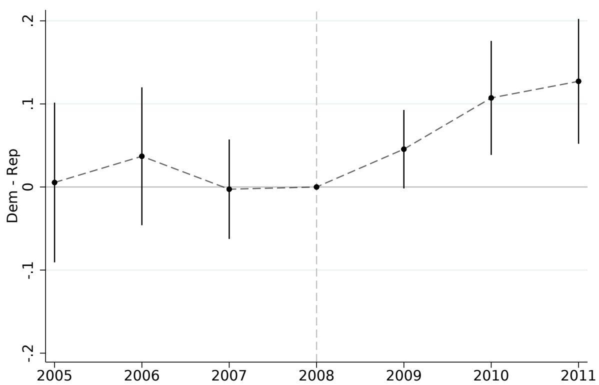
Note: Panels (a) and (b) of this figure plot the coefficients on the interactions between Democratic-leaning indicator and event time indicators from Equation 3, capturing these counties' time-varying startup rates relative to Republican-leaning counties (omitted group). Panels (c) and (d) instead use "purple" counties as the omitted group. The dependent variable is the excess startup rate: the number of excess new firm registrations per 100,000 people at or above 20 years old in a county. Purple counties are those reporting a victory margin of less than 10 percentage points in the preceding election. Event time 0 denotes the month of a presidential election and the two subsequent months. For example, for the 2016 election event time 0 is November 2016 through January 2017. Event time -2 is the omitted period. All regressions control for county fixed effects, event time fixed effects, and county economic conditions (monthly unemployment rate, annual per capita income, and annual employment share by NAICS-2 industries). Regressions are weighted by county population at or above 20 years old. Standard errors are clustered by county. Regression coefficients for panels (a) and (b) are reported in Table A12 columns (1) and (2).



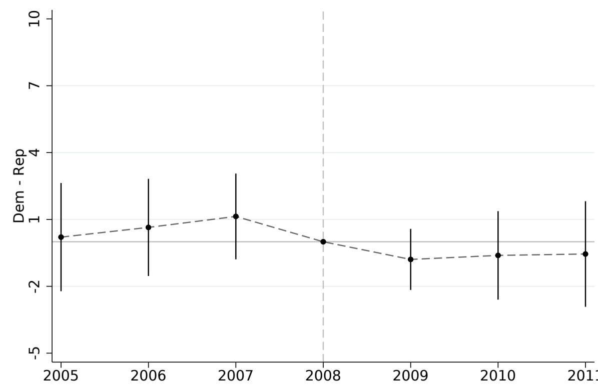
(a) 2016, number of employees



(b) 2016, sales/employee



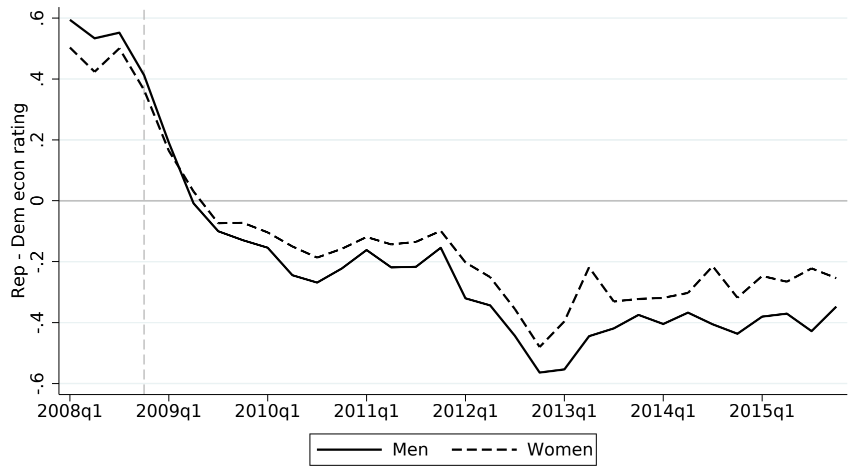
(c) 2008, number of employees



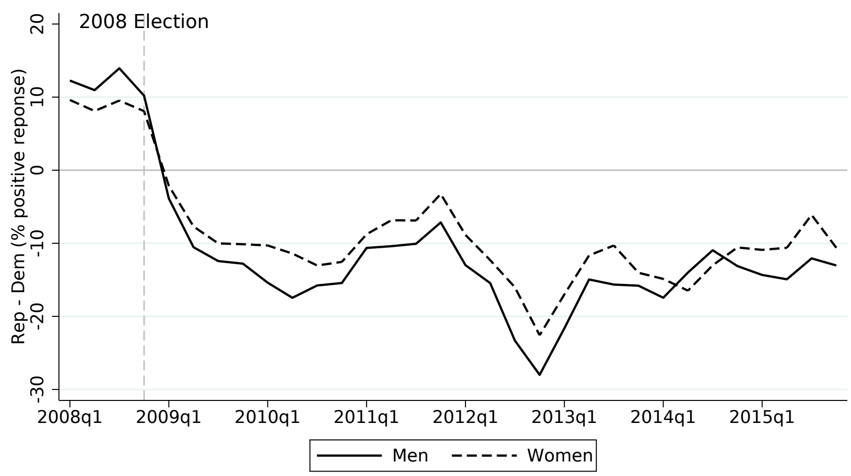
(d) 2008, sales/employee

Figure 6. Political mismatch and performance of pre-election firms: Democratic vs. Republican

Note: The figure reports the estimated difference in the performance of Democratic vs. Republican firms founded before the 2008 and 2016 elections, using data from Reference USA. The sample in panels (a)-(b) (panels c-d) consists of firm-founder pairs where the founder was in our main unique-name sample and the firm was incorporated in 2009-2012 (2001-2004), and the firms have non-missing sales and employment data in Infogroup. "Number of employees" refers to the number of employees at the firms. "Sales/employee" denotes the sales (in thousands) per employee at the firms; Reference USA compiles sales data from annual reports, newspapers, and periodicals. *Dem* is one for firm-founder pairs with a Democratic founder, and zero otherwise; firm-founder pairs with a Republican founder are the omitted group. The sample period is from three years before to three years after an election; the election year is the omitted period. All regressions control for county×year, county×incorporation year, industry×year, and industry×incorporation year fixed effects, as well as founder demographics (i.e., gender, age groups, race). Standard errors are clustered by county. Regression coefficients are reported in Table A10.



(a) Gallup question: *Economic conditions in the country today*



(b) Gallup question: *Standard of living*

Figure 7. Optimism by party and gender

Note: This figure plots the quarterly difference in responses to the Gallup U.S. Daily Survey between Republicans and Democrats among men (black line) and women (black dashed line). Panel (a) uses respondents' average rating ("Poor", "Only fair", "Good", and "Excellent", translated into a 1-4 range) to the question "How would you rate economic conditions in this country today?" and panel (b) the fraction of respondents choosing "Getting better" to the question "Right now, do you feel your standard of living is getting better or getting worse?"

Table 1
Pr(start a business), Pr(ever a founder) and summary statistics

	Full sample			Democrat			Republican		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean	SD	%Sample	Mean	SD	%Sample	Mean	SD	%Sample
P(start business in a year):									
All	0.50	1.48	100.00	0.39	1.32	100.00	0.61	1.65	100.00
Male	0.75	1.90	41.29	0.60	1.78	36.14	0.90	2.03	44.60
Female	0.32	1.07	58.71	0.27	0.95	63.86	0.38	1.20	55.40
Educ.≥College	0.69	1.64	47.13	0.55	1.51	45.60	0.78	1.70	49.79
Educ. others	0.41	1.34	52.87	0.32	1.19	54.40	0.49	1.46	50.21
White	0.47	1.18	75.69	0.37	1.10	62.17	0.58	1.26	90.92
Black	0.35	1.36	11.13	0.34	1.08	20.04	0.48	3.43	1.52
Hispanic	0.45	1.80	9.42	0.34	1.36	14.04	0.73	2.64	5.11
Asian	0.90	3.06	3.76	0.72	2.71	3.75	1.00	3.74	2.45
Low income	0.24	1.27	21.29	0.21	1.06	25.74	0.30	1.53	17.29
Middle income	0.39	1.22	42.80	0.33	1.11	42.36	0.47	1.33	42.83
High income	0.77	1.62	35.91	0.63	1.52	31.90	0.89	1.72	39.88
Age 18-29	0.25	1.09	18.29	0.20	0.95	18.36	0.35	1.47	11.86
Age 30-39	0.65	1.77	18.30	0.53	1.60	17.49	0.81	2.09	15.33
Age 40-49	0.66	1.67	21.69	0.54	1.53	20.45	0.77	1.78	23.41
Age 50-59	0.53	1.46	23.15	0.42	1.30	23.67	0.64	1.55	26.62
Age 60-70	0.34	1.24	18.57	0.27	1.10	20.03	0.41	1.29	22.79
N voter×year		477,728,978			173,281,910			153,846,085	
N state		33			33			33	
P(ever founder):									
All	4.59	20.92	100.00	3.69	18.85	100.00	5.53	22.86	100.00
Male	6.57	24.78	41.32	5.39	22.59	36.15	7.72	26.69	44.62
Female	3.19	17.57	58.68	2.72	16.28	63.85	3.77	19.04	55.38
Educ.≥College	6.22	24.16	46.76	5.11	22.03	45.26	6.91	25.37	49.42
Educ. others	3.94	19.46	53.24	3.14	17.45	54.74	4.66	21.07	50.58
White	4.44	20.60	75.81	3.51	18.41	62.46	5.29	22.38	91.00
Black	3.38	18.08	11.07	3.30	17.86	19.82	4.41	20.54	1.50
Hispanic	4.10	19.82	9.40	3.17	17.52	13.99	6.28	24.26	5.08
Asian	7.72	26.70	3.72	6.31	24.32	3.73	8.29	27.57	2.41
Low income	2.25	14.83	22.76	1.93	13.76	27.23	2.69	16.18	19.28
Middle income	3.87	19.29	42.32	3.27	17.79	41.74	4.59	20.93	42.19
High income	7.01	25.54	34.92	5.85	23.46	31.02	7.97	27.08	38.53
Cohort 1990+	1.19	10.82	7.88	0.95	9.72	7.44	1.54	12.31	4.79
Cohort 1980-89	3.93	19.44	15.26	3.16	17.50	15.45	5.08	21.96	10.06
Cohort 1970-79	6.53	24.71	17.09	5.44	22.67	16.17	7.81	26.84	14.98
Cohort 1960-69	6.30	24.30	20.53	5.15	22.10	19.22	7.34	26.07	22.94
Cohort 1950-59	4.95	21.70	20.97	3.98	19.56	22.05	5.96	23.68	23.90
Cohort 1940−	2.43	15.40	18.27	1.95	13.82	19.67	2.86	16.66	23.32
N voter		40,420,508			14,696,895			13,083,051	
N state		33			33			33	

Note: This table reports summary statistics (sample described in Section 2) and two probabilities by population subset. *P(start business in a year)* is the annual probability of starting a business among individuals aged 18 to 70 in our sample. *P(ever founder)* is the probability of having started at least one business between 2005 and 2017 for the same sample. Units are in percentage points. Columns (1)-(3), (4)-(6) and (7)-(9) are calculated for samples of all individuals, Democrats, and Republicans, respectively (see Section 2.2 for partisanship definition). *%Sample* refers to the proportion of observations with a certain characteristic in the corresponding sample. *Female* is an indicator for being female; *Educ.* ≥ *College* (*Educ. others*) is an indicator for having a college degree or higher (no college degree); *Low income*, *Middle income* and *High income* are indicators for annual household incomes of \$1,000 – \$49,999, \$50,000 – \$99,999, and \$100,000 or above, respectively; *Age xx-yy* is an indicator for being between xx and yy years old in a year; *Cohort 19xx-yy* is an indicator for being born between 19xx and 19yy.

Table 2
Probability of starting a business by *individual characteristics*

VARIABLES	(1) Party	(2) +Age	(3) +Male	(4) +Race	(5) +Educ.	(6) +Income	(7) Party×Male
Dem	-0.0815***	-0.0771***	-0.0421***	-0.0161***	-0.0242***	-0.0220***	0.0027
	(0.0093)	(0.0089)	(0.0076)	(0.0055)	(0.0057)	(0.0054)	(0.0064)
Rep	0.1621***	0.1539***	0.1529***	0.1460***	0.1258***	0.1087***	0.0550***
	(0.0061)	(0.0059)	(0.0058)	(0.0054)	(0.0052)	(0.0050)	(0.0045)
Age 18-29		-0.0605***	-0.0609***	-0.0449***	-0.0018	-0.0452***	-0.0469***
		(0.0061)	(0.0061)	(0.0055)	(0.0059)	(0.0056)	(0.0056)
Age 30-39		0.3226***	0.3302***	0.3419***	0.3611***	0.3009***	0.2999***
		(0.0141)	(0.0145)	(0.0153)	(0.0166)	(0.0143)	(0.0143)
Age 40-49		0.3296***	0.3343***	0.3415***	0.3493***	0.2954***	0.2949***
		(0.0137)	(0.0140)	(0.0145)	(0.0150)	(0.0128)	(0.0128)
Age 50-59		0.2037***	0.2044***	0.2078***	0.2095***	0.1776***	0.1773***
		(0.0082)	(0.0083)	(0.0085)	(0.0086)	(0.0074)	(0.0074)
Male			0.4330***	0.4278***	0.4256***	0.4193***	0.4048***
			(0.0208)	(0.0202)	(0.0200)	(0.0198)	(0.0198)
Black				-0.0593*	-0.0619*	-0.0948***	-0.0910***
				(0.0353)	(0.0349)	(0.0337)	(0.0338)
Hispanic				0.1508***	0.1221***	0.0582***	0.0615***
				(0.0203)	(0.0192)	(0.0178)	(0.0178)
Asian				0.4442***	0.3984***	0.3213***	0.3260***
				(0.0282)	(0.0268)	(0.0250)	(0.0250)
College+					0.1939***	0.1438***	0.1432***
					(0.0106)	(0.0082)	(0.0082)
Mid income						0.0847***	0.0852***
						(0.0042)	(0.0042)
High income						0.3504***	0.3510***
						(0.0163)	(0.0163)
Dem×Male							-0.0718***
							(0.0084)
Rep×Male							0.1191***
							(0.0103)
R^2	0.070	0.082	0.102	0.106	0.111	0.118	0.119
Outcome mean	.496	.496	.496	.496	.496	.496	.496
N obs	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978
N clusters (county)	2,123	2,123	2,123	2,123	2,123	2,123	2,123
County×Year FE	Y	Y	Y	Y	Y	Y	Y

Note: This table relates individuals' annual probability of starting a business to their personal characteristics. The sample is composed of Democrats, Republicans, and Independents, and the outcome is an indicator for starting a business in a year. Units are in percentage points. *Dem* is one for Democrats and zero for others; *Rep* is defined analogously (see Section 2.2). Apart from the reported coefficients, columns (4)-(7) also include indicators for missing race and/or missing income and the interactions between these indicators and *Dem* and *Rep*. Regressions are run at the county-party-characteristic-year cell level and are weighted by the number of observations in each cell. Standard errors are clustered by county. *** 1%, ** 5%, * 10% significance level.

Table 3
Political mismatch and the probability of starting a business

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cell-level regression				Weighted person-level regression			
	Regular voter	Active voter	Donor voter	FEC voter	Regular voter	Active voter	Donor voter	FEC voter
Mismatch	-0.0165***	-0.0119***	-0.0138***	-0.0150***	-0.0179***	-0.0138***	-0.0156***	-0.0162***
	(0.0017)	(0.0019)	(0.0019)	(0.0016)	(0.0016)	(0.0019)	(0.0019)	(0.0015)
Mismatch×Active		-0.0097***	-0.0067***	-0.0360***		-0.0080***	-0.0058***	-0.0330***
		(0.0020)	(0.0021)	(0.0128)		(0.0019)	(0.0021)	(0.0122)
Dem	-0.1641***	-0.1653***	-0.1644***	-0.1507***	-0.1706***	-0.1712***	-0.1716***	-0.1560***
	(0.0069)	(0.0085)	(0.0076)	(0.0065)	(0.0071)	(0.0089)	(0.0079)	(0.0067)
Dem×Active		-0.0049	0.0093*	-0.7080***		-0.0052	0.0103*	-0.7046***
		(0.0071)	(0.0052)	(0.0371)		(0.0072)	(0.0054)	(0.0369)
Active		0.1112***	0.0507***	1.6428***		0.1135***	0.0481***	1.6266***
		(0.0082)	(0.0045)	(0.0651)		(0.0079)	(0.0044)	(0.0623)
Male	0.4349***	0.4363***	0.4341***	0.4208***	0.4069***	0.4083***	0.4060***	0.3936***
	(0.0207)	(0.0208)	(0.0207)	(0.0202)	(0.0188)	(0.0189)	(0.0187)	(0.0183)
Age 18-29	-0.0472***	-0.0014	-0.0354***	-0.0095*	-0.0574***	-0.0102	-0.0464***	-0.0205***
	(0.0064)	(0.0071)	(0.0064)	(0.0056)	(0.0066)	(0.0071)	(0.0067)	(0.0059)
Age 30-39	0.3403***	0.3747***	0.3497***	0.3695***	0.3463***	0.3819***	0.3555***	0.3749***
	(0.0158)	(0.0158)	(0.0163)	(0.0169)	(0.0163)	(0.0163)	(0.0167)	(0.0173)
Age 40-49	0.3316***	0.3551***	0.3349***	0.3519***	0.3354***	0.3598***	0.3387***	0.3554***
	(0.0140)	(0.0140)	(0.0142)	(0.0149)	(0.0142)	(0.0142)	(0.0144)	(0.0150)
Age 50-59	0.2041***	0.2156***	0.2047***	0.2141***	0.2046***	0.2165***	0.2052***	0.2144***
	(0.0083)	(0.0083)	(0.0083)	(0.0087)	(0.0083)	(0.0083)	(0.0083)	(0.0086)
Asian	0.2508***	0.2616***	0.2511***	0.2555***	0.2580***	0.2695***	0.2583***	0.2631***
	(0.0199)	(0.0207)	(0.0199)	(0.0196)	(0.0198)	(0.0205)	(0.0197)	(0.0195)
Black	-0.1590***	-0.1564***	-0.1521***	-0.1432***	-0.1585***	-0.1555***	-0.1517***	-0.1423***
	(0.0216)	(0.0216)	(0.0213)	(0.0211)	(0.0216)	(0.0216)	(0.0213)	(0.0210)
Hispanic	-0.2151***	-0.2015***	-0.2060***	-0.1976***	-0.2120***	-0.1978***	-0.2030***	-0.1938***
	(0.0264)	(0.0269)	(0.0263)	(0.0255)	(0.0254)	(0.0259)	(0.0253)	(0.0245)
Mismatch as %mean	3.33	2.4	2.8	3.03	3.68	2.85	3.21	3.33
Mismatch×Active as %mean	-	1.94	1.35	7.26	-	1.64	1.19	6.78
R^2	0.105	0.070	0.071	0.082	0.005	0.005	0.005	0.005
Outcome mean	.495	.495	.495	.495	.485	.486	.485	.485
N obs	327,127,995	326,699,233	327,127,995	327,127,995	327,127,995	326,699,233	327,127,995	327,127,995
N clusters (county)	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how individuals' annual probability of starting a business relates to being politically mismatched with the sitting president. The sample is composed of Democrats and Republicans, and the outcome is an indicator starting a business in a year. Units are in percentage points. *Mismatch* is an indicator equal to one if an individual's political party is different from the party of the sitting president (it is one for Republicans in 2009-2016 and for Democrats in 2005-2008 and 2017). *Dem* is an indicator for Democratic individuals. *Active* is an indicator for politically active individuals, defined as (i) if they vote in an above-median share of their available even-year general and primary elections as of 2020 (columns 2 and 6); (ii) if the household has made at least one political donation by 2020 (columns 3 and 7); (iii) if the individual has made at least one FEC donation by 2020 (columns 4 and 8). Standard errors are clustered by county. "Cell-level regression" is equivalent to an unweighted individual-level regression: it is run at the county-party-characteristic-year cell level and weighted by number of observations in each cell. "Weighted person-level regression" is run at the individual level with each observation weighted so that the means of covariates in the re-weighted sample match those in the U.S. voter population. The matched characteristics are share of Democrats and, within each party, the shares of men, racial groups, and birth cohorts (see Section 3.3.2 for details). Results are similar if we match sample means to means among all voters in sample counties. *** 1%, ** 5%, * 10% significance level.

Table 4
Political mismatch and the probability of starting a business
Presidential vs. governor mismatch

	(1)	(2)	(3)
Mismatch	-0.0179***		-0.0184***
	(0.0017)		(0.0021)
Governor mismatch		-0.0206***	-0.0210***
		(0.0036)	(0.0039)
Dem	-0.1422***	-0.1407***	-0.1450***
	(0.0097)	(0.0096)	(0.0097)
Male	0.3582***	0.3582***	0.3582***
	(0.0281)	(0.0281)	(0.0281)
Age 18-29	-0.0328***	-0.0332***	-0.0332***
	(0.0071)	(0.0071)	(0.0070)
Age 30-39	0.2822***	0.2822***	0.2821***
	(0.0198)	(0.0198)	(0.0198)
Age 40-49	0.2719***	0.2718***	0.2718***
	(0.0178)	(0.0178)	(0.0178)
Age 50-59	0.1654***	0.1652***	0.1654***
	(0.0106)	(0.0106)	(0.0106)
Asian	0.1878***	0.1876***	0.1876***
	(0.0170)	(0.0170)	(0.0170)
Black	-0.1400***	-0.1394***	-0.1395***
	(0.0223)	(0.0221)	(0.0221)
Hispanic	-0.2183***	-0.2184***	-0.2184***
	(0.0440)	(0.0440)	(0.0440)
Pres. mismatch as %mean	4.38	-	4.49
Gov. mismatch as %mean	-	5.04	5.13
R^2	0.110	0.110	0.110
Outcome mean	.409	.409	.409
N obs	185,542,623	185,542,623	185,542,623
N clusters (county)	1,057	1,057	1,057
County×Year FE	Y	Y	Y

Note: This table examines how individuals' annual probability of starting a business relates to being politically mismatched with the sitting president (*Mismatch*) and with the sitting state governor (*Governor mismatch*). The sample consists of voters in states that had at least one change in the party of the governor (from Democratic to Republican or vice versa) from 2005 through 2017. All other variable definitions and specifications mirror those of Table 3 column (1). Standard errors clustered by county. *** 1%, ** 5%, * 10% significance level.

Table 5
Political mismatch and the probability of starting a business
By gender and by age

	(1) Male	(2) Female	(3) Age 18-29	(4) Age 30-49	(5) Age 50-70
Mismatch	-0.0283***	-0.0049***	-0.0188***	-0.0221***	-0.0090***
	(0.0025)	(0.0013)	(0.0021)	(0.0025)	(0.0016)
Dem	-0.2737***	-0.0896***	-0.1085***	-0.2040***	-0.1523***
	(0.0121)	(0.0047)	(0.0061)	(0.0092)	(0.0061)
Male			0.2475***	0.5636***	0.3922***
			(0.0136)	(0.0272)	(0.0184)
Age 18-29	-0.0972***	-0.0200***			
	(0.0107)	(0.0045)			
Age 30-39	0.4897***	0.2422***		0.0126***	
	(0.0225)	(0.0119)		(0.0039)	
Age 40-49	0.4567***	0.2467***			
	(0.0203)	(0.0104)			
Age 50-59	0.2679***	0.1597***			0.1997***
	(0.0117)	(0.0063)			(0.0081)
Asian	0.3752***	0.1529***	0.1351***	0.3758***	0.1642***
	(0.0364)	(0.0119)	(0.0144)	(0.0299)	(0.0140)
Black	-0.2931***	-0.0894***	-0.0976***	-0.2128***	-0.1342***
	(0.0392)	(0.0124)	(0.0154)	(0.0275)	(0.0191)
Hispanic	-0.3567***	-0.1250***	-0.0913***	-0.2739***	-0.2111***
	(0.0480)	(0.0164)	(0.0202)	(0.0339)	(0.0233)
Mismatch as %mean	3.75	1.54	7.4	3.39	2.04
R^2	0.117	0.077	0.065	0.122	0.098
Outcome mean	.756	.32	.254	.653	.444
N obs	131,246,407	195,881,588	50,051,494	125,332,715	151,743,786
N clusters (county)	2,115	2,120	2,114	2,116	2,116
County×Year FE	Y	Y	Y	Y	Y

Note: This table examines how individuals' annual probability of starting a business relates to being politically mismatched with the sitting president in different subsamples. Columns (1) through (5) re-estimate Table 3 column (1) for men, women, voters ages 18-29, voters ages 30-49, and voters ages 50-70, respectively. All specifications and variable definitions mirror those in Table 3 column (1). *** 1%, ** 5%, * 10% significance level.

Table 6
Political mismatch and the probability of starting *different types of firm*

	(1) LLC	(2) Corporation	(3) VC backed	(4) Patent firm	(5) Q: top 5%	(6) Q: 80-100%	(7) Q: 60-80%	(8) Q: 40-60%	(9) Q: 20-40%	(10) Q: 0-20%
Mismatch	-0.003*	-0.014***	-0.0000	-0.0001	-0.001***	-0.004***	-0.003***	-0.002***	-0.001**	-0.003***
	(0.001)	(0.001)	(0.0000)	(0.0001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Dem	-0.124***	-0.042***	-0.0000	-0.0006***	-0.004***	-0.022***	-0.033***	-0.035***	-0.030***	-0.031***
	(0.006)	(0.003)	(0.0000)	(0.0001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Male	0.308***	0.130***	0.0003***	0.0026***	0.020***	0.078***	0.087***	0.093***	0.080***	0.080***
	(0.014)	(0.010)	(0.0001)	(0.0002)	(0.005)	(0.011)	(0.006)	(0.007)	(0.005)	(0.005)
Age 18-29	-0.024***	-0.023***	-0.0000*	-0.0006***	-0.003***	-0.011***	-0.012***	-0.016***	-0.004***	0.004**
	(0.005)	(0.002)	(0.0000)	(0.0001)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Age 30-39	0.249***	0.094***	0.0002***	0.0007***	0.011***	0.049***	0.059***	0.066***	0.064***	0.080***
	(0.011)	(0.009)	(0.0001)	(0.0001)	(0.003)	(0.007)	(0.004)	(0.005)	(0.004)	(0.006)
Age 40-49	0.237***	0.097***	0.0002***	0.0013***	0.013***	0.054***	0.062***	0.066***	0.062***	0.068***
	(0.010)	(0.007)	(0.0000)	(0.0001)	(0.003)	(0.007)	(0.004)	(0.005)	(0.003)	(0.005)
Age 50-59	0.150***	0.055***	0.0001***	0.0007***	0.007***	0.030***	0.037***	0.042***	0.040***	0.045***
	(0.006)	(0.004)	(0.0000)	(0.0001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Asian	0.124***	0.129***	0.0003**	0.0024***	0.043***	0.124***	0.064***	0.038***	0.019***	0.008
	(0.018)	(0.008)	(0.0002)	(0.0005)	(0.008)	(0.012)	(0.012)	(0.007)	(0.004)	(0.006)
Black	-0.141***	-0.018*	-0.0001***	-0.0008***	-0.003*	-0.017***	-0.017***	-0.040***	-0.032***	-0.028***
	(0.015)	(0.009)	(0.0000)	(0.0001)	(0.002)	(0.006)	(0.005)	(0.008)	(0.005)	(0.005)
Hispanic	-0.186***	-0.028*	-0.0002***	-0.0015***	-0.018***	-0.048***	-0.050***	-0.051***	-0.020***	-0.038***
	(0.014)	(0.016)	(0.0000)	(0.0002)	(0.006)	(0.018)	(0.009)	(0.004)	(0.003)	(0.006)
Mismatch as %mean	.74	10.71	15.89	4.73	4.77	6.36	3.04	2.01	1.28	2.48
R^2	0.093	0.051	0.004	0.004	0.048	0.063	0.052	0.057	0.034	0.055
Outcome mean	.363	.134	0	.0015	.014	.069	.09	.101	.089	.101
N obs	327,126,172	327,127,995	327,127,995	327,127,995	326,925,933	326,925,933	326,925,933	326,925,933	326,925,933	326,925,933
N clusters (county)	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how individuals' annual probability of starting different types of firms relates to being politically mismatched with the sitting president. It is identical to the specification in Table 3 column (1) except that the dependent variable is an indicator for starting a specific type of firm in a year, which differs by column. Units are in percentage points. "LLC" refers to limited liability companies registered under the jurisdiction of their headquarters (or local) state. "Corporation" refers to corporations registered under local state jurisdiction. "VC backed" refers to firms that ever receive venture capital investment. "Patent firm" refers to firms that have ever filed for patents according to the USPTO data. "Q: xx" refers to businesses who score in a certain percentile range of entrepreneurial quality (Guzman and Stern, 2020).*** 1%, ** 5%, * 10% significance level.

Table 7
Political mismatch and *employer* firms: County-level business dynamics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New firm		Existing firm				All firm
	Firm entry	Job creation rate	Estab. entry	Estab. exit	Firm death	Net job creation rate	Net job creation rate
Mismatch	-5.460***	-0.003	-0.284***	0.762***	0.655***	-0.327***	-0.324***
	(0.856)	(0.002)	(0.088)	(0.172)	(0.132)	(0.064)	(0.063)
Unemp(%)	-2.503***	-0.000	0.051	1.980***	1.358***	-0.685***	-0.679***
	(0.341)	(0.000)	(0.052)	(0.169)	(0.135)	(0.067)	(0.066)
Income(k)	0.234	-0.000	-0.004	-0.042	0.174***	0.011	0.011
	(0.397)	(0.000)	(0.022)	(0.049)	(0.033)	(0.011)	(0.011)
Mismatch as %mean	2.86	0.01	1.02	1.07	1.38	30.5	33.88
R^2	0.913	0.075	0.673	0.777	0.817	0.251	0.954
Outcome mean	191.548	199.997	28.088	70.61	47.262	-1.071	0.956
N obs	41,265	40,854	126,179	146,475	138,241	170,106	210,970
N clusters (county)	3,059	3,033	3,059	3,059	3,059	3,058	3,058
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N	N	N
Firm age×Year FE	N	N	Y	Y	Y	Y	Y
Industry share	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how the entry, exit, expansion, and contraction of *employer* firms relate to being in counties that are politically mismatched with the sitting president between 2005 and 2018. "Firm entry", "Estab. entry", "Estab. exit", and "Firm death" are the annual number of new firms, newly opened establishments among existing firms, newly closed establishments among existing firms, and firms that have closed all their establishments, per 100,000 county residents at or above 20 years old, respectively. "Job creation rate" is the number of newly created jobs in year t as a percentage of the average employment between years t and t-1. "Net job creation rate" is the difference between the number of newly created jobs and the number of newly destroyed jobs in year t as a percentage of average employment between years t and t-1. The regression weight for outcomes "Job creation rate" and "Net job creation rate" is the average employment in years t and t-1; the regression weight for other outcomes is the county population ages 20 or more. Columns (1) and (2) control for county fixed effects, year fixed effects, and county economic conditions (i.e., annual unemployment rate, income per capita, and employment share for NAICS-2 industries). Columns (3) through (7) replace year fixed effects with firm age-by-year fixed effects. Standard errors are clustered by county. *** 1%, ** 5%, * 10% significance level.

Table 8
Political mismatch and the probability of starting a business:
Alternative *geographic fixed effects*

	(1)	(2)	(3)	(4)	(5)
	Level of geography fixed effects				
	State	County	Zip	Tract	Block grp
Mismatch	-0.0182***	-0.0165***	-0.0157***	-0.0153***	-0.0153***
	(0.0017)	(0.0017)	(0.0015)	(0.0014)	(0.0014)
Mismatch as %mean	3.68	3.33	3.17	3.09	3.09
R^2	0.004	0.005	0.006	0.009	0.013
Outcome mean	0.495	0.495	0.495	0.495	0.495
N obs	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995
N clusters (county)	2,120	2,120	2,120	2,120	2,120
Demographics	Y	Y	Y	Y	Y
Geo×Year FE	Y	Y	Y	Y	Y

Note: This table presents robustness checks for Table 3 column (1) under various geography-by-year fixed effects. Specifications mirror Table 3 column (1), except that each column now includes a different set of geography-by-year fixed effects. Columns (1) through (5) include state-by-year, county-by-year, zip code-by-year, census tract-by-year, and census block group-by-year fixed effects, respectively. Standard errors are clustered by county. *** 1%, ** 5%, * 10% significance level.

Table 9
Political mismatch and the probability of starting a business
By industry and county political risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Industry political risk			County-level political risk		
	Low	Middle	High	Low	Middle	High
Mismatch	-0.0027***	-0.0021***	-0.0065***	-0.0060**	-0.0184***	-0.0174***
	(0.0004)	(0.0004)	(0.0006)	(0.0028)	(0.0025)	(0.0026)
Dem	-0.0145***	-0.0302***	-0.0386***	-0.1280***	-0.1716***	-0.1656***
	(0.0009)	(0.0011)	(0.0018)	(0.0072)	(0.0104)	(0.0113)
Male	0.0605***	0.0557***	0.1124***	0.2893***	0.5144***	0.4020***
	(0.0031)	(0.0021)	(0.0047)	(0.0108)	(0.0365)	(0.0257)
Age 18-29	-0.0008	-0.0127***	-0.0045**	-0.0110**	-0.0752***	-0.0263***
	(0.0009)	(0.0009)	(0.0019)	(0.0053)	(0.0116)	(0.0076)
Age 30-39	0.0537***	0.0337***	0.1079***	0.2361***	0.3915***	0.3226***
	(0.0027)	(0.0013)	(0.0047)	(0.0111)	(0.0266)	(0.0221)
Age 40-49	0.0535***	0.0365***	0.0933***	0.2147***	0.3824***	0.3175***
	(0.0023)	(0.0013)	(0.0039)	(0.0096)	(0.0225)	(0.0205)
Age 50-59	0.0319***	0.0251***	0.0544***	0.1440***	0.2340***	0.1949***
	(0.0013)	(0.0009)	(0.0022)	(0.0061)	(0.0128)	(0.0127)
Asian	0.0534***	0.0111***	0.0233***	0.1450***	0.2407***	0.2751***
	(0.0042)	(0.0024)	(0.0040)	(0.0373)	(0.0251)	(0.0330)
Black	-0.0003	-0.0293***	-0.0383***	-0.1724***	-0.2108***	-0.1233***
	(0.0028)	(0.0024)	(0.0051)	(0.0192)	(0.0471)	(0.0200)
Hispanic	-0.0164***	-0.0364***	-0.0464***	-0.2458***	-0.2384***	-0.1811***
	(0.0046)	(0.0023)	(0.0064)	(0.0164)	(0.0445)	(0.0210)
Mismatch as %mean	3.74	3.34	5.1	1.7	3.14	3.88
R^2	0.016	0.016	0.034	0.035	0.129	0.112
Outcome mean	.072	.063	.127	.355	.587	.448
N obs	327,127,995	327,127,995	327,127,995	39,370,497	135,693,120	152,064,378
N clusters (county)	2,120	2,120	2,120	700	699	721
County×Year FE	Y	Y	Y	Y	Y	Y

Note: This table presents the heterogeneity in the mismatch effect in Table 3 column (1) by examining individuals' propensity to start businesses in industries with low, middle, and high levels of political risk (columns 1-3, respectively) and in counties whose industry employment-weighted political risk is low, middle, and high (columns 4-6, respectively). For example, if a county has 50% employment in industry A and 50% in industry B, then the county's sensitivity is the equal-weighted average of the political risk of A and B. "Finance & Insurance" (NAICS 52) is excluded. All specifications and variable definitions mirror Table 3 column (1). *** 1%, ** 5%, * 10% significance level.

Table 10
Political mismatch and the probability of starting a business
By counties' correlation with the national economy

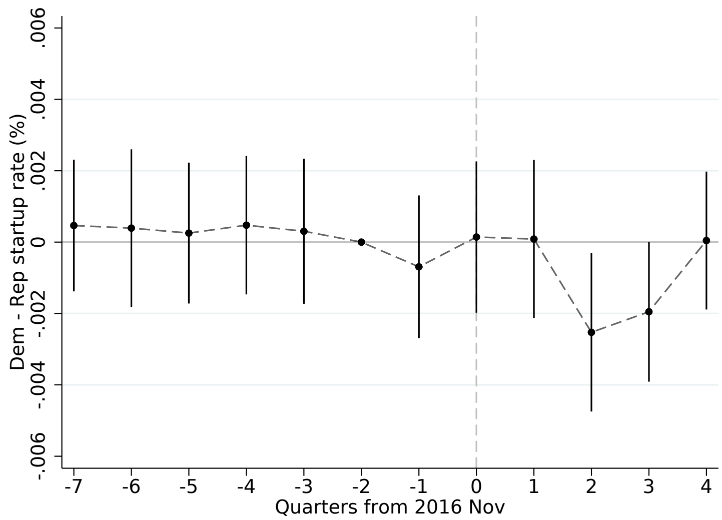
	(1)	(2)	(3)	(4)
	Quartile of county correlation with US GDP growth			
	First	Second	Third	Fourth
Mismatch	-0.0060**	-0.0124***	-0.0145***	-0.0206***
	(0.0030)	(0.0033)	(0.0036)	(0.0025)
Dem	-0.1405***	-0.1651***	-0.1327***	-0.1841***
	(0.0130)	(0.0149)	(0.0113)	(0.0109)
Male	0.3034***	0.3559***	0.3632***	0.5280***
	(0.0182)	(0.0228)	(0.0330)	(0.0346)
Age 18-29	-0.0188***	-0.0485***	-0.0376***	-0.0545***
	(0.0066)	(0.0086)	(0.0127)	(0.0105)
Age 30-39	0.2618***	0.2956***	0.2853***	0.4019***
	(0.0176)	(0.0232)	(0.0252)	(0.0267)
Age 40-49	0.2347***	0.2776***	0.2854***	0.3951***
	(0.0144)	(0.0191)	(0.0252)	(0.0229)
Age 50-59	0.1518***	0.1696***	0.1781***	0.2420***
	(0.0089)	(0.0100)	(0.0162)	(0.0134)
Asian	0.1559***	0.1666***	0.2730***	0.2727***
	(0.0224)	(0.0332)	(0.0533)	(0.0264)
Black	-0.2270***	-0.1752***	-0.1006***	-0.1739***
	(0.0386)	(0.0400)	(0.0229)	(0.0378)
Hispanic	-0.2059***	-0.1962***	-0.2169***	-0.2228***
	(0.0210)	(0.0193)	(0.0192)	(0.0433)
Mismatch as %mean	1.56	2.76	3.34	3.65
R^2	0.039	0.065	0.097	0.159
Outcome mean	.383	.449	.435	.565
N obs	35,914,427	51,788,941	80,490,173	158,934,454
N clusters (county)	566	517	519	518
County×Year FE	Y	Y	Y	Y

Note: This table explores heterogeneity in the mismatch effect in Table 3 column (1) by restricting the sample to counties in each quartile of the correlation between counties' GDP growth and national GDP growth between 2001 and 2017 (quartile cutoffs are 0.21, 0.70, and 0.88). Note that counties with a higher correlation are larger, so the number of observations increases from column (1) to (4) despite a roughly equal number of counties in each column. All specifications and variable definitions mirror Table 3 column (1). *** 1%, ** 5%, * 10% significance level.

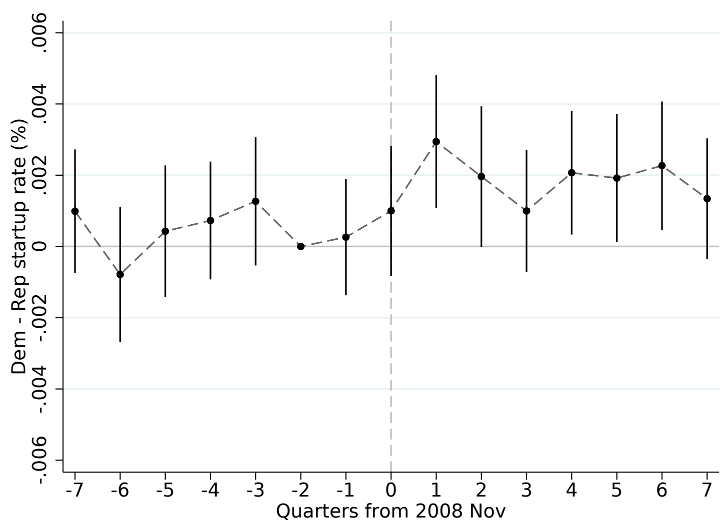
A. Internet Appendix

“Partisan Entrepreneurship”

by Joseph Engelberg, Jorge Guzman, Runjing Lu and William Mullins



(a) 2016 election

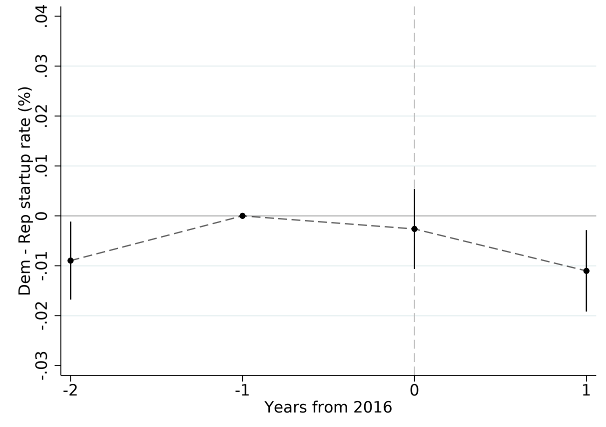


(b) 2008 election

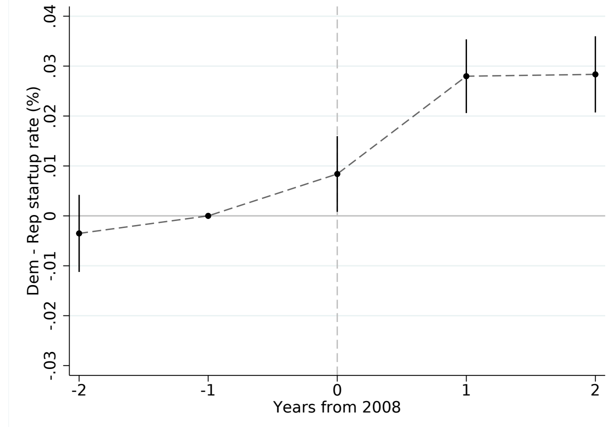
Figure A1. Political mismatch and the probability of starting a business: *Active* Democratic vs. *active* Republican individuals

Note: This figure plots the coefficients on the interactions between Democrat and event time indicators from Equation 1, capturing politically *active* Democrats' time-varying excess probability of starting a business relative to *active* Republican voters (omitted group). Units are in percentage points. Active partisans are defined as those who vote in an above-median percentage of their available even-year general and primary elections as of 2020. Event time 0 refers to the month of a presidential election, plus the two subsequent months. For example, for the 2016 election event time 0 is November 2016 through January 2017. Event time -2 is the omitted period. All regressions control for county×event time fixed effects and personal characteristics (gender, age groups, race). Regressions are run at the county-party-characteristic-month cell and are weighted by the number of observations in each cell. Standard errors are clustered by county.

All voters

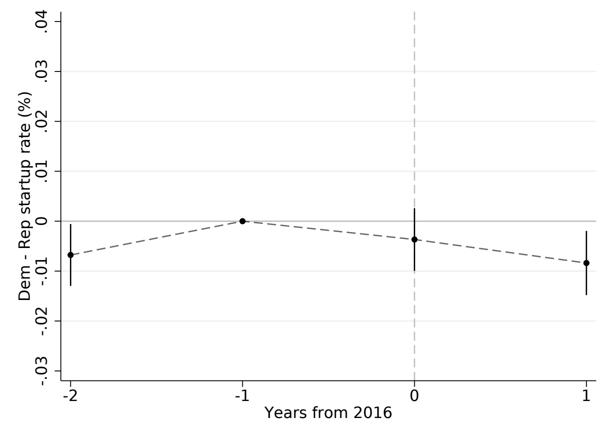


(a) 2016 election

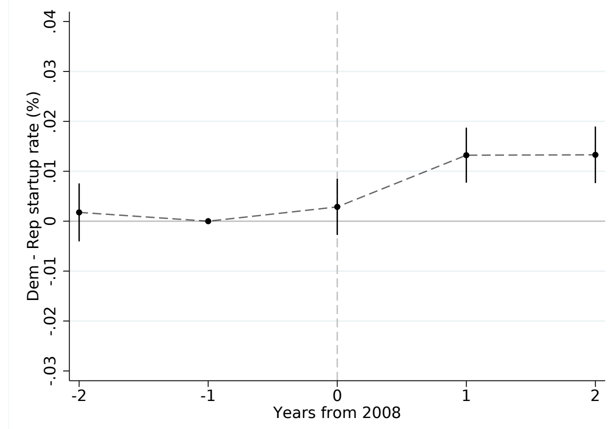


(b) 2008 election

Drop voters in multi-founder firms



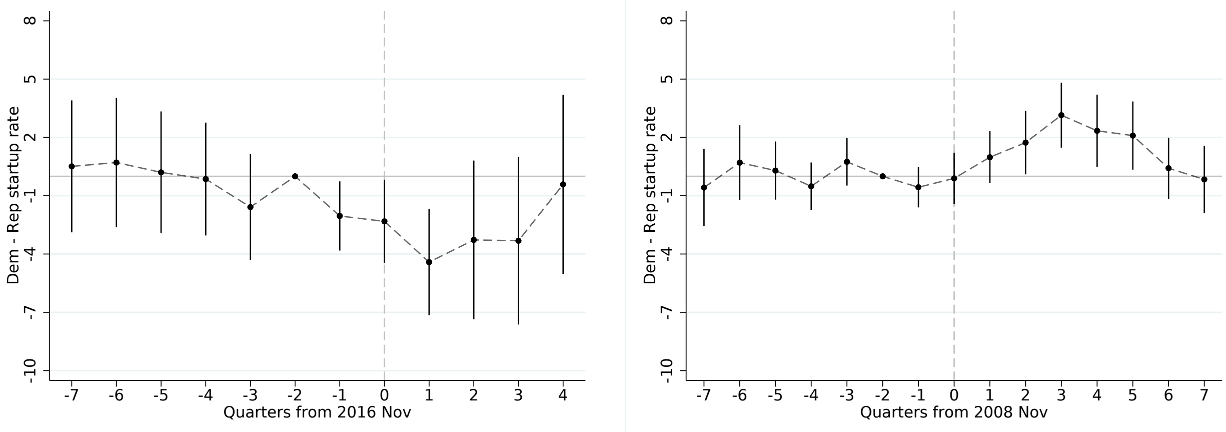
(c) 2016 election



(d) 2008 election

Figure A2. Political mismatch and the *annual* probability of starting a business Democratic vs. Republican *individuals*

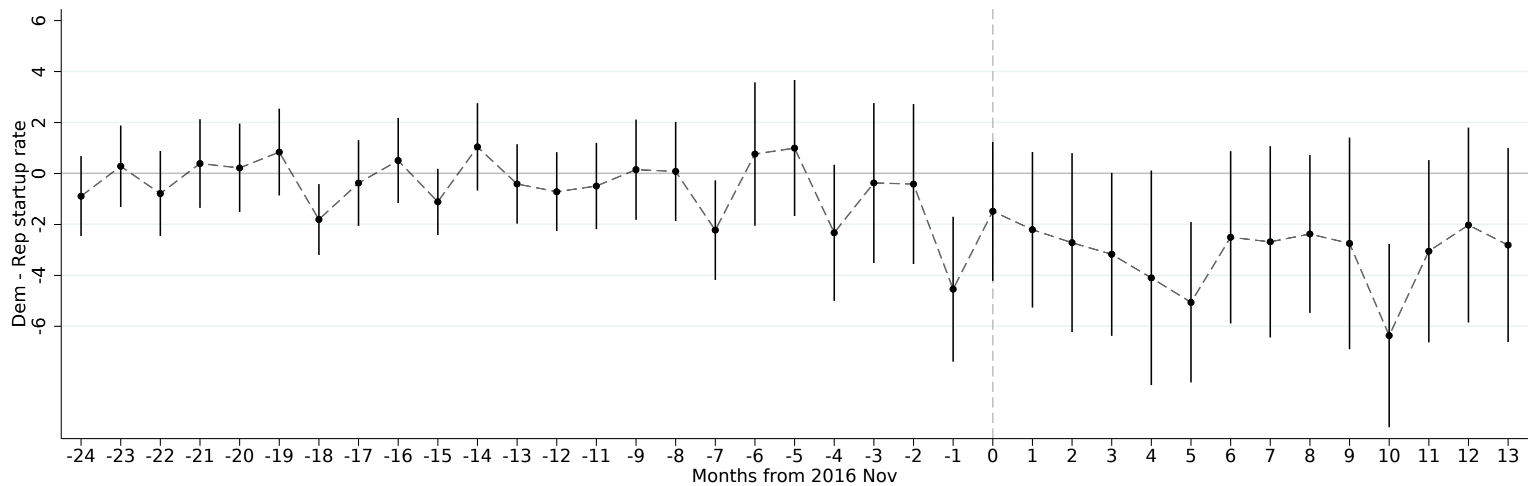
Note: This figure plots the coefficients on the interactions between Democrat and event time indicators from Equation 1 but changes data frequency from quarterly to yearly, capturing Democrats' annual excess probability of starting a business relative to Republican voters (omitted group). Event time 0 denotes the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip×year×demographic cell (interacted gender, race, and age group bins) fixed effects. Regressions are run at the zip-party-characteristic-year cell and are weighted by the number of observations in each cell. Standard errors are clustered by zip code. Panels (a) and (b) include all voters in the main sample, while (c) and (d) exclude voters if they ever started a multi-founder firm in our sample. Regression coefficients are reported in Table A3.



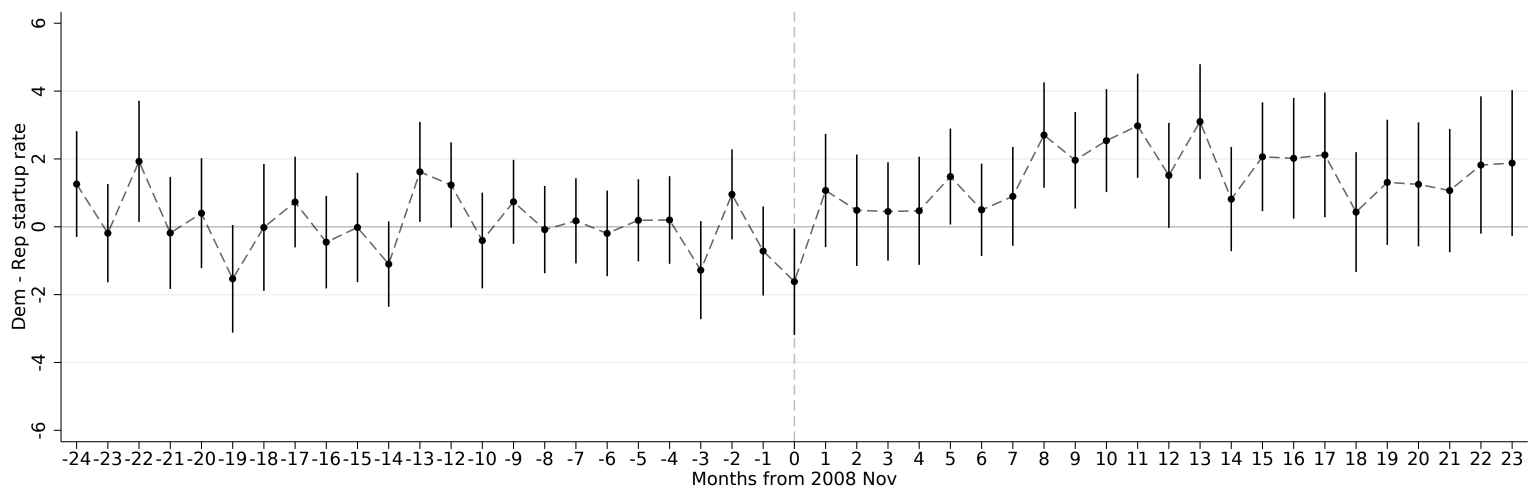
(a) 2016 election **(b)** 2008 election

Figure A3. Political mismatch and new firms: Democratic and Republican *counties* – YoY change

Note: This figure provides a robustness test for Figure 5 panels (a) and (b) by replacing the excess startup rate with the year-over-year change in the startup rate. Everything else follows Figure 5. Regression coefficients are reported in Table A12 columns (3)-(4).



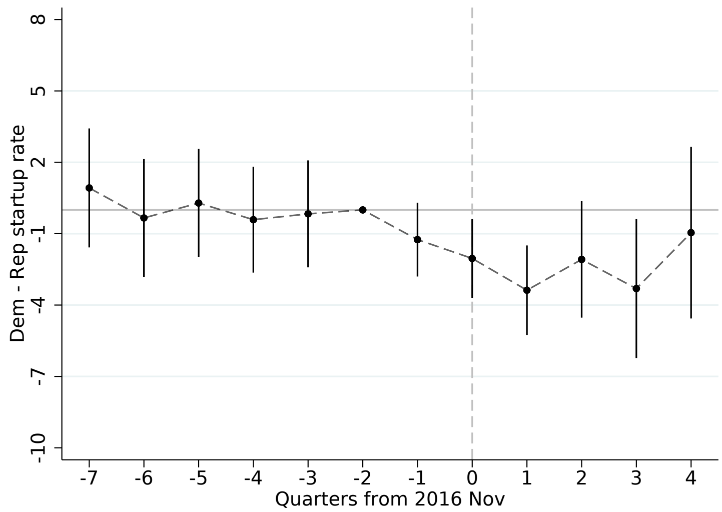
(a) 2016 election



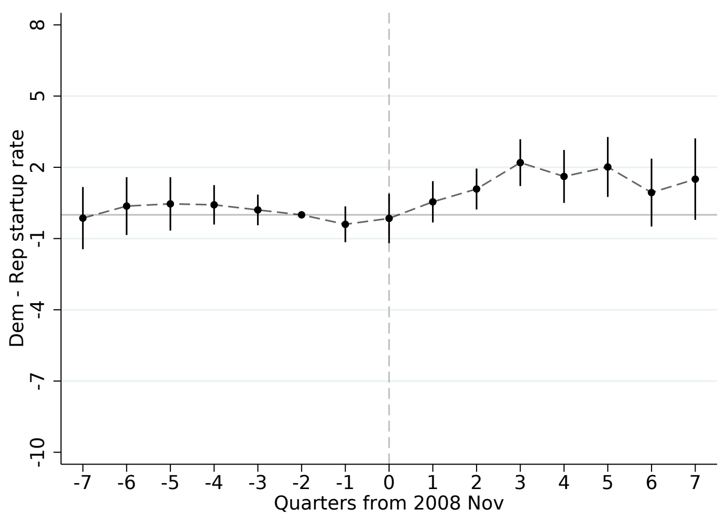
(b) 2008 election

Figure A4. Political mismatch and new firms – Democratic vs. Republican *counties* (monthly frequency)

Note: This figure plots the the monthly counterpart of Figure 5, capturing Democratic-leaning counties' startup rates relative to Republican-leaning counties (omitted group) in each month. Event time 0 refers to the month of a presidential election; the omitted period is the month before the first presidential primary/caucus election in the respective election season (Iowa caucus on January 3, 2008 and Iowa caucus on February 1, 2016), i.e., event -10 for the 2008 election and -11 for the 2016. All regressions control for county fixed effects, event time fixed effects, and county economic conditions (monthly unemployment rate, annual per capita income, and annual employment share for 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county.



(a) 2016 election

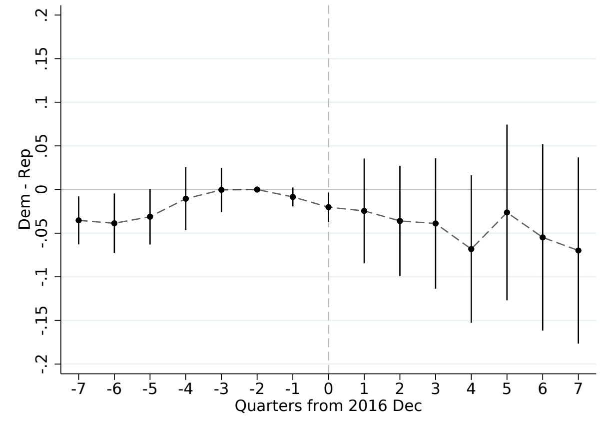


(b) 2008 election

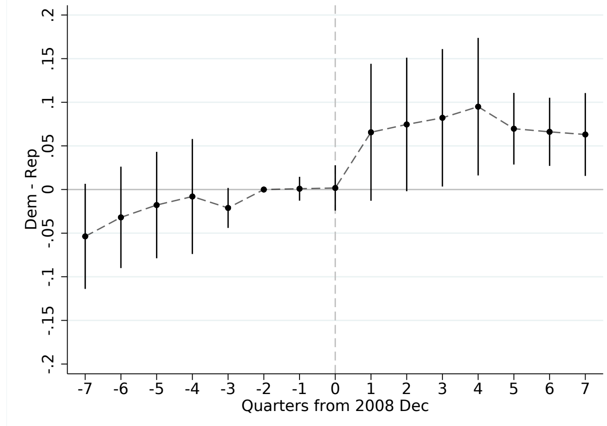
Figure A5. Political mismatch and new firms
Democratic vs. Republican *counties* (excluding economic controls)

Note: This figure presents a robustness check for Figure 5. All specifications are the same except that we *exclude* controls for county economic conditions in this figure.

Establishment count change

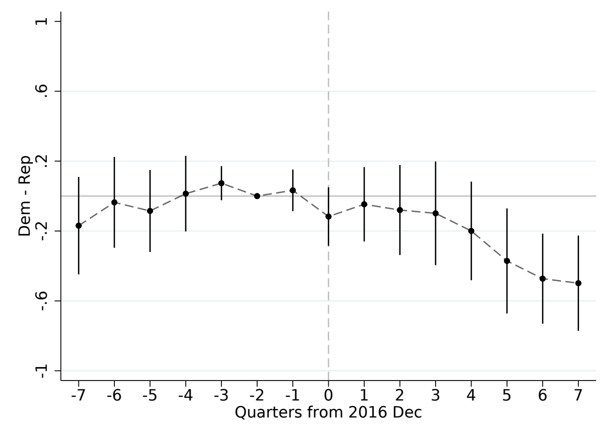


(a) 2016 election

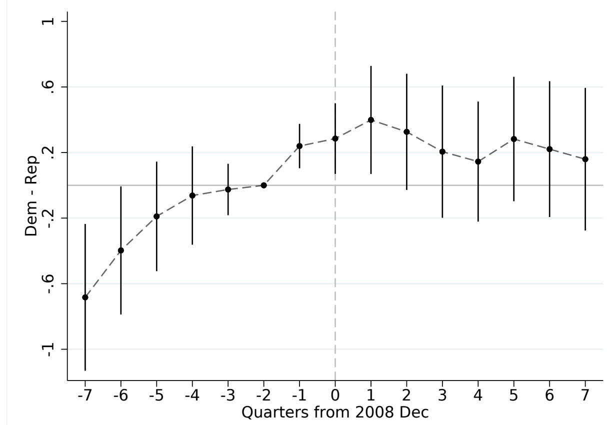


(b) 2008 election

Employment growth rate



(c) 2016 election



(d) 2008 election

Figure A6. Political mismatch and county economic outcomes from QCEW

Note: This figure plots the coefficients on the interactions between Democratic-leaning and event time indicators from Equation 3, capturing these counties' year-over-year economic performance relative to Republican-leaning counties (omitted group) in each time period. The data is from the BLS Quarterly Census of Employment and Wages (QCEW) The dependent variables are (i) the change in establishment count from the same quarter of the preceding year (per 100,000 county residents aged 20 and above), and (ii) the growth rate in employment from the same quarter last year using the Davis-Haltiwanger-Schuh (DHS) denominator. The data is at the county-by-industry-by-quarter level, so all regressions control for county fixed effects and industry-by-quarter fixed effects; industry is defined at the NAICS 6-digit level. Regressions are weighted by county population ages 20 and above (first row) or the DHS denominator (second row). Standard errors are clustered by county.

Table A1
Voter characteristics across samples

	%All parties	% Democrat	% Republican
Panel A: All US voters			
Male	46.57	41.81	49.97
White	75.80	61.76	91.19
Black	10.39	19.42	1.42
Hispanic	10.97	16.13	5.55
Asian	2.83	2.69	1.84
Cohort 1990+	7.37	6.87	4.63
Cohort 1980-89	15.00	14.74	9.88
Cohort 1970-79	15.33	14.26	13.09
Cohort 1960-69	18.77	17.54	20.55
Cohort 1950-59	19.24	20.03	21.57
Cohort 1940-	24.30	26.56	30.29
N voters	159,029,424	61,168,464	49,201,960
N States	51	51	51
Panel B: Voters in sample states			
Male	46.68	41.90	49.82
White	75.40	62.05	90.06
Black	9.30	16.33	1.39
Hispanic	12.37	18.83	6.53
Asian	2.93	2.79	2.02
Cohort 1990+	7.42	6.80	4.73
Cohort 1980-89	15.11	14.77	10.11
Cohort 1970-79	15.25	14.20	13.14
Cohort 1960-69	18.54	17.39	20.20
Cohort 1950-59	19.21	20.09	21.36
Cohort 1940-	24.46	26.74	30.46
N voters	107,914,168	40,744,516	34,203,120
N States	33	33	33
Panel C: Voters in regression sample			
Male	41.32	36.15	44.62
White	75.81	62.46	91
Black	11.07	19.82	1.50
Hispanic	9.40	13.99	5.08
Asian	3.72	3.73	2.41
Cohort 1990+	7.88	7.44	4.79
Cohort 1980-89	15.26	15.45	10.06
Cohort 1970-79	17.09	16.17	14.98
Cohort 1960-69	20.53	19.22	22.94
Cohort 1950-59	20.97	22.05	23.90
Cohort 1940-	18.27	19.67	23.32
N voters	40,420,508	14,696,895	13,083,051
N States	33	33	33

Note: This table reports summary statistics of demographics for all voters in L2's 2014 voter file (panel A), all voters in counties included in our regression sample (panel B), and voters in our regression sample (panel C). See Section 2 for sample construction and note to Table 1 for variable definitions.

Table A2
Political mismatch and the probability of starting a business
Democratic vs. Republican *Individuals*

	(1) Election 2008	(2) Election 2016
Dem×-7Q	-0.00001	0.00005
	(0.00071)	(0.00075)
Dem×-6Q	-0.00113	0.00047
	(0.00079)	(0.00077)
Dem×-5Q	-0.00042	0.00039
	(0.00071)	(0.00072)
Dem×-4Q	-0.00099	0.00101
	(0.00064)	(0.00068)
Dem×-3Q	-0.00009	0.00070
	(0.00070)	(0.00074)
Dem×-1Q	-0.00002	-0.00042
	(0.00064)	(0.00075)
Dem×0Q	0.00097	-0.00055
	(0.00071)	(0.00074)
Dem×1Q	0.00148**	-0.00045
	(0.00068)	(0.00074)
Dem×2Q	0.00144*	-0.00240***
	(0.00077)	(0.00083)
Dem×3Q	0.00101	-0.00123*
	(0.00063)	(0.00072)
Dem×4Q	0.00154**	-0.00052
	(0.00067)	(0.00073)
Dem×5Q	0.00047	
	(0.00069)	
Dem×6Q	0.00099	
	(0.00066)	
Dem×7Q	0.00007	
	(0.00068)	
Avg 1-4Q as %mean	3.35	-2.38
R^2	0.004	0.004
Outcome mean	.04	.048
N obs	1,156,960,752	864,092,632
N clusters (county)	2,119	2,118
Demographics	Y	Y
County×Event FE	Y	Y

Note: This table reports regression coefficients plotted in Figure 2. See note to the figure for details. *** 1%, ** 5%, * 10% significance level.

Table A3
Political mismatch and the *annual* probability of starting a business
Democratic vs. Republican *Individuals*

	(1)	(2)	(3)	(4)
	All voters		Drop voters in multi-founder firms	
	2008	2016	2008	2016
Dem×-2Y	-0.0035	-0.0090*	0.0018	-0.0068*
	(0.0047)	(0.0047)	(0.0035)	(0.0038)
Dem×0Y	0.0084*	-0.0026	0.0029	-0.0037
	(0.0046)	(0.0049)	(0.0034)	(0.0038)
Dem×1Y	0.0280***	-0.0110**	0.0132***	-0.0084**
	(0.0045)	(0.0050)	(0.0034)	(0.0039)
Dem×2Y	0.0283***		0.0133***	
	(0.0046)		(0.0034)	
Avg 1-2Y as %mean	5.96	-2.04	4.82	-2.54
R^2	0.171	0.177	0.164	0.170
Outcome mean	.472	.539	.275	.331
N obs	128,138,349	96,930,280	124,589,911	94,204,727
N clusters (zip)	22,621	22,599	22,617	22,595
Zip×Year×Demographics FE	Y	Y	Y	Y

Note: This table reports regression coefficients plotted in Figure A2. See note to the figure for details. *** 1%, ** 5%, * 10% significance level.

Table A4
Political mismatch and the probability of starting a business
By household income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High household income				Low household income			
	Regular voter	Active voter	Donor voter	FEC voter	Regular voter	Active voter	Donor voter	FEC voter
Mismatch	-0.0223***	-0.0149***	-0.0194***	-0.0194***	-0.0145***	-0.0118***	-0.0122***	-0.0138***
	(0.0029)	(0.0034)	(0.0036)	(0.0027)	(0.0012)	(0.0014)	(0.0015)	(0.0012)
Mismatch×Active		-0.0151***	-0.0063	-0.0524***		-0.0054***	-0.0063***	-0.0226
		(0.0040)	(0.0041)	(0.0171)		(0.0019)	(0.0020)	(0.0142)
Dem	-0.1755***	-0.1628***	-0.1778***	-0.1568***	-0.1124***	-0.1083***	-0.1132***	-0.1066***
	(0.0092)	(0.0109)	(0.0098)	(0.0089)	(0.0046)	(0.0056)	(0.0054)	(0.0045)
Dem×Active		-0.0387***	0.0095	-0.8082***		-0.0112**	0.0074*	-0.4724***
		(0.0100)	(0.0066)	(0.0490)		(0.0047)	(0.0043)	(0.0256)
Active		0.0929***	0.0332***	1.8234***		0.1040***	0.0320***	1.1304***
		(0.0143)	(0.0065)	(0.0852)		(0.0048)	(0.0031)	(0.0324)
Male	0.6883***	0.6893***	0.6881***	0.6617***	0.2866***	0.2878***	0.2859***	0.2812***
	(0.0388)	(0.0388)	(0.0388)	(0.0377)	(0.0113)	(0.0114)	(0.0113)	(0.0113)
Age 18-29	-0.1463***	-0.1161***	-0.1381***	-0.0651***	-0.0217***	0.0200***	-0.0141***	-0.0040
	(0.0125)	(0.0137)	(0.0125)	(0.0103)	(0.0039)	(0.0039)	(0.0040)	(0.0038)
Age 30-39	0.4072***	0.4299***	0.4140***	0.4707***	0.2345***	0.2672***	0.2409***	0.2499***
	(0.0216)	(0.0206)	(0.0220)	(0.0244)	(0.0117)	(0.0119)	(0.0120)	(0.0120)
Age 40-49	0.4156***	0.4313***	0.4179***	0.4607***	0.2153***	0.2380***	0.2180***	0.2282***
	(0.0199)	(0.0192)	(0.0201)	(0.0221)	(0.0089)	(0.0091)	(0.0090)	(0.0092)
Age 50-59	0.2704***	0.2783***	0.2708***	0.2943***	0.1401***	0.1511***	0.1407***	0.1471***
	(0.0131)	(0.0127)	(0.0131)	(0.0142)	(0.0053)	(0.0054)	(0.0053)	(0.0055)
Asian	0.2979***	0.3052***	0.2979***	0.3078***	0.1308***	0.1395***	0.1313***	0.1330***
	(0.0301)	(0.0313)	(0.0300)	(0.0293)	(0.0107)	(0.0108)	(0.0107)	(0.0107)
Black	-0.1017***	-0.1015***	-0.0984***	-0.0766***	-0.0860***	-0.0855***	-0.0818***	-0.0802***
	(0.0259)	(0.0259)	(0.0258)	(0.0253)	(0.0135)	(0.0136)	(0.0133)	(0.0134)
Hispanic	-0.2320***	-0.2256***	-0.2265***	-0.2080***	-0.1322***	-0.1205***	-0.1264***	-0.1245***
	(0.0303)	(0.0313)	(0.0300)	(0.0287)	(0.0177)	(0.0180)	(0.0179)	(0.0176)
Mismatch as %mean	2.91	1.94	2.54	2.53	4.21	3.41	3.53	3.99
Mismatch×Active as %mean	-	1.97	.81	6.82	-	1.56	1.81	6.54
R^2	0.185	0.124	0.124	0.134	0.073	0.047	0.048	0.055
Outcome mean	.767	.767	.767	.767	.345	.345	.345	.345
N obs	114,056,924	113,945,835	114,056,924	114,056,924	205,764,381	205,463,991	205,764,381	205,764,381
N clusters (county)	2,108	2,108	2,108	2,108	2,111	2,111	2,111	2,111
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how the annual probability of starting a business relates to being politically mismatched with the sitting president for individuals with different levels of household income. Columns (1) through (4) re-estimate Table 3 columns (1) through (4) for voters whose annual household income is above $100,000 and columns (5) through (8) for those whose household income is lower. All specifications and variable definitions mirror the corresponding columns in Table 3. *** 1%, ** 5%, * 10% significance level.

Table A5
Political mismatch and the probability of starting a business
Alternative sample construction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Alternative name probability cutoff					Large counties	Using M.I. to match			Drop voters in
	.001	.0005	.0001	.00001	.000001	only	M.I.≥50%	M.I.≥40%	All states	multi-founder firms
Mismatch	-0.0165***	-0.0159***	-0.0145***	-0.0137***	-0.0130***	-0.0215***	-0.0153***	-0.0163***	-0.127***	-0.0097***
	(0.0017)	(0.0017)	(0.0017)	(0.0019)	(0.0021)	(0.0039)	(0.0015)	(0.0012)	(0.0011)	(0.0011)
Mismatch as %mean	3.33	3.29	3.13	3.1	3.01	3.42	3.73	5.45	4.8	3.28
R^2	0.105	0.097	0.083	0.072	0.073	0.256	0.094	0.087	0.077	0.104
Outcome mean	.495	.485	.464	.443	.433	.628	.411	.3	.265	.297
N obs	327,127,995	300,585,237	247,047,846	194,067,313	164,502,939	115,683,441	336,951,143	351,738,489	352,708,613	318,961,581
N clusters (county)	2,120	2,119	2,117	2,113	2,109	98	2,120	2,120	2,120	2,120
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table reports robustness tests for our main mismatch specification – Table 3 column (1). Column (1) replicates the baseline result, while columns (2)-(5) restrict the sample to voters whose name probability is below the alternative name-uniqueness cutoffs reported in the table header. Column (6) restricts the sample to counties with at least 300,000 voters in the voter file data (approximately the 95th percentile of US counties). The fraction of L2 voters with non-missing middle initials (M.I.) is roughly 80% across all states in our sample. However, this fraction among founders in SCP data varies from less than 10% in Arizona to above 60% in Colorado, indicating state-level differences in recording M.I. in the business registry. Therefore, in columns (7)-(9) we use M.I. to construct the sample and match voters to founders only in states whose M.I. non-missing rate is at least 50%, at least 40%, and in all states, respectively; for the remaining states in each column, we do not use M.I. Column (10) excludes voters if they ever started a multi-founder firm in our sample; in other words, founders in this column are the sole personnel listed on the business registry of their firms. All specifications and variable definitions mirror Table 3 column (1). *** 1%, ** 5%, * 10% significance level.

Table A6
Political mismatch and the probability of starting a *corporation*
Presidential vs. governor mismatch

	(1)	(2)	(3)
Mismatch	-0.0127***		-0.0127***
	(0.0009)		(0.0009)
Governor mismatch		-0.0002	-0.0005
		(0.0014)	(0.0011)
Dem	-0.0348***	-0.0319***	-0.0349***
	(0.0019)	(0.0019)	(0.0020)
Male	0.1109***	0.1109***	0.1109***
	(0.0125)	(0.0126)	(0.0126)
Age 18-29	-0.0223***	-0.0223***	-0.0223***
	(0.0017)	(0.0018)	(0.0018)
Age 30-39	0.0735***	0.0736***	0.0735***
	(0.0099)	(0.0099)	(0.0099)
Age 40-49	0.0771***	0.0771***	0.0771***
	(0.0083)	(0.0083)	(0.0083)
Age 50-59	0.0433***	0.0432***	0.0433***
	(0.0049)	(0.0049)	(0.0049)
Asian	0.1249***	0.1250***	0.1249***
	(0.0110)	(0.0110)	(0.0110)
Black	-0.0062	-0.0061	-0.0061
	(0.0044)	(0.0044)	(0.0044)
Hispanic	-0.0613***	-0.0613***	-0.0613***
	(0.0196)	(0.0196)	(0.0196)
Pres. mismatch as %mean	11.82	-	11.83
Gov. mismatch as %mean	-	.2	.44
R^2	0.041	0.041	0.041
Outcome mean	.107	.107	.107
N obs	185,542,623	185,542,623	185,542,623
N clusters (county)	1057	1057	1057
County×Year FE	Y	Y	Y

Note: This table examines how individuals' annual probability of starting a *corporation* relates to being politically mismatched with the sitting president (*Mismatch*) vs. with the sitting state governor (*Governor mismatch*). This is the same analysis as Table 4 except that the dependent variable is now an indicator for starting a new corporation in a year. The sample consists of voters in states that had at least one change in the party of the governor (from Democratic to Republican or vice versa) from 2005 through 2017. All variable definitions and specifications mirror those in Table 4. *** 1%, ** 5%, * 10% significance level.

Table A7
Political mismatch and the ex-ante quality of firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Ex-ante firm quality					
	Top 5%	Top 10%	Top 25%	Top 5%	Top 10%	Top 25%
Mismatch	0.158***	0.281***	0.201**	0.151***	0.270***	0.142
	(0.056)	(0.067)	(0.098)	(0.054)	(0.066)	(0.095)
Dem	0.316**	0.389**	0.431**	0.291**	0.324**	0.311**
	(0.152)	(0.180)	(0.168)	(0.140)	(0.157)	(0.133)
Mismatch as %mean	7.98	4.38	1.74	7.34	3.65	1.26
R^2	0.130	0.231	0.290	0.136	0.240	0.325
Outcome mean	3.964	8.874	24.634	3.964	8.874	24.634
N obs	1,236,680	1,236,680	1,236,680	1,236,680	1,236,680	1,236,680
N clusters (county)	1578	1578	1578	1578	1578	1578
Demographics	Y	Y	Y	Y	Y	Y
County×Inc. year FE	Y	Y	Y	Y	Y	Y
Industry×Inc. year	N	N	N	Y	Y	Y

Note: This table compares the ex-ante quality of firms started in years when the founders are politically matched vs. mismatched with the sitting president. The outcome is an indicator for whether the firm is in the top 5, 10, or 25th percentile of the Guzman and Stern (2020) quality distribution; units are in percentage points. The sample is a cross-section of firm-founder pairs for firms incorporated between 2005 and 2017. Columns (1)-(3) control for founder demographics and county-by-incorporation year fixed effects; columns (4)-(6) additionally control for the 2-digit NAICS industry-by-incorporation year fixed effects. Standard errors are clustered by county. *** 1%, ** 5%, * 10% significance level.

Table A8
Political mismatch and the probability of starting firms *by industry*

VARIABLES	(1) Science & Tech	(2) Real estate	(3) Health & Social	(4) Cons-truction	(5) Other service	(6) Retail trade	(7) Accom. & Food	(8) Agri-culture	(9) Public admin.	(10) Trans-portation	(11) Admin.	(12) Arts & Entmt.
Mismatch	-0.0001	-0.0026***	-0.0016***	-0.0048***	-0.0025***	-0.0007***	-0.0002	0.0006***	-0.0004**	-0.0006***	-0.0006***	-0.0000
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Dem	-0.0123***	-0.0232***	-0.0106***	-0.0150***	-0.0090***	-0.0043***	-0.0030***	-0.0070***	-0.0046***	-0.0005**	-0.0034***	-0.0016***
	(0.0008)	(0.0011)	(0.0007)	(0.0006)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Male	0.0387***	0.0399***	0.0185***	0.0526***	0.0217***	0.0153***	0.0135***	0.0124***	0.0122***	0.0144***	0.0115***	0.0059***
	(0.0020)	(0.0018)	(0.0013)	(0.0019)	(0.0011)	(0.0009)	(0.0008)	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0004)
Age 18-29	-0.0052***	-0.0147***	-0.0078***	0.0054***	-0.0035***	0.0006*	-0.0013***	-0.0026***	-0.0032***	0.0007***	0.0031***	0.0020***
	(0.0009)	(0.0009)	(0.0008)	(0.0006)	(0.0006)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Age 30-39	0.0432***	0.0192***	0.0284***	0.0352***	0.0227***	0.0138***	0.0115***	0.0039***	0.0065***	0.0098***	0.0107***	0.0075***
	(0.0024)	(0.0009)	(0.0016)	(0.0013)	(0.0012)	(0.0007)	(0.0006)	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0005)
Age 40-49	0.0356***	0.0242***	0.0262***	0.0306***	0.0218***	0.0135***	0.0130***	0.0040***	0.0071***	0.0098***	0.0088***	0.0060***
	(0.0018)	(0.0010)	(0.0014)	(0.0011)	(0.0010)	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Age 50-59	0.0203***	0.0175***	0.0161***	0.0177***	0.0130***	0.0079***	0.0080***	0.0046***	0.0044***	0.0056***	0.0049***	0.0028***
	(0.0010)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Mi race	0.0061***	0.0068***	0.0096***	-0.0003	0.0033***	0.0057***	0.0033***	-0.0014***	0.0008*	0.0021***	-0.0002	-0.0001
	(0.0012)	(0.0019)	(0.0018)	(0.0009)	(0.0010)	(0.0010)	(0.0006)	(0.0003)	(0.0005)	(0.0006)	(0.0002)	(0.0002)
Asian	0.0112***	0.0145***	0.0258***	-0.0078***	0.0174***	0.0125***	0.0317***	-0.0033***	0.0018**	0.0042***	-0.0028***	-0.0019***
	(0.0023)	(0.0025)	(0.0028)	(0.0012)	(0.0016)	(0.0012)	(0.0019)	(0.0006)	(0.0008)	(0.0011)	(0.0004)	(0.0005)
Black	-0.0264***	-0.0229***	0.0020	-0.0135***	0.0127***	-0.0045***	-0.0060***	-0.0070***	-0.0049***	0.0075***	-0.0024***	-0.0001
	(0.0029)	(0.0021)	(0.0019)	(0.0013)	(0.0016)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0010)	(0.0004)	(0.0004)
Hispanic	-0.0291***	-0.0214***	-0.0160***	-0.0029	-0.0098***	-0.0050***	-0.0034***	-0.0098***	-0.0074***	0.0032***	-0.0021***	-0.0048***
	(0.0027)	(0.0018)	(0.0027)	(0.0023)	(0.0013)	(0.0010)	(0.0011)	(0.0006)	(0.0005)	(0.0012)	(0.0005)	(0.0005)
Mismatch as %mean	.21	6.02	4.21	13.18	7.59	3.7	.97	4.4	2.86	5.15	5.56	.35
R^2	0.020	0.015	0.011	0.014	0.009	0.006	0.005	0.008	0.005	0.006	0.006	0.004
Outcome mean	.051	.043	.038	.036	.033	.017	.016	.012	.012	.011	.01	.007
N obs	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995
N clusters (county)	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how individuals' annual probability of starting businesses in different NAICS-2 industries relates to being politically mismatched with the sitting president. It is identical to the specification in Table 3 column (1) except that the dependent variable is an indicator for starting firms in a specific industry in a year, which differs by column. Units are in percentage points. Firms are classified into industries based on the presence of industry-specific keywords in their names (see Appendix A). We report the 12 most populated industries in our sample. *** 1%, ** 5%, * 10% significance level.

Table A9
Political mismatch and employer firms
County-level business dynamics (excluding economic controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New firm		Existing firm				All firm
	Firm entry	Job creation rate	Estab. entry	Estab. exit	Firm death	Net job creation rate	Net job creation rate
Mismatch	-4.964***	-0.003	-0.287***	0.484***	0.518***	-0.188***	-0.186***
	(1.017)	(0.002)	(0.091)	(0.175)	(0.122)	(0.058)	(0.057)
Mismatch as %mean	2.6	0.01	1.02	0.68	1.09	17.55	19.46
R^2	0.902	0.075	0.671	0.775	0.816	0.235	0.953
Outcome mean	191.523	199.997	28.123	70.618	47.256	-1.069	0.954
N obs	41,986	41,575	128,475	149,157	140,668	173,018	214,603
N clusters (county)	3,111	3085	3,111	3,111	3,111	3,110	3,110
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N	N	N
Firm age×Year FE	N	N	Y	Y	Y	Y	Y
Economic controls	N	N	N	N	N	N	N

Note: This table presents a robustness test for Table 7. All specifications mirror those in the corresponding columns of Table 7 except that we exclude controls for county economic conditions.

Table A10
Political mismatch and performance of pre-election firms and founders
Democratic vs. Republican individuals

	Election 2008		Election 2016		
	(1) Num. of employees	(2) Sales/Employee	(3) Num. of employees	(4) Sales/Employee	(5) Founder income (L2)
Dem×Y2005	0.005	0.207			
	(0.058)	(1.475)			
Dem×Y2006	0.037	0.643			
	(0.050)	(1.324)			
Dem×Y2007	-0.003	1.136			
	(0.036)	(1.170)			
Dem×Y2009	0.046	-0.793			
	(0.029)	(0.832)			
Dem×Y2010	0.107**	-0.613			
	(0.042)	(1.206)			
Dem×Y2011	0.127***	-0.551			
	(0.046)	(1.439)			
Dem×Y2013			0.030	3.228	
			(0.063)	(2.721)	
Dem×Y2014			-0.018	2.084	
			(0.049)	(2.412)	
Dem×Y2015			-0.037	0.452	-0.229
			(0.038)	(1.760)	(0.437)
Dem×Y2017			-0.056	0.647	-0.344
			(0.034)	(2.160)	(0.220)
Dem×Y2018			-0.074*	0.065	0.292
			(0.041)	(2.468)	(0.289)
Dem×Y2019			-0.043	1.046	0.677**
			(0.047)	(2.805)	(0.281)
Dem×Y2020					0.475
					(0.308)
Dem	-0.477***	-1.696	-0.144**	-3.763	-6.959***
	(0.069)	(1.635)	(0.060)	(2.327)	(0.400)
Post avg. as %mean	2.39	-.38	-1.75	.31	.25
Observations	337,340	337,340	285,815	285,815	1,202,005
R^2	0.369	0.790	0.404	0.791	0.301
Outcome mean	3.885	173.916	3.323	185.52	108.2
N clusters (county)	1,821	1,821	1,793	1,793	1,842
Demographics	Y	Y	Y	Y	Y
Geo×Year FE	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y
Geo×Inc. year FE	Y	Y	Y	Y	Y
Industry×Inc. year FE	Y	Y	Y	Y	Y

Note: Columns (1)-(4) report the regression coefficients plotted in Figure 6. See note to figure for details. Column (5) studies the annual household income of voters who founded LLCs in 2009-2012. Income data (in \$ thousands) is obtained by L2 from Experian and is available for 2015-2020. All regressions control for geography×year, geography×incorporation year, industry×year, and industry×incorporation year fixed effects, as well as founder demographics (i.e., gender, age groups, race). Geography refers to county in columns (1)-(4) and zip code in column (5). "Post avg." refers to the average of coefficients in the three years after the election year in columns (1)-(4) and in the four years afterwards in column (5). Standard errors are clustered by county. *** 1%, ** 5%, * 10% significance level.

Table A11
Political mismatch and the probability of starting a business: Alternative *geographic fixed effects*

	(1)	(2)	(3)	(4)	(5)
	Level of geography fixed effects				
	State	County	Zip	Tract	Block grp
Panel A: Active voter					
Mismatch	-0.0136***	-0.0119***	-0.0112***	-0.0107***	-0.0107***
	(0.0019)	(0.0019)	(0.0016)	(0.0016)	(0.0016)
Mismatch×Active	-0.0100***	-0.0097***	-0.0091***	-0.0091***	-0.0091***
	(0.0020)	(0.0020)	(0.0019)	(0.0019)	(0.0019)
R^2	0.004	0.005	0.007	0.009	0.013
Panel B: HH Donor					
Mismatch	-0.0156***	-0.0138***	-0.0131***	-0.0127***	-0.0127***
	(0.0019)	(0.0019)	(0.0017)	(0.0017)	(0.0017)
Mismatch×Active	-0.0065***	-0.0067***	-0.0066***	-0.0064***	-0.0063***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
R^2	0.004	0.005	0.007	0.009	0.013
Panel C: FEC Donor					
Mismatch	-0.0167***	-0.0150***	-0.0143***	-0.0139***	-0.0139***
	(0.0016)	(0.0016)	(0.0014)	(0.0013)	(0.0013)
Mismatch×Active	-0.0364***	-0.0360***	-0.0353***	-0.0353***	-0.0346***
	(0.0130)	(0.0128)	(0.0127)	(0.0126)	(0.0126)
R^2	0.005	0.005	0.007	0.009	0.014
Outcome mean	0.495	0.495	0.495	0.495	0.495
N obs	327,127,995	327,127,995	327,127,995	327,127,995	327,127,995
N clusters (county)	2,120	2,120	2,120	2,120	2,120
Demographics	Y	Y	Y	Y	Y
Geo×Year FE	Y	Y	Y	Y	Y

Note: This table presents robustness checks for Table 3 under various geography-by-year fixed effects. Specifications in panels A, B, and C mirror Table 3 columns (2), (3), and (4), respectively, except that each column now includes a different set of geography-by-year fixed effects. Columns (1) through (5) control for state-by-year, county-by-year, zip code-by-year, census tract-by-year, and census block group-by-year fixed effects, respectively. Standard errors are clustered by county. *** 1%, ** 5%, * 10% significance level.

Table A12
Political mismatch and new firms
Democratic vs. Republican *counties*

	Dep. var.: startups per 100k		Dep. var.: YoY change	
	(1) Election 2008	(2) Election 2016	(3) Election 2008	(4) Election 2016
Dem×-7Q	-0.463	1.037	-0.579	0.511
	(0.789)	(1.540)	(1.208)	(2.064)
Dem×-6Q	0.058	-0.216	0.703	0.709
	(0.727)	(1.534)	(1.169)	(2.017)
Dem×-5Q	0.136	0.432	0.296	0.202
	(0.663)	(1.425)	(0.909)	(1.906)
Dem×-4Q	0.228	-0.294	-0.513	-0.141
	(0.505)	(1.377)	(0.743)	(1.764)
Dem×-3Q	0.213	-0.255	0.746	-1.585
	(0.394)	(1.385)	(0.742)	(1.658)
Dem×-1Q	-0.414	-1.376	-0.563	-2.041*
	(0.466)	(0.957)	(0.631)	(1.082)
Dem×0Q	-0.084	-2.188**	-0.105	-2.319*
	(0.635)	(1.019)	(0.802)	(1.303)
Dem×1Q	0.731	-3.796***	0.982	-4.416***
	(0.536)	(1.164)	(0.813)	(1.659)
Dem×2Q	1.294**	-2.500*	1.735*	-3.274
	(0.552)	(1.519)	(0.994)	(2.482)
Dem×3Q	2.413***	-3.834**	3.144***	-3.315
	(0.612)	(1.820)	(1.014)	(2.622)
Dem×4Q	1.730**	-1.511	2.342**	-0.417
	(0.686)	(2.232)	(1.130)	(2.802)
Dem×5Q	1.984***		2.096**	
	(0.767)		(1.066)	
Dem×6Q	0.910		0.416	
	(0.842)		(0.954)	
Dem×7Q	1.500		-0.161	
	(1.018)		(1.044)	
Avg 1-4Q as %mean	2.29	-3.51	3.05	-3.44
R^2	0.109	0.183	0.118	0.222
Mean rate	67.11	83	67.11	83
N obs	129,240	103,392	129,240	103,392
N clusters (county)	2,872	2,872	2,872	2,872
County FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Economic controls	Y	Y	Y	Y

Note: This table reports the regression coefficients from Equation 3; columns (1)-(2) correspond to Figure 5 and columns (3)-(4) to Figure A3. See note to figures for details. Note that "mean rate" refers to the sample mean of the level of the start up rate rather than the year-over-year change. *** 1%, ** 5%, * 10% significance level.

Table A13
Political mismatch and the probability of starting a business
Democratic and Republican vs. *Independent individuals*

	(1) Election 2008	(2) Election 2016
Dem×-7Q	-0.00036	-0.00089
	(0.00064)	(0.00078)
Dem×-6Q	-0.00110	0.00010
	(0.00077)	(0.00075)
Dem×-5Q	-0.00069	-0.00012
	(0.00061)	(0.00066)
Dem×-4Q	-0.00106	-0.00002
	(0.00066)	(0.00066)
Dem×-3Q	-0.00044	-0.00019
	(0.00064)	(0.00071)
Dem×-1Q	-0.00066	-0.00035
	(0.00064)	(0.00074)
Dem×0Q	0.00011	-0.00019
	(0.00063)	(0.00070)
Dem×1Q	0.00036	-0.00028
	(0.00060)	(0.00075)
Dem×2Q	0.00029	-0.00162**
	(0.00065)	(0.00081)
Dem×3Q	-0.00033	-0.00004
	(0.00062)	(0.00076)
Dem×4Q	-0.00001	-0.00078
	(0.00061)	(0.00083)
Dem×5Q	-0.00036	
	(0.00065)	
Dem×6Q	0.00046	
	(0.00063)	
Dem×7Q	0.00105*	
	(0.00063)	
Rep×-7Q	-0.00013	-0.00071
	(0.00076)	(0.00080)
Rep×-6Q	0.00013	-0.00038
	(0.00083)	(0.00087)
Rep×-5Q	-0.00012	-0.00036
	(0.00077)	(0.00077)
Rep×-4Q	-0.00013	-0.00101
	(0.00073)	(0.00077)
Rep×-3Q	-0.00033	-0.00082
	(0.00074)	(0.00076)
Rep×-1Q	-0.00044	0.00015
	(0.00076)	(0.00079)
Rep×0Q	-0.00087	0.00051
	(0.00079)	(0.00080)
Rep×1Q	-0.00100	0.00041
	(0.00074)	(0.00080)
Rep×2Q	-0.00102	0.00094
	(0.00080)	(0.00084)
Rep×3Q	-0.00126*	0.00104
	(0.00073)	(0.00078)
Rep×4Q	-0.00151**	-0.00006
	(0.00074)	(0.00081)
Rep×5Q	-0.00081	
	(0.00070)	
Rep×6Q	-0.00052	
	(0.00075)	
Rep×7Q	0.00103	
	(0.00071)	
Avg Dem 1-4Q as %mean	.19	-1.36
Avg Rep 1-4Q as %mean	-3	1.15
R^2	0.004	0.004
Outcome mean	.039	.05
N obs	1,670,169,242	1,288,433,150
N clusters (county)	2,122	2,122
Demographics	Y	Y
County×Event FE	Y	Y

Note: This table reports regression coefficients plotted in Figure 3. See note to the figure for details. *** 1%, ** 5%, * 10% significance level.

Industry Tagging Algorithm

Our firm registration data does not include industry codes. To assign firms to industries we develop an industry tagging algorithm based on the words in firm names. Our approach proceeds in three steps.

First, we consider all firms with a primary NAICS code assigned in a large firm dataset provided by Infogroup USA.[1] We count the number of times a word appears in firm names for each NAICS two-digit industry. Second, we define *word quotient* as the number of times a word appears in an industry divided by the number of firms in an industry - we scale the word frequency to avoid industries with many firms dominating the classification. For example, words like "mining" or "biotechnology" are highly relevant to industries with relatively few firms. Third, we assign each word to an industry if (i) it has the highest word quotient and (ii) the quotient is at least twice as high as the next highest one (quotient ratio ≥ 2). Firms are then linked to industries if the words in their names are assigned to a specific industry.

Words with the highest quotient ratio (i.e., those that are most closely associated with specific industries), include "wharehousing" (NAICS 49), "mining" and "quarry" (NAICS 21), and "winery" and "panaderia" (NAICS 31). The median value of the quotient ratio is 8.5. Words around this value include "attorneys" (NAICS 52), "volkswagen" (NAICS 44), "key" (NAICS 56), "powerwashing" (NAICS 23), "abstract" (NAICS 54), and "cooling" (NAICS 23).

In total, we have 5,507 words which tag about 54.6% of companies in our regression sample. We exclude N55 and N99. Within these tagged companies, 81% are assigned to exactly one industry, 17.2% to two, and 1.8% to three or more. Many of the companies tagged in two industries are those that span multiple sectors, such as "Commercial Properties Magazine, Inc", which is tagged as NAICS 51 (Information) and 53 (Real Estate), or "Stella

[1] Infogroup USA dataset includes firms covering the majority of the U.S. economy (similar to Dunn & Brandstreet).

Kids Yoga" which is tagged as NAICS 61 (Educational Services) and 62 (Health Care and Social Assistance).

In our main analysis, we assign a firm an industry as long as it is tagged to that industry, i.e., a firm can be tagged to multiple industries. In untabulated results, our findings are robust to assigning a firm an industry when the firm is tagged to only one industry.