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PARTISAN ENTREPRENEURSHIP

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ABSTRACT

Republicans start more firms than Democrats. In 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 markedly more optimistic than Democrats during the administrations of George W. Bush and Donald Trump – by almost two standard deviations (Figure 1) – but this difference disappeared during the Democratic administrations of Bill Clinton and Barack Obama.

This paper examines whether changes in political regime and the corresponding shifts in partisan beliefs translate into a critical economic behavior: entrepreneurship. To illustrate, Figure 3 compares Republican to Democratic counties before versus after the 2008 and 2016 presidential elections in a difference-in-differences (DID) framework. A clear pattern emerges: start-up rates in Democratic counties rise (relative to Republican ones) after the election of Barack Obama and fall after the election of Donald Trump. Specifically, following the 2008 election the number of new firms per capita in Democratic (relative to Republican) counties rose by 2.4% of the mean over the year; for the 2016 election, the corresponding increase was 3.4% for Republican counties. Extrapolating across all counties, this change corresponds to a partisan shift of approximately 42,000 new firms in the year following the 2016 election and 20,000 firms after the 2008 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 in a DID event study design.

To do this, we consider a sample of approximately 40 million Americans for whom we have political party identification and who live in the 33 states for which we have complete data on firm founders from the Startup Cartography Project (Andrews et al., 2020).[1] We find that Republicans are more likely to be entrepreneurs than Democrats: over our 13-year sample, 5.5% of Republicans started a business, compared to 3.7% of Democrats. After controlling for age, gender, education, and county-year fixed effects, Republicans are still 36% more likely than Democrats to start a business in a given year, relative to the mean.

A within-county individual-level DID event study using this sample 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 same county and increase their relative entrepreneurship after Trump's election by 2.4%. Taken together, our evidence shows politically sensitive entrepreneurship not only *across* Republican and Democratic counties, but also between Republicans and Democrats *within* the same county in the same quarter.

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 — have a probability of starting a business that is 3.3% of the mean lower than those whose party is in power. Our effect size corresponds to an annual difference of 13,000 new firms between politically matched versus mismatched individuals, or about 170,000 firms over our sample period.

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

[1] These 33 states cover 69% of U.S. GDP as of 2016. We focus on individuals with unique names (e.g., Silvia Teston rather than Robert Smith) so that we can accurately match voters with founders using names and addresses. 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, indicating high match quality.

political engagement, the effect 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 economic impact (Schoar, 2010, Guzman and Stern, 2020, Sterk et al., 2021). We find that corporations are much more responsive than LLCs (an effect size of 10.8% versus 0.7% of the mean).[2] Our main result is present 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, which represent over half of high growth firms, is over six times as large as that of LLCs (4.7% versus 0.7% of the mean).

Next, we turn to founder characteristics, where we find strong partisan differences by gender, age, and income. First, we find the well-known gender gap in entrepreneurship in our data: 6.6% of men and 3.2% of women started a business in our 13-year sample. After controlling for individual characteristics and county-year fixed effects, men are about 0.4 percentage points (pp) per year more likely to start a business than women, 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 changes 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 this likelihood is only 1.6% lower.

We also find substantial heterogeneity of effects by age and income. 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;

[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.

among the oldest individuals (50 to 70 years old), this number is only 2%. While lower income households are *less* likely to start a business (an annual probability of 0.35% versus 0.77%), they are *more* more responsive to political regime changes, with an effect size of 4%, compared to 3% for higher income households.

A possible driver of our findings is that the party in power implements *policies* favoring same-party entrepreneurs. To examine this, we estimate effects within geography and within industry. While policy is often focused on specific geographies or industries, we find strong partisan effects both *within* finely-grained geographic units (including within census block groups) and *across* almost all two-digit NAICS industries, including the least policy sensitive industry: retail (Hassan et al., 2019). Taken together, the evidence is inconsistent with partisan policy being the sole driver of our estimated effects.

Another explanation for the evidence runs through partisan swings in *economic sentiment* around elections. While this is difficult to conclusively establish, we find circumstantial evidence. Specifically, we find a partisan swing in economic expectations among business owners in Gallup survey microdata which mirrors the patterns in entrepreneurship we document. Moreover, we find a stronger increase in entrepreneurship in the aligned counties with larger post-election increases in economic optimism.

Finally, we examine *existing* firms using the Business Dynamics Statistics data from the U.S. Census Bureau. Despite using a different data source and focusing on a different firm population, we continue to find partisan effects. Existing firms in mismatched counties are less likely to open new establishments, more likely to close existing ones, and more likely to shut down the entire business, resulting in a net loss of jobs. For example, the net job creation rate of existing firms in counties mismatched with the party of the president is 6% of a standard deviation lower than in matched counties.

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

Our findings relate to several strands of the literature in entrepreneurship and political economy. In entrepreneurship, many have explored the links between founder characteristics and the decision to start a firm, such as age, race, wealth, and gender (e.g., Evans and Jovanovic, 1989, Holtz-Eakin et al., 1994, Hurst and Lusardi, 2004, Guzman and Kacperczyk, 2019, Azoulay et al., 2020, Fairlie et al., 2021, Bellon et al., 2021). Our paper shows that political affiliation is another important characteristic, representing 40% of the size of the well-known gender gap in entrepreneurship even 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 (Puri and Robinson, 2013, Levine and Rubinstein, 2017, Kerr et al., 2019, Barrios et al., 2021). 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 provide evidence of *time-varying* economic optimism among business owners induced by partisan sentiment.

We also contribute to the literature exploring determinants of the entrepreneurship decision. Existing work has focused on the impacts of financial constraints, risk-reduction policies, training, entrepreneurial peers, and the availability of reproductive healthcare.[3] We uncover a new driver of entrepreneurial entry – political sentiment – that is correlated across founders and time, thus contributing to the business cycle.

Finally, our paper contributes to a new literature on the economic consequences of partisanship. At the corporate level, several papers have found evidence of partisan effects on credit ratings, syndicated lending, and the composition of 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 partisanship affects economic optimism around elections (e.g., Bartels 2002, Evans and Andersen 2006). However, there is mixed evidence that such optimism matters for important economic outcomes. Some papers report a link between spending on consumer goods and political alignment (Gerber and Huber, 2009, Gillitzer and Prasad, 2018, Benhabib and Spiegel, 2019), while others argue against this connection (McGrath et al., 2017, Mian et al., 2021).[4]

The rest of the paper proceeds as follows. Section 2 covers the 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]Recent papers link partisanship with financial decisions such as tax evasion, stock market trading, retirement investing and residential sorting (Cookson et al., 2020, Cullen et al., 2021, Meeuwis et al., 2021, Bernstein et al., 2021, McCartney et al., 2021).

2. Data and sample construction

2.1 Entrepreneurship data from business registrations

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

We use data from the Startup Cartography Project (Andrews et al., 2020), which contains business registration records across 49 U.S. states and Washington D.C. from 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 ensure individuals are startup founders, we exclude personnel whose titles imply that they play only an administrative role.[5] Since the data are business registrations, sole proprietorships and self-employed individuals without formal registration are not in our sample.

2.2 Voter and donor data

We obtain data on registered voters from L2, an established 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 the 2014 voter roll to assign voter partisanship. This strategy resolves such concerns for the 2016 election, and mitigates them for the 2008 election to the extent possible with L2 data. Party status is largely invariant: the annual probability of changing from Republican to Democrat or vice versa is 1.8%. We add individuals' voting histories, which we need to construct political activeness measures, from the most recent L2 voter file we have (October 2020) to the 2014 voter population, dropping those without this data.[9] 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

[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, 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.

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

which describe political donation behavior. The first is a variable identifying donations recorded by the Federal Election Commission (FEC). Using the L2-linked FEC data, we call individuals *active FEC donors* if they have made a political donation by 2020 (2.3% of the sample). L2 also identifies individuals whose household members have made a contribution to any political cause as of 2020, which we call *active household donors* (40% of our voters).

L2 provides a suite of demographic variables, such as registered state and county, birth year, gender, and education level, which we use as controls in the main specifications. We include race/ethnicity only in some specifications because it is missing for 10% of the sample.[10]

2.3 Sample of registered voters

We match voters between the ages of 18 and 70 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 among all voters in a 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 enable 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 pp.[11] 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 robustness, we show results weighting individuals in our sample to match the U.S. voter population, and

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

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

we also present our main analysis separately for men and women.

L2 has 140 million registered voters in the 33 states for which we have data on firm founders and addresses. After restricting the sample to unique names we have around 40 million voters. Of these, 1.9 million (4.6%) started a company during our sample period. Conditional on both voter and founder having middle initials, the matched individuals have the same middle initials 88% of the time, indicating a high match quality between voter and founder databases.

A voter is coded as starting a business in a period if they register at least one firm in that period. The resulting sample is a voter-time panel with approximately 40 million observations at any point in time. For computational tractability we collapse the regression sample to a set of fully saturated county-party-characteristic-time cells, where each cell is a combination of county, party identification (Democrat, Republican, other), gender (male, female), age (18-29, 30-29, 40-29, 50-29, 60-70), 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 and the probability of ever starting a business during our sample period. It also reports the distribution of the sample across political parties and demographics, as well as the likelihood of starting a business in these various political and demographic subgroups. The political demographics of our sample appear broadly consistent with those of voters in general and by party. For example, female voters are more likely to be Democrats, as are younger individuals and minorities (Doherty et al., 2018). We further discuss the representativeness of our sample in Section 4.3.2.

Out of over 40 million voters in our sample, around 4.6% started a business at some point between 2005 and 2017. The likelihood of starting a business in a given year is approximately 0.5 pp.[12] When we split the data by political party, a consistent theme emerges: Republicans are more likely to start a business than Democrats. For example, while 5.5% of Republicans ever start a firm in our data, only 3.7% of Democrats do. In a given year, the probability that a Republican starts a business is 0.6%, while for a Democrat this is 0.4%.

When we examine the entrepreneurship rate across demographic characteristics, we note a few differences. First, consistent with prior results in Fairlie et al. (2021), whites are more likely to start a business in a year than Blacks and Hispanics, as are college graduates (Hurst and Lusardi, 2004). Second, the entrepreneurship rate is the highest in the middle of our age distribution (between 30 and 49 years old), with a 0.7% chance of starting a business in a year, consistent with the pattern described in Azoulay et al. (2020) using administrative data from 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 (e.g., Guzman and Kacperczyk, 2019).

To move beyond summary statistics, in Table 2 we estimate regressions of the likelihood of starting a business as a function of party affiliation and demographic characteristics. All regressions include age-group (except column 1) 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.

Column (2) confirms the well-known relationships between education, gender and en-

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

trepreneurship. 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 graduates 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 parties. The gender gap among Independents is similar to the mean, while Democrats have a 16% smaller gap and Republicans have a 27% larger one.

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 between Democrats and 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%, 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 (and county-year fixed effects). 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 and optimism

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 it was lower than the CCI of Democrats during the administration of Barack Obama.

In addition, there are sharp swings in the views of Republicans and Democrats after party-changing presidential elections, especially after those of Obama (2008), Trump (2016) and Biden (2020).[13] Non-party-changing elections (and midterms) appear to have little to no effect on economic optimism. Mian et al. (2021) finds 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

[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.

unchanged. Meeuwis et al. (2021) also reports little change in the savings rate of partisans. Taken together, the swings in economic optimism around elections likely reflect partisan updating about the national economy rather than individual 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.

4.1.2 County-level evidence

We begin by comparing the changes in firm startup rates in Democratic versus Republican counties, before versus after a party-changing presidential election, in an event study DID framework.

We classify a county as Democratic if its vote share for the Democratic party is above the sample median in the preceding presidential election, and Republican otherwise.[14] The outcome of interest is the total number of new firms registered in a month, per 100,000 county residents. If there are no new firms in a county $\times$ month, we code it as a zero. We de-seasonalize the outcome by regressing it on county $\times$ month-of-year indicators and county annual linear trends using data starting from 2004 (for the 2008 election) and 2012 (for the 2016 election). We refer to the resulting variable as the *excess* firm registration rate.

We use the following specification:

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

Y_{ct} is the excess firm registration rate in county c in time t, the number of time periods rela-

[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 in these states.

tive 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, and the employment share in each two-digit NAICS industry (excluding non-classifiable establishments) as controls for contemporaneous economic conditions and industry importance in each county. We include county fixed effects α_c and event time fixed effects α_t to absorb the average firm registration rate in a county and national registration trends. We cluster standard errors by county.

While the data is monthly, for precision and clarity we estimate quarterly averages, and report the monthly version in the Appendix. We define $t = 0$ as the three-month period following an election month. For example, November 2016 to January 2017 constitute $t = 0$ for the 2016 election. We omit the indicator for $t = -2$ to form 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 moved in parallel in the absence of elections. As we will show, this condition appears to hold.

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 (2.3% 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 (3.9% of the mean) in the year following the 2016 election.[15]

The entrepreneurship response we document is immediate, appearing in the same quarter

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

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

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 before the election, a period of political turbulence which included FBI director Comey's letter to Congress about candidate Clinton's emails.

4.2 Individual-level evidence

We now turn to individual data, which allows us to exploit different identifying variation than the cross-county analysis reported in the preceding section. 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 *excess* likelihood that an individual starts a business in a month.[16] 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

[16]To obtain the excess likelihood, we de-seasonalize the raw likelihood by subtracting its party-specific county × month-of-year average and county annual trend using data starting from 2004 (for the 2008 election) or 2012 (for the 2016 election).

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 $t = -2$ to form 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 $\times$ time fixed effects $\alpha_{c(i),t}$ to control for county-specific time-varying startup likelihood. $\mathbf{X_{it}}$ is a vector of gender, education, and age group bins.[17]

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

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 A6 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.[18] 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

[17] 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).

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

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 Independents as the control group. Figure 5 plots the β_t estimates for each party. 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 their startup rate, and 60 percent comes from Democrats decreasing their rate.

The above results 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 presidential elections and use less than half of the sample years as a result. In this section, we use the entire sample (2005-2017) to estimate the average relationship between entrepreneurship and being politically mismatched with the sitting president. To do so, we exploit the panel structure of our individual-level data and estimate the following:

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

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 Democrats and zero for Republicans. $Mismatch_{it}$ is an indicator equal to one when individual i's party identification *differs* from the party of the president in year t, namely one for Republicans during 2009-2016 and for Democrats during 2005-2008 and 2017. $\alpha_{c(i),t}$ denotes county $\times$ year fixed effects. We additionally control for $\mathbf{X_i}$, a vector of demographic characteristics (gender, age, and education). Standard errors are clustered by county.[19]

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

4.3.1 Main estimates

Table 3 panel A reports the estimates from equation 3. 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, equal to 3.3% of the sample mean. Extrapolating across the U.S., this amounts to an annual change in the partisan gap of around 13,000 founders, or approximately 170,000 over our 13-year sample.

To support the idea that it is political sentiment that drives differential entrepreneurship, 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 interactions) to equation 3 and re-estimate the model. The negative and significant coefficient on $Mismatch \times Active$ 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 mismatch is 82% stronger than that of less active partisans.[20]

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

[20] 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 somewhat stronger for the 2016 election.

Turning to active *donors*, columns (3) and (4) indicate that household and FEC donor voters, respectively, are 0.007 and 0.04 pp less likely to start a company when mismatched, relative to their non-active counterparts. This represents an additional 1.4% and 7.3% of the average annual probability of starting new firms. While the effect for FEC donors is much larger, they are a selected and much smaller subset of registered voters: 2.3% of individuals vs. 50% for active voters and 40% for HH donors.[21]

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

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

4.3.2 Robustness of main estimates

Next, we consider the representativeness of our sample. Recall that we focus on voters with unique names in a county to ensure an accurate match between the voter file and the business registration data. To examine how this unique-named sample compares with the full voter file, Appendix Table A1 reports individual characteristics for the full 2014 U.S. voter population (panel A - 160 million voters), for the 33 states which we can match to entrepreneurship data (panel B - 108 million voters), and for voters in our regression

[21]The fraction of FEC donors in our sample is comparable to statistics from OpenSecrets (2021): 1.2% of women and 1.6% of men donated over $200 in the 2020 election.

sample (panel C - 40 million voters). Panels A and B are very similar, suggesting that the states in our sample are representative in terms of the voter characteristics we can measure. However, panel C displays some differences from the other two panels. This is likely the result of the unique name filter we use to generate our sample. For example, women and African-Americans are more likely to have unique names, while this is less likely for Hispanics.

To ensure that the differences between our sample and the U.S. voter population are not driving our reported results, in panel B of Table 3 we re-estimate the specifications in panel A using individual-level data and an entropy-balance method (Hainmueller, 2012) that weights each observation so that the means of the covariates in the re-weighted sample match those in the U.S. voter population.[22] For example, since our regression sample under-samples men, this procedure will give more weight to male observations to correct for this. Estimates in panel B are very similar to the unweighted ones in panel A, providing support to the view that our estimates are representative of the underlying dynamics of partisan entrepreneurship. We report unweighted results in the remainder of the paper.

4.3.3 Heterogeneity by gender, age and income

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, as discussed above. Columns (1) and (2) of Table 4 replicate Table 3 column (1) for men and women separately. Men appear more sensitive to political power shifts than women. Relative to their respective means, men are 3.7% less likely to engage in entrepreneurship when politically mismatched with the presidential regime, but

[22] The characteristics we match are share of Democrats, and, within each party, the shares of men, college graduates, Hispanics, African Americans, whites, and birth cohorts.

for women the effect is only 1.6%.[23]

In columns (3) to (5) we explore heterogeneity by age (Azoulay et al. 2020). Individuals between 18 and 29 years old show the largest effect relative to their mean (7%), 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.

Because wealth is correlated with the ability to start a business (e.g., Evans and Jovanovic, 1989, Fairlie, 1999, Hurst and Lusardi, 2004), columns 6 and 7 separately consider individuals with annual household incomes above and below $100,000, respectively. While the mismatch coefficient is larger among high-income individuals, the relative effect is actually larger among low-income individuals (4% vs. 3%); this difference obtains because, consistent with the literature, high-income individuals are more than twice as likely to start a business.

4.3.4 Heterogeneity by firm type

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

We begin by plotting firm quality as a function of party and gender in Figure 2. The

[23]Consistent with this, in Gallup daily survey data we find that the economic expectations of men react more strongly to regime changes than those of women.

figure shows that Democrats are more likely than Republicans to start firms in the highest quality quintile. Moreover, men are more likely to start top-quality firms and less likely to start bottom-quality firms than women. In untabulated results, we find that these quality differences across gender and party persist even after we control for demographics and county $\times$ year fixed effects.

Next, we reconsider our main specification among firms of different ex ante quality. Specifically, Table 5 replaces 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: politically mismatched individuals are only 0.7% of the mean less likely to start an LLC compared to 10.8% for corporations.

Columns (3) to (5) focus on firm types that have high ex ante growth potential: VC backed, firms that filed for a patent, and firms in the top five percent of the Guzman and Stern (2020) quality distribution. Despite finding large economic magnitudes for the effect size (16% of the mean for VC-backed and 5% for patent firms), the rarity of these firm types limits power and hence the statistical significance of these estimates. However, firms in the top 5 percent by ex ante quality show a mismatch effect of 4.7% of the mean that is statistically significant.

Columns (6)-(10) consider quintiles of the quality distribution and show a near-monotonic decrease in the estimated sensitivity to mismatch as firm quality declines. For example, firms in the top quintile have a mismatch coefficient of -0.004 (6% 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 lower-quality firms.[24]

[24]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.

4.3.5 Examining mechanisms

Mechanism: Policy

A natural explanation for our findings is that regime switches lead to policies 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, while the 2010 Affordable Care Act may have benefited Democratic areas more than Republican ones.

While it is possible that policy changes contribute to our findings, our evidence is not consistent with an explanation that is *solely* policy-based. First, the DID event studies (Figure 3) show rapid effects on entrepreneurship, often within the first two quarters after an election. But policy takes time to design and implement, in contrast to expectations (regarding future policies or the economy as a whole) which can change almost immediately, as suggested by Figure 1. Second, we find stronger effects among the most partisan individuals (Table 3), i.e., those that vote more or donate. It is unclear, for example, why a new federal policy would favor Republicans who vote more often than other Republicans in the same county. But it seems likely that an active Republican would be especially optimistic (pessimistic) during Republican (Democratic) administrations. Third, we find significant heterogeneity by personal characteristics (Table 4), with men and younger people showing larger effects. Again, it seems unclear why a new policy would disproportionately favor, for example, young Democrats (relative to old ones) or Democratic men (relative to Democratic women) in the same county.

We further investigate a policy-based channel by conducting tests in two domains that policy often targets: geography and industry. Mian et al. (2021) finds little evidence of changes in tax rates, personal income growth, and transfers at the county and state levels around U.S. presidential elections. In addition, to examine whether partisans' economic situation differentially improves, they use zip code-by-month fixed effects, assuming that people within zip codes are subject to the same government policies. Similarly, we re-estimate the model in Table 3, adding fine-unit geographic fixed effects so that identification comes, for example, via differences between Democrats and Republicans who live in the same census block group at the same time. If policy is targeted to geography, we would expect our main result to disappear as we include these fixed effects. However, we find little evidence that this is the case. In Table A5, we progressively add finer geography-by-year fixed effects, from state-level (column 1) to census block group-level (column 5).[25] The point estimates under these alternative geography × year fixed effects are all similar to the estimates under the main specification shown in column (2). Moreover, to the extent that policies are different by income group (e.g., tax policies), these fine geography fixed effects would also absorb such targeting.

Turning to industry, we categorize companies into two-digit NAICS industries using a word-tagging approach based on company names.[26] We run the same specification used in Table 3, but change 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 mismatched 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

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

[26]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. We categorize over 81% of firms in our sample in this way.

quantitatively similar when we include census block group $\times$ year fixed effects (in Table A5). The latter can be seen as an approximation to industry $\times$ 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.

Mechanism: Economic optimism

In light of the evidence indicating that policy cannot be the sole driver of our findings, we now consider partisan changes in economic expectations as a possible channel. While this is difficult to pin down conclusively, we present circumstantial evidence that is consistent with this mechanism.

First, recall that our motivating Figure 1 demonstrates sharp partisan swings in economic optimism among a nationally-representative survey sample following party-switching presidential elections over the past three decades. To show that similar patterns also exist *among entrepreneurs*, we utilize the Gallup U.S. Daily Survey. Gallup elicits the views of 1,000 U.S. adults daily from 2008 to 2013, and 500 a day from 2013 to 2016, on topics related to the economy, politics and their well-being. We focus on the 2008 presidential election because the number of respondents falls sharply after 2016, from 500 to only 30 per day. Importantly, respondents identify their political party (38% are Democrats, 37% are Republicans) and whether they are a business owner (2%).

In Figure 6, we show respondents' optimism about the economy and their well-being, separately for business owners and non-owners. Panel A plots the average response to the question *"How would you rate economic conditions in this country today?"* Panel B plots the share of respondents choosing *"Getting better"* to the question *"Right now, do you feel your standard of living is getting better or getting worse?"* Both panels show that the optimism of Democratic entrepreneurs rises sharply after the 2008 presidential election and continues to rally in the following years, while the optimism of Republican entrepreneurs falls after the election and remains relatively flat until 2014. Moreover, compared to non-entrepreneurs, business owners appear to respond slightly more to the 2008 election than non-owners.

To further examine the economic optimism channel, we focus on the 2008 presidential election and examine whether counties that experience a larger rise in optimism after the election exhibit a stronger increase in entrepreneurship. To do so, we aggregate the optimism of respondents by MSA and year (for precision) and apply this MSA-level optimism measure to each component county. We then adjust equation 1 by interacting the indicator for Democratic counties with indicators for whether the counties have an above- or below-median *change* in the two optimism measures between 2008 and 2009. The resulting DID coefficients are reported in Figure 7. Using Republican counties as the omitted group, Democratic counties with an above-median change in optimism after the 2008 election saw a greater increase in entrepreneurship than Democratic counties with a below-median change in optimism. In other words, we see the strongest partisan entrepreneurship effects in the counties that had the largest increase in optimism around the election.

Taken together, the swing in business owner sentiment along party lines around elections and the larger effect observed in more ex post optimistic counties both indicate that changes in economic expectations may contribute to partisan patterns in entrepreneurship.

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. County partisanship is defined in section 4.1.2. We include a vector of county-level, time-varying variables X_{ct}, i.e., annual unemployment rate, annual per-capita income, and the employment share of each two-digit NAICS industry (excluding NAICS=99) to control for economic conditions and industry importance in the county. When the outcomes are for existing firms, we include firm age bin fixed effects.[27] We also include county fixed effects α_c and year fixed effects α_t to absorb any persistent difference across counties and a national trend in business dynamics.

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

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 in politically mismatched counties relative to matched ones, amounting to 2.9% of the outcome mean. In terms of economic magnitude, the relationship between a county's political misalignment and new firm startups is roughly equivalent to a 2.2 pp increase in the local unemployment rate, using the coefficient on *Unemp(%)* from the table.

[27]Because the BDS data are counts and rates in bins at the county-year level, we cannot include any other firm-level controls. However, we do include county-level controls, as described in the text. However, our results are robust to excluding contemporaneous economic controls: see Table A7.

Column (2) indicates that there is no economic or statistical difference in the job creation rate of new firms between matched and mismatched counties, implying that new firms that are born during aligned periods have, on average, the same number of employees as firms that begin during times of mismatch.

Turning to intensive margin effects, columns (3) through (5) show that firms in politically mismatched counties open fewer establishments (1% of the mean), close more establishments (1% of the mean), and experience more firm death (1.4% of the mean), relative to those in matched counties. These business dynamics have implications for the labor market, as the net job creation rate (job creation minus destruction) among existing firms in mismatched counties is 0.33 pp of annual employment lower than that of their counterparts in matched counties, amounting to around 30% of the mean or 6% of the standard deviation (5.2). Summing across new and existing firms (column (7)), politically mismatched counties experience a relative fall in their net job creation rate of 0.32 pp of annual employment.

Aggregating up, we find that the extensive margin effects from columns (1) and (5) translate to approximately 82,000 new employer firms in politically matched counties (relative to mismatched ones), and the death of over 10,000 employer firms in mismatched counties over 13 years.[28] 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 net jobs in matched counties (relative to mismatched ones) over our sample period.[29]

5. Conclusion

This 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

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

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

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., Fisman, 2001, Faccio, 2006, Robinson and Verdier, 2013), with policy prescriptions aimed at reducing clientelism and regulatory capture. In contrast, the effect we document on supporters seems likely to arise organically via the economic optimism of partisans. Given anti-corruption measures are not appropriate in this circumstance, what policy actions might be serve to incentivize individuals from the losing political party to become entrepreneurial? Would such policies be welfare-improving?

Finally, we find stronger partisan effects on entrepreneurship around recent party-changing elections, not only across Republican versus Democratic counties but also between Republican and Democratic individuals within the same county. This seems to align with the increasingly polarized responses to election outcomes, as well as broad increases in political polarization generally (Abramowitz and Saunders, 2008, Gentzkow et al., 2019, Alesina et al., 2020). If polarization continues to rise, will the role of political identity become more central to entrepreneurial decisions? We leave these questions to future research.

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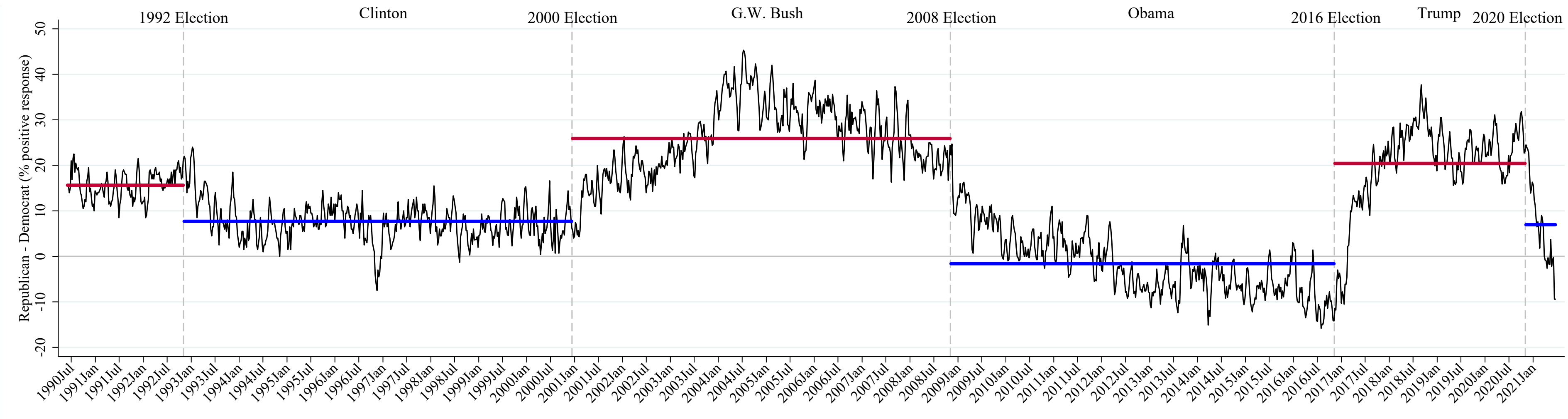
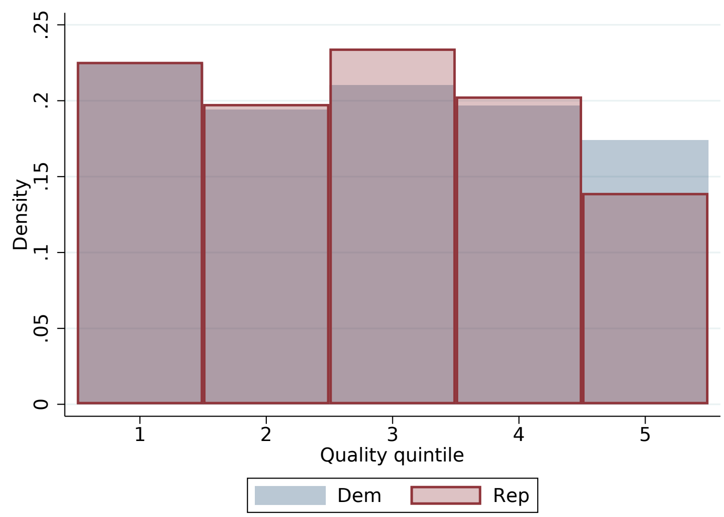
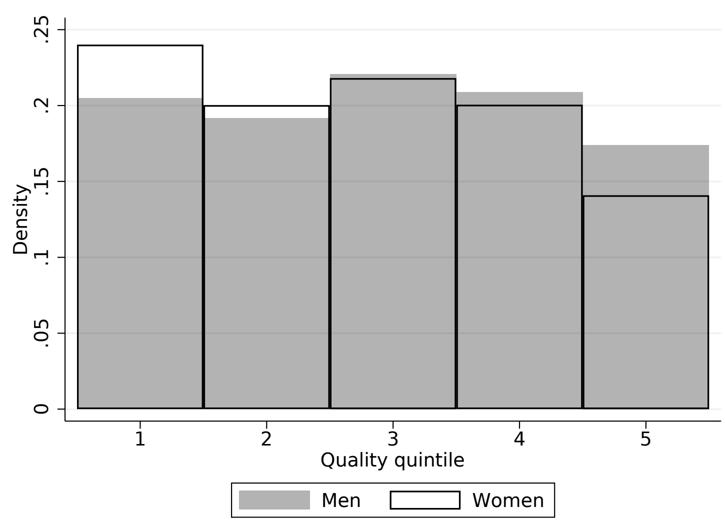


Figure 1. National Optimism: the Bloomberg Consumer Comfort Index by Party Affiliation

Note: The black line plots the difference in The Bloomberg Consumer Comfort Index between Republicans and Democrats, and the horizontal 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.



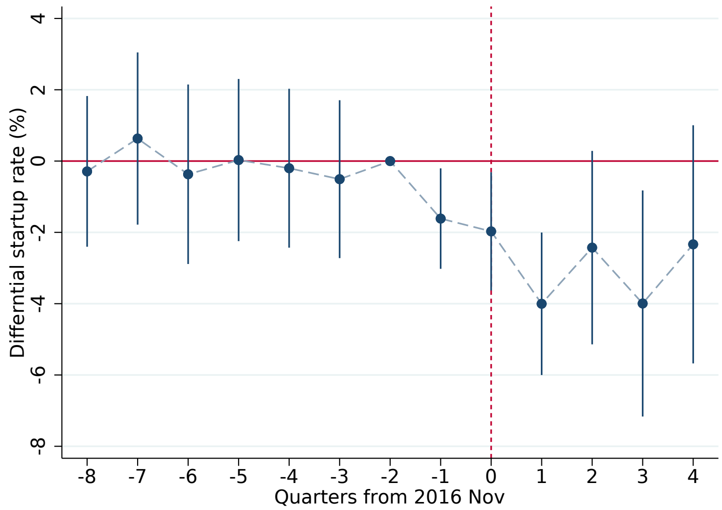
(a) By party



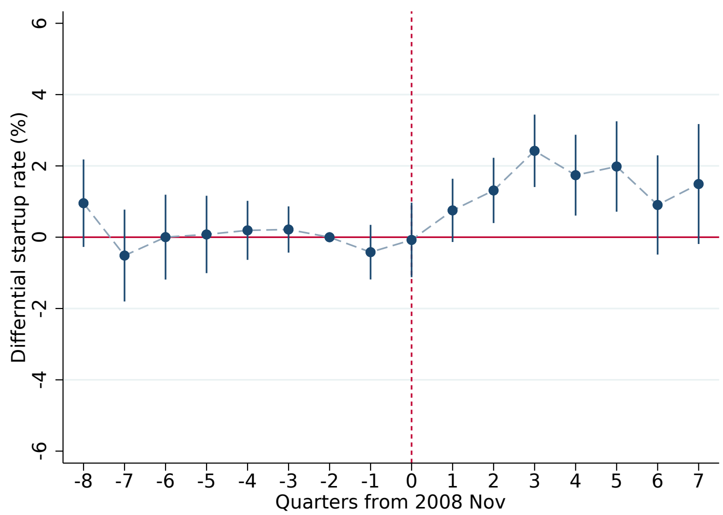
(b) By gender

Figure 2. Firm Quality Distribution by Party and Gender

Note: This figure plots the quintile of firm entrepreneurial quality (Guzman and Stern, 2020) by founders' party and gender. Quintile 1 corresponds to the lowest quality.



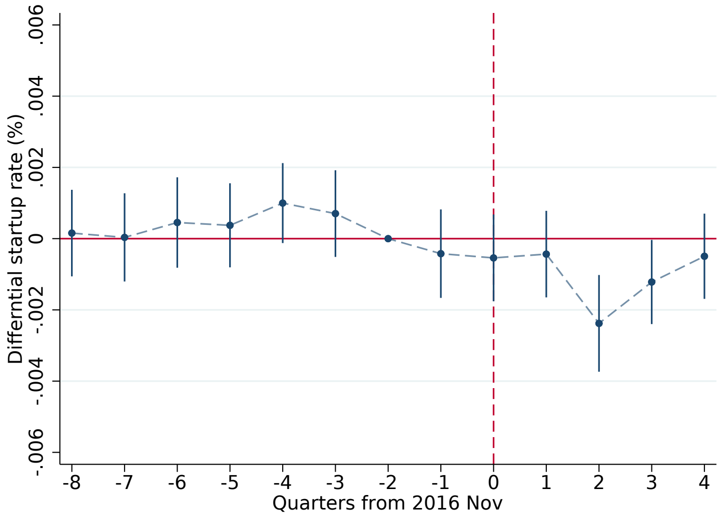
(a) 2016 election



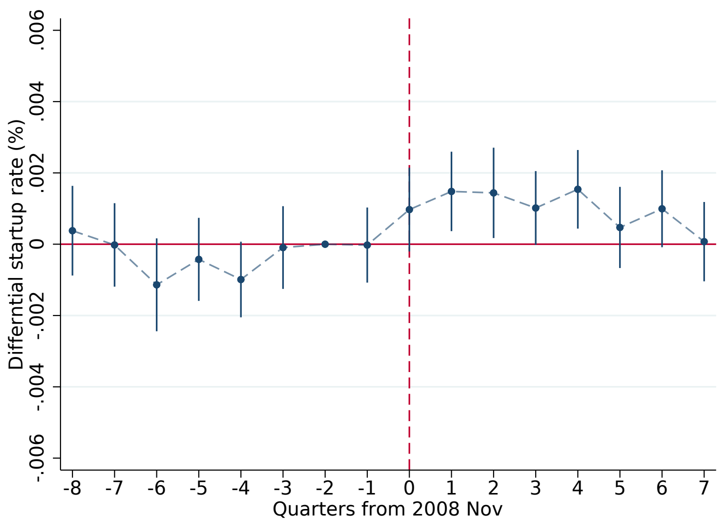
(b) 2008 election

Figure 3. Political Mismatch and New Firms
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 time-varying county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county. Regression results are reported in Table A2.



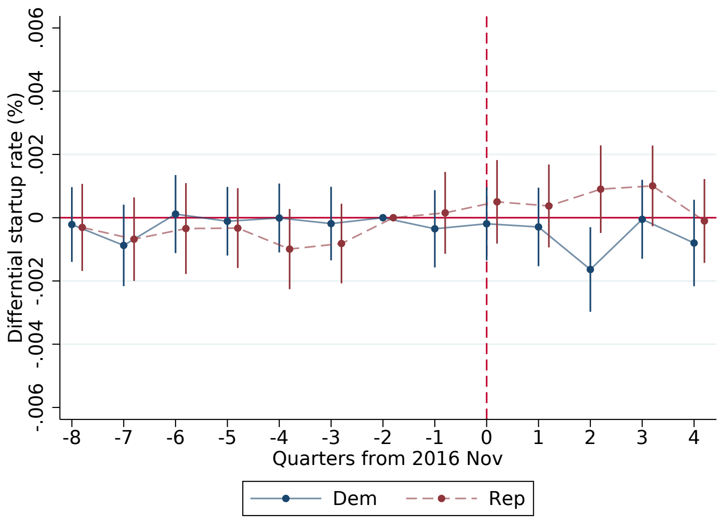
(a) 2016 election



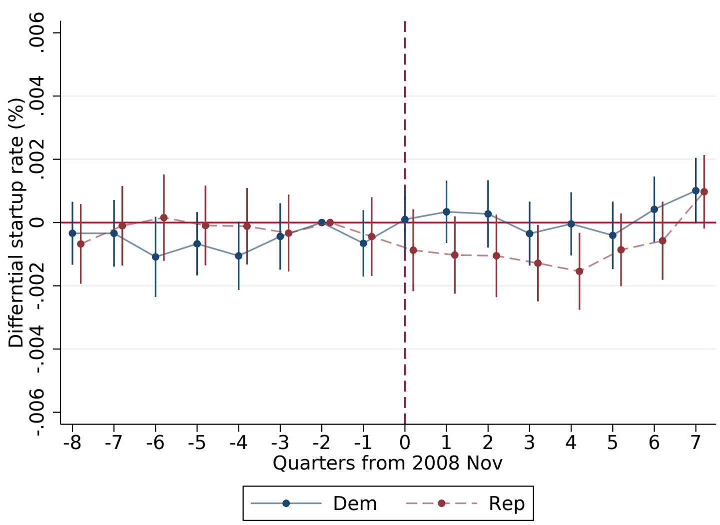
(b) 2008 election

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 A6.



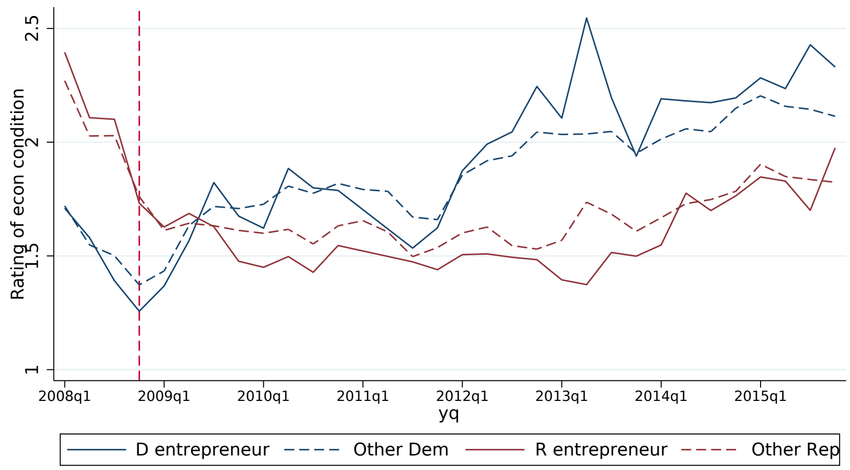
(a) 2016 election



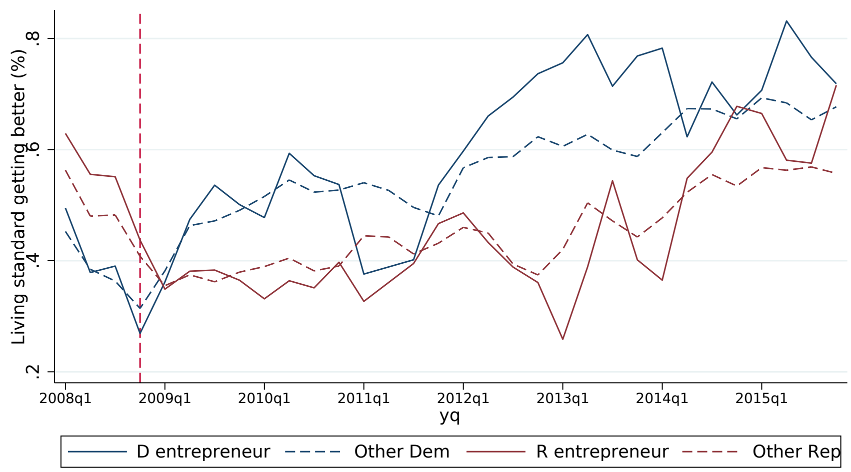
(b) 2008 election

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 solid line) and Republican voters (red dash 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.



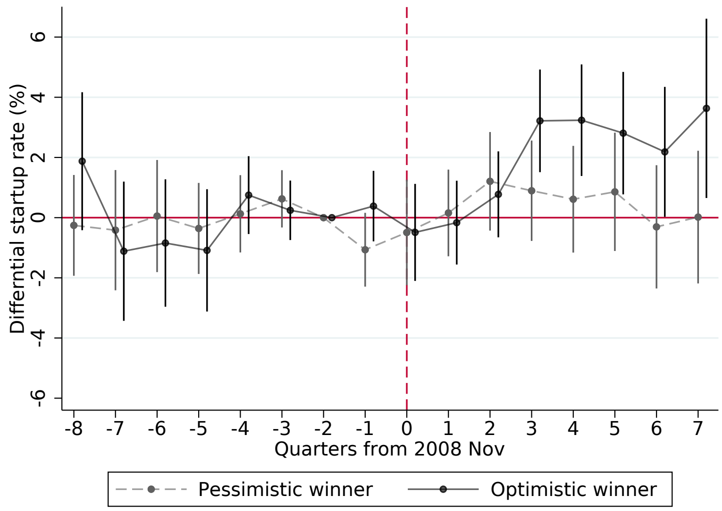
(a) Rating of economic conditions



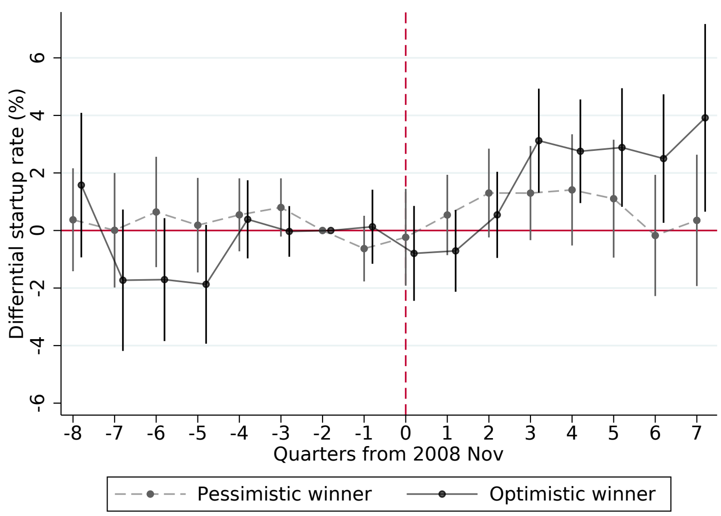
(b) Living standards are getting better

Figure 6. Optimism of Entrepreneurs by Party Affiliation

Note: This figure plots quarterly average responses to the Gallup U.S. Daily Survey from 2008 through to the end of 2016. Section 4.3.5 describes the data. Panel (a) plots respondents' average rating ("Poor", "Only fair", "Good", and "Excellent", translated into a 1-4 range) to the question "How would you rate economic conditions in this country today?" and panel (b) the percentage of respondents choosing "Getting better" to the question "Right now, do you feel your standard of living is getting better or getting worse?" Entrepreneurs are self-identified business owners, while "other" refers to all other respondents.



(a) Optimism about the economy



(b) Optimism about living standards

Figure 7. Political Mismatch and New Firms

More Optimistic and Less Optimistic 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 more optimistic and less optimistic Democrat-leaning counties relative to Republican-leaning counties around the 2008 election. More (less) optimistic counties are those that have an above-median (below-median) change in optimism between 2008 and 2009. Panel (a) measures optimism using respondents' average response ("Poor", "Only fair", "Good", and "Excellent") to the question "How would you rate economic conditions in this country today?" and panel (b) the percentage of respondents choosing "Getting better" to the question "Right now, do you feel your standard of living is getting better or getting worse?" in the Gallup U.S. Daily Survey. Republican-leaning counties are the omitted group. Event time 0 refers to November 2008 to January 2009. Event time -2 is the omitted period. All regressions control for county fixed effects, event time fixed effects, and time-varying county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county. Regression results are reported in Table A3.

Table 1
Pr(start a business), Pr(ever a founder), and Summary Statistics

	Full sample			Democrat			Republican		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean	SD	%Sample	Mean	SD	%Sample	Mean	SD	%Sample
P(start business in a year):									
All	0.50	1.08	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
Educ.≥College	0.69	1.25	47.13	0.55	1.13	45.60	0.78	1.31	49.79
Educ. others	0.41	0.95	52.87	0.32	0.84	54.40	0.49	1.05	50.21
White	0.47	0.78	75.69	0.37	0.70	62.17	0.58	0.84	90.92
Black	0.35	0.94	11.13	0.34	0.73	20.04	0.48	2.44	1.52
Hispanic	0.45	1.27	9.42	0.34	0.93	14.04	0.73	1.90	5.11
Asian	0.90	2.31	3.76	0.72	2.04	3.75	1.00	2.87	2.45
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	4.59	20.92	100.00	3.69	18.85	100.00	5.53	22.86	100.00
Male	6.57	24.78	41.32	5.39	22.59	36.15	7.72	26.69	44.62
Female	3.19	17.57	58.68	2.72	16.28	63.85	3.77	19.04	55.38
Educ.≥College	6.22	24.16	46.76	5.11	22.03	45.26	6.91	25.37	49.42
Educ. others	3.94	19.46	53.24	3.14	17.45	54.74	4.66	21.07	50.58
White	4.44	20.60	75.81	3.51	18.41	62.46	5.29	22.38	91.00
Black	3.38	18.08	11.07	3.30	17.86	19.82	4.41	20.54	1.50
Hispanic	4.10	19.82	9.40	3.17	17.52	13.99	6.28	24.26	5.08
Asian	7.72	26.70	3.72	6.31	24.32	3.73	8.29	27.57	2.41
Cohort 1990+	1.19	10.82	7.88	0.95	9.72	7.44	1.54	12.31	4.79
Cohort 1980-89	3.93	19.44	15.26	3.16	17.50	15.45	5.08	21.96	10.06
Cohort 1970-79	6.53	24.71	17.09	5.44	22.67	16.17	7.81	26.84	14.98
Cohort 1960-69	6.30	24.30	20.53	5.15	22.10	19.22	7.34	26.07	22.94
Cohort 1950-59	4.95	21.70	20.97	3.98	19.56	22.05	5.96	23.68	23.90
Cohort 1940−	2.43	15.40	18.27	1.95	13.82	19.67	2.86	16.66	23.32
N voter		40,420,508			14,696,895			13,083,051	
N state		33			33			33	

Note: This table reports summary statistics for our main sample (see section 2 for sample construction) and two probabilities by population subset. *P(start business in a year)* and *P(ever founder)* are the annual probability of starting a business and the probability of ever starting a business among individuals who are between 18 and 70 years old during 2005-2017, respectively. Units are in percentage points. Columns (1)-(3), (4)-(6) and (7)-(9) are calculated for samples including all individuals, Democrats, and Republicans, respectively (see section 2.2 for partisanship definition). *%Sample* refers to the proportion of observations with a certain characteristic in the corresponding sample. *Male* (*Female*) is an indicator for being male (female), *Educ.* $\geq$ *College* (*Educ. others*) is an indicator for having a college or above degree (or not), *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
Age group FE	N	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 individuals' political and demographic characteristics. The sample includes Democrats, Republicans, and Independents from our main sample, and the outcome is the likelihood of starting a business in a year. 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). Column (8) has fewer *N obs* because we do not have race or ethnic information for some individuals; it has more *N cell* because we collapse the data along an additional dimension (i.e., race/ethnicity). 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.

Table 3
Political Mismatch and the Probability of Starting a Business

VARIABLES	(1) Regular voter	(2) Active voter	(3) HH donor	(4) FEC donor
Panel A: Cell-level				
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
Panel B: Weighted person-level				
Mismatch	-0.0170***	-0.0136***	-0.0149***	-0.0155***
	(0.0016)	(0.0019)	(0.0019)	(0.0016)
Mismatch×Active		-0.0071***	-0.0060***	-0.0289**
		(0.0019)	(0.0021)	(0.0128)
Dem	-0.1926***	-0.1947***	-0.1993***	-0.1764***
	(0.0086)	(0.0105)	(0.0097)	(0.0081)
Dem×Active		-0.0002	0.0223***	-0.6883***
		(0.0075)	(0.0059)	(0.0374)
Active		0.1096***	0.0125***	1.6035***
		(0.0081)	(0.0048)	(0.0606)
Mismatch as %mean	3.62	2.89	3.17	3.3
Mismatch×Active as %mean	-	1.51	1.28	6.13
R-squared	0.005	0.005	0.005	0.005
Outcome mean	0.47	0.47	0.47	0.47
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. The sample is includes Democrats and Republicans from our main sample, and 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 party of the sitting president (i.e., it is one for Republicans in 2009-2016 and for Democrats in 2005-2008 and 2017). *Dem* is an indicator of a Democratic individual (see section 2.2). *Active* is an indicator of a politically active individual. An individual is defined as being politically active (i) if they vote in an above-median share of available even-year general and primary elections as of 2020 (column 2); (ii) if the household has made at least one political donation by 2020 (column 3); (iii) if the individual has made at least one FEC donation by 2020 (column 4). Standard errors are clustered by county. Panel A is run at the county-party-characteristic-year cell level and weighted by number of observations in each cell. Panel B is run at the individual level and weighted to match averages of characteristics in the sample to those of all US voters (Hainmueller, 2012). Results are similar if we match sample averages to averages among all voters in sample counties.

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

VARIABLES	(1) Male	(2) Female	(3) Age 18-29	(4) Age 30-49	(5) Age 50-70	(6) High income	(7) Low income
Mismatch	-0.0277***	-0.0051***	-0.0182***	-0.0210***	-0.0089***	-0.0224***	-0.0144***
	(0.0025)	(0.0013)	(0.0021)	(0.0025)	(0.0016)	(0.0029)	(0.0012)
Dem	-0.3000***	-0.1001***	-0.1199***	-0.2254***	-0.1669***	-0.1784***	-0.1263***
	(0.0149)	(0.0052)	(0.0070)	(0.0110)	(0.0072)	(0.0099)	(0.0054)
Male			0.2495***	0.5727***	0.3895***	0.6876***	0.2887***
			(0.0140)	(0.0280)	(0.0184)	(0.0392)	(0.0116)
College+	0.3311***	0.1180***	0.0982***	0.2573***	0.1939***	0.2140***	0.1115***
	(0.0203)	(0.0066)	(0.0083)	(0.0158)	(0.0105)	(0.0148)	(0.0048)
Edu missing	-0.0734***	-0.0433***	-0.0728***	-0.1038***	0.0016	-0.0380***	-0.0498***
	(0.0130)	(0.0054)	(0.0060)	(0.0106)	(0.0069)	(0.0087)	(0.0064)
Age 18-29	-0.0425***	-0.0022				-0.1144***	0.0015
	(0.0105)	(0.0050)				(0.0118)	(0.0050)
Age 30-39	0.5171***	0.2448***		0.0254***		0.4156***	0.2459***
	(0.0244)	(0.0123)		(0.0043)		(0.0217)	(0.0128)
Age 40-49	0.4678***	0.2445***				0.4121***	0.2215***
	(0.0209)	(0.0105)				(0.0195)	(0.0095)
Age 50-59	0.2725***	0.1570***			0.1971***	0.2646***	0.1424***
	(0.0119)	(0.0063)			(0.0081)	(0.0127)	(0.0055)
Mismatch as %mean	3.66	1.59	7.17	3.23	2	2.93	4.17
R-squared	0.505	0.418	0.336	0.504	0.468	0.366	0.270
Outcome mean	.756	.32	.254	.653	.444	.767	.345
N cell	794,515	801,268	313,360	638,071	644,352	1,391,777	1,575,892
N obs	131,246,407	195,881,588	50,051,494	125,332,715	151,743,786	114,056,924	205,764,381
N cluster (county)	2,115	2,120	2,114	2,116	2,116	2,108	2,111
Demographics	Y	Y	Y	Y	Y	Y	Y
County×Year FE	Y	Y	Y	Y	Y	Y	Y

Note: This table examines how the annual probability of starting a business relates to being politically mismatched with the sitting president in different subsamples. Columns (1) through (7) re-estimate Table 3 panel A column (1) for men, women, voters ages 18-29, voters ages 30-49, voters ages 50-70, voters whose annual household income is above $100,000, and voters whose annual household income is below $100,000, respectively. All specifications and variable definitions mirror those in Table 3 panel A column (1).

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

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)
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)	2,120	2,120	2,120	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	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 panel A column (1) except that the dependent variable is the annual probability of starting firms in a specific industry, which differs by column. Units are in percentage points. Firms are classified into industries based on the presence of industry-specific keywords in their names (see section 4.3.5). We report the top 13 most populated industies in our sample.

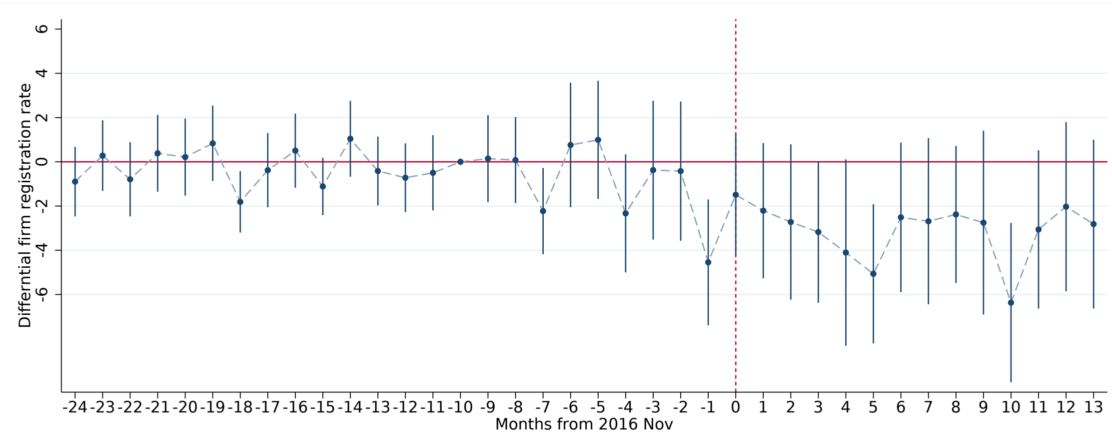
Table 7
Political Mismatch and Employer Firms:
County-Level Business Dynamics

	(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

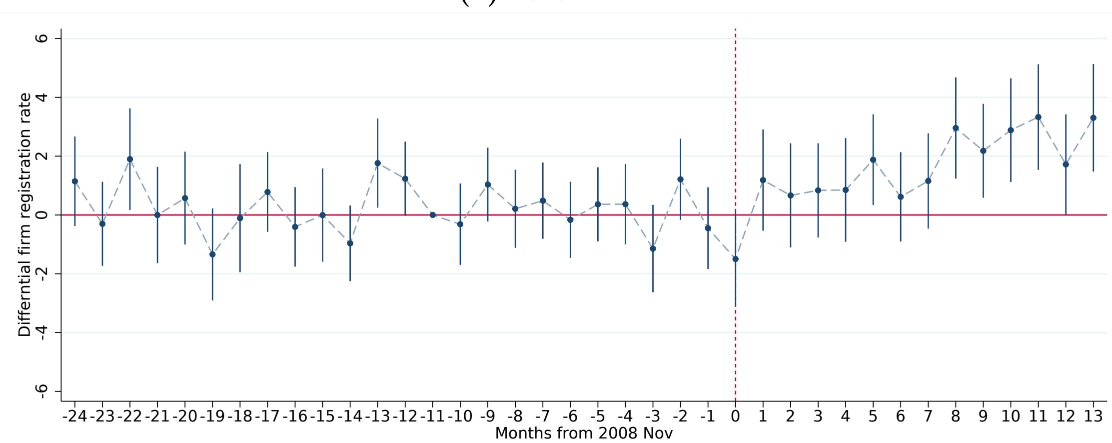
Note: This table examines how the entry, exit, expansion, and contraction of *employer* firms relate to being in counties that are politically mismatched with the sitting president between 2005 and 2018. The omitted group is Republican-leaning counties. "Firm entry", "Estab. entry", "Estab. exit", and "Firm death" are the annual number of new firms, newly opened establishments among existing firms, newly closed establishments among existing firms, and firms that have closed all their establishments, per 100,000 county residents ages 20 or above, respectively. "Job rate" is the number of newly created jobs as a percent of the average employment between years t and t-1. "Net job rate" is the difference between the number of newly created jobs and the number newly destroyed jobs as a percent of the average employment between years t and t-1. The regression weight for outcomes "Job rate" and "Net job rate" is the average employment between years t and t-1; the regression weight for other outcomes is the number of the county population ages 20 or above. Columns (1) and (2) control for county fixed effects, year fixed effects, and time-varying county economic conditions (i.e., annual unemployment rate, income per capita, and employment share for 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.

Internet Appendix for "Partisan Entrepreneurship"

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



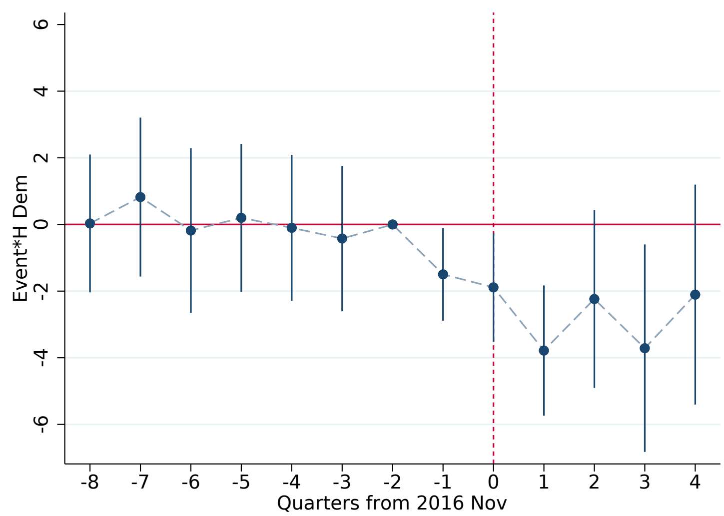
(a) 2016 election



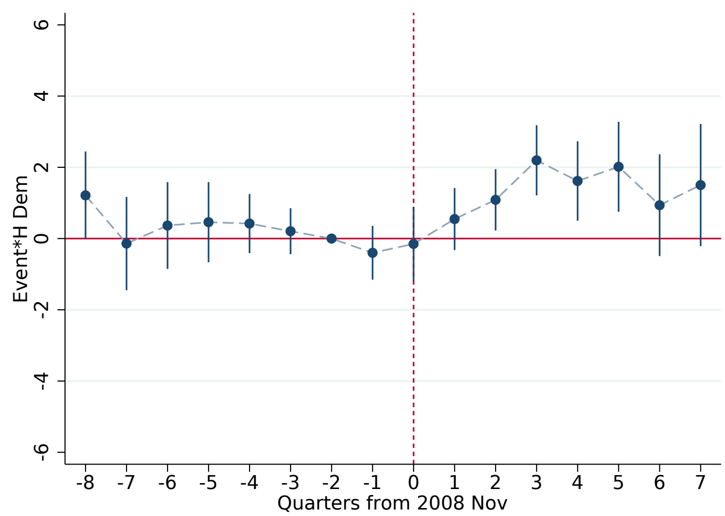
(b) 2008 election

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

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. This is the monthly counterpart of Figure 3. 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 time-varying county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county.



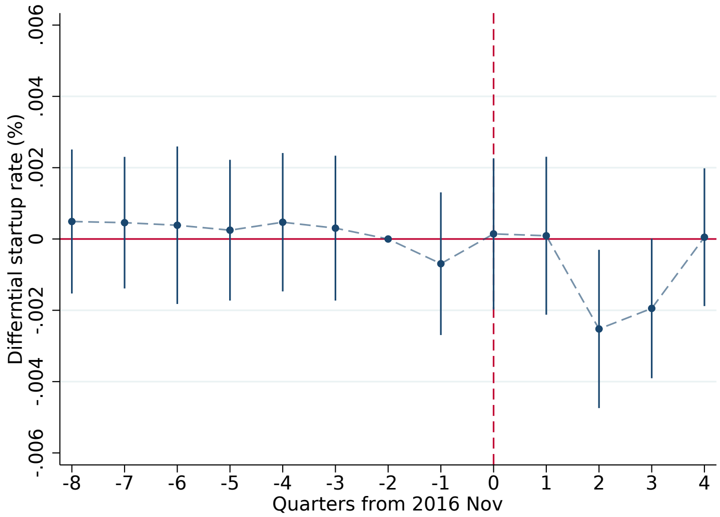
(a) 2016 election



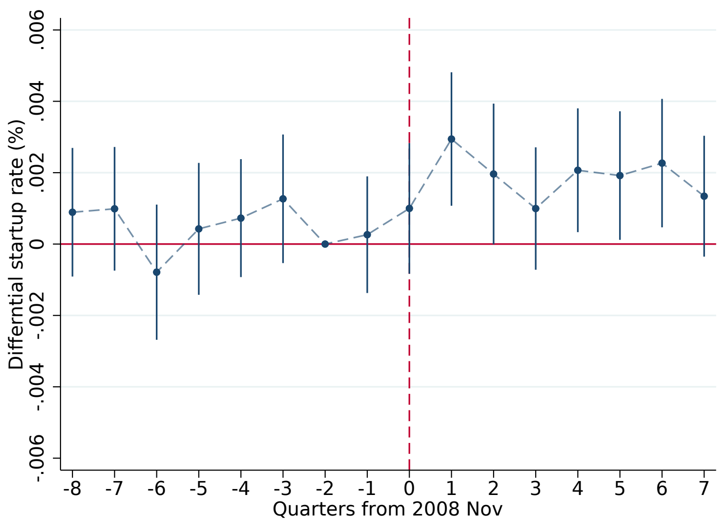
(b) 2008 election

Figure A2. Political Mismatch and New Firms
Democratic versus Republican *Counties* (Excluding Economic Controls)

Note: This figure presents a robustness check for Figure 3. All specifications are the same except that we *exclude* controls for county economic conditions in this figure.



(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. Active partisans are defined as those who vote in an above-median percentage of available even-year general and primary elections as of 2020. 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
Voter Characteristics Across Samples

	%All parties	% Democrat	% Republican
Panel A: All US voters			
Male	46.57	41.81	49.97
Educ.≥College	46.62	44.79	49.72
White	75.80	61.76	91.19
Black	10.39	19.42	1.42
Hispanic	10.97	16.13	5.55
Asian	2.83	2.69	1.84
Cohort 1990+	7.37	6.87	4.63
Cohort 1980-89	15.00	14.74	9.88
Cohort 1970-79	15.33	14.26	13.09
Cohort 1960-69	18.77	17.54	20.55
Cohort 1950-59	19.24	20.03	21.57
Cohort 1940-	24.30	26.56	30.29
N voter	159,029,424	61,168,464	49,201,960
N State	51	51	51
Panel B: Voters in sample states			
Male	46.68	41.90	49.82
Educ.≥College	46.28	44.36	49.60
White	75.40	62.05	90.06
Black	9.30	16.33	1.39
Hispanic	12.37	18.83	6.53
Asian	2.93	2.79	2.02
Cohort 1990+	7.42	6.80	4.73
Cohort 1980-89	15.11	14.77	10.11
Cohort 1970-79	15.25	14.20	13.14
Cohort 1960-69	18.54	17.39	20.20
Cohort 1950-59	19.21	20.09	21.36
Cohort 1940-	24.46	26.74	30.46
N voter	107,914,168	40,744,516	34,203,120
N State	33	33	33
Panel C: Voters in regression sample			
Male	41.32	36.15	44.62
Educ.≥College	46.76	45.26	49.42
White	75.81	62.46	91
Black	11.07	19.82	1.50
Hispanic	9.40	13.99	5.08
Asian	3.72	3.73	2.41
Cohort 1990+	7.88	7.44	4.79
Cohort 1980-89	15.26	15.45	10.06
Cohort 1970-79	17.09	16.17	14.98
Cohort 1960-69	20.53	19.22	22.94
Cohort 1950-59	20.97	22.05	23.90
Cohort 1940-	18.27	19.67	23.32
N voter	40,420,508	14,696,895	13,083,051
N State	33	33	33

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

Table A2
Political Mismatch and New Firms
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)	2,872	2,872
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 time-varying county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county.

Table A3
Political Mismatch and New Firms
More Optimistic and Less Optimistic Democratic versus Republican Counties

VARIABLES	(1) Econ condition	(2) Living standard
Optimistic Dem×-8	1.875	1.578
	(1.392)	(1.525)
Optimistic Dem×-7	-1.116	-1.729
	(1.404)	(1.492)
Optimistic Dem×-6	-0.843	-1.706
	(1.286)	(1.297)
Optimistic Dem×-5	-1.088	-1.869
	(1.234)	(1.254)
Optimistic Dem×-4	0.749	0.388
	(0.786)	(0.824)
Optimistic Dem×-3	0.244	-0.032
	(0.600)	(0.534)
Optimistic Dem×-1	0.384	0.131
	(0.711)	(0.782)
Optimistic Dem×0	-0.490	-0.796
	(0.978)	(1.001)
Optimistic Dem×1	-0.166	-0.708
	(0.845)	(0.862)
Optimistic Dem×2	0.774	0.544
	(0.867)	(0.909)
Optimistic Dem×3	3.216***	3.123***
	(1.036)	(1.097)
Optimistic Dem×4	3.238***	2.754**
	(1.125)	(1.093)
Optimistic Dem×5	2.808**	2.885**
	(1.235)	(1.251)
Optimistic Dem×6	2.186*	2.500*
	(1.311)	(1.356)
Optimistic Dem×7	3.632**	3.915**
	(1.809)	(1.980)
Pessimistic Dem×-8	-0.257	0.373
	(1.017)	(1.086)
Pessimistic Dem×-7	-0.416	0.009
	(1.213)	(1.209)
Pessimistic Dem×-6	0.053	0.644
	(1.131)	(1.164)
Pessimistic Dem×-5	-0.359	0.185
	(0.918)	(0.997)
Pessimistic Dem×-4	0.127	0.544
	(0.780)	(0.770)
Pessimistic Dem×-3	0.624	0.801
	(0.578)	(0.614)
Pessimistic Dem×-1	-1.067	-0.629
	(0.745)	(0.693)
Pessimistic Dem×0	-0.493	-0.236
	(1.064)	(1.022)
Pessimistic Dem×1	0.156	0.540
	(0.874)	(0.847)
Pessimistic Dem×2	1.207	1.302
	(0.995)	(0.937)
Pessimistic Dem×3	0.894	1.300
	(1.012)	(0.994)
Pessimistic Dem×4	0.612	1.412
	(1.077)	(1.173)
Pessimistic Dem×5	0.858	1.107
	(1.194)	(1.244)
Pessimistic Dem×6	-0.306	-0.172
	(1.243)	(1.279)
Pessimistic Dem×7	0.018	0.352
	(1.338)	(1.386)
R-squared	0.190	0.191
Outcome mean	75.063	75.063
N obs	34,320	34,320
N cluster (county)	715	715
County FE	Y	Y
Quarter FE	Y	Y
Economic controls	Y	Y

Note: This figure presents the estimated number of (excess) monthly new firm registrations per 100,000 people 20 years old or older (averaged within quarter) in more optimistic and less optimistic Democrat-leaning counties relative to Republican-leaning counties around the 2008 election. More (less) optimistic counties are those that have an above-median (below-median) change in optimism between 2008 and 2009. Column (1) measures optimism using respondents' average response ("Poor", "Only fair", "Good", and "Excellent") to the question "How would you rate economic conditions in this country today?" and column (2) the percentage of respondents choosing "Getting better" to the question "Right now, do you feel your standard of living is getting better or getting worse?" in the Gallup U.S. Daily Survey. Republican-leaning counties are the omitted group. Event time 0 refers to November 2008 to January 2009. Event time -2 is the omitted period. All regressions control for county fixed effects, event time fixed effects, and time-varying county economic conditions (i.e., monthly unemployment rate, annual per capita income, and annual employment share for 2-digit NAICS industries). Regressions are weighted by county population ages 20 and above. Standard errors are clustered by county.

Table A4
Political Mismatch and the Probability of Starting a Business
by Household Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High household income				Low household income			
VARIABLES	Regular voter	Active voter	Donor voter	FEC voter	Regular voter	Active voter	Donor voter	FEC voter
Mismatch	-0.0224***	-0.0149***	-0.0196***	-0.0195***	-0.0144***	-0.0117***	-0.0121***	-0.0137***
	(0.0029)	(0.0034)	(0.0036)	(0.0027)	(0.0012)	(0.0014)	(0.0015)	(0.0012)
Mismatch×Active		-0.0153***	-0.0063	-0.0523***		-0.0054***	-0.0063***	-0.0227
		(0.0041)	(0.0041)	(0.0171)		(0.0019)	(0.0020)	(0.0142)
Dem	-0.1784***	-0.1625***	-0.1847***	-0.1577***	-0.1263***	-0.1233***	-0.1302***	-0.1196***
	(0.0099)	(0.0120)	(0.0108)	(0.0097)	(0.0054)	(0.0062)	(0.0063)	(0.0053)
Dem×Active		-0.0423***	0.0143**	-0.7992***		-0.0083*	0.0132***	-0.4646***
		(0.0106)	(0.0071)	(0.0491)		(0.0044)	(0.0042)	(0.0256)
Active		0.0782***	-0.0020	1.8049***		0.0937***	0.0110***	1.1202***
		(0.0150)	(0.0066)	(0.0843)		(0.0052)	(0.0037)	(0.0321)
Mismatch as %mean	2.93	1.95	2.56	2.55	4.17	3.39	3.5	3.96
Mismatch×Active as %mean	-	1.98	.82	6.81	-	1.55	1.82	6.58
R-squared	0.366	0.252	0.253	0.242	0.270	0.167	0.169	0.145
Outcome mean	.767	.767	.767	.767	.345	.345	.345	.345
N cell	1,391,777	2,471,734	2,481,182	1,895,014	1,575,892	3,000,208	2,971,254	2,209,636
N obs	114,056,924	113,945,835	114,056,924	114,056,924	205,764,381	205,463,991	205,764,381	205,764,381
N cluster (county)	2108	2108	2108	2108	2111	2111	2111	2111
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 being politically mismatched with the sitting president for individuals with different levels of household income. Columns (1) through (4) re-estimate Table 3 panel A columns (1) through (4) for voters whose annual household income is above $100,000 and columns (5) through (8) for those whose household income is lower. All specifications and variable definitions mirror those in Table 3 panel A.

Table A5
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 checks for Table 3 under various geography-by-year fixed effects. Regression samples are at the individual-by-year level. Specifications in panels A, B, C, and D mirror Table 3 panel A columns (1), (2), (3), and (4), respectively, except that each column now includes a different set of geography-by-year fixed effects. Columns (1) through (5) control for state-by-year, county-by-year, zip code-by-year, census tract-by-year, and census block group-by-year fixed effects, respectively. Standard errors are clustered by county.

Table A6
Political Mismatch and the Probability of Starting a Business
Democrat versus Republican *Individuals*

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 presents 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.

Table A7
Political Mismatch and Employer Firms
County-Level Business Dynamics (Excluding Economic Controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New firm		Existing firm				All firm
VARIABLES	Firm entry	Job rate	Estab. entry	Estab. exit	Firm death	Net job rate	Net job rate
Mismatch	-4.964***	-0.003	-0.287***	0.484***	0.518***	-0.188***	-0.186***
	(1.017)	(0.002)	(0.091)	(0.175)	(0.122)	(0.058)	(0.057)
Mismatch as %mean	2.6	0.01	1.02	0.68	1.09	17.55	19.46
R-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 a robustness test for Table 7. All specifications mirror those in the corresponding columns of Table 7 except that we exclude controls for county economic conditions in this table.