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Political Contributors by American Inventors: Evidence from 30,000 Cases

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Abstract

Has the Democratic Party's commitments to the knowledge economy allowed it to reap electoral rewards among inventors who produce new technologies or have American political institutions confined those payoffs to only a few regions and candidates? To answer these questions, one must observe changes in the political behavior of American inventors over time. I therefore merged U.S. patent and campaign contribution (DIME) data to develop a unique dataset capturing donations and ideology scores for 30,603 American inventors who donated to political campaigns from 1980 through 2014. Aggregate trends suggest the Democratic Party has made inroads among the constituency of American inventors and that inventors who give to Democrats have become much more liberal over time. But closer scrutiny of the data suggests that these trends are explained mostly by changes in political geography as Democratic inventors increasingly reside in a few strong liberal enclaves. As a result, their growing numbers and contribution amounts are increasingly concentrated on a relatively small number of political candidates. These findings suggest that the geographic disparities inherent to the nation's chosen strategy for knowledge economy development may ultimately limit that strategy's political viability.

1 Introduction

Inventors, or those who produce valuable intellectual property, are central actors in the American knowledge economy and are an equally important constituency for those elected officials within the Democratic Party who have embraced the knowledge economy and have worked to hasten its development (Haskel and Westlake, 2018; Schwartz, 2022; Short, 2022). But despite the importance of inventors in the American political economy, social scientists know surprisingly little about the political beliefs and behaviors of those who produce intellectual property and even less about how their behavior has changed over time. As a result, it is difficult to determine whether the Democratic Party's attempts to cultivate the knowledge economy have allowed it to reap electoral rewards.

Theory offers potentially competing answers to this question. On the one hand, because prominent Democrats have publicly championed the knowledge economy since at least 1972 (Geismer, 2015), we might expect those efforts to have motivated American inventors to express deeper levels of support for Democratic candidates over time, much in the way that the Party's positions on racial liberalism and labor legislation cultivated deeper levels of support for Democrats among minorities and the working-class (Schickler, 2016; Schlozman, 2015). On the other hand, the imperatives of divided government forced lawmakers to rely heavily on market-based reforms, like changes to U.S. patent law, to promote knowledge economy development (Short, 2022) and, as a result, knowledge economy development to date has generally been confined to only a few regions, like California's Silicon Valley (Moretti, 2013; Short, n.d.). Accordingly, we might also expect that American political institutions—namely winner-take-all elections in single-member

districts—have concentrated the electoral payoffs to a few Congressional Districts or states (Rodden, 2019).

To determine if either hypothesis has empirical support, I developed a unique data set containing ideology scores and information on the donation behavior for 30,603 American inventors across 18 election cycles. Specifically, I used the research data sets provided by the U.S. Patent and Trademark Office to identify U.S. residents listed as a named inventors on a U.S. patent applied for on or after January 1, 1979. I then merged the inventor data with campaign contribution data from the Database on Ideology, Money in Politics (DIME) (Bonica, 2016) to capture campaign donations and the common-factor ideology scores imputed from those donations among U.S. inventors for every election cycle from 1980 through 2014. Finally, I linked the self-reported donor employer names to organizations in the Capital IQ database to obtain unique employer identifiers and industry data (4-digit SIC codes), where available. With such data, it is possible to analyze changes in aggregate donation patterns and their geographic expression; it is also possible to determine whether American inventors are unique in their behavior after controlling for things like geography, place of work (firm), and sector. I briefly describe and motivate the construction of the data set in section 2 (and more details on construction can be found in Appendix A).

Analysis of the data set confirms that, while the Democratic Party has made significant inroads among American inventors in terms of garnering higher shares of donors and donations, the vast majority of those benefits have increasingly come from only a few regions and have flown to a relatively small number of candidates, as shown in section 3. Similarly, though the subset of American inventors who contribute to Democratic

candidates has become much more liberal over time, this development seems to be driven by changes in political geography, as shown in section 4. The average ideology scores of Democratic inventors are not substantively different from those of their peers (those of the same gender who work at the same firm and live in the same Congressional District), and the large observed decline in ideological variance among Democratic inventors has been significantly driven by similar declines in the average ideology scores across the districts in which American inventors reside. Taken together, the results suggest that American political institutions have limited the electoral payoffs for the Democratic Party, that American inventors who donate to campaigns increasingly live in liberal enclaves of similar ideological persuasion, and that knowledge economy participation motivates regional rather than individual differences in political behavior.

This study is closest in nature to Broockman, Ferenstein, and Malhotra (2019) in which the authors surveyed technology entrepreneurs[1] and found them to be as liberal or more liberal than Democratic donors on issues related to economic redistribution, globalization, and social issues but closely aligned with Republican donors on issues of government regulation. A key benefit of that study is that it sheds light on the heterogeneity of political preferences among economic elites, including technology entrepreneurs, in today's political environment. The present study sacrifices that nuance by focusing on aggregate ideological scores and donation patterns. But an important benefit of this strategy is that it allows researchers to analyze changes over time (across 18 election cycles) and across geographic space, both of which are essential to understanding the way in which American political

[1]Specifically, the authors randomly sampled 8,499 individuals listed as founders or CEOs of companies in Crunchbase and interviewed nearly 700 of them.

institutions may constrain the electoral payoffs to be derived from championing a specific vision for the nation's economic future. The present study also differs in focusing more on innovators than entrepreneurs, or those who produce new and valuable IP (often for incumbent firms) rather than those who start their own businesses.[2]

By analyzing ideological changes among American inventors, this study contributes to a large and established literature on political polarization in the United States (Levendusky, 2009; Fiorina, Abrams, and Pope, 2010; Abramowitz, 2013; McCarty, Poole, and Rosenthal, 2016), especially those studies exploring the connection between polarization and the rural-urban divide in American politics (Cramer, 2016; Rodden, 2019). But it contributes much more directly to a small and growing literature on the ways in which American political institutions have shaped knowledge economy development in the United States (Soskice, 2022; Barnes, 2022; Gingrich, 2022). A key implication is that American institutions have the potential to create a political form of "double marginalization" when it comes to promoting new models of economic growth, an effect that may cast doubt on the viability or sustainability of "third-way" or "neoliberal" economic reforms more broadly. By first constraining the economic policy choice set to those policies that exacerbate geographic inequalities and then impeding the formation of cross-regional coalitions that might advocate for a more equitable geographic distribution of resources, American institutions may doom many such reforms to marginal (and highly unequal) success. I comment on this possibility and other implications in the Conclusion. Importantly, though, this study moves beyond prior work to consider the ways in which institutions plausibly influence political behavior. To do so requires disentangling the effects of inventorship—

[2]Though, in the absence of inventor surveys, it is difficult to know if this distinction is salient.

an individual characteristic—from the effects of geography when explaining aggregate changes in behavioral patterns, which is a difficult undertaking. A secondary implication, then, is that, to the extent we associate Democratic gains among inventors or rising inventor liberalism with the knowledge economy transition, these shifts appear to be rooted in regional rather than individual behaviors.

2 Construction of the Dataset

The process for creating the inventor-donor data set involved three main steps: (1) identify all inventors (first and last name, firm, and city and state of residence) listed on U.S. patents that were applied for on or after January 1, 1979 and who resided within the United States using research datasets provided by the U.S. Patent and Trademark Office; (2) identify the subset of these U.S. inventors that also appear in the DIME database using fastLink (Enamorado, Field, and Imai, 2019) and acquire data on their contribution history and imputed ideology; and (3) match the self-reported employer names from the DIME database to organizations in Capital IQ to generate unique identifiers for these organizations plus other information, like SIC codes, where available. More details on each of these steps and statistics characterizing the aggregate dataset are provided in Appendix A.

A primary advantage of this dataset is that it allows us to study the political behavior of the people and organizations that produce new technologies while remaining agnostic as to the boundaries of what constitutes "technology," which can bias the results of any political analysis. U.S. patent law places very few restrictions on what constitutes patent eligible

subject matter,[3] and so subject to certain disclosure requirements and an examination of prior art, the Patent and Trademark Office generally issues patents for any new and non-obvious invention, broadly construed. Accordingly, the technologies that are the subject of this study are not limited to the computer and internet technologies that tend to dominate the news cycle but also include new drugs, nanotechnology, genetically modified crops, and many other lesser-known domains of invention, like the design (look and feel) of new sneakers. While this may seem over-inclusive to some, it is important to cast a broad net to avoid the bias inherent in individual judgments about what constitutes "technology."

Table 1 illustrates this point. To generate the table, I identified the primary technological domain of each inventor-donor using the classification scheme developed by the National Bureau of Economic Research, and then tabulated the total dollar amount of campaign contributions across all election cycles within each domain. The table presents the top 7 results in two tranches: the top 7 technology domains with the highest share of donations going to Democratic candidates and committees ("High Dem Share") and the top 7 with the highest share of donations going to Republican candidates and committees ("High Rep Share"). The table shows that inventors in computing (computer hardware and software, computer peripherals, and semiconductor devices) and some other areas like optics and genetics give quite heavily to Democratic candidates and committees. At the same time, inventors in other technological domains, including those related to agriculture and resource extraction, donate quite heavily to Republican candidates and committees. All of these inventors are arguably working at the technological frontier within their

[3] *Diamond v. Chakrabarty*, 447 U.S. 303, 309 (1980) ("The Committee Reports accompanying the 1952 [Patent] Act inform us that Congress intended statutory subject matter to 'include anything under the sun that is made by man.'").

Table 1: **Donations by Technology Classes Show Political Bias**

NBER Subcategory	Dem Share (%)	Rep Share (%)	Total (Mil USD)
High Dem Share			
optics	66.84	29.72	3.73
computer hardware & software	63.29	31.40	57.73
computer peripherals	60.33	23.07	3.45
semiconductor devices	58.92	28.64	3.60
information storage	50.19	23.45	19.36
resins	48.91	38.93	2.98
genetics	48.23	35.25	0.91
High Rep Share			
pipes & joints	5.54	93.06	3.83
heating	7.29	89.13	4.05
misc. mechanical	14.21	81.61	16.99
gas	14.79	81.27	1.92
agriculture, husbandry, & food	11.86	79.93	14.35
earth working & wells	16.74	78.89	9.32
motors, engines, & parts	10.29	77.55	3.59

Note:
In this table, each inventor-donor is associated with a technological subcategory according to the scheme developed by the National Bureau of Economic Research. Each row captures the aggregate contributions made by inventor-donors in that technological subcategory (in millions of 2019 dollars) as well as the share of that total going to Democratic candidates and committees and the share going to Republican candidates and committees. There are 37 technology subcategories in the NBER scheme but only 14 are presented in the table, capturing the top 7 results in each of two tranches: the top 7 with the highest share going to Democratic candidates and committees and the top 7 with the highest share going to Republican candidates and committees.

respective industries and are therefore participating in the knowledge economy. But an exclusive focus on those who work in computer and internet technology would suggest—inappropriately in my view—that commanding majorities of knowledge economy workers have a strong partisan attachment to the Democratic Party. An analysis of all inventor-donors helps avoid this bias.

Though the lack of comparable databases makes it difficult to benchmark descriptive

statistics, the database can be used to replicate prior findings in ways that provide some confidence that it is soundly constructed. For example, Rodden (2019, Fig. 3.1) reports that Democratic presidential vote share was not correlated with measures of patent output (patents per thousand people on the log scale) as recently as 1996, but the two variables have become strongly correlated since then. Data from the inventor-donor data set produces similar findings, albeit with respect to donor rather than vote shares. For each of four election cycles (1980, 1996, 2004, and 2012), Figure 1 shows the share of all patents applied for by inventors located in each Congressional District against the share of all inventor donations to Democratic candidates and committees by inventor-donors located in that same district. The blue line shows the results of regressing Democratic contribution shares on patent shares. The figure shows that, from 1980 through 1996, the patent share of a Congressional District was not significantly associated with the share of total donations to Democratic candidates or committees by inventor-donors. But since 1996 that relationship has grown more positive. In this way, changes in regional donation patterns from the inventor-donor dataset mirror changes in regional voting patterns reported in other studies.

3 American Political Institutions Shape Donation Patterns

If the Democratic Party's commitments to the knowledge economy have produced electoral payoffs, we would expect to observe the Democratic Party earning larger aggregate shares of either inventor donations or inventor donors, the latter of which neutralizes any potential bias from a small number of donors who contribute exceptionally high amounts

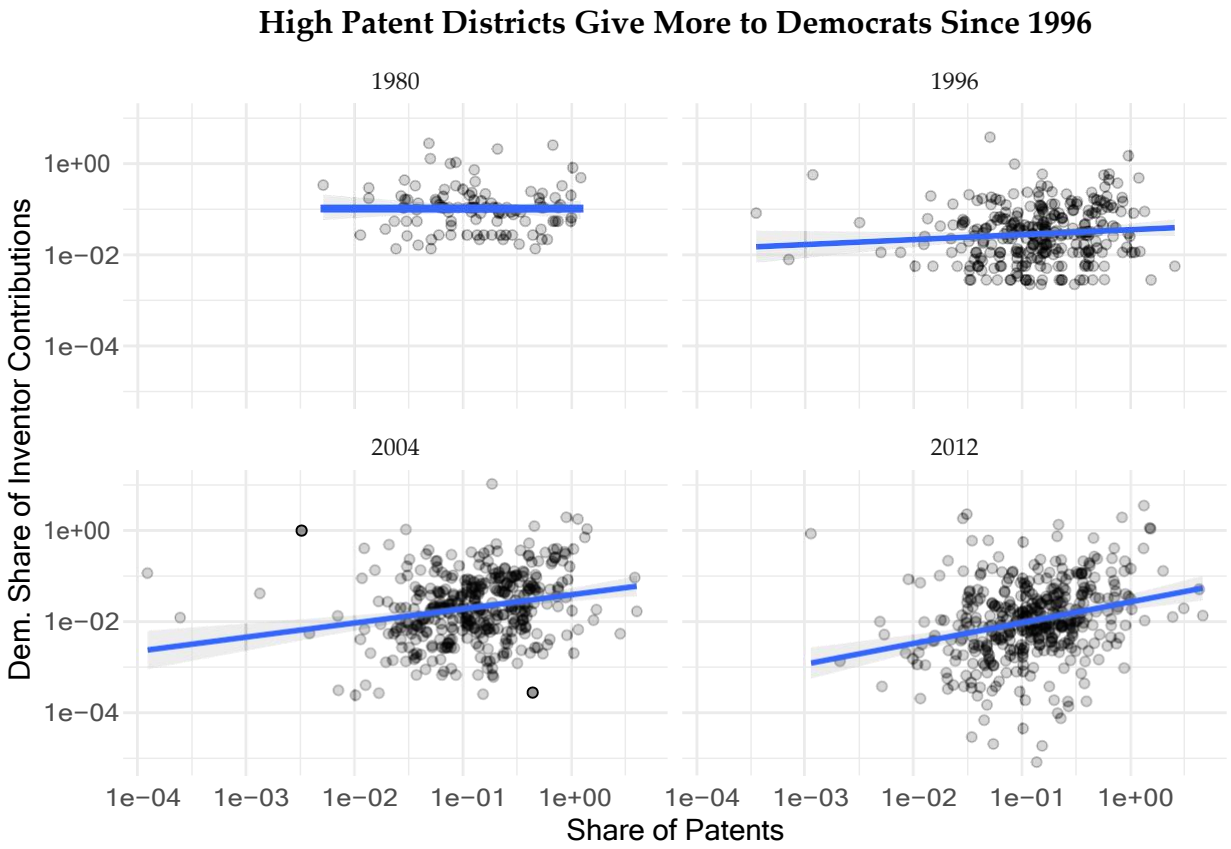

Figure 1: Each plot in this figure shows the share of all patents applied for by U.S. inventors in each Congressional District against the share of all contributions to Democratic candidates and committees from inventor-donors in the same District. Each panel shows the results from one of four presidential election cycles (1980, 1992, 2004, and 2012). Patents with more than one inventor were counted as a fractional share (1 divided by the number of inventors) accruing to each inventor. Congressional District boundaries are based on the 1990 Census and held constant across all election cycles. Districts that produced no patents or no campaign contributions are treated as missing data. The blue line shows the best linear fit given the data (i.e., a regression of contribution share on patent share).

to political campaigns. Figure 2 shows that this has in fact occurred. In each election cycle from 1980 to 2014, the figure shows the total amount of political contributions (in millions of 2019 dollars) that American inventors made to each of the two major parties (left panel) as well as the total number of inventors that donated to each of the two major parties (right panel). Though Republicans attracted about 73.3 percent of inventor donations in the 1980 election cycle, the parties were almost at parity in the 2008 election cycle, and though Republicans still held an advantage in the 2014 cycle, it was significantly smaller than in prior years (58.5 percent of donations in a cycle where 67.7 million dollars was raised by the two parties). Democratic gains among inventors are even more significant when considering the share of donors rather than donations: though 68.5 percent of inventors contributed to Republicans in the 1980 election cycle, 62.9 percent of inventors contributed to Democrats in the 2014 cycle. This suggests that, between 1980 and 2014, the Democratic Party's commitments to knowledge economy development effectively reversed the Republican Party's commanding advantage in the number of donors.

While Figure 2 suggests that the Democratic Party has made significant progress in courting inventors as a constituency, is amenable to multiple interpretations. Importantly, changes in aggregate donation patterns do not reveal whether inventors, as a class, have begun to favor Democratic candidates and committees by virtue of their status as producers of new technologies or whether inventors increasingly reside in metropolitan areas that have acquired strong attachments to the Democratic Party over time.

To disentangle the effects of geography and the effects of inventorship, I matched inventor donors to non-inventor donors who have the same (imputed) gender, work at the same

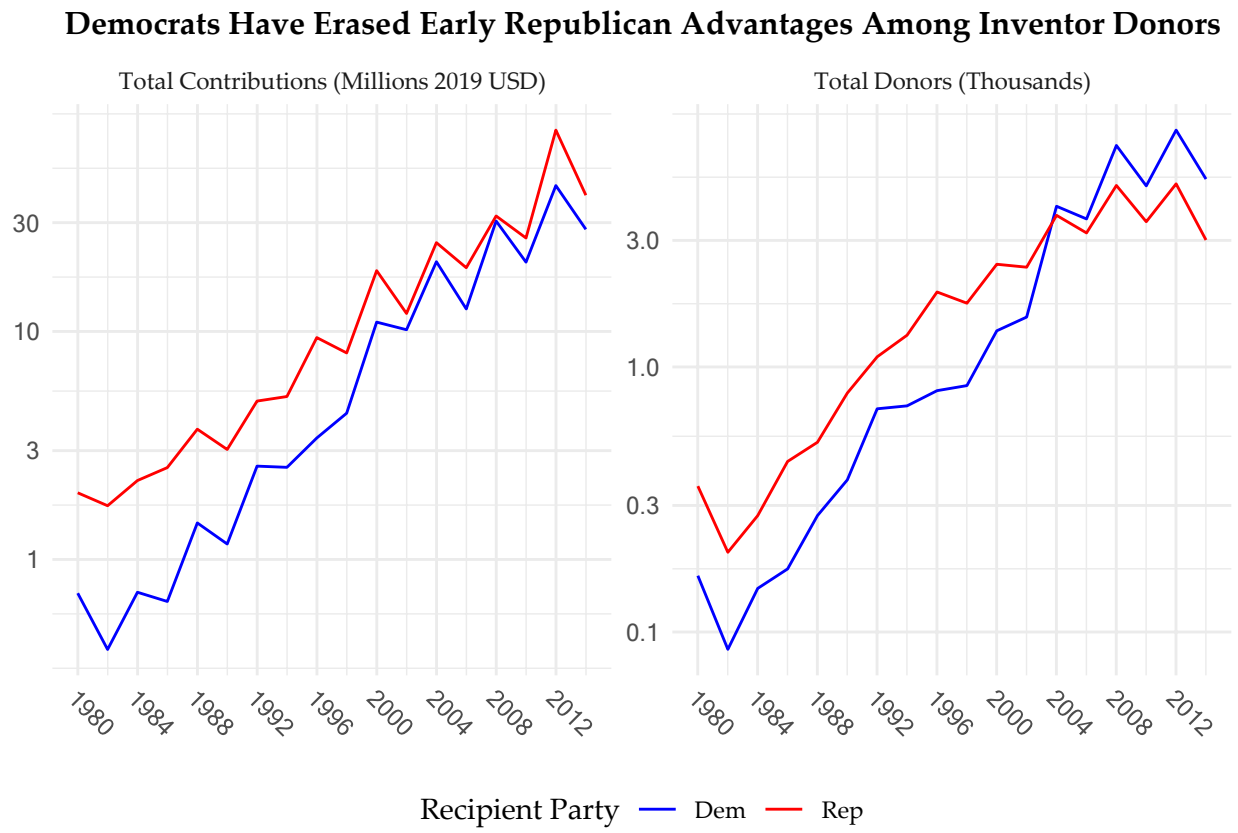

Figure 2: The left panel in this figure shows total contributions by American inventor-donors in all federal elections from 1980-2014 broken down by recipient type: Democratic candidates and PACs (blue line) and Republican candidates and PACs (red line). The contribution amounts are reported in millions of 2019 dollars. The right panel shows the total number of American inventor-donors that contributed to each recipient type for each election cycle from 1980-2014. Inventor-donors are political donors who reside in the United States and are listed as an inventor on any United States patent applied for on or after January 1, 1979. Both vertical axes are on the logarithmic scale.

organization, and reside in the same Congressional District. For each election cycle, I then regressed a binary variable indicating whether the donor contributed to Democratic candidates or committees on another binary variable indicating whether the donor is an inventor. The over time evolution in the coefficients on the inventorship variable reveal whether inventors have developed a stronger propensity to contribute to Democrats after controlling for differences arising from gender, place of work, and place of residence. The regressions were run in matched data sets including all inventors (any donor that applied for a patent in the current election cycle or any time prior) and the subset of "switchers," which are inventors who had not applied for a patent in the prior election cycle but did in the current election cycle (i.e., donors who only became inventors in the current election cycle). The estimates from the subset of switchers are not a separate quantity of interest, but provide a robustness check to ensure that that the estimates observed among all inventors are comparable to those observed among first-time inventors and that the groups are not materially different.

The regression output is reported in Appendix B, but the main result is illustrated in Figure 3, which shows the estimated coefficients on the inventorship variable in each election cycle. The solid points and confidence intervals show the results from estimating the coefficients using the full matched data set, while the crossed points (with no confidence intervals) show the point estimates from running the same regressions using the subset of switchers. As shown, from the 1980 through the 2006 election cycles, inventors were just as likely as their peers (those of the same gender, place or work, and place of residence) to donate to Democratic candidates and committees, but since the 2008 election cycle, they

have become slightly *less* likely than their peers to donate to Democratic candidates and committees. These results are consistent with Broockman, Ferenstein, and Malhotra (2019) to the extent they suggest that inventors have somewhat unique political preferences and may be more conservative than their peers in certain dimensions. But they also suggest that changes in political geography are driving Democratic gains among inventors: after controlling for geography, inventorship actually pulls in the opposite direction and would alone suggest that the Democratic Party has been losing, not gaining, ground with this constituency.

In a majoritarian political system with single member districts, the tendency for knowledge economy work to cluster (or agglomerate) in a handful of regions with strong pre-existing advantages might limit the electoral payoffs to be earned from supporting the knowledge economy transition (Moretti, 2013; Rodden, 2019). If this were true, we would expect to see patterns of political behavior that reflect patterns of economic behavior, with an increasing geographic concentration in innovation translating to an increasing geographic concentration in inventor donations. Table 2 indicates that this has taken place. For each of four presidential election cycles (1988, 1996, 2004, and 2012), the table shows the number of counties that participated in the knowledge economy (as evidenced by patenting) and the share of all U.S. patents flowing from the top 1 percent of those counties (the first two rows). As shown, innovation has spread modestly across geographic space from roughly 78 percent of the nation's 3,006 counties in 1988 to roughly 84 percent of all counties in 2012, but it has also become more concentrated: the top 1 percent of counties have increased their share of all patents from 30.4 to 43.6 percent.

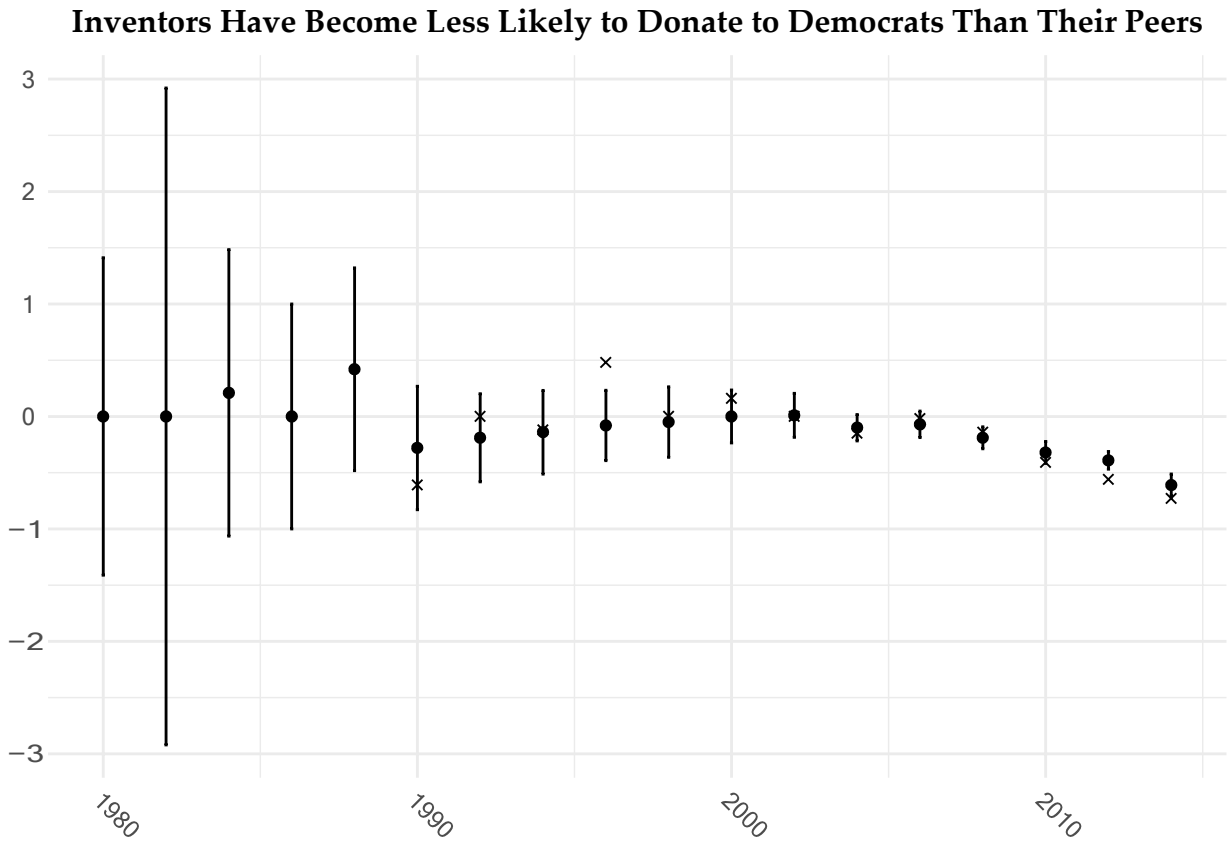

Figure 3: This figure shows the point estimates and 95 percent confidence intervals from regressing a binary variable indicating whether the donor contributed to a Democratic candidate or committee on a binary variable indicating whether the donor is an inventor, after matching inventors with non-inventors who have the same imputed gender, place of work, and place of residence. The regressions are run for each matched data set within each election cycle from 1980 through 2014. The vertical axis reflects the estimated difference in the logged odds of donating to a Democratic candidate or committee between inventors and non-inventors, with negative numbers implying less than even (50-50) odds. The solid points and confidence intervals illustrate the results from running regressions using the full matched data set where an inventor is any individual that applied for a patent in the current election cycle or any time prior. The crossed points illustrate the point estimates (with no confidence intervals) from running the same regression after confining the matched data set to switchers, or those who were not inventors in the prior election cycle but are in the current election cycle.

Table 2: **Inventor Donations Have Become More Concentrated by Geography**

Variable	1988	1996	2004	2012
Inventions by County				
Number of Counties	2322.0	2502.0	2539.0	2514.0
Share of Patents from Top 1% of Counties	30.4	32.8	36.0	43.6
Inventor Donations by Zip Code				
Number of Zip Codes	712.0	2200.0	6204.0	14832.0
Share of Dem. Donations from Top 1% of Zip Codes	20.6	44.0	54.5	60.3
Share of Rep. Donations from Top 1% of Zip Codes	15.9	25.9	41.4	59.8

Note:
This table shows growth in the concentration of patenting (first two rows) and in inventor donations (next three rows) across four election cycles (1988, 1996, 2004, 2012). The first two rows show the number of counties in which inventors applied for US patents and the share of all patents flowing from the top 1 percent of those counties in each election cycle. The third row shows the number of zip codes in which inventors made political contributions in each election cycle. The fourth and fifth rows show the share of donations to Democrats (fourth row) and to Republicans (fifth row) flowing from the top 1 percent of those zip codes in each election cycle.

Table 2 also shows that these economic trends are mirrored—to an even more extreme degree—in the political behavior of inventors. The next three rows show the number of zip codes from which inventors donated to political campaigns followed by the Democratic Party's share (and the Republican Party's share) of party donations flowing from the top 1 percent of those zip codes. Campaign contributions, by this measure, have become much more concentrated than inventions. The Democratic Party's share of donations flowing from the top 1 percent of zip codes has grown, for example, from about 20 percent in the 1988 election cycle to more than 60 percent in the 2012 election cycle.

Given that most campaign donations in non-presidential races goes to local candidates, we would also expect to see the growing geographic concentration in donations (shown in Table 2) to be reflected in a tendency for higher shares of donations to go to only a few candidates. Tables 3 and 4 indicate that this has occurred for presidential and mid-term

Table 3: **Higher Shares of Donations in Presidential Races Go to a Few Candidates**

Variable	1988	1996	2004	2012
Number of Dem. Candidates	144.0	310.0	340.0	489.0
Number of Rep. Candidates	178.0	450.0	423.0	537.0
Share of Donations to Top 1% of Dem. Candidates	13.1	15.1	40.6	67.3
Share of Donations to Top 1% of Rep. Candidates	26.5	18.9	33.8	58.7

Note:
This table shows the number of Democratic and Republican candidates that received donations from inventors (rows one and two) and the share of party donations going to the top 1 percent of candidates (rows three and four) for each of four presidential election cycles (1988, 1996, 2004, and 2012).

elections, respectively. Table 3 shows that, while the number of candidates who receive donations from inventors grew significantly for both parties from 1988 to 2012, the share of donations going to the top 1 percent of candidates also become more concentrated, growing from 13 to 67 percent for Democrats and from 27 to 59 percent for Republicans. Table 4 shows that, while this dramatic acceleration in concentration among recipients is driven largely by donations to presidential candidates, the trends still exist in midterm elections. Between 1990 and 2014, the share of inventor donations going to the top 1 percent of Congressional candidates grew from 12 to 20 percent for Democrats and from 14 to 20 percent for Republicans.

Closer inspection of the top recipients suggests that inventor donations remain concentrated partly because inventors (from both parties) behave like conventional donors in giving mostly to local candidates and partly because Democratic donors send much of their more expressive or strategic donations to candidates who either reside in states that are leading knowledge economy development or who have publicly promoted the knowledge economy. On the whole, local giving among inventors has declined, but still

Table 4: **Higher Shares of Donations in Midterm Races Go to a Few Candidates**

Variable	1990	1998	2006	2014
Number of Dem. Candidates	221.0	285.0	408.0	433.0
Number of Rep. Candidates	261.0	376.0	405.0	523.0
Share of Donations to Top 1% of Dem. Candidates	11.5	19.7	18.5	19.7
Share of Donations to Top 1% of Rep. Candidates	14.2	12.0	15.1	19.8

Note:
This table shows the number of Democratic and Republican candidates that received donations from inventors (rows one and two) and the share of party donations going to the top 1 percent of candidates (rows three and four) for each of four midterm election cycles (1990, 1998, 2006, and 2014).

made up a majority of donations in the 2014 election cycle (down from 71.6 percent to 51.8 percent of all inventor donations from 1982 to 2014). Among Democratic recipients, in the 2012 presidential election, three of the biggest recipients of inventor donations behind presidential candidate Barack Obama were Senate candidate Elizabeth Warren from Massachusetts, Senator Maria Cantwell of Washington, and Congresswoman Nancy Pelosi of California. Pelosi raised almost all (98.6 percent) of those donations from local donors, but Warren and Cantwell both raised higher shares from out of state donors (47.2 and 33.5 percent, respectively). Similarly, in the 2014 midterm elections, Senators Ed Markey of Massachusetts and Kay Hagan of North Carolina were two of the top four recipients and both drew significant shares of inventor donations from out of state donors (47.9 and 37.5 percent, respectively). But the top recipient in that cycle was Senator Cory Booker of New Jersey, who has taken prominent positions on the knowledge economy (Techonomy, 2015) and who received 81.8 of his donations from out of state inventors; the fourth largest recipient was Senator Gary Peters of Michigan who has sought to promote technological innovation in his home state, especially within the auto industry (Detroit Economic Club,

2018), and who received 73.1 of his donations from out of state inventors. As these examples suggest, there is some opportunity to cultivate inventor support for candidates in non-leading states, but those few have successfully capitalized on those opportunities. The dominant tendency is instead for large shares of Democratic inventor donations to flow to candidates in regions that are leading the knowledge economy transition.

To summarize, the analyses above suggest that, while the Democratic Party has made great inroads within the constituency of American inventors, they have achieved those gains not because these knowledge economy workers have become more strongly attached to the Democratic Party by virtue of their status as inventors, but because these knowledge economy workers increasingly work and reside in regions that have developed strong preferences for Democratic candidates. And, consistent with the hypothesis that American political institutions have constrained the electoral payoffs the Democratic Party can earn from its commitments to the knowledge economy, increasing shares of inventor donations flow from only a few regions and increasing shares of those donations in turn accrue to only a few candidates. The next section looks for evidence of an alternative payoff. Has the Democratic Party's positions on the knowledge economy turned a relatively moderate group of donors and voters into more ardent and committed liberals?

4 Changes in Inventor Ideology Arise Primarily from Geographic Trends

The analyses in the previous section focused on changes in patterns of inventor donations, but a main advantage of the inventor donor database is that it also enables analysis of ideological changes among inventors. Figure 4 depicts how inventor ideology has changed over time. For each election cycle from 1980 through 2014, it shows the average ideology score (left panel) and the variance in ideology scores (right panel) for two sub-populations: those who contributed to Democratic candidates and committees (blue line) and those who contributed to Republican candidates and committees (red line).

As shown, the average ideology score among Republican donors remained relatively stable at about 0.75 until the 2006 election cycle, when it increased a bit. This suggests that inventors who contribute to Republicans were fairly conservative to begin with and have become slightly more conservative since 2006. In contrast, the average ideology score among Democratic donors remained constant and close to zero (at about -0.08) through 1990 but then dropped dramatically over the next twelve election cycles, reaching a low of -1.23 in the 2012 election cycle. This suggests that inventors who contribute to Democrats were a relatively moderate group to begin with but became much more liberal beginning with the election of 1992.

Similarly, the variance or spread in ideology scores for Republican donors was quite small from the beginning and appears to have slightly increased over the course of the entire time series. In contrast, inventors who gave to Democrats appeared to be relatively

moderate, on average, because they were a somewhat heterogeneous bunch and had widely varying ideology scores in early election cycles. But from roughly 1992 through 2012, the variance in ideology scores for Democratic donors dropped dramatically so that in recent elections, Democratic donors have been as tightly distributed about their mean as Republican donors were in 1980 and 1982. In short, American inventors that contribute to political campaigns have become more polarized, as we observe both higher separation between average ideology scores and lower variances around those means, but that polarization arises mostly from ideological changes that took place among inventors who contribute to Democrats.

Inventors Have Become More Polarized Over Time

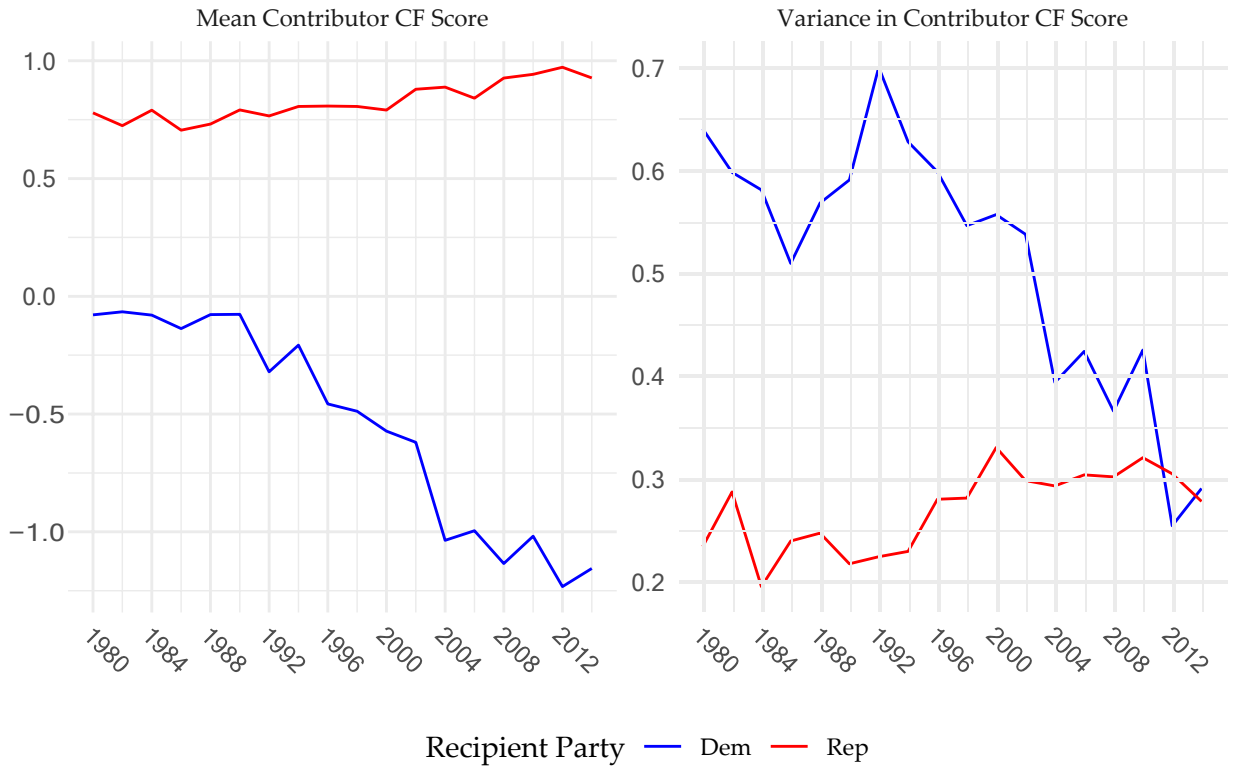

Figure 4: This figure shows the average (left panel) and variance (right panel) of the ideology scores for those inventor-donors who contributed to Democratic candidates and committees (blue line) and those who contributed to Republican candidates and committees (red line) in each election cycle from 1980 through 2014.

As with the aggregate donation patterns depicted in Figure 2, these aggregate ideological shifts are amenable to multiple explanations. It is possible that the Democratic Party's efforts to promote the knowledge economy have brought more inventors into the Party and made them more sympathetic to the Party's positions on issues like social welfare spending thereby causing them to become more liberal in their overall ideology. In this sense, the Party may reap electoral rewards from its knowledge economy position-taking by not only attracting more inventors but also inducing them to behave more like mainstream Democrats. The fact that the turning point for Democratic donors appears to be the 1992 election cycle, an election in which the Democratic presidential candidate successfully courted Silicon Valley entrepreneurs (Miles, 2001; O'Mara, 2019), might support this interpretation. Alternatively, the acceleration of knowledge economy development in the mid-1990s associated with the rise of the internet may have simply attracted many more inventors to metropolitan areas that have become increasingly liberal, and inventor ideologies have simply tracked these changes in political geography.

To disentangle the effects of geography and the effects of inventorship, I used the subset of matched inventor donors (described above in connection with Figure 3) and regressed ideology scores on a binary variable indicating whether the donor is an inventor. The over time evolution in the coefficients on the inventorship variable reveal whether inventors have become more liberal after controlling for differences arising from gender, place of work, and place of residence.

The regression output is reported in Appendix B, but the main result is illustrated in Figure 5. As with Figure 3, the solid points and confidence intervals illustrate the results from

estimating the results using the full matched data set, while the crossed points (with no confidence intervals) show the point estimates from running the same regressions using the subset of switchers (those who applied for their first patent in the same election cycle). The figure shows that inventors were somewhat more conservative than their peers in early election cycles and slowly became more liberal than their peers over time, though the effect is not precisely estimated and is not significantly different from zero until 2002. That trend, however, appears to have reversed around 2006 and by 2014, inventors were only slightly more liberal than their peers (differing only by -0.13 points on the common factor ideology scale in 2012).[4] Accordingly, after controlling for geography and other factors, differences between inventors and non-inventors explain only about 11 percent of the total change in average ideology scores among Democratic donors (of about -1.15 points).

Though individual characteristics, like inventorship, do not seem to explain increasing liberalism among Democratic donors, it is still possible that we are confounding geographic with firm-level or sectoral behaviors. For example, it is difficult to know whether rising liberalism among inventors who contribute to Democrats is an artifact of living in places like the Silicon Valley or Seattle, or is instead an artifact of working as a software engineer (for evidence of sectoral patterns, refer to Table 1) or working for a firm like Google or Microsoft, which happen to have headquarters in those locations.

To explore this question, I first expanded the inventor donor database, for the 1992 and 2012 election cycles, to include campaign contribution data on all workers at firms that produce intellectual property. Specifically, as described in Appendix A, I used patent data

[4]Note that this turning point, in the 2006 election cycle, matches the point in time when inventors began developing a lower propensity to donate to Democratic candidates and committees, shown in Figure 3.

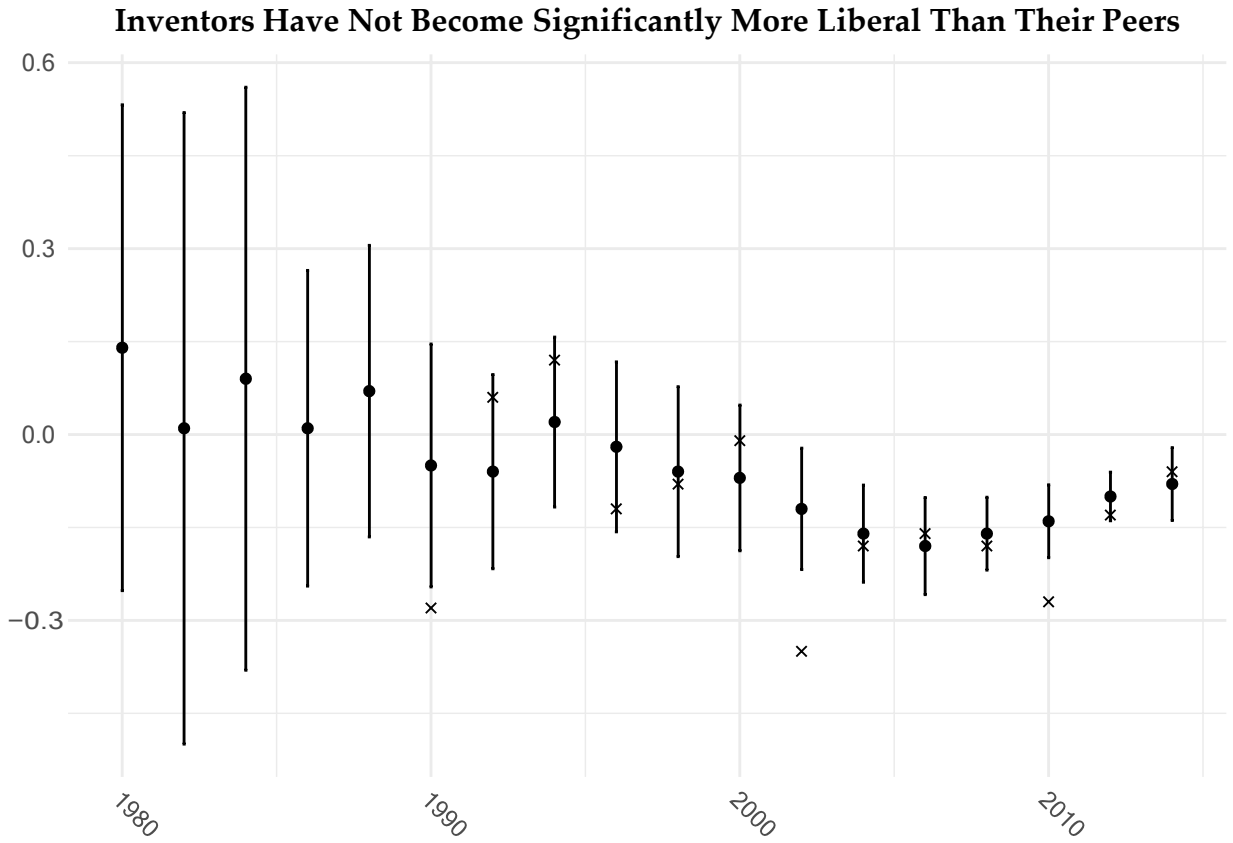

Figure 5: This figure shows the point estimates and 95 percent confidence intervals from regressing ideology scores on a binary variable indicating whether the donor is an inventor. The regressions are run for each matched data set within each election cycle from 1980 through 2014. The vertical axis reflects an estimated difference in mean ideology scores between inventors and non-inventors. The solid points and confidence intervals illustrate the results from running regressions using the full matched data set where an inventor is any individual that applied for a patent in the current election cycle or any time prior. The crossed points illustrate the point estimates (with no confidence intervals) from running the same regression after confining the matched data set to switchers, or those who were not inventors in the prior election cycle but are in the current election cycle.

to identify all companies that produced intellectual property in the five years prior to each election cycle. I merged these firm names with the DIME database to gather contribution and ideology data on all employees for these firms (inventors and non-inventors alike) in each election cycle. I then linked new firm names (for those firms which did not have inventor donors) to Capital IQ firm identifiers and 4-digit SIC codes.

With this dataset, I performed a variance decomposition on the subsets of knowledge economy workers who contribute to Democrats and who contribute to Republicans. This analysis was predicated upon and modeled after similar analyses conducted in prominent studies of rising wage inequality (Barth et al., 2016; Song et al., 2019). In those studies, the question was whether increasing wage inequality—reflected by an increasing variance in the overall wage distribution over time—was best explained by changes between firms, with the average wages of some superior firms pulling away from the average wages of their competitors, or within firms, with executive pay (for example) pulling away from pay for administrative staff across many firms.

Here, the phenomenon to explain is not increasing variance in the wage distribution over time but decreasing variance in the ideology distribution over time among the subset of knowledge economy workers that give to Democratic candidates and committees. To determine whether geographic or firm-level shifts are driving the declining ideological variance among Democratic inventors, I implemented a Bayesian form of ANOVA decomposition for each subset of knowledge economy workers in the 1992 and 2012 election cycles using the `runjags` library in R (Denwood, 2016). Specifically, I fit the following

non-nested hierarchical model to each data set in each election cycle:

$$y_i \sim \mathsf{N}\,(a_{j[i]} + b_{k[i]}, \sigma_y^2)$$

$$a_j \sim \mathsf{N}\,(0, \sigma_a^2)$$

$$b_j \sim \mathsf{N}\,(0, \sigma_b^2)$$

Here y_i represents the ideology score for donor i residing in Congressional District $j[i]$ and working at organization $k[i]$. The estimated standard deviations, σ_a, σ_b, σ_y can be interpreted as point estimates of the variation in the average ideology across districts, the average ideology across organizations, and the residual variation within districts and organizations, respectively. Following (Gelman and Hill, 2007, Ch. 22), I report finite population empirical standard deviations since there is no super-population of Congressional Districts beyond those observed in the data, though this choice does not impact the results.

A Bayesian form of ANOVA is preferable, here, because the goal is not to test whether the batches of coefficients for Congressional Districts and organizations, $a_{j[i]}$ and $b_{k[i]}$, are statistically significant sources of variation in ideology among Democratic knowledge economy workers. Both variables are highly significant in this respect in both election cycles. The goal is rather to precisely estimate (and efficiently compute) the amount of observed variation between the batch of district effects and organization effects in each period, and the residual variation within both districts and organizations, and determine which plausibly explains the overall decline in the variance of ideology scores among

Democratic knowledge economy workers.

Such an analysis suggests that Democratic knowledge economy workers are becoming more polarized primarily by virtue of the place they live rather than the place they work, though residual variation in ideology scores within districts and organizations remains an important contributor as well. Figure 6 illustrates the main results. It shows the point estimates and 95 percent confidence intervals for each of the parameters of the model when the model is fitted to data for Democratic knowledge economy workers (left panel) and Republican knowledge economy workers (right panel) in the 1992 election cycle (black points) and the 2012 election cycle (gray points). The figure reveals that, for both Democratic and Republican knowledge economy workers, the estimated variance in the average ideology scores between organizations did not materially change between 1992 and 2012. This effectively means that differences between organizations cannot explain increasing polarization among knowledge economy workers.

In contrast, for Democratic knowledge economy workers, the estimated variance in the average ideology scores between Congressional Districts plummeted by about 84 percent and, as of 2012, was close to zero (the point estimate is 0.058). In other words, Democratic knowledge economy workers have come to increasingly reside in homogeneous liberal enclaves, so that there is almost no variation left in the average ideology scores across the districts in which these workers reside. This effectively means that changes in political geography can plausibly explain increasing polarization among Democratic knowledge economy workers. A significant decline in the residual variance, by about 40 percent between 1992 and 2012, also suggests that polarization among Democratic knowledge

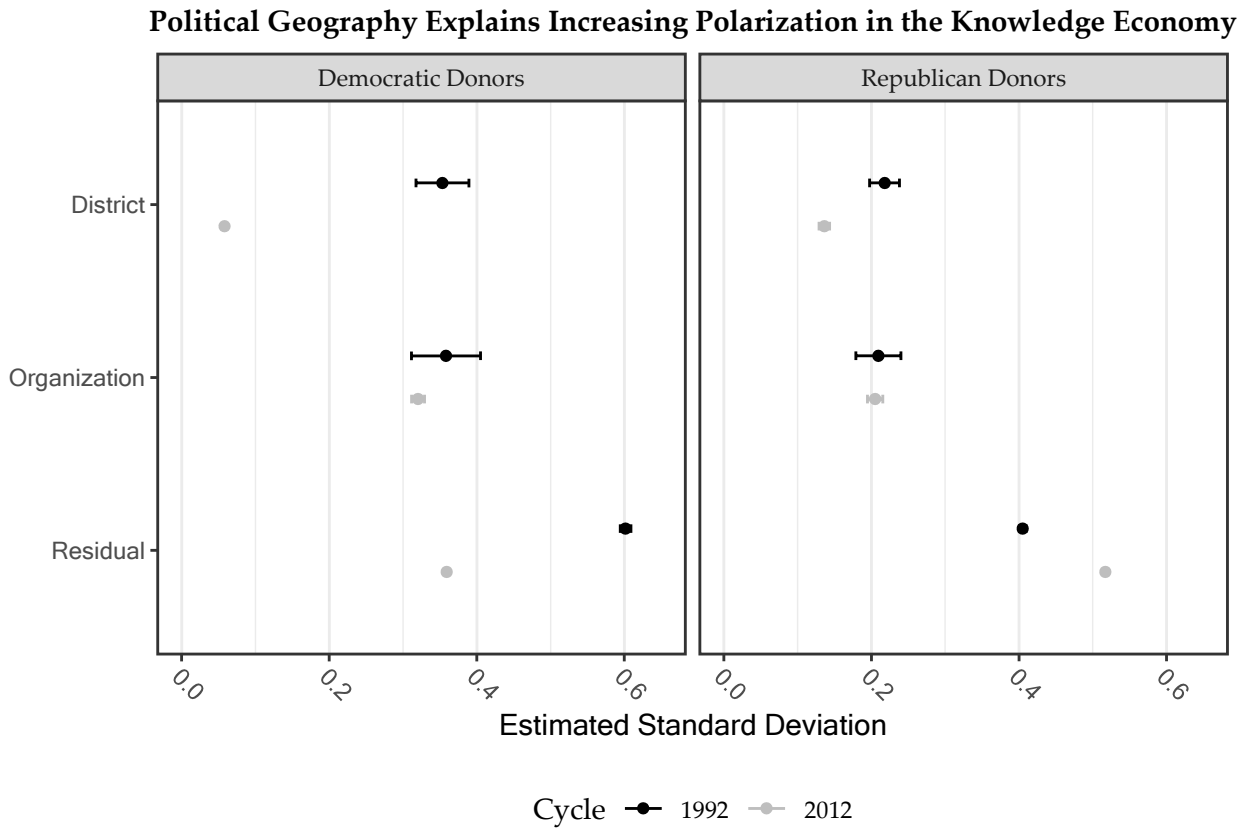

Figure 6: This figure shows the empirical standard deviation in the distribution of average ideology scores across Congressional District (top line) and across organizations (middle line) as well as the residual deviation within districts and organizations (bottom line). The estimates are produced by fitting the model described in the text. The estimates are reported for two different election cycles: 1992 (black points and 95 percent confidence intervals) and 2012 (gray points and confidence intervals). And estimates are reported from fitting the model to two different data sets: Democratic donors (left panel) and Republican donors (right panel). The estimates suggest that increasing polarization among knowledge economy workers comes predominately from changes among Democratic rather than Republican contributors and is most likely explained by increasing polarization between districts rather than between organizations.

economy workers increased within organizations and districts as well. But the amount of ideological variation remaining within organizations and districts is still relatively large (comparable in size to the variance between organizations). The most salient and surprising result is the virtual dissipation of any meaningful variation between districts.

The results are similar when the variance decomposition is run using Congressional Districts and 4-digit SIC codes instead of organizations. Whether the alternative source is hypothesized to be place of work or industrial affiliation, increasing geographic polarization emerges as the more plausible source of increasing polarization among knowledge economy workers who contribute to Democrats.

5 Conclusion

Inventors, or those who produce the new technologies that shape the knowledge economy, have come to favor Democratic candidates and committees when donating to political campaigns, and those who contribute to Democrats have also become more liberal since the 1992 election cycle. These aggregate findings generally support the hypothesis that the Democratic Party's rhetoric and policy commitments on knowledge economy formation have allowed it to reap electoral rewards.

But when we examine the geographic expression of these trends, it appears that American political institutions have constrained those payoffs in ways that call into question the knowledge economy's viability as a dominant platform of economic development. Just as inventiveness has become increasingly concentrated in geographic space, so have dona-

tions from inventors become more concentrated, with roughly 60 percent of donations to each party coming from only 148 zip codes in the 2012 election cycle. And larger shares of these donations increasingly flow to presidential candidates and a small number of Congressional candidates who either live in states that are leading knowledge economy development or who have publicly supported the knowledge economy. In a majoritarian system with single-member districts, the concentration of knowledge economy development to a few regions seems to be generating larger political payoffs for some candidates but producing more muted results for many others. Of course, the campaign finance system has developed institutions for distributing money to more competitive races, but it is not yet clear whether it does so in ways that create concrete electoral incentives for the many Democratic candidates outside of known knowledge economy hubs to take up or maintain the cause of knowledge economy development. And if as yet unobserved voting behavior among inventors follows their donation behavior, institutions for redistributing donations may offer little recourse, as inventor votes will remain concentrated nevertheless.

More broadly, these results suggest that American political institutions create at least two major perils for those who seek to mobilize the force of the government to undertake bold new programs of economic development. In a setting where the two main political parties have staked out divergent philosophies on macroeconomic management, separation of powers may tend to give neoliberal or "third-way" strategies a higher likelihood of becoming law (Short, 2022), but the market-oriented reforms that those strategies rely upon and the unequal (and limited) response of state governments in a federalist system may also

tend to exacerbate pre-existing regional inequalities (Short, n.d.). In the absence of a more robust effort by the federal government to equalize regional patterns of economic development, winner-take-all elections in single-member districts may then cause economic agglomeration (Moretti, 2013) to turn into political agglomeration (Rodden, 2019), where geographic concentration in economic gains leads to concentration in electoral payoffs and relatively few political candidates perceive a benefit from supporting the policies driving the economic transition. This in turn may impede the formation of the kinds of broader cross-regional coalitions that would be needed to overcome the imperatives of divided government and assert the federal government's hand more forcefully which will continue to make neoliberal strategies attractive for political pragmatists. Though we observe something like this happening with respect to the knowledge economy, it remains an open question whether other economic platforms, including those that depend on infrastructure investments or social welfare spending, are prone to the same dynamics.

References

Abramowitz, Alan I. 2013. "The Electoral Roots of America's Dysfunctional Government." *Presidential Studies Quarterly* 43 (4): 709–731.

Barnes, Lucy. 2022. "Public Investment in the Knowledge Economy." In *The American Political Economy: Politics, Markets, and Power*, ed. Jacob S. Hacker & Alexander Hertel-Fernandez & Paul Pierson & Kathleen Thelen. Cambridge University Press: New York.

Barth, Erling, Alex Bryson, James C. Davis, and Richard Freeman. 2016. "It's Where You

Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States." *Journal of Labor Economics* 34 (2): S67-S97.

Bonica, Adam. 2016. "Database on Ideology, Money in Politics, and Elections: Public version 2.0 [Computer file]." Stanford, CA: Stanford University Libraries.

Broockman, David E., Gregory Ferenstein, and Neil Malhotra. 2019. "Predisposition and the Political Behavior of American Economic Elites: Evidence from Technology Entrepreneurs." *American Journal of Political Science* 63 (1): 212-233.

Cramer, Katherine J. 2016. *The Politics of Resentment: Rural Consciousness in Wisconsin and the Rise of Scott Walker*. The University of Chicago Press: Chicago & London.

Denwood, Matthew J. 2016. "runjags: An R Package Providing Interface Utilities, Model Templates, Parallel Computing Methods and Additional Distributions for MCMC Models in JAGS." *Journal of Statistical Software* 71 (9): 1–25.

Detroit Economic Club. 2018. "Michigan Should Lead the Next Frontier of Innovation." Recorded interview. https://www.econclub.org/meeting/senator-peters/.

Enamorado, Ted, Benjamin Field, and Kosuke Imai. 2019. "Using a Probablistic Model to Assist Merging Large-Scale Administrative Records." *The American Political Science Review* 113 (2): 353–371.

Fiorina, Morris P., Samuel J. Abrams, and Jeremy C. Pope. 2010. *Culture War? The Myth of a Polarized America*. Longman: London.

Geismer, Lily. 2015. *Don't Blame Us: Suburban Liberals and the Transformation of the Democratic Party*. Princeton University Press: Princeton & Oxford.

Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press: New York.

Gingrich, Ben Ansell & Jane. 2022. "Concentration and Commodification: The Political Economy of Postindustrialism in America and Beyond." In *The American Political Economy: Politics, Markets, and Power*, ed. Jacob S. Hacker & Alexander Hertel-Fernandez & Paul Pierson & Kathleen Thelen. Cambridge University Press: New York.

Haskel, Jonathan, and Stian Westlake. 2018. *Capitalism Without Capital: The Rise of the Intangible Economy*. Princeton University Press: Princeton & Oxford.

Levendusky, Matthew. 2009. *The Partisan Sort: How Liberals Became Democrats and Conservatives Became Republicans*. University of Chicago Press.

McCarty, Nolan, Keith T. Poole, and Howard Rosenthal. 2016. *Polarized America: The Dance of Ideology and Unequal Riches*. The MIT Press: Cambridge.

Miles, Sara. 2001. *How to Hack a Party Line: The Democrats and Silcon Valley*. Farrar, Straus, and Girroux: New York.

Moretti, Enrico. 2013. *The New Geography of Jobs*. Mariner Books of Houghton Mifflin Harcourt: Boston and New York.

O'Mara, Margaret. 2019. *The Code: Silicon Valley and the Remaking of America*. Penguin Books: New York.

Rodden, Jonathan. 2019. *Why Cities Lose: The Deep Roots of the Urban-Rural Political Divide*. Basic Books.

Schickler, Eric. 2016. *Racial Realignment: The Transformation of American Liberalism, 1932-1965*. Princeton University Press: Princeton & Oxford.

Schlozman, Daniel. 2015. *When Movements Anchor Parties: Electoral Realignments in American History*. Princeton University Press: Princeton & Oxford.

Schwartz, Herman Mark. 2022. "Mo' Patents, Mo' Problems: Corporate Strategy, Structure, and Profitability in America's Political Economy." In *The American Political Economy: Politics, Markets, and Power*, ed. Jacob S. Hacker & Alexander Hertel-Fernandez & Paul Pierson & Kathleen Thelen. Cambridge University Press: New York.

Short, Nicholas. 2022. "The Politics of the American Knowledge Economy." *Studies in American Political Development*.

Short, Nicholas. N.d. "The Distributional Consequences of the American Knowledge Economy: Inequality in an Age of Intellectual Property Production." Working Paper. https://scholar.harvard.edu/nickshort/publications/distributional-consequences-american-knowledge-economy.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter. 2019. "Firming Up Inequality." *The Quarterly Journal of Economics* 134 (1): 1–50.

Soskice, David. 2022. "The United States as Radical Innovation Driver: The Politics of Declining Dominance?" In *The American Political Economy: Politics, Markets, and Power*, ed. Jacob S. Hacker & Alexander Hertel-Fernandez & Paul Pierson & Kathleen Thelen. Cambridge University Press: New York.

Techonomy. 2015. "Booker, Fischer, and Parker: Technollgy, Innovation and American

Progress." Videotaped interview. https://techonomy.com/video/booker-fischer-parker-technology-innovation-and-american-progress/.

Appendices – Political Contributions by American Inventors: Evidence from 30,000 Cases

1 Appendix A: Constructing the Inventor-Donor Database

To implement the first step, I used the research datasets published by the PTO on the Patentsview website to build a database containing the first and last name, city and state, and organizational assignee (a firm, a university, a government agency, etc.) for all inventors who applied for a U.S. patent on or after January 1, 1979, who listed an address in the U.S. in their correspondence with the PTO (i.e., were American residents at the time of the patent application), and who assigned their patent to some organizational entity. Assignees are usually employers; by law, the inventors named on a patent must be people, but ownership of the patent routinely passes to that person's employer by virtue of the employment contract. If that does not happen, ownership passes to the inventors (there is no assignee). Because employer is an essential field for matching with DIME data, I exclude instances where ownership passes to the inventors and keep only instances where patent ownership passes to some organization.

To implement the second step, I gathered the same information (name, city and state, and employer) from the DIME database (Bonica, 2016). Using fastLink (Enamorado et al., 2019),

I then identified those American inventors who also contributed to a political campaign at some point from 1979 through 2014 (the 1980-2014 cycles). I completed the matching in three steps. First, I stratified the patent and donor data by both election cycle and state. The algorithm would therefore only find a match if an inventor both applied for a patent and made a campaign contribution in the same election cycle (an election year and the prior year). These matches are the strongest because the invention and donation occur close in time. Second, I stratified the remaining data (after purging matches from the first step) by state and repeated the matching for inventors in all states except California, New York, and Texas. These results introduce the possibility of more error because the acts of invention and donation are not close in time. But it captures instances where, for example, an inventor at Microsoft who lives in Washington and stays in Washington applies for a patent in, say, 1991 but does not donate to a campaign until, say, 2008. Third, and finally, for the remaining data in California, New York, and Texas, I stratified by both state and the first letter of the inventor's last name. Without this further stratification for these three large states, probabilistic matching was not computationally feasible.

The administrators of both the Patentsview and the DIME data sets have run their own disambiguation algorithms to generate unique identifiers for inventors (in Patentsview) and donors (in DIME). To ensure a higher quality of matching, I kept only those high probability matches where both datasets agreed that the match identified a unique individual. In other words, I abandoned instances where a single DIME identifier was matched to more than one Patentsview identifier and vice versa. This produced a dataset of 30,603 American inventors who contributed to a political campaign from 1979 through 2014.

Once inventor-donors are matched in this fashion, it is possible to use the unique identifiers in both data set to construct an invention record, containing data on all patents applied for by these inventor-donors from 1979-2019, and a donor record, containing data on all campaign contributions made by these inventor-donors from 1979-2014. Below, I focus exclusively on analyzing the donor record of American inventor-donors.[1] I also confine the donor record to campaign contributions made in all federal elections from the 1980 cycle through the 2014 cycle. The donor and recipient party coding in the DIME database appear to be a mix of FEC codes and legacy Voteview codes. In the analysis below, I re-coded the recipient types as Democratic candidates and committees, Republican candidates and committees, and political actions committees of unknown partisan affiliation (PAC-UPAs) and ignored contributions to other partisan entities (which were not substantial in any time period). As explained in the Introduction, PAC-UPAs are committees that either do not have a partisan designation in the underlying DIME data, do not have an ideological score or have a "middling" ideological score (greater than -0.5 and less than 0.5) which makes it difficult to impute a partisan tendency based on donation patterns, and do not have the text strings "Republican" or "Democrat" in their name.

The DIME dataset does not have disambiguated firm or organizational identifiers, and it is problematic to use those provided in the Patentsview dataset for several reasons. I therefore implemented my own name matching between the self-reported employer listed in the donation record of American inventor-donors and the organizations in Standard & Poor's Capital IQ database. To execute this third step, I first excluded instances where the

[1] In the Introduction, I appealed to the invention record to identify the technological domain (based on patent data) in which each inventor-donor predominately works.

DIME employer was missing or appeared to be conflated with occupation or employment status (CEO, engineer, retired, etc.). I then ranked the remaining employer names in descending order by the number of inventor donations (not the dollar amount) associated with that employer. I fed all of these names into Capital IQ's proprietary lookup algorithm to generate a suggested match and then audited the matches in two steps. First, because the top 2,212 of these names account for roughly 74.6 percent of all inventor donations across all election cycles, I manually audited the proposed matches, leading to 2,050 valid matches. For the remaining results, I implemented a relatively soft constraint on name similarity: that the DIME employer name and Capital IQ organization name had a Jaro-Winkler distance less than or equal to 0.15, which produced another 21,204 matches.[2] Together, these 23,254 self-reported employer names were linked to 14,735 unique organizations with Capital IQ identifiers.

The matching analysis implemented in Section 3 utilizes the subset of inventor-donor data where the DIME employer was linked to a Capital IQ organization through one of these 23,254 matches. Table 1 presents some summary statistics about this subset of the inventor-donor data for each election cycle. The second column shows the total number of donors in the DIME database in thousands. The third column shows the percentage of all donors that are inventor-donors, which varies over time between 0.5 and 2.4 percent of all donors. The fourth column shows the percentage of all donors that are linked to Capital IQ organizations. It reveals that the link between DIME employers and Capital IQ organizations is weakest in the 1980s, which is to be expected given that the Capital IQ

[2]That cutoff was chosen because, after auditing small samples, I observed that the proposed matches below this cutoff generated very few potentially false matches, while matches with a Jaro-Winkler distance between 0.15 and 0.2 had about 30 percent potentially false matches.

database has the best coverage from the mid-1990s to the present. The fifth column shows the share of all donors that are linked to Capital IQ organizations that are inventor-donors, which essentially defines the pool of inventor-donors eligible for matching. It shows that the linking to Capital IQ organizations slightly reduces the share of inventors compared to all donors (column three) in the 1980s, that there is no relative loss in the 1990s, and that the linking slightly reduces the relative share of non-inventors from 2000 to 2014. But it does not do so dramatically in any election cycle. The sixth column shows the number of inventor-donors that were matched to non-inventor donors by organization, Congressional District, and imputed gender, and the seventh columns shows the matching success rate, which is number of matched inventor-donors as a share of inventor-donors linked to Capital IQ organizations. It shows that matching succeeds in 20-31 percent of cases in the 1980s, 35-44 percent of cases in the 1990s, and in 56-67 percent of cases from 2002 to 2014.

The ANOVA analysis implemented in Section 4 is slightly different. Here, the goal is to understand whether polarization is increasing among knowledge economy workers who contribute to Democrats even if that organization's inventors do not donate. For this exercise, carried out only in the 1992 and 2012 election cycles, I supplemented the data set with data on non-inventor donors at known IP producers. Specifically, I used patent data to first identify all IP producers (any organization that was issued a patent) from 1987-1991 and from 2007-2011 (the five years prior to each relevant election year). I then linked self-reported DIME employers to these IP producers and, for those employers not already matched above, I linked the IP producer names to Capital IQ firm names. This

Table 1: **Summary of the Inventor-Donor Dataset**

Cycle	Total Donors (Thousands)	Inventor Share (%)	CIQ Linked Share (%)	Linked Inventor Share (%)	Matched Inventors	Matched Share (%)
1980	225.1	0.5	6.3	0.5	22	31.0
1982	101.4	1.9	5.6	0.9	10	20.0
1984	152.9	1.8	4.3	1.2	21	26.6
1986	155.9	2.3	6.6	1.3	42	30.9
1988	247.6	1.8	6.4	1.0	49	29.7
1990	287.8	2.0	8.1	1.4	125	38.0
1992	451.1	1.5	7.8	1.6	251	44.3
1994	428.7	1.9	9.2	1.8	275	38.9
1996	595.8	1.7	8.8	1.9	357	35.8
1998	487.2	2.4	9.6	2.2	379	36.9
2000	777.2	1.8	9.6	2.1	582	37.4
2002	894.2	1.7	11.9	1.9	1,149	56.7
2004	1,693.3	1.0	11.9	1.9	2,317	59.2
2006	1,357.0	1.4	14.2	2.1	2,338	58.8
2008	2,603.7	0.8	12.0	2.1	4,018	62.2
2010	1,689.6	1.4	13.2	2.4	3,276	60.7
2012	3,310.9	0.8	11.5	2.2	5,470	66.6
2014	2,433.0	1.1	10.9	2.3	3,852	64.2

Note:
This table presents basic summary statistics about the inventor-donor data set and the subset of that data linked to Capital IQ organizations used for the matching analysis in Section 3. For each election cycle (column 1), it shows the total number of donors in the DIME data (column 2), the share of total donors that are inventors (column 3), the share of total donors and that are linked to Capital IQ organizations (column 4), and the share of donors linked to Capital IQ organizations that are also inventors (column 5). The last two columns show the number of inventor-donors matched to non-inventor donors by firm, gender, and Congressional District (column 6) and the matching success rate as a share of inventor-donors linked to Capital IQ organizations (column 7).

allowed me to link DIME employers to an additional 887 Capital IQ organizations in 1992 and an additional 7,200 Capital IQ organizations in 2012. These organizations produced IP in the years leading up to the election cycle and had employees who donated in federal elections but did not have inventor-donors who made contributions.

Table 2 characterizes the data set used in the ANOVA analysis. For each election cycle, column 2 shows the total number of donors in the DIME data and column 3 shows the share of those donors (inventors and non-inventor employees at IP producers) that are linked to Capital IQ organizations. Columns four through six show the number of organizations, Congressional Districts, and industries (4-digit SIC codes) that are represented in this data set. As shown, the data set covers virtually all Congressional Districts in each election cycle,[3] and captures data on donors from 957 organizations in 339 industries in 1992 and 6,038 organizations in 714 industries in 2012.

2 Appenidx B: Regression Output

[3]There is a 436th district because the at-large district for the District of Columbia is included

Table 2: **Summary of the Knowledge Economy Worker Dataset**

Cycle	Total Donors (1,000s)	Linked Share (%)	Orgs.	Districts	Industries
1992	451.1	1.88	957	434	339
2012	3,310.9	5.99	6038	436	714

Note:
This table presents basic summary statistics about the supplemented inventor-donor data set used for the ANOVA analysis in Section 4, which includes inventor-donors and non-inventor employees at firms that produce IP. For each election cycle (column 1), it shows the total number of donors in the DIME data (column 2), the share of total donors that are inventors or non-inventor donors employed by IP producers (column 4). Non-inventor donors employed by IP producers are donors that worked at organizations that were issued at least one patent from 1987-1991 (for the 1992 election cycle) or from 2007-2011 (for the 2012 election cycle), where the IP producer firm name was linked to a Capital IQ firm. The last three columns show the number of organizations (column 4), Congressional Districts (column 5), and 4-digit SIC industries (column 6) represented in the data.

Table 3: Regression Results for Ideology Model - Full Matched Dataset

	Dependent variable: Common Factor Ideology Score					
	1980	1982	1984	1986	1988	1990
inventor	0.143	0.009	0.091	0.010	0.072	−0.052
	(0.200)	(0.263)	(0.235)	(0.134)	(0.119)	(0.096)
Constant	0.531***	0.783***	0.424**	0.533***	0.606***	0.525***
	(0.127)	(0.186)	(0.162)	(0.091)	(0.082)	(0.062)
Observations	35	20	38	76	92	216
R^2	0.015	0.0001	0.004	0.0001	0.004	0.001
Adjusted R^2	−0.015	−0.055	−0.024	−0.013	−0.007	−0.003
Residual Std. Error	0.580 (df = 33)	0.587 (df = 18)	0.724 (df = 36)	0.581 (df = 74)	0.571 (df = 90)	0.695 (df = 214)
F Statistic	0.508 (df = 1; 33)	0.001 (df = 1; 18)	0.150 (df = 1; 36)	0.005 (df = 1; 74)	0.369 (df = 1; 90)	0.293 (df = 1; 214)
	1992	1994	1996	1998	2000	2002
inventor	−0.062	0.020	−0.023	−0.063	−0.074	−0.121**
	(0.080)	(0.073)	(0.070)	(0.072)	(0.062)	(0.050)
Constant	0.394***	0.441***	0.401***	0.297***	0.256***	0.298***(0.031)
	(0.052)	(0.048)	(0.047)	(0.049)	(0.042)	
Observations	433	479	656	694	1,095	1,825
R^2	0.001	0.0002	0.0002	0.001	0.001	0.003
Adjusted R^2	−0.001	−0.002	−0.001	−0.0004	0.0004	0.003
Residual Std. Error	0.817 (df = 431)	0.792 (df = 477)	0.888 (df = 654)	0.948 (df = 692)	1.017 (df = 1093)	1.037 (df = 1823)
F Statistic	0.614 (df = 1; 431)	0.076 (df = 1; 477)	0.108 (df = 1; 654)	0.751 (df = 1; 692)	1.431 (df = 1; 1093)	5.900** (df = 1; 1823)
	2004	2006	2008	2010	2012	2014
inventor	−0.161***	−0.176***	−0.157***	−0.142***	−0.097***	−0.082***
	(0.037)	(0.038)	(0.029)	(0.033)	(0.025)	(0.029)
Constant	−0.106***	−0.103***	−0.268***	−0.248***	−0.492***	−0.494***
	(0.024)	(0.024)	(0.019)	(0.021)	(0.016)	(0.018)
Observations	3,945	3,818	6,938	5,305	9,321	6,158
R^2	0.005	0.006	0.004	0.004	0.002	0.001
Adjusted R^2	0.004	0.005	0.004	0.003	0.002	0.001
Residual Std. Error	1.155 (df = 3943)	1.138 (df = 3816)	1.188 (df = 6936)	1.159 (df = 5303)	1.184 (df = 9319)	1.112 (df = 6156)
F Statistic	18.667*** (df = 1; 3943)	21.838*** (df = 1; 3816)	29.627*** (df = 1; 6936)	19.100*** (df = 1; 5303)	15.267*** (df = 1; 9319)	7.971*** (df = 1; 6156)

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing common factor (CF) ideology scores on a binary variable indicating whether the donor is an inventor in the matched inventor data set (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 4: Regression Output for Ideology Model - Switchers

	Dependent variable: Common Factor Ideology Score					
	1982	1984	1986	1988	1990	1992
inventor	0.277	0.147	−0.135	0.052	−0.276	0.062
	(0.269)	(0.268)	(0.234)	(0.240)	(0.234)	(0.197)
Constant	0.830**	0.607**	0.828***	0.691***	0.563***	0.271**
	(0.190)	(0.190)	(0.165)	(0.163)	(0.152)	(0.126)
Observations	6	6	8	13	38	75
R^2	0.210	0.069	0.053	0.004	0.037	0.001
Adjusted R^2	0.012	−0.163	−0.105	−0.086	0.011	−0.012
Residual Std. Error	0.329 (df = 4)	0.329 (df = 4)	0.331 (df = 6)	0.431 (df = 11)	0.712 (df = 36)	0.838 (df = 73)
F Statistic	1.060 (df = 1; 4)	0.299 (df = 1; 4)	0.333 (df = 1; 6)	0.047 (df = 1; 11)	1.398 (df = 1; 36)	0.098 (df = 1; 73)
	1994	1996	1998	2000	2002	2004
inventor	0.115	−0.118	−0.083	−0.011	−0.352**	−0.183*
	(0.212)	(0.229)	(0.177)	(0.162)	(0.151)	(0.102)
Constant	0.260*	0.353**	0.167	0.317***	0.427***	−0.197***
	(0.139)	(0.157)	(0.122)	(0.111)	(0.091)	(0.067)
Observations	65	91	130	151	214	500
R^2	0.005	0.003	0.002	0.00003	0.025	0.006
Adjusted R^2	−0.011	−0.008	−0.006	−0.007	0.020	0.004
Residual Std. Error	0.846 (df = 63)	1.089 (df = 89)	1.010 (df = 128)	0.994 (df = 149)	1.059 (df = 212)	1.133 (df = 498)
F Statistic	0.297 (df = 1; 63)	0.266 (df = 1; 89)	0.220 (df = 1; 128)	0.005 (df = 1; 149)	5.428** (df = 1; 212)	3.174* (df = 1; 498)
	2006	2008	2010	2012	2014	
inventor	−0.160	−0.177**	−0.268***	−0.127*	−0.060	
	(0.109)	(0.090)	(0.093)	(0.072)	(0.084)	
Constant	−0.146**	−0.341***	−0.235***	−0.578***	−0.640***	
	(0.069)	(0.059)	(0.057)	(0.046)	(0.052)	
Observations	429	738	670	1,071	668	
R^2	0.005	0.005	0.012	0.003	0.001	
Adjusted R^2	0.003	0.004	0.011	0.002	−0.001	
Residual Std. Error	1.109 (df = 427)	1.204 (df = 736)	1.166 (df = 668)	1.152 (df = 1069)	1.058 (df = 666)	
F Statistic	2.154 (df = 1; 427)	3.910** (df = 1; 736)	8.247*** (df = 1; 668)	3.124* (df = 1; 1069)	0.508 (df = 1; 666)	

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing common factor (CF) ideology scores on a binary variable indicating whether the donor is an inventor among switchers (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 5: Regression Results for Democratic Donor Model - Full Matched Dataset

	Dependent variable: Democratic Donor					
	1980	1982	1984	1986	1988	1990
inventor	0.000	0.000	0.214	0.000	0.421	−0.281
	(0.725)	(1.491)	(0.654)	(0.514)	(0.462)	(0.284)
Constant	−1.163**	−2.197**	−0.619	−1.131***	−1.240***	−0.828***
	(0.512)	(1.054)	(0.469)	(0.364)	(0.342)	(0.194)
Observations	42	20	40	82	98	250
Log Likelihood	−23.053	−6.502	−26.409	−45.554	−56.276	−146.793
Akaike Inf. Crit.	50.105	17.003	56.818	95.108	116.553	297.586
	1992	1994	1996	1998	2000	2002
inventor	−0.190	−0.137	−0.080	−0.050	−0.000	0.010
	(0.195)	(0.185)	(0.163)	(0.158)	(0.124)	(0.100)
Constant	−0.760***	−0.688***	−0.775***	−0.787***	−0.631***	−1.223***
	(0.135)	(0.129)	(0.115)	(0.112)	(0.088)	(0.071)
Observations	502	538	704	748	1,152	2,252
Log Likelihood	−305.668	−336.862	−433.918	−461.522	−743.858	−1,209.641
Akaike Inf. Crit.	615.336	677.723	871.835	927.044	1,491.716	2,423.281
	2004	2006	2008	2010	2012	2014
inventor	−0.102*	−0.067	−0.187***	−0.319***	−0.391***	−0.607***
	(0.060)	(0.062)	(0.045)	(0.051)	(0.039)	(0.047)
Constant	−0.274***	−0.578***	0.014	−0.186***	0.420***	0.283***
	(0.042)	(0.043)	(0.032)	(0.036)	(0.028)	(0.033)
Observations	4,574	4,596	7,910	6,394	10,736	7,472
Log Likelihood	−3,109.524	−2,980.247	−5,467.983	−4,319.290	−7,325.466	−5,093.655
Akaike Inf. Crit.	6,223.047	5,964.493	10,939.970	8,642.579	14,654.930	10,191.310

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing a binary variable indicating whether the donor contributed to a Democratic candidate or committee on a binary variable indicating whether the donor is an inventor in the full matched dataset (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 6: Regression Results for Democratic Donor Model - Switchers

	Dependent variable: Democratic Donor					
	1982	1984	1986	1988	1990	1992
inventor	0.000	1.386	0.000	0.000	−0.613	0.000
	(106,969.800)	(1.732)	(1.633)	(1.183)	(0.646)	(0.450)
Constant	−24.566	−0.693	−1.099	−0.916	−0.368	−0.659**
	(75,639.060)	(1.225)	(1.155)	(0.837)	(0.434)	(0.318)
Observations	6	6	8	14	44	88
Log Likelihood	−0.000	−3.819	−4.499	−8.376	−27.775	−56.464
Akaike Inf. Crit.	4.000	11.638	12.997	20.752	59.549	116.928
	1994	1996	1998	2000	2002	2004
inventor	−0.117	0.480	−0.000	0.161	0.000	−0.155
	(0.483)	(0.441)	(0.354)	(0.328)	(0.296)	(0.168)
Constant	−0.496	−0.990***	−0.565**	−0.619***	−1.315***	−0.119
	(0.339)	(0.325)	(0.250)	(0.234)	(0.209)	(0.118)
Observations	74	96	138	160	274	574
Log Likelihood	−48.527	−59.791	−90.354	−105.205	−141.431	−394.705
Akaike Inf. Crit.	101.054	123.582	184.708	214.410	286.863	793.409
	2006	2008	2010	2012	2014	
inventor	−0.017	−0.142	−0.411***	−0.563***	−0.727***	
	(0.185)	(0.138)	(0.142)	(0.114)	(0.142)	
Constant	−0.595***	0.047	−0.239**	0.535***	0.414***	
	(0.131)	(0.097)	(0.098)	(0.082)	(0.101)	
Observations	512	844	840	1,278	824	
Log Likelihood	−332.589	−584.424	−558.162	−863.701	−557.539	
Akaike Inf. Crit.	669.178	1,172.847	1,120.324	1,731.402	1,119.078	

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing a binary variable indicating whether the donor contributed to a Democratic candidate or committee on a binary variable indicating whether the donor is an inventor among switchers (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 7: Regression Results for Democratic Share Model - Full Matched Dataset

	Dependent variable: Democratic Share of Donations					
	1980	1982	1984	1986	1988	1990
inventor	−2.111	−0.000***	−17.198***	−4.461	−3.747	−1.470
	(5.332)	(0.000)	(6.028)	(3.401)	(3.816)	(2.427)
dem_donor	60.096***(6.259)	100.000***	76.415***	76.309***(3.960)	71.244***	72.724***
		(0.000)	(6.225)		(4.307)	(2.705)
Constant	1.056	0.000***	8.255*	2.231	1.742	0.760
	(4.054)	(0.000)	(4.782)	(2.591)	(2.841)	(1.900)
Observations	42	20	40	82	97	247
R^2	0.703	1.000	0.808	0.825	0.745	0.749
Adjusted R^2	0.688	1.000	0.798	0.821	0.739	0.747
Residual Std. Error	17.276 (df = 39)	0.000 (df = 17)	19.036 (df = 37)	15.398 (df = 79)	18.696 (df = 94)	19.037 (df = 244)
F Statistic	46.173*** (df = 2; 39)	38,330,146,607,691,530,952,077,391,953,920.000*** (df = 2; 17)	77.803*** (df = 2; 37)	186.563*** (df = 2; 79)	137.025*** (df = 2; 94)	363.990*** (df = 2; 244)

	1992	1994	1996	1998	2000	2002
inventor	−0.125	−3.114*	−0.510	−0.106	−2.545**	−1.097
	(1.665)	(1.591)	(1.425)	(1.316)	(1.081)	(0.706)
dem_donor	74.837***	76.332***	75.435***	77.164***	80.722***	74.284***
	(1.812)	(1.703)	(1.542)	(1.424)	(1.132)	(0.839)
Constant	0.064	1.578	0.258	0.053	1.281	0.547
	(1.313)	(1.258)	(1.121)	(1.033)	(0.865)	(0.535)
Observations	496	535	698	745	1,135	2,236
R^2	0.776	0.792	0.775	0.798	0.818	0.778
Adjusted R^2	0.775	0.791	0.774	0.798	0.818	0.778
Residual Std. Error	18.517 (df = 493)	18.388 (df = 532)	18.826 (df = 695)	17.957 (df = 742)	18.213 (df = 1132)	16.699 (df = 2233)
F Statistic	854.673*** (df = 2; 493)	1,009.887*** (df = 2; 532)	1,197.789*** (df = 2; 695)	1,468.023*** (df = 2; 742)	2,547.524*** (df = 2; 1132)	3,917.237*** (df = 2; 2233)

	2004	2006	2008	2010	2012	2014
inventor	−1.233**	−0.216	0.175	1.123**	−0.468	−0.658
	(0.490)	(0.527)	(0.412)	(0.481)	(0.326)	(0.412)
dem_donor	89.208***	81.852***	86.351***	78.483***	90.435***	89.994***
	(0.496)	(0.551)	(0.412)	(0.487)	(0.329)	(0.412)
Constant	0.630	0.110	−0.092	−0.599	0.260	0.379
	(0.408)	(0.424)	(0.358)	(0.406)	(0.304)	(0.372)
Observations	4,539	4,536	7,823	6,309	10,681	7,431
R^2	0.877	0.830	0.849	0.805	0.878	0.868
Adjusted R^2	0.877	0.830	0.849	0.805	0.877	0.868
Residual Std. Error	16.488 (df = 4536)	17.759 (df = 4533)	18.185 (df = 7820)	19.028 (df = 6306)	16.791 (df = 10678)	17.554 (df = 7428)
F Statistic	16,226.480*** (df = 2; 4536)	11,053.980*** (df = 2; 4533)	22,025.750*** (df = 2; 7820)	13,050.360*** (df = 2; 6306)	38,245.970*** (df = 2; 10678)	24,467.720*** (df = 2; 7428)

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing the share of donations given to Democratic candidates and committees on a binary variable indicating whether the donor is an inventor (inventor) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (dem_donor). Conditional on being a Democratic donor, it captures the difference between inventors and non-inventors in the share of total contributions made to Democratic candidates and committees. The regressions were run in the full matched dataset (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 8: Regression Results for Democratic Share Model - Switchers

	Dependent variable: Democratic Share of Donations					
	1982	1984	1986	1988	1990	1992
inventor	0.000	−34.375	−8.655	0.851	−10.747*	−2.530
	(0.000)	(23.868)	(6.704)	(14.308)	(6.194)	(4.524)
dem_donor		65.625*	32.690***	55.655***(15.836)	77.635***	68.339***
		(23.868)	(7.741)		(6.534)	(4.733)
Constant	0.000	11.458	4.327	−0.426	5.930	1.288
	(0.000)	(17.790)	(5.120)	(11.083)	(5.092)	(3.635)
Observations	6	6	8	14	44	85
R^2		0.724	0.796	0.529	0.789	0.718
Adjusted R^2		0.540	0.714	0.443	0.779	0.711
Residual Std. Error	0.000 (df = 4)	27.560 (df = 3)	9.481 (df = 5)	26.767 (df = 11)	20.330 (df = 41)	20.854 (df = 82)
F Statistic		3.934 (df = 2; 3)	9.749** (df = 2; 5)	6.178** (df = 2; 11)	76.655*** (df = 2; 41)	104.454*** (df = 2; 82)
	1994	1996	1998	2000	2002	2004
inventor	−6.086	−0.497	−0.917	−4.270	−1.507	0.630
	(5.103)	(4.071)	(3.486)	(2.878)	(1.922)	(1.393)
dem_donor	71.844***	73.674***	75.154***	83.835***(2.978)	78.590***	89.904***
	(5.300)	(4.329)	(3.615)		(2.349)	(1.399)
Constant	3.108	0.221	0.458	2.093	0.750	−0.326
	(4.127)	(3.058)	(2.801)	(2.297)	(1.445)	(1.188)
Observations	74	94	136	159	273	568
R^2	0.724	0.764	0.765	0.836	0.806	0.880
Adjusted R^2	0.716	0.758	0.761	0.833	0.804	0.879
Residual Std. Error	21.938 (df = 71)	19.569 (df = 91)	20.329 (df = 133)	18.132 (df = 156)	15.876 (df = 270)	16.588 (df = 565)
F Statistic	93.122*** (df = 2; 71)	146.983*** (df = 2; 91)	216.093*** (df = 2; 133)	396.318*** (df = 2; 156)	559.941*** (df = 2; 270)	2,068.380*** (df = 2; 565)
	2006	2008	2010	2012	2014	
inventor	−1.178	0.461	1.235	1.141	−0.272	
	(1.655)	(1.236)	(1.441)	(0.971)	(1.269)	
dem_donor	80.267***	87.459***	73.059***	90.399***(0.980)	89.812***	
	(1.725)	(1.236)	(1.472)		(1.270)	
Constant	0.595	−0.238	−0.666	−0.666	0.161	
	(1.329)	(1.082)	(1.208)	(0.923)	(1.169)	
Observations	504	835	826	1,270	821	
R^2	0.812	0.858	0.751	0.872	0.863	
Adjusted R^2	0.811	0.857	0.750	0.872	0.863	
Residual Std. Error	18.574 (df = 501)	17.849 (df = 832)	20.605 (df = 823)	17.131 (df = 1267)	17.892 (df = 818)	
F Statistic	1,083.590*** (df = 2; 501)	2,505.006*** (df = 2; 832)	1,240.425*** (df = 2; 823)	4,330.088*** (df = 2; 1267)	2,586.726*** (df = 2; 818)	

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing the share of donations given to Democratic candidates and committees on a binary variable indicating whether the donor is an inventor (inventor) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (dem_donor). Conditional on being a Democratic donor, it captures the difference between inventors and non-inventors in the share of total contributions made to Democratic candidates and committees. The regressions were run among switchers (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 9: Regression Results for Republican Share Model - Full Matched Dataset

	Dependent variable: Republican Share of Donations					
	1980	1982	1984	1986	1988	1990
inventor	−13.827	−1.860	14.857	3.173	−0.255	−10.928**
	(13.953)	(1.908)	(10.916)	(8.169)	(8.491)	(5.407)
dem_donor	−25.069	−98.967***	−61.767***	−57.887***	−48.375***	−26.626***
	(16.380)	(3.180)	(11.274)	(9.512)	(9.585)	(6.026)
Constant	66.812***(10.609)	99.897***(1.386)	77.868***(8.660)	77.491***(6.225)	65.930***(6.321)	47.405***
						(4.233)
Observations	42	20	40	82	97	247
R^2	0.079	0.983	0.457	0.320	0.215	0.085
Adjusted R^2	0.031	0.981	0.428	0.303	0.198	0.077
Residual Std. Error	45.212 (df = 39)	4.266 (df = 17)	34.474 (df = 37)	36.989 (df = 79)	41.606 (df = 94)	42.414 (df = 244)
F Statistic	1.662 (df = 2; 39)	484.748*** (df = 2; 17)	15.590*** (df = 2; 37)	18.594*** (df = 2; 79)	12.879*** (df = 2; 94)	11.304*** (df = 2; 244)
	1992	1994	1996	1998	2000	2002
inventor	−8.362**	−6.047*	−5.206*	−4.510	−3.796*	−5.871***
	(3.747)	(3.664)	(3.056)	(3.067)	(2.218)	(1.682)
dem_donor	−25.045***	−34.805***	−50.822***	−43.115***	−57.927***	−15.798***
	(4.079)	(3.922)	(3.305)	(3.319)	(2.321)	(1.999)
Constant	43.715***(2.956)	52.469***(2.897)	70.686***(2.403)	57.661***(2.408)	71.569***(1.773)	30.415***
						(1.273)
Observations	496	535	698	745	1,135	2,236
R^2	0.078	0.132	0.255	0.187	0.356	0.032
Adjusted R^2	0.074	0.128	0.253	0.185	0.355	0.032
Residual Std. Error	41.689 (df = 493)	42.352 (df = 532)	40.360 (df = 695)	41.852 (df = 742)	37.354 (df = 1132)	39.776 (df = 2233)
F Statistic	20.775*** (df = 2; 493)	40.359*** (df = 2; 532)	119.217*** (df = 2; 695)	85.212*** (df = 2; 742)	312.792*** (df = 2; 1132)	37.397*** (df = 2; 2233)
	2004	2006	2008	2010	2012	2014
inventor	−8.046***	−5.464***	−8.656***	−6.382***	−8.772***	−5.376***
	(1.096)	(1.022)	(0.808)	(0.852)	(0.638)	(0.725)
dem_donor	−32.021***	−17.324***	−38.636***	−22.130***	−40.166***	−23.783***
	(1.109)	(1.067)	(0.809)	(0.863)	(0.643)	(0.725)
Constant	41.680***(0.913)	26.300***(0.821)	46.707***(0.704)	29.204***(0.720)	46.665***(0.595)	28.585***
						(0.656)
Observations	4,539	4,536	7,823	6,309	10,681	7,431
R^2	0.162	0.060	0.231	0.098	0.271	0.127
Adjusted R^2	0.162	0.060	0.231	0.098	0.271	0.127
Residual Std. Error	36.905 (df = 4536)	34.404 (df = 4533)	35.701 (df = 7820)	33.751 (df = 6306)	32.819 (df = 10678)	30.907 (df = 7428)
F Statistic	438.471*** (df = 2; 4536)	144.684*** (df = 2; 4533)	1,177.555*** (df = 2; 7820)	343.496*** (df = 2; 6306)	1,983.195*** (df = 2; 10678)	540.543*** (df = 2; 7428)

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing the share of donations given to Republican candidates or committees on a binary variable indicating whether the donor is an inventor (inventor) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (dem_donor). Conditional on being a Democratic donor, it captures the difference between inventors and non-inventors in the share of contributions made to Republican candidates and committees. The regressions were run in the full matched dataset (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 10: Regression Results for Republican Share Model - Switchers

	Dependent variable: Republican Share of Donations					
	1982	1984	1986	1988	1990	1992
inventor	−6.200	34.375	8.655	−9.030	−2.085	−6.097
	(6.200)	(23.868)	(6.704)	(9.706)	(13.424)	(9.017)
dem_donor		−65.625*	−32.690***	−7.152	−31.366**	−17.557*
		(23.868)	(7.741)	(10.743)	(14.160)	(9.433)
Constant	100.000***	88.542**	95.672***	15.835*	46.525***	39.344***
	(4.384)	(17.790)	(5.120)	(7.518)	(11.036)	(7.244)
Observations	6	6	8	14	44	85
R^2	0.200	0.724	0.796	0.106	0.107	0.045
Adjusted R^2	0.000	0.540	0.714	−0.056	0.064	0.022
Residual Std. Error	7.593 (df = 4)	27.560 (df = 3)	9.481 (df = 5)	18.158 (df = 11)	44.059 (df = 41)	41.560 (df = 82)
F Statistic	1.000 (df = 1; 4)	3.934 (df = 2; 3)	9.749** (df = 2; 5)	0.654 (df = 2; 11)	2.467* (df = 2; 41)	1.950 (df = 2; 82)
	1994	1996	1998	2000	2002	2004
inventor	0.398	−4.317	−5.015	−8.402	−7.198	−11.568***
	(9.552)	(8.448)	(7.002)	(5.704)	(4.583)	(2.996)
dem_donor	−25.945**	−50.221***	−45.000***	−58.817***	−14.351**	−31.140***
	(9.922)	(8.983)	(7.261)	(5.903)	(5.602)	(3.008)
Constant	39.796***	73.091***	56.971***	75.166***	27.308***	42.865***
	(7.725)	(6.346)	(5.625)	(4.553)	(3.445)	(2.555)
Observations	74	94	136	159	273	568
R^2	0.088	0.265	0.226	0.397	0.032	0.174
Adjusted R^2	0.062	0.249	0.215	0.389	0.025	0.171
Residual Std. Error	41.070 (df = 71)	40.608 (df = 91)	40.830 (df = 133)	35.940 (df = 156)	37.864 (df = 270)	35.679 (df = 565)
F Statistic	3.426** (df = 2; 71)	16.394*** (df = 2; 91)	19.460*** (df = 2; 133)	51.280*** (df = 2; 156)	4.522** (df = 2; 270)	59.572*** (df = 2; 565)
	2006	2008	2010	2012	2014	
inventor	−4.967*	−10.250***	−6.530***	−10.029***	−5.054***	
	(2.858)	(2.437)	(2.187)	(1.752)	(1.949)	
dem_donor	−13.294***	−40.337***	−12.672***	−30.970***	−18.618***	
	(2.978)	(2.437)	(2.234)	(1.767)	(1.950)	
Constant	22.665***	48.537***	21.473***	37.711***	22.526***	
	(2.295)	(2.133)	(1.833)	(1.666)	(1.794)	
Observations	504	835	826	1,270	821	
R^2	0.044	0.257	0.044	0.200	0.101	
Adjusted R^2	0.040	0.255	0.042	0.199	0.099	
Residual Std. Error	32.076 (df = 501)	35.189 (df = 832)	31.271 (df = 823)	30.901 (df = 1267)	27.468 (df = 818)	
F Statistic	11.418*** (df = 2; 501)	143.584*** (df = 2; 832)	19.055*** (df = 2; 823)	158.775*** (df = 2; 1267)	46.004*** (df = 2; 818)	

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing the share of donations given to Republican candidates or committees on a binary variable indicating whether the donor is an inventor (inventor) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (dem_donor). Conditional on being a Democratic donor, it captures the difference between inventors and non-inventors in the share of contributions made to Republican candidates and committees. The regressions were run among switchers (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 11: Regression Results for PAC-UPA Share Model - Full Matched Dataset

	Dependent variable: PAC-UPA Share of Donations					
	1980	1982	1984	1986	1988	1990
inventor	15.939	1.860	2.340	1.288	4.003	12.398**
	(13.086)	(1.908)	(9.016)	(7.527)	(8.490)	(5.382)
dem_donor	−35.027**	−1.033	−14.647	−18.422**	−22.869**	−46.098***
	(15.362)	(3.180)	(9.311)	(8.764)	(9.583)	(5.998)
Constant	32.133***	0.103	13.877*	20.278***	32.329***	51.835***
	(9.950)	(1.386)	(7.152)	(5.735)	(6.320)	(4.213)
Observations	42	20	40	82	97	247
R^2	0.146	0.058	0.063	0.053	0.058	0.215
Adjusted R^2	0.103	−0.052	0.013	0.029	0.038	0.208
Residual Std. Error	42.402 (df = 39)	4.266 (df = 17)	28.472 (df = 37)	34.079 (df = 79)	41.598 (df = 94)	42.218 (df = 244)
F Statistic	3.341** (df = 2; 39)	0.528 (df = 2; 17)	1.253 (df = 2; 37)	2.224 (df = 2; 79)	2.875* (df = 2; 94)	33.382*** (df = 2; 244)
	1992	1994	1996	1998	2000	2002
inventor	8.487**	9.161**	5.716**	4.616	6.341***	6.968***
	(3.674)	(3.601)	(2.898)	(3.040)	(2.163)	(1.690)
dem_donor	−49.791***	−41.527***	−24.614***	−34.049***	−22.795***	−58.487***
	(3.999)	(3.855)	(3.135)	(3.290)	(2.264)	(2.009)
Constant	56.221***	45.953***	29.056***	42.285***	27.150***	69.038***
	(2.898)	(2.847)	(2.279)	(2.387)	(1.730)	(1.279)
Observations	496	535	698	745	1,135	2,236
R^2	0.249	0.189	0.087	0.129	0.089	0.279
Adjusted R^2	0.246	0.186	0.084	0.127	0.087	0.278
Residual Std. Error	40.869 (df = 493)	41.631 (df = 532)	38.280 (df = 695)	41.487 (df = 742)	36.436 (df = 1132)	39.965 (df = 2233)
F Statistic	81.597*** (df = 2; 493)	62.071*** (df = 2; 532)	33.067*** (df = 2; 695)	54.895*** (df = 2; 742)	55.084*** (df = 2; 1132)	432.001*** (df = 2; 2233)
	2004	2006	2008	2010	2012	2014
inventor	9.278***	5.680***	8.480***	5.259***	9.240***	6.035***
	(1.078)	(1.053)	(0.840)	(0.917)	(0.663)	(0.776)
dem_donor	−57.187***	−64.528***	−47.715***	−56.353***	−50.269***	−66.211***
	(1.091)	(1.099)	(0.841)	(0.929)	(0.668)	(0.776)
Constant	57.690***	73.590***	53.385***	71.394***	53.076***	71.037***
	(0.898)	(0.846)	(0.732)	(0.774)	(0.618)	(0.702)
Observations	4,539	4,536	7,823	6,309	10,681	7,431
R^2	0.386	0.435	0.302	0.376	0.364	0.509
Adjusted R^2	0.385	0.435	0.302	0.375	0.364	0.509
Residual Std. Error	36.286 (df = 4536)	35.445 (df = 4533)	37.125 (df = 7820)	36.303 (df = 6306)	34.121 (df = 10678)	33.079 (df = 7428)
F Statistic	1,424.310*** (df = 2; 4536)	1,744.568*** (df = 2; 4533)	1,692.067*** (df = 2; 7820)	1,896.364*** (df = 2; 6306)	3,059.940*** (df = 2; 10678)	3,854.735*** (df = 2; 7428)

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing the share of donations given to PAC-UPAs (PACs of unknown partisan affiliation) on a binary variable indicating whether the donor is an inventor (inventor) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (dem_donor). Conditional on being a Democratic donor, it captures the difference between inventors and non-inventors in the share of contributions made to PAC-UPAs. The regressions were run in the full matched dataset (as described in Sections 2 and 3) for each election cycle from 1980-2014.

Table 12: Regression Results for PAC-UPA Share Model - Switchers

	Dependent variable: PAC-UPA Share of Donations					
	1982	1984	1986	1988	1990	1992
inventor	6.200	0.000	0.000	8.179	12.832	8.627
	(6.200)	(0.000)	(0.000)	(16.104)	(12.959)	(8.571)
dem_donor		0.000	0.000	−48.502**	−46.269***	−50.781***
		(0.000)	(0.000)	(17.823)	(13.669)	(8.967)
Constant	−0.000	0.000	0.000	84.591***	47.545***	59.368***
	(4.384)	(0.000)	(0.000)	(12.474)	(10.654)	(6.886)
Observations	6	6	8	14	44	85
R^2	0.200			0.411	0.250	0.288
Adjusted R^2	0.000			0.303	0.214	0.271
Residual Std. Error	7.593 (df = 4)	0.000 (df = 3)	0.000 (df = 5)	30.127 (df = 11)	42.533 (df = 41)	39.506 (df = 82)
F Statistic	1.000 (df = 1; 4)			3.832* (df = 2; 11)	6.843*** (df = 2; 41)	16.593*** (df = 2; 82)
	1994	1996	1998	2000	2002	2004
inventor	5.688	4.814	5.932	12.673**	8.705*	10.937***
	(9.582)	(7.772)	(7.212)	(5.395)	(4.595)	(2.912)
dem_donor	−45.899***	−23.453***	−30.153***	−25.018***	−64.240***	−58.764***
	(9.953)	(8.264)	(7.479)	(5.584)	(5.616)	(2.923)
Constant	57.097***(7.749)	26.688***(5.838)	42.571***(5.794)	22.741***(4.306)	71.942***(3.454)	57.461***
						(2.482)
Observations	74	94	136	159	273	568
R^2	0.235	0.082	0.113	0.138	0.332	0.429
Adjusted R^2	0.213	0.062	0.100	0.127	0.327	0.427
Residual Std. Error	41.198 (df = 71)	37.358 (df = 91)	42.055 (df = 133)	33.995 (df = 156)	37.959 (df = 270)	34.668 (df = 565)
F Statistic	10.896*** (df = 2; 71)	4.060** (df = 2; 91)	8.465*** (df = 2; 133)	12.450*** (df = 2; 156)	67.164*** (df = 2; 270)	212.422*** (df = 2; 565)
	2006	2008	2010	2012	2014	
inventor	6.145**	9.789***	5.296**	8.888***	5.326**	
	(3.006)	(2.558)	(2.378)	(1.858)	(2.185)	
dem_donor	−66.973***	−47.121***	−60.387***	−59.429***	−71.194***	
	(3.133)	(2.558)	(2.428)	(1.874)	(2.186)	
Constant	76.740***(2.413)	51.701***(2.239)	79.193***(1.992)	62.955***(1.767)	77.313***	
					(2.012)	
Observations	504	835	826	1,270	821	
R^2	0.480	0.302	0.438	0.463	0.580	
Adjusted R^2	0.478	0.300	0.436	0.463	0.579	
Residual Std. Error	33.737 (df = 501)	36.936 (df = 832)	33.999 (df = 823)	32.771 (df = 1267)	30.796 (df = 818)	
F Statistic	230.959*** (df = 2; 501)	179.658*** (df = 2; 832)	320.322*** (df = 2; 823)	547.038*** (df = 2; 1267)	565.816*** (df = 2; 818)	

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of regressing the share of donations given to PAC-UPAs (PACs of unknown partisan affiliation) on a binary variable indicating whether the donor is an inventor (inventor) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (dem_donor). Conditional on being a Democratic donor, it captures the difference between inventors and non-inventors in the share of contributions made to PAC-UPAs. The regressions were run among swtichers (as described in Sections 2 and 3) for each election cycle from 1980-2014.