Does Politics Matter in Entrepreneurship?
Political Polarization, Nonpartisans, and Entrepreneurial Team Performance

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Abstract

Social homophily has been shown to be a feature of entrepreneurial team formation, but its performance implications remain unclear. This paper examines the recent rise of a new source of social homophily—political homophily—and its relationship to the performance of entrepreneurial founding teams. We construct a dataset linking over 13,000 founders of 3,700 California-based startups to their voter registration records from 2007 to 2019. We first document substantial and rising levels of political homophily. We then analyze how team political composition relates to fundraising outcomes, focusing on the likelihood and speed of raising subsequent funding. We find that teams composed entirely of similar political partisans underperform relative to politically mixed teams. The highest-performing teams include substantial political heterogeneity, encompassing Democrats, Republicans, and Nonpartisan founders. These results remain qualitatively consistent in two-stage estimations using time-varying measures of negative and positive political advertising in each of California's 14 media markets as instrumental variables. These findings suggest that Nonpartisan founders may serve a cross-cutting or boundary-spanning role, helping teams navigate the coordination challenges of ideological diversity.

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1. Introduction

Homophily is a pervasive feature of formal and informal organization. Numerous studies have demonstrated that individuals prefer to associate with others who are similar across a range of characteristics, including race, gender, education or work experience (McPherson et al. 2001; Ruef et al. 2003; Kleinbaum et al. 2013; Neal et al. 2022). Strikingly, evidence indicates that the propensity for homophily along these dimensions has remained stable for nearly 20 years (Smith et al. 2014). Research has subsequently documented homophily based on values and preferences, indicating that the taste for similar partners extends to shared attitudes or beliefs (Phillips et al. 2013; Trapido 2013; DellaPosta et al. 2015).

Despite consistent evidence of homophily in team formation, theoretical expectations and empirical findings regarding its performance implications remain mixed. On one hand, diverse teams are likely to enjoy superior problem-solving due to greater heterogeneity of knowledge, skills, information flow, or perspectives. On the other, diverse teams often face communication challenges, lower intrinsic trust, and differing conceptual paradigms, potentially inhibiting problem-solving and effective execution. The empirical research reflects this tension, with some studies finding a positive association between homophily and performance while others report a negative association or null result (see Ertug et al. 2022 for a survey of this literature).

Recent research has focused on the potential moderating role of "cross-cutting" individuals, members of a diverse team or organization whose characteristics overlap partially with multiple subgroups within the team. The presumption is that such cross-cutting individuals – a type of boundary spanner – can enhance the communication and trust among team members with disparate characteristics. To date, however, empirical research in this area has emphasized computational simulation (Mas et al. 2013) or inference from national surveys on friendship ties (Horowitz and Gomez 2018) to generate results.

In this paper, we examine such cross-cutting individuals by analyzing political affiliations within entrepreneurial founding teams. This setting offers several advantages. First, team formation is central to entrepreneurial ventures, and prior research has documented widespread homophily across multiple founder technical and social characteristics (Beckman et al. 2007; Esen et al. 2023), most recently political partisanship (de Figueiredo et al. 2023; Kovacs & Sels 2024). Second, although many studies link team capability to firm outcomes, the relationship between founding-team diversity and performance remains empirically ambiguous (Ruef et al. 2003; Healey et al., 2021; Boss et al. 2021).

Third, political partisanship offers a structured spectrum in which Nonpartisan individuals—registered voters who are unaffiliated with a party—plausibly occupy an intermediate position between Republicans and Democrats (Pew Research Center 2024), allowing us to group founders ordinally on the political spectrum. This, in turn, offers leverage to explore the possibility that these individuals serve as cross-cutters or boundary spanners, bridging ideological distance within politically diverse teams.

Empirically, we study this by analyzing founding-team formation and performance of technology-based entrepreneurial startups in California during the 2007-2019 period. Our empirical approach leverages a novel dataset that combines detailed founder information with high-quality voter registration data to analyze the relationship between team political composition and early venture performance. We begin with a comprehensive dataset on all California-based VC-funded startups that raised Series A funding between 2007 and 2019, drawn from Crunchbase. Each record encompasses a large number of fields; the most relevant for our analysis are the founding team members' names and locations, the startup's technology area, the date on which the startup raised its Series A funding round, whether the startup subsequently raised a Series B round, and the date of the Series B round if applicable. We then match these founders to

voter registration records from California. The voter registration records contain information on each person's address, demographic information, and, most importantly, political affiliation and aspects of voting history. With this information, we can determine the political composition of entrepreneurial teams. We identify the political composition of over 3,700 cofounding teams (involving over 13,000 founders) at the time that they receive Series A funding. We then examine the performance of these teams, measured as their success and speed at attracting Series B funding.

We first document that startup cofounders in our sample exhibit political homophily, much as they do racial or gender homophily, consistent with prior studies (de Figueiredo et al. 2023; Kovacs & Sels 2024). We next document an increase in political homophily during our sample period. This is consistent with scholarly understanding of increased political polarization in the United States over this time period (Mason 2018; Iyengar et al. 2019). Thus, while other forms of homophily have remained relatively stable over this time period, political homophily has increased, such that by the end of our sample period the level of political homophily is greater than the levels of gender homophily and racial homophily in terms of "unexpectedly" high rates of homogeneous teams (defined below). Third, in our core analysis, we find a consistent pattern of performance as a function of team homophily. Homogeneous teams are least likely to obtain Series B funding, but statistically indistinguishable from mixed teams that are composed of Democrats and Republicans. Mixed teams that include Nonpartisans outperform homogenous teams, with teams that include at least one Democrat, Republican, and Nonpartisan performing best of all. This is consistent with the idea that Nonpartisans provide a buffering or cross-cutting function that enables a team to enjoy the benefits of diversity while mitigating diversity's costs.

The above performance analysis is correlational, not causal. Although it is difficult to identify a natural experiment, we gain some insight into causality by using an instrumental variables (IV) approach. We introduce Democratic and Republican negative and positive political television ads in each of California's 14 media markets in each election cycle as instrumental variables. The volume of positive and negative ads varies by media market and over time, and is driven by electoral factors, such as the closeness of elections and the funding position of political candidates. Negative (and to some extent, positive) political ads have been shown to impact affective polarization and thus should influence entrepreneurial team formation in a given county. We propose that such ads are plausibly uncorrelated with the likelihood that a Series A team secures Series B funding and thus provide reasonable instrumental variables to begin to tease out causal effects of team formation partisanship on team performance.

The results of the IV analysis support the earlier findings. Politically homogeneous teams are 5% to 10% less likely to secure Series B funding relative to other teams, depending on the statistical specification. Moreover, mixed teams that include Nonpartisans generally perform best. We interpret these results cautiously, as econometric tests indicate that the instrumental variables do not satisfy the most stringent tests of strength. Nevertheless, in conjunction with the previous analyses, these results extend our understanding of how political polarization affects entrepreneurship. Ideally, future research will shine greater light on causal relationships.

Ultimately, we extend the prior literature in three ways. First, contributing to work on values-based homophily, we explore the role of political partisanship as a factor that contours formation of founding teams in the United States, extending recent work by examining the effect of political partisanship over time. Second, we identify the performance implications of political partisanship—a cardinal measure—to examine the performance effects of team homogeneity and heterogeneity. We show performance results consistent with expectations regarding cross-cutting

or boundary-spanning individuals within heterogeneous teams. Third, we introduce a new instrumental variable that may be of use to researchers attempting to understand the relationship between affective polarization and business performance.

2. Homophily and Performance

The tendency of individuals to form connections with similar others is so pervasive that management and sociology scholars have termed it an "organizing principle" (McPherson et al. 2001) and a "law of social relationships "(Reagans 2005). This phenomenon has been documented in informal social ties (Smith et al. 2014; Kossinets & Watts 2009), school-project teams (Boss et al. 2021; Calder-Wang et al. 2024), public-sector organizations (Gerber et al. 2013), and at a range of levels in large firms (Damaraju & Makhija 2018; Frake et al., 2023). Founding teams of startups have been shown to exhibit homophily along gender (Ruef et al. 2003), race/ethnicity (Steffens 2012), educational background (Beckman & Burton 2008) and, most recently, political partisanship lines (de Figueiredo et al. 2023; Kovacs & Sels 2024). Indeed, recent qualitative studies have demonstrated how founders may construct narratives to play up homophilous connections when seeking cofounders or other stakeholders who possess valuable resources (Philips et al. 2013; Busch & Mudida 2024; Gray et al. 2024).

The politics literature highlights "affective polarization" as a relevant factor that likely increases team homophily (Iyengar et al. 2019). Political parties create in-groups and out-groups. In the United States these groups are aligned with two major political parties, Democrats and Republicans. Evidence suggests that, through the 1980s, individuals joined political parties based primarily on policy differences but were happy to mix socially and in work settings with out-group partisans. Since that time, a host of evidence suggests that relations of individuals between these groups have become more disharmonious (Iyengar et al. 2012, Pew Research Center 2017)

and that this disharmony influences behavior in non-political, economic settings. This expansion of political identity and in-group/out-group bias is known as "affective polarization." Field experiments have shown that resumes sent to heavily Democratic (Republican) geographic areas were less likely to get interviews if they indicated a Republican (Democratic) affiliation than a Democratic (Republican) affiliation, thus providing evidence that labor markets are affected by political orientation (Gift and Gift 2015). Relatedly, McConnell et al. (2018) explore how employees behaved with respect to partisan employers by hiring workers to complete an online editing task. While they find no significant difference in counter-partisan wages compared to a control group, they do find that workers are willing to accept lower wages when working for a co-partisan employer, compared to a control group.

Given the widespread expectation that team composition should impact team performance, this tendency toward homophily has sparked substantial theoretical debate about likely performance consequences. Yet the theory is ambiguous, highlighting a fundamental tradeoff for homophilous teams. One line of reasoning, drawing on shared-identity theory, proposes that homophily will enhance performance by facilitating smoother coordination, better communication, and higher levels of trust among team members (Ertug et al. 2022). These features should also reduce turnover within teams, further contributing to better performance.

In contrast, an alternative line of reasoning, drawing largely on knowledge- or information-based theories, proposes that homophilous teams are likely to possess a narrower range of knowledge or information, and to process than knowledge through a narrower set of perspectives, than more diverse teams (Williams & O'Reilly 1998). This may be driven by correlation between the homophilous characteristics and knowledge/perspective (e.g., individuals with similar training or similar personal experiences will process information similarly), or by correlation between homophilous characteristics and structural position (e.g., homophilous

individuals may occupy similar network positions and thus not have access to widely varying sources of knowledge). Consequently, homophilous teams will underperform diverse teams.

Not surprisingly, the empirical literature on the homophily-performance relationship is decidedly mixed. Reagans & McEvily (2003) find evidence that homophilous teams experience smoother knowledge-sharing among members of R&D teams in a technology-driven firm, while Melamed et al (2020) find evidence that such teams enjoy greater cooperation. Lu et al. (2023) examine durability of tennis doubles partnerships, finding evidence that homophilous teams exhibit greater stability in the face of adverse events. At the same time, studies have uncovered evidence that such teams are marred by more limited information processing: Reagans et al. (2004) find that the smoother knowledge-sharing within homophilous teams is offset by a narrower range of available external knowledge, while Gompers et al. (2016) document that homophily among venture capitalists is associated with lower investment performance. Given these patterns, the evidence on homophily's relationship with aggregate performance has been mixed, with studies finding statistically positive, negative, and insignificant relationships (Ertug et al. 2022).

Specifically for entrepreneurial ventures, Ruef (2010) relies on census data to demonstrate that homophilous teams in the U.S. are more likely to incorporate and have greater survival rates, while Hellerstadt et al. (2007) show less turnover among members of homophilous founding teams in Swedish startups. Conversely, Henderson et al. (2017) finds that homophilous teams have lower valuations, and Steffens et al. (2012) demonstrates that such teams tend to have worse long-term outcomes. Two laboratory experiments involving university students enrolled in entrepreneurship courses have similarly found mixed results. Calder-Wang et al. (2024) conduct an experiment in which they manipulate the formation of project teams that then develop business plans. The plans are evaluated by outside observers, thus providing a performance

measure. In some cases teams self-organize, while in others teams are exogenously assigned. Calder-Wang et al. find no significant relationship between team homophily and business-plan quality for the self-organized teams (and a positive relationship between homophily and quality for assigned teams). Boss et al (2021) conduct an experiment with similar manipulations and business-plan deliverable output, and also with manipulations whereby the business plan idea is self-chosen or is exogenously assigned. The main focus of their study is on the joint effect of autonomy of topic and team composition. However, a secondary finding in their study is that self-organized homophilous teams tend to perform less well than other self-organized teams when developing their own topic, with some evidence that such teams converge too rapidly on lower-quality ideas due to overconfidence that grows among the team members (Boss et al. 2021). With specific regard to political partisanship, Kovacs & Sels (2024), excluding Nonpartisans from the sample, find that politically homogeneous founding teams outperform mixed Democrat-Republican teams in terms of startup survival.

2.1 Managing the cost/benefit tradeoff of homophilous teams

Is there a way to get the best of both worlds – that is, to get at least some of the benefits normally associated with homophily (or, alternatively, diversity) while ameliorating some of the downsides? Recent research has explored moderating factors that may facilitate this. One approach conceives of a diverse team as being composed of homophilous subgroups and focuses on the extent to which certain individuals on that team might serve as a form of boundary-spanner across the different subgroups. For example, as Mas et al (2013) describe, a team composed of white male engineers and nonwhite female lawyers is likely to experience a deep "faultline" given that all three socio-demographic dimensions cleave the group into the same subgroups; in contrast, a similar team that includes some female engineers or white lawyers will

experience a shallower faultline due to the individuals who connect to different subgroups depending on the dimension. In principle, the latter team is expected to enjoy benefits of diversity and (some of the) benefits of homophily.

Most studies in this sphere rely on assessment of multiple dimensions of potential similarity and define the depth of a faultline by the extent to which subgroup division is replicated across these multiple dimensions. This is driven largely by the absence of a "distance" measure for most of the conventional dimensions in the literature. For most ascribed and many achieved characteristics, one can impose categories on team members (which is already a somewhat arbitrary decision), but one cannot arrange these categories ordinally on, say, a continuum, to infer that (for example) East Asian people are "closer" to Hispanic people than to Eastern European people. Hence, the most tractable way to measure the proximity of people in different subgroups is to identify criss-crossers across multiple characteristics.[1]

In contrast, some values-based characteristics can be placed on a continuum. For example, in political ideology, adherents of different parties can often be conceived to lie on a line. In the United States, the liberal-conservative ideological continuum maps closely onto the Democratic and Republican parties, with Democrats on the liberal end of the continuum and Republicans on the conservative end. Of particular note, nearly one-third of registered voters in the U.S. are "Nonpartisans," meaning that they prefer not to be a member of either the Democrats or the Republicans (or any other organized party such as the Libertarian Party).[2] Nonpartisan voters tend to have political views that lie in between those of Democrats and Republicans (Pew 2019). There is also some evidence that Nonpartisans exhibit lower levels of affective polarization

[1] The ascribed characteristic that most clearly has distance would be age. Some achieved characteristics might have a distance component – for example, years of education would, and one might be able to infer distance between different majors.
[2] Different states use different names to record nonpartisan voters, such as "Unaffiliated" in North Carolina and "Independent" in California.

toward partisans of either of the major political parties, and in turn are not viewed as negatively by Democrats or Republicans as members of the opposing party (Iyengar & Westwood 2015).

Given this, we can extend our analysis beyond homophily and examine the predictions associated with cross-cutting. That lens would argue that Nonpartisans will be able to communicate and cooperate more easily with their partisan cofounders than partisans of opposing parties can with each other. Consequently, mixed teams that include Nonpartisans should perform better than mixed teams without Nonpartisans, all else equal. And, to the extent that Nonpartisans facilitate communication and cooperation that approaches that of homogeneous teams, mixed teams that include Nonpartisans should enjoy knowledge-based benefits of diversity while achieving some of the communication-based benefits of homophily. In sum, *cross-cutting theory predicts that diverse cofounding teams that include at least one Nonpartisan cofounder will be associated with higher performance than either homogenous c-founding teams or diverse teams that lack a Nonpartisan member*. We explore this prediction in the forthcoming statistical analysis.

3. Data and sample statistics

3.1 Data

There are two main datasets employed in our analysis. The first, obtained from the commercial data vendor, L2, contains the voter registration and voting history information of every voter in California from 2007 to 2019. In the United States, federal elections are managed by each of the fifty states. Citizens resident in a state register to vote, usually within their voting districts, online or in-person at local government offices. These local government voter lists are aggregated at the state level, usually at the Secretary of State's or Board of Election's office; access to a state's voter registration data is regulated by a given state's laws and rules. Most

states impose obstacles that make it difficult to access these records freely. However, L2's business model is to collect these voter records, verify and enhance their quality through third-party sources, and license segments of its datasets to political campaigns; it now also licenses its data to U.S. universities and academic researchers.

In the U.S., citizens who register to vote must specify membership in the political party of their choice or that they prefer to be officially unaffiliated with any party. Voters are generally motivated to specify affiliation with a particular party because party affiliation is increasingly part of an individual's identity (Iyengar et al. 2019). The most prominent affiliations for California voters in this paper are Democrat, Republican, and No Party Preference (which we will call "Nonpartisan" hereafter).[3] It is possible for a registered voter to change his/her party membership at any time by filing a new registration form, although this is not common. There are, on average, 18.2 million registered voters in California in each year of the data. Since some voters do change party over time, we must look at these registered voters' affiliations in each year, resulting in more than 236 million voter-year records. The L2 data have substantial information about each voter, including name, address, gender, race/ethnicity, year of birth, and political party.[4] The data also note in which elections the voter has voted, but not for whom she voted. This dataset provides a comprehensive snapshot of every registered voter in California over this 13-year period. Scholars have compared L2 data to actual voter records, finding that the L2 data are exceptionally reliable and generate similar regression results as do the actual voter records (de Figueiredo et al. 2021). These L2 data have been used in an increasing variety of

[3] California has 23 smaller parties such as Libertarian, Green, Marxist, Peace & Freedom, and Socialist. But these parties collectively comprise less than 5% of the data set and are relegated to the omitted category in our analysis.
[4] Voter registration records include self-reported gender, race, and ethnicity information. However, California is among a small number of states that refuses to divulge this information. Consequently, L2 estimates each California voter's gender, race, and ethnicity based on names and other attributes.

academic papers (e.g., Enamorado et al. 2019; Raffiee et al. 2022; de Figueiredo et al. 2023; Spenkuch et al. 2023; Kovacs & Sels 2024).

A second core dataset is obtained from Crunchbase. The Crunchbase database is a comprehensive dataset of start-ups that wish to receive or have received venture capital funding. This self-reported dataset is used extensively in the entrepreneurship and management literature to catalog such firms (Samila and Sorenson 2017; ter Wal et al. 2016; Wang et al. 2022; Guzman and Li 2023; Zhao 2025). The Crunchbase dataset contains information on each start-up that is updated with each funding round, including the name of the firm, the name of each founder, the firm's technology area and geographic location, the firm's founding date, the date and size of each funding round, and the names of all key employees. From this dataset, we extracted only those firms located in California that appeared in Crunchbase at least once between 2007 and 2019.

We matched the names from the Crunchbase entrepreneur dataset to the L2 voter registration records to obtain information on the founders' political affiliations and other demographic information. This is not a simple task. There are entrepreneurs who are not registered to vote in California because they are foreign citizens, or they are U.S. citizens who have chosen not to register, or they reside in a different state; there may be registered voters who have the same names as those in the entrepreneur dataset but who are not actually the entrepreneur; there may be individuals with multiple names in one or both datasets; people may use legal names in one dataset and nicknames in the other (e.g., William and Bill); the same entrepreneur may provide one address for voter registration and a different address for Crunchbase. The record-matching problem here is exceptionally challenging.

To overcome these issues, we used the FastLink method developed by and described in Enamorado et al. (2019) (see also Enamorado undated). This method, which was specifically

developed for leveraging voter registration records, uses Bayesian estimation to support fast computational methods for massive record linkage on names and has been used in numerous academic studies.[5] In order to link records of this extremely large dataset in a timely manner, we extended the extant FastLink R package to block on county and gender in the match.

To reduce difficult-to-interpret heterogeneity across startups, we further limited our analysis to founding teams at the time that they received Series A funding. In many analyses we then eliminated all single-founder startups, since these do not offer insight into team formation or team performance. Finally, we hand-checked outlier observations to investigate whether data had been erroneously coded – for example, the small handful of ostensibly 95-year-old founders – and audited a number of observations to ensure the remainder of the data is valid. This process generated a final dataset consisting of 15,518 founders distributed among 3,748 Series A start-ups with two or more cofounders. We apply statistical analysis to this final dataset.

3.2 Descriptive Statistics and Facts

We begin by describing several facts and inferences about the characteristics of entrepreneurs and their founding teams. Approximately 50% of California entrepreneurs at Series A-funded startups are U.S. citizens, based on our ability to match them to voter registration data.[6] Consistent with previous literature, these citizen-entrepreneurs tend to be white (63%) and male (90%).

Politically, Republicans are under-represented, and Nonpartisan voters are substantially over-represented among California entrepreneurs relative to the underlying distribution of voters

[5] As of 04/13/2025, over one hundred academic papers have used the FastLink technology.
[6] This 50% figure is broadly consistent with previous work. See: https://news.crunchbase.com/venture/foreign-born-entrepreneurs-drive-americas-unicorn-boom-strebulaev-stanford/ or Bill Kerr (see Appendix Table 3) https://www.hbs.edu/ris/Publication%20Files/24-068_ea168005-112d-42ef-afba-9c1dd36117c1.pdf

in the state. Whereas the underlying voter registration data for 2007-2019 for the entire CA population is 45% Democrat, 28% Republican, 22% Nonpartisan and 5% Other Party, among entrepreneurs the breakdown is 41% Democrat, 19% Republican, 35% Nonpartisan, and 5% Other Party. These entrepreneurs are slightly above-average in their political engagement. In U.S. presidential general elections, approximately 58% of California voters choose to vote. In our dataset, approximately 64% of these entrepreneurs voted in a federal general election. Descriptive statistics for entrepreneurs are presented in Table 1, Panel A.

Table 1, Panel B presents descriptive statistics for multiple-founder teams at the level of the founding team. In our data, 77% of such teams exhibit gender homogeneity, meaning that all members of the founding team are the same gender. 38% exhibit homogeneity in terms of the race/ethnicity categories provided, 14% of teams exhibit geographic homogeneity in that all cofounders reside in the same county, and 27% of teams exhibit political homogeneity. We can further break down that political homogeneity: 14% of the teams have only Democratic founders, 9% of teams have only Nonpartisan founders, and 4% of teams have only Republican founders. Note that homogeneity figures are difficult to interpret without considering the underlying proportions of founders on the relevant criteria. For example, since 90% of founders are male, one would expect a high rate of male-only firms even if teams were to form randomly. In contrast, with three political-affiliation categories and the modal category accounting for 41% of founders, one would expect a much lower rate of same-party teams under random team formation. We consider this further below.

Table 2 and Figure 1 provide information on changes in founder and team characteristics over time. Table 2 shows that, between 2007 and 2019, there is a steady increase in the proportion of Series A founders who are female. In contrast, the political affiliation proportions of founders are relatively stable, suggesting that changes in the political composition of teams

reported later in this paper are not attributable to changing baseline rates of founders' political affiliations. The table also indicates that there is a modest decrease in average team size at Series A. Figure 1 provides complementary information on changes in the prevalence of homogeneous teams over time. Panel A shows a simple metric: the proportion of all firms raising Series A funds in a given year that have homogeneous founding teams in terms of gender, race, and political party. In this panel, the proportion of same-gender teams remains stable throughout the sample period, while the proportions of same-race and same-party teams increase, with same-party teams displaying the sharpest increase.

However, the information in Figure 1, Panel A is difficult to interpret for at least two reasons. First, changes in the proportions of founder types will generate changes in the proportion of homogeneous teams even under random sorting – for example, as the mix of male and female founders becomes more balanced, the proportion of homogeneous teams should decrease, so an ostensibly stable proportion of same-gender teams (as in Figure 1A) could mask an increase in "excessive" homogeneity, meaning a proportion of homogeneous teams above that which would be expected given random team formation. Second, as Table 2 indicates, team size has decreased during the sample period. A smaller average team size will increase the probability of a homogenous team under random sorting, since randomly drawing an all-male team is more likely when forming a two-person team than a three-person team.

To address this, Figure 1, Panel B calculates a measure of excessive homogeneity. The basic approach is as follows (details are provided in Appendix A): For a given year, we can observe how many founders there are of a given party (or gender, or race). We can also observe the number of two-person, three-person, four-person, etc., teams formed in that year, and how many of each of those are same-party (or same-gender or same-race) teams. Given this, we can calculate expected numbers of such teams, assuming random team formation. Finally, we can

take the ratio of observed homogeneous teams to expected homogeneous teams. A ratio of 1.0 would indicate that there is no "excess homogeneity." Ratios above 1.0 indicate excess homogeneity among these teams, with higher numbers indicating greater excess.[7]

Whereas Figure 1, Panel A showed a high proportion of same-gender founding teams, Panel B demonstrates that this proportion is not markedly different than what one should expect if teams form without regard to gender. Over the course of the sample period, the ratio of observed to expected same-gender teams hovers around 1.04, suggesting 4% more homogeneous teams than randomness would predict. Same-race teams similarly demonstrate a stable pattern in Panel B, with an observed/expected ratio of roughly 1.3. In contrast, partisan-based homogeneity appears to increase during the sample period, notably in the post-2015 period. Although the average observed/expected ratio for same-party teams over the course of the sample period is 1.15, over time this ratio comes to exceed that of race-based homogeneity, and, by the latter years of the sample, reaches almost 1.60.

With these data as background we now move to our statistical analysis. We first estimate the propensity for cofounding teams to exhibit homophily, both at a dyadic level among cofounders and at a team-homogeneity level. We then estimate the relationship between founding-team homogeneity and startup performance.

4. Empirical Analysis – Team Formation

4.1 Dyadic analysis

[7] For example, imagine that Republicans comprise 30% of all founders in 2010. The probability of a two-person all-Republican team is 0.3*0.3=0.09. If our sample includes 20 two-person firms that raised Series A in 2010, then we would expect to see 1.8 all-Republican two-person teams in that year. If we see four such firms, then that would indicate excess homogeneity. This approach is similar to that introduced in Ruef (2002). We will use a more ambitious version of this method in later statistical analysis.

We begin our analysis with an examination of team formation using two complementary statistical methods. The first method, a dyadic analysis, applies a methodology similar to that of Calder-Wang et al.'s (2024) analysis of racial and gender homophily in entrepreneurial teams. Conceptually, this approach entails identifying a risk-set of all potential cofounders for each given focal founder and creating dyad-level observations between founder and each potential cofounder. The dependent variable is binary, set equal to 1 for cofounding dyads that actually were formed and 0 for potential dyads that were not realized.[8]

A key challenge for this approach is to identify the appropriate risk-set of potential cofounders. Consistent with Calder-Wang et al. (2024), we identify Founder A's risk-set as all other individuals in our sample who founded a California-based startup in the same year and same industry as Founder A's startup. Our startups span 39 different Crunchbase-identified primary industry categories. The five most populated categories – Biotechnology, Commerce and Shopping, Data Analytics, Advertising, and Hardware – comprise 42% of all of our startups. There is a long tail of industries with a small number of startups: 16 industries have fewer than 20 startups during our sample period; these include Design, Professional Services, and Food & Beverage.

We identify every unique individual founder and create dyads with each potential partner they could have teamed with according to the criteria described above. Thus, for example, if Founder A is involved in founding a Data Analytics startup that raises Series A funding in 2017, then that entrepreneur's cofounder risk-set would be all other entrepreneurs (Founder B's) identified in the Crunchbase database who were involved in founding a Data Analytics startup

[8] Calder-Wang et al. (2024) apply this method to both a sample of students in several sections of a Harvard Business School elective course, and a sample of startups listed in VentureXpert. They do not consider political characteristics in their analysis.

that also received Series A funding in 2017. The resulting database has 347,199 dyads. Of these, 5,474 dyads were actually formed.

We estimate the following model:

$$Cofounders_{ijkt} = \beta_1 SameParty_{ijkt} + \beta_2 SameGender_{ijkt} + \beta_3 SameRace_{ijkt} + \beta_4 SameCounty_{ijkt} + \gamma_1 Industry_k + \varphi_1 Year_t + \varepsilon_{ijkt} \quad (1)$$

where i and j are two individuals whose firms raised Series A funding in industry k in year t. the variables are defined as follows:

Dependent variable: The dependent variable for this analysis, *Cofounder Dyad*, is a binary variable set equal to 1 if founders i and j actually cofounded a venture, and 0 otherwise.

Independent variables: The independent variables of interest are measures of political homophily. *Same Party* is a binary variable set equal to 1 if both members of the dyad have the same political affiliation, and 0 otherwise. We break this down further by party. *Both Democrats* is a binary variable set equal to 1 if both members of the dyad are registered Democrats, and 0 otherwise. *Both Republicans* and *Both Nonpartisans* are defined analogously.

Control variables: Prior research demonstrates that homophily can be driven by demographic characteristics and structural proximity. Research also indicates that political preferences are correlated with demographic characteristics and location (Pew Research 2018). We therefore control for conventional drivers of homophily-based team formation. *Same Gender* is a binary variable set equal to 1 if both members of the dyad have the same gender, and 0 otherwise. *Same Race/Ethnicity* and *Same County* are analogously defined. We also include fixed effects for year and industry.

Table 3 presents the results of linear probability estimations of *Cofounder Dyad*. Standard errors are clustered by industry-year. The top half of the table shows model coefficients for the

various dyad political configurations while the bottom half of the table indicates which other dyadic variables were included. Industry and year fixed effects are included in all specifications.

Model 1 and 2 present results aggregating dyadic political similarity into the variable *Same Party*. Model 1 excludes the control variables, while Model 2 includes them. In these models, the omitted category consists of all non-homogeneous dyads – Democrat-Republican; Democrat-Nonpartisan; Republican-Nonpartisan, etc. The coefficient on *Same Party* thus reveals the effect of political homophily vs. the weighted average of heterogenous dyads. In these models, the coefficients on this variable are positive, but the coefficient loses statistical significance when we introduce the controls for other sources of homophily.

Models 3 and 4 decompose political homogeneity into the particular political parties. Again, the omitted category consists of all non-homogeneous dyads. The coefficients on *Both Democrats* and *Both Nonpartisans* are positive and statistically significant in three of the four cases, while *Both Republicans* has a negative coefficient that is statistically significant in both models.

Earlier we discussed how Democrats (Republicans) may view Nonpartisans differently – likely more favorably – than they view Republicans (Democrats). In Models 5 and 6, we decompose the heterogeneous dyads into three different types: Democrat-Nonpartisan, Republican-Nonpartisan, and Democrat-Republican. In these models, Democrat-Republican is the omitted category. The coefficients on the political variables are stable across the two models. In the fully specified Model 6, relative to the Democrat-Republican dyad configuration, Democrat-only and Nonpartisan-only dyads are 0.2 percentage points and 0.3 percentage points more likely than the Democrat-Republican combination, respectively. Given that the mean probability that a dyad occurs is 1.6% in our sample (5,474/347,199 = 1.6%), this translates into a 13% boost in probability of a realized dyad for Democrat-only dyads, and a 19% boost in

probability of a realized dyad for Nonpartisan-only dyads. In contrast, a Republican-only dyad is 0.2 percentage points less common. Interestingly, the politically heterogeneous ties of a Democratic-Nonpartisan and Republican-Nonpartisan are more common than a Democratic-Republican dyad, although the coefficient on Republican-Nonpartisan falls just outside conventional thresholds of statistical significance. [9]

Overall, these results indicate that Democrats and Nonpartisans each tend to join with politically similar cofounders on Series A entrepreneurial teams, while Republicans are less likely to join together. In addition, Democrats, and to a lesser extent Republicans, partner with Nonpartisans at a higher-than-random rate relative to Democrat-Republican pairings. The results for Democrat-only and Nonpartisan-only dyads are consistent with prior general expectations about homophily, and the Democrat-Nonpartisan and Republican-Nonpartisan are consistent with our above conjectures about the relative appeal of Nonpartisans vs. adherents of the opposing party. The one unexpected result in these models is the lower-than-random rate of Republican-Republican pairings. This result deserves future investigation.

4.2 Team-level Analysis

A second method to explore homophily examines team-level characteristics following Ruef (2002) and Ruef et al. (2003). In this method, the potential team configuration is the unit of observation, and the dependent variable is the number of teams with that configuration that "enter" – i.e., raise Series A funding – in a given industry-year. For example, if our sample includes three firms that are "DD" – in other words, they have two founders and both are

[9] In addition, we present a Probit model estimation in Appendix B, Table B1. For the interested reader, we present the coefficients for all variables, including those in the bottom half of the table, in Appendix B, Table B2.

Democrats – and that raise Series A in the biotechnology industry in 2010, then the dependent variable for Biotechnology-2010-DD is 3.

There are six potential two-person team configurations: DD, DN, DR, NN, NR, and RR. There are 10 potential three-person team configurations, 15 potential four-person team configurations, and 21 potential five-person team configurations, for a total of 52 different team types, in each of 39 industries and 13 years.[10] This creates 26,364 industry-year-team-configuration cells. We restrict our sample to observations for which there was at least one team of that team size. In other words, if there are no two-person teams at all in the Internet industry in 2008, then this estimation excludes the six observations for two-person teams in that industry and that year (DD, DN, DR, NN, NR, and RR), rather than include six observations that, as an artifact of the data, must have both an expected and actual count of zero. The resulting dataset has 8,600 industry-year-team-configuration observations.

We thus estimate the following model:

$$Count_{jkt} = \beta_1 ExpectedCount_{jkt} + \beta_2 AllDem_{jkt} + \beta_3 AllNon_{jkt} + \beta_4 AllRep_{jkt} + \beta_5 DemNon_{jkt} + \beta_6 RepNon_{jkt} + \beta_7 DemRepNon_{jkt} + \beta_8 DemRep_{jkt} + \beta_8 TeamSize_{jkt} + \gamma_1 Industry_k + \varphi_1 Year_t + \varepsilon_{jkt} \quad (2)$$

where *Count* is the number of teams of configuration *j* that raise Series A funding in industry *k* during year *t* (for example, a DDD team in Biotechnology in 2010). *ExpectedCount* is the number of teams that one would expect to see raising Series A funding in industry *k* during year *t*, assuming random formation of teams from among all founders raising Series A funding in

[10] We restrict this analysis to teams of five or fewer members. This is because the number of observations explodes exponentially as we include larger and larger team sizes, and these observations have almost exclusively zero counts of firms. For example, adding 6-member configurations would add more than 10,000 observations yet only 16 of these would have non-zero counts of firms.

industry *k* during year *t*. The next seven variables constitute a vector of binary variables that encompass all potential political configurations; *TeamSize* is measured either as a count of team members or through binary variables denoting 2-person, 3-person, 4-person, and 5-person teams, and *Industry* and *Year* are fixed effects.[11]

Consistent with Ruef et al. (2003), we calculate *ExpectedCount* in a fashion that is also consonant with our dyadic approach: Let us assume that all founders in a given industry-year are potential cofounders with each other. Then one can calculate the expected count of firms with a particular configuration, absent political homophily, by calculating the multinomial probability of that configuration. For example, in our sample we have 78 unique founders involved in Series A firms in biotechnology in 2009: 39 Democrats, 23 Nonpartisans, and 16 Republicans. The probability that any given two-person firm will be DD is 39/78 * 38/77 = 0.247. The probability that any given two-person firm will be DN is 39/78 * 23/77 * 2 = 0.299. The probability that any given two-person firm will be RR 16/78 * 15/77 = 0.040. And so on, and the same for teams of other sizes. In our sample, there are eight two-person teams in biotechnology in 2009. Given the 0.247 probability that any one of them will be DD, the *ExpectedCount* of Biotechnology-2009-DD is 0.247 * 8 = 1.97. The actual number of DD teams is 3. This reflects an instance where the observed *Count* exceeds the *ExpectedCount* based on random sorting. If this happens persistently, then the coefficient on *AllDem* will be positive.

[11] Unlike the dyad-formation estimations and the upcoming performance estimations, in this estimation we do not include controls for other forms of homophily. In this econometric method, such controls would require constructing separate "cells" for each combination of gender/race/geographic homophily and political configuration. For example, to incorporate gender homophily, we would need to split the Biotechnology-2010-DD cell into Biotechnology-2010-AllMale-DD, Biotechnology-2010-AllFemale-DD, and Biotechnology-2010-MixedMaleFemale-DD. This would both explode the number of cells (especially cells with zero counts), and reduce the counts in each given cell that currently experiences entry.

Table 4 presents the main results of our Poisson estimations. *DemRep* teams represent the omitted category. Model 1 presents results for all teams. Models 2, 3, 4, and 5 present the coefficients for two-person, three-person, four-person, and five-person teams, respectively.

In Model 1, the all-team model, the coefficients on *AllDem* and *AllNon* are positive and statistically significant. The incidence ratios (provided in brackets below the coefficient and standard error) indicate that all-Democratic and all-Nonpartisan teams are 31% and 17%, respectively, more likely to occur than random formation would predict. In contrast, AllRep is negative and statistically significant. The incidence ratio indicates that all-Republican teams occur 33% less frequently than we would expect from random sorting. The coefficient on *DemNon* and on *DemRepNon* are both positive, statistically significant and of substantial magnitude. *DemNon* teams are 60% more likely, and *DemRepNon* teams 80% more likely, than random sorting would expect. The results offer striking evidence that Nonpartisans are viewed favorably by Democrats, and possibly by Republicans as well.

Each of Models 2-5 focuses solely on teams of a specific size. The results for homophily become somewhat muted, although this is driven in part by the increase in standard errors associated with smaller sample sizes. The coefficient on *AllDem* remains positive throughout the four models, of substantial magnitude in three of the models, and statistically significant in two of the models. In contrast, the coefficient on *AllNon* loses significance and fluctuates in sign in these models. *AllRep*'s coefficient remains consistently negative while fluctuating in magnitude and significance; this likely reflects the relatively small number of Republicans in a given industry-year-team size. Again, the coefficients on *DemNon* and *DemRepNon* are consistently statistically significant, and the incidence ratios indicate dramatically higher rates of occurrence for these teams than would be expected.

In sum, at both the dyad level and team level, the startup teams in our sample reflect political homophily among Democrats and among Nonpartisans, as well as some aversion of Democrats for Republicans (or vice versa). Republicans do not exhibit homophily in their team formation. Finally, Democrat-Nonpartisan teams and Democrat-Nonpartisan-Republican teams occur more frequently than random sorting would predict. (Indeed, the Republicans that are not joining all-Republican teams tend to join Democrat-Republican-Nonpartisan teams). This broader team composition analysis is consistent with the potentially important role that Nonpartisan founders play in entrepreneurial teams—a role that cannot be measured in the dyadic analysis.

5. Empirical analysis – team political composition and performance

5.1 Reduced form estimation

We next turn to our core analysis: examining the relationship between a startup founding team's political composition and the startup's performance. As discussed above, the effect of homophily on team performance is theoretically ambiguous, as homogeneous teams are expected to suffer from less diverse informational or cognitive diversity but to benefit from smoother coordination and collaboration (or, conversely, diverse teams should enjoy greater informational and cognitive diversity but encounter greater challenges in collaborating and coordinating). Depending upon which effect is stronger, homogeneous or heterogenous teams might perform better. However, there is a third possibility: The theoretical literature on cross-cutting and faultlines would predict that heterogeneous teams that include Nonpartisans should exhibit superior performance to either homogeneous teams or diverse teams composed of only Democrats and Republicans, as the presence of Nonpartisan cofounders should facilitate collaboration and coordination benefits while still affording the knowledge/perspective diversity of non-homogenous teams.

Figure 2 presents the summary information regarding team configuration and the securing of Series B funding. The data in this figure are consistent with the benefits of boundary-spanners. In our sample, homogenous teams have the lowest likelihood of a successful Series B raise, various mixed teams have a higher likelihood of success, and mixed teams that include at least one Democrat, Republican, and Nonpartisan have the highest likelihood of success. However, this figure does not take into account factors such as team size, the industry or year of a given startup, and other sources of homophily.

We consequently turn to multivariate estimation to control for other factors. The estimations we initially present document correlational relationships rather than causal relationships. We then turn to two-stage instrumental variables analysis.

The unit of observation for this analysis is the startup founding team. We construct two measures of performance. The first is whether a given firm in our sample successfully raises a Series B round of funding (recall that all firms in our sample have raised Series A funding). The second, constructed for those firms that did successfully raise Series B funding, is the time in months between the Series A raise and the Series B raise. We interpret success at raising Series B funding, and shorter time to Series B, as positive indicators of performance.

We estimate the following model:

$$Outcome_{jkt} = \beta_1 AllDem_{jkt} + \beta_2 AllNon_{jkt} + \beta_3 AllRep_{jkt} + \beta_4 DemNon_{jkt} + \beta_5 RepNon_{jkt} + \beta_6 DemRepNon_{jkt} + \beta_7 DemRep_{jkt} + \beta_8 SameGender_{jkt} + \beta_9 SameRace_{jkt} + \beta_{10} SameCounty_{jkt} + \beta_{11} TeamSize_{jkt} + \beta_{11} MultipleA\ Rounds_{jkt} + \gamma_1 Industry_k + \varphi_1 Year_t + \varepsilon_{jkt} \quad (3)$$

where *Outcome* is either *RaisedSeriesB*, a binary variable set equal to 1 if firm *j* successfully raised Series B funding during our sample window and 0 otherwise, or *TimeToB*, a

count of the number of months between firm *j*'s Series A and Series B fundings (for those firms that raised Series B). For the subset of firms that successfully raised Series B funds, we define *TimeToB* as the number of months from the first Series A round to the Series B round.

Table 5 presents results for our estimations of *RaisedSeriesB*. The estimations are linear probability models, with standard errors clustered by industry-year. The first eight models present four different specifications of independent variables; in each case the odd-numbered models exclude control variables for other forms of homophily while the even-numbered models include all such variables. Models 1 and 2 include the aggregate political homophily variable, *SameParty*. In both models, *SameParty* has a negative and statistically significant coefficient, indicating that homogeneous startup teams have a lower probability of raising Series B funding. The coefficient on *SameParty* is reduced by one-third when we include all of the control variables in Model 2. In this model, the coefficient on *SameParty* indicates a politically homogeneous founding team of a Series A startup has a 3.7% lower probability of raising a Series B round relative to a politically mixed Series A team, on average.

Models 3 and 4 disaggregate political homogeneity into its component parts. These models show that all three types of team political homogeneity variables – Democratic, Republican, and Nonpartisan – have negative coefficients, but the coefficient on Democratic homogeneity is both the largest and the only statistically significant coefficient. The result suggests that all-Democratic teams have on average a 6.3% lower probability of raising a Series B round relative to politically heterogeneous start-ups.

In Models 5 and 6 we disaggregate political heterogeneity into its component parts. We already know from Models 1 and 2 that politically mixed teams will perform better than the omitted category in Models 5 and 6 (*SameParty*). But this disaggregation provides a first look at the differential benefits of different types of mixed teams. Of particular note, mixed teams that

include at least one Nonpartisan all exhibit coefficients that are higher than that on Democrat-Republican mixed teams. Further, the variable *DemRepNon*, indicating teams that include at least one each of Democrats, Republicans, and a (potentially cross-cutting) Nonpartisan, has the largest positive coefficient of all types of heterogeneous teams, although this difference is not statistically significant. *DemRepNon* teams have a 6.9% higher probability of raising Series B funding relative to homogeneous political teams. These results are consistent with the theory and the role that crosss-cutters play.

Models 7 and 8 include all seven types of homogeneity and heterogeneity in teams, with *AllDem* as the omitted category. In Model 8, none of the homogeneous coefficients is statistically significant, nor is the coefficient on mixed Democrat-Republican teams, *DemRep*. In contrast, the coefficients on all three mixed teams including Nonpartisans – *Mixed DN*, *Mixed RN*, and *Mixed DRN* – are positive and statistically significant, indicating that these three team types outperform homogeneous Democratic teams to a statistically significant degree. The coefficients on *Mixed RN* and *Mixed DRN* are also significantly different from the coefficient on *AllRep* at the 95% level. Taking the point estimates of Model 8 at face value, teams that include a Nonpartisan are between 5% and 10% more likely to raise Series B funding than an *AllDem* team, and between 2.5% and 6% more likely to raise such funding than an *AllRep* team.

We extend this analysis by examining time to Series B for the subset of firms that successfully raised Series B funding. Table 6 presents the results of OLS estimations of *TimeToB*, with standard errors again clustered by industry-year. The model specifications follow an identical pattern to those in Table 5. Overall, the results are broadly consistent with those in Table 5: politically homogeneous firms take longer to raise Series B than politically heterogeneous firms. At the level of disaggregated team types, for *TimeToB* the *Mixed-DR* teams tend to fare as well as mixed teams that include Nonpartisans.

Models 1 and 2 again focus on *SameParty*. In Model 2, the coefficient on *SameParty* indicates that politically homogenous teams take roughly 2.5 additional months to raise Series B than politically heterogeneous teams. Models 3 and 4 disaggregate this into *AllDem*, *AllRep*, and *AllNon* homogeneity. Whereas only the *AllDem* teams had a significant performance disadvantage vs. mixed teams in terms of *RaisedB*, here the *AllRep* and *AllNon* teams both take significantly longer, as well; the coefficient on *AllRep* has a p-value of 0.11. Models 5 and 6 demonstrate that all mixed teams raise Series B faster than politically homogenous teams, with *Mixed-DR* teams achieving times comparable to those of other mixed teams. This pattern continues in Models 7 and 8. In Model 8, the coefficients on *Mixed-DN* and *Mixed-DRN* have p values of 0.105 and 0.12, respectively. This indicates that they are not statistically significantly different from *TimeToB* for *AllDem* firms at conventional levels of significance. They are, however, statistically significantly different from the coefficient on *AllRep*.

Appendix B presents results of several robustness checks, including different estimation methodologies, inclusion of additional control variables, and estimation on different subsets of the data. The results are broadly consistent with those presented in the paper.

Overall, then, politically diverse startups teams that include a Nonpartisan cofounder experience better performance than politically homogenous teams across both performance measures, and experience better performance than politically diverse teams that lack a Nonpartisan cofounder in terms of success at raising Series B funding. This is, again, consistent with theory of cross-cutting.

5.2 Two-stage analysis using instrumental variables

In this section, we begin to shine light on causality by employing political advertising campaigns as instrumental variables. Advertisements can be positive, negative, or neutral (see

data below). In this paper we focus on negative and positive political advertising. Negative advertising has repeatedly been shown to temporarily exacerbate affective political polarization (Iyengar et al 2012, Iyengar et al 2019, Lee 2021). Exposure to negative advertising increases partisans' dislike of the opposing political party and its members by enhancing latent feelings about an outgroup or moving their feelings toward the outgroup in the negative direction (Levendusky and Malhotra 2016a, 2016b; Sood & Iyengar 2016; Iyengar et al 2012; Lau et al 2017; Martin & Nai 2024; Michelitch & Utych 2018). Consequently, negative advertising causes in-partisans to dislike out-partisans more strongly. The effects of positive advertising on affective polarization are more modest, with empirical studies suggesting that positive advertising has no effect or increases in-group affinity while not affecting out-group animus (Lau et al 2017; Nai & Maier 2023).

Political advertising possesses many attractive properties as an instrumental variable in our setting. First, political advertising is likely to affect entrepreneurs' preferences for teaming with other individuals of the same or different political party, as noted above. Second, there is substantial variation in political advertising across time and across county. Political advertising is driven by the competitiveness of statewide and regional elections and how well candidates are funded (Ansolabehere and Iyengar 1995; Fowler & Ridout 2010). For example, California has 53 congressional districts, many with competitive congressional elections at different times and in different geographies. These types of elections are largely exogenous to the entrepreneurial team formation and entrepreneurial team performance that occurs in California. Third, our data on TV political advertising varies by media market and over time. In California, there are 14 media markets that cover the state, providing us with 14 points of cross-sectional variation in the political advertising variables. In addition, our sample period encompasses eight election cycles of data, providing time-series variation in the instrumental variables. Consequently, the

entrepreneurs in our data set are exposed to vastly different levels of advertising based on the year and location of founding. Fourth, political advertising, while producing a potential shock to preferences of individuals within a media market, is unlikely to be correlated directly with the likelihood that an entrepreneurial firm secures a Series B funding round. That is, political advertising is likely correlated with team formation, but uncorrelated with the error term.

We employ a dataset on political advertising frequently used in the political science literature: data collected by the private company Kanter/CMAG and made publicly available through the Wesleyan Media Project (see Fowler et al. 2020 for a more comprehensive description of the data). This dataset catalogs every televised political ad in every campaign season for every media market in the United States. The data measures and records a variety of characteristics of each ad, including the political party supported and the tone of the ad – positive, negative, or neutral. We construct $\ln NegR_{mt}$ as the ln(1 + a count of negative ads by Republicans in media market m in year t). We construct $\ln NegD_{mt}$, $\ln PosR_{mt}$, and $\ln PosD_{mt}$ analogously.[12]

Figure 3 shows the cross-sectional and time-series variation in negative and positive political ads aired in each of California's media markets during our sample period. Notably, there is substantial variation in the number of Democratic and Republican negative and positive ads grouped by media markets and grouped over time. The median number of negative ads in a DMA-year is 775, while the median number of positive ads is 1,326.

In order to pursue unbiased estimation of the parameters, we estimate an instrumental variable probit model which uses a linear model in the first stage and a probit in the second stage.[13] Table 7 presents four different specifications for the first- and second-stage results. The

[12] Because elections and their accompanying ads occur every two years, if the ads occur in year *t* (e.g. 2008), we assume that the effect lingers until *t+1* (e.g. 2009). Our results are qualitatively similar for a range of depreciation weights for *t*.

[13] We are not aware of an instrumental variables bivariate probit model that yields unbiased parameter estimates.

second-stage dependent variable in all models is equal to 1 if the firm obtained a Series B round, and 0 otherwise. All models control for team size and industry and year fixed effects in both stages. Because the omitted category includes different team configurations in each of the second stage models, we define the omitted category for each model in Table 7.

Model 1 uses only negative Republican and Democratic ads as instruments to estimate the effect of two second stage endogenous RHS variables: all-Democratic teams, and all-Republican teams. Model 2 uses both negative and positive ads by Republicans and Democrats (four variables) to instrument for the same two second-stage variables as Model 1. Model 3 uses the same four instruments as Model 2, but instruments for all three types of homogeneous teams: Democratic, Republican, and Nonpartisan. Finally, Model 4 includes the same instruments as Models 2 and 3 and estimates the formation mixed DR teams as well as each of the homogeneous political teams. In this final model, the omitted category of teams is all mixed teams that include a nonpartisan.

Before interpreting the results, we briefly discuss instrument validity. A more detailed discussion of instrument validity can be found in Appendix C. Earlier in this section, we discussed why we believe political ads are likely to cause exogenous shocks to affective polarization but be orthogonal to the first-stage error terms and thus not directly driving the probability of Series B funding. Most first-stage coefficients are signed as expected and many are statistically significant. For example, negative Republican advertising lowers the probability of All-D teams and raises the probability of All-R teams. Democratic negative ads have similar effects, but not in all specifications.[14] Positive Democratic and Republican ads increase the likelihood of Mixed-DR teams. Test statistics such as the Wald Statistic and F-statistic are

[14] This is consistent with the findings in the political science literature on electoral polarization, where Republicans are more responsive than Democrats to negative advertising (Ansolabehere and Iyengar 1995:10).

statistically significant at the 99% level in most specifications (and 90% level in one specification). The correlations among the political advertising instruments range from 0.46 to 0.80. Overall, the instruments meet many but not all tests for validity, and we believe the IV Probit analysis can be informative as a first step, albeit incomplete step, in addressing mechanisms and causal factors.

We now turn to the second stage results of the IV Probit estimation. The coefficients in all four models of the All-D and All-R teams are all negative, relatively stable, and statistically significant at the 99% level of confidence in six of the eight estimations. Across the models, homogenous Democratic (Republican) teams have an 8%-10% (5%-7%) lower likelihood of securing Series B funding, relative to the omitted category in each model.

In Models 3 and 4, the coefficients on All-N are also negative, but not statistically significant. At their reported values, All-N are 6%-7% less likely to secure a Series B round, respectively. Finally, in Model 4, the coefficient on Mixed-DR is slightly positive but imprecisely estimated, with a standard error nearly 25 times larger than the estimated coefficient.

Taken together, these results are consistent with reduced form results presented in Table 5: Teams that are politically homogeneous teams underperform heterogeneous teams in the quest for Series B funding. Moreover, politically mixed teams that include a nonpartisan are likely to outperform other team configurations (except a noisily estimated Mixed DR) in securing a Series B round. This result is consistent with cross-cutting or boundary-spanning theory. Nevertheless, given the empirical evidence that the instruments do not meet all tests for validity, we acknowledge that these instrumental variable results are suggestive rather than definitive.

6. Discussion

Polarization is an increasingly prominent feature of the political landscape. This polarization is seeping into the business arena — so deeply that it affects the contours of entrepreneurship. This paper examines how political affiliation of founders affects the formation of entrepreneurial teams and the performance of the teams formed.

On team formation, organization theory suggests that individuals prefer to collaborate with people who possess similar characteristics. Previous literature has demonstrated that innovation teams formed by inventors tend to be more racially and gender homogeneous than one would expect with random assignment. Consistent with recent research (e.g., Kovacs & Sels 2024), our paper shows that this idea extends to political preferences as well. Using a dataset of thousands of Series A entrepreneurs in California from 2007 to 2019, we demonstrate that political homogeneity is pervasive in Democratic and Nonpartisan teams, though not Republicans, and extend prior research by demonstrating that political homogeneity in entrepreneurial teams has grown faster over the past 15 years then racial or gender homogeneity.[15]

This then raises the question whether politically homogeneous entrepreneurial teams outperform their politically heterogeneous counterparts. Using the same California dataset, we employ reduced form and instrumental variables analysis. Both analyses demonstrate that the highest-performing teams are those that are politically mixed and include at least one Nonpartisan cofounder. Teams that include at least one Democrat, Republican, and Nonpartisan ("D-N-R") teams are the most likely to raise a Series B round of venture capital, and, conditional on raising a B-round, D-N-R teams do so more quickly than teams of any other political configuration. This

[15] We also document that Democrats and Republicans are both likely to form teams with Nonpartisan cofounders than with members of the opposing party, consistent with the idea that Nonpartisans are perceived more positively by each party.

finding is consistent with the role that cross-cutters play on teams: Namely, that the Nonpartisan member of the team is able to span the Democratic-Republican divide in a way that allows a team to enjoy creative breadth while still achieving execution efficiency through the Nonpartisan(s) mediating differences in views between Democrat(s) and Republican(s).

In addition to making a contribution to the entrepreneurship, innovation, and teams literatures, the paper raises additional opportunities for future researchers. First, future research may be able to extend the IV analysis by locating natural experiments for endogenous team formation decision in the statistical analysis to better understand the causal relationship of heterogeneous and homogeneous political teams on entrepreneurial performance. Second, future research in a more microanalytic study could also examine in more detail the mechanisms in teams to understand how cross-cutters facilitate higher team performance. One limitation of this study is that our data do not enable us to explore the mechanisms that underlie our results. The theory on which we draw proposes that Nonpartisans may reduce conflict on teams while continuing to allow them to benefit from cognitive diversity or disparate sources of information. It is also possible that founders' political preferences correlate with distinct skills or experiences. Ideally, future studies can make progress on this front, perhaps through qualitative methodologies. Third, more generally, understanding the role of political partisanship and polarization on innovation and entrepreneurship would seem to be a worthwhile endeavor. Innovation drives modern economies, and it would seem that politics should play a limited role in the technical success of projects. Nevertheless, political polarization is increasingly entering the technology and innovation space. Understanding its effects, and how to enhance the positive effects and reduce the negative effects that the injection of politics may have in the innovation and entrepreneurial process, would seem to be a worthwhile endeavor to maximize social welfare.

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Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: Founders					
Republican	15,518	0.19	0.39	0	1
Democrat	15,518	0.41	0.49	0	1
Nonpartisan	15,518	0.35	0.48	0	1
Female	15,518	0.10	0.30	0	1
White	15,518	0.63	0.48	0	1
Indian	15,518	0.12	0.33	0	1
East Asian	15,518	0.05	0.22	0	1
Hispanic	15,518	0.02	0.13	0	1
Black	15,518	0.01	0.12	0	1
Other Race/Undisclosed	15,518	0.17	0.38	0	1
Raised Series B	15,518	0.70	0.46	0	1
Months from Series A to B	10,778	21.16	15.17	1	165
Multiple Series A Rounds	15,518	0.18	0.38	0	1
Panel B: Teams					
Members	3,748	2.89	1.41	2	10
Same Gender	3,748	0.77	0.42	0	1
Same Race	3,748	0.38	0.49	0	1
Same Region	3,748	0.51	0.50	0	1
Same County	3,748	0.14	0.35	0	1
Same Party	3,748	0.27	0.44	0	1
All Democrats	3,748	0.14	0.34	0	1
All Nonpartisans	3,748	0.09	0.29	0	1
All Republicans	3,748	0.04	0.19	0	1
Raised Series B	3,748	0.73	0.44	0	1
Months from Series A to Series B	2,736	21.15	15.18	1	165
Multiple Series A Rounds	3,748	0.18	0.38	0	1

Notes: The *Teams* summary statistics exclude 3,982 single-founder startups, since team homophily is meaningless for a single-person team. We also exclude 37 outlier firms whose Series A founding team size exceeded 10 members.

Table 2: Summary Statistics for Founding Teams over Time

Year	Teams	Avg Members	Female	Male	White	Indian	E. Asian	Hispanic	Black	Other	Republican	Democrat	Nonpartisan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(7)	(8)	(9)	(10)
2007	158	3.69	0.08	0.92	0.64	0.10	0.06	0.02	0.02	0.16	0.20	0.41	0.34
2008	201	3.33	0.08	0.92	0.66	0.12	0.05	0.01	0.01	0.15	0.21	0.39	0.36
2009	238	3.17	0.08	0.92	0.65	0.12	0.04	0.02	0.01	0.16	0.20	0.41	0.33
2010	289	2.84	0.09	0.91	0.64	0.11	0.05	0.01	0.02	0.17	0.23	0.41	0.32
2011	213	3.09	0.10	0.90	0.62	0.11	0.05	0.02	0.02	0.18	0.22	0.39	0.35
2012	201	2.85	0.11	0.89	0.67	0.11	0.05	0.01	0.02	0.14	0.20	0.43	0.32
2013	307	2.93	0.10	0.90	0.62	0.13	0.04	0.01	0.02	0.18	0.17	0.42	0.37
2014	429	2.91	0.11	0.89	0.60	0.15	0.06	0.02	0.01	0.16	0.20	0.40	0.35
2015	462	2.74	0.11	0.89	0.60	0.13	0.05	0.02	0.02	0.18	0.19	0.42	0.34
2016	380	2.78	0.11	0.89	0.61	0.12	0.05	0.01	0.01	0.20	0.18	0.43	0.33
2017	552	2.71	0.11	0.89	0.63	0.14	0.04	0.01	0.01	0.17	0.19	0.40	0.37
2018	219	2.61	0.13	0.87	0.63	0.11	0.05	0.02	0.01	0.18	0.17	0.45	0.33
2019	99	2.45	0.14	0.86	0.62	0.11	0.08	0.00	0.01	0.18	0.19	0.41	0.37

Notes: These summary statistics exclude single-founder startups, since team homophily is meaningless for a single-person team. We also exclude 37 outlier firms whose Series A founding team size exceeded 10 members

Table 3: Homophily in startup team formation – dyad analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Same Party	0.002***	0.001				
	(0.001)	(0.001)				
Both Dem			0.002**	0.001	0.003**	0.002**
			(0.001)	(0.001)	(0.001)	(0.001)
Both Non			0.003***	0.002**	0.004***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
Both Rep			-0.002**	-0.003***	-0.001	-0.002*
			(0.001)	(0.001)	(0.001)	(0.001)
Dem-Non					0.003***	0.003***
					(0.001)	(0.001)
Rep-Non					0.001	0.001
					(0.001)	(0.001)
Same Gender		Yes				
Same Race		Yes				
Same County		Yes		Yes		Yes
Both Female				Yes		Yes
Both Male				Yes		Yes
Both White				Yes		Yes
Both Indian				Yes		Yes
Both Black				Yes		Yes
Both Hispanic				Yes		Yes
Both East Asian				Yes		Yes
Both Undisclosed				Yes		Yes
Fixed effects						
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	347196	347196	347196	347196	347196	347196
adj. R-sq	0.023	0.024	0.023	0.024	0.023	0.024
F	8.912	11.91	7.168	7.605	5.545	6.674

Notes: Linear probability models. Dependent variable is binary, set equal to 1 if the dyad was actually realized (i.e., the two entrepreneurs actually cofounded a firm) and 0 otherwise. The risk set for potential cofounders is all other entrepreneurs who founded or cofounded a startup in the same industry and year as the focal founder. The omitted category in the fully specified models is Dem-Rep – a dyad consisting of one Democrat and one Republican. Standard errors clustered by industry-year are in parentheses. *** $p < 0.01$, ** $p < 005$, * $p < 0.10$

Table 4: Homophily in startup team formation – team analysis

	All teams, 2-5 persons	2-person teams	3-person teams	4-person teams	5-person teams
	(1)	(2)	(3)	(4)	(5)
All Dem	0.273***	0.272***	0.027	0.398 ***	0.887
	(0.066)	(0.078)			
			(0.160)	(0.254)	(0.730)
	[1.314]	[1.312]	[1.027]	[1.489]	[2.428]
All Non	0.160**	0.213	-0.228	0.111	-14.826
	(0.073)	(0.085)			
			(0.187)	(0.289)	(1507.76)
	[1.173]	[1.237]	[0.796]	[1.117]	[0.000]
All Rep	-0.399***	-0.145	-2..331***	-1.244**	-14.826
	(0.098)	(0.106)	(0.509)	(0.521)	(1514.70)
	[0.671]	[0.865]	[0.097]	[0.288]	[0.000]
Dem-Non	0.488***	0.259***	0.595***	0.921***	2.250***
	(0.057)	(0.073)	(0.111)	(0.169)	(0.469)
	[1.631]	[1.300]	[1.811]	[2.513]	[9.489]
Rep-Non	-0.045	0.016	-0.042	-0.462*	0.487
	(0.069)	(0.087)	(0.137)	(0.239)	(0.570)
	[0.956]	[1.017]	[0.959]	[0.630]	[1.629]
DemNonRep	0.597***		0.494***	0.472***	2.246**
	(0.080)		(0.294)	(0.801)	(0.461)
	[1.818]		[1.639]	[1.604]	[9.448]
TeamSize	-0.761***				
	(0.024)				
	[0.467]				
Fixed effects					
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	sYes
N	8600	1836	2180	2505	2079
Wald chi-square	1242.8***	34.6***	92.1***	76.2***	49.7***
Log-likelihood	-4013.7	-1336.3	-947.3	-702.7	-342.6

Notes: Poisson models using xtpoisson command in STATA. Dependent variable is the count of Series A firms in a given industry-year-team configuration, e.g. Biotechnology-2010-DD founding team. Standard errors clustered at the industry-year are in parentheses. Sample restricted to observations where there was at least one team of that team size. In other words, if there are no two-person teams at all in the Internet industry in 2008, then this estimation excludes the six observations for two-person teams in that industry and that year (DD, DN, DR, NN, NR, and RR). The omitted category is Dem-Rep – a team composed of Democrats and Republicans. Incidence ratios are in brackets. There is no coefficient for DemNonRep in Model 2 because it is impossible to have a two-member team that has a Democrat, a Republican, and a Nonpartisan cofounder. Per the methodology developed by Ruef (2002) and Ruef et al. (2003), *ExpectedCount* is included in the estimation as a fixed parameter with a coefficient constrained to 1.0. We use the exposure option in xtpoisson to do this. Results are qualitatively identical if we instead include *ExpectedCount* as a conventional dependent variable in the estimation.

*** $p < 0.01$, ** $p < 005$, * $p < 0.10$

Table 5: Startup performance as a function of team political composition: Probability of Raising B round

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Party	-0.056***	-0.037**						
	(0.019)	(0.019)						
All-D			-0.080***	-0.063***				
			(0.025)	(0.024)				
All-R			-0.059	-0.025			0.020	0.037
			(0.040)	(0.039)			(0.043)	(0.041)
All-N			-0.019	-0.000			0.061*	0.063*
			(0.027)	(0.028)			(0.033)	(0.031)
Mixed DR					0.035	0.015	0.058**	0.042
					(0.027)	(0.027)	(0.030)	(0.029)
Mixed DN					0.050**	0.029	0.074***	0.056**
					(0.022)	(0.022)	(0.027)	(0.027)
Mixed RN					0.081***	0.062**	0.105***	0.090***
					(0.027)	(0.028)	(0.031)	(0.031)
Mixed DRN					0.099***	0.077**	0.123***	0.103***
					(0.030)	(0.030)	(0.033)	(0.033)
Team Size	0.037***	0.030***	0.037***	0.030***	0.033***	0.026***	0.033***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Controls								
Same Race	No	Yes	No	Yes	No	Yes	No	Yes
Same Gender	No	Yes	No	Yes	No	Yes	No	Yes
Same County	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3019	3019	3019	3019	3019	3019	3019	3019
adj. R-sq	0.116	0.122	0.117	0.123	0.117	0.123	0.118	0.123
F	29.19	15.93	16.39	12.70	14.22	11.99	11.15	10.54

Notes: Linear probability models. Sample excludes teams with founders from parties other than Democrat, Republican, or Nonpartisan. Dependent variable is binary, set equal to 1 if the startup raised Series B funding and 0 otherwise. The omitted category in Models 7-8 is All-D. Standard errors clustered by industry-year are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 6: Startup performance as a function of team political composition: Time to Series B round (conditional on raising a Series B round)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Party	3.027***	2.509***						
	(0.779)	(0.802)						
All-D			2.176**	1.791				
			(1.093)	(1.111)				
All-R			5.379***	4.395***			3.202*	2.589
			(1.502)	(1.528)			(1.738)	(1.729)
All-N			3.225***	2.767**			1.048	0.973
			(1.214)	(1.202)			(1.570)	(1.560)
Mixed DR					-3.208***	-2.724***	-2.352*	-2.001*
					(0.904)	(0.913)	(1.204)	(1.209)
Mixed DN					-2.765***	-2.188**	-1.914*	-1.478
					(0.862)	(0.898)	(1.166)	(1.199)
Mixed RN					-3.388***	-2.997**	-2.536*	-2.274
					(1.365)	(1.360)	(1.551)	(1.547)
Mixed DRN					-3.094***	-2.480**	-2.259*	-1.782
					(1.134)	(1.145)	(1.320)	(1.334)
Team Size	-0.357*	-0.119	-0.349*	-0.125	-0.364	-0.136	-0.355	-0.139
	(0.202)	(0.222)	(0.202)	(0.222)	(0.251)	(0.272)	(0.250)	(0.271)
Controls								
Same Race	No	Yes	No	Yes	No	Yes	No	Yes
Same Gender	No	Yes	No	Yes	No	Yes	No	Yes
Same County	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2210	2210	2210	2210	2210	2210	2210	2210
adj. R-sq	0.029	0.033	0.030	0.033	0.028	0.032	0.028	0.032
F	10.56	8.18	6.78	6.47	4.81	5.14	4.36	4.58

Notes: Linear probability models. Sample excludes teams with founders from parties other than Democrat, Republican, or Nonpartisan. Dependent variable is the number of months between raising Series A funding and raising Series B funding. The omitted category in Models 7-8 is All-D. Standard errors clustered by industry-year are in parentheses. *** $p < 0.01$, ** $p < 005$, * $p < 0.10$

Table 7: Two-stage estimation of startup performance as function of team political composition: Instrumenting for team formation with time-varying and county-varying political advertisements

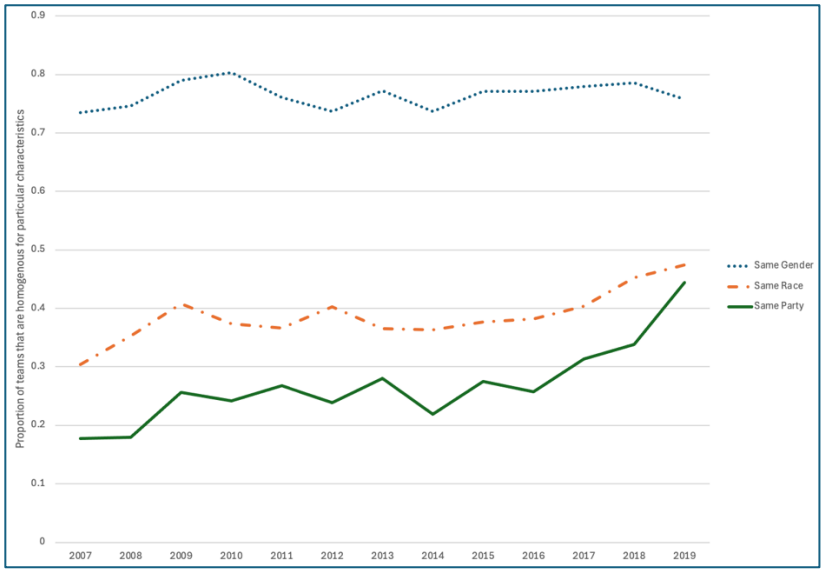
Dependent variable: Probability of raising Series B round

	(1)	(2)	(3)	(4)
2nd stage: DV = Raised B				
All-D	-2.101***	-1.897***	-1.256	-1.160
	(0.727)	(0.650)	(1.349)	(2.520)
All-R	-3.125***	-3.324***	-3.967***	-4.011***
	(1.158)	(1.098)	(0.779)	(1.310)
All-N			-1.840	-1.908
			(1.913)	(2.033)
Mixed-DR				0.102
				(2.546)
Team Size	-0.069***	-0.066***	-0.108***	-0.107***
	(0.020)	(0.019)	(0.032)	(0.037)
Year & Industry fixed effects	Yes	Yes	Yes	Yes
1st stage: DV = All-D				
Team Size	-0.020***	-0.023***	-0.023***	-0.023***
	(0.006)	(0.006)	(0.006)	(0.006)
LnNegativeAds-R	-0.008**	-0.007*	-0.006	-0.006
	(0.003)	(0.004)	(0.004)	(0.004)
LnNegativeAds-D	0.007*	-0.002	-0.003	-0.003
	(0.004)	(0.005)	(0.006)	(0.006)
LnPositiveAds-R		-0.003	-0.004	-0.004
		(0.003)	(0.004)	(0.004)
LnPositiveAds-D		0.014**	0.015**	0.015**
		(0.007)	(0.007)	(0.007)
Year & Industry fixed effects	Yes	Yes	Yes	Yes
1st stage: DV = All-R				
Team Size	-0.013***	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
LnNegativeAds-R	0.005***	0.004*	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
LnNegativeAds-D	0.001	-0.001	-0.002	-0.002
	(0.002)	(0.003)	(0.003)	(0.003)
LnPositiveAds-R		0.001	0.000	0.000
		(0.002)	(0.002)	(0.002)
LnPositiveAds-D		0.003	0.004	0.004
		(0.003)	(0.003)	(0.003)
Year & Industry fixed effects	Yes	Yes	Yes	Yes
1st stage: DV = All-N				
Team Size			-0.023***	-0.023***
			(0.005)	(0.005)
LnNegativeAds-R			-0.007**	-0.007**
			(0.003)	(0.003)
LnNegativeAds-D			0.003	0.003
			(0.005)	(0.005)
LnPositiveAds-R			0.002	0.002
			(0.003)	(0.003)
LnPositiveAds-D			-0.003	-0.003
			(0.006)	(0.005)
Year & Industry fixed effects	Yes	Yes	Yes	Yes

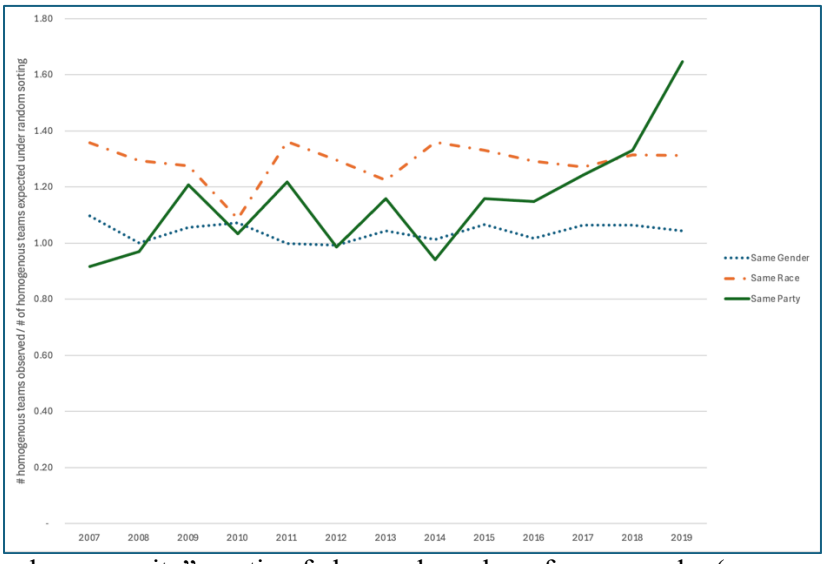
1st stage: DV = Mixed-DR				
Team Size				-0.024*** (0.006)
LnNegativeAds-R				0.000 (0.004)
LnNegativeAds-D				-0.001 (0.006)
LnPositiveAds-R				0.007* (0.004)
LnPositiveAds-D				0.016** (0.007)
Year & Industry fixed effects	Yes	Yes	Yes	Yes
Marginal effects				
All-D	-8.2%	-8.0%	-8.9%	-10.0%
All-R	-5.5%	-5.3%	-6.2%	-7.4%
All-N			-6.1%	-7.2%
Mixed-DR				-4.7%
Other info				
N	2851	2851	2851	2851
Wald test of exogeneity	17.88***	30.20***	53.04***	53.70***

Notes: Two-stage models using ivprobit command in STATA. Sample excludes teams with founders from parties other than Democrat, Republican, or Nonpartisan. Second-stage dependent variable is binary, set equal to 1 if the startup raised Series B funding and 0 otherwise. First-stage dependent variables are binary, set equal to 1 if the startup's founding team is AllD (AllR) [AllN] {Mixed-DR}. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Figure 1: Homogeneity of Founding Teams, 2007-2019



Panel A: Proportion of same gender, same race, and same party founding teams



Panel B: "Excess homogeneity" – ratio of observed number of same gender (same race) [same party] teams / expected number of same gender (same race) [same party] teams

Figure 2: Probability of Successfully Raising a Series B Funding Round

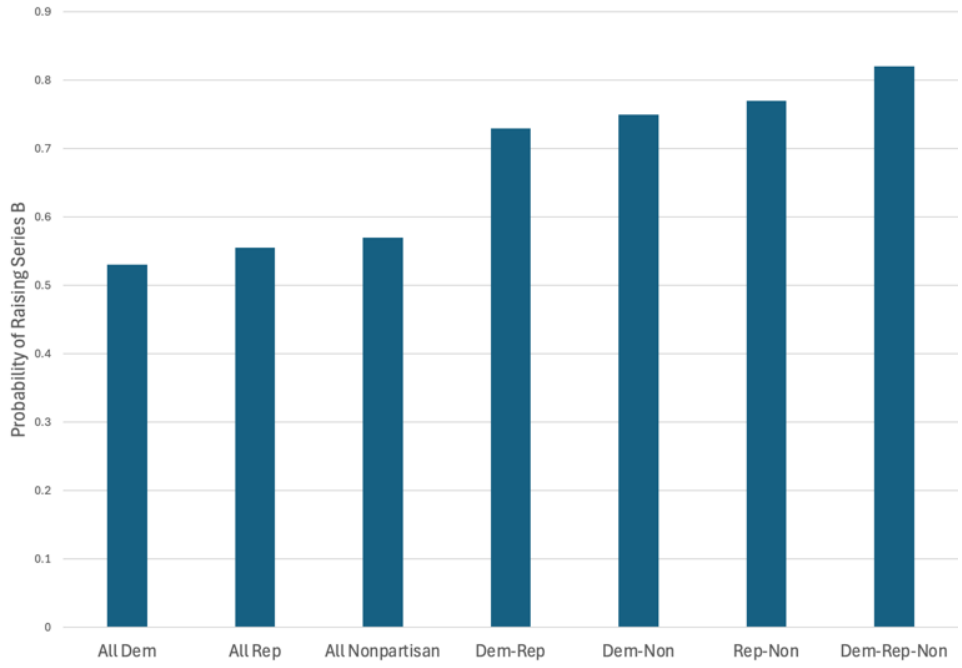


Figure 3: Time- and Media Market-based variation in Political Advertising

Negative advertising



Notes: Y-axis = count of advertisements in a given media market (DMA) and a given year. Source: Wesleyan Media Project.

Figure 3: Time- and Media Market-based variation in Political Advertising (continued)

Positive advertising



Notes: Y-axis = count of advertisements in a given media market (DMA) and a given year. Source: Wesleyan Media Project.

Appendix A: Detailed Description of Excess Homophily Measure

One challenge with assessing the extent of homophily in teams is constructing a benchmark for the expected baseline level of homogeneity that would be observed even if individuals did not engage in homophily-based team formation. This is a function of both the proportion of individuals in the sample who exhibit each relevant characteristic and the size of the teams formed.

First, consider a sample of 1000 founders, 90% of whom are male and 10% of whom are female. For now, assume that all teams consist of two people. Then, under random pairing of cofounders, we would expect that 82% of teams should be same-gender: 81% of teams will be all-male (900/1000*899/999=80.99%) and 1% of teams will be all-female (100/1000*99/999=0.99%). If we observe that 80% of all teams in this sample are same-gender, then although this is a high rate of same-gender teams, it does not reflect a tendency toward homophily. Further, if this sample of founders is, say, 60% Democrat and 40% Republican, and 60% of teams are same-party (whereas the expected rate would be 52%), then although the 60% same-party figure is lower than the 80% same-gender figure, these founders exhibit greater homophily based on political affiliation than based on gender. Thus, an informative calculation of homophily must take into account the baseline proportions of the relevant characteristics.

Next, let us relax the assumption that all teams consist of two people. Imagine that the 1000 founders described above form teams of either two or three people, such that instead of the 500 two-person teams above, we observe 200 two-person teams and 200 three-person teams. Under random team formation, we would still expect 82% of the two-person teams to be same-gender. But for the three-person teams, we would expect only 73% to be same-gender: 900/1000*899/999*898/998=72.88% and 100/1000*99/999*98/998=0.10%. Our expectation for the sample overall would be 77.5%. Thus, an informative calculation of homophily must take into account the team sizes that appear in the sample.

We construct a measure of excess homophily that takes into account both of these factors. First, we identify all founders in our sample whose startup raised Series A funding in year t. We tabulate the proportion of these founders according to their political party, gender, and race/ethnicity. We identify the number of startups in year t of each team size – two founders, three founders, … , ten founders. Next, we calculate the expected number of homogenous two-person (three-person)…[ten-person] startups, given

the number of startups and given the baseline proportions of founders with the relevant characteristics. We sum this number across all team sizes to get the aggregate expected number of homogenous teams for year t. Finally, we divide the observed number of homogenous teams from year t by this expected number. Ratios greater than 1 indicate a higher frequency of homogenous teams than would occur under random team formation. The larger the number, the greater the deviation from randomness, which we interpret as a higher tendency toward homophily.

Table A1 provides the data for our calculation of excess gender-homophily for two different years. Based on these calculations, the ratio of observed to expected same-gender teams was 1.10 in 2007 and 1.06 in 2018. We interpret this as evidence that excess homophily was lower in 2018 than in 2007. The full set of calculations for all years and for all relevant characteristics is available from the authors upon request.

This presentation of descriptive statistics assumes that a given founder in year t is equally likely to cofound with any other founder in year t. This is unlikely, given that startups span a range of technology/industry categories, and a founder of a biotechnology startup is unlikely to be "at risk" of partnering with a founder of a computing startup. In the main paper, we address this via multivariate statistical analysis of team formation through a method pioneered by Ruef (2002) and Ruef et al. (2003).

Table A1: Calculation of excess homophily based on gender for 2007 and 2018

Year	Team Size	Total firms	Observed All-Male	Observed All-Female	Expected All-Male	Expected All-Female	Observed/ Expected Ratio
2007	2	59	50	0	46.6	0.7	
2007	3	40	31	0	28.1	0.1	
2007	4	18	15	0	11.2	0.0	
2007	5	13	9	0	7.2	0.0	
2007	6	7	1	0	3.5	0.0	
2007	7	8	4	0	3.5	0.0	
2007	8	9	5	0	3.5	0.0	
2007	9	2	1	0	0.7	0.0	
2007	10	2	0	0	0.6	0.0	
2007	Aggregate		116		105.8		1.10
2018	2	126	94	6	95.8	2.1	
2018	3	24	18	1	15.9	0.1	
2018	4	8	8	0	4.6	0.0	
2018	5	4	0	0	2.0	0.0	
2018	6	3	2	0	1.3	0.0	
2018	7	1	1	0	0.4	0.0	
2018	8	3	1	0	1.0	0.0	
2018	Aggregate		131		123.2		1.06

Appendix B: Robustness of Reduced Form Results

In this Appendix, we examine the robustness of our results and begin to explore potential causal identification.

The first issue that might arise is that whereas most of the paper relies on linear probability models, the binary dependent variableS for dyadic team formation (Table 3) and for likelihood of raising Series B funding (Table 5) make probit or logit models more appropriate. We therefore estimate the same models as those in Tables 3 and 5 using probit estimation, and obtain similar results. These are presented in Appendix Table B1 and B2. Per footnote 9, we also present the full linear probability results of Table 3 in Appendix Table B3.

A second concern might stem from the fact that a subset of the sample firms report raising multiple Series A rounds. These firms may have different characteristics than other firms that correlate with our variables of interest in both of the performance regressions. [1] To control for this, Appendix Table B4 replicates the performance estimations from Tables 5 and 6, but include the control variable *Multiple A Rounds*. *Multiple A Rounds* is a binary variable set equal to 1 if firm *j* raised multiple A rounds of funding, and 0 if it only raised a single Series A round. As Model 1 indicates, the coefficients on the political homogeneity and heterogeneity variables are qualitatively unchanged in this model. The coefficient on *Multiple A Rounds* is negative and statistically significant, suggesting that firms that raise multiple A rounds are less likely to ultimately raise a B round. This is consistent with conventional wisdom in the venture capital industry, whereby firms raise a second A round when they have failed to reach the level of success that would warrant a (typically larger) Series B investment. Model 3 shows that the

[1] Roughly 18% of our firms raise multiple Series A rounds.

previous political patterns persist in the timing of receiving a Series B round when we include *Multiple A Rounds*. Not surprisingly, the coefficient on *Multiple A Rounds* is positive and substantively large – firms that have a second A round take, on average, almost one additional year to raise Series B conditional on successfully raising B. This is consistent with the conventional wisdom that a second A round typically occurs as a stopgap measure when a firm has difficulty achieving the record necessary to successfully pursue Series B funding.

A third concern that might arise in the core analysis is that one type of mixed team – Mixed DRN – is only feasible for teams of three or more cofounders, whereas the other types are feasible with two-member teams. Although all team performance models include a TeamSize variable, one might worry that the positive coefficient on Mixed DRN is conflated with benefits associated with larger teams. To address this, Models 2 and 4 in Appendix Table B4 present results for the subset of firms that have three or more members, i.e., excluding two-member firms. Model 2 offers qualitatively similar results as the previous models for the likelihood obtaining a Series B round, although the coefficient on *AllRep* is now large and statistically significant.[2] In Model 4, although all coefficients retain the same signs as before, almost none is statistically significant. The one coefficient that does not exhibit this pattern is the coefficient on *AllRep*, which, as in Model 2, is large and statistically significant.

Mechanisms

One might be concerned that political partisanship is correlated with more general lifestyle differences that actually drive team formation, and hence only spuriously correlated with team homophily (DellaPosta et al. 2015). To address this, we explore whether political homophily is

[2] There are only eight all-Republican teams of 3+ members that successfully raise Series B.

more pronounced during presidential election years. Our core assumption is that political differences are more salient during presidential elections. The relevant estimations are presented in Appendix Table B5. Model 1 replicates our fully specified estimation of dyad formation from Table 3, but only for years in which a Presidential election was held (2008, 2012, 2016). Model 2 replicates this estimation for non-Presidential election years. The coefficients on Democrat-only and Nonpartisan dyads are substantially larger for startups that raise a Series A round during a Presidential election year, and the negative coefficient on Republican-only dyads effectively disappears. To the extent that firms are founded during the same calendar year in which they seek Series A funding, this suggests that political homophily in team formation is exacerbated when political issues are more salient. This result motivates our instrumental variables analysis.

Appendix Table B1:
Homophily in startup team formation – dyad analysis - PROBIT

(This table replicates Table 3 in the paper, but estimates a Probit model)

	(1)	(2)	(3)	(4)	(5)	(6)
Same Party	0.041***	0.015				
	(0.003)	(0.013)				
Both Dem			0.043**	0.011	0.088***	0.055**
			(0.019)	(0.019)	(0.023)	(0.024)
Both Non			0.075***	0.044**	0.120***	0.088***
			(0.018)	(0.018)	(0.022)	(0.022)
Both Rep			-0.074**	-0.091***	-0.029	-0.050
			(0.030)	(0.030)	(0.031)	(0.031)
Dem-Non					0.892***	0.086***
					(0.029)	(0.019)
Rep-Non					0.028	0.031
					(0.019)	(0.019)
Same Gender						
		Yes				
Same Race		Yes				
Same County		Yes				
				Yes		Yes
Both Female				Yes		Yes
Both Male				Yes		Yes
Both White				Yes		Yes
Both Indian				Yes		Yes
Both Black				Yes		Yes
Both Hispanic				Yes		Yes
Both East Asian				Yes		Yes
Both Undisclosed				Yes		Yes
Fixed effects						
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	347196	347196	347196	347196	347196	347196
pseudo R-sq	0.077	0.080	0.077	0.082	0.078	0.083
Log-lklhd	-25982	-25928	-25973	-25830	-25954	-25815

Notes: Probit estimation. Dependent variable is binary, set equal to 1 if the dyad was actually realized (i.e., the two entrepreneurs actually cofounded a firm) and 0 otherwise. The risk set for potential cofounders is all other entrepreneurs who founded or cofounded a startup in the same industry and year as the focal founder. The omitted category in the fully specified models is Dem-Rep – a dyad consisting of one Democrat and one Republican. Standard errors clustered by industry-year are in parentheses. *** $p < 0.01$, ** $p < 005$, * $p < 0.10$

Appendix Table B2:
Startup performance as a function of team political composition:
Probability of Raising Series B round--PROBIT

(This table replicates Table 5 in the paper, but estimates a Probit model)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Party	-0.168***	-0.099						
	(0.073)	(0.075)						
All-D			-0.240***	-0.183**				
			(0.090)	(0.091)				
All-R			-0.170	-0.044			0.071	0.140
			(0.145)	(0.140)			(0.154)	(0.151)
All-N			-0.053	0.012			0.188	0.195
			(0.100)	(0.103)			(0.118)	(0.118)
Mixed DR					0.070	0.003	0.142	0.086
					(0.102)	(0.102)	(0.110)	(0.110)
Mixed DN					0.149*	0.078	0.222**	0.163
					(0.087)	(0.089)	(0.105)	(0.106)
Mixed RN					0.285***	0.220**	0.359***	0.306***
					(0.106)	(0.110)	(0.120)	(0.124)
Mixed DRN					0.332**	0.261*	0.403***	0.343***
					(0.141)	(0.142)	(0.149)	(0.149)
Team Size	0.170***	0.141***	0.171***	0.141***	0.153***	0.124***	0.154***	0.125***
	(0.036)	(0.035)	(0.036)	(0.035)	(0.039)	(0.038)	(0.039)	(0.038)
Controls								
Same Race	No	Yes	No	Yes	No	Yes	No	Yes
Same Gender	No	Yes	No	Yes	No	Yes	No	Yes
Same County	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2683	2683	2683	2683	2683	2683	2683	2683
pseudo R-sq	0.132	0.137	0.132	0.138	0.134	0.139	0.134	0.140
Log-lklihood	-1475.6	-1366.8	-1374.2	-1365.2	-1372.5	-1363.7	-1371.1	-1362.1

Notes: Probit estimation. Sample excludes teams with founders from parties other than Democrat, Republican, or Nonpartisan. Dependent variable is binary, set equal to 1 if the startup raised Series B funding and 0 otherwise. The omitted category in Models 7-8 is All-D. Standard errors clustered by industry-year are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix Table B3:
Homophily in startup team formation – dyad analysis

(This table replicates Table 3 in the paper, but shows the coefficients for the control variables)

	(1)	(2)	(3)	(4)	(5)	(6)
Same Party	0.002***	0.001				
	(0.001)	(0.001)				
Both Dem			0.002**	0.001	0.003**	0.002**
			(0.001)	(0.001)	(0.001)	(0.001)
Both Non			0.003***	0.002**	0.004***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
Both Rep			-0.002**	-0.003***	-0.001	-0.002*
			(0.001)	(0.001)	(0.001)	(0.001)
Dem-Non					0.003***	0.003***
					(0.001)	(0.001)
Rep-Non					0.001	0.001
					(0.001)	(0.001)
Same Gender		-0.001				
		(0.001)				
Same Race		0.003***				
		(0.001)				
Same County		0.009***		0.009***		0.009***
		(0.002)		(0.002)		(0.002)
Both Female				0.004*		0.004**
				(0.002)		(0.002)
Both Male				-0.002**		-0.002**
				(0.001)		(0.001)
Both White				0.002***		0.002***
				(0.001)		(0.001)
Both Indian				0.032***		0.031***
				(0.005)		(0.005)
Both Black				-0.004		-0.004
				(0.018)		(0.018)
Both Hispanic				0.015		0.014
				(0.019)		(0.019)
Both East Asian				0.008		0.008
				(0.008)		(0.008)
Both Undisclosed				0.002**		0.002**
				(0.001)		(0.001)
Fixed effects						
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	347196	347196	347196	347196	347196	347196
adj. R-sq	0.023	0.024	0.023	0.024	0.023	0.024
F	8.912	11.91	7.168	7.605	5.545	6.674

Notes: Linear probability models. Dependent variable is binary, set equal to 1 if the dyad was actually realized (i.e., the two entrepreneurs actually cofounded a firm) and 0 otherwise. The risk set for potential cofounders is all other entrepreneurs who founded or cofounded a startup in the same industry and year as the focal founder. The omitted category in the fully specified models is Dem-Rep – a dyad consisting of one Democrat and one Republican. Standard errors clustered by industry-year are in parentheses. *** p < 0.01, ** p < 005, * p < 0.10

Appendix Table B4:
Robustness checks: Multiple A rounds and teams of three or more cofounders

	(1)	(2)	(3)	(4)
	DV: raised Series B		DV: time to Series B	
Same Party				
All-D				
All-R	0.038	0.205**	2.419	11.340**
	(0.042)	(0.089)	(1.659)	(5.393)
All-N	0.062*	0.095	0.817	1.935
	(0.032)	(0.070)	(1.508)	(2.423)
Mixed DR	0.035	0.097*	-1.381	-0.709
	(0.029)	(0.054)	(1.147)	(1.849)
Mixed DN	0.052*	0.072	-1.203	-0.679
	(0.027)	(0.057)	(1.126)	(1.676)
Mixed RN	0.088***	0.138**	-2.212	-0.115
	(0.031)	(0.058)	(1.475)	(2.528)
Mixed DRN	0.098**	0.112**	-1.438	-0.447
	(0.033)	(0.056)	(1.270)	(1.760)
Team Size	0.026***	0.004	-0.113	-0.056
	(0.007)	(0.007)	(0.269)	(0.307)
Multiple A rounds	-0.113***	-0.076**	11.526***	11.398***
	(0.028)	(0.038)	(1.254)	(2.298)
Controls				
Same Race	Yes	Yes	Yes	Yes
Same Gender	Yes	Yes	Yes	Yes
Same County	Yes	Yes	Yes	Yes
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	3019	1263	2518	1051
adj. R-sq	0.129	0.084	0.103	0.101
F	11.77	2.48	11.95	3.73

Notes: Linear probability models. Sample excludes teams with founders from parties other than Democrat, Republican, or Nonpartisan. The omitted category is All-D. Models 2 and 4 are restricted to teams of three or more members, since mixed DRN teams are not possible for a two-person team. Standard errors clustered by industry-year are in parentheses. *** p < 0.01, ** p < 005, * p < 0.10

Appendix Table B5: Robustness checks: Homophily in team formation during Presidential election years. vs. non-election yearss

	(1) Presidential election year	(2) Non-election year
Both Dem	0.005*	0.002
	(0.002)	(0.001)
Both Non	0.008***	0.002**
	(0.003)	(0.001)
Both Rep	-0.001	-0.002*
	(0.002)	(0.001)
Dem-Non	0.006***	0.002***
	(0.002)	(0.001)
Rep-Non	0.002	0.001
	(0.002)	(0.001)
Same County	Yes	Yes
Both Female	Yes	Yes
Both Male	Yes	Yes
Both White	Yes	Yes
Both Indian	Yes	Yes
Both Black	Yes	Yes
Both Hispanic	Yes	Yes
Both East Asian	Yes	Yes
Both Undisclosed	Yes	Yes
Fixed effects		
Industry	Yes	Yes
Year	Yes	Yes
N	63172	284024
adj. R-sq	0.039	0.023
F	3.557	5.271

Notes: Linear probability models. Dependent variable is binary, set equal to 1 if the dyad was actually realized (i.e., the two entrepreneurs actually cofounded a firm) and 0 otherwise. The risk set for potential cofounders is all other entrepreneurs who founded or cofounded a startup in the same industry and year as the focal founder. The omitted category is Dem-Rep – a dyad consisting of one Democrat and one Republican. Standard errors clustered by industry-year are in parentheses. *** $p < 0.01$, ** $p < 005$, * $p < 0.10$

Appendix C: Assessment of Instrument Validity

Exclusion restriction: An ideal instrumental variable will be correlated with the first-stage dependent variable, but uncorrelated with the second-stage dependent variable except through the first-stage dependent variable. In our IV specifications we use Democratic and Republican positive and negative political advertisements in each election cycle in each of the 14 California DMA's. The paper briefly explains why we believe political advertising is likely to be correlated with the political makeup of entrepreneurial teams through affective polarization, but uncorrelated directly with a team securing a Series B round.

Two specific exclusion-restriction violations may come to mind. First, political ad blitzes happen in markets in which there is uncertainty around the electoral outcome. That uncertainty could change the way investors view the likelihood of success of startups in regulated sectors (e.g. health, fintech, energy) or more generally how demand might shift for a given product or service. In this way, political ad blitzes could directly impact firm performance directly, rather than solely through the endogenous regressor.

This would be a concern if the legislator in a given district determined regulatory policy for that district uniquely. In fact, political advertisements are overwhelmingly comprised of U.S. House elections or statewide elections (President, U.S. Senate, Governor, Treasurer). Regulatory policy is determined by the election outcome across the entire state of California (for Governor or Treasurer) of across the entire country (House, Senate, President, and affects the entire state (or nation) rather than an individual district. Thus, electoral uncertainty in a given district does not map into regulatory policy uncertainty in a given district. Electoral uncertainty is district- (or media market-) specific, whereas regulatory uncertainty is statewide or nationwide.

A second concern might be that negative political ads may tend to concentrate in high population, high-income markets, which are the same places that startups cluster and scale (e.g. Los Angeles, Bay Area, and San Diego). In this case, the instrument would incorporate these factors which are correlated with the likelihood of receiving Series B. In fact, the opposite is true empirically—the media markets saturated with negative political advertising (on average) are NOT Los Angeles, Bay Area, and San Diego, largely because the electoral districts in these markets are not very competitive. Reno is the second most saturated market;

advertising in this media market spills over largely into Lake Tahoe. Sacramento is the third most saturated market; it is super-competitive politically. In fact, Las Vegas is first most saturated market because its ads spill over into counties in Southeastern California.

Signs and statistical significance of the coefficient estimates: One aspect of instrument validity is the sign and statistical significance of the first-stage coefficient estimates. As noted earlier in the paper, the political science literature does not have strong hypotheses on the signs of all of the instruments. The most consistent expectation from this literature, however, is that negative ads create/enhance negative sentiments on out-group members and may have a muted positive effect on in-group members. Along these lines, in Table 7, negative Republican advertising lowers the probability of All-D teams and raises the probability of All-R teams. Democratic negative ads have similar in-group/out-group effects, but not in all specifications. The coefficients on the Republican negative ads are as predicted and frequently statistically significant at the 90% or above level. The coefficients on the Democratic negative ads are generally as predicted and mostly not statistically significant at the 90% or above level. This could be an artifact of the estimation or could mean that Republican negative ads are more effective with this group of entrepreneurs relative to Democratic negative ads.[3]

There are not strong theoretical predictions in the literature for the effect of positive ads. So perhaps it is not surprising that the positive ad variables in Table 7 have coefficients that are not statistically significant. There are two exceptions to the former statement. Positive Democratic ads enhance the probability of Democratic team formation at a statistically significant level across all models. Second, positive Democratic and Republican ads increase the likelihood of Mixed-DR teams at a statistically significant level. This suggests there is an effect of positive ads on entrepreneurial team formation.

In sum, the negative political advertising instruments for Republicans perform as expected, alienating out-groups while modestly supporting in-groups. The negative political advertising instruments for Democrats are signed as expected but largely not statistically significant. The theory of positive advertising's role in

[3] This is consistent with the findings of Ansolabehere and Iyengar (1995: 10), who find Republicans are more responsive to negative ads and Democrats are more responsive to positive ads. However, as noted in the text of the paper, the studies of the effect of positive ads on affective polarization is mixed.

affective polarization is mixed and so are our empirical results. At times, there seems to be a strong and intuitive effect, while other times there is no statistically meaningful effect.

Test statistics: Another way to test the validity of instruments are tests for exogeneity. The rule-of-thumb test is an F-statistic of 10 or more, or to conduct Stock-Yogo tests for bounds of bias in the IV estimation (Stock & Yogo 2005). We begin by noting these tests are for linear models (2SLS). There has been no work (that we are aware of) that develops similar tests for nonlinear instrumental variables (Wooldridge 2014). Moreover, in first stage linear probability models, F-statistics, in particular, may be probablematic because of the dichotomous nature of the dependent variable.[4]

Because of the nonlinear nature of the estimation, we use the Wald test for exogeneity which is appropriate for MLE nonlinear estimation. The Wald statistics of all models are reported in Table 7 and are statistically significant at the 99% level. Thus, the Wald test for exogeneity also suggests the instruments pass exogeneity filters. This give us some confidence in instruments.

Correlation of instruments: Another concern is that positive and negative ads may be highly correlated within and across political party, making it difficult to separately identify the effects of various instrumental variables. To address this concern, we present a correlation matrix of the political advertising instruments in Appendix Table C1. The table shows that the correlation between the political advertising instruments ranges from 0.46 to 0.80. The two negative advertising variables have a correlation of 0.60, the two positive advertising variables have a correlation of 0.46. While this level of correlation avoids collinearity, there is sufficient correlation that some of the variance in the instruments used for causal analysis will be absorbed by the other variable. We believe, however, that there is sufficient difference in the variables to obtain some meaningful, albeit incomplete, results.

[4] Despite the shortcomings, of these statistics in nonlinear estimation, we do find the F-statistics are all (but one) statistically significant at the 90% or 99% level in all the Table 7 models, but none reach the value of 10. The Cragg Donald statistics for linear models also do not reach the standand levels of statistical significance outlined in Stock-Yogo in models with year and industry fixed effects, but do reach the levels in models without fixed effects.

Plausibility of instrumented effects: One concern that may arise in any instrumental variables estimation is that the estimated effects in the instrumented models are implausible. This does not appear to be a challenge in this study. All of the estimated effects are 10.0% or lower. To further demonstrate the shift in results, Appendix Table C2 presents a comparison of the instrumented results and uninstrumented "naïve" probit results. The IV-estimated effects of the independent variables are slightly smaller than the single-stage probit estimated effects. This leads us to have some confidence in the general range of the effects.

Table C1 – Correlation matrix for the instrumental variables

	lnavgNegR	lnavgNegD	lnavgPosR	lnavgPosD
lnavgNegR	1.00			
lnavgNegD	0.61	1.00		
lnavgPosR	0.73	0.49	1.00	
lnavgPosD	0.53	0.80	0.47	1.00

Table C2 – Comparison of instrumented and uninstrumented probit results
DV = Raised Series B round

2nd stage of ivprobit (identical to Table 7)

	(1)	(2)	(3)	(4)
2nd stage: DV = Raised B				
All-D	-2.101***	-1.897***	-1.256	-1.160
	(0.727)	(0.650)	(1.349)	(2.520)
All-R	-3.125***	-3.324***	-3.967***	-4.011***
	(1.158)	(1.098)	(0.779)	(1.310)
All-N			-1.840	-1.908
			(1.913)	(2.033)
Mixed-DR				0.102
				(2.546)
Team Size	-0.069***	-0.066***	-0.108***	-0.107***
	(0.020)	(0.019)	(0.032)	(0.037)
Year & Industry fixed effects	Yes	Yes	Yes	Yes

Uninstrumented probit estimation

	(1)	(2)	(3)	(4)
All-D	-0.286**	-0.286**	-0.316***	-0.361***
	(0.072)	(0.072)	(0.073)	(0.075)
All-R	-0.206	-0.206	-0.238*	-0.284**
	(0.135)	(0.135)	(0.136)	(0.137)
All-N			-0.211**	-0.256***
			(0.088)	(0.090)
Mixed-DR				-0.192**
				(0.078)
Team Size	-0.003	-0.003	-0.009	-0.013
	(0.021)	(0.021)	(0.021)	(0.021)
Year & Industry fixed effects	Yes	Yes	Yes	Yes
Other info				
N	2851	2851	2851	2851
Log-likelihood	-1464.7	-1464.7	-1461.9	-1458.9
LR chi2	316.5***	316.5***	322.2***	328.2***
Pesudo R2	0.097	0.097	0.100	0.101

Notes: The uninstrumented probit estimation results in Models 1 and 2 are the same because the uninstrumented estimation is identical in both models. For the instrumented estimations, Models 1a and 2a are different because the first stage in each model uses different sets of instruments.