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

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Abstract

Intellectual property (IP) plays a crucial role in the American knowledge economy, but political scientists know surprisingly little about the political beliefs and behaviors of the firms and individuals who produce IP. 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 from 1980 through 2014. Regression analysis suggests that, compared to their peers, inventors have only become slightly more liberal over time and are no more likely to donate to Democratic candidates and committees. An audit of their non-partisan PAC donations suggests that inventors are unique in the extent they divide their contributions between candidates of their preferred party and their employer's corporate PAC. Inventors have also become more polarized over time, and a variance decomposition suggests the trend is driven by increasing geographic segregation, not by increasing polarization across firms or industries.

Contents

1 Introduction

Intellectual property (IP) plays a crucial role in the American knowledge economy (Haskel and Westlake, 2018; Schwartz, 2020; Short, n.d.) but we know surprisingly little about the political beliefs and behaviors of the firms and individuals who produce IP and who are therefore central actors in the modern political economy. The picture improved substantially with a recent study by Broockman, Ferenstein, and Malhotra (2019) who surveyed technology entrepreneurs[1] and found them to be as liberal or more liberal than Democratic citizens on issues related to economic redistribution, globalization, and social issues but closely aligned with Republican donors on issues of government regulation. Their study focuses more on entrepreneurs than innovators—people who start their own companies rather than inventors who often work for large established companies—but it confirms prior beliefs that many knowledge economy workers adhere to a rather unique ideology, seeking more government intervention in the economy when it comes to taxing and spending but less intervention when it comes to business regulation. At the same time, being the first survey of its kind, questions remain about how the ideology of knowledge economy workers has evolved over time and about the political behavior of knowledge economy workers who do not start their own businesses.

To address these and other questions, I merged patent data and campaign contribution data to develop a data set showing campaign contributions and ideological scores for 30,603 inventors on U.S. patents from 1979 through November 2018 and for all election cycles from 1980 through 2014. Specifically, I used research data sets provided by the U.S. Patent and Trademark Office (PTO) 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 distribution of ideological 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, for these inventor-donors. I briefly describe the construction of the data set in Section 2.

A primary advantage of this approach 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 [2], and so subject to certain disclosure requirements and an examination of prior art, the PTO 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 and public interest 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

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

[2] *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 (%)	PAC-UPA Share (%)	Total (Mil USD)
High Dem Share				
optics	66.84	29.72	3.34	3.73
computer hardware & software	63.29	31.40	4.83	57.73
computer peripherials	60.33	23.07	14.52	3.45
semiconductor devices	58.92	28.64	6.20	3.60
information storage	50.19	23.45	26.10	19.36
resins	48.91	38.93	11.21	2.98
genetics	48.23	35.25	4.00	0.91
High Rep Share				
pipes & joints	5.54	93.06	1.33	3.83
heating	7.29	89.13	3.27	4.05
mechanical - misc	14.21	81.61	3.54	16.99
gas	14.79	81.27	3.52	1.92
agriculture,husbandry,food	11.86	79.93	7.57	14.35
earth working & wells	16.74	78.89	3.89	9.32
motors & engines + parts	10.29	77.55	11.61	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 dolars) as well as the share of that total going to Democratic candidates and committees, Republican candidates and committees, and PACs of unknown partisan affiliation (PAC-UPA). PAC-UPAs are PACs with no partisan designation in the underlying DIME data, no imputed ideology score, or an ideology score greater than -0.5 and less than 0.5, as explained in the text. There are 37 technology subcategories in the NBER scheme but only 14 are presented, 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.

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 going to Democratic candidates and committees ("High Dem Share") and the top 7 with the highest share going to Republican candidates and committees ("High Rep Share"). Within each tranche, the table also shows the share of donations going to political action committees of unknown partisan affiliation (PAC-UPA), which 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 have the text strings "Republican" or "Democrat" in their name.

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 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 all knowledge economy workers have a strong partsan attachment to the Democratic Party. An analysis of all inventor-donors helps avoid this bias.

Characterization of the inventor-donor data set reveals several important insights about the political behavior of inventor-donors, two of which are the central focus of this article. The first observation is that American inventors do not lean as heavily towards Democrats as commonly believed. Figure 1 shows the total amount of political contributions (in 2019 dollars) that American inventor-donors made (left) as well as the total number of inventor-donors (right panel) in each election cycle from 1980 to 2014. In each graph, the amount of contributions and the number of donors is broken down by recipient: the blue line is for donations to Democratic candidates and committees, the red line is for donations to Republican candidates and committees, and the purple line is for donations PAC-UPAs. The graphs show that American inventors consistently contributed more to Republican than to Democratic candidates and committees until 2008. In that election, contributions to both parties were about equal and, for the first time, there were more Democratic inventor-donors than Republican inventor-donors. The graph also shows that there has also been somewhat tremendous growth in the number of inventors contributing to PAC-UPAs since the 2000 election cycle.

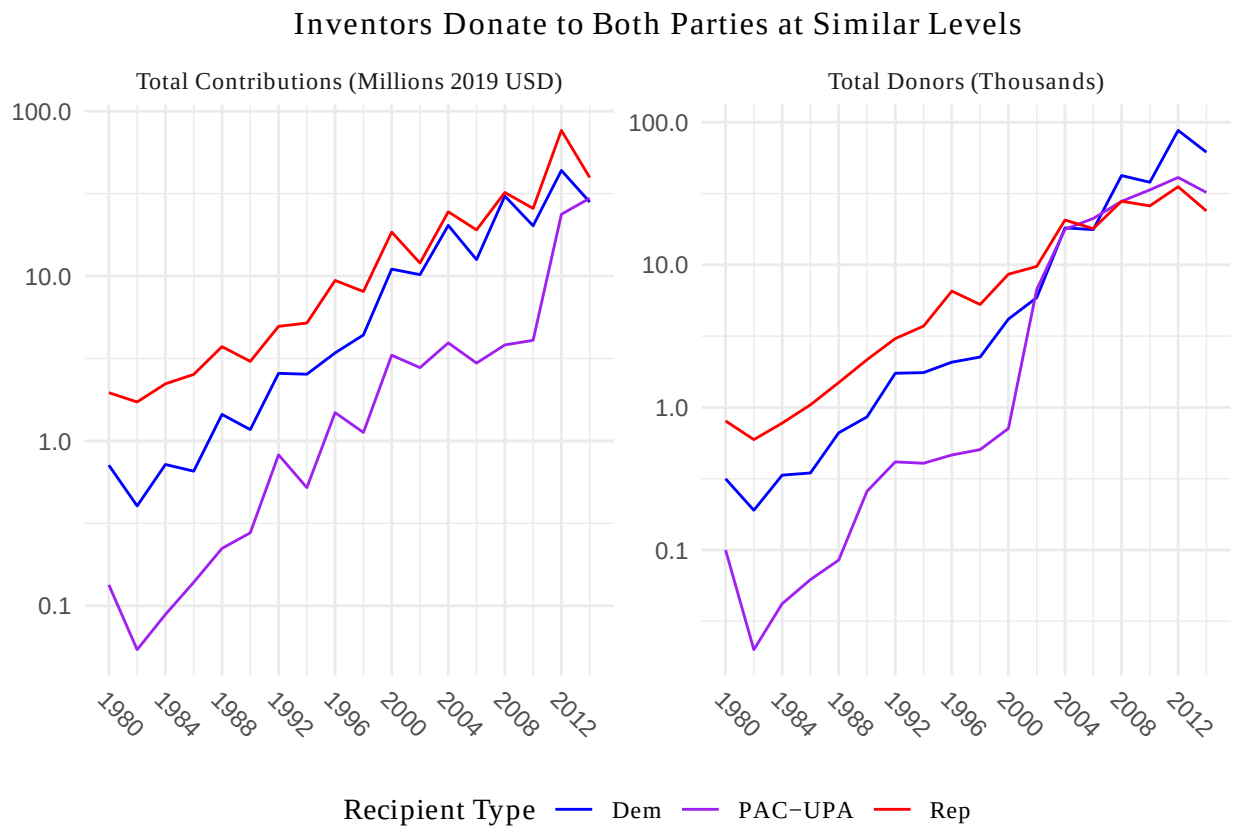

Figure 1: The left panel in this figure shows total contributions by American inventor-donors in all federal elections from 1980-2014 broken down by recipient type: Democratic candidates and PACs (blue line), Republican candidates and PACs (red line), and PACs of unknown partisan affiliation (purple line). The contribution amounts are reported in millions of inflation-adjusted (2019 constant) 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.

This observation raises important questions about whether inventorship—being named as an

inventor on a U.S. patent—is a meaningful predictor of political attitudes among knowledge economy workers, whether inventors meaningfully differ from their non-inventor peers in terms of their underlying ideology or donation behavior, and whether the strength of these hypothesized relationships has changed over time. To gain some insight on these questions, I first matched inventor-donors with non-inventor donors who work at the same firm, reside in the same Congressional District, and have the same imputed gender in each election cycle. I then used regression to analysis to explore the relationship between inventorship and political outcomes like ideology scores, propensity to donate to a Democratic candidate or committee, and the share of total donations to each recipient type. The results suggest that inventors have become more liberal over time, though the effect only became significant in 2002 and the trend reversed in 2006. At the same time, being an inventor does not make a person more likely to contribute to Democratic candidates and committees. Based on a manual audit of PAC-UPA donations in 1992 and 2012, this outcomes seems to stem from the fact that American inventors are much more likely to divide their contributions between their preferred candidates and their employer's corporate PAC, and this trend has strengthened somewhat over time. This raises the possibility that knowledge economy workers are especially supportive of their firm's lobbying activities or especially susceptible to their employer's appeals to do so (Hertel-Fernandez, 2018). This analysis is presented in Section 3.

The second main observation is that inventor-donors have become more polarized over time, largely because Democratic inventor-donors have become much more liberal since 1980. Figure 2 illustrates these developments. For each election cycle from 1980 through 2014, it shows the average common factor ideological score (left panel) and the variance in ideology scores (right panel) for two sub-populations of inventor-donors: those who contributed to Democratic candidates and committees (blue line) and those who contributed to Republican candidates and committees (red line). The figure demonstrates that the average ideology score among Republican inventor-donors remained relatively stable around 0.75 until about the 2006 election cycle, when it increased a bit, suggesting Republican inventor-donors were fairly conservative to begin with but have become slightly more conservative since 2006. In contrast, the average ideology score among Democratic inventor-donors remained constant and close to zero through 1990, and then dropped dramatically over the next 12 election cycles. This suggests that Democratic inventor-donors 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 inventor-donors was quite small from the beginning and appears to have slightly increased over the course of the entire time series, though there is no discernible turning point. In contrast, Democratic inventor-donors were broadly distributed, in terms of ideology scores, in early election cycles. But over the same time frame in which the mean ideology score plummeted—roughly 1992 through 2012—the variance in Democratic inventor-donor scores also dropped dramatically so that in recent elections, Democratic inventor-donors are as tightly distributed about their mean as Republican inventor-donors were in 1980 and 1982.

Rising polarization among inventor-donors is unique in two respects. First, as demonstrated above, polarization within this group has been asymmetric, but the asymmetry comes from the political left not the political right. The trend is therefore the opposite of what we observe among members of Congress, where the rightward shift among Republican representatives explains most of growing distance between the party median (or mean) ideology score (Dimock et al., 2014; Mann and Ornstein, 2016; McCarty, Poole, and Rosenthal, 2016). Similarly, while there is ongoing debate about whether the broader public is as polarized as their representatives in Washington, most of that debate centers on whether the public is about as polarized or significantly *less* polarized than the representatives they vote for (Levendusky, 2009; Fiorina, Abrams, and Pope,

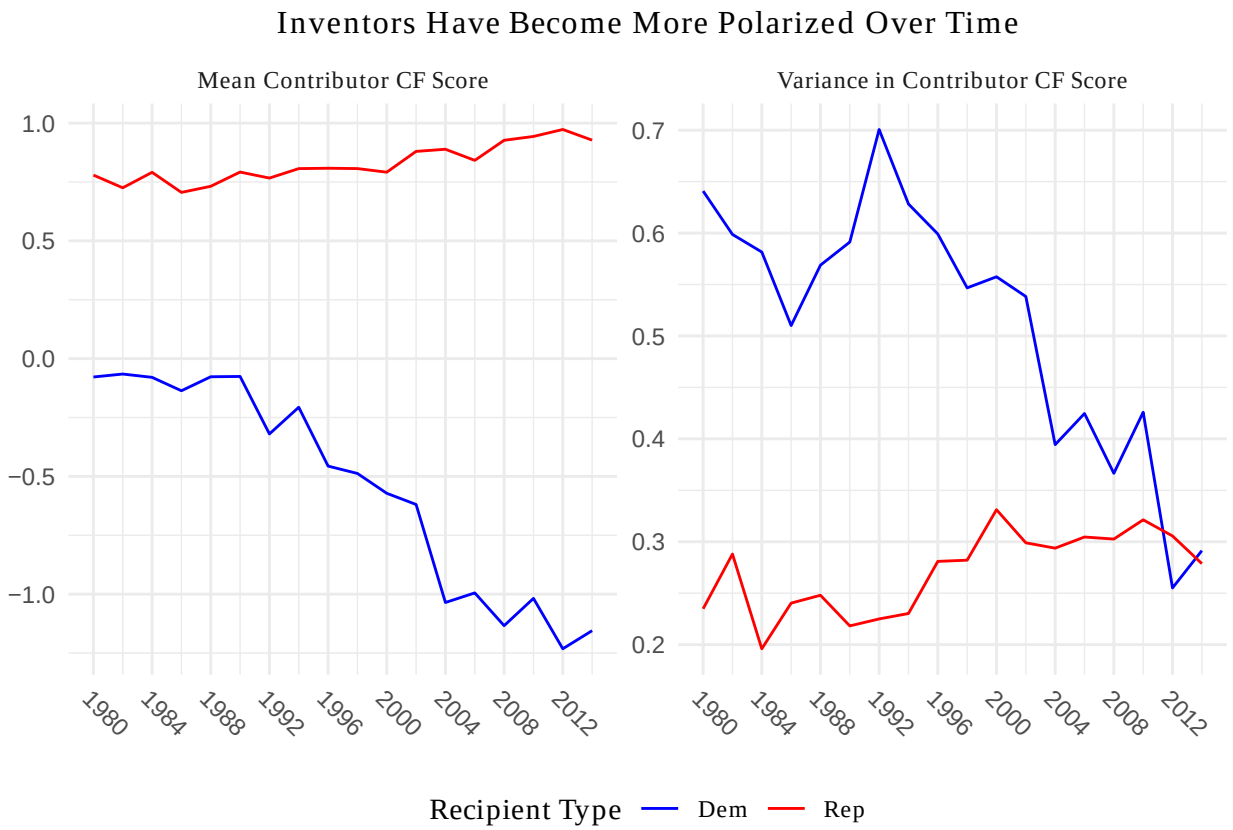

Figure 2: This figure shows the average (left panel) and variance (right panel) of the ideology scores for those inventor-donors who contributed to Democratic candidates and committees (blue line) and those who contributed to Republican candidates and committees (red line) in each election cycle from 1980 through 2014.

2010; Abramowitz, 2013; Dimock et al., 2014). But a comparison of the ideological distance between the median Republican and Democratic inventor-donors and between the median candidates to which each group donates (reported) reveals that, since 1998, inventor-donors have in fact become *more* polarized than the candidates to which they donate.

Knowledge economy workers may have become polarized for multiple reasons. One possibility is that knowledge economy workers are embedded in Congressional Districts surrounding urban and suburban areas that have become much more polarized in recent years (Geismer, 2015; Rodden, 2019). For example, Rodden (2019, Fig. 3.1) shows 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 supports this finding. For each of four election cycles (1980, 1996, 2004, and 2012), Figure 3 shows the share of all patents applied for by inventors located in a given 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. If these knowledge economy regions have have become much more liberal, and if inventor-donors are somewhat representative of all donors in the region, then we might observe rising polarization among knowledge economy workers simply because of underlying shifts in political geography.

Another possibility, suggested by Table 1, is that certain firms or industries have become more partisan over time because knowledge economy workers are increasingly sorting into firms whose employees have similar political leanings or because workers in certain technological domains have developed stronger partisan attachments over time by virtue of the work that they do rather than the place that they live. Going back to George McGovern's presidential bid in 1972, Democratic Party leaders have aggressively championed the potential of new technologies to inspire economic growth and provide remedies to problems like environmental degradation and global climate change (Geismer, 2015; Short, n.d.). And it is possible that this message resonates more strongly with knowledge economy workers in certain firms or industries or has led to a kind of sorting by firm based on whether or not the firm's managers are positioning the company as a knowledge economy participant or leader.

Figure 4 suggests another way of posing the question. It shows the estimated density of ideology scores for all Microsoft employees (not just inventors) in every presidential election cycle from 1992 through 2012. Though these donors reside in 263 different Congressional Districts (across all election cycles), they may have become more strongly liberal because the bulk of Microsoft's employees and donors reside in Washington's 1st Congressional District surrounding the company's headquarters in Redmond, and that District as a whole shows a remarkably similar ideological evolution (not shown). At the same time, the temporal evolution of ideology scores among computer software and hardware engineers (also not shown) is similar to that for all inventor-donors shown in Figure 2. This raises the possibility that the District's polarization is a coincidence or is a byproduct of increasing polarization by firm and occupation.

It is difficult to adjudicate between these competing hypotheses with observational data. But it is possible to test the plausibility of each by doing a variance decomposition or analysis of variance (ANOVA). In two high profile studies, economists recently deployed a similar type of analysis to determine that the vast majority of rising wage inequality (or increasing wage variance) from

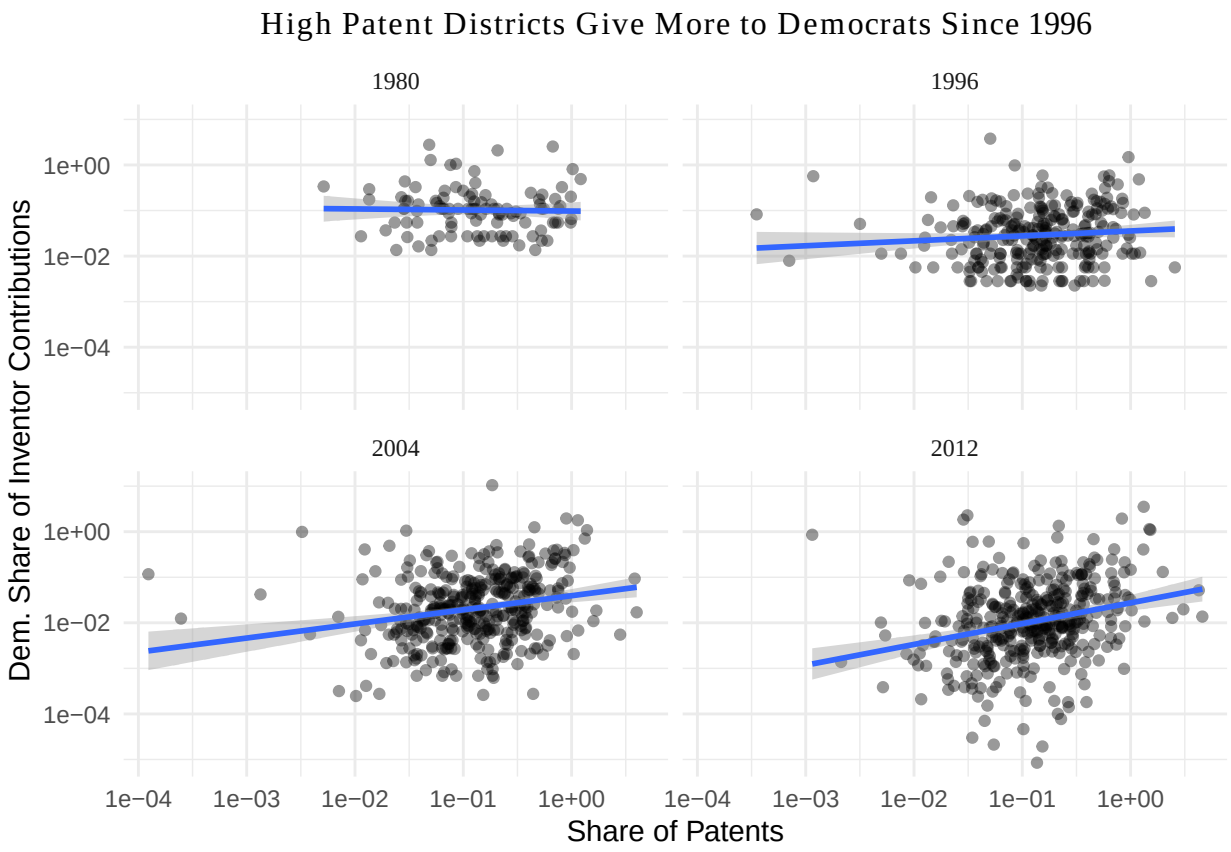

Figure 3: This figure shows the share of all patents applied for by U.S. inventors in a given Congressional District in an election cycle against the share of all inventor-donor contributions from that District in the same election cycle. Each panels shows the results form one of four presidential election 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).

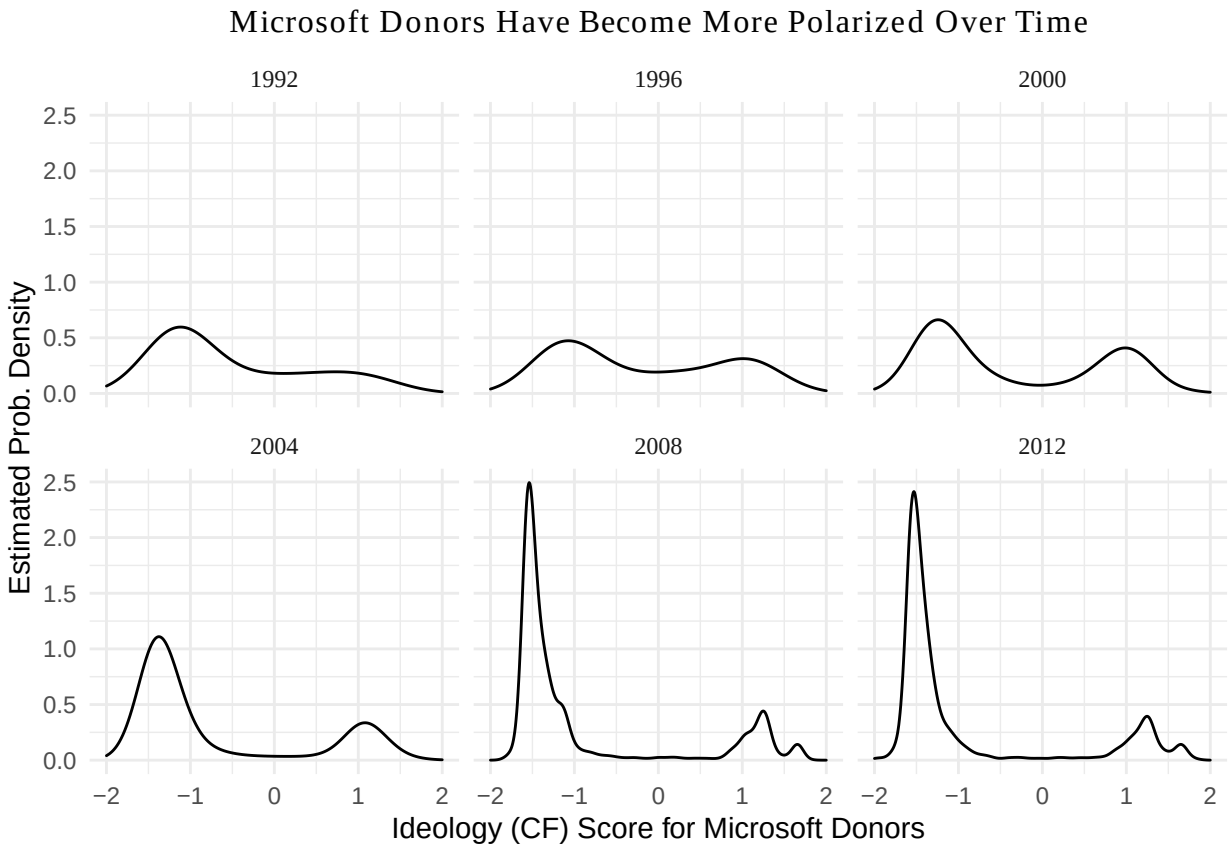

Figure 4: This figure shows the kernel density estimate of the ideology scores for all Microsoft employees in every presidential election cycle from 1992 through 2012.

the 1970s to 2010 is explained by increasing variance in the average wages *across* firms rather than increasing disparities *within* firms (Barth et al., 2016; Song et al., 2019). If we bifurcate the inventor-donor data into two sub-populations of Democratic and Republican contributors so that the distributions are not bi-modal, we can deploy a similar analysis to determine whether increasing ideological polarization (or decreasing ideology variance) is explained by increasing polarization across Congressional Districts, across firms (or industries), or within both. The results strongly support the geography-driven hypothesis of Rodden (2019). Among knowledge economy workers that contribute to Democratic candidates and committees, the variation in average ideology scores between firms (or industries) remained stable between 1992 and 2012, but the variation in average ideology scores between Congressional Districts dropped dramatically and is now close to zero. The residual variation within both firms and districts also plays a substantial role in increasing polarization. But the most surprising outcome is that, as of 2012, there is almost no variation left in the average ideological scores, across Districts, of knowledge economy workers who contribute to Democratic candidates and committees. This analysis is presented in Section 4.

This paper responds to the call by scholars working in the emerging field of American political economy to fill in the gaps of what we know about the politics surrounding the transition from an economy rooted in Fordist manufacturing to the knowledge economy, and to do so in ways that remain sensitive to how political trends have evolved over time (Hacker et al., 2019). It supplements the substantive findings of Broockman, Ferenstein, and Malhotra (2019) albeit with an emphasis on inventors rather than entrepreneurs and on campaign contributions rather than public opinion. It contributes to a large literature on rising political polarization while focusing on a subset of campaign donors who play a pivotal role in the knowledge economy and may have outsized influence in politics and public policy. And it explores how the political behavior of knowledge economy workers has changed over time without introducing the bias the comes with focusing on one or a few specific technological domains or industries. I summarize the results and comment on their broader significance in the Conclusion.

2 Construction of the Dataset

The process for creating the inventor-donor data set involved three main steps: (1) to identify the names of all inventors listed on U.S. patents that were applied for on or after January 1, 1979 and who resided within the United States; (2) to identify the subset of these U.S. inventors that also appear in the DIME database and acquire data on their contribution history and imputed ideology; and (3) to 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.

To implement the first step, I used the researched 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; the inventors named on a patent have to 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, Field, and Imai, 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 Patentsivew identifier and vice versa. This produced a dataset of 30,603 American inventors who also 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 [3]. 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 codings in the DIME database appear to be a mix of FEC codes and legacy voteview codes. In the analysis below, I recoded 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 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 also do not have the 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 a number of 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 the Standard & Poor's Capital IQ

[3] 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.

database. To execute this third step, I first excluded instances where the 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.[4] 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 2 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 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 firm 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 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

[4] 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 J-W distance between 0.15 and 0.2 had about 30 percent potentially false matches.

Table 2: **Construction 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).

Table 3: **Construction of the Knolwedge Economy Worker Datasets for 1992 and 2012**

Cycle	Total Donors (Thousands)	Linked Share (%)	Organizations	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.

not have inventor-donors who made contributions. Table 3 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,[5] and captures data on donors from 957 organizations in 339 industries in 1992 and 6,038 organizations in 714 industries in 2012.

3 Political Behavior of Inventor-Donors

Figure 1 suggests that political donations by inventors have grown substantially since the 1980 election and that inventors have, since about 2008, slightly favored Democratic candidates and committees, though it also shows substantial growth in donations to PAC-UPAs in aggregate amounts that are now comparable to the amount of partisan donations to each party. Have inventor-donors become more liberal, over time, when compared to their non-inventor peers? And if so, has this translated into a higher propensity to donate to Democratic candidates and committees?

To explore these questions, I matched inventor-donors to non-inventor donors who have the same gender, work at the same firm, and reside in the same Congressional District, as described above. In regression analysis, this effectively controls for gender, place of work, and place of residence. Within each election cycle, I then regressed ideology scores and a binary variable for whether or not the donor contributed to a Democratic candidate or committee on a binary variable indicating whether or not the donor is an inventor. I also regressed the share of total contributions given to each group (Democratic candidates and committees, Republican candidates and committees, and PAC-UPAs) on the inventor dummy and the Democratic donor dummy.

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

The regressions were run in matched data sets including all inventor-donors (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 included not as a separate quantity of independent interest, but as 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 purpose of this exercise is not to identify the causal effect of being issued a U.S. patent on an individual's political behavior, but to explore the how the political behavior of inventors—in terms of their ideological leanings and their donation patterns—has changed over time and how it differs from the political behavior of their peers. The regression output is reported in the Appendix. Here, I illustrate the results in two figures.

Figure 5 shows the results of regressing, within each election cycle, donor ideology scores (left panel) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (right panel) on a binary variable indicating whether the donor is an inventor. 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.

The ideology model on the left 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, the last election cycle for which we have data, inventors were only slightly more liberal than their peers (differing only by -0.08 points on the common factor ideology scale). The Democratic donor model on the right shows that, despite these changes in inventor ideology, inventors have not become more likely to donate to Democratic candidates over time. Up through 2006, inventors were just as likely as their peers to donate to Democratic candidates and committees, and since 2008, they have become slightly *less* likely than their peers to donate to Democratic candidates and committees. These results contradict the common assumption that knowledge economy workers have grown stronger in their attachments to the Democratic Party over time, at least when donations are the behavior of interest.

To better understand why the attachment of inventor-donors to the Democratic Party seems to have declined, I also regressed the share of donations given to each party and to PAC-UPAs on a binary variable indicating whether the donor is an inventor and a binary variable indicating whether the donor contributed to a Democratic candidate or committee. This shows whether, conditional on being a Democratic donor, inventors contribute more or less of their money to Democratic candidates and committees compared to their peers.

Figure 6 summarizes the results. It shows that, conditional on being a Democratic donor, inventors do not give higher shares of their money to Democratic candidates and committees than their peers, and this behavior has been relatively constant over time. What has changed is that, since 1990, inventors who contribute to Democratic candidates and committees give higher shares of their total donations to PAC-UPAs and (accordingly) lower shares of their total donations to Republican candidates and committees when compared to their peers. Similar results (not shown) are produced when conditioning on being a Republican rather than a Democratic donor. This is consistent with evidence suggesting inventors have become more polarized: compared to their peers, they are

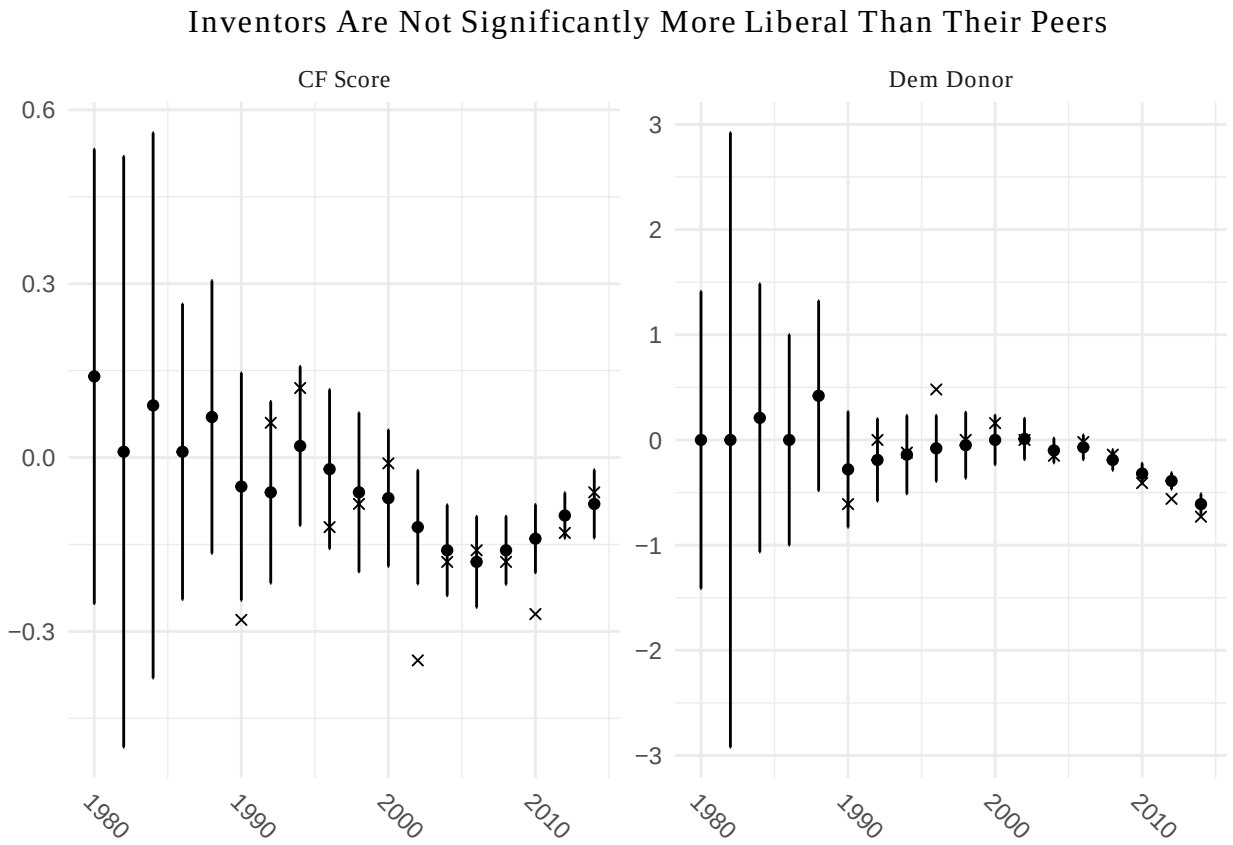

Figure 5: This figure shows the point estimates and 95 percent confidence intervals from regressing ideology scores (left panel) and a binary variable indicating whether the donor contributed to a Democratic candidate or committee (right panel) on a binary variable indicating whether the donor is an inventor. The regressions are run for each matched data set within each election cycle from 1980 through 2014. Note that the ideology score model is linear (because the dependent variable is continuous) while the Democratic donor model is logistic (because the dependent variable is binary). As a result, the vertical axis in the ideology model reflects an estimated difference in mean ideology scores between inventors and non-inventors, while the vertical axis in the Democratic donor model 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 4: **The PAC-UPAs Inventors Favor Are Employer Corporate PACs**

PAC Type	Share (%) in 1992	Share (%) in 2012
Corporate PACs	83.11	88.65
Trade and Prof. Ass'n PACs	16.02	9.02
Union PACs	0.00	0.03
Unknown Affiliation	0.87	2.30

Note:
This table shows the results of categorizing the PAC-UPAs the inventor-donors in the matched data set contributed to during the 1992 and 2012 election cycles. Partisan PAC-UPAs identified by manual observation are first excluded. The remaining PACs are then categorized, as per the text, as PACs representing trade and professional associations, corporations and their employees, unions, with the remainder being categorized as PACs of no discernible affiliation. The share of donations to each type of PAC are shown for the 1992 election (column 2) and the 2012 election (column 3).

significantly less likely to give to candidates or committees from both parties. But it also evidences a unique tendency to give to PAC-UPAs.

To better understand this behavior, I generated lists of the PAC-UPAs that inventor donors in the matched data set contributed to in two election cycles, 1992 and 2012. I then manually audited the lists and coded the results as: (1) partisan PACs albeit with moderate or missing ideology scores, like Michael Bloomberg's Independence USA PAC; (2) PACs for industry groups and professional associations, including general corporate lobbying groups like the National Federation of Independent Business; (3) corporate PACs representing individual companies or organizations or their employees; (4) PACs representing unions; and (5) the remaining PACs with an unknown affiliation.

Table 4 shows the results. To generate the table, I excluded the partisan PACs (group (1) above) and then calculated the share of donations accuring to each of the remaining groups. Consistent with prior work (Geismer, 2015), it shows that inventors have negligible attachments to trade unions: the inventor-donors in the matched data set gave almost no money in either election cycle to PACs associated with unions. Perhaps more surprisingly, inventor-donors give relatively little of their non-partisan donations to industry groups and professional associations, despite the fact that many have advanced degrees and are likely to belong to such groups. They only gave about 16 percent of the non-partisan donations to such groups in 1992, and that declined to 9 percent in 2012. In contrast, in both periods, the vast majority of the non-partisan donations from inventor-donors actually goes to corporate PACs tied to their employer, and the share increased from about 83 to about 89 percent of PAC-UPA donations between 1992 and 2012.

In sum, inventor-donors appear to have become slightly more liberal than their peers over time, though the trend is only significant after 2000 and it reversed a bit starting in 2006. That trend has not translated, however, in an increasing propensity for inventor-donors to contribute to Democratic candidates and committees when compared to their peers. On the contrary, inventor-donors are slightly *less* likely to contribute to Democratic candidates and committees compared to their peers. This appears to be because, compared to their peers, inventor-donors have become significantly

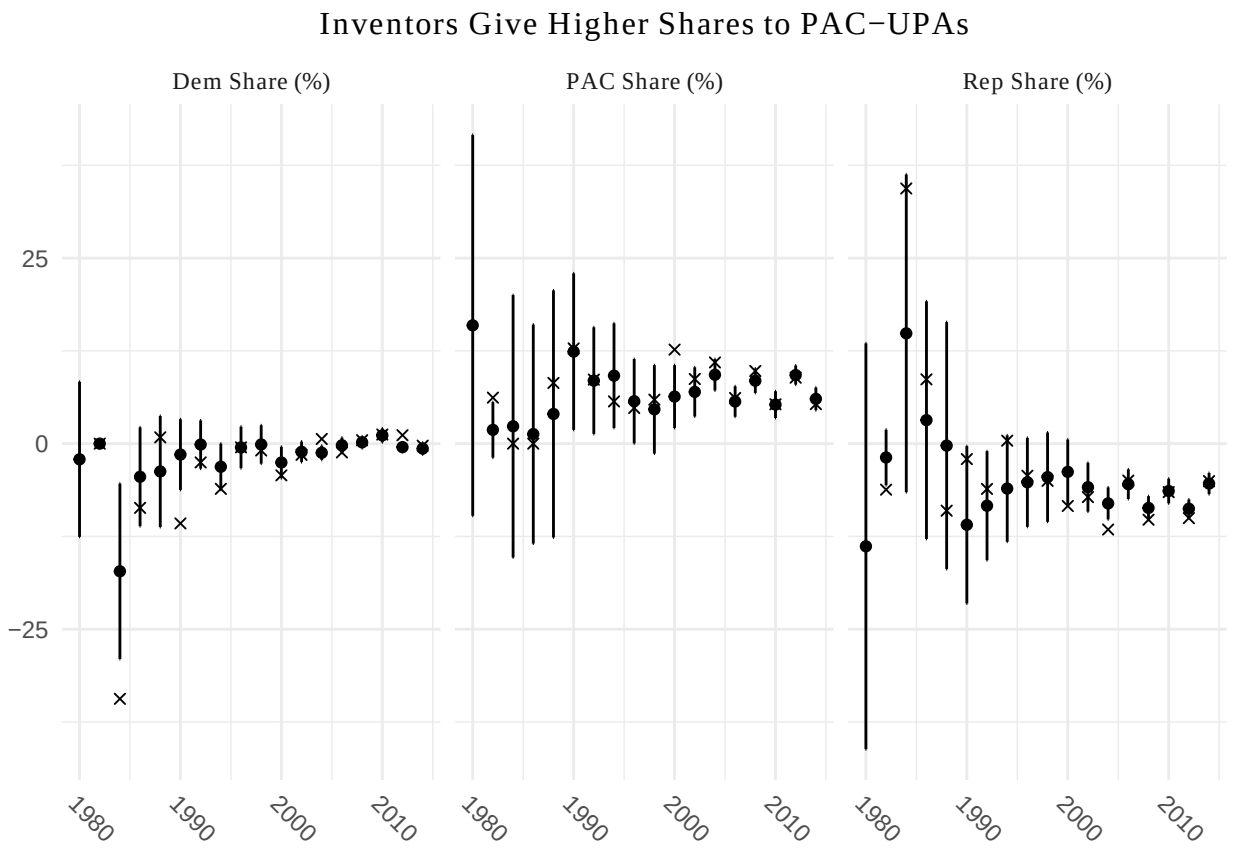

Figure 6: This figure shows the point estimates and 95 percent confidence intervals from regressing the share of donations given to Democratic candidates and commitees (left panel), PACs of unknown partisan affiliation (middle panel), and Republican candidates and commitees (right panel) on a binary variable indicating whether the donor is an inventor and a binary variable indicating whether the donor contributed to a Democratic candidate or committee. The regressions are run for each matched data set within each election cycle from 1980 through 2014. All models are linear (because the dependent variable is continuous) so the vertical axis each panel reflects the percentage point increase (or decrease) in the share of donations given to each group compared to non-inventor donors, conditional on being a Democratic donor. 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.

less likely, since 2002, to divide their contributions between candidates and committees of different parties and more likely to divide their contributions between one party and the PAC utilized by their corporate employer. Overall, the results suggest that inventor-donors are unique not in their attachments to the Democratic Party but in their willingness to channel their political contributions through their employer's corporate PAC.

4 Political Polarization in the American Knowledge Economy

Figures 2 and 4 document increasing polarization among inventor-donors, in terms of both a separating mean and a decreasing variance in ideology scores. The figures also show that most of the polarization within this group comes from inventor-donors who contribute to Democratic candidates and committees, who were quite moderate in the 1980s but became increasingly liberal (on average) starting around 1992. Are these Democratic inventor-donors becoming more polarized by virtue of the place they live (Moretti, 2013; Rodden, 2019) or the place they work?

To try and answer this question, I emulated the variance decomposition conducted in several 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 a decreasing 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. Using a one-way variance decomposition, both studies found that rising wage inequality between firms explains the vast majority of rising income inequality.

Prevailing hypotheses about rising political polarization among Democratic knowledge economy workers raise similar questions and are amenable to similar lines of analysis. 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 inventor-donors that give to Democratic candidates and committees. Echoing the work of scholars who put changes in political geography at the forefront of the analysis, it is possible that the Congressional Districts in which inventor-donors reside have become closer together in terms of their average ideology scores among Democratic inventor donors. It is also possible that these Districts have not pulled closer together in terms of their average ideology scores, and that increasing polarization reflects shrinking variation in ideology scores within Districts. As argued in the Introduction, similar claims can also be made for declining ideological variance between and within organizations and industries.

To test the plausibility of these competing hypotheses, I implemented a Bayesian form of ANOVA decomposition using all of the data on inventor-donors in election cycles 1992 and 2012, with the addition of some non-inventor donors who work for IP producers as described in Section 2. In each election cycle, I split the data into two separate data sets: those for contributors to Democratic candidates and committees and those for contributors to Republican candidates and committees. This produces four separate data set for Democratic and Republican donors in 1992 and 2012 respectively. I then used the `runjags` library in R (Denwood, 2016) to fit the following non-nested hierarchical model:

$$
\begin{aligned}
y_i &\sim \mathcal{N}(a_{j[i]} + b_{k[i]}, \sigma_y^2) \\
a_j &\sim \mathcal{N}(0, \sigma_a^2) \\
b_j &\sim \mathcal{N}(0, \sigma_b^2)
\end{aligned}
$$

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 between Districts, the average ideology between 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 inventor-donors. Both variables are highly significant in this respect in both election cycles. The goal is rather to precisely estimate 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 inventor-donors.

Such an analysis suggests that Democratic inventor-donors 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 7 illustrates the main results. It shows the point estimates and 95 percent confidence intervals for the each of the parameters of the model when the model is fitted to data for Democratic inventor-donors (left panel) and Republican inventor-donors (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 donors, 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, there is almost no variation left in average ideology scores of knowledge economy workers between the Districts in which these workers reside. This effectively means that differences between Congressional Districts can plausibly explain increasing polarization among knowledge economy workers. A significant decline in the variance of the residuals, by about 40 percent between 1992 and 2012, also suggests that polarization among Democratic inventor-donors 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.

Figure 2 suggests that Republican knowledge economy workers did become slightly more conservative over time, on average, but that they also became less polarized in the sense that the variance in ideology scores slightly *increased* over the same time frame. The results of the variance

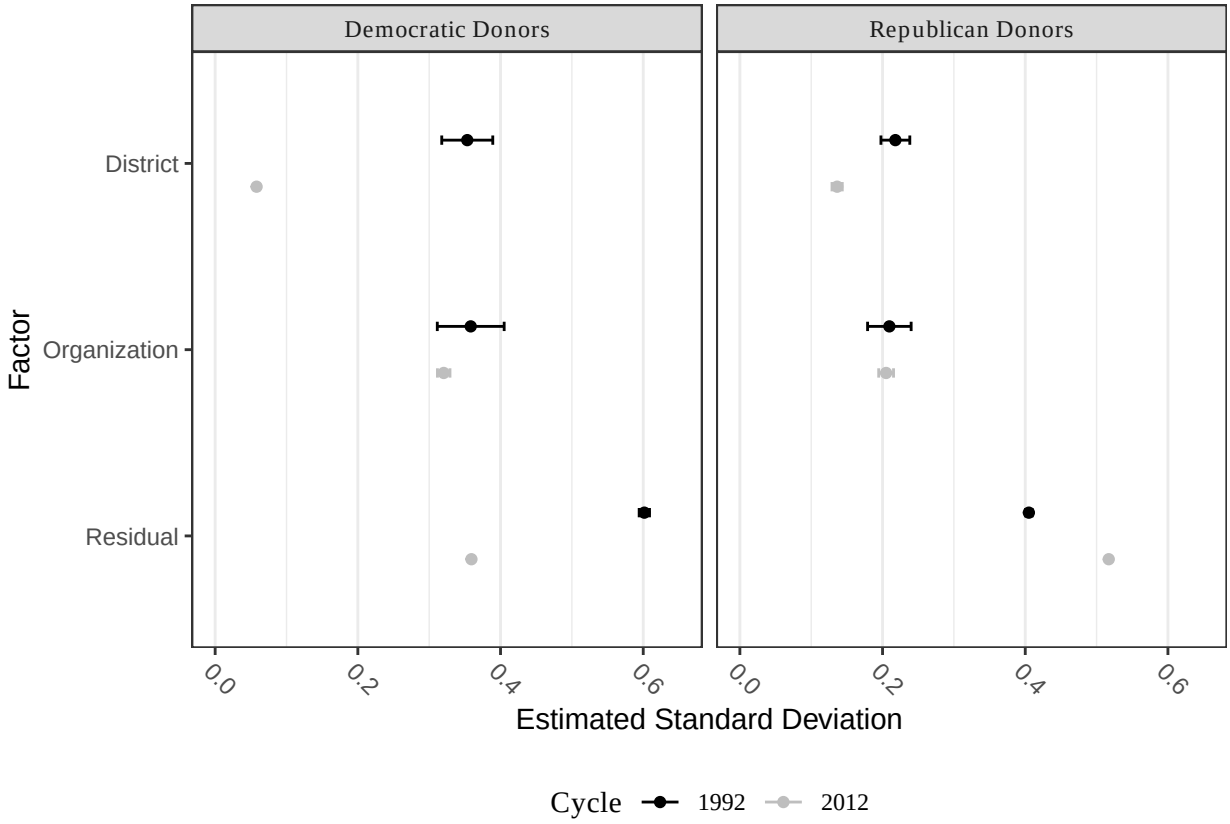

Figure 7: This figure shows the empirical standard deviation in the distribution of average ideology scores across Congressional District (top line) and across organizations (middle line) as well as the residual deviation within Districts and organizations (bottom line). The estimates are produced by 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 likley explained by increasing polarization between Districts rather than between organizations.

decomposition illustrated in Figure 7 suggest that there was much less variation in average ideology scores between Districts in 1992, for Republican donors, but that these donors also became slightly more polarized by virtue of the place they live (they experienced a declining variance in average ideology scores between Districts by 2012). At the same time, that trend was slightly offset by decreasing polarization within organizations and Districts for Republican donors.

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

Just as it is important to understand the political behavior of wealthy Americans in a setting of rising economic inequality (Page, Bartels, and Seawright, 2013), it is also important to understand the political behavior of IP producers in a setting where the knowledge economy transition has made IP producers increasingly pivotal players in the macroeconomic order (Short, n.d.). An analysis of campaign contributions by American inventors disabuses us of some notions. For example, despite the fact that leaders within the Democratic Party since Bill Clinton have championed the knowledge economy and its workers, the American inventors that contribute to campaigns remain a fairly heterogeneous bunch in terms of their overall ideology scores and their willingness to donate to each major political party. Such an analysis also reveals new previously unknown facts. For example, while inventors may not be materially different from their non-inventor peers in terms of their willingness to donate to either party, they are unique in the extent to which they channel contributions to their employer's corporate PAC. Finally, such an analysis confirms some prior work suggesting that the Democratic Party's efforts to court knowledge economy workers has created stark political division not between firms (Microsoft versus Raytheon) or industries (biotech versus agritech) but between the urban and suburban areas that knowledge economy workers heavily populate and the more rural outlying areas where they are less predominant (Rodden, 2019).

6 Appendix

Table 5: 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***
	(0.052)	(0.048)	(0.047)	(0.049)	(0.042)	(0.031)
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 6: 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 7: 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 8: 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 9: 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***	100.000***	76.415***	76.309***	71.244***	72.724***
	(6.259)	(0.000)	(6.225)	(3.960)	(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 10: 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***	77.635***	68.339***
		(23.868)	(7.741)	(15.836)	(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***	78.590***	89.904***
	(5.300)	(4.329)	(3.615)	(2.978)	(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***	89.812***	
	(1.725)	(1.236)	(1.472)	(0.980)	(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 11: 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***	99.897***	77.868***	77.491***	65.930***	47.405***
	(10.609)	(1.386)	(8.660)	(6.225)	(6.321)	(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***	52.469***	70.686***	57.661***	71.569***	30.415***
	(2.956)	(2.897)	(2.403)	(2.408)	(1.773)	(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***	26.300***	46.707***	29.204***	46.665***	28.585***
	(0.913)	(0.821)	(0.704)	(0.720)	(0.595)	(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 12: 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 13: 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 14: 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***	26.688***	42.571***	22.741***	71.942***	57.461***
	(7.749)	(5.838)	(5.794)	(4.306)	(3.454)	(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***	51.701***	79.193***	62.955***	77.313***	
	(2.413)	(2.239)	(1.992)	(1.767)	(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.

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