Partisan Entrepreneurship

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Abstract

Republicans start more firms than Democrats. Using a sample of 40 million party-identified Americans between 2005 and 2017, we find that 6% of Republicans and 4% 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.

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1. Introduction

In the United States, political identity is central to economic expectations, with Americans far more optimistic about the economy when their political party is in power. Republicans were almost two standard deviations more optimistic than Democrats during the Republican administrations of George W. Bush and Donald Trump, but this difference disappears during the Democratic administrations of Bill Clinton and Barack Obama (Figure 1). The importance of political identity is also growing: Mian et al. (2021) document a four-fold increase in the explanatory power of political party for economic expectations over the last 20 years.

This paper examines whether political regime changes and the corresponding shifts in partisan beliefs translate into a critical economic behavior: entrepreneurship. To illustrate, consider Figure 2, which plots the rate of new firm registrations in the five states (including Washington D.C.) between 1997 and 2017 with the highest average Republican and Democrat vote shares in Presidential elections since 2000 (hereafter, Red states and Blue states). While there are clear pro-cyclical swings in firm starts through the Dot-Com Crash and Financial Crisis, the difference in firm registrations between Red states and Blue states expands during the Bush administration (2001 - 2008), shrinks during the Obama administration (2009 - 2016), and expands again following Trump's election in 2016.

These patterns are particularly sharp around party-changing elections. For example, the partisan gap in the number of new businesses per 100,000 people in Red versus Blue states fell by 7.4% of the average around the election of Barack Obama. Similarly, around the election of Donald Trump, the partisan gap in the rate of new business registrations in Red versus Blue states rose by 10.8% of the average.

These dynamics hold more generally when we consider all U.S. counties in a difference-in-differences (DID) framework. In Figure 3, we compare Republican to Democratic counties before versus after the 2008 and 2016 Presidential elections. We observe a clear pattern of increasing startup rates in Democratic counties following the election of President Obama, and increasing startup rates in Republican counties after the election of President Trump. Specifically, new firms in Democratic (relative to Republican) counties rose by 2.3% of the mean over the year following the 2008 election, while following the 2016 election the corresponding increase for Republican counties was 3.9%. Extrapolating across all counties, this change corresponds to a partisan shift of approximately 42,000 new firms in the year following the 2016 election.

However, cross-county differences in rates of entrepreneurship around elections might arise for other reasons, such as the 2008 Financial Crisis differentially affecting Republican and Democratic counties. For this reason, we also compare party-identified *individuals* living in the *same county* at the *same time* across different political regimes. To do this, we consider a sample of approximately 40 million Americans for whom we have both political party identification (via registration, primary voting and donation behavior) and who live in the 33 states for which we have data on firm founders.[1]

Focusing on party-identified individuals, we find that Republicans are more likely to be entrepreneurs than Democrats. Over our 13 year sample, 5.8% of Republicans started a business, compared to 3.8% of Democrats. After controlling for gender, education and age, as well as county-year fixed effects, we find that Republicans are 36% more likely than Democrats to start a business in a given year, relative to the mean.

Using a within-county DID design and individual-level data also reveals a partisan response to elections. 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 in the

[1]These 33 states cover 69% of U.S. GDP as of 2016. Our sample consists of individuals with unique names (e.g., Silvia Teston rather than Robert Smith) so that we can accurately match voter names with those of founders. Using a subset of data for which we have middle initials in both datasets, we find that the matched individuals have the same middle initials approximately 88% of the time.

same county, and increase their relative entrepreneurship after Trump's election by 2.4%. In other words, we find evidence of politically sensitive entrepreneurship not only across Republican and Democratic counties, but also between Republicans and Democrats within the same county.

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 (2005 - 2017), we find that politically mismatched individuals — that is, voters whose party did not control the Presidency — see their probability of starting a business fall by 3.3% of the mean relative to 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, or about 170,000 firms over our sample period. This is approximately the total number of firms founded in Mississippi over the same period.

Moreover, the largest estimated effects occur among the most politically active individuals. For partisans with a below-median voting propensity the effect shrinks to 2.4% of the mean, but for those with an above-median voting propensity the effect expands to 4.4%. Using FEC-reported donations to a political party as an alternative measure of political engagement, the effect size jumps to 10% among politically active individuals.

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 new firms' economic impact (Schoar, 2010, Guzman and Stern, 2020, Sterk et al., 2021). Our results are driven by corporations, as opposed to LLCs (an effect size of 10.8% vs. 0.7% of the mean).[2] We find our main result across the full range of the firm quality distribution of Guzman and Stern (2020), with high quality startups appearing to be especially sensitive to political regime change. Our mismatch estimate for firms in the top 5% of the quality distribution,

[2] Corporations are better suited to have investors, are more likely to be employer firms, and are less likely to be used as pass-through entities than LLCs. Our sample excludes unregistered businesses.

which represent over half of high growth firms, is over six times as large as that of LLCs (4.7% vs. 0.7% of the mean). The estimates generally decline as we move down the quality distribution.

When we examine founder characteristics, we find strong partisan differences by gender and age. First, the well-known gender gap in entrepreneurship exists in our sample: 6.8% of all men and 3.3% of all women started a business in our 13 year sample. After controlling for individual characteristics and including county-year fixed effects, men are about 0.4 percentage points (pp) per year more likely to start a business than women, which is approximately 90% of the annual mean. This gender gap varies by political party. Among Democrats this gap is almost 20% smaller than the gap among independents, while among Republicans it is nearly 30% larger. Moreover, male entrepreneurs are more sensitive to political regime change than female entrepreneurs. Relative to their respective means, men are 3.7% less likely to engage in entrepreneurship when politically mismatched with the president, but for women it is only 1.6%.

We also find substantial age heterogeneity. The startup decisions of the youngest individuals (18 to 29 years old) are the most sensitive to regime changes. Their propensity to start a business is 7% of their mean lower when politically mismatched; among the oldest individuals (aged 50 to 70), this number is only 2%.

While our preferred interpretation of the evidence runs through economic sentiment, an alternative explanation is that the party controlling the presidency implements policy that favors same-party entrepreneurs. To examine this alternative story we consider effects within geography and within industry. While policy is often focused on specific geographies or industries, we find strong partisan effects within both finely-grained geographic units, and across almost all two-digit NAICS industries, including the least policy sensitive industry: retail (Hassan et al., 2019). Taken together, our evidence is inconsistent with policy being the main driver of our estimated effects.

Finally, we examine *existing* firms using the Business Dynamics Statistics data from the U.S. Census Bureau. We find strong support for partisan effects among these data, which represent not only a different data source but also capture a new firm population: both new and existing *employer* firms. Existing firms in mismatched counties are less likely to open new establishments, more likely to close them, and more likely to shut down the entire business. Because these firms are employer firms we can also estimate employment effects. Aggregating nationwide over 13 years, we find partisan effects amount to a relative shift of over 2.4 million jobs across red and blue counties.

Our findings relate to several strands of the literature in entrepreneurship and political economy. In entrepreneurship, many have explored which founder characteristics correlate with the decision to start a firm, such as age, race, wealth and gender (Evans and Jovanovic, 1989, Holtz-Eakin et al., 1994, Hurst and Lusardi, 2004, Azoulay et al., 2020, Fairlie et al., 2020, Bellon et al., 2021, Guzman and Kacperczyk, 2019). Our paper shows that political affiliation is another important characteristic, representing 40% of the size of the well-known gender gap in entrepreneurship, after controlling for founder age, gender, education, 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 (Levine and Rubinstein, 2017, Barrios et al., 2021, Kerr et al., 2019, Puri and Robinson, 2013). These characteristics are generally viewed as static throughout adulthood; for example, Astebro et al. (2014) notes that "optimism is considered to be a ... stable individual trait." We contribute with evidence of *time-varying* changes in partisan sentiment, likely correlated with economic optimism.

We also contribute to the literature exploring the determinants of the entrepreneurship decision. Existing work has focused on the impacts of financial constraints, risk-reduction policies, training, entrepreneurial peers, and the availability of reproductive healthcare.[3] We uncover a new driver of entrepreneurial entry: political sentiment as a result of election outcomes.

Finally, our paper contributes to a growing literature on the economic consequences of political polarization. At the corporate level, several papers have found evidence of partisan effects in credit ratings, syndicated lending, and the composition of executive teams (Kempf and Tsoutsoura, 2021, Dagostino et al., 2020, Fos et al., 2021). At the household level there is strong evidence from surveys that partisans' economic optimism tracks their parties' political fortunes 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).[4] We provide evidence of real effects of partisanship on an outcome – entrepreneurship – that has important downstream consequences for both the labor market and productivity dynamics (Haltiwanger et al., 2013, Decker et al., 2014, Adelino et al., 2017).

The rest of the paper proceeds as follows. Section 2 covers our data and sample construction. Section 3 describes patterns in the data. Section 4 describes our empirical strategies and estimates, and Section 5 concludes.

[3]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 policies reducing risk see Hombert et al. (2020), Gottlieb et al. (2021). For training, peers and access to reproductive healthcare see Karlan and Valdivia (2011), Drexler et al. (2014), Fairlie et al. (2015), Lerner and Malmendier (2013), Nanda and Sørensen (2010), and Zandberg (2021).

[4]A recent series of papers links partisanship with financial outcomes such as tax evasion, stock market liquidity, and retirement investing (Cullen et al., 2021, Cookson et al., 2020, Meeuwis et al., 2021).

2. Data and sample construction

2.1 Entrepreneurship data from business registrations

We measure entrepreneurship 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, the latter favored by growth-oriented firms because of its corporation law and court system.

We use business registration records obtained through the Startup Cartography Project (Andrews et al., 2020), which contains business registration records across 49 U.S. states and Washington D.C. from 1988 to 2017. 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 focus on startup founders, we exclude personnel whose titles imply that they play only an administrative role.[5] Our data also imply that we also exclude those who are self-employed with no formal registration.

2.2 Voter and donor data

We obtain data on registered voters from L2, a well-known non-partisan data vendor used by political campaigns and the academic literature (e.g., Allcott et al., 2020, Billings

[5]The titles we exclude are: incorporator, applicant, secretary, clerk, treasurer, director, and general partner. We also exclude names that appear in more than five different firm registrations in a year, as they are unlikely to have an operative role. Our results remain quantitatively similar when we do not impose these restrictions.

et al., 2021, Bernstein et al., 2021, Spenkuch et al., 2021), for the 33 states for which we have information on firm founders.[6] For 21 of these states, L2 assigns political affiliation using self-reported voter registration.[7] 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. Roughly 43% of entrepreneurs in our sample are in these states.[8]

L2 has complete coverage of the U.S. voter population starting in 2014. To minimize concerns over survivorship bias and reverse causality we use this 2014 dataset to assign voter partisanship. Because 2014 precedes 2016, this strategy resolves such concerns for the 2016 election and mitigates them for 2008 to the extent possible with L2 data. However, in the yearly files we note that the probability of changing from Republican to Democrat or vice versa is only 1.8%. We merge on individuals' voting histories from the most recent L2 voter file we have (October 2020) to the 2014 population, dropping those without voting information, because this is needed to construct activeness measures. 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

[6]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.

[7]L2's data is subject to repeated testing by political campaigns in the field, suggesting high accuracy, and Brown and Enos (2021) validates the accuracy of the partisan classifications.

[8]These states are: Alabama, Georgia, Hawaii, Indiana, Minnesota, Missouri, Montana, Ohio, Texas, Vermont, Virginia, Washington. 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.

recorded by the Federal Election Commission (FEC). Using the L2-linked FEC data, we call individuals *active FEC donors* if they made a political donation by 2020 (2.3% of the sample). L2 also identifies whether an individual's *household* has made a contribution to any political cause as of 2020, which we call *active household donors* (40% of our voters).

The voter database also includes a suite of demographic variables, such as registered state and county, birth year, gender, and education level, which use as controls in the main specifications. We include race/ethnicity only in some specifications because it is missing for 10% of the sample.[9]

2.3 Sample of registered voters

We match voters to firm founders in the business registration database by name and county. To do this, we focus on voters whose combination of first and last names is unique in the L2 data spanning all voters in the county. 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 facilitate matching. However, name uniqueness within the voter database does not guarantee uniqueness among all county residents because many people are non-voters. 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 percentage points.[10] 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). For this reason, we present our main analysis separately for men and women. We also restrict the sample to voters aged between 18 and 70 in each year in our sample period (2005-2017).

[9] L2 infers some race data, e.g., describing the Black race variable as "likely African-American." See Brown and Enos (2021) for details.

[10] Estimating the 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.

L2 has 140 million registered voters in the 33 states for which we have founder data. After restricting the sample to unique names we have nearly 40 million unique-name voters. Of these, 4.8% (1.9 million) started a company during our sample period. Conditional on both voter and founder having middle initials, the matched individuals have the same middle initials 88% of the time, indicating a high quality of match between the voter and founder databases.

A voter is coded as starting a business in a year if they register at least one firm in that year. 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 one possible combination of county, party identification (Democrat, Republican, other), gender (male, female), age (18-29, 30-29, 40-29, 50-29, 60-70), education level (high school or below, college or above), race/ethnicity (white, Black, Hispanics, Asian, where available), and time (either calendar year or 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).

3. Descriptive statistics

Table 1 reports summary statistics on the annual likelihood of starting a business, as well as the probability of starting a business at some point 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 various political and demographic subgroups. The 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 (Doherty et al., 2018).

Out of approximately 40 million voters in our sample, around 4.8% started a business at some point between 2005 and 2017. The likelihood of starting a business in a given year is approximately 0.5 percentage points.[11]

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 5.8% of Republicans ever start a firm in our data, only 3.8% 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 distribution across demographic characteristics, we note a few differences. First, consistent with prior results in Fairlie et al. (2020), white individuals are more likely to start a business in a year than Blacks and Hispanics, as are college-educated ones (Hurst and Lusardi, 2004). Second, the startup rate is 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 administrative data at the U.S. Census Bureau. 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 (such as Guzman and Kacperczyk, 2019).

To move beyond summary statistics and account for correlations between these political and demographic variables, in Table 2 we estimate regressions of the likelihood of starting a business as a function of these characteristics. Each regression includes age-group and 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 48% of the outcome mean.[12]

[11]Serial entrepreneurs, defined as people founding a business in more than one year, make up 18.4% of all entrepreneurs in our sample (similar to Lafontaine and Shaw (2016)).

[12]We run a similar specification in Table 5 for firms at different points in the quality distribution (columns 5-10). We find that Democrats are also less likely than Republicans to found high-quality firms. Note, however, that these estimates are all *within*-county.

Column (2) confirms the well-known relationships between education, gender and entrepreneurship. Men are over 0.4 pp more likely to start a business in a year than women, all else equal, which is nearly 90% of the mean likelihood. Similarly, college-educated individuals are 40% of the mean more likely to start a business. Column (3) includes both partisan indicators and demographics, which reduces the Republican - Democrat spread to 0.18 pp. However, this still means that, after controlling for gender, education, age, and county-year, Republicans are 26% of the mean more likely to start a firm in a given year than Democrats.

In column (4) we examine whether the gender gap in entrepreneurship is different for Republicans and Democrats by interacting our partisan indicators with gender. We see a sizable difference across political parties. The gender gap is similar to the mean gap for independents, it is 16% smaller for Democrats, and it is 27% larger for Republicans.

In columns (5) through (7) we interact our partisan indicators with age and education, finding only small differences in the explanatory power of these variables on entrepreneurship among Democrats and among Republicans. Finally, column (8) considers the relationship between race, political party and entrepreneurship for the subset of voters for whom we have either race or ethnicity data. Non-partisan Blacks and Hispanics are significantly less likely to start a business compared to whites (effect sizes are 21% and 29% of the mean respectively), while Asians are more likely (80% of the mean). These racial differences generally shrink among Republicans and expand among Democrats. For example, among Republicans, the Hispanic - white gap in entrepreneurship shrinks by 30% of the non-partisan racial gap, while among Democrats the racial gap is 42% larger.

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 start more firms than Democrats, even after controlling for founder characteristics. Moreover, well-known gender and racial gaps in entrepreneurship differ between Republicans and Democrats.

4. Empirical strategy and results

4.1 Evidence from aggregate data

4.1.1 Elections, optimism, and state-level entrepreneurship

To motivate our analysis, consider Figure 1 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 Figure 1 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 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 elections, especially after those of Obama (2008), Trump (2016) and Biden (2020).[13] Non-party-changing elections appear to have little to no effect on economic optimism. Mian et al. (2021) find that the explanatory power of political party for economic expectations over the last 25 years has increased four-fold. Using the University of Michigan Survey, Meeuwis et al. (2021) reports that while Republicans' expectations for national business conditions increased (and Democrats' decreased) following the 2016 election, partisan expectations of their own economic situation remained essentially unchanged. Meeuwis et al. (2021) also

[13]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.

reports little change in the savings rate of partisans. Taken together, this evidence suggests that the swings in economic optimism around elections reflect partisan updating about the national economy, rather than one's own economic prospects.

Entrepreneurship is a future-oriented activity, so an entrepreneur's decision to start a business is necessarily tied to their belief about the current and future economic climate (e.g., Bengtsson and Ekeblom 2014). 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. Figure 2 considers the five most Democratic "Blue" states (including Washington D.C.) by vote share in presidential elections since 1996 (DC, HI, MA, NY and RI) and the corresponding Republican "Red" states (WY, UT, ID, OK and NE) and plots the number of new firms (per 100,000 residents who are at least 20 years old) since 1997. All other states are plotted in gray.

In terms of levels, there are clear pro-cyclical swings. Entrepreneurship slows during the Dot-Com Crash, falls sharply during the Financial Crisis, and recovers beginning in 2010. In terms of differences across states, the figure shows the same partisan gap in entrepreneurship as in section 3, with Red states creating more new firms per capita than Blue states. Moreover, the Red minus Blue gap is time varying, expanding during the Bush administration (2001 - 2008), shrinking during the Obama administration (2009 - 2016) and expanding again following Trump's election in 2016. In other words, Republican entrepreneurship increases during Republican administrations relative to Democrat entrepreneurship, and vice versa.

The time-varying patterns appear particularly sharp around party-changing elections. For example, the number of new businesses per 100,000 residents in Red states fell from 989 to 894 between 2008 and 2009. The decline in Blue states over the same period was one-third the magnitude, falling from 752 to 722. The difference (Red minus Blue) amounts to 7.4% of the annual average across all states during the two years before and after the election. The opposite pattern appears during the next party-changing election, that of Donald Trump in 2016. Between 2016 and 2017, the Red states increased their firm registration rate from 1,440 to 1,621 per 100,000 people, while the Blue states saw a more moderate increase from 989 to 1060. This difference (Red minus Blue) amounts to 10.8% of the annual average during the two years before and after the election.

4.1.2 County-level evidence

To understand the time-varying partisan gap at a finer geographic level, we compare the changes in firm startup rates in Democratic versus Republican counties, before versus after a presidential election, in an event study DID framework.

We classify a county as Democratic-leaning if its vote share for the Democrat party is above the sample median in the preceding presidential election, and Republican-leaning otherwise.[14] The outcome of interest is the total number of new firms registered in a month, per 100,000 county residents aged 20 and older. If there are no new firms in a county *times* month, we code it as a zero. To account for seasonality and general trends in startups, we residualize the outcome by regressing it on county $\times$ month-of-year indicators and county annual linear trends. We refer to the resulting variable as the *excess* firm registration rate.

We use the following specification:

$$\mathrm{Y}_{ct} = \sum_{t=-8}^{7} \beta_t \times Dem_c + \gamma' X_{ct} + \alpha_c + \alpha_t + \epsilon_{ct} \qquad (1)$$

Y_{ct} is the excess firm registration 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 Democratic, and zero otherwise. X_{ct} includes the county annual unemployment rate, per-capita income,

[14] In this subset analysis we drop MI, NV, ME, AL and DC (leaving us with 45 states) because we are unable to match more than 50% of firms to counties.

and the employment share in each two-digit NAICS industry (except 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 firm registration rate in a county and national registration trends. We cluster standard errors by county.

While the data is monthly, for precision and ease of presentation 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 to January 2017 constitute $t = 0$ for the 2016 election. We omit the indicator for $t = -2$ as our base period.

The β_t coefficients identify the causal effect of presidential elections on firm registrations if registration rates in Democratic and Republican counties would have been parallel in the absence of elections. As we will show, this condition appears to hold.

The county-level event study DID reveals the same partisan gap dynamics as those in the state-level time series. In Figure 3, we compare Republican to Democratic counties before versus after the 2008 and 2016 presidential elections. We see a clear pattern of Democratic counties increasing their firm registration rate relative to Republican counties following the election of President Obama, and Republican counties increasing their relative rate after the election of President Trump. More specifically, Democratic counties on average see 13 more firms per 100,000 residents (2.31% of the mean) relative to Republican counties in the year following the 2008 election. Further, Republican counties experience a relative increase of 37 firms per 100,000 residents (3.91% of the mean) in the year following the 2016 election.[15]

Appendix Figure A1 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 3 is entirely driven by the month

[15] In a robustness test, we drop contemporaneous economic controls from equation 1 and find quantitatively similar estimates. See Figure A2.

before the election.

4.2 Individual-level evidence

We now turn to individual data, which allows us to exploit different identifying variation than the cross-county analysis. 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 counties. Moreover, we can control for important founder characteristics that predict entrepreneurship, such as gender, age, and education. Despite the different identifying variation and the additional controls, we find very similar results.

The specification is similar to the county-level analysis. The outcome is the likelihood that an individual starts a business in a month, after residualizing the outcome by regressing it on county × month-of-year indicators and county × party annual linear trends. We refer to this variable as the *excess* likelihood of starting a business. We then estimate the following regression:

$$\mathrm{Y}_{it} = \sum_{t=-8}^{7} \beta_t \times Dem_i + \gamma' \mathbf{X_{it}} + \alpha_{c(i),t} + \epsilon_{it} \tag{2}$$

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 month. Similar to equation 1, 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 (see section 2.2 for partisanship definitions). We include county-by-time fixed effects $\alpha_{c(i),t}$ to control for the time-varying startup likelihood by county. $\mathbf{X_{it}}$ is a vector of gender, education, and age group bins.[16]

Our coefficients of interest are β_t, which identify the impact of presidential elections on

[16] 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).

the likelihood of starting a business among Democrats (relative to Republicans) living in the same county and time around party-changing elections.

Consistent with the patterns documented in the county-level analysis, individual partisans also adjust their startup propensity in response to political regime changes. Figure 4 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* at the *same time*, before versus after the 2008 and 2016 presidential elections. Table A3 reports the individual 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 months. Extrapolating across the U.S., this represents a narrowing of the entrepreneurship gap by 13,000 entrepreneurs.[17] There is no indication of a differential pre-trend.

For the 2016 presidential election the estimates for the pre-period in Figure 4 also support the assumption of parallel trends. In the 12 months following the election, Republicans' startup probability rose by 2.4% of the mean relative to Democrats, increasing the entrepreneurship gap by 10,000 founders.

To understand the relative contributions of Republicans and Democrats to changes in the partisan entrepreneurship gap following presidential elections, we include voters who are *neither* Democrats *nor* Republicans as the control group. Thus, Figure 5 plots the β_t estimates for each party *relative to independents*. Approximately all of 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

[17]The extrapolation, and those that follow, is obtained by multiplying the sum of coefficients in quarters 0 to 3 by three (to translate the monthly average to a quarterly total), multiplying by one-third of the U.S. population (assuming that Democrats, Republicans, and independent groups are equally sized), and dividing by 100 (to adjust the outcome unit from percentage to one).

their startup rate, while 60 percent comes from from Democrats decreasing their rate.

The results in this section using individual data point to changes in political regimes affecting entrepreneurship, similar to the evidence from the cross-county DIDs.

4.3 Partisanship and startups over the full sample

Our DID event studies focus on the years immediately surrounding party-changing elections and so use less than half of the sample years. In this section we use the entire sample period (2005-2017) to estimate the average relationship between entrepreneurship and being in partisan mis-alignment with the sitting President. To do so we exploit the panel structure of the individual-level data and estimate the following:

$$\mathrm{Y}_{it} = \beta \, Mismatch_{it} + \gamma_D \, Dem_i + \gamma_{\mathbf{x}}' \mathbf{X_i} + \alpha_{c(i),t} + \epsilon_{it} \tag{3}$$

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 individuals identified as Democrats, and equal to 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, equal to one for Republicans during 2009-2016 and for Democrats during 2005-2008 and 2017. $\alpha_{c(i),t}$ is a county by year fixed effect. We additionally control for $\mathbf{X_i}$, a vector of demographic characteristics (gender, age and education). Standard errors are clustered by county.[18]

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 mis-aligned with that of the sitting President, relative to when their party is aligned.

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

4.3.1 Main estimates

Table 3 reports the estimates from equation 3, using various measures of partisan identification. Column (1) uses all registered Republican and Democrat voters. The coefficient on *Mismatch* is negative and significant, with a point estimate of -0.017, i.e., 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, representing 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, we compare regular partisans to *active* partisans, 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 its interactions to equation 3, and re-estimate the model. The negative and significant coefficient on *Mismatch*×*Active* in column (2) means that active voters are 0.010 pp 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 mis-alignment is 82% stronger than that of less active partisans.[19]

Turning to active *donors*, columns (3) and (4) mean that household and FEC donor voters, respectively, are 0.007 and 0.08 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 probability of starting up. While the effect for FEC donors voters is an order of magnitude larger, note that they are a selected and a much smaller subset of registered

[19] Appendix Figure A3 plots the event study by election for active Republicans and Democrats. Effects for the 2008 election are stronger for active voters and only weakly stronger for the 2016 election.

voters (2.3% of individuals vs. 50% for active voters, and 40% for HH donors).[20]

Taken together, the larger effects we find for active voters points towards partisanship driving the time-varying differences we find in entrepreneurship between Republicans and Democrats.

4.3.2 Heterogeneity by voter gender and age

In Table 4 we begin by considering how partisan effects vary across gender not only because there is evidence that women's economic expectations react differently to those of men (e.g., Meeuwis et al. 2021, D'Acunto et al. 2020), but also because our unique name approach over-samples women. Columns (1) and (2) of Table 4 replicate Table 3 column (1) for men and women separately. Men are more sensitive to political power shifts than women. Relative to their respective means, men are 3.7% less likely to engage in entrepreneurship when politically mismatched with the presidential regime, but for women the effect is only 1.6%. Given that women are over-represented in our sample, our estimates with individual data *understate* the true relationship between political regime changes and entrepreneurship.

In columns (3) to (5) we explore heterogeneity by age. Individuals between 18 and 29 years old show the largest effect relative to their mean (7%), followed by those between 30 and 49 (3.2%), 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.

4.3.3 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).

[20] 1.2% of women and 1.6% of men donated over $200 in the 2020 election OpenSecrets21

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) combine these founding characteristics into a measure of "entrepreneurial quality," which we use to examine the ex ante quality of the entrepreneurship induced by partisan sentiment.

Table 5 considers entrepreneurial quality by replacing the dependent variable of Table 3 column (1) with indicators for firm type. Column (1) examines LLCs, while column (2) focuses on corporations. We observe a larger coefficient on *Mismatch* for corporations: mismatched individuals are 0.7% of the mean less likely to start an LLC compared to 10.8% for corporations.[21]

Columns (3) to (5) focus on firms 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 (16% for VC-backed and 5% for patent firms) the rarity of these firm types limits the power and hence the statistical significance of these tests. However, firms in the top 5 percent by ex ante quality show a mismatch effect of 4.7% of the mean that is strongly 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 (over 6% 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.

In summary, when looking across various measures we find effects across the entire distribution of firm quality, and these are stronger among higher-quality firms and weaker among

[21]These are corporations registered under their local state jurisdiction.

lower-quality firms.[22]

4.3.4 Examining mechanisms: political sentiment versus partisan policy

Swings in economic optimism along party lines driven by shifts in political power (Figure 1) is our preferred explanation for the change in the partisan entrepreneurship gap. An alternative explanation is that regime switches lead to policy changes favoring individuals who are members of the party in power. For example, President Trump's 2017 Tax Cuts and Jobs Act included a state and local tax cap of $10,000 which disproportionately hurt taxpayers in Blue States.

Some of the evidence presented above is already inconsistent with a policy-based explanation. First, the event time DIDs (Figure 3) show entrepreneurship effects *immediately* (often within the first two quarters after an election). Policy changes take time to implement, while expectation changes are immediate, as is clear from Figure 1. Second, we find stronger effects among the most partisan individuals (Table 3), i.e., those that vote or donate more. It is unclear, for example, why a new policy would favor Republicans who actively vote or donate more than other Republicans. However, it seems likely that an active Republican would be especially optimistic (pessimistic) during Republican (Democratic) administrations. Third, we find significant heterogeneity along personal characteristics (Table 4), with men and younger people showing larger effects. Again, it seems unclear why a new policy would disproportionately favor young Democrats (relative to old ones) or Democratic men (relative to Democratic women).

In this section, we continue to investigate a policy-based channel by conducting tests in two domains that policy may affect: geography and industry. Mian et al. (2021) finds little evidence of changes in tax rates, personal income growth, and transfers at the county and

[22] 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.

state levels around presidential elections. Moreover, in order to examine whether partisans' economic situation differentially improves, they use zip code-month fixed effects, relying on the assumption that people within zip codes are subject to the same government policies. Similarly, we re-estimate the model in Table 3, adding fine-unit geographic fixed effects so that identification comes, for example, via differences in Democrats and Republicans who live in the same census block at the same time. If policy is targeted to geography, we would expect our main result to weaken as we include these fixed effects. However, we find little evidence that this is the case. In Table A2, we progressively add finer geography-by-year fixed effects, from state-level (column (1)) to census block group-level (column (5)).[23] The point estimates under these alternative geography-by-year fixed effects are all similar to the estimates under the main specification shown in column (2).

Turning to industry, we categorize companies into two-digit NAICS industries using a word tagging approach based on company names.[24] We run the same specification used in Table 3, but changing the dependent variable to be an indicator for whether an individual starts a firm in a *specific* NAICS-2 industry. Table 6 presents results for the 13 most populated NAICS-2 industries in the sample.

We observe effects for mis-aligned entrepreneurs across *all* industries, which is inconsistent with a *pure* policy-based mechanism. This is particularly true for 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-by-year fixed effects (in Table A2).

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

[24]Using the Reference USA dataset of firms (Infogroup, 2014) we link company names to industries by first keeping all words in Reference USA that occur at least 50 times and then scoring the relative importance of each word-industry pair. Specifically, for a word i that appears n_{ij} times in industry j, we estimate $\frac{n_{ij}/N_j}{n_i/N}$ and we keep all words that either (i) are at least ten times more common in this industry group than in the rest of the data, or (ii) are one of the 300 highest-scored words for this industry. We exclude N55 and N99 from our analysis. We categorize over 81% of firms in our sample in this way.

The latter can be seen as an approximation to industry-by-year fixed effects, because in our data the firms started by two founders in the same census block group and year have a 25 percent chance of being in the same industry.

4.4 Partisan sentiment and existing firms

Thus far we have explored the effects of partisan sentiment along the *extensive* margin of entrepreneurship. In this section, we examine the *intensive* margin, exploring how the expansion, contraction, and death of *existing* firms co-vary with the political alignment of their counties. We use the Census Bureau's Business Dynamics Statistics (BDS), which 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 and year through 2018. 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, such as the annual number of new firms, newly opened or closed establishments of existing firms, and firm deaths, per 100,000 county residents (20 years or older) 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.[25] We include a vector of county-level, time-varying variables X_{ct}, i.e., annual unemployment rate, annual per-capita income, and employment share of each two-digit NAICS industry (excluding NAICS=99) to control for economic conditions and industry importance in the county. When the outcomes are for existing firms, we include firm age fixed effects. We also include county fixed effects α_c and year fixed effects α_t to absorb any persistent difference

[25] County partisanship is defined using its vote share in the preceding presidential election. For example, $Mismatch$ equals one between 2005 and 2008 for counties whose Democratic vote share is above the national median in the 2000 presidential election.

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 mis-aligned with the party of the sitting President, relative to those in aligned counties.

Table 7 reports the estimates from equation 4. Column (1) confirms our earlier results along the extensive margin, showing that there are around five fewer *new* firms per 100,000 county residents (ages 20 and above) in politically mis-aligned counties relative to aligned 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 startups is similar 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 aligned and mis-aligned 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 mis-alignment.

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

Aggregating up, we find that the 2.9% mean effect from column (1) translates to approximately 82,000 new firms in politically aligned counties (relative to mis-aligned ones), and the death of over 10,000 firms in mis-aligned counties over 13 years. These aggregate estimates are substantially smaller than those we obtain using county- or individual-level data because BDS only captures *employer* firms. The intensive margin effects in columns (3), (4) and (6) indicate a broader impact on business dynamism, amounting to 4,000 new establishments and 2.4 million jobs in aligned counties (relative to mis-aligned ones) during the whole period.[26] In a robustness check, we exclude contemporaneous economic controls and re-estimate equation 4. Results are quantitatively similar (see Table A4).

5. Conclusion

Our paper documents a relationship between political identity and entrepreneurship, with Republicans over 36% more likely to start a firm in a given year than Democrats, after controlling for 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 a new way in which 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., Faccio, 2006, Fisman, 2001, Robinson and Verdier, 2013), with policy prescriptions aimed at reducing clientelism. In contrast, the effect we document on supporters likely arises organically via the economic optimism of partisans. Given anti-corruption measures are not appropriate in this circumstance, what policy actions might be appropriate to incentivize individuals from the losing political party to become entrepreneurial? And would such policies be welfare-improving?

Finally, we find stronger partisan effects on entrepreneurship around recent party-changing

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

elections, not only across Red vs. Blue counties but also between Red and Blue individuals within the same county. This seems to align with increasingly polarized responses to election outcomes (Figure 1) as well as broad increases in political polarization generally (Abramowitz and Saunders, 2008, Gentzkow et al., 2019). If political polarization continues to rise, will the role of political identity become more important for entrepreneurial decisions? We leave these questions to future research.

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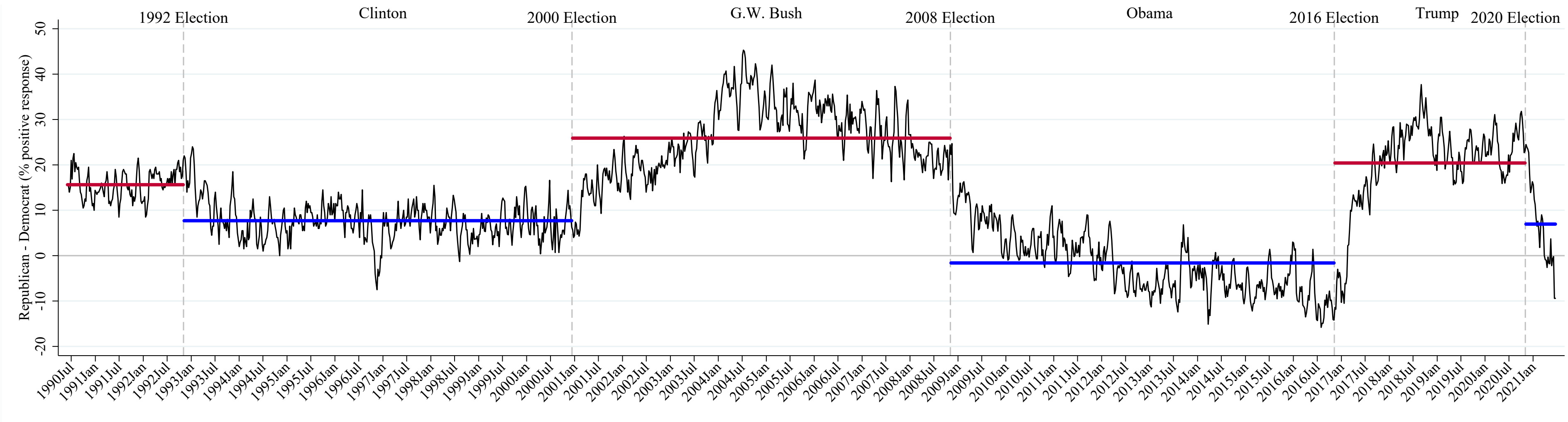


Figure 1. Optimism Survey: the Bloomberg Consumer Comfort Index by Party Affiliation

Note: The black line plots the difference in The Bloomberg Consumer Comfort Index between Republicans and Democrats, and the flat lines plot the average of this difference between each party-switching presidential election. Survey respondents in the Bloomberg Consumer Comfort Index 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 four-week rolling average fraction of positive responses ("Good" or "Excellent") across the three questions. The sample is derived from 1,000 landline and cellular telephone interviews (national random sample), 250 per week, weighted to adjust for probabilities of selection by household size, telephone use, age, sex, race, education, metro status, and region.

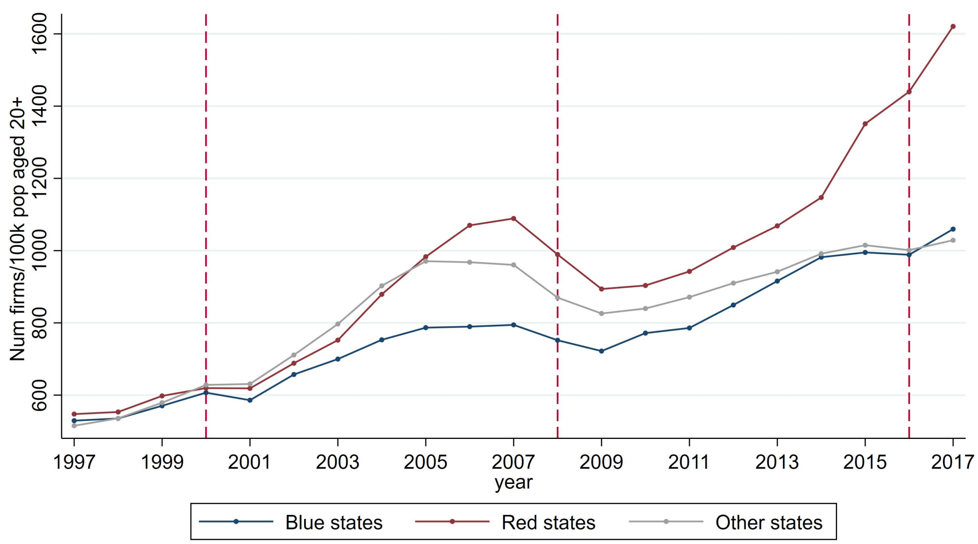
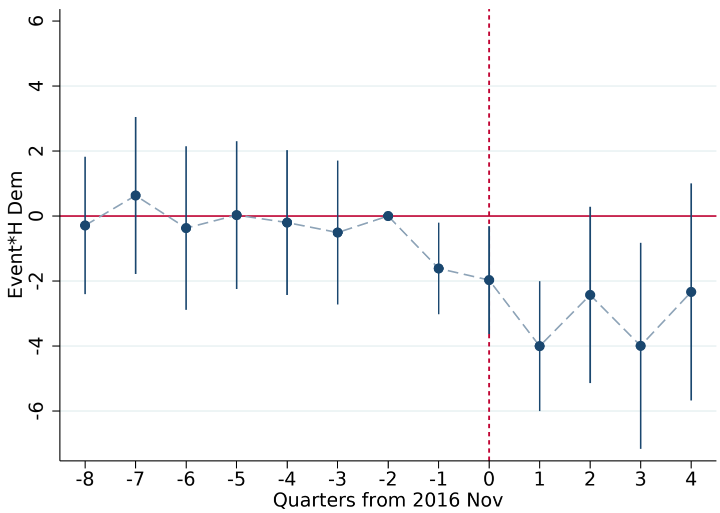
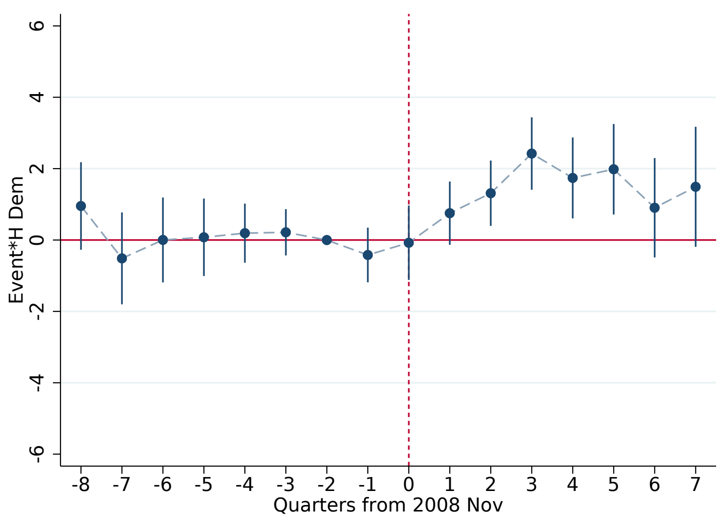


Figure 2. Firm Registration Rate by State Partisanship

Note: This figure plots the number of new firm registrations per 100,000 people ages 20 and older in Blue states, Red states, and other states. Blue states are the top five states (including Washington D.C.) which have had the highest average Democrat vote share in Presidential elections between 1996 and 2016 (DC, HI, MA, NY, RI); Red states are the top five states which have had the highest average Republican vote share (WY, UT, ID, OK, NE). All other states are plotted in gray.



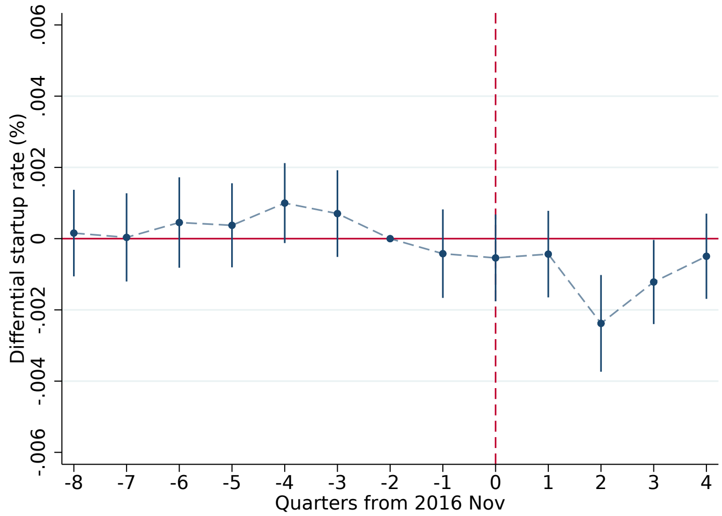
(a) 2016 election



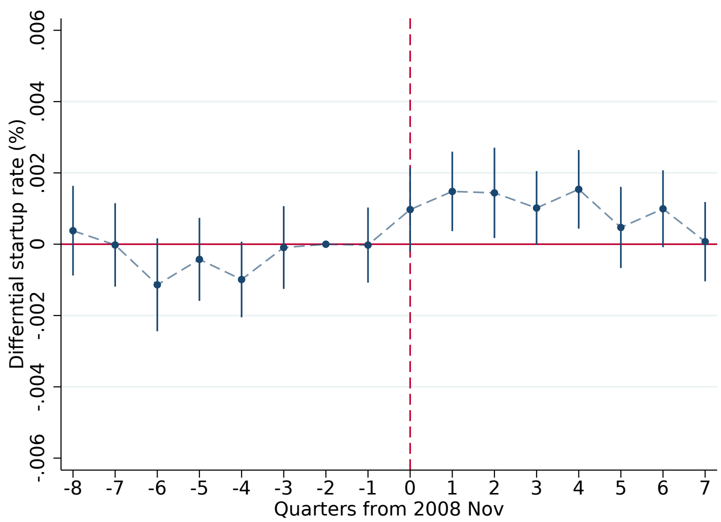
(b) 2008 election

Figure 3. Political Mismatch and New Firm Registration Rate
Democratic versus Republican *Counties*

Note: This figure plots the estimated number of (excess) monthly new firm registrations per 100,000 people 20 years old or older (averaged within quarter) in Democrat-leaning counties relative to Republican-leaning counties. Republican-leaning counties are the omitted group. Event time 0 refers to the three months following the month of a presidential election. For example, for the 2016 election event time 0 is November 2016 to January 2017. Event time -2 is the omitted period. All regressions control for county fixed effects, event time fixed effects, and county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for all 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county. Regression results are reported in Table A1.



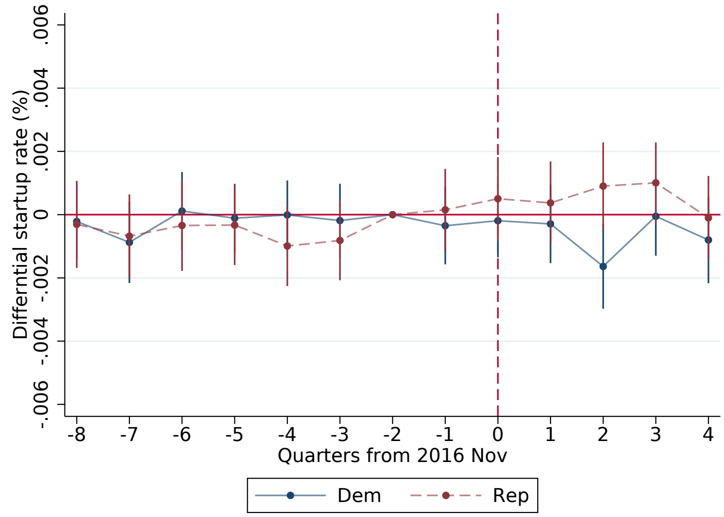
(a) 2016 election



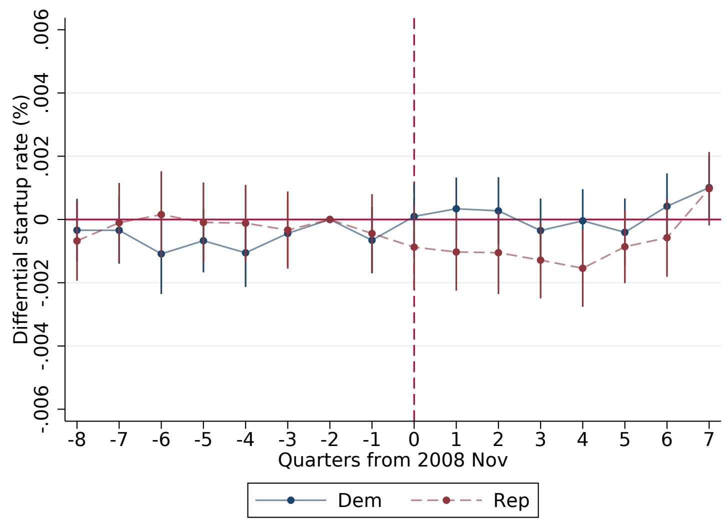
(b) 2008 election

Figure 4. Political Mismatch and the Probability of Starting a Business
Democrat versus Republican *Individuals*

Note: This figure plots the estimated (excess) monthly probability of starting a business for Democrat voters relative to Republican voters. Units are in percentage points and the omitted group is Republican. Individuals are identified as Democrat or Republican in 21 states by their party registration. In the remaining 12 states, our political data provider infers an individual's party. Event time 0 refers to the three months following the month of a presidential election. For example, for the 2016 election event time 0 is November 2016 to January 2017. Event time -2 is the omitted period. All regressions control for county×event fixed effects and voter characteristics (i.e., gender, education, age groups). 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 results are reported in Table A3.



(a) 2016 election



(b) 2008 election

Figure 5. Political Mismatch and the Probability of Starting a Business
Democrat and Republican Individuals versus *Independents*

Note: This figure plots the estimated (excess) monthly probability of starting a business for Democrat voters (blue line) and Republican voters (red line) relative to non-partisan voters. Units are in percentage points. Individuals are identified as Democrat or Republican in 21 states by their party registration. In the remaining 12 states, our political data provider infers an individual's party. Event time 0 refers to the three months following the month of a presidential election. For example, for the 2016 election event time 0 is November 2016 to January 2017. All regressions control for county×event time fixed effects and voter characteristics (i.e., gender, education, age groups). 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.

Table 1
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	1.08	100.00	0.39	0.95	100.00	0.61	1.21	100.00
Male	0.75	1.39	41.29	0.60	1.29	36.14	0.90	1.50	44.60
Female	0.32	0.75	58.71	0.27	0.66	63.86	0.38	0.84	55.40
Edu≥College	0.69	1.25	34.40	0.55	1.13	32.71	0.78	1.31	39.85
Edu≤HS	0.41	0.95	38.59	0.32	0.84	39.03	0.49	1.05	40.19
Black	0.35	0.94	9.42	0.34	0.73	17.12	0.48	2.44	1.30
White	0.47	0.78	64.06	0.37	0.70	53.10	0.58	0.84	77.37
Hispanic	0.45	1.27	7.97	0.34	0.93	11.99	0.73	1.90	4.35
Asian	0.90	2.31	3.18	0.72	2.04	3.20	1.00	2.87	2.08
Age 18-29	0.25	0.79	18.29	0.20	0.68	18.36	0.35	1.06	11.86
Age 30-39	0.65	1.32	18.30	0.53	1.18	17.49	0.81	1.56	15.33
Age 40-49	0.66	1.24	21.69	0.54	1.12	20.45	0.77	1.32	23.41
Age 50-59	0.53	1.05	23.15	0.42	0.92	23.67	0.64	1.12	26.62
Age 60-70	0.34	0.85	18.57	0.27	0.74	20.03	0.41	0.88	22.79
N voter×year		477,728,978			173,281,910			153,846,085	
N state		33			33			33	
P(ever founder):									
All	4.75	21.27	100.00	3.82	19.16	100.00	5.76	23.30	100.00
Male	6.84	25.24	41.16	5.61	23.02	36.02	8.08	27.25	44.46
Female	3.29	17.83	58.84	2.81	16.52	63.98	3.91	19.37	55.54
Edu≥College	6.04	23.82	47.41	4.97	21.73	44.81	6.85	25.26	53.60
Edu≤HS	3.58	18.59	25.25	2.85	16.65	26.73	4.29	20.27	26.29
Black	3.48	18.33	9.39	3.39	18.11	16.94	4.58	20.90	1.28
White	4.61	20.97	64.15	3.65	18.75	53.32	5.52	22.84	77.47
Hispanic	4.22	20.11	7.98	3.26	17.77	11.97	6.52	24.69	4.33
Asian	7.99	27.11	3.14	6.53	24.71	3.18	8.60	28.03	2.05
Cohort 1990+	1.30	11.33	7.93	1.05	10.19	7.48	1.69	12.88	4.82
Cohort 1980-89	4.00	19.59	15.26	3.20	17.61	15.45	5.17	22.14	10.06
Cohort 1970-79	6.64	24.90	17.04	5.51	22.82	16.13	7.95	27.06	14.94
Cohort 1960-69	6.40	24.47	20.49	5.22	22.24	19.19	7.46	26.27	22.91
Cohort 1950-59	5.02	21.84	20.97	4.03	19.67	22.04	6.05	23.85	23.89
Cohort 1940-	2.95	16.92	18.31	2.36	15.18	19.70	3.49	18.36	23.38
N voter		39,879,837			14,526,993			12,889,274	
N state		33			33			33	

Note: This table reports summary statistics for our main sample (see section 2 for detailed construction). *P(start business in a year* is the annual probability of starting a business among individuals who are between 18 and 70 years old during 1997-2017. *P(ever founder)* is the probability of ever starting a business among individuals who are between 18 and 70 years old during 2005-2017. Units are in percentage points. Columns (1)-(3), (4)-(6) and (7)-(9) are calculated based on all individuals, Democrats, and Republicans, respectively (see section 2.2 details of partisanship definition). *%Sample* refers to the proportion of observations with a certain characteristic in the corresponding sample. $Male$ ($Female$) is an indicator for being male (female), $Edu \geq College$ ($Edu \leq HS$) is an indicator for having college or above degree (having high school or below degree), *Age xx-yy* is an indicator for being between xx and yy years old in a year, and *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) Demo	(3) Party&Demo	(4) Party×Male	(5) Party×Edu	(6) Party×Age	(7) Party×Demo	(8) Party×Race
Dem	-0.0815***		-0.0469***	-0.0233***	-0.0337***	-0.0502***	-0.0113	-0.0042
	(0.0093)		(0.0075)	(0.0083)	(0.0079)	(0.0078)	(0.0094)	(0.0034)
Rep	0.1621***		0.1297***	0.0782***	0.1341***	0.1242***	0.0787***	0.1357***
	(0.0061)		(0.0055)	(0.0045)	(0.0046)	(0.0057)	(0.0049)	(0.0048)
Male		0.4383***	0.4302***	0.4164***	0.4301***	0.4301***	0.4162***	0.3990***
		(0.0209)	(0.0205)	(0.0205)	(0.0205)	(0.0205)	(0.0205)	(0.0166)
College+		0.2162***	0.2084***	0.2080***	0.2286***	0.2084***	0.2285***	0.1775***
		(0.0123)	(0.0121)	(0.0121)	(0.0133)	(0.0121)	(0.0133)	(0.0079)
Dem×Male				-0.0694***			-0.0692***	
				(0.0085)			(0.0085)	
Rep×Male				0.1147***			0.1147***	
				(0.0103)			(0.0102)	
Dem×College+					-0.0412***		-0.0409***	
					(0.0067)		(0.0067)	
Rep×College+					-0.0155**		-0.0166**	
					(0.0070)		(0.0069)	
Dem×Age<40						0.0073	0.0017	
						(0.0050)	(0.0050)	
Rep×Age<40						0.0153***	0.0129**	
						(0.0051)	(0.0051)	
Dem×Black								-0.0262*
								(0.0146)
Dem×Hisp								-0.0575***
								(0.0187)
Dem×Asian								-0.1263***
								(0.0179)
Rep×Black								0.0045
								(0.0135)
Rep×Hisp								0.0410***
								(0.0144)
Rep×Asian								-0.0950***
								(0.0211)
Black								-0.1005***
								(0.0146)
Hisp								-0.1368***
								(0.0260)
Asian								0.3780***
								(0.0254)
R-squared	0.298	0.446	0.456	0.459	0.456	0.456	0.459	0.241
Outcome mean	0.496	0.496	0.496	0.496	0.496	0.496	0.496	0.472
N cell	2,391,003	2,391,003	2,391,003	2,391,003	2,391,003	2,391,003	2,391,003	5,859,381
N obs	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	404270209
N cluster (county)	2,123	2,123	2,123	2,123	2,123	2,123	2,123	2,123
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
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 political and demographic characteristics. The sample includes Democrats, Republicans, and Independents from our main sample. Units are in percentage points. *Dem* is one for Democrats and zero for others; *Rep* is one for Republicans and zero for others (see section 2.2 for definitions of partisanship). Column (8) has fewer observations because some individuals do not have race or ethnic information. 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. All other specifications and variable definitions mirror those in Table 3 column (1).

Table 3
Political Mismatch and the Probability of Starting a Business

VARIABLES	(1) Regular voter	(2) Active voter	(3) HH donor	(4) FEC donor
Mismatch	-0.0165***	-0.0119***	-0.0138***	-0.0150***
	(0.0017)	(0.0019)	(0.0019)	(0.0016)
Mismatch×Active		-0.0097***	-0.0068***	-0.0362***
		(0.0020)	(0.0021)	(0.0128)
Dem	-0.1811***	-0.1824***	-0.1875***	-0.1661***
	(0.0083)	(0.0101)	(0.0093)	(0.0079)
Dem×Active		-0.0030	0.0195***	-0.6913***
		(0.0072)	(0.0055)	(0.0371)
Active		0.0939***	0.0130***	1.6191***
		(0.0089)	(0.0047)	(0.0641)
Mismatch as %mean	3.33	2.4	2.79	3.03
Mismatch×Active as %mean	-	1.95	1.37	7.31
R-squared	0.450	0.324	0.327	0.275
Outcome mean	0.495	0.495	0.495	0.495
N cell	1,595,783	3,070,208	3,038,710	2,379,482
N obs	327,127,995	326,699,233	327,127,995	327,127,995
N cluster (county)	2,120	2,120	2,120	2,120
Demographics	Y	Y	Y	Y
County×Year FE	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. All columns include Democrats and Republicans in our main sample. The outcome is the likelihood of 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 sitting president, equalling one for Republicans in 2009-2016 and for Democrats in 2005-2008 and 2017 and zero otherwise. *Dem* is one for Democrats and zero for Republicans (see section 2.2 for definitions of partisanship). *Active* is an indicator of being politically active. It equals one if a person votes in an above-median percentage of available general and primary elections as of 2020 (column 2), if the household has made at least one political donation by 2020 (column 3), if the individual has made at least one FEC donation by 2020 (column 4), and equals zero otherwise. Regressions are run at county-party-characteristic-year cell. Regressions are weighted by the number of observations in each cell. Standard errors are clustered by county.

Table 4
Political Mismatch and the Probability of Starting a Business
by Gender and Age

VARIABLES	(1) Men	(2) Women	(3) Age 18-29	(4) Age 30-49	(5) Age 50-70
Mismatch	-0.0277***	-0.0051***	-0.0182***	-0.0210***	-0.0089***
	(0.0025)	(0.0013)	(0.0021)	(0.0025)	(0.0016)
Dem	-0.3000***	-0.1001***	-0.1199***	-0.2254***	-0.1669***
	(0.0149)	(0.0052)	(0.0070)	(0.0110)	(0.0072)
Male			0.2495***	0.5727***	0.3895***
			(0.0140)	(0.0280)	(0.0184)
College+	0.3311***	0.1180***	0.0982***	0.2573***	0.1939***
	(0.0203)	(0.0066)	(0.0083)	(0.0158)	(0.0105)
Edu missing	-0.0734***	-0.0433***	-0.0728***	-0.1038***	0.0016
	(0.0130)	(0.0054)	(0.0060)	(0.0106)	(0.0069)
Mismatch as %mean	3.66	1.59	7.17	3.23	2
R-squared	0.505	0.418	0.336	0.504	0.468
Outcome mean	0.756	0.32	0.254	0.653	0.444
N cell	794,515	801,268	313,360	638,071	644,352
N obs	151743786	195881588	50051494	125332715	151743786
N cluster (county)	2115	2120	2114	2116	2116
Demographics	Y	Y	Y	Y	Y
County×Year FE	Y	Y	Y	Y	Y

Note: This table examines how the relationship between political mismatch and the annual probability of entrepreneurship varies by gender and age. Columns (1) through (5) re-estimate Table 3 column (1) for men, women, individuals ages 18-29, individuals ages 30-49, and individuals ages 50-70, respectively. All specifications and variable definitions mirror those in Table 3.

Table 5
Political Mismatch and the Probability of Starting Different *Types of Firms*

VARIABLES	(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	-0.141***	-0.041***	-0.0000**	-0.0007***	-0.005***	-0.024***	-0.035***	-0.040***	-0.033***	-0.034***
	(0.007)	(0.003)	(0.0000)	(0.0001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Male	0.309***	0.131***	0.0003***	0.0027***	0.021***	0.079***	0.088***	0.094***	0.080***	0.079***
	(0.014)	(0.010)	(0.0001)	(0.0002)	(0.005)	(0.012)	(0.007)	(0.007)	(0.005)	(0.005)
College+	0.157***	0.049***	0.0001***	0.0015***	0.009***	0.033***	0.043***	0.044***	0.036***	0.040***
	(0.009)	(0.004)	(0.0000)	(0.0001)	(0.002)	(0.006)	(0.004)	(0.004)	(0.002)	(0.003)
Edu missing	-0.034***	-0.021***	0.0000**	0.0002***	-0.001	-0.007**	-0.004***	-0.011***	-0.009***	-0.013***
	(0.004)	(0.004)	(0.0000)	(0.0001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Age 18-29	-0.004	-0.012***	-0.0000	-0.0005***	-0.002***	-0.007***	-0.007***	-0.010***	0.002	0.011***
	(0.005)	(0.002)	(0.0000)	(0.0001)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Age 30-39	0.253***	0.099***	0.0002***	0.0007***	0.011***	0.051***	0.060***	0.068***	0.066***	0.082***
	(0.011)	(0.009)	(0.0001)	(0.0001)	(0.003)	(0.007)	(0.004)	(0.005)	(0.004)	(0.006)
Age 40-49	0.235***	0.099***	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	0.148***	0.055***	0.0001***	0.0007***	0.007***	0.030***	0.037***	0.041***	0.039***	0.044***
	(0.006)	(0.004)	(0.0000)	(0.0001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Mismatch as %mean	0.72%	10.76%	15.79%	4.67%	4.67%	6.33%	3.04%	1.99%	1.3%	2.5%
R-squared	0.419	0.306	0.035	0.039	0.289	0.338	0.304	0.317	0.223	0.288
Outcome mean	0.363	0.134	0	0.0015	0.014	0.069	0.09	0.101	0.089	0.101
N cell	1,595,783	1,595,783	1,595,783	1,595,783	1,595,777	1,595,777	1,595,777	1,595,777	1,595,777	1,595,777
N obs	327,127,995	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 cluster (county)	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how the annual probability of starting various 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 the likelihood of starting a specific type of firms, which differs by column. "LLC" are new businesses registered as limited liability companies under the jurisdiction of their headquarters (or local) state. "Corporations" are new corporations registered under local state jurisdiction. "VC backed" is a firm that has ever received venture capital investment. "Patent firm" is a firm that has ever filed patents according to USPTO records. "Q:xx" refers to businesses who score in a certain percentile range of entrepreneurial quality (Guzman and Stern, 2020); this measure is only available up to 2016.

Table 6
Political Mismatch and the Probability of Starting Firms *by Industry*

VARIABLES	(1) Science & Tech	(2) Health & Social	(3) Accom. & Food	(4) Cons-truction	(5) Real estate	(6) Trans-portation	(7) Agri-culture	(8) Arts & Entmt.	(9) Ware-housing	(10) Mining	(11) Retail trade	(12) Public admin.	(13) Other service
Mismatch	-0.0018***	-0.0026***	-0.0013***	-0.0040***	-0.0030***	-0.0021***	-0.0010***	-0.0011***	-0.0010***	-0.0017***	-0.0007***	-0.0013***	-0.0026***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Dem	-0.0205***	-0.0158***	-0.0174***	-0.0197***	-0.0302***	-0.0091***	-0.0256***	-0.0143***	-0.0146***	-0.0187***	-0.0098***	-0.0149***	-0.0074***
	(0.0010)	(0.0011)	(0.0010)	(0.0009)	(0.0015)	(0.0010)	(0.0010)	(0.0008)	(0.0007)	(0.0010)	(0.0006)	(0.0008)	(0.0005)
Male	0.0515***	0.0322***	0.0457***	0.0552***	0.0473***	0.0459***	0.0457***	0.0334***	0.0392***	0.0408***	0.0152***	0.0365***	0.0297***
	(0.0022)	(0.0020)	(0.0025)	(0.0022)	(0.0023)	(0.0041)	(0.0014)	(0.0018)	(0.0019)	(0.0019)	(0.0012)	(0.0017)	(0.0014)
College+	0.0267***	0.0364***	0.0202***	0.0181***	0.0295***	0.0084***	0.0176***	0.0182***	0.0145***	0.0167***	0.0107***	0.0199***	0.0072***
	(0.0012)	(0.0021)	(0.0014)	(0.0009)	(0.0017)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0011)	(0.0007)	(0.0011)	(0.0006)
Edu missing	-0.0073***	-0.0035***	-0.0055***	-0.0095***	-0.0037***	-0.0076***	-0.0058***	-0.0043***	-0.0056***	-0.0028***	-0.0059***	-0.0024***	-0.0075***
	(0.0011)	(0.0012)	(0.0010)	(0.0010)	(0.0008)	(0.0008)	(0.0006)	(0.0007)	(0.0007)	(0.0005)	(0.0007)	(0.0007)	(0.0008)
Age 18-29	-0.0024**	-0.0048***	-0.0050***	-0.0047***	-0.0140***	-0.0011	-0.0071***	0.0006	-0.0003	-0.0045***	0.0036***	-0.0082***	-0.0004
	(0.0010)	(0.0011)	(0.0007)	(0.0008)	(0.0010)	(0.0012)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)
Age 30-39	0.0474***	0.0476***	0.0340***	0.0365***	0.0242***	0.0348***	0.0225***	0.0355***	0.0309***	0.0231***	0.0311***	0.0198***	0.0267***
	(0.0024)	(0.0029)	(0.0017)	(0.0017)	(0.0012)	(0.0028)	(0.0009)	(0.0018)	(0.0014)	(0.0010)	(0.0017)	(0.0010)	(0.0014)
Age 40-49	0.0437***	0.0425***	0.0371***	0.0346***	0.0287***	0.0327***	0.0226***	0.0320***	0.0288***	0.0228***	0.0276***	0.0203***	0.0260***
	(0.0021)	(0.0023)	(0.0016)	(0.0014)	(0.0012)	(0.0025)	(0.0008)	(0.0014)	(0.0012)	(0.0009)	(0.0013)	(0.0010)	(0.0012)
Age 50-59	0.0264***	0.0264***	0.0239***	0.0224***	0.0207***	0.0188***	0.0182***	0.0173***	0.0179***	0.0152***	0.0174***	0.0132***	0.0155***
	(0.0012)	(0.0013)	(0.0010)	(0.0009)	(0.0009)	(0.0013)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0006)	(0.0007)
Mismatch as %mean	2.85	4.28	2.32	7.11	5.73	4.59	2.05	2.41	2.23	4.23	1.88	3.47	6.96
R-squared	0.138	0.146	0.116	0.109	0.134	0.245	0.089	0.105	0.100	0.095	0.099	0.093	0.083
Outcome mean	0.064	0.061	0.055	0.056	0.052	0.046	0.049	0.045	0.042	0.039	0.038	0.038	0.036
N cell	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783	1,595,783
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	327,127,995
N cluster (county)	2120	2120	2120	2120	2120	2120	2120	2120	2120	2120	2120	2120	2120
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how the annual probability of starting businesses in different 2-digit NAICS 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 the likelihood of starting a firm in a specific industry, which differs by column. Firms are classified into industries based on the presence of industry-specific keywords in their names (see section 4.3.4).

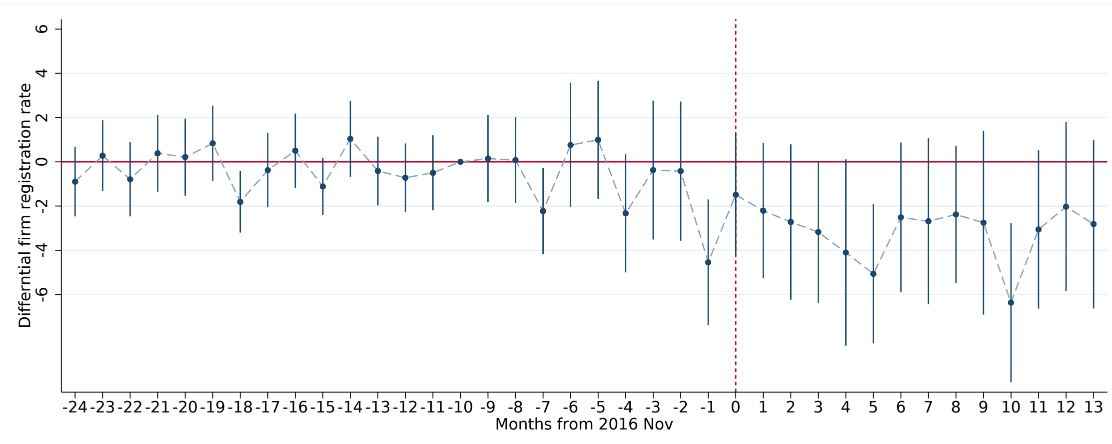
Table 7
Political Mismatch and Employer Firms:
County-Level Business Dynamics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New firm		Existing firm				All firm
VARIABLES	Firm entry	Job rate	Estab. entry	Estab. exit	Firm death	Net job rate	Net job 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-squared	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 cluster (county)	3059	3033	3059	3059	3059	3058	3058
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

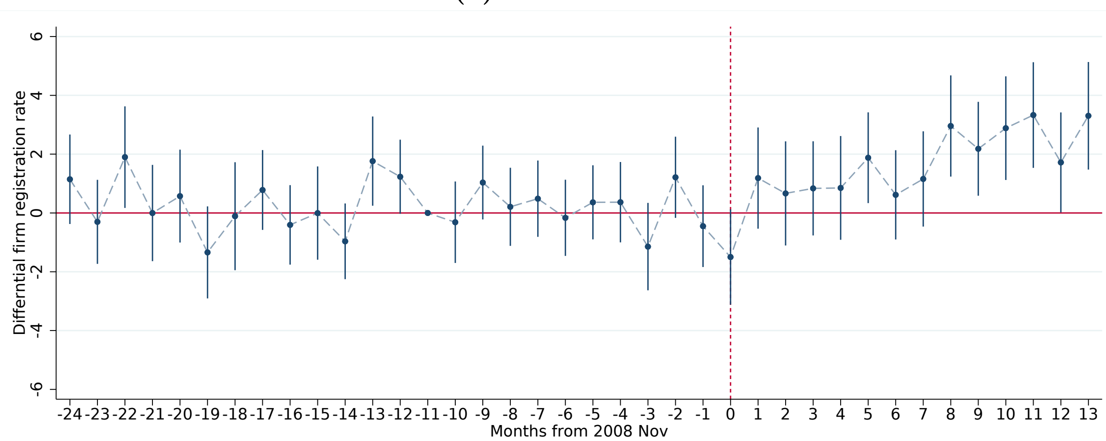
Note: This table examines how entry, exit, expansion, and contraction of both new and existing *employer* firms relate to being in counties that are politically mismatched with the sitting president between 2005 and 2018. The omitted group is Republican-leaning counties. “Firm entry”, “Estab. entry”, “Estab. exit”, and “Firm death” are the annual number of new firms, number of newly opened establishments among existing firms, number of newly closed establishments among existing firms, and number of firms that have closed all their establishments, per 100,000 county residents ages 20 or above, respectively. The regression weight is the number of the county population ages 20 or above. “Job rate” is the number of newly created jobs as a percent of the average of employment for years t and t-1. “Net job rate” is the number of newly created jobs less the number newly destroyed as a percent of the average employment for years t and t-1; the regression weight is average employment for years t and t-1. 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 all 2-digit NAICS industries). Columns (3) through (7) replace year fixed effects with firm age-by-year fixed effects. Standard errors are clustered by county.

Appendix for "Partisan Entrepreneurship"

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



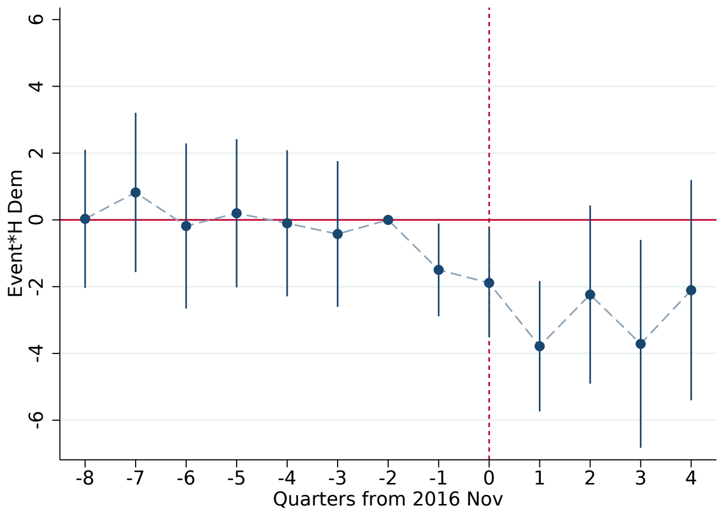
(a) 2016 election



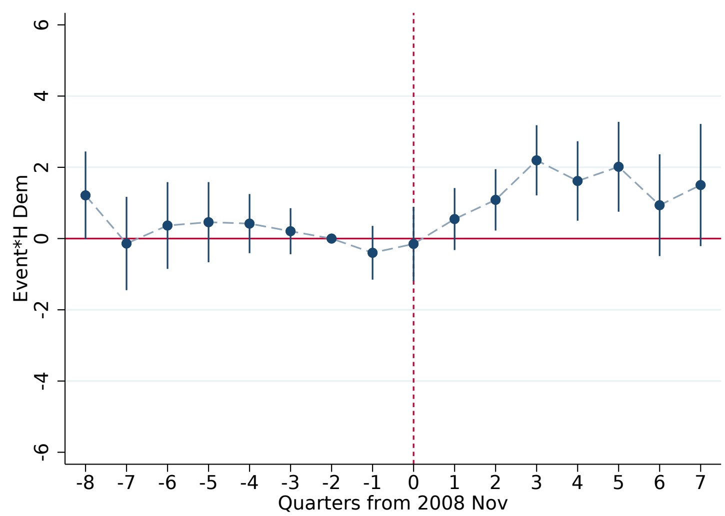
(b) 2008 election

Figure A1. Political Mismatch and New Firm Registration Rate
Democratic versus Republican *Counties* (Monthly Frequency)

Note: This figure plots the estimated number of (excess) monthly new firm registrations per 100,000 people ages 20 and above in Democrat-leaning counties relative to Republican-leaning counties. This is the monthly counterpart of Figure 3. Republican-leaning counties are the omitted group. Event time 0 refers to the month of a presidential election. The omitted period is the month of the earliest presidential primary (or caucus) in the repspective election, i.e., event time -11 for the 2008 election and -10 for the 2016 election. All regressions control for county fixed effects, year-month fixed effects, and county economic conditions (i.e., monthly unemployment rate, annual per capita income and annual employment share for all 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county.



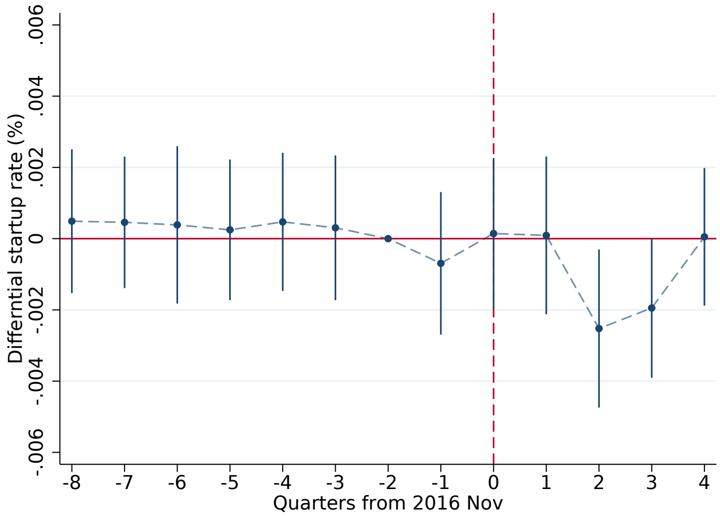
(a) 2016 election



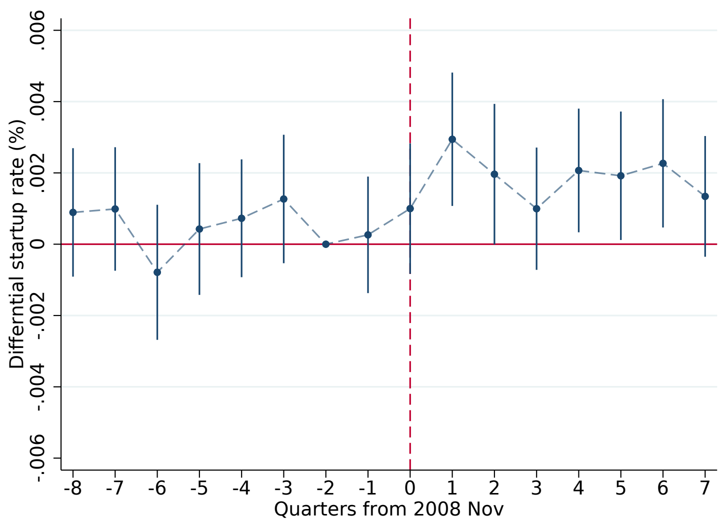
(b) 2008 election

Figure A2. Political Mismatch and new Firm Registrations: *Cross-County* Evidence Robustness Check *without* Economic Controls

Note: This figure presents robustness check for Figure 3. All specifications are the same as those in Figure 3 except that we do not control for contemporaneous conuty economic conditions.



(a) 2016 election



(b) 2008 election

Figure A3. Political Mismatch and the Probability of Starting a Business: *Active* Democrat versus *Active* Republican Individuals

Note: This figure plots the estimated (excess) monthly probability of starting a business for *active* Democrats relative to *active* Republicans. Units are in percentage points and the omitted group is Republicans. Individuals are identified as Democrat or Republican in 21 states by their party registration. In the remaining 12 states, our political data provider infers an individual's party. Active voters are those who vote more often. Event time 0 refers to the three months following the month of a presidential election. For example, for the 2016 election event time 0 is November 2016 to January 2017. Event time -2 is the omitted period. All regressions control for county×event time fixed effects and voter characteristics (i.e., gender, education, age groups). 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.

Table A1
Political Mismatch and New Firm Registration Rate
Democratic versus Republican *Counties*

VARIABLES	(1) Election 2008	(2) Election 2016
Dem×-8Q	0.954	-0.289
	(0.745)	(1.285)
Dem×-7Q	-0.514	0.632
	(0.783)	(1.468)
Dem×-6Q	0.002	-0.370
	(0.723)	(1.530)
Dem×-5Q	0.078	0.029
	(0.659)	(1.382)
Dem×-4Q	0.192	-0.201
	(0.503)	(1.354)
Dem×-3Q	0.216	-0.508
	(0.394)	(1.346)
Dem×-1Q	-0.419	-1.613*
	(0.465)	(0.856)
Dem×0Q	-0.076	-1.971*
	(0.635)	(1.008)
Dem×1Q	0.752	-4.003***
	(0.539)	(1.215)
Dem×2Q	1.312**	-2.427
	(0.556)	(1.649)
Dem×3Q	2.423***	-3.994**
	(0.617)	(1.927)
Dem×4Q	1.740**	-2.335
	(0.689)	(2.030)
Dem×5Q	1.983**	
	(0.771)	
Dem×6Q	0.905	
	(0.846)	
Dem×7Q	1.491	
	(1.022)	
Avg 1-4Q as %mean	2.31%	-3.91%
R-squared	0.115	0.013
Outcome mean	67.468	81.65
N obs	137,856	109,136
N cluster (county)	2872	2872
County FE	Y	Y
Quarter FE	Y	Y
Economic controls	Y	Y

Note: This table presents the estimated number of (excess) monthly new firm registrations per 100,000 people 20 years old or older (averaged within quarter) in Democrat-leaning counties relative to Republican-leaning counties. Republican-leaning counties are the omitted group. Event time 0 refers to the three months following the month of a presidential election. For example, for the 2016 election event time 0 is November 2016 to January 2017. Event time -2 is the omitted period. All regressions control for county fixed effects, event time fixed effects, and county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for all 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county.

Table A2
Political Mismatch and the Probability of Starting a Business:
Alternate *Geographic Fixed Effects*

VARIABLES	(1) State	(2) County	(3) Zip	(4) Tract	(5) Block grp
Panel A: Regular voter					
Mismatch	-0.0183***	-0.0165***	-0.0158***	-0.0154***	-0.0154***
	(0.0017)	(0.0017)	(0.0015)	(0.0014)	(0.0014)
Panel B: Active voter					
Mismatch	-0.0137***	-0.0119***	-0.0113***	-0.0109***	-0.0109***
	(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-squared	0.004	0.005	0.007	0.009	0.013
Panel C: HH Donor					
Mismatch	-0.0158***	-0.0138***	-0.0132***	-0.0128***	-0.0129***
	(0.0019)	(0.0019)	(0.0017)	(0.0017)	(0.0017)
Mismatch×Active	-0.0066***	-0.0068***	-0.0066***	-0.0064***	-0.0063***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Panel D: FEC Donor					
Mismatch	-0.0169***	-0.0150***	-0.0144***	-0.0140***	-0.0141***
	(0.0016)	(0.0016)	(0.0014)	(0.0013)	(0.0013)
Mismatch×Active	-0.0366***	-0.0362***	-0.0353***	-0.0353***	-0.0346***
	(0.0130)	(0.0128)	(0.0127)	(0.0126)	(0.0126)
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 cluster (county)	2,120	2,120	2,120	2,120	2,120
Demographics	Y	Y	Y	Y	Y
Year×Geo FE	Y	Y	Y	Y	Y

Note: This table presents robustness check for Table 3 under various geography-by-year fixed effects. Regression samples are at the individual-by-year level. Outcomes and specifications in panels A, B, C, and D mirror Table 3 columns (1), (2), (3), and (4) except that each column in the current table 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.

Table A3
Political Mismatch and Starting a Business - Election Event Study: Democrat versus Republican Voters

VARIABLES	(1) 2008	(2) 2016
Dem×-8Q	0.00038	0.00016
	(0.00076)	(0.00074)
Dem×-7Q	-0.00002	0.00004
	(0.00071)	(0.00075)
Dem×-6Q	-0.00114	0.00045
	(0.00079)	(0.00077)
Dem×-5Q	-0.00042	0.00037
	(0.00071)	(0.00072)
Dem×-4Q	-0.00099	0.00100
	(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	-0.00054
	(0.00071)	(0.00074)
Dem×1Q	0.00148**	-0.00043
	(0.00068)	(0.00074)
Dem×2Q	0.00144*	-0.00238***
	(0.00077)	(0.00083)
Dem×3Q	0.00102	-0.00122*
	(0.00063)	(0.00072)
Dem×4Q	0.00154**	-0.00049
	(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%	-2.36%
R-squared	0.041	0.036
Outcome mean	0.04	0.048
N cell	5,909,403	4,758,727
N obs	1,233,491,758	938,448,427
N cluster (county)	2,119	2,118
Demographics	Y	Y
County×Event FE	Y	Y

Note: This table compares the likelihood of starting a business between Democrats and Republicans in the same county in the months around the 2008 and 2016 presidential elections. The outcome is the excess likelihood of starting a business in a month, and units are in percentage points. *Dem* is one for Democrats and zero for Republicans. Event time 0 refers to the three months following the month of a presidential election. For example, for the 2016 election, event time 0 refers to November 2016 to January 2017. Event time -2 is the omitted period. All regressions control for county×event fixed effects and individual characteristics (i.e., gender, education, age groups). 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.

Table A4
Political Mismatch and Employer Firms: County-Level Business Dynamics
Robustness Check *without* Economic Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New firm		Existing firm				All firm
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-squared	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 cluster (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 robustness check for Table 7. All specifications mirror those in the corresponding columns of Table 7 except that we do not control for contemporaneous county economic conditions in this tab;e.