Partisanship in Venture Capital *

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Abstract

I study the effect of partisanship on venture capitalist (VC) investment. Specifically, I examine whether a VC's investment decisions and the resulting outcomes are influenced when the VC general partners share the same political party affiliation as the startup founder or CEO. Results show that VCs exhibit a higher probability of investing in politically aligned startups on the extensive margin and, conditional on investing, commit larger capital and assign higher valuations on the intensive margin. I provide evidence that the partisanship effect in VC investment operates through an information-based mechanism rather than favoritism-induced behavioral bias, as startups aligned with their VC partners' party affiliation exhibit superior exit outcomes and reduced failure probabilities.

Keywords: Venture Capital, Political Partisanship, Startup Financing, Information Channel, Capital Allocation

JEL classification: G24, D72, D82, G41, M13, D83

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1 Introduction

The finance literature has long documented that partisanship affects capital allocation, despite policymakers' efforts to promote capital formation through bipartisan initiatives.[1]. Financing innovative startups is arguably the most important facet of capital formation within the economy. For decades, venture capitalist (VC) has stood as one of the most significant financial intermediaries facilitating funding of startups and their innovative ideas. VC-backed firms accounted for more than 60% of all IPOs in the United States before 2010 (Kaplan and Lerner, 2010) and still nearly half afterwards (Lerner and Nanda, 2020). Moreover, among all firms that were publicly traded in the US at the end of 2019, VC-backed firms contributed more than half of total revenue, more than three quarters of market capitalization, and approximately 90% of R&D expenditure (Lerner and Nanda, 2020).

Despite its potential importance, the role of partisanship in shaping VC investment decisions remains largely unexplored. VC investment is highly concentrated in deep-blue states like California, New York, and Massachusetts, reflecting a strong geographic bias[2]. However, it is still uncertain whether political considerations affect investment behavior and startup outcomes more generally, beyond this geographic imbalance. This study contributes to the nascent literature by providing evidence on how partisanship influences investment in the venture capital industry.

In this paper, I explore the influence of partisanship in the VC industry by examining the effect of common party affiliation between VC partners and startup founders/CEOs on investment choice and outcome. New datasets such as PitchBook offer relatively comprehensive information that facilitates the identification of VC partners and startup founders/CEOs. Individuals' party affiliations are inferred using both FEC political contribution data and

[1]For example, Patrick McHenry, chairman of the House Financial Services Committee, made the statement that *"capital formation should not be a partisan issue"* as he closed his remark on the debate of the *Expanding Access to Capital Act* on March 6, 2024. This act aims to build on the successful, bipartisan JOBS Act of 2012 to facilitate capital formation by strengthening public markets, helping small businesses and entrepreneurs, and creating new opportunities for all investors.

[2]See Figure 1.

voter registration records, while accounting for the respective strengths and weaknesses documented in earlier research[3].

To test whether political party alignment influence VC investment decisions, I first construct a sample with actual and counterfactual deals to examine the effect on the extensive margin. I find that VC partners are about 0.3 percentage points more likely to invest in startups whose founders/CEOs lean toward the same political party, an effect that amounts to about a third of the sample's mean investment rate. This effect is comparable to Garfinkel et al. (2025); Huang (2023) where they tested how same alma mater affect VC investment decisions.

I then move on to intensive margin tests. Using a deal-startup-VC-partner level sample of actual deals from 2001 to 2024, I find that VC partners allocate 2.3–2.8% more capital per deal when the startup founder/CEO shares their party affiliation. This increase corresponds to about $0.6 million in dollar amount. In addition, VCs are around 1% more likely to assign the startup a higher valuation in the current funding round. These results indicate that VC partners disproportionately favor startups affiliated with the same political party. All of the above results control for homophily in other socio-demographic characteristics between startup founders/CEOs and VC partners, including shared ethnicity, gender, alma mater, and age group, as well as fixed effects for state, industry, year, financing stage, and VC firm.

The next question is critical: why do VCs invest more in startups that share their political party affiliation, and what mechanism drives this portfolio tilt? Understanding this is essential for uncovering potential biases and efficiency implications in VC investment.Prior research shows that shared socio-demographic characteristics between VCs and startups influence investment decisions through different mechanisms, primarily favoritism or informa-

[3]Kempf and Tsoutsoura (2024) provide a summary of the advantages and limitations of these two datasets. Political contribution records are publicly available and contain rich information. Nevertheless, they have two main limitations: only a small fraction of U.S. voters make contributions, and contributions may reflect a desire to exert political influence or respond to social pressure rather than true ideology. Voter registration records serve as a reliable indicator of individuals' self-reported party affiliation and provide more comprehensive coverage. However, it is not easily accessible and may be missing key matching information, such as the registrant's employer.

tion advantages[4]. Favoritism is a behavioral bias that stems from taste-based discrimination (Becker, 1957). Under the favoritism channel, VCs invest disproportionately more in startups that are similar to them along socio-demographic dimensions, but the outcomes worsen as they potentially underinvest in high-quality projects outside the group or overinvest in lower-quality projects within the group. Under the information-advantage channel, VCs allocate more capital to socio-demographically similar startups, not out of discrimination, but because shared social backgrounds or identities facilitate information flow. In such cases, startups backed by same-party VCs are expected to exhibit better realized outcomes, as improved information flow increases the efficiency of screening process. Enlightened by this stream of literature, I test whether partisanship influences VC investment through pure behavior bias induced by favoritism, or whether it is instead driven by an information channel.

As an initial step, I perform four sets of politically relevant heterogeneity tests. If favoritism is the channel through which partisanship affects VC investment, one would expect the effect to be stronger for politically active individuals and during periods when political events attract greater attention or political conflict intensifies. I first split the VC partners into political donors and non-donors based on their political contribution record. Regression analysis demonstrates that donors are more likely to fund same-party startups, commit greater amounts per deal, and assign higher valuations. I then test whether in presidential election years, post the 2016 election and during high political conflict periods, the effect of partisanship is stronger. The results from the election-year tests show that VCs invest more in same-party startups on the extensive margin during election years. There is no effect on the intensive margin, however. Interestingly, relative to the period before 2016, the effect of partisanship on the extensive margin diminishes following Trump's 2016 election victory, which is widely regarded as the onset of intensified political conflict between Democrats and

[4]For example, Gompers, Mukharlyamov and Xuan (2016) show that VCs syndicate more if they share the same ethnicity, educational or career back ground. This affinity results in worse outcome of the startups they invested in. Findings in Huang (2023) align with this insight using a sample of VCs and startups who share common alumni network. Garfinkel et al. (2025), however, disagreed by showing that same alma mater shared by VC partner and startup CEO actually results in enhanced outcome due to better information sharing.

Republicans. There is a concern that political conflict may already have been intensifying before the 2016 election, potentially complicating my interpretation of post-2016 changes. To capture variations in political conflict more accurately, I use the measure developed by Azzimonti (2018) to construct high political conflict indicators. The results consistently indicate a weakened effect of partisanship during periods of high political conflict, offering evidence that runs against the favoritism mechanism.

An alternative explanation is that favoritism reflects time-invariant individual characteristics rather than time-varying factors. To address this, I conduct formal tests based on startup performance. Poorer outcomes for startups financed by same-party VCs would provide evidence that the partisanship effect operates mainly through the favoritism channel. Conversely, better performance would indicate that the information channel predominates.

I first test whether startups that lean toward the same party as their VC partner have a higher probability of a successful exit. The results indicate that aligned startups are 1-2% more likely to exit successfully, mainly though IPO. The failure rate also declines by around 1.3%. Patenting is also an important metric of startup performance, capturing the degree of innovation within a firm. I find that startups funded by VCs who share the same party affiliation produce more patents, measured both by the total number at the end of the sample period and by the number generated after the investment.

To strengthen the evidence for the information channel, I perform two supplementary tests. Under an information-based mechanism, partisanship effect should attenuate during periods in which information transmission is restricted, while improve screening efficiency for information-disadvantaged agents. Prior research documents that the COVID-19 pandemic curtailed in-person interactions, thereby diminishing the information flow between investors and investees (Gompers et al., 2021; Vorsatz, 2022; Garfinkel et al., 2025; Han et al., 2025). I utilize this shock and divide the 2020 sample into three periods: before COVID, during COVID, and after COVID. The results show that VCs selected better same-party startups in both the pre- and post-COVID periods. In contrast, during COVID, startups receiving investment from same-party VCs exhibit poorer performance. Next, I conduct heterogeneity test based on the specialization level of VCs. More specialized VC partners possess superior information about the areas in which they operate and perform better (Gompers, Kovner and Lerner, 2009). I find that VCs with low specialization benefited from investing in same-party startups, as same-party startups backed by low-specialization VCs perform significantly better in exit outcomes than other startups. Collectively, the evidence from these two sets of tests corroborates the interpretation that partisanship influences VC investment behavior primarily through an information-based mechanism.

In summary, this research provides evidence that partisanship influence VC investment decision and outcome. VC partners increase capital allocation to startups whose founders or CEOs share common political party affiliation, both on the extensive and intensive margin. By showing that startups backed by same-party VCs perform better, I demonstrate that the partisanship effect is not driven by favoritism-induced behavioral bias. Instead, it operates through the rational information channel, where shared social backgrounds or identities enhance information flow, thereby increasing screening efficiency.

Related Literature

This study contributes to the following streams of literature. First, the finance literature has long documented that partisanship influences capital allocation. For instance, at mutual fund level, Hong and Kostovetsky (2012) indicate that Democratic mutual fund managers hold less socially irresponsible companies, Addoum and Kumar (2016) suggest that when there is a shift of party in power, investors would change their portfolio composition; for bank loans, Dagostino, Gao and Ma (2023) demonstrate that bankers whose party does not align with the US President charge higher loan spreads; at firm level, Di Giuli and Kostovetsky (2014) show that Democratic firms invest more capital in CSR, Azzimonti (2018) reveals that when political conflict is intense, firms reduce their investment; even at individual level, Bonaparte, Kumar and Page (2017) illustrate that individuals allocate more into risky assets when their preferred party is in power. Several studies also investigate the broader influence of partisanship on the finance industry. At financial analysts level, Kempf and Tsoutsoura (2021) show that credit analysts' partisan recognition has price effects and may influence firms' investment policies; at regulartor level, Engelberg et al. (2023*a*) provide evidence that partisanship among SEC Commissioners reached unprecedented levels between 2010 and 2019. This study contributes to the literature by providing evidence on how partisanship-related information affects investment behavior in the venture capital sector.

Second, this study also contribute to the literature on how political alignment between economic agents affect the outcome of economic activities. The literature presents mixed evidence, with studies reporting both positive and negative effects. On the positive side, as Fos, Kempf and Tsoutsoura (2024) propose that executives who are misaligned with the political majority of their team are more likely to leave the firm, and their company's stock price responds negatively. Garfinkel et al. (2025) find that VCs are more likely to invest in and disburse larger amount for alumni from their alma mater, they also show that these startups have better outcomes after receiving the funding. Hegde and Tumlinson (2014) discuss the positive impact of proximity in ethnicity between VC and startup. On the negative side, for example, Lee, Lee and Nagarajan (2014) suggests that political alignment between CEO and independent directors leads to lower value and worse performance, and Rice (2020) argue that managers whose party affiliation aligns with the president becomes too optimistic and invest too much. Huang (2023) shows that startups receiving funding from VC alumni perform worse. My study contributes to this literature by showing that partisanship affects VC investment through an information channel, rather than through behavior bias induced by favoritism, as startups backed by same-party VCs perform better.

Third, this study also contribute to the study on the interaction between VCs and the startup team. One focus of the literature on VC is how VC financing is determined. Da Rin, Hellmann and Puri (2013) provides an early survey on this issue. Using a randomized field experiment, Bernstein, Korteweg and Laws (2017) propose that details regarding founding teams might be the most important factor for enticing VC investment. Gompers et al. (2020) survey venture capitalists and find similar results, suggesting that VCs value the management team at deal screening stage and also attribute the success or failure of the investment more to the team rather than business. Jang and Kaplan (2023) add on previous papers and reveal that team explains most of the investment of at least $1 million, however market and product explains more for deals with $10 million and above, implying that VCs overweight teams when making decisions on initial investment. This paper provide evidence that political alignment between VC partners and startup CEOs enhances the likelihood of matching, primarily by improving the flow of information between the two sides.

Evidence of partisanship has also been documented in other areas of fund management. Wintoki and Xi (2020) shows that in mutual fund industry, fund managers are more likely to allocate assets to firms whose executives or directors share their political affiliation. The venture capital market differs from the mutual fund market in at least two important ways. First, the two markets differ substantially in their underlying risk profiles. The VC market is far more volatile and illiquid than the stock market. Investment decisions are much harder to adjust in the VC market, often remaining fixed until the next financing round or the startup's exit. In contrast, fund managers in the stock market can adjust their portfolios in a much more timely and flexible manner. Second, the information environment differs. Unlike the stock market, where firms disclose public information such as financial records, startup investments rely heavily on intensive person-to-person communication. VC partners often undertake costly searches to gather private or even personal information about startups. Together, these differences underscore the importance of thorough pre-investment screening in the VC market. Indeed, this study provides evidence that the partisanship effect in VC investment is primarily driven by ex ante information screening, contrasting with the favoritism-induced behavior bias channel highlighted in the mutual fund context by Wintoki and Xi (2020). Several contemporaneous works (Homroy, Lowry and Mkrtchyan, 2025; Wang, 2025; Wu, Symitsi and Bozos, 2025; Chen et al., 2025) study topics similar to this paper. Chen et al. (2025) study how partisanship change VC syndication patterns, while the other three investigate the how political homophily between VCs and startups affect VC investment. This study differentiates itself by providing clear evidence that the partisanship effect in VC investment is driven by an information mechanism, rather than by behavior bias induced from favoritism. Importantly, this study employs robust exogenous shocks, such as COVID-19 and VC partner deaths, to provide additional empirical support for the findings. It also relies on more comprehensive datasets, including voter registration records covering all 50 states and the District of Columbia, as well as PitchBook data that capture a more complete universe of VC deals.

The remaining parts of the paper are structured as follows. Section 2 introduces the data and sample construction process. Section 3 presents the regression analysis results and provides discussions. Section 4 provides several robustness tests. Section 5 concludes.

2 Data and Sample Construction

This section introduces the data used in this paper and the construction process of the main regression samples.

2.1 VC Data

PitchBook is a leading provider for data on private companies, especially for VC-backed ones[5]. One distinguish advantage of PitchBook is that for most of VC and PE deals in the database, it provides not only investor information at VC/PE firm level (e.g. Sequoia, Andreessen Horowitz, Blackstone), but also at partner level. Names of the lead partner from each investing firm participating in the deal are recorded when the information is available. This data is stored in deal-investor relationship file at deal-investor-partner level, providing IDs for each unique partner and investor firm. This granular information allows me to

[5] E.g. Retterath and Braun (2020); Gompers et al. (2021); Ewens, Gorbenko and Korteweg (2022)

capture a relatively comprehensive picture of active general partners (GPs)[6]

PitchBook also provides rich information on details of each VC deals and the startups involved. I collect all data entries of the deal-investor relationship file for VCs in north America. The names of these partners are stored as long as they have served as the lead partner for at least one deal in the whole dataset. There are 115,269 unique partner-firm pairs, 96,107 unique partner names and 78,600 unique VC firms identified under this criteria. I also collect startup and deal information from Pitchbook. There are 158,205 CEOs working for 158,313 different startups in the whole sample. They raised 395,112 rounds of financing deals in total. At the deal level, I collect information on deal size, deal date, deal status, financing stage, valuation changes, and other relevant details. I collect information on the startups including their CEO's name, firm location, industry, current ownership status, and other relevant characteristics.

I also construct several VC charateristics following the literature. Experience is measure by number of deals the focal VC participated prior to the current deal; industry/stage specialization is calculated as experience in the industry/financing stage divided by total experience, following Gompers, Kovner and Lerner (2009). Network counts in the past five years, how many other VCs did the focus VC worked with, following Hochberg, Ljungqvist and Lu (2007). Reputation is the computed as the sum of previous IPO deal dollar amount backed by the focal VC divided by previous IPO dollar amount backed by the whole VC industry, following Nahata (2008).

2.2 Measure of Political Party Affiliation

There are two main data sources of individual's political party affiliation: political contribution records from FEC and voter registration. There are literature using both measures[7].

[6]In this paper, *VC partner/partner* refers to the GPs, who make investment decisions for the VC fund. There are two types of partners in the VC industry, limited partner (LP) and general partner (GP). LPs refers to investors who supply funds to VCs. They can be individuals or organizations. GPs are general partners of VC funds, typically employed by the corresponding VC firm and manage the investments.

[7]For example: political contribution: Hong and Kostovetsky (2012); Di Giuli and Kostovetsky (2014); Vorsatz (2022); Wang (2023); Babenko, Fedaseyeu and Zhang (2020); Pandey, Shen and Wu (2025), and

The pros and cons of different data sources are discussed in detail by Kempf and Tsoutsoura (2024).

Specifically, in the context of this research, the advantages of political contribution records are their public availability and the relative precision with which they can be matched to individuals, thanks to employer information included in the datasets. The disadvantage of contribution records, however, is that most startup founders/CEOs likely lack the financial means to donate to their favorite political party, potentially skewing the data. The key benefit of voter registration data, on the contrary, lies in its much broader coverage for US citizens. Nevertheless, a main challenge is that PitchBook provides very limited information on demographics, such as age, gender, ethnicity or address, making it difficult to accurately match individuals with voter records. Therefore, I utilize both sources in this study to generate a sample as comprehensive as possible. Given the critiques by Kempf and Tsoutsoura (2024) that campaign contributions might be motivated by a desire to gain political influence or by social pressures, and therefore may not accurately represent the donor's genuine ideological beliefs, I prioritize voter registration data over contribution records in cases where the two sources conflict each other.

2.2.1 Political Contribution Records

Following the literature (e.g. Hong and Kostovetsky, 2012; Di Giuli and Kostovetsky, 2014; Vorsatz, 2022; Wang, 2023), I construct the political affiliation of VC partners using political contribution data from the Federal Election Commission (FEC). I collect all contribution records from 1975 to 2022 and use past ten years donation sum to determine an individual's political party leaning. For example, if a VC partner donated $500 in 2010 to Democrats and nothing else, this partner would be labeled as Democrats from 2010 to 2019; if a startup CEO donated $200 in 2012 to Democrats and $400 to Republican in 2016, this CEO would be labeled as a Democrats from 2012 to 2015, and would be labeled as a

voter registration: Dagostino, Gao and Ma (2023); Engelberg et al. (2023*a*,*b*); Fos, Kempf and Tsoutsoura (2024).

Republican from 2016 to the end of the sample period. More details on this process can be found in Appdendix A.

2.2.2 Voter Registration Records

I use voter registration record provided by L2. L2 is a leading provider of voter registration record and used in previous studies (e.g. Fos, Kempf and Tsoutsoura, 2024; Engelberg et al., 2022). It provides comprehensive coverage of all 50 states in the U.S. and District of Columbia from 2013 to the present. Party identification is straightforward when using voter registration records. Individuals are labeled according to the political party listed in the files for each year of the sample period. The matching process is, however, much more excruciating. I therefore follow a similar strategy as in Engelberg et al. (2022), where they pick unique names matched entrepreneur within a county. More details on this process can be found in Appdendix A.

Finally, I combine the panels of individuals' party leaning data from both data sources and merge with Pitchbook data. There are 22,244 VC partners and 25,636 founders/CEOs with observations of political party for some years between 2001 and 2024.

2.3 Other Data Sources

Patent data are collected from PatentsView, provided by United States Patent and Trademark Office (USPTO). I performed fuzzy match based on company names at a 95% fuzzy match ratio. Socio-demographic data, including ethnicity, gender, age and universities attended are collected from four sources: 1. voter registration record, 2. LinkedIn information, 3. bibliography from Capital IQ database and 4. estimated using popular packages like "pred_census_ln" in python.

2.4 Sample construction and Summary Statistics

2.4.1 Intensive Margin Sample

The deal level sample is built from the North America deal file from Pitchbook. I begin by removing non-US startups and deals that are grants or other non-standard types. I then merge the deal-investor relationship file to the deal file to establish the connection between the investee and investor. After that, I match individuals political party leaning and other firm level information to the sample. This process produces a deal-startup-VC-partner level sample. The sample used to study startup exit outcomes is constructed by keeping only the first deal between a startup and a VC partner, inspired by Sørensen (2007), which argues that the first investment has the greatest impact on startup outcomes. This process collapse the sample into startup-VC-partner level. The deal-level sample consists of 172,760 deal-startup-VC-partner observations, ranging from 2001 to 2024. The exit-outcome sample consists of 92,333 observations ranging from 2001 to 2020.

2.4.2 Extensive Margin Sample

To investigate how VC's investment decision is affected by the effect of common party leaning between VC partners and the startup founder/CEO on the extensive margin, the main regression sample is not competent. This sample only include deals that actually happened, but no the whole set of VC's potential investment opportunity. A sample with counterfactual investments is thus needed, as suggested by Gompers, Mukharlyamov and Xuan (2016); Hegde and Tumlinson (2014); Huang (2023); Garfinkel et al. (2025).

I start by slicing the whole sample into markets defined by different year, state, industry sector and financing stage. Each unique combination of these four factors is defined as a market. I then collect all startups that receive funding in this market, and all VC partners that make investments in the same market. Subsequently, I construct a complete panel of startup–VC partner combinations in that market. This panel encompasses all observed deals as well as potential matches that did not happen. For realized deals, the indicator $Invested$ is set to 100, otherwise it remains at zero. I scale it to 100 (rather than 1) for easier interpretation. Finally I merge the individual party leaning data to the constructed sample. The extensive margin sample consists of 23,353,464 deals. Mean of $Invested$ is 0.716. This average is close to findings from prior literature that VCs consider approximately 100 potential investments before making one successful deal (Gompers et al., 2020).

A potential concern in this sample construction process is that not all VCs have the resources to screen all available deals. While top VCs can get in touch with many startups, others operate with limited capacity. To address this issue, I construct a top-VC indicator based on the VC's experience and network measure. A VC is classified as a top VC in a given year if both measures are higher than the annual median. 35.75% of VC-year observations fall into top-VC category by this criterion. I then randomly drop half of the counterfactual deals for all non-top VCs. This process reduces the number of deals by approximately 15%. For subsequent analyses that investigate the extensive margin, I rely mainly on this "drop 50% of non-top VCs' counterfactual deals" sample.

2.4.3 Summary Statistics

Summary statistics of selected variables are shown in Table 1. The key variable of interest is SP. It is an indicator that equals one if both the VC partner and the startup founder/CEO in the deal are affiliated with Democrats or Republican party, and zero otherwise. Other variable definitions can be found in the corresponding sections or in Appendix A1. Full Sumamry statistics is presented in Appendix A2. The extensive-margin sample summarized here is the "drop 50%" sample, which serves as the main dataset for analysis. The probability of investment in this sample is approximately 0.76%. On average, 35.9% of startup-VC observations successfully exited, while 12.6% confirmed failure. About 35.2% of observations hold patents. These ratios remain similar when the sample is collapsed to the startup level.

Insert Table 1 here.

3 Results

In this section, I present regression analysis results investigating the effect of partisanship on VC investment decisions and outcomes.

3.1 Do VCs Invest More to Same-party Startups

3.1.1 Extensive Margin

To examine whether VC partners favor startups with founders or CEOs from the same party more, I first test how leaning towards the same party affect VC investment decisions on the extensive margin. The sample used here is constructed as described in Section 2.4.2 above, including counterfactual deals. I use the following regression specification:

$$Invested_{i,j,m} = \beta \times SP_{i,j,m} + \gamma \times Socio.Control + FEs + \epsilon_{i,j,m} \tag{1}$$

where $Invested_{i,j,m}$ is 100 if VC partner j invested in startup i in market m, and zero other wise; market m is defined by year×industry sector×state×financing stage. $SP_{i,j}$ equals one if the startup founder/CEO party and the VC partner party are both Democrat of Republican, and zero otherwise; $Socio.Control$ captures other socio-demographic relationships and includes indicators for same ethnicity, gender, school, and age group; FEs include combinations of VC firm, year, industry, state, and financing stage fixed effects. The coefficient of interest is β. A positive β indicates VC partners would invest more into same-party startups than startups not leaning towards the same party.

Insert Table 2 here.

Table 2 reports the regression results. In column (1), the coefficient on the key explanatory variable SP is positive and significant at 1% level, controlling for VC firm, year, state, industry and financing stage fixed effects. This result indicates that compared with the pairs of VC partner and startup founder/CEO without shared political leanings, the probability of a successful deal between those who show leaning towards the same party is 0.267% higher. This result is robust to different sets of fixed effects. In column (2) I use market fixed effect, which is essentially the interaction of year, state, industry and financing stage, instead of including them individually. The results remain largely unchanged, with a positive significant coefficient 0.262. In column (3), I further interact VC firm fixed effect with market fixed effect, and the coefficient increase slightly to 0.279. On the economic significance, the coefficient is significant relative to the sample mean of $Invested$, which is 0.764. This magnitude is comparable to the effect of alumni network on VC investment decisions documented in Garfinkel et al. (2025)(0.22% and 2.03%) and Huang (2023)(0.17% and 1.04%), despite differences in sample construction methods across papers. In sum, VC partners are more likely to invest in startups whose founders or CEOs show leaning towards the same party as the partners on extensive margin.

In column (4) to (6), I repeated the tests using the sample in which half of the counterfactual deals of non–top VCs are randomly dropped. The coefficient of SP remains positive and significant, ranging from 0.297 to 0.314. In this sample, the mean of increases to 0.841%. The magnitudes are comparable to those from the whole sample.

I then split the sample by industry sector and year and estimate the coefficient of SP within each sub-sample. Figure 2 presents the results by industry. Sectors such as Materials and Resources as well as Energy are strongly affected by partisanship, while Information Technology exhibits significant but comparatively smaller effects. In the time-series, despite an initial peak in the early years, the coefficient remains relatively stable around the sample mean, as shown in Figure 3.

3.1.2 Intensive Margin

In this subsection, I look at how partisanship affects VC investment decision on the intensive margin. Specifically, I first examine, conditioned on that the deal is made, will

VC partners invest more for each deal if the startup founder/CEO leans towards the same party as the VC partners. Next, I assess whether these VC partners assign higher valuations to startups relative to previous financing round. The regressions use the deal-startup-VC-partner level sample. The specification is:

$$Y_{i,j,d} = \beta \times SP_{i,j,d} + \gamma_s \times Socio.Control + \delta_c \times VC\,Cha.Control + FEs + \epsilon_{i,j,d} \quad (2)$$

where $Y_{i,j,d}$ is the outcome variable for deal d between startup i and VC partner j; SP and $Socio.Control$ are defined the same as above; $VC\,Cha.Control$ include VC firms' experience, network, reputation, sector specialization and stage specialization; FEs include combinations of VC firm, year, state, industry and financing stage fixed effects.

The first intensive margin outcome variable analyzed is deal size. It is measured as natural log of dollar amount (in millions) invested in each deal, $ln(Dealsize)$. The regression results are presented in Table 3 column (1) and (2). More stringent fixed effects are added into the regression as the column number increases. The coefficient of SP is 2.8% in column (1), and becomes 2.3% with more stringent fixed effects in column (2). Importantly, the coefficients are both positive and significant, indicating that VCs invest more dollar per deal in startups whose founders or CEOs lean toward the same political party as the partners, compared with startups that do not. The sample mean of deal size is about \$22.54 million, thus the coefficient corresponds to approximately \$0.6 million dollar increase per deal.

Insert Table 3 here.

Next, I check if these VCs assign higher valuations to startups that lean toward the same political party compared with the previous financing round. The regression model is the same as in above subsection, except that the dependent variable is now a dummy variable $Upround$ that equals one if in the current round of financing, the startup's valuation increases, and zero otherwise. The results are presented in Table 3 column (3) and (4). The coefficients on

SP is positive and significant across specifications, suggesting that VC partners would be more likely to increase startup valuation if the startup founder/CEO show leaning toward the same party as the VC partners. The estimated coefficients imply an approximately 1% higher probability of an increase in valuation, representing 2.98% of the sample mean of 33.59%. These results demonstrate another way in which partisanship impacts the intensive margin of VC investment, distinct from its effect on deal size.

In summary, evidence from regression analysis presented in this section supports that VC's intensive margin investment decision is affected by common party leaning between the partners and the startup founder/CEO. VC partners are more willing to provide favorable deal terms, including larger deal amount and higher valuation, to startups leaning towards the same party, relative to others.

3.2 Mechanism of the Partisanship Effect in VC Investment

The above results show that partisanship affects VC investment decisions, as VCs favor startups whose founder or CEO shares their political affiliation on both the extensive and intensive margins. A critical question arises: why VCs invest more in startups that share their political affiliation? Understanding the mechanism behind this portfolio tilt is crucial, as it sheds light on how partisanship shapes investment decisions and startup outcomes.

Prior research shows that shared socio-demographic characteristics between VCs and startups influence investment decisions via different mechanisms. Gompers, Mukharlyamov and Xuan (2016) show that VCs syndicate more if they share the same ethnicity, educational or career back ground. This affinity results in worse outcome of the startups they invested in. Huang (2023) show similar results using VCs and startups who share common alumni network. The channel that works here is favoritism. In-group favoritism is a behavioral bias that stems from taste-based discrimination (Becker, 1957), where agents gain direct utility interacting with similar people, or disutility when interacting with others. Under the favoritism channel, VCs invest disproportionately more in startups that are similar to them along socio-demographic dimensions, but the outcomes worsen as they potentially underinvest in high-quality projects outside the group or overinvest in lower-quality projects within the group. Findings from the alternative channel indicate a divergent outcome. For instance, Garfinkel et al. (2025) show that same alma mater shared by VC partner and startup CEO actually results in enhanced outcome due to better information sharing. Under the information-advantage channel, VCs allocate more capital to socio-demographically similar startups, not out of discrimination, but because shared social backgrounds or identities improve communication, enhance trust, and allow VCs to better assess the quality and potential of the startups. In such cases, startups backed by same-party VCs are expected to achieve better outcomes, as improved information flow enables VCs to evaluate startup potential more accurately, deploy resources effectively, and ultimately enhance the overall efficiency of the screening process. Motivated by findings in this line of research, I test whether partisanship influences VC investment through pure behavior bias induced by favoritism, or whether it is instead driven by an information channel.

3.2.1 Heterogeneity Tests for the Favoritism Channel

I first perform four sets of politically relevant heterogeneity tests. If favoritism is the channel through which partisanship affects VC investment, one would expect the effect to be stronger for politically active individuals and during periods when political events attract greater attention or political conflict intensifies. From cross-sectional perspective, I examine whether being a political donor increases a VC partner's investment towards same-party startups along both the extensive and intensive margins. From time-series perspective, I assess whether in election years, after the 2016 presidential election, and during high political conflict period, the impact of within-party favoritism becomes stronger.

3.2.2 Cross-section: Political Donor

First I look into the heterogeneous effect of VC political donor on the cross-section. I follow the same procedure when using donation as measure of political party leaning, as described in the data section 2.2 above: VC partner-year observation is labeled as $Donor = 1$ if the partner has donation record within the past ten years, and zero otherwise. In Table 4, I report the regression results adding $Donor$ and the interaction of SP and $Donor$ into the analysis. Extensive margin results are reported in Panel A. Column (1) to (3) use increasingly stringent fixed effects. The coefficients of the interaction term $SP \times Donor$ is positive and significant across all three specifications. This result suggests that VC donors invest more frequently among the startups that share the same political party leaning than those who do not donate.

In Panel B, I report the results on the intensive margin. Columns (1) and (3) share the same specification, as do columns (2) and (4), with the latter pair estimated under more restrictive fixed effects. The coefficients of $SP \times Donor$ is positive and significant in column (1) and (2), where the dependent variable is $ln(Dealsize)$, and positive but insignificant in column (3) and (4), where the dependent variable is $Upround$. These results indicate that political donors invest a larger dollar amount per deal in startups that lean toward the same party than non-donors do, while they award higher valuations to same-party startups at roughly the same frequency as non-donors. Combined with the evidence from extensive margin, these results are consistent with the favoritism channel, as political donors exhibit stronger preferences for same-party startups.

Insert Table 4 here.

3.2.3 Time series: Election Years, Post 2016 and High Political Conflict Periods

Next I perform the heterogeneity tests from time-series perspective. I check whether in presidential election years, post the 2016 election and during high political conflict periods, VC partners favor same-party startups more.

In table 5, I report the regression results interacting $Election\,Year$ with SP. Presidential election years are 2004, 2008, 2012, 2016, 2020 and 2024 in my sample period from 2001 to 2024. $Election\,Year$ equals one if the corresponding deals happen in these years, and zero otherwise. Panel A shows the effect of election year on the extensive margin. Column (1) excludes year fixed effects, allowing the $Election\,Year$ indicator to be estimated rather than absorbed. Column (2) to (4) use the same sets of fixed effects as above analysis. The coefficient on the interaction term $SP \times Election\,Year$ is positive among all four specifications, but only significant at 10% in the last column.

In Panel B, I report the results on the intensive margin. In column (1) and (4) I remove the year fixed effect and include the $Election\,Year$ indicator variable. Other columns use same fixed effect settings as previous tests on the intensive margin. None of the coefficients on $SP \times Election\,Year$ is statistically significant, and they are positive only in the specifications in columns (2) and (3) where the dependent variable is $ln(Dealsize)$. Taken together with the extensive margin results, during election years, VC partners still favor same-party startups more, but the effect is weaker compared with donors.

Insert Table 5 here.

Table 6 reports the results examining the favoritism channel after the 2016 election. The post-2016 election indicator, $Post\,Trump$, equals one if the deals happen in or after 2016, and zero otherwise. In Panel A I show the effect of post-2016 election on the extensive margin of VC investment decision. I include the indicator and exclude year fixed effect in column (1) as in above analysis. Surprisingly, all coefficients on the interaction term $SP \times Post\,Trump$ is negative and significant, suggesting that after the 2016 election, VCs invest in same-party startups less frequently than pre-2016. Panel B reports the intensive margin results. Columns (1) and (4) omit year fixed effects in order to retain the indicator variable, as done in the above analysis. The coefficients of $SP \times Post\,Trump$ are insignificant in the first three columns where the dependent variable is $ln(Dealsize)$, while significant and positive in the last three columns where the dependent variable is $Upround$. These results imply that in the post-2016 periods, VCs do not increase per deal dollar investment for same-party startups, but they are willing to offer higher valuation more often.

Insert Table 6 here.

The two time-series tests above are intuitively linked to political favoritism, reflecting the general public's perception of the intensity of partisan conflict in the U.S. Next I use a more educated measure of political conflict, proposed by Azzimonti (2018). The political conflict index (PCI) uses a semantic search methodology to measure the frequency of newspaper articles reporting lawmakers' disagreement about policy. The PCI data is monthly. I first compute the mean PCI for each year. I then rank these annual PCIs from 2001 to 2024 and use the median as the cutoff. Years with an annual PCI above the median are labeled $High\,Conflict = 1$, and the remaining years are coded as 0. After that, I perform regression analysis using the interaction of $High\,Conflict$ and SP.

The results are presented in Table 7. The specifications in Panel A and B are the same as in the previous two tables. In Panel A, the coefficients on the interaction terms are all negative and significant, suggesting that in periods of high political conflict, VC partners' willingness to invest in same-party startups are weaker than low conflict periods. On the intensive margin side, in panel B, all coefficients of the interaction term are negative, and they are significant in the columns where the dependent variable is $Upround$.

Insert Table 7 here.

Since now monthly data on political conflict index is available, I am able to conduct finer analysis using this higher frequency data. I construct $High\,Conf.\,M$, which is an indicator variable that equals one if the PCI is larger than the monthly median, and zero otherwise. Also I standardize the PCI to be mean zero and standard deviation of one in $Conflict\,Index$. I then interact them with SP and test the effect on the intensive margin. Panel C of Table 7 reports the regression results. In the first two columns, I use $High\,Conf.\,M$. The coefficient estimates on the interaction term $SP \times High\,Conf.\,M$ are insignificant for both dependent variables, $ln(Dealsize)$ and $Upround$. In column (3 and (4), I interact SP with the standardized $Conflict\,Index$. The coefficients of the interaction term are both negative, and significant in when the dependent variable is $Upround$. The findings on the intensive margin suggest that partisanship effect does not intensify during periods of elevated political conflict in the U.S. These results based on time-series analysis provide evidence working against the favoritism channel.

3.3 The Information Channel

A possible alternative interpretation for the above results is that favoritism reflects time-invariant individual characteristics rather than time-varying factors. To address this, I conduct formal tests based on startup performance. If startups financed by same-party VCs experience worse realized outcomes, this provides evidence that the partisanship effect operates primarily through the favoritism channel. Conversely, enhanced startup performance would provide evidence that the information-based mechanism, rather than favoritism, dominates the observed partisanship effect.

3.3.1 Startup Performance

Exit, through either IPO or M&A, is the most common measure of startup performance in the literature (e.g. Gompers and Lerner, 2000; Hochberg, Ljungqvist and Lu, 2007; Sørensen, 2007; Nahata, 2008; Ewens and Sosyura, 2023; Garfinkel et al., 2025; Huang, 2023). Hochberg, Ljungqvist and Lu (2007) also show that demonstrate that this measure is a reasonable proxy for VC fund returns. I thus test this potential information channel using the exit-outcome sample. This sample is constructed by collapsing the startup-VC-partner-deal level sample, picking only the first time a startup and a VC partner ever matched in a deal in Pitchbook. The regression model is otherwise similar as the one used in the intensive margin section above. The set of fixed effects used in the below analysis is different to accommodate the new data structure. The fixed effects used in this regression analysis include state, VC firm, first financing year and startup founding year. The last two are added to control for firm age and time elapsed to result observation. I then restrict the sample to include only deals completed in or before 2020 so that younger startups have enough time to exhibit observable outcomes. I also include results of samples ending by the year 2016 to 2019 as robustness tests.

The exit results are represented by four indicator variables: $Exit = 1$ if the startup successfully exited, either through merger/acquisition or IPO; $MA = 1$ if the startup exited through merger/acquisition; $IPO = 1$ if the startup exited through IPO; and $Fail = 1$ if startup failed. The construction process is included in Appendix B.

Insert Table 8 here.

The regression results are shown in Table 8. The dependent variables in column (1) to (4) are $Exit$, MA, IPO and $Fail$, respectively. In Panel A, the coefficient of SP is significant and positive in column (1), suggesting that startups whose founders/CEOs show same party leaning as their VC investor are more likely to successfully exit. Coefficient in column (2) is insignificant, but positive and significant in column (3), suggesting that most of the extra exit probability are from startups who successfully go through IPO. Results in column (4) indicates a lower failure rate among startups who enjoy an investor from same party. In Panel B, I repeated the same tests using sample consists of deals invested on/before 2016 to 2019. The resulting coefficients on SP have the same structure as those in Panel A, positive and significant when the dependent variable is $Exit$ and IPO, and negative and significant when the dependent variable is $Fail$. These results consistently demonstrate that startups backed by politically aligned VCs achieve superior exit performance, highlighting the dominating role of the information channel.

Patenting is also an important metrics on startup performance. It evaluates how innovative these startups are and is used in many studies (e.g. Bernstein, Giroud and Townsend, 2016; Ewens and Sosyura, 2023; Zhang, 2025). Therefore, I also check the patenting performance of startups that receive investment from same-party VC partners. The regression model used is the same as above, while the dependent variable are now: $Have\,Patent$, which equals one if the startup has any patent; $\#\,Patent$, the number of patents the startup has; $\#\,Pat. > 0$, the number of patents the startup has, conditioned on that the startup has any patent; and $\#\,after\,Inv.$, the increase of number of patent after the investment was made, all evaluated at the end of the sample period, 2024.

Table 9 Panel A reports the results. In column (1), the dependent variable is $Have\,Patent$, and the coefficient on SP is not significant, implying that on the extensive margin, startups that receive investment from VC partners that lean towards the same political party are not more likely to have patents. In column (2) and (3), the dependent variable is $\#\,Patent$; in column (4), the dependent variable is $\#\,Pat. > 0$; and in column (5) and (6), the dependent variable is $\#\,after\,Inv.$. Since most startups do not have patent, $\#\,Patent$ (and also $\#\,after\,Inv.$) have many zeros. To tackle this issue, I use a Poisson regression as an alternative specification to OLS in column (3) (and column (6)). The coefficients on SP are significant and positive from column (2) to (6), suggesting that on the intensive margin, startups that receive funding from same-party VCs produce extra patent compare to the others. In Panel B, I repeat the tests on the 2016-2019 sample and the results are similar as the 2020 sample. These results demonstrate that VC investments involving the same party perform better than those without such connections, further validating that partisanship effect works through information channel instead of favoritism channel.

Insert Table 9 here.

3.3.2 Time-series Evidence from the COVID-19 Shock

To strengthen the evidence for the information channel, I perform two supplementary tests. The first utilizes the COVID-19 pandemic in 2020 as a shock to the information environment VCs face. Studies have shown that during the COVID-19 pandemic, in-person communication is restricted and the information flow between investors and investees is reduced (Gompers et al., 2021; Vorsatz, 2022; Garfinkel et al., 2025; Han et al., 2025). If information channel is driving the partisanship effect, one would anticipate that VC investments involving same-party startups perform better if happened before and after COVID, and perform worse if happened during the pandemic.

To conduct the test, I split the sample in year 2020 into three parts, before COVID (Month 1-2), during COVID (Month 3-7) and after COVID (Month 8-12). The choice of March as the starting month is unambiguous, since states began issuing stay-at-home orders at that time. I then split the remaining months of 2020 by half, resulting in two 4-month periods. I also report placebo tests results in the next table using June and August as alternative cutoff.

Insert Table 10 here.

In Table 10, I report the results utilizing Covid-19 shock to test the information channel. In column (1) where the dependent variable is $Exit$, the coefficient on SP is positive and significant in the "before Covid-19 (Month 1-2)" sub-sample. This suggests that VC investments involving the same party perform better before Covid-19 reduce potential information flow between VCs and the startups.

More importantly, the coefficient becomes negative and significant in the "during Covid-19 (Month 3-7)" sub-sample. This finding strongly suggests that same-party VC investments perform worse due to limited information flow. In addition, as the effect of Covid-19 reduce in the "after Covid-19 (Month 8-12)" sub-sample period, the coefficient of SP restore to a positive number, although not statistically significant. This pattern of coefficient signs (positive–negative–positive) is similarly observed in columns (2) and (3), where the dependent variables are MA and IPO. These results firmly supported the role information channel plays in the effect of partisanship on VC investment.

Insert Table 11 here.

In Table 11, I conduct three placebo tests. The first one involve the cutoff choice discussed above. In Panel A, I estimate the "during" and "before" sub-sample using June and August as alternative cutoff. The coefficients on SP show similar sign pattern as in the above analysis, although they are not statistically significant. This tests imply that the results presented in the previous table is not sensitive to the cutoff choice. In the second one, I extend the "before" sub-sample to four month, including 2019 November and December, the resulting coefficient on SP remains similar sign pattern, and is significant in the $Exit$ column. This finding confirms the consistent superior performance of VC investment involving same-party startups before the Covid-19 shock. In the third placebo test, the year 2019 is used in place of 2020. In Panel C, the year 2019 is partitioned using the same approach applied in Table 10. All coefficients on SP is positive in the column where the dependent variable is $Exit$. I also present results using data from 2021 and plot them alongside the earlier results in Figure 4. This test confirms that the findings reported in the previous table are attributable to the COVID-19 shock that occurred in 2020.

In summary, VC investments involving same-party startups perform better before and after Covid-19, and perform worse during the pandemic, which serves as evidence that the information channel is driving the partisanship effect on VC investment.

3.3.3 Cross-sectional Evidence from VC Specialization Heterogeneity

In this subsection, I provide extra evidence that information channel is driving the partisanship effect on VC investment through a heterogeneity test based on the cross-section of VCs. Gompers, Kovner and Lerner (2009) showed that VC's specialization improve performance. More specialized VC partners possess superior information about the areas in which they operate. If the information channel is driving how partisanship affects VC investment, the performance gap between VCs with low specialization and specialized VCs should narrow. I classify a VC as having low specialization if its industry and stage specialization measures are both below the corresponding annual medians. The indicator variable $Bot.Inv.Spe.$ equals one for VCs with low specialization.

Insert Table 12 here.

In Table 12 Panel A, I show the results adding $Bot.Inv.Spe.$ and its interaction with SP into the exit outcome regressions. In column (1), the dependent variable is $Exit$, and the coefficient on the interaction term $SP \times Bot.Inv.Spe.$ is positive and statistically significant. Moreover, the coefficient is also economically significant, at 0.105, while the sample mean of exit is 0.389. In column (4) where the dependent variable is $Fail$, the coefficient on the interaction term is economically small and statistically insignificant. Results in Panel B confirm the robustness of the above findings for samples ending in the years 2016–2019, where same-party startups backed by low-specialization VCs outperform on exit outcome and do not under-perform in failure rates. These results imply that the performance gap between low-specialization VCs and other VCs is largely mitigated through the information channel underlying the partisanship effect in VC investment.

In summary, to corroborate that information channel is driving how partisanship affects VC investment decision, I present two sets of evidence. From time-series perspective, I use the pandemic happened in 2020 as an exogenous shock. Before and after the Covid shock, VCs backing same-party startups can pick better performed companies. However, during the lock down period when information flow is reduced between startup and VC partners, the startups they picked performed worse. From cross-sectional perspective, I further demonstrate that information-disadvantaged VCs, measured by low specialization, benefited from investing in same-party startups, as the performance of these startups improved markedly. Collectively, the evidence suggests that partisanship influences VC investment primarily through information channel.

4 Robustness

In this subsection, I perform several robustness tests of the main results presented in this paper.

4.1 Finer Industry Classification

To begin with, I use a finer alternative industry definition to better control for unobserved startup characteristics and VC areas of expertise. This new industry definition is based on vertical information collected from Pitchbook. An industry vertical is a specific term that refers to a group of firms focused on a common niche or specialized market that may span multiple traditional industries and is widely used by VC and private equity practitioners. Relative to standard industry classifications in the finance literature, such as SIC or NAICS, industry verticals provide a more appropriate framework for grouping startups at the industry level.

However, startups may belong to multiple industry verticals. In other words, these 58 categories are not mutually exclusive. To avoid creating industries with very few startups, I do not rely on the raw combinations of verticals. Instead, I aggregate verticals into broader vertical groups based on their conceptual relatedness and, more importantly, their degree of political sensitivity. These groups are reported in Table A3. I then interact the vertical groups with the industry classification previously used to construct a new industry definition comprising more than 2,800 industries. Under this definition, for example, an energy firm employing green technology is assigned to a different industry than an otherwise similar firm that does not.

Utilizing the new industry definition, I reconstruct the extensive margin sample. I also add startups' first financing deal amount as a proxy for startup quality into the regression. In Table A4 Panel A, I present the regression results using the new sample. The resulting coefficients of SP remains positive and significant across three specifications.

A potential concern regarding the extensive margin results is that states with relatively few VCs and startups, particularly certain Republican-leaning states, may exhibit highly concentrated political affiliation distributions, thereby driving the findings. I perform the regression based on subsamples of states and plot the results in Figure A2. Several states are associated with extremely large coefficient estimates, such as Montana, Nevada and Kansas. Taking this factor into consideration, To mitigate the potential influence of small and thin markets, I implement robustness tests that remove markets in the lowest 5% and 10% of the size distribution. REsults are presented in Table A4 Panel B. The coefficients on SP remain positive and significant. Thees findings suggest the extensive margin results found in Section 2.4.2 are robust to different sampling choices.

I then perform robustness tests using the new industry classification and first financing amount for both intensive margin and exit outcome. Results are included in Table A5 and are consistent with the main findings.

4.2 Potential Concern on Effort

There is a potential concern that if VC partners exert greater effort in supporting same-party startups, those startups may still outperform others as a result (e.g. Bottazzi, Da Rin and Hellmann, 2008; Hegde and Tumlinson, 2014; Bernstein, Giroud and Townsend, 2016; Fu, 2024). To investigate the effort channel, I use the death of a VC partner as an exogenous shock that clearly prevents the deceased partner from providing additional effort, inspired by Ewens and Sosyura (2023)[8]. I follow their design and created a stacked-difference-in-

[8]The study shows that following the death of a VC partner on a startup's board, the startup experiences a lower likelihood of obtaining funding, smaller funding amounts, reduced patent output, fewer new investors, and longer duration between financing rounds.

differences (stacked-DID) experiment[9]. If VC partners provide extra effort to same-party startups compared with others, the loss of such a partner is expected to more severely harm the performance of these startups.The regresison results using stacked DID is reported in Table A6. I find that, relative to other VC partner deaths, the death of a same-party VC partner does not induce measurable differences in startup performance. I also examine whether the death of a same-party VC partner influences startup exit outcomes in Table A7 and do not find significant effects. Although the results may not fully rule out the possibility of an effort channel, they do not undermine the dominating role of information mechanism over the behavioral-bias channel.

4.3 Other Robustness Tests

4.3.1 Add DP

In Table A8, I add the indicator variable DP, which equals one if the party affiliation combinations of the VC partner and the startup founder/CEO are either (Democrats, Republican) or (Republican, Democrats). This variable would catch the effect of leaning towards opposite parties, as my sample contains observations that people are not affiliated with any party or explicitly identify themselves as "independent". I first test the effect on extensive margin. In Table A8 Panel A, the coefficients on SP are positive and significant, while the coefficients on DP are negative, sometimes significant. These results indicate that VCs are more likely to invest into same-party startups while less likely to invest into different-party startups.

I then test the effect on intensive margin. Results are presented in Table A8 Panel B. In column (5) and (6), where the dependent variables are $Upround$, the coefficients on SP are positive and significant, while the coefficients on DP are insignificant. In column (1) and (2), where the dependent variables are deal size, both SP and DP are significant and

[9] The detailed procedure on creating the sample of VC partner death events and the stacked-DID estimation process are included in Appendix C

positive. However, in column (3) and (4), when I restrict the sample to include only deals with deal size smaller than or equal to \$10 million, DP is no longer significant. Deal size varies largely across different types of deals and follows a highly right-skewed distribution, with a median of only about \$7 million. There are mega deals each totaling billions of dollars, where obviously factors other than socio-demographic homophily plays more important roles. By shifting attention away from mega deals, partisanship keeps its influence influences on the intensive margin of VC investment.

Next, I perform robustness test for startups' exit outcome. In Table A8 Panel C, SP keeps the same performance. The coefficients are positive and significant in column (1) and (3), where the dependent variables are $Exit$ and IPO respectively, and negative and significant in column (4), where the dependent variable is $Exit$. Startups invested by same-party VC partners still outperform. The coefficients on DP, are insignificant in column (1), (3) and (4), and negative and significant in column (2), suggesting that VC and CEO, either from opposite party or being independent, do not benefit from the extra information advantage associated with shared partisanship.

4.3.2 Heterogeneity on VC Characteristics

I also conduct robustness test for the results in Section 3.3.3, where I show cross-sectional evidence for the information channel using heterogeneity in VC specialization level. In Table A9, I define "bottom" VCs with two extra VC characteristics on top of industry and stage specialization: experience and network. The resulting coefficients on the interaction term $SP \times Bot.Inv.$ are not significant. However, the signs of the coefficients are positive in the $Exit$ and MA columns, and they offset the negative coefficients on $Bot.Inv.$. These findings suggest that “bottom” VCs, when defined by more stringent criteria, enhance their screening of high-quality startups by leveraging the information advantage provided by shared partisanship.

4.4 Republicans versus Democrats

I also examine how the effects differ between Republicans and Democrats in Figure A3 as well as Table A10. The results suggest that Republicans exhibit stronger partisanship effects on the extensive margin, whereas Democrats place larger bets on the intensive margin. Regarding the outcome results, although Republicans perform better in terms of both higher relative exit rates and lower failure rates, the differences in coefficients are not statistically significant. The only statistically different coefficients are shown in the regression on patent ownership, showing that republicans are better at selecting innovative same-party startups.

5 Conclusion

This study establishes that partisanship significantly influences VC investment decisions and outcomes. On the extensive margin, VCs are more likely to invest in startups led by individuals sharing their political affiliation, while on the intensive margin, these aligned startups receive larger capital allocations and higher valuations. Crucially, the research demonstrates that this phenomenon is driven by an information advantage channel rather than behavioral bias induced by favoritism– startups backed by same-party VCs exhibit superior exit outcomes, such as higher IPO rates and lower failure probabilities.

These findings enrich the partisanship-in-finance literature by demonstrating that in venture capital, the effect operates through the information channel rather than through favoritism as observed in other contexts. While prior studies on social homophily, such as shared ethnicity or alumni networks, have yielded mixed results regarding performance, this paper aligns with the view that social proximity enhances investment outcome via improved screening efficiency. By leveraging exogenous shocks like the COVID-19 pandemic and VC partner deaths, the study methodologically advances beyond contemporaneous work, providing robust evidence that shared political values serve as a vital conduit for soft information transfer rather than a source of discriminatory capital misallocation.

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Figure 1: Count of VC Investment in the U.S. by State

Note: This figure displays U.S. VC investment counts by state from 2013 to 2024Q1. Regions colored bluer (darker) correspond to greater investment, and those colored oranger (lighter) correspond to smaller investment totals. Data Source: National Venture Capital Association (NVCA).

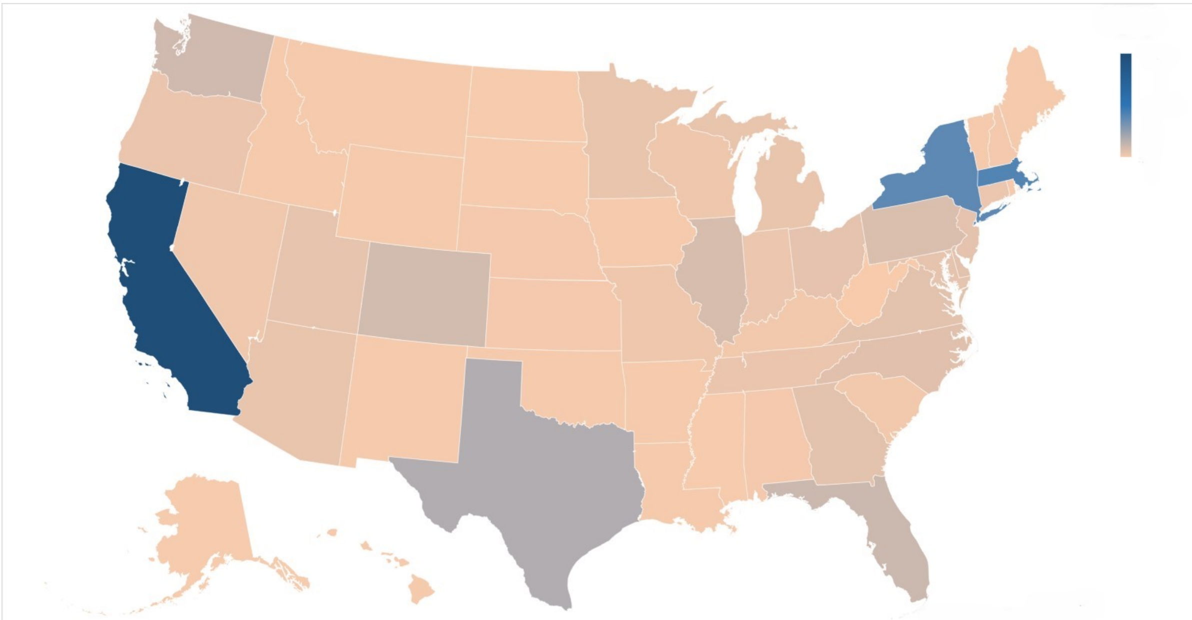


Figure 2: Partisanship Effect on VC Investment Decision–Extensive Margin by Industry Sector

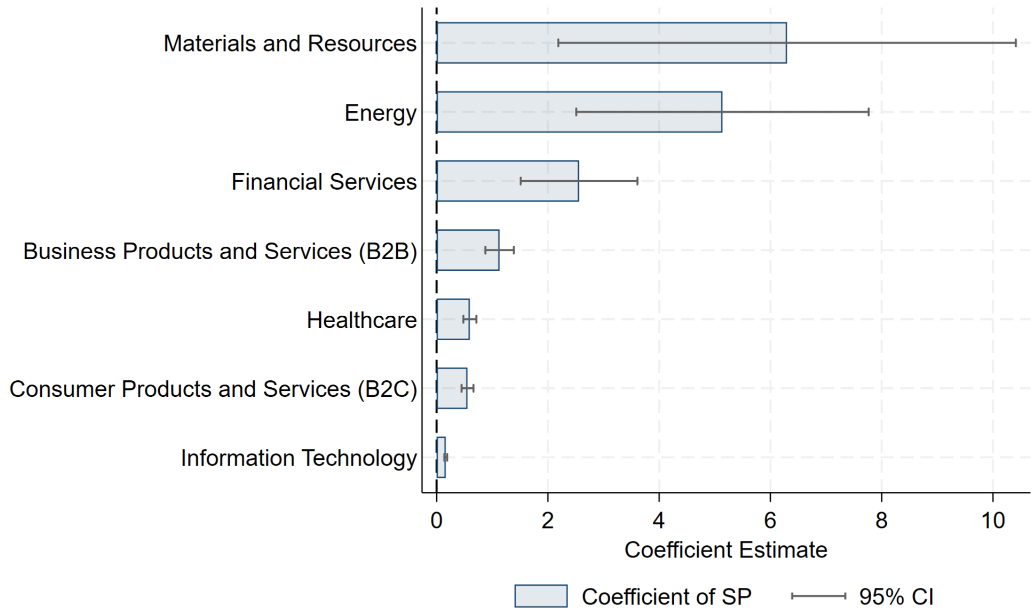


Figure 3: Partisanship Effect on VC Investment Decision–Extensive Margin by Year

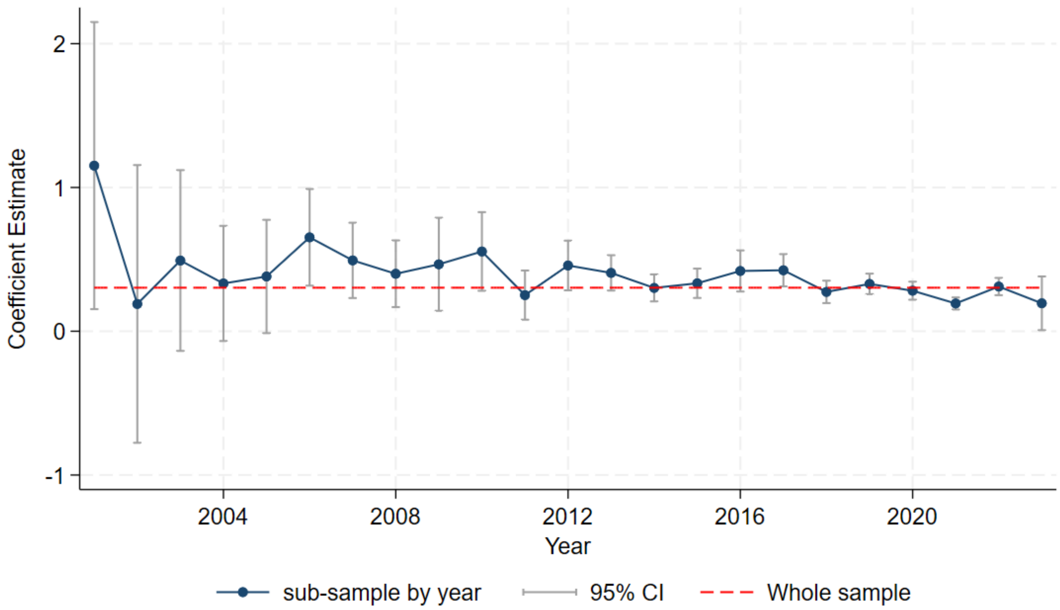


Figure 4: Evidence from the COVID-19 Shock

Note: This figure reports regression results of partisanship effect on VC investment outcome, utilizing the Covid-19 shock. The regressions run at startup-VC-partner level. The dependent variables is *Exit*. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. This figure presents regression coefficients on *SP* across different subsamples over the period 2019–2021. Confidence intervals are at 10% level.

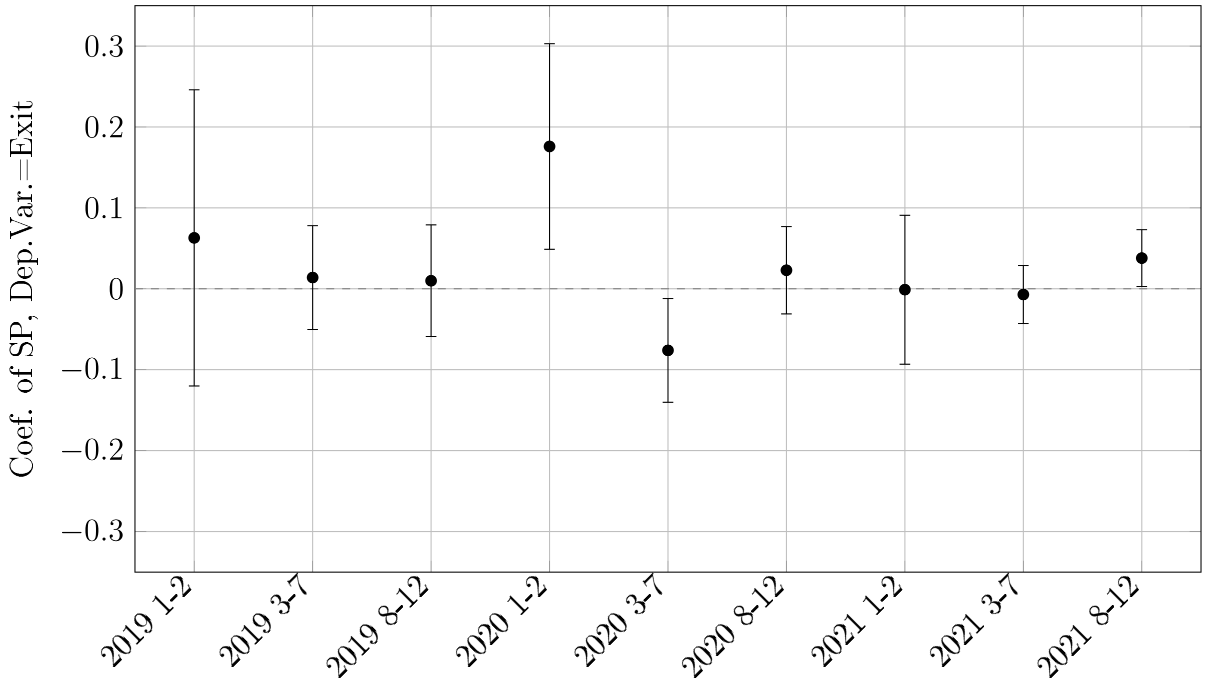


Table 1: Summary Statistics

Note: This table shows selected summary statistics for three different samples. Panel A shows the statistics of the deal-startup-VC-partner level sample. Panel B shows the statistics for investigating exit outcome, where the sample is at startup-VC-partner level. Variable definitions are in Appendix A1

VARIABLES	N	Mean	St.dev	p25	Median	p75
Extensive Margin						
Invested	21,905,219	0.764	8.706	0	0	0
SP	21,905,219	0.057	0.232	0	0	0
Intensive Margin						
Sample: Deal-Startup-VC-Partner Level						
ln(Dealsize)	160,023	1.818	1.643	0.771	1.946	2.996
Upround	172,760	0.294	0.456	0	0	1
SP	172,760	0.085	0.278	0	0	0
Sample: Startup-VC-Partner Level						
Exit	92,333	0.359	0.480	0	0	1
MA	92,333	0.314	0.464	0	0	1
IPO	92,333	0.044	0.205	0	0	0
Fail	92,333	0.126	0.332	0	0	0
Have Patent	92,333	0.352	0.478	0	0	1
# Patent	92,333	9.768	71.43	0	0	3
# Pat.>0	32,524	27.73	118.3	2	6	18
# after Inv.	92,333	7.631	66.45	0	0	1
SP	92,333	0.082	0.274	0	0	0

Table 2: Partisanship Effect on VC Investment Decision–Extensive Margin

Note: This table reports regression results of partisanship effect on VC investment on the extensive margin. The sample is constructed in Section 2.4.2. The dependent variable *Invested* equals 100 if VC partner invests in the startup and zero otherwise. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Market FE* is industry-by-year-by-state-by-financing-stage fixed effect. *Socio. Control* includes same ethnicity, gender, alma mater, and age group. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Sample:	Whole			Non-top Drop 50%		
	(1) Invested	(2) Invested	(3) Invested	(4) Invested	(5) Invested	(6) Invested
SP	0.267***	0.262***	0.279***	0.303***	0.297***	0.314***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	No	No	Yes	No	No
State FE	Yes	No	No	Yes	No	No
Stage FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Market FE	No	Yes	No	No	Yes	No
VC $\times$ Market FE	No	No	Yes	No	No	Yes
Observations	23351263	23349767	23343276	19879990	19878367	19870513
Adjusted R^2	0.045	0.061	0.055	0.052	0.069	0.061

Table 3: Partisanship Effect on VC Investment Decision–Intensive Margin

Note: This table reports regression results of partisanship effect on VC investment on the intensive margin. The regressions run at deal-startup-VC-partner level. The dependent variable $ln(Dealsize)$ is natural log of dollar amount (in millions) invested in each deal. The dependent variable $Upround$ equals one if in the current round of financing, the startup's valuation increases, and zero other wise. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. $Socio.Control$ includes same ethnicity, gender, alma mater, and age group. $VC\,Cha.Control$ includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) Upround	(4) Upround
SP	0.028**	0.023*	0.010**	0.008*
	(0.012)	(0.012)	(0.005)	(0.005)
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Stage FE	Yes	No	Yes	No
Year*State FE	No	Yes	No	Yes
Year*Stage FE	No	Yes	No	Yes
Year*Industry FE	No	Yes	No	Yes
VC FE	Yes	Yes	Yes	Yes
Observations	138234	138076	138234	138076
Adjusted R^2	0.680	0.691	0.215	0.235

Table 4: Partisanship Effect on VC Investment Decision–VC Political Donor

Note: This table reports regression results of and partisanship effect on VC investment utilizing heterogeneity between donor and non-donors. In Panel A, The sample is constructed in Section 2.4.2. The dependent variable *Invested* equals 100 if VC partner invests in the startup and zero otherwise. *Market FE* is industry-by-year-by-state-by-financing-stage fixed effect. In Panel B, the regressions run at deal-startup-VC-partner level. The dependent variable $ln(Dealsize)$ is natural log of dollar amount (in millions) invested in each deal. The dependent variable *Upround* equals one if in the current round of financing, the startup's valuation increases, and zero other wise. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Socio.Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha.Control* includes VC experience, industry/stage specialization, network and reputation. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Extensive Margin

	(1) Invested	(2) Invested	(3) Invested
SP x Donor	0.120***	0.115***	0.066***
	(0.029)	(0.028)	(0.030)
Donor	-0.148***	-0.132***	-0.075***
	(0.015)	(0.015)	(0.015)
SP	0.240***	0.235***	0.274***
	(0.024)	(0.024)	(0.025)
Socio. Control	Yes	Yes	Yes
VC FE	Yes	Yes	No
Year FE	Yes	No	No
State FE	Yes	No	No
Stage FE	Yes	No	No
Industry FE	Yes	No	No
Market FE	No	Yes	No
VC x Market FE	No	No	Yes
Observations	19879990	19878367	19870513
Adjusted R^2	0.052	0.069	0.061

Panel B: Intensive Margin

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) Upround	(4) Upround
SP x Donor	0.056***	0.054***	0.002	0.003
	(0.021)	(0.021)	(0.009)	(0.009)
Donor	0.053***	0.049***	-0.006	-0.005
	(0.011)	(0.011)	(0.005)	(0.005)
SP	-0.011	-0.015	0.009	0.007
	(0.017)	(0.017)	(0.007)	(0.007)
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Stage FE	Yes	No	Yes	No
Year*State FE	No	Yes	No	Yes
Year*Stage FE	No	Yes	No	Yes
Year*Industry FE	No	Yes	No	Yes
VC FE	Yes	Yes	Yes	Yes
Observations	138234	138076	138234	138076
Adjusted R^2	0.680	0.691	0.215	0.235

Table 5: Partisanship Effect on VC Investment Decision–Election Year

Note: This table reports regression results of and partisanship effect on VC investment utilizing heterogeneity between election- and non-election-year. In Panel A, The sample is constructed in Section 2.4.2. The dependent variable $Invested$ equals 100 if VC partner invests in the startup and zero otherwise. $Market\,FE$ is industry-by-year-by-state-by-financing-stage fixed effect. In Panel B, the regressions run at deal-startup-VC-partner level. The dependent variable $ln(Dealsize)$ is natural log of dollar amount (in millions) invested in each deal. The dependent variable $Upround$ equals one if in the current round of financing, the startup's valuation increases, and zero other wise. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. $Socio.Control$ includes same ethnicity, gender, alma mater, and age group. $VC\,Cha.Control$ includes VC experience, industry/stage specialization, network and reputation. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Extensive Margin

	(1) invested	(2) invested	(3) invested	(4) invested
SP x Election Year	0.039	0.047	0.044	0.058*
	(0.028)	(0.029)	(0.028)	(0.030)
Election Year	0.118***			
	(0.005)			
SP	0.269***	0.293***	0.288***	0.302***
	(0.015)	(0.015)	(0.015)	(0.015)
Socio. Control	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	No
Year FE	No	Yes	No	No
State FE	Yes	Yes	No	No
Stage FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Market FE	No	No	Yes	No
VC x Market FE	No	No	No	Yes
Observations	19879990	19879990	19878367	19870513
Adjusted R^2	0.052	0.052	0.069	0.061

Panel B: Intensive Margin

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) ln(Dealsize)	(4) Upround	(5) Upround	(6) Upround
SP x Election Year	-0.004	0.007	0.010	-0.011	-0.009	-0.005
	(0.021)	(0.021)	(0.020)	(0.010)	(0.010)	(0.010)
Election Year	-0.078***			-0.009***		
	(0.007)			(0.003)		
SP	0.061***	0.026**	0.020	0.020***	0.012**	0.010*
	(0.013)	(0.013)	(0.013)	(0.005)	(0.005)	(0.005)
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	No	Yes	No
State FE	Yes	Yes	No	Yes	Yes	No
Industry FE	Yes	Yes	No	Yes	Yes	No
Stage FE	Yes	Yes	No	Yes	Yes	No
Year*State FE	No	No	Yes	No	No	Yes
Year*Stage FE	No	No	Yes	No	No	Yes
Year*Industry FE	No	No	Yes	No	No	Yes
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138234	138234	138076	138234	138234	138076
Adjusted R^2	0.648	0.680	0.691	0.194	0.215	0.235

Table 6: Partisanship Effect on VC Investment Decision–Post trump

Note: This table reports regression results of and partisanship effect on VC investment utilizing heterogeneity between pre-2016 and post-2016. In Panel A, The sample is constructed in Section 2.4.2. The dependent variable *Invested* equals 100 if VC partner invests in the startup and zero otherwise. *Market FE* is industry-by-year-by-state-by-financing-stage fixed effect. In Panel B, the regressions run at deal-startup-VC-partner level. The dependent variable *ln*(*Dealsize*) is natural log of dollar amount (in millions) invested in each deal. The dependent variable *Upround* equals one if in the current round of financing, the startup's valuation increases, and zero other wise. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Socio. Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha. Control* includes VC experience, industry/stage specialization, network and reputation. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Extensive Margin

	(1) invested	(2) invested	(3) invested	(4) invested
SP x Post Trump	-0.175***	-0.168***	-0.147***	-0.161***
	(0.035)	(0.034)	(0.033)	(0.034)
Post Trump	-0.435***			
	(0.010)			
SP	0.412***	0.418***	0.397***	0.424***
	(0.032)	(0.032)	(0.031)	(0.032)
Socio. Control	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	No
Year FE	No	Yes	No	No
State FE	Yes	Yes	No	No
Stage FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Market FE	No	No	Yes	No
VC x Market FE	No	No	No	Yes
Observations	19879990	19879990	19878367	19870513
Adjusted R^2	0.052	0.052	0.069	0.061

Panel B: Intensive Margin

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) ln(Dealsize)	(4) Upround	(5) Upround	(6) Upround
SP x Post Trump	-0.009	-0.008	0.003	0.019**	0.018**	0.021**
	(0.023)	(0.022)	(0.022)	(0.009)	(0.009)	(0.009)
Post Trump	0.614***			0.096***		
	(0.017)			(0.006)		
SP	0.044***	0.032*	0.021	0.004	-0.000	-0.003
	(0.016)	(0.017)	(0.016)	(0.007)	(0.006)	(0.006)
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	No	Yes	No
State FE	Yes	Yes	No	Yes	Yes	No
Industry FE	Yes	Yes	No	Yes	Yes	No
Stage FE	Yes	Yes	No	Yes	Yes	No
Year*State FE	No	No	Yes	No	No	Yes
Year*Stage FE	No	No	Yes	No	No	Yes
Year*Industry FE	No	No	Yes	No	No	Yes
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138234	138234	138076	138234	138234	138076
Adjusted R^2	0.665	0.680	0.691	0.199	0.215	0.235

Table 7: Partisanship Effect on VC Investment Decision–High Political Conflict

Note: This table reports regression results of and partisanship effect on VC investment utilizing heterogeneity between high and low political conflict periods. In Panel A, The sample is constructed in Section 2.4.2. The dependent variable $Invested$ equals 100 if VC partner invests in the startup and zero otherwise. $Market\,FE$ is industry-by-year-by-state-by-financing-stage fixed effect. In Panel B and C, the regressions run at deal-startup-VC-partner level. The dependent variable $ln(Dealsize)$ is natural log of dollar amount (in millions) invested in each deal. The dependent variable $Upround$ equals one if in the current round of financing, the startup's valuation increases, and zero other wise. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. $Socio.Control$ includes same ethnicity, gender, alma mater, and age group. $VC\,Cha.Control$ includes VC experience, industry/stage specialization, network and reputation. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Extensive Margin

	(1) invested	(2) invested	(3) invested	(4) invested
SP x High Conflict	-0.050*	-0.058**	-0.044	-0.053*
	(0.028)	(0.027)	(0.027)	(0.028)
High Conflict	-0.029***			
	(0.007)			
SP	0.313***	0.344***	0.328***	0.351***
	(0.026)	(0.025)	(0.025)	(0.026)
Socio. Control	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	No
Year FE	No	Yes	No	No
State FE	Yes	Yes	No	No
Stage FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Market FE	No	No	Yes	No
VC x Market FE	No	No	No	Yes
Observations	19879990	19879990	19878367	19870513
Adjusted R^2	0.052	0.052	0.069	0.061

Panel B: Intensive Margin–Annual

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) ln(Dealsize)	(4) Upround	(5) Upround	(6) Upround
SP x High Conflict	-0.002	-0.011	-0.011	-0.026***	-0.019**	-0.019**
	(0.022)	(0.020)	(0.020)	(0.009)	(0.009)	(0.009)
High Conflict	-0.085***			0.040***		
	(0.011)			(0.004)		
SP	0.059***	0.030*	0.030*	0.036***	0.022***	0.022***
	(0.018)	(0.017)	(0.017)	(0.008)	(0.008)	(0.008)
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Stage FE	Yes	No	No	Yes	No	No
Year*State FE	No	Yes	Yes	No	Yes	Yes
Year*Stage FE	No	Yes	Yes	No	Yes	Yes
Year*Industry FE	No	Yes	Yes	No	Yes	Yes
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138234	138076	138076	138234	138076	138076
Adjusted R^2	0.648	0.691	0.691	0.195	0.235	0.235

Panel C: Intensive Margin–Monthly

	(1) ln(Dealsize)	(2) Upround	(3) ln(Dealsize)	(4) Upround
SP x High Conf. M	-0.003	0.002		
	(0.021)	(0.009)		
High Conf. M	-0.020**	-0.002		
	(0.009)	(0.004)		
SP x Conflict Index			-0.003	-0.008*
			(0.010)	(0.004)
Conflict Index			-0.018***	-0.004*
			(0.005)	(0.002)
SP	0.025	0.008	0.024**	0.011**
	(0.018)	(0.008)	(0.012)	(0.005)
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
Year*State FE	Yes	Yes	Yes	Yes
Year*Stage FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Observations	138076	149197	138076	138076
Adjusted R^2	0.691	0.235	0.691	0.235

Table 8: Partisanship Effect on VC Investment Outcome–Startup Exit Performance

Note: This table reports regression results of partisanship effect on VC investment outcome. The regressions run at startup-VC-partner level. The dependent variables in column (1) to (4) are $Exit$, MA, IPO and $Fail$, respectively. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. $Socio.Control$ includes same ethnicity, gender, alma mater, and age group. $VC Cha.Control$ includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Invested on/before 2020

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP	0.013**	0.004	0.009***	-0.013***
	(0.007)	(0.007)	(0.003)	(0.005)
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	74331	74331	74331	74331
Adjusted R^2	0.174	0.141	0.102	0.068

Panel B: Invested on/before 2019 to 2016

	Coef. of SP			
	(1) Exit	(2) MA	(3) IPO	(4) Fail
2019	0.020***	0.009	0.011***	-0.013**
	(0.007)	(0.007)	(0.004)	(0.005)
2018	0.022***	0.008	0.014***	-0.013**
	(0.008)	(0.008)	(0.004)	(0.006)
2017	0.020**	0.006	0.015***	-0.015**
	(0.009)	(0.009)	(0.005)	(0.006)
2016	0.021**	0.005	0.016***	-0.014**
	(0.009)	(0.010)	(0.005)	(0.007)

Table 9: Partisanship Effect on VC Investment Outcome–Startup Patent Performance

Note: This table reports regression results of partisanship effect on VC investment outcome. The regressions run at startup-VC-partner level. The dependent variables definitions are in Appendix A1. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. $Socio.Control$ includes same ethnicity, gender, alma mater, and age group. $VC\,Cha.Control$ includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Invested on/before 2020

	OLS (1) Have Patent	OLS (2) # Patent	Poisson (3) # Patent	OLS (4) # Pat.>0	OLS (5) # after Inv.	Poisson (6) # after Inv.
SP	0.010	3.050**	0.207**	8.870**	2.585*	0.219**
	(0.006)	(1.379)	(0.089)	(3.840)	(1.319)	(0.104)
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74331	74331	65395	24492	74331	63076
Adjusted R^2	0.247	0.027		0.065	-0.001	
Pseudo R^2			0.556			0.555

Panel B: Invested on/before 2019 to 2016

	Coef. of SP					
	OLS (1) Have Patent	OLS (2) # Patent	Poisson (3) # Patent	OLS (4) # Pat.>0	OLS (5) # after Inv.	Poisson (6) # after Inv.
2019	0.008	3.356**	0.204**	9.537**	3.189**	0.223**
	(0.007)	(1.592)	(0.094)	(4.318)	(1.557)	(0.107)
2018	0.004	3.902**	0.207**	10.672**	3.705**	0.225**
	(0.007)	(1.829)	(0.097)	(4.860)	(1.791)	(0.109)
2017	0.005	4.465**	0.195**	11.174**	4.188**	0.208*
	(0.008)	(2.046)	(0.099)	(5.272)	(2.006)	(0.111)
2016	0.008	4.702**	0.195*	10.310*	4.465**	0.209*
	(0.008)	(2.231)	(0.104)	(5.491)	(2.186)	(0.116)

Table 10: Information Channel–Time-series Evidence from Covid Shock

Note: This table reports regression results of partisanship effect on VC investment outcome, utilizing the Covid-19 shock. The regressions run at startup-VC-partner level. The dependent variables in column (1) to (4) are *Exit*, *MA*, *IPO* and *Fail*, respectively. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Socio.Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha.Control* includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

	Coef. of SP			
Year=2020	(1)	(2)	(3)	(4)
Month	Exit	MA	IPO	Fail
1-2	0.176**	0.136*	0.041	-0.017
	(0.077)	(0.069)	(0.034)	(0.074)
Observations	438	438	438	438
Adjusted R^2	0.271	0.233	0.399	0.080
3-7	-0.076*	-0.054	-0.022	-0.009
	(0.039)	(0.037)	(0.019)	(0.021)
Observations	1725	1725	1725	1725
Adjusted R^2	0.158	0.105	0.253	0.081
8-12	0.023	0.021	0.002	-0.012
	(0.033)	(0.031)	(0.015)	(0.016)
Observations	2090	2090	2090	2090
Adjusted R^2	0.095	0.044	0.270	0.073
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes

Table 11: Placebo Tests–Time-series Evidence from Covid Shock

Note: This table reports placebo tests results of partisanship effect on VC investment outcome, utilizing the Covid-19 shock. The regressions run at startup-VC-partner level. The dependent variables in column (1) to (4) are *Exit*, *MA*, *IPO* and *Fail*, respectively. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Socio.Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha.Control* includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

	Coef. of SP			
	(1)	(2)	(3)	(4)
Month	Exit	MA	IPO	Fail
Panel A				
2020.3-2020.6	-0.073	-0.062	-0.011	-0.010
	(0.049)	(0.046)	(0.026)	(0.026)
2020.7-2020.12	0.003	0.013	-0.009	-0.012
	(0.028)	(0.026)	(0.012)	(0.014)
2020.3-2020.8	-0.049	-0.031	-0.018	-0.011
	(0.034)	(0.031)	(0.016)	(0.016)
2020.9-2020.12	0.056	0.046	0.010	-0.024
	(0.037)	(0.034)	(0.019)	(0.020)
Panel B				
2019.11-2020.2	0.108**	0.113**	-0.005	-0.004
	(0.049)	(0.047)	(0.018)	(0.033)
Panel C				
2019.1-2019.2	0.063	0.108	-0.044	-0.024
	(0.111)	(0.100)	(0.048)	(0.074)
2019.3-2019.7	0.014	0.032	-0.018	-0.016
	(0.039)	(0.037)	(0.016)	(0.017)
2019.8-2019.12	0.010	0.034	-0.023	-0.015
	(0.042)	(0.041)	(0.018)	(0.026)

Table 12: Information Channel–Cross-section Evidence from VC Specialization

Note: This table reports regression results of partisanship effect on VC investment outcome, utilizing heterogeneity in VC specialization level. The regressions run at startup-VC-partner level. The dependent variables in column (1) to (4) are *Exit*, *MA*, *IPO* and *Fail*, respectively. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Socio.Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha.Control* includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Invested on/before 2020

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP x Bot.Inv. Spe.	0.105**	0.109**	-0.004	-0.001
	(0.047)	(0.047)	(0.023)	(0.039)
Bot.Inv. Spe.	-0.022*	-0.021	-0.001	0.006
	(0.013)	(0.014)	(0.008)	(0.010)
SP	0.011	0.002	0.009***	-0.013***
	(0.007)	(0.007)	(0.003)	(0.005)
VC Cha. Control	No	No	No	No
Socio. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	74331	74331	74331	74331
Adjusted R^2	0.173	0.138	0.100	0.066

Panel B: Invested on/before 2019 to 2016

	Coef. of SP x Bot.Inv. Spe.			
	(1) Exit	(2) MA	(3) IPO	(4) Fail
2019	0.101**	0.107**	-0.006	-0.005
	(0.048)	(0.048)	(0.023)	(0.039)
2018	0.101**	0.107**	-0.006	-0.005
	(0.048)	(0.048)	(0.023)	(0.039)
2017	0.101**	0.107**	-0.006	-0.005
	(0.048)	(0.048)	(0.023)	(0.039)
2016	0.101**	0.107**	-0.006	-0.005
	(0.048)	(0.048)	(0.023)	(0.039)

APPENDIX

A Detailed Construction of Political Leaning

A.1 Political Contribution

The FEC was established in 1974 following an amendment to the Federal Election Campaign Act (FECA). The FECA requires political committees to keep track of the name, occupation, address, and amount that any person contributes if the amount exceeded $10. Under current (2015-present) disclosure requirement, an individual contribution must be filed to the FEC by the receiving political committee if the contribution's election cycle-to-date amount is over $200 for contributions to candidate committees, or its calendar year-to-date amount is over $200 for contributions to political action committees (PACs) and party committees[10]. In actual records, smaller amounts are still reported by some committees.

I collect all contribution record from 1999 to 2022 from FEC website[11] under "Contributions by individuals" file. In total, there are about 159 million entries of individual contribution record. I retrieve the receiving committee ID, contributing amount and date and contributing individual's name, occupation and employer from the dataset. To ease computing effort, I first exclude observations where either "EMPLOYER" or "OCCUPATION" is "NONE", "RETIRED", "NOT EMPLOYED", "INFO REQUESTED", "NOT PROVIDED", "VARIOUS" or "HOUSEWIFE". After that, I use a regularization algorithm to extract contributing individuals' first name and last name. For entries that recorded employer as "SELF", "MYSELF", "SELF EMPLOYED" and "SELF-EMPLOYED", I replace their employer with their names. The reason I did not exclude them is that there are many investors in the VC/PE industry, especially angel investors, invest on individual basis. The recorded "investor" names for these individuals are their own names in PitchBook, which

[10]From 1989 to 2014, a contribution will be included if the reporting period amount is $200 or more. From 1975 to 1988, the amount is $500 and above.

[11]https://www.fec.gov/data/browse-data/?tab=bulk-data

would be used later to help the matching process between the political contribution record and the PitchBook data. For other entries, employer names are processed with another regularization algorithm, which mainly focuses on removing common suffixes and irregular terms like "LLC", "Ltd" and ",". I then remove all entries that either algorithm produced results with errors, for instance, missing first name or last name, names recorded as "[BLANK]" or names with irregular symbols.

After the data clearing process, there remains more than 99 million contribution records. There are about 2.4 million unique contributor names and around 5.9 million name-employer pairs. The average contribution per entry is about $373, the median value is $50, and the standard deviation is about $39,183. The distribution has a very long right tail, with a maximum value of 125 million. These large values typically result from individual contribution to "super PACs", which were made possible after two cases from 2010, *Citizens United v. FEC* and *Speechnow.org v. FEC*.

Next, I identify the party affiliation of the contributions. FEC keeps record on political committee information under "Committee master" file. The data contains record for each committee registered with the FEC, which includes federal political action committees and party committees, campaign committees for presidential, house and senate candidates, as well as groups or organizations who are spending money for or against candidates for federal office. Committee party affiliation records for committees that are already registered with certain party is recorded in this file.

For committees that are not registered with certain party, I check the committee spending record under "Contributions from committees to candidates" file. In this data, committees report their transaction to other committees and spending to specific candidates. Candidates party affiliation can be found under "Candidate master" file. Notably as previously mentioned, spending against candidates are also reported by these committee. Specifically, entries that transaction type are "24A-Independent expenditure opposing election of candidate" or "24N-Communication cost against candidate" record spending against certain candidate indicate spending against the reported candidate. I label these antagonistic spending as spending for the Democrat (Republican) if the original candidate party affiliation is Republican(Democrat). Transactions from the focal committee to another committee that is affiliated with certain party will be labeled as spending for that party. I then infer these committees' political leaning based on their total spending. If the committee spent more for Democrat (Republican) than Republican(Democrat), it is labeled as Democrat (Republican). Eventually, combining information from the committees that self-report party affiliation, out of 50,339 committees sourced from FEC data, 15,628 of them are labeled as Democrat and 17,278 are Republican. The rest are labeled as "OTHER".

Refunds types are recorded as "20Y", "21Y", "22Y", "41Y" and "40Y". I converted these amounts to negative values.

A.1.1 Merge Contributions to Pitchbook and Decide Party Leaning

The next step is to match political contribution record from FEC to partner names from PitchBook. First, I apply the same aforementioned regularization algorithms to extract partners' first name and last name and remove common suffixes from firm names. Second, I perform exact match based on the first and last names, combining the contribution records from FEC and partner records from PithBook. This process successfully matches 27,815 partner names from Pitchbook to the contribution record from FEC. Third, I apply three fuzzy match algorithms on the employer name from contribution data to the firm name from PitchBook and calculate the average. I keep two types of matches: matches with average matching score greater than or equal to 95 and matches with partial match score>=90 and token set/sort match score>=50. The later captures abbreviations in company names well. This procedure finally keeps 16,524 unique partners keeping about 17.2% partners of the Pitchbook data. On the startup founder/CEO side, I identified political party leaning of 10,249 founders/CEOs. Total contributions from 2000 to 2022 by these two groups of people are presented in A1.

I then generate the party Leaning of the identified partners based on their contribution from past ten years following Wang (2023). To be more specific, I first sum up the contribution as partner-year-party level. After that, I add up all contributions from each partner to one of the three parties for the past ten years. I then compare the total amount and find the party receiving most contribution from this partner. This party is then labeled as the party affiliation of this partner-year observation. For example, if a partner contributed to the Republican in 2008 once and never contributed again, the party leaning of this partner from 2009 to 2018 would be "REP" and missing for preceding and following years. This results in an unbalanced panel of partner-year-party data. The final results of partner party is a an unbalanced panel ranging from 2001 to 2023. It contains 216,041 VC-partner-year observations and 84,822 startup-CEO-year observations.

A.2 Voter Registration

First, I match voter registration with first names and last names of individuals from Pitchbook state by state. Second, since there is no individual address in Pitchbook, I use VC firm/startup headquarter address as a fallback. I exclude all matches where the "as the crow flies" distance between the voter registration home address' zip code centroid and the PitchBook office address' zip code centroid exceeding 100 miles, since it is very unlikely that anyone would live more than 100 miles from their offices. Third, I use middle name and suffixes from Pitchbook to drop the unmatched pairs. I also utilize age information acquired from Capital IQ database for a limited amount of individuals to further reduce wrong matches. Forth, I collect all the VC partners and startup founders/CEOs who are uniquely matched to voter registration and claim these successful matches. Fifth, I shrink the distance by 10 miles to 90 miles and collect the unique matches again. I repeat this process until 20 miles. There are 14,156 VC partners and 58,963 founders/CEOs matched through this process. At last, I check the remaining matched voter records for the same name, if more than 90% of entries are registered as the same party, I allocate that party to the corresponding name. This increase the number of matched VC partners by 440 and founders/CEOs by 1,785. The final panel contains 385,248 VC-partner-year observations and 1,511,736 startup-CEO-year observations, ranging from 2001 to 2024.

I then combine the two sources of individuals' political affiliation. In the VC panel, 43,891 observations have information from both resources, with approximately 51% showing agreement between them. For the startup sample, 44,487 observations appear in both sources, with agreement observed in roughly 59% of cases.

B Exit Status Variable Construction

The exit status of a startup is determined as follows. First, I collect "ownership status" provided by PitchBook, including "Privately Held", "M/A", "publicly Held", etc, and also "Out of Business". Second, I collect the "last financing deal type" of all startups. Third, I create four indicator variables (1) $Exit$, (2) MA, (3) IPO and (4) $Fail$, and set them as one if (1) current ownership status is either "M/A", "Publicly held" or "In IPO Registration"; (2) current ownership status is "M/A"; (3) current ownership status is "Publicly held" or "In IPO Registration"; (4) current ownership status is "Out of Business", and zero otherwise. Fourth, I adjust these indicators based on their "last financing deal type". For startups that neither exited or failed based on ownership status: if their last financing round type is "Merger/Acquisition", they are labeled as $MA = 1$; if their last financing round type is "PIPE", "IPO" or "Public Investment 2nd Offering", they are labeled as $IPO = 1$; if their last financing round type is "Bankruptcy: Liquidation" or "Out of Business", they are labeled as $Fail = 1$.

C Construction of VC Partner Death Sample and Estimation

The procedure on creating the sample of VC partner death events is described as follows. First, I identify all death events of VC partners from Capital IQ database by searching "passed away" in the biography of all VC partners. I also collect the date of the death event whenever the information is available. Second, I use name of these partners and the name of VC funds they worked for to match with information from Pitchbook. Third, I clear the matched data so that all death events have valid impact on the performance of the startups. For death events with no date information, I use the year of the last deal they made as the year of death. I then include only death events that take place before the startup exits or completes its most recent financing round. This process generates a sample with 598 startup-death event sample. 576 startups experienced only one death event and is viewed as clean treated group.

I then follow the empirical design in Ewens and Sosyura (2023) and create a stacked difference-in-difference (DID) experiment. I first exclude startups that experienced multiple VC partner death to avoid repeated treatment effect. After that, for each death event, I collect all startups that are active in the year before the death event happens as the control group for the sub-experiment. I then trim the sample period of the control group so that it has the same length of observations as the treated startup, both before and after the death event. Lastly, I stack the 576 sub-experiments together.

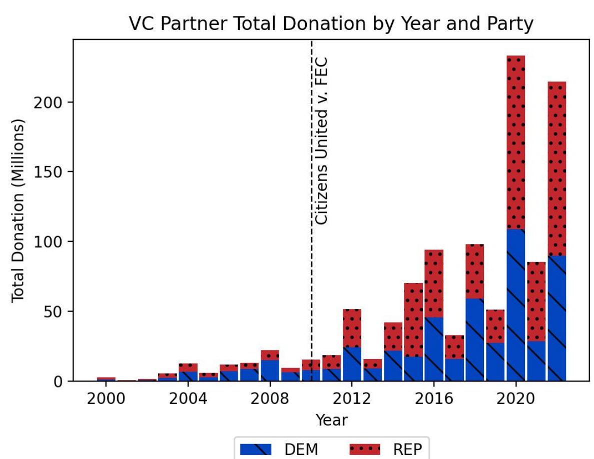
The regression model used is:

$$Y_{i,t} = \beta \times SP_i \times Post_t \times Death_i + \gamma \times Post_t \times Death_i + FEs + \epsilon_{i,t} \tag{3}$$

where $Y_{i,t}$ are outcome variables of interest of startup i in event year$t$; SP_i equals one if the VC partner passed away share same party affiliation with the startup founder/CEO at the time of the investment; $Post_t$ equals one if the event year is 0 or positive; $Death_i$ equals one if the startup ever experienced VC partner death event; FEs include sub-experiment-startup and sub-experiment-event-year fixed effects. There are several changes made to accommodate the stacked DID setting. Since the stacked DID is performed at startup-year level, it is very hard to include all VC side variables into the regression, as most startups receive investment from multiple VCs. Thus, only sub-experiment-startup and -event-year fixed effects are included, as in standard two-way fixed effect model. In addition, the variables used in previous analysis are at deal or startup level. To implement the stacked DID, I collapse the sample by aggregating the variables within each year. Under this design, the coefficient of interest β captures the difference of outcome between startups that experience same-party VC partner death and different-party death, controlling for general effect of partner death.

Figure A1: Political Contribution by VC partners and startup CEOs

Note: This figure displays total amount of political contribution made by VC partners and startup CEOs from 2000 to 2022.



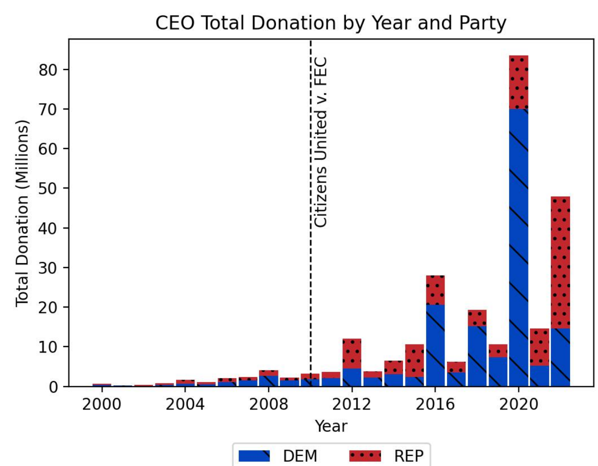


Figure A2: Partisanship Effect on VC Investment Decision–Extensive Margin by State

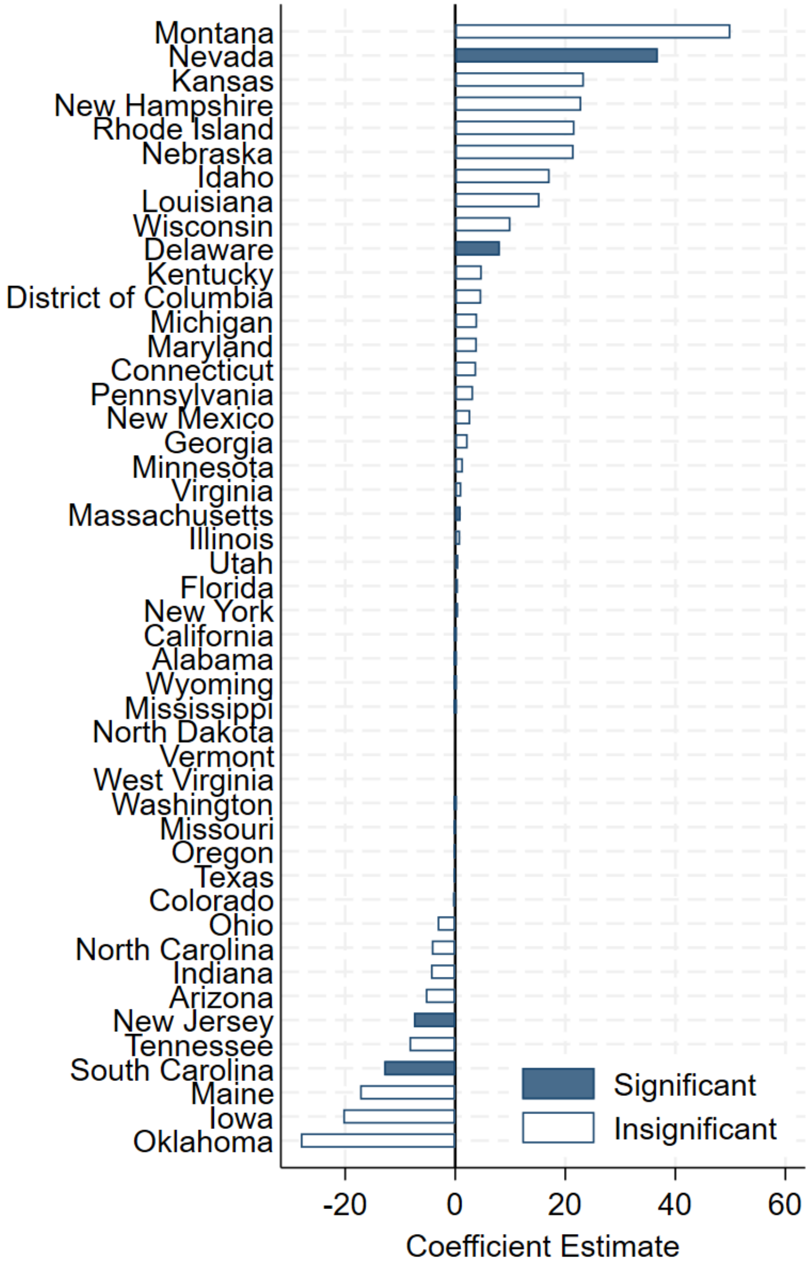


Figure A3: Democrats v.s. Republican

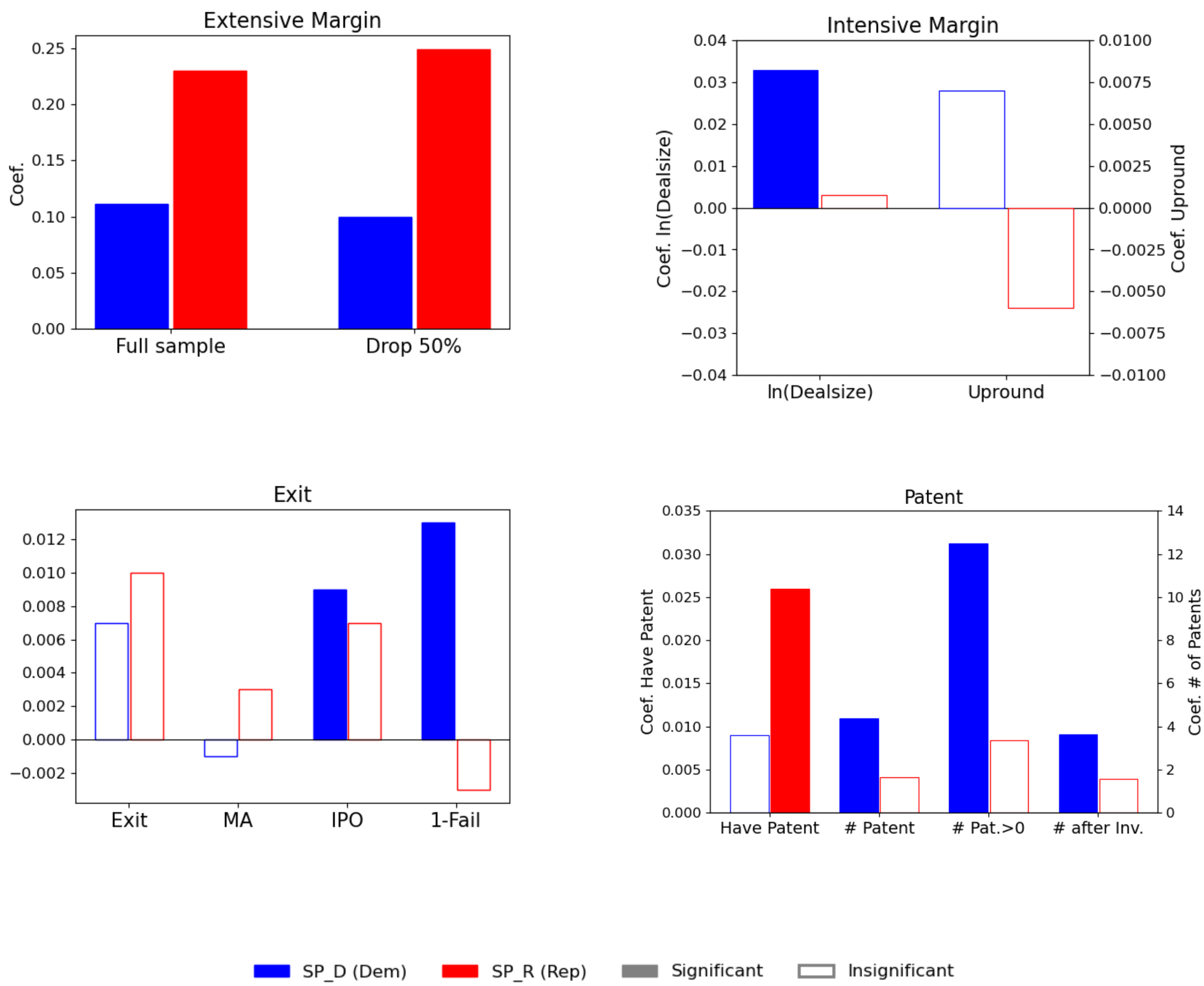


Table A1: Variable Definitions

Variable	Definition
SP	Equals one if both the VC partner and the startup founder/CEO in the deal are affiliated with Democrats or Republican party, and zero otherwise.
Invested	Equals 100 for realized deals, equals zero for counterfactual deals.
Same School	Equals one if both the VC partner and the startup founder/CEO in the deal attended the same university, and zero otherwise.
Same Ethnicity	Equals one if both the VC partner and the startup founder/CEO in the deal belongs to the same ethnicity group, and zero otherwise.
Same Gender	Equals one if both the VC partner and the startup founder/CEO in the deal belongs to the same gender, and zero otherwise.
Same Age Group	Equals one if age difference between the VC partner and the startup founder/CEO in the deal is smaller than or equal to 10 years, and zero otherwise.
Donor	Equals one if the VC partner have political contribution record within past ten years of the deal, and zero otherwise.
Election Year	Equals one if year is 2004, 2008, 2012, 2016, 2020, and 2024, and zero otherwise.

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Table A1 – continued from previous page

Variable	Definition
Post Trump	Equals one if year greater than 2016, and zero otherwise.
High Conflict	Equals one if the annual political conflict index is greater than median, and zero otherwise.
ln(Dealsize)	Natural logarithm of dollar amount of deal size (in millions), winsorized at 95% every year.
Upround	Equals one if valuation of the startup increases in the current financing round, and zero otherwise.
VC Experience	Number of deals the focal VC participated prior to the current deal.
VC Industry Specialization	Experience in current industry divided by total experience, zero if first deal in current industry.
VC Stage Specialization	Experience in current financing stage divided by total experience, zero if first deal in current financing stage.
VC Reputation	The sum of previous IPO deal dollar amount backed by the focal VC divided by previous IPO dollar amount backed by the whole VC industry.
VC Network	Number of other VCs the focus VC worked with in the past five years.
High Conf. M	Equals one if the monthly political conflict index is greater than median, and zero otherwise.
Exit	Equals one if either MA=1 or IPO=1, and zero otherwise.

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Table A1 – continued from previous page

Variable	Definition
MA	Equals one if (1) current ownership status is "M/A", or (2) current ownership status is "Privately held", but last financing round type is "Merger/Acquisition", and zero otherwise.
IPO	Equals one if (1) current ownership status is "Publicly held" or "In IPO Registration", or (2) current ownership status is "Privately held", but last financing round type is "PIPE", "IPO" or "Public Investment 2nd Offering", and zero otherwise.
Fail	Equals one if (1) current ownership status is "Out of Business", or (2) current ownership status is "Privately held", but last financing round type is "Bankruptcy: Liquidation" or "Out of Business", and zero otherwise.
Have Patent	Equals one if have patent at the end of sample period, and zero otherwise.
# Patent	Number of patents at the end of sample period.
# Pat.>0	Number of patents at the end of sample period if patent number is greater than zero.
# after Inv.	Number of patents produced after the deal and before the end of sample period.

Table A2: Extended Summary Statistics

VARIABLES	N	Mean	St.dev	p25	Median	p75
Extensive Margin						
Invested	21,905,219	0.764	8.706	0	0	0
SP	21,905,219	0.057	0.232	0	0	0
Same School	21,905,219	0.003	0.057	0	0	0
Same Ethnicity	21,905,219	0.080	0.271	0	0	0
Same Gender	21,905,219	0.116	0.320	0	0	0
Same Age Group	21,905,219	0.067	0.251	0	0	0
Donor	21,905,219	0.388	0.487	0	0	1
Election Year	21,905,219	0.195	0.396	0	0	0
Post Trump	21,905,219	0.670	0.470	0	1	1
High Conflict	21,905,219	0.715	0.452	0	1	1
Intensive Margin						
Sample: Deal-Startup-VC-Partner Level						
ln(Dealsize)	160,023	1.818	1.643	0.771	1.946	2.996
Upround	172,760	0.294	0.456	0	0	1
SP	172,760	0.085	0.278	0	0	0
Same School	172,760	0.019	0.137	0	0	0
Same Ethnicity	172,760	0.152	0.359	0	0	0
Same Gender	172,760	0.169	0.375	0	0	0
Same Age Group	172,760	0.104	0.306	0	0	0
VC Experience	172,760	126.2	303.2	2	22	101
VC Industry Specialization	172,760	0.379	0.340	0.028	0.327	0.663

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Table A2 – continued from previous page

VARIABLES	N	Mean	St.dev	p25	Median	p75
VC Stage Specialization	172,760	0.368	0.284	0.083	0.383	0.548
VC Reputation	172,760	0.018	0.063	0	0	0.001
VC Network	172,760	0.008	0.013	0.001	0.003	0.010
Donor	172,760	0.314	0.464	0	0	1
Election Year	172,760	0.220	0.414	0	0	0
Post Trump	172,760	0.548	0.498	0	1	1
High Conflict	172,760	0.719	0.450	0	1	1
High Conf. M	172,760	0.718	0.450	0	1	1
Conflict Index	172,760	0.413	0.928	-0.063	0.395	0.895
Sample: Startup-VC-Partner Level						
Exit	92,333	0.359	0.480	0	0	1
MA	92,333	0.314	0.464	0	0	1
IPO	92,333	0.044	0.205	0	0	0
Fail	92,333	0.126	0.332	0	0	0
Have Patent	92,333	0.352	0.478	0	0	1
# Patent	92,333	9.768	71.43	0	0	3
# Pat.>0	32,524	27.73	118.3	2	6	18
# after Inv.	92,333	7.631	66.45	0	0	1
SP	92,333	0.082	0.274	0	0	0
Same Age Group	92,333	0.097	0.296	0	0	0
Same School	92,333	0.017	0.130	0	0	0
Same Ethnicity	92,333	0.144	0.351	0	0	0
Same Gender	92,333	0.158	0.365	0	0	0

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Table A2 – continued from previous page

VARIABLES	N	Mean	St.dev	p25	Median	p75
VC Experience	92,333	85.84	225	1	11	59
VC Industry Specialization	92,333	0.335	0.339	0	0.227	0.600
VC Stage Specialization	92,333	0.349	0.305	0	0.355	0.559
VC Reputation	92,333	0.015	0.061	0	0	0
VC Network	92,333	0.007	0.012	0.000	0.002	0.009

Table A3: Vertical Group Classification

Vertical Group	Included Verticals
Green Economy	CleanTech, Climate Tech, Impact Investing
Oil & Gas	Oil & Gas
FemTech	FemTech
Cannabis	Cannabis
Education	EdTech
Food & Ag	AgTech, FoodTech
BioTech	Life Sciences, Nanotechnology, Oncology
Healthcare	Digital Health, HealthTech, Wearables & Quantified Self
Trad. Manufacturing	Construction Technology, Industrials, Infrastructure, Manufacturing
Adv. Manufacturing	Advanced Manufacturing, Internet of Things, Robotics and Drones, Space Technology, Supply Chain Tech
FinTech	B2B Payments, Cryptocurrency/Blockchain, FinTech, InsurTech, Mortgage Tech
Consumer Retail	Beauty, E-Commerce, LOHAS & Wellness, Mobile Commerce, Pet Technology
Mobility & Gig	Autonomous cars, Car-Sharing, Micro-Mobility, Mobility Tech, Ridesharing
IT & Digital Services	3D Printing, AdTech, Artificial Intelligence & Machine Learning, AudioTech, Augmented Reality, Big Data, CloudTech & DevOps, Cybersecurity, Ephemeral Content, Esports, Gaming, HR Tech, Legal Tech, Marketing Tech, Mobile, Real Estate Technology, Restaurant Technology, SaaS, TMT, Virtual Reality

Table A4: Robustness–Extensive Margin

Note: This table reports robustness tests results of partisanship effect on VC investment on the extensive margin. The sample is constructed using new industry definition described in Section 4. The dependent variable *Invested* equals 100 if VC partner invests in the startup and zero otherwise. *Market FE* is industry-by-year-by-state-by-financing-stage fixed effect. *F.Fin. Amount* is natural log of startups' first financing deal amount. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: New Sample

Sample:	Whole			Non-top Drop 50%		
	(1) Invested	(2) Invested	(3) Invested	(4) Invested	(5) Invested	(6) Invested
SP	0.127***	0.111***	0.114***	0.137***	0.118***	0.120***
	(0.034)	(0.031)	(0.033)	(0.037)	(0.035)	(0.037)
F.Fin. Amount	Yes	Yes	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	No	No	Yes	No	No
State FE	Yes	No	No	Yes	No	No
Stage FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Market FE	No	Yes	No	No	Yes	No
VC $\times$ Market FE	No	No	Yes	No	No	Yes
Observations	5456839	5441405	5400144	4684905	4669281	4626266
Adjusted R^2	0.329	0.341	0.153	0.341	0.351	0.155

Panel B: Drop Small Markets

Sample:	Market Size>=350			Market Size>=1917		
	(1) Invested	(2) Invested	(3) Invested	(4) Invested	(5) Invested	(6) Invested
SP	0.088***	0.076***	0.084***	0.069***	0.067***	0.073***
	(0.028)	(0.028)	(0.029)	(0.025)	(0.025)	(0.026)
F.Fin. Amount	Yes	Yes	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	No	No	Yes	No	No
State FE	Yes	No	No	Yes	No	No
Stage FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Market FE	No	Yes	No	No	Yes	No
VC x Market FE	No	No	Yes	No	No	Yes
Observations	4432142	4432142	4431722	4184705	4184705	4184671
Adjusted R^2	0.024	0.027	0.030	0.009	0.010	0.009

Table A5: Robustness–Intensive Margin and Exit Outcome

Note: This table reports regression results of partisanship effect on VC investment on the intensive margin and exit outcome with new industry definition. *Market FE* is industry-by-year-by-state-by-financing-stage fixed effect. *F.Fin. Amount* is natural log of startups' first financing deal amount. *Socio. Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha. Control* includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Intensive Margin

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) ln(Dealsize)	(4) Upround	(5) Upround	(6) Upround
SP	0.024**	0.025**	0.024**	0.008*	0.004	0.010**
	(0.011)	(0.011)	(0.010)	(0.005)	(0.005)	(0.005)
F.Fin. Amount	Yes	Yes	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
State FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Stage FE	Yes	No	No	Yes	No	No
Year*State FE	No	Yes	No	No	Yes	No
Year*Stage FE	No	Yes	No	No	Yes	No
Year*Industry FE	No	Yes	No	No	Yes	No
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	No	No	Yes	No	No	Yes
Observations	137939	135200	122189	137939	135200	122189
Adjusted R^2	0.710	0.736	0.786	0.237	0.316	0.482

Panel B: Exit Outcome

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP	0.015**	0.005	0.011***	-0.009*
	(0.007)	(0.007)	(0.004)	(0.005)
F.Fin. Amount	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	62844	62844	62844	62844
Adjusted R^2	0.214	0.181	0.202	0.110

Table A6: Effort Channel–Evidence From VC Partner Death in Stacked DID

Note: This table reports regression results using sample constructed in Appendix C. The variables definitions are in Appendix A1. Standard errors are clustered at VC firm level and reported in parentheses. $Sub-Startup\,FE$ controls for sub-experiment-by-startup fixed effect. $Sub-Time\,FE$ controls for sub-experiment-by-event-time fixed effect. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: ± 3 Years

	(1) Have Fin.	(2) Fin. Amount	(3) N.Inv.	(4) Have N.Inv.	(5) Have Patent	(6) # Patent	(7) Time since Last Fin.
SP x Post x Death	0.023	3.684	-0.595	-0.005	0.034	0.021	2.369
	(0.045)	(5.495)	(0.808)	(0.042)	(0.023)	(0.330)	(78.561)
Post x Death	-0.097***	-2.743*	-0.637***	-0.095***	-0.029***	-0.218*	-155.569***
	(0.017)	(1.559)	(0.205)	(0.016)	(0.010)	(0.130)	(28.372)
Sub-Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21094689	21094689	21094689	21094689	21094689	21094689	20780054
Adjusted R^2	0.200	0.125	0.157	0.189	0.160	0.341	0.889

Panel B: ± 5 Years

	(1) Have Fin.	(2) Fin. Amount	(3) N.Inv.	(4) Have N.Inv.	(5) Have Patent	(6) # Patent	(7) Time since Last Fin.
SP x Post x Death	0.012	4.044	-0.408	-0.008	0.028	0.266	-22.431
	(0.044)	(4.940)	(0.667)	(0.041)	(0.024)	(0.312)	(110.070)
Post x Death	-0.125***	-2.070	-0.762***	-0.120***	-0.034***	-0.314**	-191.173***
	(0.015)	(1.606)	(0.171)	(0.014)	(0.010)	(0.159)	(36.747)
Sub-Startup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25222521	25222521	25222521	25222521	25222521	25222521	24769244
Adjusted R^2	0.202	0.119	0.158	0.192	0.158	0.337	0.859

Table A7: Effort Channel–VC Partner Death and Startup Exit Outcome

Note: This table reports tests results of partisanship effect on VC investment outcome interacting with partner death. The regressions run at startup-VC-partner level. The dependent variables in column (1) to (4) are *Exit*, *MA*, *IPO* and *Fail*, respectively. The independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Exp. Death* equals one if the startup ever experienced partner death. *Socio. Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha. Control* includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Invested on/before 2020

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP x Exp. Death	-0.056	-0.024	-0.032	-0.052
	(0.071)	(0.070)	(0.042)	(0.061)
Exp. Death	-0.144***	-0.185***	0.041*	-0.116***
	(0.037)	(0.038)	(0.023)	(0.021)
SP	0.013**	0.004	0.009***	-0.013***
	(0.007)	(0.007)	(0.003)	(0.005)
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	74331	74331	74331	74331
Adjusted R^2	0.174	0.141	0.102	0.068

Panel B: Invested on/before 2019 to 2016

	Coef. of SP x Exp. Death			
	(1) Exit	(2) MA	(3) IPO	(4) Fail
2019	-0.066	-0.044	-0.021	-0.035
	(0.077)	(0.073)	(0.045)	(0.063)
2018	-0.103	-0.088	-0.015	-0.047
	(0.105)	(0.095)	(0.057)	(0.080)
2017	-0.088	-0.063	-0.025	-0.031
	(0.106)	(0.096)	(0.060)	(0.082)
2016	-0.130	-0.120	-0.010	-0.065
	(0.101)	(0.086)	(0.074)	(0.093)

Table A8: Robustness–Add DP

Note: This table reports robustness tests results of partisanship effect on VC investment. The key independent variable SP is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party (D,D or R,R). DP is an indicator variable that equals 1 if the VC partner and the startup founder/CEO in the deal are affiliated with different political parties (D,R or R,D). $Market\,FE$ is industry-by-year-by-state-by-financing-stage fixed effect. $F.Fin.\,Amount$ is natural log of startups' first financing deal amount. $Socio.\,Control$ includes same ethnicity, gender, alma mater, and age group. $VC\,Cha.\,Control$ includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Extensive Margin

	(1) invested	(2) invested	(3) invested	(4) invested	(5) invested	(6) invested
SP	0.114***	0.105***	0.106***	0.121***	0.110***	0.109***
	(0.034)	(0.031)	(0.033)	(0.038)	(0.035)	(0.037)
DP	-0.103**	-0.044	-0.063	-0.128***	-0.063	-0.080*
	(0.042)	(0.041)	(0.042)	(0.048)	(0.046)	(0.047)
F.Fin. Amount	Yes	Yes	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	No	No	Yes	No	No
State FE	Yes	No	No	Yes	No	No
Stage FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Market FE	No	Yes	No	No	Yes	No
VC $\times$ Market FE	No	No	Yes	No	No	Yes
Observations	5456839	5441405	5400144	4684905	4669281	4626266
Adjusted R^2	0.329	0.341	0.153	0.341	0.351	0.155

Panel B: Intensive Margin

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) ln(Dealsize)	(4) ln(Dealsize)	(5) Upround	(6) Upround
SP	0.029**	0.030***	0.028**	0.035***	0.008*	0.011**
	(0.011)	(0.011)	(0.013)	(0.013)	(0.005)	(0.005)
DP	0.028**	0.029**	0.002	0.016	-0.000	0.008
	(0.012)	(0.012)	(0.015)	(0.015)	(0.005)	(0.005)
F.Fin. Amount	Yes	Yes	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
State FE	Yes	No	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No	Yes	No
Stage FE	Yes	No	Yes	No	Yes	No
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	No	Yes	No	Yes	No	Yes
Observations	137939	122189	75902	62331	137939	122189
Adjusted R^2	0.710	0.786	0.601	0.695	0.237	0.482

Panel C: Exit Outcome

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP	0.014*	0.002	0.012***	-0.010*
	(0.008)	(0.008)	(0.004)	(0.005)
DP	-0.009	-0.014*	0.005	-0.005
	(0.009)	(0.009)	(0.004)	(0.006)
F.Fin. Amount	Yes	Yes	Yes	Yes
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	62844	62844	62844	62844
Adjusted R^2	0.214	0.181	0.202	0.110

Table A9: Robustness–Information Channel–Cross-section Evidence from VC Specialization

Note: This table reports robustness tests results of partisanship effect on VC investment outcome, utilizing heterogeneity in VC specialization level. The regressions run at startup-VC-partner level. The dependent variables in column (1) to (4) are *Exit*, *MA*, *IPO* and *Fail*, respectively. The key independent variable *SP* is an indicator variable that equals 1 if both the VC partner and the startup founder/CEO in the deal are affiliated with the same political party. *Socio.Control* includes same ethnicity, gender, alma mater, and age group. *VC Cha.Control* includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Invested on/before 2020

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP x Bot.Inv.	0.075	0.076	-0.001	0.030
	(0.063)	(0.063)	(0.025)	(0.052)
Bot.Inv.	-0.047**	-0.030	-0.016*	0.014
	(0.020)	(0.020)	(0.010)	(0.015)
SP	0.012*	0.003	0.009***	-0.013***
	(0.007)	(0.007)	(0.003)	(0.005)
VC Cha. Control	No	No	No	No
Socio. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	74331	74331	74331	74331
Adjusted R^2	0.173	0.138	0.100	0.066

Panel B: Invested on/before 2019 to 2016

	Coef. of SP x Bot.Inv.			
	(1) Exit	(2) MA	(3) IPO	(4) Fail
2019	0.074	0.078	-0.004	0.025
	(0.065)	(0.065)	(0.026)	(0.052)
2018	0.078	0.081	-0.003	0.025
	(0.065)	(0.066)	(0.027)	(0.054)
2017	0.066	0.073	-0.006	0.028
	(0.066)	(0.067)	(0.027)	(0.055)
2016	0.062	0.070	-0.008	0.029
	(0.067)	(0.068)	(0.028)	(0.057)

Table A10: Republicans vs Democrats

Note: This table reports regression results of and partisanship effect on VC investment utilizing heterogeneity between Democrats and Republicans. The key independent variable SP is split into SP_D and SP_R, representing investment made from Democrats to Democrats and Republicans to Republicans, respectively. In Panel A, The sample is constructed in Section 2.4.2. The dependent variable $Invested$ equals 100 if VC partner invests in the startup and zero otherwise. $Market\,FE$ is industry-by-year-by-state-by-financing-stage fixed effect. In Panel B, the regressions run at deal-startup-VC-partner level. The dependent variable $ln(Dealsize)$ is natural log of dollar amount (in millions) invested in each deal. The dependent variable $Upround$ equals one if in the current round of financing, the startup's valuation increases, and zero other wise. In Panel C and D, the regressions run at startup-VC-partner level. The dependent variables definitions are in Appendix A1. $Socio.Control$ includes same ethnicity, gender, alma mater, and age group. $VC\,Cha.Control$ includes VC experience, industry/stage specialization, network and reputation. Standard errors are clustered at VC firm level and reported in parentheses. $*$, $**$, and $***$ corresponds to statistically significant at 10%, 5% and 1% respectively.

Panel A: Extensive Margin

	(1) Invested	(2) Invested	(3) Invested
SP_D	0.258***	0.253***	0.267***
	(0.015)	(0.015)	(0.015)
SP_R	0.556***	0.545***	0.573***
	(0.055)	(0.052)	(0.054)
P(SP_D=SP_R)	0.000	0.000	0.000
F-stat	27.36	29.34	30.46
Socio. Control	Yes	Yes	Yes
VC FE	Yes	Yes	No
Year FE	Yes	No	No
State FE	Yes	No	No
Stage FE	Yes	No	No
Industry FE	Yes	No	No
Market FE	No	Yes	No
VC x Market FE	No	No	Yes
Observations	19879990	19878367	19870513
Adjusted R^2	0.052	0.069	0.061

Panel B: Intensive Margin

	(1) ln(Dealsize)	(2) ln(Dealsize)	(3) Upround	(4) Upround
SP_D	0.029**	0.026**	0.016***	0.015***
	(0.013)	(0.013)	(0.005)	(0.005)
SP_R	0.022	0.011	-0.009	-0.012
	(0.023)	(0.022)	(0.010)	(0.010)
P(SP_D=SP_R)	0.763	0.531	0.034	0.019
F-stat	0.09	0.39	4.51	5.53
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Stage FE	Yes	No	Yes	No
Year*State FE	No	Yes	No	Yes
Year*Stage FE	No	Yes	No	Yes
Year*Industry FE	No	Yes	No	Yes
VC FE	Yes	Yes	Yes	Yes
Observations	138234	138076	138234	138076
Adjusted R^2	0.680	0.691	0.215	0.235

Panel C: Outcome–Exit

	(1) Exit	(2) MA	(3) IPO	(4) Fail
SP_D	0.010	-0.000	0.010***	-0.016***
	(0.008)	(0.008)	(0.004)	(0.005)
SP_R	0.023*	0.017	0.006	-0.003
	(0.013)	(0.013)	(0.006)	(0.010)
P(SP_D=SP_R)	0.341	0.219	0.551	0.219
F-stat	0.91	1.51	0.36	1.51
Socio. Control	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes
Observations	74331	74331	74331	74331
Adjusted R^2	0.174	0.141	0.102	0.068

Panel D: Outcome–Patent

	OLS (1) Have Patent	OLS (2) # Patent	Poisson (3) # Patent	OLS (4) # Pat.>0	OLS (5) # after Inv.	Poisson (6) # after Inv.
SP_D	-0.006	6.370**	0.289**	14.595*	6.290**	0.311**
	(0.010)	(3.059)	(0.134)	(8.108)	(3.005)	(0.145)
SP_R	0.037**	1.115	0.015	3.406	0.543	0.000
	(0.015)	(3.162)	(0.165)	(6.695)	(3.083)	(0.194)
P(SP_D=SP_R)	0.016	0.252	0.209	0.299	0.201	0.206
F-stat	5.83	1.31	1.58	1.08	1.64	1.60
Socio. Control	Yes	Yes	Yes	Yes	Yes	Yes
VC Cha. Control	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
First fin.year FE	Yes	Yes	Yes	Yes	Yes	Yes
VC FE	Yes	Yes	Yes	Yes	Yes	Yes
Founding year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43121	43121	38719	15333	43121	37846
Adjusted R^2	0.249	0.039		0.074	0.031	
Pseudo R^2			0.543			0.545