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

IN THE UNITED STATES, POLITICAL identity is central to economic expectations: Americans are much more optimistic about the economy when their political party is in power. For example, 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.

In this paper, we examine whether changes in political regime and the corresponding shifts in partisan beliefs translate into a critical economic behavior: entrepreneurship. To do so, we consider a sample of approximately

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40 million Americans for whom we have political party identification and who live in the 33 states for which we have complete data on firm registrations from the Startup Cartography Project (Andrews et al., 2022).[1] We find that Republicans are more likely to be entrepreneurs than Democrats: Over our 13-year sample, 5.5% of Republicans started a business, compared to 3.7% of Democrats. Even after controlling for age, gender, race, education, income, and county-year fixed effects, Republicans are 26% more likely than Democrats to start a business in a given year, relative to the mean.

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

Our DID event studies focus on the years immediately surrounding party-changing elections and thus use less than half of the sample years. When we consider the entire sample period (2005 to 2017), we find that the probability of starting a business for politically mismatched individuals—that is, voters whose party did not control the presidency—is 3.3% of the mean lower than for those whose party is in power. This effect corresponds to an annual difference of 13,000 new firms between politically matched versus mismatched individuals.[2]

We further find that the largest estimated effects occur among the most *politically active* individuals. In particular, the effect size for partisans with a below-median voting propensity is 2.4% of the mean, but for those with an above-median voting propensity the effect expands to 4.3%. If we instead use Federal Election Commission (FEC)-reported donations to a political party to capture political engagement, the effect among politically active individuals jumps to 10%.

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

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

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

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

firms, is nearly seven times as large as that of LLCs (4.8% versus 0.7% of the mean).

When we turn to founder characteristics, we find partisan differences by gender, age, and income. Specifically, we first find the well-known gender gap in our data: 6.6% of men and 3.2% of women started a business in our 13-year sample. After controlling for individual characteristics and county-year fixed effects, men are about 0.4 percentage points (pp) per year more likely to start a business than women, a difference of approximately 90% of the annual mean. This gender gap varies by political party. Among Democrats this gap is 14% smaller than the gap among independents, while among Republicans it is 24% larger. Moreover, male entrepreneurs are more sensitive to political regime changes than female entrepreneurs, consistent with the pattern in economic expectations from survey data. Relative to their respective means, men are 3.8% less likely to engage in entrepreneurship when politically mismatched with the president, while for women this likelihood is only 1.5% lower.

The evidence thus far compares individual Democrats to Republicans within the same county. We can also compare Republican-leaning counties to Democratic-leaning counties around changes in presidential regimes. In comparing counties we lose the precise identification that obtains at the individual level, but we gain two advantages. First, county-level data are available for almost all states, and second, more economic data exist at the county level, such as job creation and firm closures, which allows us to explore how the startup decisions of partisans aggregate at the level of local economies following elections.

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

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

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

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

Overall, the effects we document aggregate into a substantial component of economic activity. Between 2005 and 2017, we estimate a partisan shift of around 170,000 new firms, which is approximately the total number of firms created in the state of Mississippi over the same period. These new firms also contribute to local employment growth, consistent with the evidence in Adelino, Ma, and Robinson (2017) and Glaeser, Kerr, and Kerr (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, Jarmin, and Miranda, 2013; Decker et al., 2014; Clementi and Palazzo, 2016). Understanding and anticipating these effects could improve place-based policies (Kline and Moretti, 2014), which are of increasing interest given the declining trend in U.S. business dynamism and job reallocation since the 1980s (Decker et al., 2016).

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

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

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

Finally, our paper contributes to a new literature on the economic consequences of partisanship. At the corporate level, several papers find evidence of partisan effects on credit ratings, syndicated lending, and the composition of employees (Kempf and Tsoutsoura, 2021; Dagostino, Gao, and Ma, 2023; Fos, Kempf, and Tsoutsoura, 2023; Colonnelli, Neto, and Teso, 2022). At the household level, there is strong survey evidence that partisanship affects economic optimism around elections (e.g., Bartels, 2002; Evans and Andersen, 2006). However, evidence that such optimism matters for important economic outcomes is mixed. 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, 2017; Mian, Sufi, and Khoshkhou, 2023).[6] We provide evidence that a key driver of economic activity—new firm formation—changes in response to partisan sentiment.

[4] For financial constraints, see, for example, Bertrand, Schoar, and Thesmar (2007); Kerr and Nanda (2009); Chatterji and Seamans (2012); Robb and Robinson (2014); Kerr, Kerr, and Nanda (2015); Adelino, Schoar, and Severino (2015); Schmalz, Sraer, and Thesmar (2017). For risk reduction, training, and peers, see Gottlieb, Townsend, and Xu (2022), Karlan and Valdivia (2011); Drexler, Fischer, and Schoar (2014); Fairlie, Karlan, and Zinman (2015); Fehder and Hochberg (2021); Lerner and Malmendier (2013); and Nanda and Sørensen (2010).

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

[6] Recent papers link partisanship with household decisions such as tax evasion, stock market trading, retirement investing, fertility choices, and residential sorting (Cullen, Turner, and Washington, 2021; Cookson, Engelberg, and Mullins, 2020; Addoum and Kumar, 2016; Meeuwis et al., 2022; Dahl, Lu, and Mullins, 2022; Bernstein et al., 2022a; McCartney, Orellana-Li, and Zhang, 2024).

The rest of the paper proceeds as follows. Section I describes the data. Section II provides evidence from individual data, while Section III examines evidence at the county level. Section IV explores the expectations of partisan entrepreneurs and Section V concludes.

I. Data

A. 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 LLC 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 (SCP; Andrews et al., 2022), which contains business registration records across 49 U.S. states and Washington D.C. from 2005 to 2017. Since the data are business registrations, sole proprietorships and self-employed individuals without formal registration are not in our sample. The data include the name of the firm, the firm type (corporation, partnership, or LLC), 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. Thirty-three states also include information on the names and titles of firm directors and detailed firm location. We focus on these states for our individual-level analysis. To ensure individuals are startup founders, we exclude personnel whose titles imply that they play only an administrative role.[7] Nonetheless, some individuals who we identify as founders may be early employees. To address this concern, in the Internet Appendix we consider only solo-founder firms, for which we do not need to distinguish between a founder and an early employee in business registration records.[8] We find similar patterns and magnitudes.

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

[8] The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

B. Voter and Donor Data

We use data on registered voters from L2, a leading nonpartisan data vendor used by political campaigns and the academic literature (e.g., Brown and Enos, 2021; Billings, Chyn, and Haggag, 2021; Bernstein et al., 2022a; Spenkuch, Teso, and Xu, 2023), for the 33 states for which we have sufficient information on firm founders to permit accurate matching.[9] For 21 of these states, L2 assigns political affiliation using self-reported voter registration. For the remaining states, L2 infers party identification using a variety of data sources, including voter participation in primaries, demographics, exit polling, and commercial lifestyle data.[10],[11] In most analyses, we compare Republicans to Democrats because they have clear directional sentiment. However, in Table II and Figure 3, we compare both groups to registered Independents.

L2 has complete coverage of the U.S. voter population starting in 2014. To minimize concerns over survivorship bias and reverse causality, we use the 2014 voter roll to assign voter partisanship. This strategy resolves such concerns for the 2016 election, and mitigates them for the 2008 election to the extent possible with L2 data. Party status is largely stable: The annual probability of changing from Republican to Democrat or vice versa is 1.8%. We add individuals' voting histories, which we need to construct political activeness measures, from the most recent L2 voter file that we have (October 2020) to the 2014 voter population, dropping those without this information.[12] 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 that they voted in by 2020 (out of elections they were eligible for) exceeds their party's sample median, which is about half of elections. L2 includes two variables that describe political donation behavior. The first is a variable identifying donations recorded by the FEC. Using the L2-linked FEC data, we classify individuals as *active FEC donors* if

[9] 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, and Wyoming.

[10] These states are: Alabama, Georgia, Hawaii, Indiana, Minnesota, Missouri, Montana, Ohio, Texas, Vermont, Virginia, Washington. In our sample, 43% of entrepreneurs are in these states. L2's party inference varies according to features in each state. For example, in states such as 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 such as Minnesota, Missouri, and Montana, where states provide no information to indicate likely party affiliation, L2 models each voter's party based on characteristics it collects independently.

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

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

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 refer to as *active household donors* (40% of our voters).

L2 provides a suite of demographic variables, such as registered state and county, age, gender, and race/ethnicity, which we use as controls in the main specifications.[13]

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

C. Sample of Registered Voters

We begin by keeping all voter-year observations in which individuals are between 18 and 70. We then match voters to firm founders in the business registration database by name and county. To perform this match, we further focus on voters whose combination of first and last names is unique in the L2 data among all voters in a county.[14] We use unique names because no other common identifier (e.g., home address or social security number) exists in both the voter and founder data sets to enable matching. However, name uniqueness within the voter database does not guarantee uniqueness among all county residents, because some people are not registered voters. Therefore, we further require that the probability of a first and last name combination appearing among nonvoters in a county be below 0.1 pp.[15] In the Internet Appendix, we consider more stringent cutoffs, which increase the uniqueness of names and thus the precision of our matches. Our results are unchanged.

A sample of names that are unique at the county level will oversample women, because American women have a considerably wider range of first names than men.[16] It may also over- or undersample other population subgroups. To mitigate this concern, we report results that weight individuals in our sample so as to match observable characteristics of the full U.S. voter population (political party, as well as gender, race/ethnicity, and birth cohorts within each party). We also conduct our main analysis separately for men and

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

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

[15] 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 unregistered 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 unregistered individuals using the binomial formula.

[16] *Time Magazine*, 2016, Why there are so many more names for baby girls, May 10.

women. In Section II.D, we discuss the representativeness of the sample and compare its characteristics to those of all U.S. voters and to voters in sample states (see Internet Appendix Table IA.I).

L2 has 110 million registered voters in the 33 states for which we have data on firm founders and addresses. After restricting the sample to unique names within a county as described above, we have around 40 million voters. Of these, 1.9 million (4.6%) started a company during our sample period. Conditional on both voter and founder having M.I., the matched individuals have the same M.I. 90% of the time, indicating high match quality between voter and founder databases.[17] Using M.I. as an additional matching criterion does not meaningfully affect our estimates (see Internet Appendix Table IA.VIII), and matching errors, if anything, are likely to cause attenuation bias in our setting.[18]

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

D. Descriptive Statistics

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

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

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

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

Table I

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

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

	Full sample			Democrat			Republican		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean (1)	*SD* (2)	%Sample (3)	Mean (4)	*SD* (5)	%Sample (6)	Mean (7)	*SD* (8)	%Sample (9)
P(start business in a year):									
All	0.50	1.48	100.00	0.39	1.32	100.00	0.61	1.65	100.00
Male	0.75	1.90	41.29	0.60	1.78	36.14	0.90	2.03	44.60
Female	0.32	1.07	58.71	0.27	0.95	63.86	0.38	1.20	55.40
Educ.$\geq$ College	0.69	1.64	47.13	0.55	1.51	45.60	0.78	1.70	49.79
Educ. others	0.41	1.34	52.87	0.32	1.19	54.40	0.49	1.46	50.21
White	0.47	1.18	75.69	0.37	1.10	62.17	0.58	1.26	90.92
Black	0.35	1.36	11.13	0.34	1.08	20.04	0.48	3.43	1.52
Hispanic	0.45	1.80	9.42	0.34	1.36	14.04	0.73	2.64	5.11
Asian	0.90	3.06	3.76	0.72	2.71	3.75	1.00	3.74	2.45
Low income	0.24	1.27	21.29	0.21	1.06	25.74	0.30	1.53	17.29
Middle income	0.39	1.22	42.80	0.33	1.11	42.36	0.47	1.33	42.83
High income	0.77	1.62	35.91	0.63	1.52	31.90	0.89	1.72	39.88
Age 18–29	0.25	1.09	18.29	0.20	0.95	18.36	0.35	1.47	11.86
Age 30–39	0.65	1.77	18.30	0.53	1.60	17.49	0.81	2.09	15.33
Age 40–49	0.66	1.67	21.69	0.54	1.53	20.45	0.77	1.78	23.41

(*Continued*)

Table I—*Continued*

	Full sample			Democrat			Republican		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean (1)	*SD* (2)	%Sample (3)	Mean (4)	*SD* (5)	%Sample (6)	Mean (7)	*SD* (8)	%Sample (9)
Age 50–59	0.53	1.46	23.15	0.42	1.30	23.67	0.64	1.55	26.62
Age 60–70	0.34	1.24	18.57	0.27	1.10	20.03	0.41	1.29	22.79
N voter × year		477,728,978			173,281,910			153,846,085	
N states		33			33			33	
P(ever a founder):									
All	4.59	20.92	100.00	3.69	18.85	100.00	5.53	22.86	100.00
Male	6.57	24.78	41.32	5.39	22.59	36.15	7.72	26.69	44.62
Female	3.19	17.57	58.68	2.72	16.28	63.85	3.77	19.04	55.38
Educ.≥ College	6.22	24.16	46.76	5.11	22.03	45.26	6.91	25.37	49.42
Educ. others	3.94	19.46	53.24	3.14	17.45	54.74	4.66	21.07	50.58
White	4.44	20.60	75.81	3.51	18.41	62.46	5.29	22.38	91.00
Black	3.38	18.08	11.07	3.30	17.86	19.82	4.41	20.54	1.50
Hispanic	4.10	19.82	9.40	3.17	17.52	13.99	6.28	24.26	5.08
Asian	7.72	26.70	3.72	6.31	24.32	3.73	8.29	27.57	2.41
Low income	2.25	14.83	22.76	1.93	13.76	27.23	2.69	16.18	19.28
Middle income	3.87	19.29	42.32	3.27	17.79	41.74	4.59	20.93	42.19
High income	7.01	25.54	34.92	5.85	23.46	31.02	7.97	27.08	38.53
Cohort 1990+	1.19	10.82	7.88	0.95	9.72	7.44	1.54	12.31	4.79
Cohort 1980-89	3.93	19.44	15.26	3.16	17.50	15.45	5.08	21.96	10.06
Cohort 1970–79	6.53	24.71	17.09	5.44	22.67	16.17	7.81	26.84	14.98
Cohort 1960–69	6.30	24.30	20.53	5.15	22.10	19.22	7.34	26.07	22.94
Cohort 1950–59	4.95	21.70	20.97	3.98	19.56	22.05	5.96	23.68	23.90
Cohort 1940–	2.43	15.40	18.27	1.95	13.82	19.67	2.86	16.66	23.32
N voters		40,420,508			14,696,895			13,083,051	
N states		33			33			33	

given year is approximately 0.5 pp.[19] 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 probability is 0.4%.

When we examine the entrepreneurship rate across demographic characteristics, we note a few differences. First, consistent with prior results in Fairlie, Robb, and Robinson (2022), Whites are more likely to start a business in a year than Blacks and Hispanics, as are college graduates (Hurst and Lusardi, 2004). Second, the entrepreneurship rate is the highest in the middle of our age distribution (between 30 and 49 years old), with a 0.7% chance of starting a business in a year, consistent with the pattern described in Azoulay et al. (2020) using U.S. Census Bureau data. As expected, higher income individuals are more likely to start a firm (Evans and Jovanovic, 1989). Finally, men are more than twice as likely to start a firm in a year than women, an estimate similar to previous work on the gender gap in entrepreneurship (e.g., Guzman and Kacperczyk, 2019).

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

Column (2) adds age controls and confirms the finding that individuals are most likely to start firms between the age of 30 and 49. However, adding age controls does little to change the partisan entrepreneurship gap. Column (3) supports previously established patterns in gender and entrepreneurship: Men are over 0.4 pp more likely to start a business in a given year than women, all else equal, which is nearly 90% of the mean likelihood. After controlling for gender, the partisan entrepreneurship gap shrinks from 49% to 39% of the mean, reflecting that men are disproportionately entrepreneurs and Republicans. Column (4) adds controls for race and shows that Asian voters are 90% of the mean more likely to start a business than Whites. Column (5) further adds controls for education—college graduates are substantially more likely to start new firms—and column (6) shows that this is also true for those in the highest income bracket. After controlling for all of these covariates, which correlate with political party and so may partially absorb the differences of interest, the partisan entrepreneurship gap remains large (at 26% of the mean) and statistically significant. Finally, column (7) explores how political party

[19] 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% × 13) because serial entrepreneurs start firms in more than one year. Serial entrepreneurs make up 18.4% of all entrepreneurs in our sample (similar to Lafontaine and Shaw, 2016).

Table II

Probability of Starting a Business by *Individual Characteristics*

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

	Party (1)	+Age (2)	+Male (3)	+Race (4)	+Educ. (5)	+Income (6)	Party × Male (7)
Dem	−0.0815***	−0.0771***	−0.0421***	−0.0161***	−0.0242***	−0.0220***	0.0027
	(0.0093)	(0.0089)	(0.0076)	(0.0055)	(0.0057)	(0.0054)	(0.0064)
Rep	0.1621***	0.1539***	0.1529***	0.1460***	0.1258***	0.1087***	0.0550***
	(0.0061)	(0.0059)	(0.0058)	(0.0054)	(0.0052)	(0.0050)	(0.0045)
Age 18–29		−0.0605***	−0.0609***	−0.0449***	−0.0018	−0.0452***	−0.0469***
		(0.0061)	(0.0061)	(0.0055)	(0.0059)	(0.0056)	(0.0056)
Age 30–39		0.3226***	0.3302***	0.3419***	0.3611***	0.3009***	0.2999***
		(0.0141)	(0.0145)	(0.0153)	(0.0166)	(0.0143)	(0.0143)
Age 40–49		0.3296***	0.3343***	0.3415***	0.3493***	0.2954***	0.2949***
		(0.0137)	(0.0140)	(0.0145)	(0.0150)	(0.0128)	(0.0128)
Age 50–59		0.2037***	0.2044***	0.2078***	0.2095***	0.1776***	0.1773***
		(0.0082)	(0.0083)	(0.0085)	(0.0086)	(0.0074)	(0.0074)
Male			0.4330***	0.4278***	0.4256***	0.4193***	0.4048***
			(0.0208)	(0.0202)	(0.0200)	(0.0198)	(0.0198)
Black				−0.0593*	−0.0619*	−0.0948***	−0.0910***
				(0.0353)	(0.0349)	(0.0337)	(0.0338)
Hispanic				0.1508***	0.1221***	0.0582***	0.0615***
				(0.0203)	(0.0192)	(0.0178)	(0.0178)
Asian				0.4442***	0.3984***	0.3213***	0.3260***
				(0.0282)	(0.0268)	(0.0250)	(0.0250)
College+					0.1939***	0.1438***	0.1432***
					(0.0106)	(0.0082)	(0.0082)

(*Continued*)

Table II—*Continued*

	Party (1)	+Age (2)	+Male (3)	+Race (4)	+Educ. (5)	+Income (6)	Party × Male (7)
Mid income						0.0847***	0.0852***
						(0.0042)	(0.0042)
High income						0.3504***	0.3510***
						(0.0163)	(0.0163)
Dem × Male							−0.0718***
							(0.0084)
Rep × Male							0.1191***
							(0.0103)
R^2	0.070	0.082	0.102	0.106	0.111	0.118	0.119
Outcome mean	0.496	0.496	0.496	0.496	0.496	0.496	0.496
N obs	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978	477,728,978
N clusters (county)	2,123	2,123	2,123	2,123	2,123	2,123	2,123
County × Year FE	Y	Y	Y	Y	Y	Y	Y

interacts with gender and shows that the entrepreneurship gender gap among Independents is similar to the mean, while Democrats have a 14% smaller gap and Republicans a 24% larger one.

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

II. Evidence from Individual Data

A. Elections and Optimism

To motivate our analysis, consider Figure 1, Panel A, which plots the difference in economic views of Republicans and Democrats via Bloomberg's Consumer Comfort Index (CCI). The index is constructed from a telephone survey of 1,000 individuals (250 individuals per week for four weeks) and reported as a four-week rolling average. Respondents are asked to rate the national economy, their personal finances, and the buying climate on a scale from Excellent to Poor. Bloomberg aggregates their answers into a 0–100 point index. As the figure demonstrates, the difference in CCI between Republicans and Democrats varies significantly across political regimes. For example, the average CCI of Republicans was almost two standard deviations higher than that of Democrats during the Republican administrations of George W. Bush and Donald Trump, but it was lower than the CCI of Democrats during the administration of Barack Obama.

In addition, there are sharp swings in the views of Republicans and Democrats after party-changing presidential elections, especially after those of Obama (2008), Trump (2016), and Biden (2020).[20] Non–party-changing elections and midterms appear to have little to no effect on economic optimism.

Entrepreneurship is a future-oriented activity, so an entrepreneur's decision to start a business is likely tied to their belief about the current and future economic climate (e.g., Bengtsson and Ekeblom 2014). Indeed, in Panels B and C, we show similar patterns for business owners between 2008 and 2016 from the Gallup survey—we discuss this evidence in detail in Section IV.C. 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.

B. Individual-Level Event-Study Evidence

We begin by comparing the changes in Republican individuals' likelihood of starting a firm relative to that of Democrats in an event-study DID framework.

[20] 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.

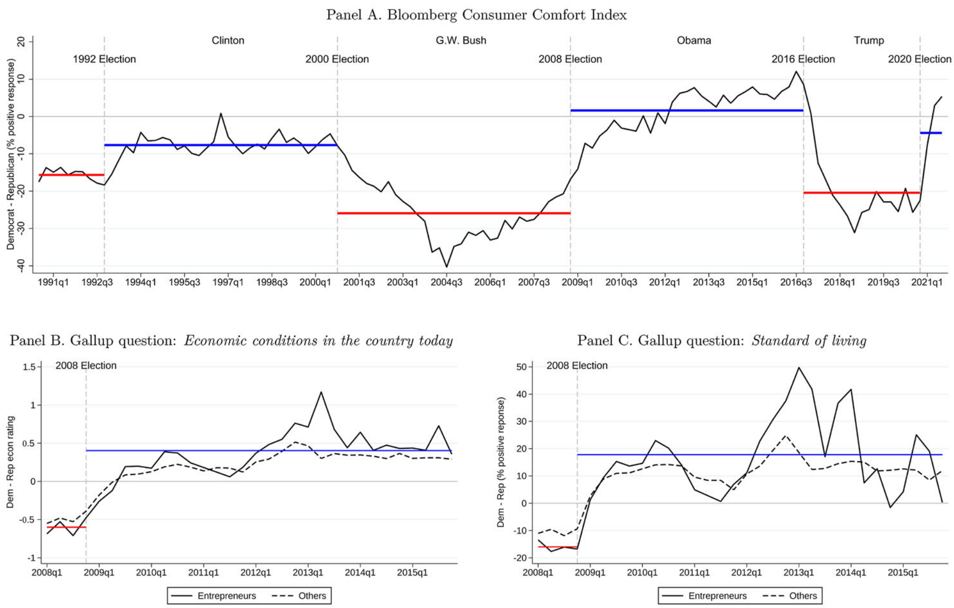

Figure 1. Optimism by party. The black line in Panel A plots the quarterly difference in the Bloomberg Consumer Comfort Index between Democrats and Republicans. Survey respondents are asked to rate (i) the national economy, (ii) their personal finances, and (iii) the buying climate as *Excellent*, *Good*, *Not so Good*, or *Poor*. The Index is calculated as the quarterly average fraction of positive responses (*Good* or *Excellent*) across the three questions. Panels B and C plot the quarterly difference in responses to the Gallup U.S. Daily Survey between Republicans and Democrats among entrepreneurs (black line) and others (dashed black line). Panel B uses respondents' average rating (*Poor*, *Only fair*, *Good*, and *Excellent*, translated into a 1 to 4 range) to the question *How would you rate economic conditions in this country today?* and Panel (C) the fraction choosing *Getting better* to *Right now, do you feel your standard of living is getting better or getting worse?* *Entrepreneurs* are self-identified business owners, while *Others* refers to all other respondents. The horizontal lines plot the average level in each period (for entrepreneurs only in Panels B and C). (Color figure can be viewed at wileyonlinelibrary.com)

In what follows, we contrast individuals of different political parties *within the same county* around presidential elections. This allows us to avoid confounding factors that may differentially affect Republican or Democratic areas. Moreover, we can control for founder characteristics associated with entrepreneurship, such as gender, age, and race.

We estimate the OLS regression:

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

Because we are estimating quarterly coefficients, seasonality is a potential confounder, so we de-seasonalize the outcome by subtracting the party-specific county $\times$ month-of-year average and county annual trend.[21] The outcome variable, Y_{it}, is the excess likelihood of individual i starting a business in time t, the number of periods relative to the presidential election. We define $t = 0$ as the three-month period following an election month and omit $t = -2$ as the base period. Because Federal elections occur every two years, there is a limit on the time periods that we can include in an event study without introducing confounding effects from the preceding or following election. To reduce the impact of such effects, we begin our event window seven quarters before the quarter of the presidential election of interest and end it seven quarters after (four quarters in the case of the 2016 election due to data constraints). Our treatment variable is Dem_i, which equals one if individual i is a Democrat and zero if they are Republican. We include county $\times$ time fixed effects, $\alpha_{c(i),t}$, to control for county-specific time-varying startup likelihood. The vector $\mathbf{X_{it}}$ contains gender, race, and age group bins.[22]

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

Our results indicate that individuals adjust their propensity to start firms along party lines in response to political regime changes. Figure 2 plots the β_t coefficients, comparing the likelihood of starting a business among Republicans to the likelihood among Democrats with the same demographics living in the same county, before versus after the 2008 and 2016 presidential elections. Internet Appendix Table IA.II reports regression coefficients.[23]

Following the election of President Obama in late 2008, the startup likelihood of Democrats relative to Republicans increases by 3.4% of the mean over 12 months. Extrapolating across the United States, this represents a narrowing of the Republican-Democrat entrepreneurship gap by around 13,000 entrepreneurs.[24] There is no indication of a differential pre-trend.

For the 2016 presidential election, the estimates for the pre-period in Figure 2 also support the assumption of parallel trends. Following the election, Republicans' startup probability rose by 2.4% of the mean relative to Democrats over 12 months, increasing the entrepreneurship gap by around 11,000 founders.

[21] To de-seasonalize, we use data starting from 2004 (for the 2008 election) or 2012 (for the 2016 election). We consider the robustness of our estimates to seasonality in Section II.D.2.

[22] Among the individual characteristics we consider, 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 I.C for details).

[23] Figure IA.I reports alternate versions of Figure 2 that employ year-over-year changes to account for seasonality and a version without seasonality adjustments.

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

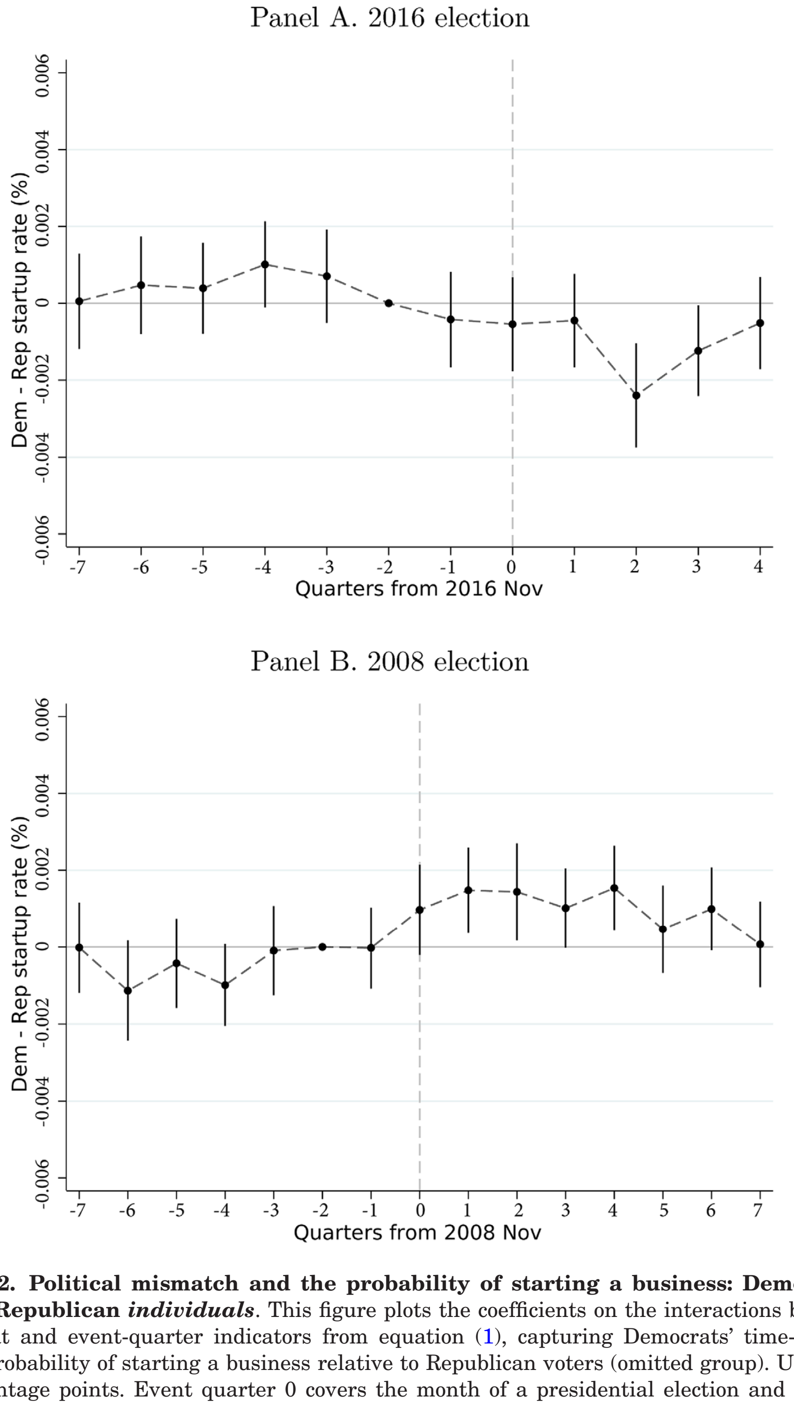

Figure 2. Political mismatch and the probability of starting a business: Democratic versus Republican *individuals*. This figure plots the coefficients on the interactions between Democrat and event-quarter indicators from equation (1), capturing Democrats' time-varying excess probability of starting a business relative to Republican voters (omitted group). Units are in percentage points. Event quarter 0 covers the month of a presidential election and the two subsequent months. For example, for the 2016 election, event quarter 0 is November 2016 through January 2017. Event quarter −2 is the omitted period. All regressions control for county × event

The entrepreneurship response we document is almost immediate, appearing in the same quarter of the Donald Trump election and in the quarter following the Barack Obama election. The speed of the reaction is consistent with other work documenting new firm starts following shocks. For example, both Fazio et al. (2021) and Haltiwanger (2022) document large changes in firm formation that begin in the month following the onset of the COVID-19 pandemic in the United States.

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

C. 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 to 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

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

where Y_{it} is an indicator equal to one if individual i starts a business in year t, Dem_i is an indicator equal to one for Democrats and zero for Republicans, $\mathit{Mismatch}_{it}$ is an indicator equal to one when individual i's party identification differs from the party of the president in year t (i.e., one for Republicans during 2009 to 2016 and for Democrats during 2005 to 2008 and 2017), $\alpha_{c(i),t}$ denotes county $\times$ year fixed effects, and $\mathbf{X_i}$ is a vector of demographic characteristics (gender, age, and race). Standard errors are clustered by county.[25]

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.

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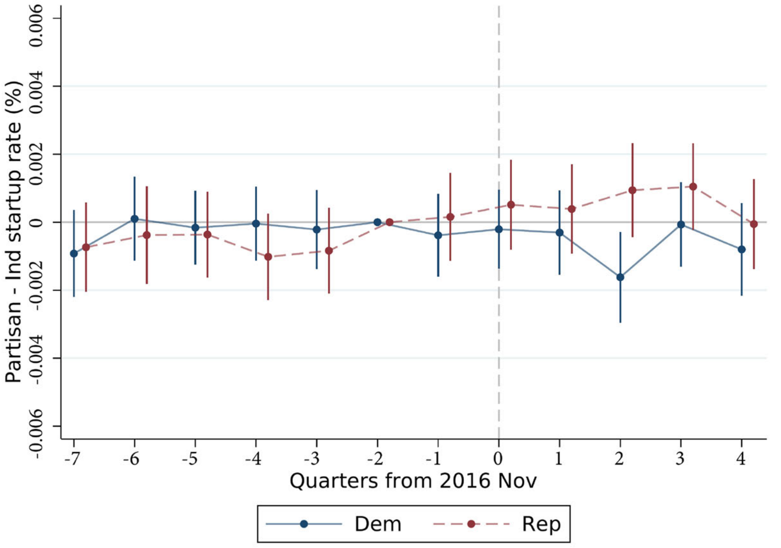
quarter fixed effects and voter characteristics (gender, age groups, race). Regressions are run at the county-party-characteristic-month cell and are weighted by the number of observations in each cell. Standard errors are clustered by county; 90% confidence intervals. Regression coefficients are reported in Internet Appendix Table IA.II. (Color figure can be viewed at wileyonlinelibrary.com)

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

Panel A. 2016 election



Panel B. 2008 election

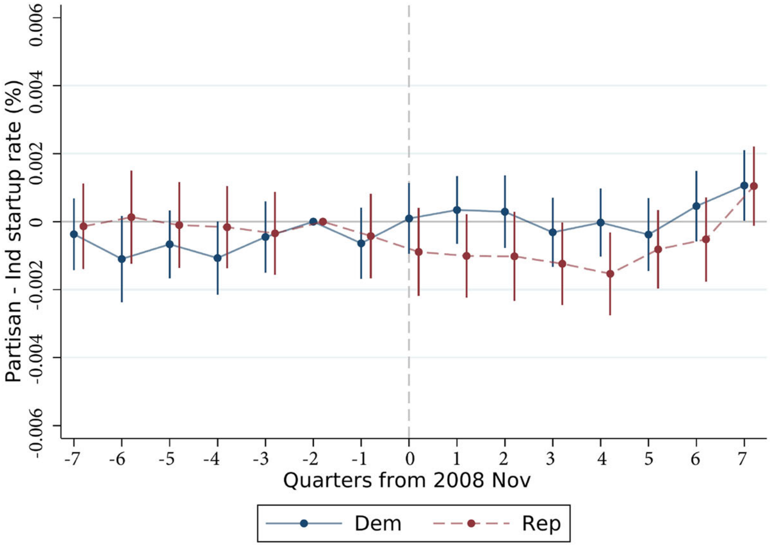


Figure 3. Political mismatch and the probability of starting a business: Democratic and Republican individuals versus *Independents*. This figure plots the coefficients on the interactions between Democrat and event-quarter indicators from a modified version of equation (1), capturing Democrats' (blue solid line) and Republicans' (red dashed line) time-varying excess probability of starting a business relative to Independents (omitted group). Units are in percentage points. Event quarter 0 covers the month of a presidential election and the two subsequent months. For example, for the 2016 election event-quarter 0 is November 2016 through January 2017. Event-quarter −2 is the omitted period. All regressions control for county × event-

C.1. Main Estimates

Table III reports the estimates from equation (2). Column (1) uses all registered Republican and Democrat voters. The coefficient on *Mismatch* is negative and significant: Individuals whose party is not in power are 0.017 pp less likely than politically aligned individuals to start a business in a given year. This is a sizeable effect, equal to 3.3% of the sample mean. Extrapolating across the United States, 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 test the idea that it is political sentiment that drives differential entrepreneurship, we compare regular partisans to more active ones, that is, those who vote more often or donate (see Section I.B for definitions). Since active partisans are more invested in politics, we hypothesize that shifts in political power will have a stronger impact on their optimism and startup decisions. We add an indicator for active partisans (and interactions) to equation (2) and reestimate the model. The negative and significant coefficient on *Mismatch* × *Active* in column (2) means that active voters are 0.01 pp (2% of the mean) less likely to found a company than their less active counterparts in the same county and year when their party is not in power. In other words, the relationship between active voters' startup decision and political mismatch is 82% stronger than that of less active partisans.[26]

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 nonactive counterparts. This represents an additional 1.4% and 7.3% of the average annual probability of starting new firms. While the effect for FEC donors is much larger, they are a much smaller subset of registered voters: 2.3% of individuals are FEC donors, while 50% are active voters and 40% are in donor households.

We view individuals who make an effort to donate to a political campaign as more likely to be actively involved in partisanship. A natural concern is that wealth and the propensity to donate are correlated, and the mismatch effect among wealthy people may be larger. In Internet Appendix Table IA.V, we find no evidence for this concern when we re-run the specifications in Table III 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 are similar to the full-sample estimates. If anything, we find stronger mismatch effects for below-median income households.

quarter fixed effects and voter characteristics (gender, age groups, race). Regressions are run at the county-party-characteristic-month cell and are weighted by the number of observations in each cell. Standard errors are clustered by county; 90% confidence intervals. Regression coefficients are reported in Internet Appendix Table IA.III. (Color figure can be viewed at wileyonlinelibrary.com)

[26] Internet Appendix Figure IA.III 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.

Table III
Political Mismatch and the Probability of Starting a Business

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

	Cell-Level Regression				Weighted Person-Level Regression			
	Regular Voter (1)	Active Voter (2)	Donor Voter (3)	FEC Voter (4)	Regular Voter (5)	Active Voter (6)	Donor Voter (7)	FEC Voter (8)
Mismatch	−0.0165***	−0.0119***	−0.0138***	−0.0150***	−0.0179***	−0.0138***	−0.0156***	−0.0162***
	(0.0017)	(0.0019)	(0.0019)	(0.0016)	(0.0016)	(0.0019)	(0.0019)	(0.0015)
Mismatch × Active		−0.0097***	−0.0067***	−0.0360***		−0.0080***	−0.0058***	−0.0330***
		(0.0020)	(0.0021)	(0.0128)		(0.0019)	(0.0021)	(0.0122)
Dem	−0.1641***	−0.1653***	−0.1644***	−0.1507***	−0.1706***	−0.1712***	−0.1716***	−0.1560***
	(0.0069)	(0.0085)	(0.0076)	(0.0065)	(0.0071)	(0.0089)	(0.0079)	(0.0067)
Dem × Active		−0.0049	0.0093*	−0.7080***		−0.0052	0.0103*	−0.7046***
		(0.0071)	(0.0052)	(0.0371)		(0.0072)	(0.0054)	(0.0369)
Active		0.1112***	0.0507***	1.6428***		0.1135***	0.0481***	1.6266***
		(0.0082)	(0.0045)	(0.0651)		(0.0079)	(0.0044)	(0.0623)
Male	0.4349***	0.4363***	0.4341***	0.4208***	0.4069***	0.4083***	0.4060***	0.3936***
	(0.0207)	(0.0208)	(0.0207)	(0.0202)	(0.0188)	(0.0189)	(0.0187)	(0.0183)
Age 18–29	−0.0472***	−0.0014	−0.0354***	−0.0095*	−0.0574***	−0.0102	−0.0464***	−0.0205***
	(0.0064)	(0.0071)	(0.0064)	(0.0056)	(0.0066)	(0.0071)	(0.0067)	(0.0059)

(*Continued*)

Table III—*Continued*

	Cell-Level Regression				Weighted Person-Level Regression			
	Regular Voter (1)	Active Voter (2)	Donor Voter (3)	FEC Voter (4)	Regular Voter (5)	Active Voter (6)	Donor Voter (7)	FEC Voter (8)
Age 30–39	0.3403***	0.3747***	0.3497***	0.3695***	0.3463***	0.3819***	0.3555***	0.3749***
	(0.0158)	(0.0158)	(0.0163)	(0.0169)	(0.0163)	(0.0163)	(0.0167)	(0.0173)
Age 40–49	0.3316***	0.3551***	0.3349***	0.3519***	0.3354***	0.3598***	0.3387***	0.3554***
	(0.0140)	(0.0140)	(0.0142)	(0.0149)	(0.0142)	(0.0142)	(0.0144)	(0.0150)
Age 50–59	0.2041***	0.2156***	0.2047***	0.2141***	0.2046***	0.2165***	0.2052***	0.2144***
	(0.0083)	(0.0083)	(0.0083)	(0.0087)	(0.0083)	(0.0083)	(0.0083)	(0.0086)
Asian	0.2508***	0.2616***	0.2511***	0.2555***	0.2580***	0.2695***	0.2583***	0.2631***
	(0.0199)	(0.0207)	(0.0199)	(0.0196)	(0.0198)	(0.0205)	(0.0197)	(0.0195)
Black	−0.1590***	−0.1564***	−0.1521***	−0.1432***	−0.1585***	−0.1555***	−0.1517***	−0.1423***
	(0.0216)	(0.0216)	(0.0213)	(0.0211)	(0.0216)	(0.0216)	(0.0213)	(0.0210)
Hispanic	−0.2151***	−0.2015***	−0.2060***	−0.1976***	−0.2120***	−0.1978***	−0.2030***	−0.1938***
	(0.0264)	(0.0269)	(0.0263)	(0.0255)	(0.0254)	(0.0259)	(0.0253)	(0.0245)
Mismatch as %mean	3.33	2.4	2.8	3.03	3.68	2.85	3.21	3.33
Mismatch × Active as %mean	—	1.94	1.35	7.26	—	1.64	1.19	6.78
R^2	0.105	0.070	0.071	0.082	0.005	0.005	0.005	0.005
Outcome mean	0.495	0.495	0.495	0.495	0.485	0.486	0.485	0.485
N obs	327,127,995	326,699,233	327,127,995	327,127,995	327,127,995	326,699,233	327,127,995	327,127,995
N clusters (county)	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120
County × Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table IV

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

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

	Male (1)	Female (2)	Age 18–29 (3)	Age 30–49 (4)	Age 50–70 (5)
Mismatch	−0.0283***	−0.0049***	−0.0188***	−0.0221***	−0.0090***
	(0.0025)	(0.0013)	(0.0021)	(0.0025)	(0.0016)
Dem	−0.2737***	−0.0896***	−0.1085***	−0.2040***	−0.1523***
	(0.0121)	(0.0047)	(0.0061)	(0.0092)	(0.0061)
Male			0.2475***	0.5636***	0.3922***
			(0.0136)	(0.0272)	(0.0184)
Age 18−29	−0.0972***	−0.0200***			
	(0.0107)	(0.0045)			
Age 30−39	0.4897***	0.2422***		0.0126***	
	(0.0225)	(0.0119)		(0.0039)	
Age 40−49	0.4567***	0.2467***			
	(0.0203)	(0.0104)			
Age 50−59	0.2679***	0.1597***			0.1997***
	(0.0117)	(0.0063)			(0.0081)
Asian	0.3752***	0.1529***	0.1351***	0.3758***	0.1642***
	(0.0364)	(0.0119)	(0.0144)	(0.0299)	(0.0140)
Black	−0.2931***	−0.0894***	−0.0976***	−0.2128***	−0.1342***
	(0.0392)	(0.0124)	(0.0154)	(0.0275)	(0.0191)
Hispanic	−0.3567***	−0.1250***	−0.0913***	−0.2739***	−0.2111***
	(0.0480)	(0.0164)	(0.0202)	(0.0339)	(0.0233)
Mismatch as %mean	3.75	1.54	7.4	3.39	2.04
R^2	0.117	0.077	0.065	0.122	0.098
Outcome mean	0.756	0.32	0.254	0.653	0.444
N obs	131,246,407	195,881,588	50,051,494	125,332,715	151,743,786
N clusters (county)	2,115	2,120	2,114	2,116	2,116
County × Year FE	Y	Y	Y	Y	Y

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

C.2. Heterogeneity by Gender, Age, and Income

In Table IV, we begin by considering how partisan effects vary across gender because there is evidence that women's economic expectations react differently to those of men (e.g., Meeuwis et al. 2022; D'Acunto, Malmendier, and Weber 2021). Columns (1) and (2) of Table IV replicate column (1) of Table III for men and women separately. Men appear more sensitive to political power shifts than women. Relative to their respective means, men are 3.8% less likely to engage in entrepreneurship when politically mismatched with the presidential regime, while for women the effect is only 1.5%.

In columns (3) to (5), we explore heterogeneity by age (Azoulay et al. 2020). Individuals between 18 and 29 years old show the largest effect relative to their mean (7.4%), followed by those between 30 and 49 (3.4%), while those between 50 and 70 respond the least (2%). This monotonic decrease across age is consistent with partisanship-induced economic optimism: As entrepreneurs age, they discount expected cash flows over shorter horizons.

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

C.3. Heterogeneity by Firm Type

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

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

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

Columns (3) to (5) focus on firm types that have high ex ante growth potential: venture capital (VC)-backed firms, firms that filed for a patent, and

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

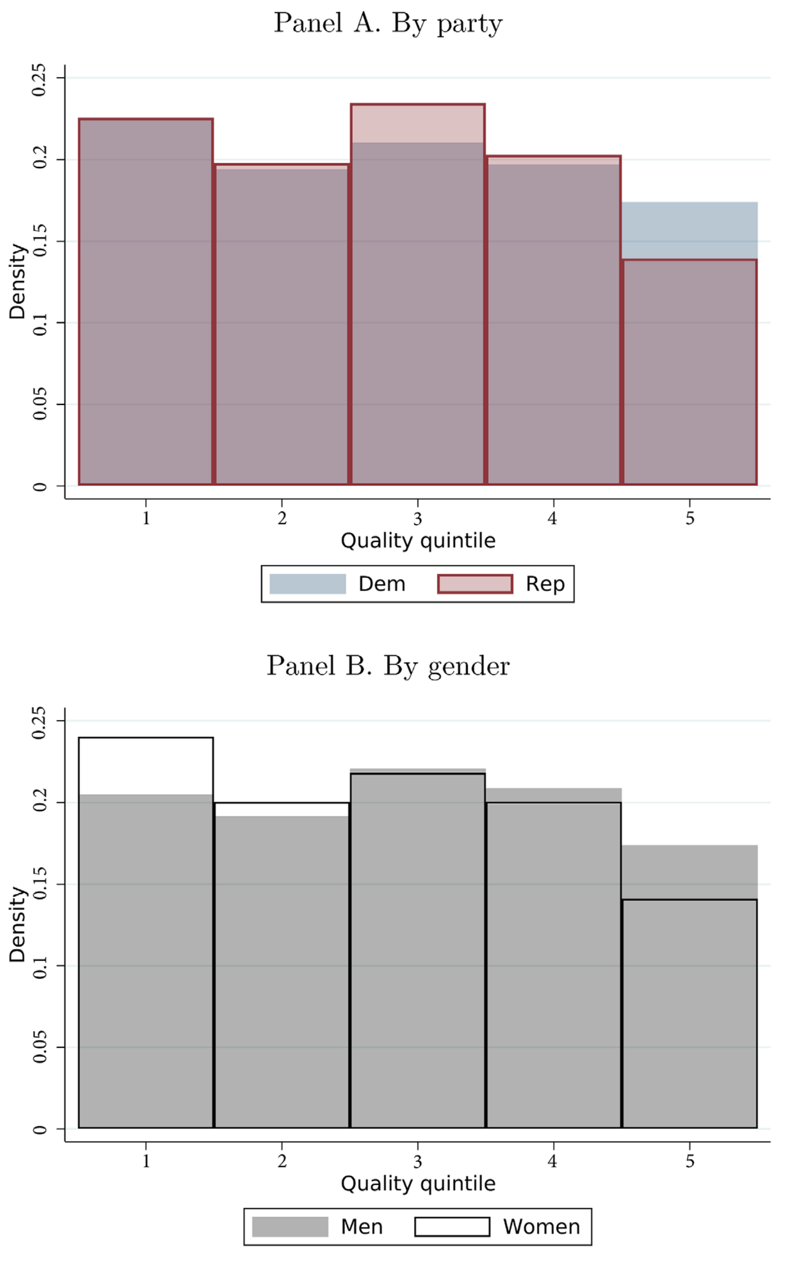


Figure 4. Firm-quality distribution by party and by gender. This figure plots the quintile of firm entrepreneurial quality (using the Guzman and Stern (2020) entrepreneurial quality index) by founder party and gender. Quintile 1 corresponds to the lowest quality. (Color figure can be viewed at wileyonlinelibrary.com)

Table V

Political Mismatch and the Probability of Starting *Different Types of Firm*

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

	LLC (1)	Corporation (2)	VC Backed (3)	Patent Firm (4)	Q: top 5% (5)	Q: 80−100% (6)	Q: 60−80% (7)	Q: 40−60% (8)	Q: 20−40% (9)	Q: 0−20% (10)
Mismatch	−0.003*	−0.014***	−0.0000	−0.0001	−0.001***	−0.004***	−0.003***	−0.002***	−0.001**	−0.003***
	(0.001)	(0.001)	(0.0000)	(0.0001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Dem	−0.124***	−0.042***	−0.0000	−0.0006***	−0.004***	−0.022***	−0.033***	−0.035***	−0.030***	−0.031***
	(0.006)	(0.003)	(0.0000)	(0.0001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Male	0.308***	0.130***	0.0003***	0.0026***	0.020***	0.078***	0.087***	0.093***	0.080***	0.080***
	(0.014)	(0.010)	(0.0001)	(0.0002)	(0.005)	(0.011)	(0.006)	(0.007)	(0.005)	(0.005)
Age 18−29	−0.024***	−0.023***	−0.0000*	−0.0006***	−0.003***	−0.011***	−0.012***	−0.016***	−0.004***	0.004**
	(0.005)	(0.002)	(0.0000)	(0.0001)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Age 30−39	0.249***	0.094***	0.0002***	0.0007***	0.011***	0.049***	0.059***	0.066***	0.064***	0.080***
	(0.011)	(0.009)	(0.0001)	(0.0001)	(0.003)	(0.007)	(0.004)	(0.005)	(0.004)	(0.006)
Age 40−49	0.237***	0.097***	0.0002***	0.0013***	0.013***	0.054***	0.062***	0.066***	0.062***	0.068***
	(0.010)	(0.007)	(0.0000)	(0.0001)	(0.003)	(0.007)	(0.004)	(0.005)	(0.003)	(0.005)
Age 50−59	0.150***	0.055***	0.0001***	0.0007***	0.007***	0.030***	0.037***	0.042***	0.040***	0.045***
	(0.006)	(0.004)	(0.0000)	(0.0001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Asian	0.124***	0.129***	0.0003**	0.0024***	0.043***	0.124***	0.064***	0.038***	0.019***	0.008
	(0.018)	(0.008)	(0.0002)	(0.0005)	(0.008)	(0.012)	(0.012)	(0.007)	(0.004)	(0.006)
Black	−0.141***	−0.018*	−0.0001***	−0.0008***	−0.003*	−0.017***	−0.017***	−0.040***	−0.032***	−0.028***
	(0.015)	(0.009)	(0.0000)	(0.0001)	(0.002)	(0.006)	(0.005)	(0.008)	(0.005)	(0.005)
Hispanic	−0.186***	−0.028*	−0.0002***	−0.0015***	−0.018***	−0.048***	−0.050***	−0.051***	−0.020***	−0.038***
	(0.014)	(0.016)	(0.0000)	(0.0002)	(0.006)	(0.018)	(0.009)	(0.004)	(0.003)	(0.006)
Mismatch as %mean	0.74	10.71	15.89	4.73	4.77	6.36	3.04	2.01	1.28	2.48
R^2	0.093	0.051	0.004	0.004	0.048	0.063	0.052	0.057	0.034	0.055
Outcome mean	0.363	0.134	0	0.0015	0.014	0.069	0.09	0.101	0.089	0.101
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 clusters (county)	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120	2,120
County × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

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

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

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

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

C.4. State-Level Elections

Party-changing elections often occur in waves. When there is a change in the executive branch at the federal level, there are often corresponding changes at the state level. To disentangle whether our results are driven by party-changing presidents or party-changing governors, we consider the 19 states that had at least one change in the party of the governor (from Democratic to Republican or vice versa) from 2005 through 2017. We create an indicator for a mismatch between a voter's party and that of their state governor, *Governor mismatch*. Table VI, column (1) reproduces our baseline result for presidential mismatch among the 19 states. Here, the mismatch effect is 4.4% of the mean, which is higher than the 3.3% in our main sample. Column (2) considers the effect of governor mismatch alone and finds a 5% effect. When we include both the presidential and governor mismatch variables in column (3), the effect sizes (and coefficients) are largely unchanged, suggesting that these are additive effects. In other words, an individual whose party matches both the governor and the president is twice as likely to start a business than if they match only one of the two.[29]

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

[29] In Internet Appendix Table IA.VII, we show that the founding of corporations (vs. other legal vehicles for startups) responds to presidential mismatch but not to governor mismatch. This

Table VI

Political Mismatch and the Probability of Starting a Business: *Presidential versus Governor Mismatch*

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

	(1)	(2)	(3)
Mismatch	−0.0179***		−0.0184***
	(0.0017)		(0.0021)
Governor mismatch		−0.0206***	−0.0210***
		(0.0036)	(0.0039)
Dem	−0.1422***	−0.1407***	−0.1450***
	(0.0097)	(0.0096)	(0.0097)
Male	0.3582***	0.3582***	0.3582***
	(0.0281)	(0.0281)	(0.0281)
Age 18−29	−0.0328***	−0.0332***	−0.0332***
	(0.0071)	(0.0071)	(0.0070)
Age 30−39	0.2822***	0.2822***	0.2821***
	(0.0198)	(0.0198)	(0.0198)
Age 40−49	0.2719***	0.2718***	0.2718***
	(0.0178)	(0.0178)	(0.0178)
Age 50−59	0.1654***	0.1652***	0.1654***
	(0.0106)	(0.0106)	(0.0106)
Asian	0.1878***	0.1876***	0.1876***
	(0.0170)	(0.0170)	(0.0170)
Black	−0.1400***	−0.1394***	−0.1395***
	(0.0223)	(0.0221)	(0.0221)
Hispanic	−0.2183***	−0.2184***	−0.2184***
	(0.0440)	(0.0440)	(0.0440)
Pres. mismatch as %mean	4.38	—	4.49
Gov. mismatch as %mean	—	5.04	5.13
R^2	0.110	0.110	0.110
Outcome mean	0.409	0.409	0.409
N obs	185,542,623	185,542,623	185,542,623
N clusters (county)	1,057	1,057	1,057
County × Year FE	Y	Y	Y

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

may be because corporations are larger and more growth-oriented, and thus more sensitive to the national economy than to the local economy.

D. Robustness

D.1. Sample Construction

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

To ensure that the differences between our sample and the U.S. voter population are not driving our reported results, in columns (5) to (8) of Table III, we reestimate the specifications in the first four columns using individual-level data and an entropy-balance method (Hainmueller, 2012) that weights each observation so that the means of covariates in the re-weighted sample match those in the U.S. voter population.[30] For example, since our regression sample under-represents men, this procedure will give more weight to male observations to correct for this. Estimates in columns (5) to (8) are very similar to the unweighted ones, providing support to the view that our estimates are representative of the underlying dynamics of partisan entrepreneurship. We report unweighted results in the remainder of the paper. Note also that we find consistent results at the county level (Section III.A) and when using the Census Bureau's Business Dynamics Statistics (Section III.C), both of which do not impose any name uniqueness constraints and cover 45 and 50 states plus DC, respectively.

We also perform several robustness checks of our matching procedure in Table IA.VIII. The first five columns present estimates using progressively more stringent name rarity requirements—replacing the baseline 0.1 pp threshold (column (1)) with 0.05 pp, 0.01 pp, 0.001 pp, and 0.0001 pp in columns (2) to (5). To address concerns that our match process operates more effectively in sparsely populated counties, we replicate our baseline specification using only counties with at least 300,000 registered voters in the voter file (approximately the 95$^{\text{th}}$ percentile of United States counties). In our main analysis, we do not use M.I. in selecting unique-name voters or matching voters to founders because the missing rates of M.I. in SCP data vary substantially across states (e.g., 10% in Arizona but 60% in Colorado). However, in this table, we use M.I. to define unique-name voters and match voters to

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

founders in states whose M.I. nonmissing rate is at least 50% in column (7), in states whose M.I. nonmissing rate is at least 40% in column (8), and in all states (column (9)); in the remaining states, we match individuals without using M.I. In the final column, we drop individuals who start a firm with more than one founder. Focusing on solo-founders mitigates the possibility that the individuals listed in the SCP data are early employees rather than founders.[31] Across all specifications, the results are similar.

D.2. Seasonality

While within-year seasonality would not affect the annual-level political mismatch estimates in Section II.C.1, it could potentially affect the event-study estimates in Figure 2. For example, if entrepreneurship in Republican-dominated industries predictably rises at the beginning of the year, then what looks like a relative Republican spike in entrepreneurship after an election outcome could simply reflect seasonal patterns. For this reason, we de-seasonalize our entrepreneurship measure following the description in Section II.B.[32]

Figure IA.1 considers the robustness of our event-study estimates in Figure 2 to seasonal adjustments. Specifically, Panels A and B of Figure IA.1 plot event-study estimates using outcome variables that are not seasonally-adjusted, while the remaining four Panels (C through F) present alternative ways to adjust for seasonality. Seasonal patterns are visible for the 2008 election (Panel B), but there appears to be relatively little seasonal variation around the 2016 election (Panel A). Panels C and D adjust for seasonality by subtracting the corresponding value from the same month in the prior year, while Panels E and F subtract the same-month average over the prior two years. For 2016, Panel C shows a relative decline in Democratic entrepreneurship in the two quarters before the election, although the decline is not statistically different from zero. This pattern is not present in Figure 2 or in Panels A or E. For 2008, the year-over-year plot that subtracts the prior year (Panel D) shows more variability in the pre-period and larger standard errors, leading to weaker statistical significance (the difference between post and pre effects is significant at the 10% level). In summary, the event-study patterns are similar, although there is some sensitivity of the dynamics to how seasonal adjustments are implemented.

An alternative approach to address within-year seasonality is to avoid it entirely using an *annual* event-study that spans the same time window as the quarterly version. In Figure IA.2, Panels A and B plot these annual estimates, which are consistent with the quarterly estimates in Figure 2. If we extend the pre-period to include year -2 (always a midterm election year), we obtain a negative coefficient for 2014 (-0.0090, standard error of 0.0047).

[31] Additionally, in Figure IA.2, we show event-study estimates excluding multi-founder firms.

[32] Including industry-by-quarter fixed effects would absorb industry-specific seasonality. However, we cannot include industry fixed effects because the vast majority of voters in the sample do not start a business and our analysis is at the entry margin. In other words, individuals who do not start a business cannot be assigned an industry.

This result could be consistent with negative sentiment effects for Democratic entrepreneurs in response to Republican success in the midterm elections.[33] However, if midterms have similar effects to presidential elections, we should see a negative effect in 2015, which we do not. The survey data in Figure 1 also do not consistently support this explanation, as only one of three panels shows falling relative optimism for Democratic entrepreneurs around 2014.

III. Evidence from County-Level Data

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

A. County-Level Evidence from the Startup Cartography Project

Similar to our event-study DID analysis at the individual level, in this subsection, we compare Democratic versus Republican *counties* across 45 states, before versus after the 2008 and 2016 elections.[34]

We classify a county as Democratic-leaning (and refer to it as a "Democratic county" for brevity) if its vote share for the Democratic party is above the sample median in the preceding presidential election, and Republican-leaning otherwise.[35] The outcome of interest is the startup rate: the total number of new firms registered in a month per 100,000 county residents. If there are no new firms in a county $\times$ month, we code it as a zero. Because we are estimating quarterly coefficients, seasonality is a potential confounder, so we de-seasonalize the startup rate by regressing it on county $\times$ month-of-year indicators and county annual linear trends using data starting from 2004 (for

[33] We note that there was no detectable entrepreneurship response to Democratic success in the 2006 midterm elections.

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

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

the 2008 election) and 2012 (for the 2016 election).[36] We refer to the resulting variable as the excess startup rate.

We run the following OLS specification:

$$\mathrm{Y}_{ct} = \sum_{t=-8}^{7} \beta_t \times Dem_c + \gamma' \mathbf{X}_{ct} + \alpha_c + \alpha_t + \epsilon_{ct}, \quad (3)$$

where Y_{ct} is the excess startup rate in county c in time t, the number of time periods relative to when each presidential election was decided (i.e., November 2008 and November 2016). Our treatment variable is Dem_c, which equals one if county c is classified as Democrat-leaning, and zero otherwise. The vector $\mathbf{X_{ct}}$ includes the county annual unemployment rate, per-capita income, and the employment share in each two-digit NAICS industry (excluding nonclassifiable establishments) as controls for contemporaneous economic conditions and industry importance in each county. We include county fixed effects α_c and event-time fixed effects α_t to absorb the average startup rate in a county and national registration trends. We cluster standard errors by county. While the data are monthly, for precision and clarity we estimate quarterly averages, and report the monthly version in the Internet Appendix. We define $t = 0$ as the three-month period following an election month. For example, November 2016 through January 2017 constitutes $t = 0$ for the 2016 election. We omit the indicator for $t = -2$ to form our base period. Similar to the individual-level DID, we interpret the β_t coefficients as the causal effect of presidential elections on startups, assuming that Republican- and Democrat-leaning counties would have moved in parallel in the absence of elections. As we will show, there are no differential pre-trends.

In Figure 5, Panels A and B plot the estimated β_t coefficients. Mirroring our results in Figure 2, Democratic counties increase their startup rate relative to Republican counties following the election of President Obama, and Republican counties increase their relative rate after the election of President Trump. Specifically, Democratic counties on average see 18 more firms per 100,000 residents (2.3% of the mean) relative to Republican counties in the year following the 2008 election. Republican counties experience a relative increase of 35 firms per 100,000 residents (3.5% of the mean) in the year following the 2016 election. The timing of the election effects generally mirrors the individual-level analysis, except for a slight anticipation effect in the county-level data in quarter -1.[37] This could be due to perceptions of Trump's likelihood of winning being different across geographic areas but not within areas.

[36] In Figure IA.4, we employ an alternative approach to accounting for seasonality by using the change in the startup rate relative to the same period in the preceding year (year-over-year). Results are very similar.

[37] Internet Appendix Figure IA.5 shows the same regression at a monthly frequency and provides strong support for the parallel trend assumption. Indeed, we see that the slightly negative coefficient in quarter -1 for the 2016 election in Figure 5 is driven entirely by the month before the election (October 2016), a period of political turbulence that included FBI director Comey's letter to Congress about candidate Clinton's emails. In another robustness test, we drop contemporaneous economic controls from equation (3) and find quantitatively similar estimates (Figure IA.6).

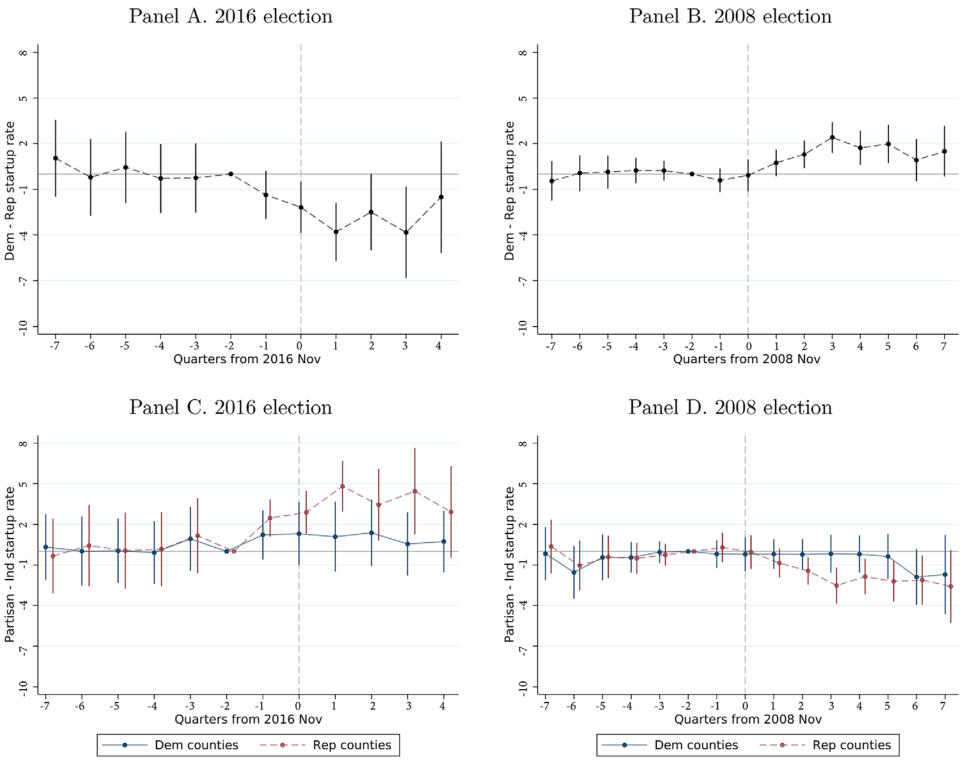


Figure 5. Political mismatch and new firms: Democratic and Republican *counties*. Panels A and B of this figure plot the coefficients on the interactions between the Democratic-leaning indicator and event-quarter indicators from equation (3), capturing these counties' time-varying startup rates relative to Republican-leaning counties (omitted group). Panels C and D instead use "purple" counties as the omitted group. The outcome variable is the excess startup rate: the number of excess new firm registrations per 100,000 people over 19 years old in a county. Purple counties are those reporting a victory margin of less than 10 pp in the preceding election. Event-quarter 0 covers the month of a presidential election and the two subsequent months. For example, for the 2016 election event-quarter 0 is November 2016 through January 2017. Event-quarter −2 is the omitted period. All regressions control for county fixed effects, event-quarter fixed effects, and county economic conditions (monthly unemployment rate, annual per capita income, and annual employment share by NAICS-2 industries). Regressions are weighted by county population aged 20 or above. Standard errors are clustered by county; 90% confidence intervals. Regression coefficients for Panels A and B are reported in Internet Appendix Table IA.IX columns (1) and (2). (Color figure can be viewed at wileyonlinelibrary.com)

Panels C and D repeat the previous analysis, except now we compare clearly Democratic- and clearly Republican-leaning counties to more politically divided ones (so-called "purple counties") rather than to each other, to examine which areas are driving the election effects. We define purple counties as those with a victory margin of less than 10 pp in the preceding election. Both panels indicate that the county-level election effects are driven by Republican counties: They experience a sharp increase in their entrepreneurship around the 2016 election and a sharp decrease around the 2008 election. These results generally mirror what we find when comparing individual Republican and Democrat voters to Independents within the same county in Figure 3, especially around the 2008 election.

The magnitudes from the individual-level and county-level analyses are similar, but they imply a different effect size across analyses. In essence, the average difference between Democrat counties and Republican counties is 30 pp of vote share, making our estimate 30% of the effect of a county going from zero to 100% Democratic. Adjusting for these differences in scale, the county estimate is approximately 2.3 times the individual-level estimate for the Obama election and 4.9 for Trump.

There are at least two reasons the cross-county effect size could be larger than the within-county (individual) effect size. The first possibility is that the ideological difference between Republicans and Democrats is not the same within county as it is across county. A Republican in Shelby County, Alabama, for example, may be very different than a Republican in Los Angeles County, California, and so the ideological distance between a Democrat and Republican in Los Angeles County may be smaller than the difference between a voter in Democratic Los Angeles County and a voter in Republican Shelby County. In other words, geography may be an additional signal of where a voter sits along the ideological spectrum.

The other possibility is that election outcomes could lead to local demand shocks and local entrepreneurs respond to these local shocks. To explore this possibility, we categorize companies into two-digit NAICS industries using a word-tagging approach based on company names—see Internet Appendix II for details. We then compare the entrepreneurial response in tradable versus nontradable industries as an event-study in Figure IA.7.[38] We do not find a difference in startup response between these two sectors: Effect sizes are comparable, and perhaps slightly larger, for the tradable sector.

B. County-Level Evidence from BLS Data

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

In Figure IA.8, we report event-study DID coefficients for the change in the number of establishments per capita and the employment growth rate around the 2016 and 2008 elections. To account for the significant seasonality in quarterly data, we focus on the year-over-year change in the dependent variable

[38] We identify the industry of 55% of firms in our sample using this word-tagging approach. We define nontradable sectors as Retail Trade (two-digit NAICS 44-45), and Accommodation and Food Services (two-digit NAICS 72) following Mian and Sufi (2014) and Adelino, Ma, and Robinson (2017).

rather than on levels. While some coefficients are significant in the second year before the election (in some panels), the overall pattern of results is similar to the other county analyses. In Panels A and B, we focus on the number of establishments per capita. By the second year after the Obama election, relative to the mean number of establishments per capita, Republican counties report 8.1% fewer establishments than Democratic ones. In contrast, in the seven quarters following the Trump election, Republican counties see a 5% of the mean increase in establishments per capita.

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

C. County-Level Evidence from Census

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

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

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

where Y_{ct} is a variable of interest from BDS in county c in year t, and $Mismatch_{it}$ is an indicator equal to one when the partisanship of county c differs from the party of the sitting president in year t. We include a vector of county-level, time-varying variables, $\mathbf{X_{ct}}$, containing annual unemployment rate, annual per-capita income, and the employment share of each two-digit NAICS industry (excluding NAICS = 99) to control for economic conditions and industry presence in the county. When the outcomes are for existing firms, we include firm-age bin fixed effects.[39] We also include county fixed effects α_c and year fixed effects α_t to absorb any persistent differences 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.

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

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

Turning to intensive margin effects, columns (3) through (5) show that firms in politically mismatched counties open fewer establishments (1% of the mean), close more establishments (1.1% of the mean), and experience more firm death (1.4% of the mean), relative to those in matched counties. These business dynamics have implications for the labor market, as the net job creation rate (job creation minus destruction) in column (6) among existing firms in mismatched counties is 0.33 pp of annual employment lower than in matched counties, amounting to 6% of the standard deviation (5.2).[40] Summing across new and existing firms (column (7)), politically mismatched counties experience a relative decrease in their net job creation rate of 0.32 pp of annual employment.

Aggregating, 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.[41] 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.[42]

IV. The Expectations of Partisan Entrepreneurs

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

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

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

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

Table VII

Political Mismatch and *Employer* Firms: County-Level Business Dynamics

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

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

In this section, we explore these expectations further. In Section IV.A, we examine whether these beliefs are correct—does the true return to entrepreneurship match these expectations? In the remaining subsections, we look for evidence that the expectations are about policy changes (Section IV.B) and economic growth (Section IV.C).

A. Expectation versus Reality: The Return to Entrepreneurship around Elections

Our evidence demonstrates that Republican entrepreneurship increases relative to that of Democrats when an election results in a newly elected Republican president (and vice versa). This increase occurs along both the extensive margin via new firms (Table III) and along the intensive margin via the expansion of existing firms (Table VII). In this section, we ask whether these investments reflect a change in the relative return to entrepreneurship. In other words, we know that Republicans invest more (relative to Democrats) when a Republican president comes to power. This could be because the expectations of Republicans are rational and the return to Republican entrepreneurship has increased, relative to Democrats. However, it could also be the case that partisan expectations are biased, and there is little change in the relative return to entrepreneurship following elections.

To test whether Republican or Democratic firms perform differently following party-changing elections, we would like to have a data set analogous to Compustat for the firms in our sample, almost all of which are private. Unfortunately, such a data set does not exist. As an alternative, we use (i) private-firm sales and employment data from Reference USA (Infogroup), a comprehensive data set of firms similar to Dunn & Bradstreet, and (ii) individual income data from Experian matched to L2 data. Before proceeding, we note that firms born soon after an election are unlikely to be random. With this in mind, we focus on existing firms, founded before the party-changing election, to determine whether the return to Democrat versus Republican investment changes after the election.[43]

Figure 6 reports evidence from Reference USA that Republican and Democratic firms founded before the 2008 and 2016 elections appear to hire more workers post-election if they are on the winning side, but do not appear to have differential productivity. Panels A and C show that the number of employees at Democratic (relative to Republican) firms increases after Obama's election and decreases after Trump's election. Increased hiring is consistent with our findings using Census BDS data (Section III.C): Founders of the winning party grow their firms after the election, thus increasing investment. Panels B and D instead consider the productivity of this investment using the only

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

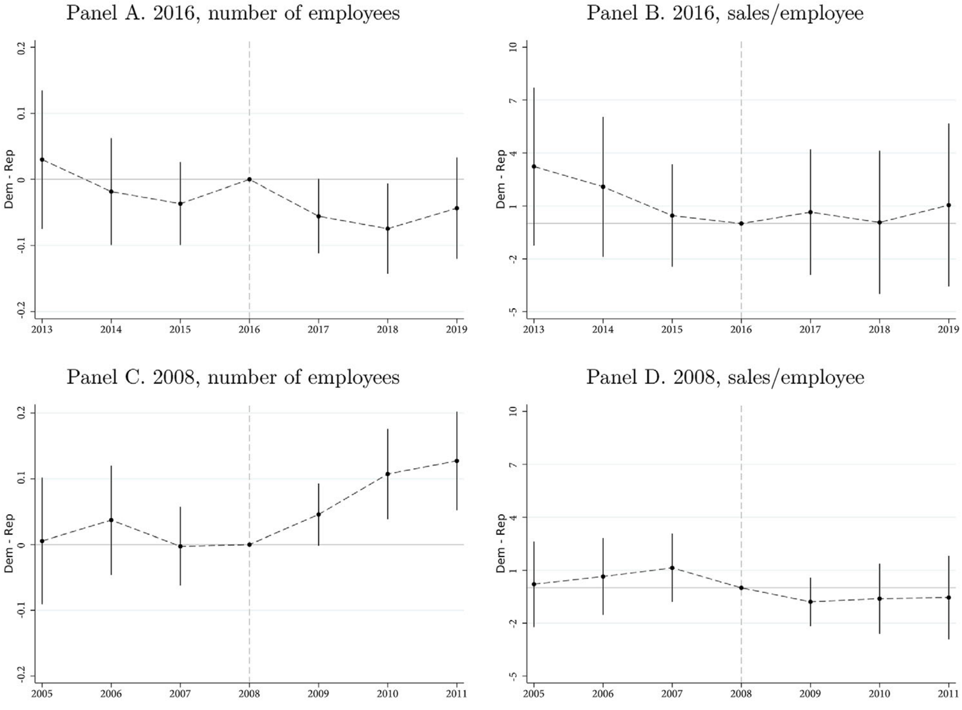


Figure 6. Political mismatch and performance of pre-election firms: Democratic versus Republican. The figure reports the estimated difference in the performance of Democratic versus Republican firms founded before the 2008 and 2016 elections, using data from Reference USA. The samples in Panels A and B (C and D) consist of firm-founder pairs such that the founder was in our main unique-name sample and the firm was incorporated in 2009 to 2012 (2001 to 2004), and the firm has nonmissing sales and employment data in Infogroup. "Number of employees" refers to the number of employees at a firm. "Sales/employee" denotes the sales (in thousands) per employee at a firm; Reference USA compiles sales data from annual reports, newspapers, and periodicals. *Dem* is equal to one for firm-founder pairs with a Democratic founder, and zero otherwise; firm-founder pairs with a Republican founder are the omitted group. The sample period is from three years before to three years after an election; the election year is the omitted period. All regressions control for county × Year, county × incorporation year, industry × Year, and industry × incorporation year fixed effects, as well as founder demographics (gender, age groups, race). Standard errors are clustered by county; 90% confidence intervals. Regression coefficients are reported in Internet Appendix Table IA.XIII. (Color figure can be viewed at wileyonlinelibrary.com)

measure available in the Reference USA data set, namely, sales per employee. Consistent with the hypothesis that the true return to entrepreneurship is unchanged, there are no discernible differences in sales per employee between pre-existing Republican and Democratic firms for at least three years following each election.[44] Table IA.VIII reports the corresponding estimates.

[44] Increased hiring would not increase profits under standard competitive market assumptions absent a change in the true return to entrepreneurship. However, productivity is directly related

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

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

B. Policy Expectations

One reason an entrepreneur might start a business immediately after their party wins an election is that they expect the new president to implement policies that disproportionately favor members of their party. For example, President Trump's 2017 Tax Cuts and Jobs Act included a state and local tax cap of $10,000 that disproportionately hurt taxpayers in Blue States, while the 2010 Affordable Care Act may have benefited Democratic areas more than Republican ones.

We investigate whether entrepreneurs' expectations anticipate future policy by conducting tests in two domains that policy often targets: geography and industry. Mian, Sufi, and Khoshkhou (2023) find 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 reestimate equation (2) but add fine-unit geography-time fixed effects so that identification comes, for example, via differences between Democrats and Republicans who live in the same census

to profitability if a startup's pre-election marginal revenues equal marginal costs and it faces an upward-sloping cost curve.

Table VIII

Political Mismatch and the Probability of Starting a Business: Alternative *Geographic Fixed Effects*

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

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

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 VIII, we progressively include finer geography-by-year fixed effects, from state level (column (1)) to census block group level (column (5)).[45] The point estimates under these alternative geography × year fixed effects are all similar to the estimates under the main specification shown in column (2). Internet Appendix Table IA.XI repeats the exercise for politically active and donor voters, with similar results. Moreover, to the extent that policies are different by income group (e.g., tax policies), geography-by-year fixed effects for zip, census tract, or block group would also absorb such targeting.

Turning to industry, we use the classification approach introduced in Section III.A, and group industries into terciles of policy sensitivity following Hassan et al. (2019). We then reestimate equation (2) but change the dependent variable to be an indicator for whether an individual starts a firm in an industry in a certain tercile of policy sensitivity. In Table IX, columns (1) to (3) show that the political mismatch effect is generally higher for firms in industries with higher policy sensitivity, suggesting that expectations regarding future policy may contribute to the partisan entrepreneurship we document. However, policy expectations cannot be the sole driver, as the industry groups with low and middle sensitivity have mismatch effects that are economically and

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

Table IX

Political Mismatch and the Probability of Starting a Business: *By Industry and County Political Risk*

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

	Industry Political Risk			County-Level Political Risk		
	Low (1)	Middle (2)	High (3)	Low (4)	Middle (5)	High (6)
Mismatch	−0.0027***	−0.0021***	−0.0065***	−0.0060**	−0.0184***	−0.0174***
	(0.0004)	(0.0004)	(0.0006)	(0.0028)	(0.0025)	(0.0026)
Dem	−0.0145***	−0.0302***	−0.0386***	−0.1280***	−0.1716***	−0.1656***
	(0.0009)	(0.0011)	(0.0018)	(0.0072)	(0.0104)	(0.0113)
Male	0.0605***	0.0557***	0.1124***	0.2893***	0.5144***	0.4020***
	(0.0031)	(0.0021)	(0.0047)	(0.0108)	(0.0365)	(0.0257)
Age 18−29	−0.0008	−0.0127***	−0.0045**	−0.0110**	−0.0752***	−0.0263***
	(0.0009)	(0.0009)	(0.0019)	(0.0053)	(0.0116)	(0.0076)
Age 30−39	0.0537***	0.0337***	0.1079***	0.2361***	0.3915***	0.3226***
	(0.0027)	(0.0013)	(0.0047)	(0.0111)	(0.0266)	(0.0221)
Age 40−49	0.0535***	0.0365***	0.0933***	0.2147***	0.3824***	0.3175***
	(0.0023)	(0.0013)	(0.0039)	(0.0096)	(0.0225)	(0.0205)
Age 50−59	0.0319***	0.0251***	0.0544***	0.1440***	0.2340***	0.1949***
	(0.0013)	(0.0009)	(0.0022)	(0.0061)	(0.0128)	(0.0127)
Asian	0.0534***	0.0111***	0.0233***	0.1450***	0.2407***	0.2751***
	(0.0042)	(0.0024)	(0.0040)	(0.0373)	(0.0251)	(0.0330)
Black	−0.0003	−0.0293***	−0.0383***	−0.1724***	−0.2108***	−0.1233***
	(0.0028)	(0.0024)	(0.0051)	(0.0192)	(0.0471)	(0.0200)
Hispanic	−0.0164***	−0.0364***	−0.0464***	−0.2458***	−0.2384***	−0.1811***
	(0.0046)	(0.0023)	(0.0064)	(0.0164)	(0.0445)	(0.0210)
Mismatch as %mean	3.74	3.34	5.1	1.7	3.14	3.88
R^2	0.016	0.016	0.034	0.035	0.129	0.112
Outcome mean	0.072	0.063	0.127	0.355	0.587	0.448
N obs	327,127,995	327,127,995	327,127,995	39,370,497	135,693,120	152,064,378
N clusters (county)	2,120	2,120	2,120	700	699	721
County × Year FE	Y	Y	Y	Y	Y	Y

statistically significant. Additionally, in Internet Appendix Table IA.XII, we show estimates for the 12 most populated industries in the sample. We observe effects for mismatched entrepreneurs across almost all industries including retail, the industry with the lowest policy sensitivity according to Hassan et al. (2019). The robustness of our result across industries is also consistent with the fact that our *Mismatch* estimates are quantitatively similar when we include census block group × year fixed effects (in Table VIII). The latter can be seen as capturing some of the variation in industry × year fixed effects, because in our data the firms started by two randomly chosen founders in the same census block group and year have on average a 25% chance of being in the same industry.

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

C. Economic Expectations

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

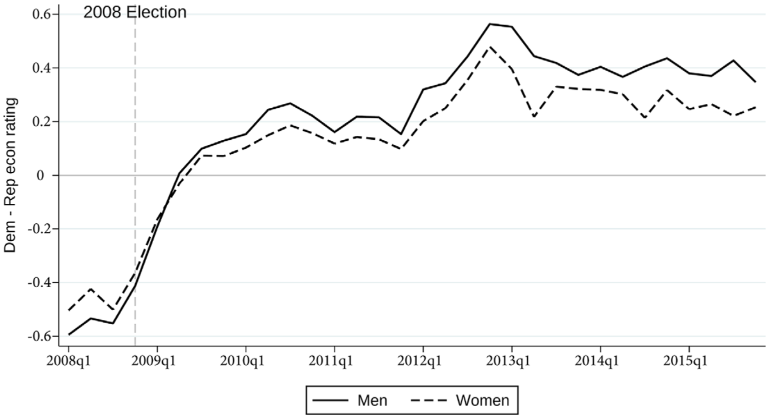
Recall that Figure 1, Panel A, demonstrates sharp partisan swings in economic expectations following party-switching presidential elections. To show that similar patterns also exist among entrepreneurs, we utilize the Gallup U.S. Daily Survey of 1,000 adults daily from 2008 to 2016. We focus on the 2008 presidential election because the number of respondents falls sharply after 2016 to only 30 per day. Importantly, respondents identify their political party (38% are Democrats, 37% are Republicans) and whether they are a business owner (2%).[46]

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

Recall from Table IV that the political mismatch effect that we document was twice as large for men than women. Examining economic expectations, we also

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

Panel A. Gallup question: *Economic conditions in the country today*



Panel B. Gallup question: *Standard of living*

Figure 7. Optimism by party and gender. This figure plots the quarterly difference in responses to the Gallup U.S. Daily Survey between Republicans and Democrats among men (black line) and women (black dashed line). Panel A uses respondents' average rating (*Poor*, *Only fair*, *Good*, and *Excellent*, translated into a 1 to 4 range) to the question *How would you rate economic conditions in this country today?*, and Panel B the fraction of respondents choosing *Getting better* to the question *Right now, do you feel your standard of living is getting better or getting worse?* (Color figure can be viewed at wileyonlinelibrary.com)

find larger partisan swings for men. Specifically, Figure 7 plots the quarterly partisan difference in responses to the Gallup U.S. Daily Survey separately for men and women around the election of Barack Obama. While the Republican-minus-Democrat difference for men was above that of women before Obama's 2008 victory, it fell below, and stayed below, throughout his presidency.

Finally, while Figure 1 shows partisan swings in optimism at the *national* level, most entrepreneurship depends on the local economy (e.g., Schoar, 2010).

Table X

Political Mismatch and the Probability of Starting a Business: *By Counties' Correlation with the National Economy*

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

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

Thus, if economic expectations drive partisan entrepreneurship, we would expect the localities whose economic growth is most connected to the national economy to be most affected by party-changing elections, and partisan entrepreneurs in these areas to be most responsive to these elections.

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

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

V. Conclusion

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

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

Finally, U.S. political polarization is growing along many dimensions (e.g., Abramowitz and Saunders, 2008; Gentzkow, Shapiro, and Taddy, 2019; Alesina, Miano, and Stantcheva, 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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Appendix S1: Internet Appendix.
Replication Code.