Polarized Technologies*

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Abstract

We document that inventors patent and cite technologies aligned with the views of their political party. We link inventors to U.S. voter registration data and map politically polarized issues to technologies. Compared to Republicans, Democrats are one-third more likely to patent technologies addressing climate change mitigation or women's reproductive health and one-third less likely to patent weapons. This holds across economic returns and organization characteristics. Republicans and Democrats are also 20% differently likely to cite these technologies. These findings highlight the importance of inventors' identity—specifically, their party affiliation—in shaping the content and diffusion of their innovation.

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1. Introduction

Democrats and Republicans hold different views on policy-relevant issues such as the urgency of addressing climate change and the importance of regulating gun sales and use (e.g., Gentzkow, 2016, Bertrand and Kamenica, 2023, Desmet et al., 2024). In this paper, we document that this divide is reflected in the content and diffusion of the new technologies inventors bring to the market.

We assemble a novel dataset combining patent and inventor data from the United States Patent and Trademark Office (USPTO) from 2001 to 2023 with voter registration data, which report individual-level information on the party affiliation of registered voters jointly with demographic characteristics including full name, gender, birth date, and address. In the main analysis, we focus on four states: Florida, New Jersey, New York, and Pennsylvania. These are the states in the top quartile of total innovation in the U.S. and with closed primary election systems. As voters in these states must register with a party to vote in its primary elections, this allows us to link a high proportion of inventors to their party affiliation.[1]

Our analysis centers on three issues at the core of the policy debate: climate change, women's reproductive rights, and gun control. We map views on climate change to green technologies, views on female reproductive rights to technologies on female reproductive health, and views on gun control to weapon-related technologies. Among highly polarized topics, we focus on these issues because they have a clear mapping to patentable technologies.

After linking polarized topics to innovations, we document that inventors patent technologies aligned with the views of their political party. Accounting for gender, year, county, technology-section, and birth cohort fixed effects, Democrat inventors are 31% more likely to ever patent a green technology and 35% more likely to ever patent technologies related to women's reproductive health. Conversely, they are 39% less likely to ever patent weapon-related technologies. Mapping these results to population differences in views over these issues, a 10% divide between Democrats and Republicans in the public opinion is associated with a similar 10% divide in the propensity of inventors to patent technologies addressing that issue.

The findings are robust to a large set of checks. First, they hold when considering inventors' total number of polarized patents, or the share of their patents represented by polarized technologies. Second, to mitigate concerns that political affiliation is influenced by the workplace, we document similar results for inventors who registered their current party affiliation at age twenty-one or younger. As most inventors are college graduates, it is plausible to

[1]Using data from the Cooperative Congressional Election Study, a large-scale survey on political preferences, we document that citizens in closed-primary states are over four times more likely to register with a political party compared to those in open-primary ones.

assume they had not yet begun full-time work at that age, and therefore their affiliation is unlikely to have been shaped by their employer. Third, the findings hold when analyzing patent applications rather than granted patents. This indicates that the observed match is not due to applications aligned with the inventor's party affiliation being more novel, or unaligned ones being less novel. Fourth, the results hold using an alternative definition of party affiliation based on inventors' campaign contributions. These data are available for all U.S. states, suggesting our results are valid beyond the four states in the main analysis.

After establishing a link between inventors' political affiliation and their propensity to patent polarized technologies, we study the role of economic returns and organizations in generating the match.

We proxy returns with patent citations, following a standard procedure in the literature. First, the match persists, across all technologies, in the sample of low- and highly-cited inventors. This suggests that party affiliation is not a proxy of inventor "quality." Second, we split the sample between patents with below- and above-median-citations. The match between inventors and polarized technologies occurs both in the former and in the latter, which are the patents with larger private and social impact.

We then study the role of organizations, documenting that our results hold across patent assignee characteristics and within assignees. This suggests that the match is primarily driven by inventors sorting into technologies, rather than into organizations. The match with polarized technologies also holds for inventors in universities, who have plausibly more freedom to choose the direction of their research, suggesting that this pattern cannot be explained solely by managers' allocation of inventors to projects within organizations.

Since the match between inventors and polarized technologies holds across economic returns and within organizations, we conclude that inventor identity, namely, inventors' information, beliefs, preferences, or early-life environment, play a crucial role in driving this result.

Last, we document a match between inventors and the views of their political party in the diffusion of new technologies. Compared to Republicans, Democrats are 13% more likely to ever cite green technologies, 19% more likely to cite female-health technologies, and 27% less likely to ever cite weapons. This suggests that polarized technologies are less likely be used in follow-on innovation by members of the opposing political party.

Our results provide novel evidence that inventors' political affiliation plays a role in shaping the direction of their innovation, adding to the literature documenting the importance of their demographic characteristics, such as gender, age, and geographic location. While our findings do not provide direct evidence on the costs of political polarization in the production of innovation, the existing evidence suggests these may have important economic implications as party-based sorting into technologies, together with lower cross-party diffusion, may reduce interaction across inventors with different party affiliation. In turn, this may lead to fewer novel ideas and make teams less productive (e.g., Posch et al., 2024, Evans et al., 2024), resulting in lower growth.

Related Literature. First, we contribute to the literature on the economic effects of partisanship, which has been linked to household decisions regarding, among others, consumption (Gerber and Huber, 2009, Conway and Boxell, 2024), financial (Kaustia and Torstila, 2011, Meeuwis et al., 2021) and real estate investment (McCartney et al., 2021), health (Allcott et al., 2020, Bursztyn et al., 2022, Wallace et al., 2022), and fertility (Dahl et al., 2022). Partisanship has also been shown to shape labor market outcomes including productivity (Teso et al., 2023, Engelberg et al., 2024), hiring practices (Gift and Gift, 2014, Colonnelli et al., 2022), job choice (McConnell et al., 2018, Engelberg et al., 2022) and on-the-job decisions (e.g., Cohen and Yang, 2019, Boxell and Conway, 2022, Jelveh et al., 2024). To the best of our knowledge, our paper is the first study to link political views to the content of work and, more specifically, to the direction of innovation.

Second, we contribute to the literature on the importance of individuals' backgrounds in determining the content of innovation. Bell et al. (2018) document that exposure to a particular technology class in childhood increases the propensity to innovate in that class later on in life. Koning et al. (2020, 2021) show that women are more likely to research and patent innovation on female diseases. Einio et al. (2022) document homophily between the gender, socio-economic status, and age of inventors and the consumers of their products. Additionally, Fry (2023) documents that scientists tend to focus on diseases that are more prevalent in their home countries, while Moscona and Sastry (2022) find that inventors disproportionately patent technologies addressing pathogens present in their country of residence. To the best of our knowledge, we are the first to document a link between the party affiliation of inventors and the direction of their innovation.

Third, we contribute to the literature on the importance of individuals' networks in shaping the diffusion of innovation. Social networks and interactions are important tools for knowledge exchange (e.g., Jaffe et al., 1993, 2000, Singh, 2005, Atkin et al., 2022). Recent evidence shows that homophily in network creation affects the citation patterns and counts of female researchers and inventors (Koffi, 2024, Subramani and Saksena, 2024). To the best of our knowledge, we are the first to show that inventors' party affiliation shapes the diffusion of innovation.

The rest of the paper is organized as follows. In Section 2, we describe the data construction and validation. In Section 3, we present our main results. In Section 4, we present the result on diffusion. In Section 5, we discuss our findings and we conclude.

2. Data

In this section, we describe the data. In Section 2.1, we provide details on the construction and validation of the dataset. In Section 2.2, we define polarized technologies.

2.1. The Matched Inventor-Political Affiliation Dataset

We start from PatentsView, a database maintained by the USPTO with information on inventors' names and cities of residence, patent grant date, assignee, title, abstract, technology, and forward citations. We restrict the sample to utility patents issued between 2001 and 2023.[2]

We merge these data with voter records for four states: Florida (FL), New Jersey (NJ), New York (NY), and Pennsylvania (PA). These are states in the top quartile by total innovation in the U.S. (Figure A.7) and operating in a closed primary system, meaning that voters need to be registered with a party in order to vote in that party's primaries. As a result, we can match a high proportion of inventors to a party affiliation, as citizens in closed-primary states are over four times more likely to register their affiliation with a political party compared to the other states, even though registration rates are similar.

Voter records contain information on each voter's name, gender, date of birth and registration, address, zip code, and political affiliation at the registration date. Our analysis is based on 2020 voter registration records for NY and PA, 2017 and 2022 for FL, and 2022 for NJ (Sood, 2017, 2020a,b). We define party affiliation as time-invariant, as standard in the literature (e.g., Cohen and Yang, 2019, Teso et al., 2023). We match inventors to voters using a combination of exact name and city of residence, and match 304,229 unique patents out of 573,324, a match rate of 53%.

We validate the matching procedure in two ways. First, we show that inventors' characteristics are in line with the literature. Second, we conduct equivalence tests and do not find any economically significant difference between matched and unmatched inventors along observable characteristics.More details on the matching are provided in Appendix Section C.

The final sample includes 95,600 unique inventors. Among them, 90.6% are linked to more than one patent. The shares of registered Democrats and Republicans are balanced (36% and 35%, respectively), while 26% are registered without affiliation and the remaining 3% are affiliated with minor parties (e.g., Independent, Conservative). Compared to Republican

[2]These are the most common type of patents issued by the USPTO and encompass virtually all types of inventions. We begin our analysis in 2001 to analyze patent applications, which are published since 2001, over a similar period. Patents are classified into technologies according to the Cooperative Patent Classification (CPC) system, which divides patents into nine sections sub-divided into classes, sub-classes, groups, and sub-groups.

inventors, Democrat inventors are twice as likely to be female (18% compared to 9%). They are on average three years younger and live in slightly wealthier zip codes ($120k compared to $110k). Republicans and Democrats also patent in different broad technology categories. For example, compared to Republicans, Democrats are 52% more likely to patent in chemistry and metallurgy and 40% less likely to patent in mechanical engineering. Accounting for year and county explains approximately half of these differences.[3]

2.2. Mapping Views to the Content of Innovation

To link views to the content of innovation, we focus on three issues at the center of the policy debate: climate change, women's reproductive rights, and gun control. Data from the CCES show that party affiliation is systematically correlated with different views on these issues in the general population, as well as among high-income, college-educated individuals, the characteristics of inventors. Compared to Republicans, Democrats are 31% more likely to support the urgency to act against climate change, 37% more likely to support abortion rights and 37% more likely to support the restriction of gun sales and use. The differences between the unaffiliated or registered with a third party and registered Republicans are approximately one-half of those with Democrats, suggesting that the views of this group are positioned approximately halfway between the views of the two major parties. We select these issues because, among the topics covered by the CCES, they can be mapped to patentable technologies.[4]

In the main analysis, we classify patents using a dictionary-based algorithm on the patent abstract. We map climate change views to green technologies, views on women's reproductive rights to female-health technologies, and views on gun control to weapon-related technologies. We classify patents as "green" if they include terms related to climate change, such as "global warming;" as related to "female health" if they mention organs or diseases more common among women due to biological sex differences, such as "endometriosis;" as "weapon-related" if they include terms referring to weapons and their components, such as "handgun" or "ammunition." Our preferred measure relies on a dictionary approach to capture patents indicating a clear intent to address the issue at stake. To address the concern that Democrats and Republicans might use different words when describing the same technology, we define alternative variables using the CPC classification. The dictionary-based measure is our preferred one for three reasons. First, it is more precise. For example, patents

[3]Descriptive statistics are reported in Appendix Section A.1.

[4]Among all topics covered by the CCES (abortion, environment, guns, public health care, immigration, military interventionism, government spending, trade, gay marriage, affirmative action, income versus sales tax), these three are the ones that clearly map to specific technologies (more details in Appendix Section B).

in group Y02A50/30, "Against vector-borne diseases" (classified as green according to the CPC classification), include technologies that are not necessarily directed at mitigating climate change, such as those addressing mosquito-borne, fly-borne, tick-borne, or waterborne diseases. Second, official classifications may not reflect the purpose of the technology as intended by the inventors, since CPC classes are assigned by patent examiners. Third, the patent abstract serves as a signal of the patent's content for follow-on innovations. In fact, the standard tool for identifying prior art is a keyword search based on the content of the innovation. More details on the construction of the outcome variables are provided in Appendix Sections A.2.2 and C.5.

3. Results

In this section, we document a match between inventors' party affiliation and their propensity to patent polarized technologies. Section 3.1 outlines the empirical specification. Section 3.2 presents the main results and Section 3.3 provides robustness checks. Sections 3.4 and 3.5 explore the roles of returns and organizations in generating this match.

3.1. Empirical Specification

We estimate a linear regression model where the outcome variable y is an indicator equal to one if inventor i ever patents technology j, which corresponds, in turn, to a green, female health, or weapon-related technology, and zero otherwise:

$$y_{i,t,c,s,a} = \beta_1 \text{Democrat}_i + \beta_2 \text{Other}_i + \beta_3 \text{Female}_i + \gamma_t + \delta_c + \zeta_s + \mu_a + \epsilon_{i,t,c,s,a} \tag{1}$$

i is an inventor, t is the year a patent has been granted, c is the county of residence of the inventor, and s is the technology-section of the patent. "Democrat" is an indicator equal to one if the inventor is a registered Democrat, and equal to zero otherwise. "Other" is an indicator equal to one if the inventor is registered without a party affiliation or with a party other than the Democratic or Republican one, equal to zero otherwise. The omitted party variable is "Republican." We include year dummies γ_t, each taking value one if inventor i was active (i.e., was granted a patent) in year t, zero otherwise, to control for potential time trends in the demand for different technologies. We include county fixed effects δ_c to control for potential differences in local labor demand. Technology-section fixed effects ζ_s control for differences in sorting of inventors into different technological fields and related education and skills. We also include birth-year fixed effects μ_a and a female dummy as these vary across inventors' party and may vary as well with the propensity to patent technology j. $\hat{\beta}_1$, our main coefficient of interest, is the average difference in the propensity of a Democrat (compared to a Republican) inventor to ever hold a patent in technology j over the period. $\hat{\beta}_2$ is the average difference in propensity to patent technology j between an inventor categorized as "Other" and a Republican inventor, and $\hat{\beta}_3$ is the average difference between a female and a male inventor. Standard errors are clustered at the county level.

3.2. Main Results

In Table 1, we report the results of estimating Equation (1) on inventors matched with voter registration data. The dependent variable in columns 1 to 3 equals one if the inventor ever patented a green technology, and zero otherwise. Controlling for year and county fixed effects, Democrat inventors are 21% more likely to patent green technologies than Republicans.[5] The gap becomes larger and equal to 32% after adding technology-section fixed effects (column 2). Our preferred specification in column 3 includes birth cohort fixed effects and a female dummy. The coefficient of "Democrat" remains positive and significant, and the scaled difference is unchanged.

Columns 4 to 6 report the results of estimating Equation (1) on a dummy equal to one if the inventor has ever patented a female-health technology, equal to zero otherwise. Across technologies, Democrat inventors are 71% more likely to patent these technologies compared to Republican ones (column 5). Adding technology-section fixed effects reduces the magnitude to 43%, and adding inventor-level controls reduces it to 35%.

In columns 7 to 9, we report the result of estimating Equation (1) on a dummy equal to one if the inventor has ever patented a weapon-related technology, equal to zero otherwise. Across all technology sections (column 7), Democrat inventors are 60% less likely to ever patent these technologies compared to Republican ones. After conditioning for technology-section in column 8, the scaled difference remains negative and statistically significant and becomes equal to 40%, and remains virtually unchanged after adding inventor-level controls in column 9.

For each specification, we also report the coefficient of "Other." Inventors registered with minor parties or unaffiliated are less likely than Democrat inventors, but more likely than Republican ones, to ever patent green technologies (column 3). A similar pattern holds for female-health technologies, although these differences are not statistically significant (column 6). This group is also more likely than Democrat inventors, but less likely than Republican ones, to ever patent weapons (column 9). The coefficient of "Other" provides a helpful benchmark to understand the drivers of the gap between Democrat and Republican inventors. Since the propensity of this group to patent polarized technologies is approximately halfway

[5] This share, which we refer to as "scaled difference," is constructed by dividing $\hat{\beta}_1$ by the mean of the dependent variable in the sample of Republican inventors.

between that of Democrats and Republicans, it suggests the gap is generated both by a higher propensity of inventors to patent technologies aligned with the views of their party, and by a lower propensity to patent unaligned ones.

Table 1 also reports the coefficients of a "Female" dummy, confirming that female inventors are more likely to patent technologies addressing typically-female diseases (Koning et al., 2020, 2021) (column 6). Our estimates uncover significant heterogeneity within the sample of male inventors, with Democrats being 32% more likely than Republicans to patent female-health technologies. The gap in propensity across parties is similar in the sample of female inventors (36%) (Appendix Table A.2).

Mapping these results back to differences in views by party affiliation from the CCES, the results suggest that, on average, a 10% larger divide in views in the public opinion is associated with a 10% higher divide in the propensity of inventors to patent the associated technologies.[6]

3.3. Robustness Checks

We run a large set of robustness checks summarized in Figure 1. In Panel A, we show the results of adding more demanding fixed effects to Equation (1). In the top rows, we control for zip code fixed effects to account for geographic spillovers in patenting activity (Ganguli et al., 2020, Engelberg et al., 2024). Our results remain unchanged, suggesting that we are not only capturing local clusters of innovation, but that, even within neighborhoods, the match between inventors and polarized technologies persists. In the middle rows, we include a set of county-by-grant year dummies to account for potential time-varying and county-specific variation in, for example, demand for specific technologies. The estimates are unaffected. In the bottom rows, we show that our findings hold (albeit with smaller magnitude) even comparing inventors patenting in close technologies, such as within CPC class Y02 ("Technologies or Applications for Mitigation or Adaptation Against Climate Change").[7]

In Panel B, we examine the robustness of our results to different definitions of the dependent variable. In the top rows, we estimate Equation (1) on a variable taking value one if inventor i ever patented technology j as first-listed inventor, and equal to zero otherwise.

[6]We map a 31% divide in public opinion between Democrats and Republicans on action against climate change to a 31% difference in the likelihood of Democrat versus Republican inventors to patent green technologies. Similarly, the 37% divide in views on abortion rights corresponds to a 35% higher likelihood of Democrat inventors to focus on female reproductive health technologies. Finally, the 37% divide in views on gun control aligns with a 39% difference in the propensity to patent weapons-related technologies.

[7]We also build a set of "placebo" technologies based on patent categories where inventors are most likely to patent jointly with the category of interest, a methodology similar to Bell et al. (2018). For all polarized technologies, the match with party affiliation is at least four times larger compared to that for the corresponding placebo technologies. More details in Appendix Section A.2.

The match with polarized technologies persists, with an even larger magnitude, for first-listed inventors. These are usually the "lead" inventor on the patent, as teams of inventors often order individuals based on their contributions. In the middle rows, the dependent variable is the proportion of patents in technology j relative to the total patents granted to inventor i over the period. The results are similar to those shown in Table 1, highlighting that the match holds in the intensive margin of inventors' innovation. Finally, in the bottom rows, we focus on total patent production. We estimate Equation (1) using a Poisson count model where the dependent variable is the total number of patents granted to inventor i in technology j over the period. The match with polarized technologies persists also in overall patent production.

In Panel C, we estimate Equation (1) on alternative samples. In the top rows, we focus on inventors who registered with their current party at age twenty-one or earlier. This restricts the analysis to inventors who plausibly registered to vote before entering the labor market. Similar findings hold in this subsample, mitigating concerns that our results are driven by inventors hired by an organization and later pivoting towards the party most aligned with that organization. In the middle rows, we document that the match also exists among patent applications, suggesting this pattern is already present at a stage closer to the idea-generating process. This finding also suggests that the match is unlikely to be generated by applications aligned with the inventor's party affiliation being more novel, or unaligned ones being less novel. In the bottom rows, we estimate Equation (1) on the sample of inventors matched to the universe of campaign contributions from Bonica (2019) (DIME). This allows us to build a different metric of party affiliation: we define inventors as "Democrat" if they donated more to the Democratic party than to the Republican one, and "Republican" inventors symmetrically. In all other cases, inventors are classified as "Other." Although political donation data are available nationwide, fewer inventors are matched as political donations are less common than voter registration. The results are qualitatively similar, albeit smaller, to those estimated in the main sample. This is plausibly due to campaign contributions being noisier proxies of party affiliation (e.g., as discussed by Fos et al., 2022).

Our results hold when technologies are defined using non-dictionary-based outcome variables. The magnitudes are lower, which is consistent with the CPC classification being a noisier proxy of the content of innovation.[8]

Finally, the match between polarized technologies and party affiliation holds, with similar magnitudes, in the sample of patents. Specifically, assigning a party affiliation to solo-authored patents based on the one of the inventor, and to team-authored patents based on the share of inventors registered with that party. While our preferred specification is at

[8]See Appendix Table A.3.

the inventor level, as inventors are the focus of the analysis, these results indicate that the match with polarized technology remains economically meaningful when looking at patent production, a more direct metric of innovation output.[9]

3.4. The Role of Returns

In this section, we show that inventor "quality" does not drive the match between inventors' party affiliation and polarized technologies. Specifically, higher-quality inventors may select into technologies with greater economic returns, which themselves may be systematically related to the technology's content.

We build two measures of returns: one for inventors, and one for patents. As returns are not observed in our data, we proxy them using forward citations, following a common practice in the literature (e.g., Akcigit et al., 2016). Citations are primarily an indicator of a patent's impact, and therefore a measure of the social returns to the innovation. However, they are also important determinants of the economic value of the patent and, as a result, of inventors' incomes (Trajtenberg, 1990).[10]

In Panel A of Figure 2, we split inventors by the median of their average citations, and estimate Equation (1) in each subsample. The match between inventors and polarized technologies remains, with similar magnitudes, in both samples. As voter records also report individuals' address, we use median household income in the zip code of residence, a widely used measure of socio-economic status, as alternative proxy of returns. Inventor-level citations are highly correlated with median zip code income, and indeed, we find results similar to those in Panel A of Figure 2 when we split the sample by inventor median income.[11]

In Panel B, we examine how the match with polarized technologies varies across patent returns. Starting from the patent-inventor dataset, we split patents by their median citation count. We then collapse them at the inventor level, and estimate Equation (1) in each subsample. The match persists, with a similar magnitude, across both samples.

This evidence shows that the match between inventors and polarized technologies is not confounded by differential quality of inventors by political party. This also highlights the match also occurs in the sample of highly-cited patents, which are the innovations with the largest private and social impact.

[9] Results are reported in Appendix Section A.2.4.

[10] As more recent patents may mechanically accumulate fewer citations, we adjust citation counts for truncation, following Hall et al. (2001), and we restrict the sample to patents issued until 2021. Our measure is weighted by the number of inventors on the patent, but results are similar without this adjustment.

[11] See Appendix Figure A.3.

3.5. The Role of Organizations

In this section, we study the role of organizations in generating the match between inventors and polarized technologies. Specifically, we study whether the allocation of workers to assignees specializing in a technology aligned with the views of the inventor's party explains this pattern.[12]

First, we examine the role of organization-level hiring policies. In Panel A of Figure 3, we study how the match varies by assignee size, measured by the total number of inventors granted a patent by the USPTO with that assignee over the period. This is motivated by evidence that smaller firms more commonly rely on networks for hiring (Colonnelli et al., 2022). We define as "small" an assignee with three or fewer inventors by year, and the remaining ones as "large." The results hold with similar magnitudes in each subsample, suggesting that differential hiring is unlikely to be an important driver of the match with polarized technologies.

In Panel B, we study the role of inventor preferences for more homogeneous workplaces. We split the data based on the political diversity of the inventors affiliated with each assignee. We define as "same-party" an assignee where, in a given year, all inventors granted a patent are affiliated with the same political party, and as "mixed-party" if at least one Democrat and one Republican are granted a patent.[13] The match persists, with a similar magnitude, in the sample of politically-homogeneous and politically-diverse firms, suggesting that inventors' homophily is unlikely to generate, per se, the match with polarized technologies.

In Panel C, we document that the match persists within organizations by estimating Equation (1) augmented with assignee fixed effects. An important caveat of this test is that over 60% of assignees are dropped from the sample. The estimates remain statistically significant, although smaller, for green and weapon-related technologies, while they are not statistically significantly different from zero for female-health technologies. The loss in significance is largely due to female-health technologies being patented by small assignees (as shown in Panel A), which are dropped from the analysis.

In Panel D, we restrict the sample to inventors patenting with an academic assignee. These are often academic researchers, who plausibly have greater freedom to choose the content of their innovation compared to those working with corporate assignees (e.g., Aghion et al., 2008). The match persists in this subsample, although the estimates are noisier due to a small sample size. This result suggests that the match is unlikely to be generated by

[12] Assignees are the owners of the intellectual property right associated with the patent, and are the organizations employing or collaborating with the inventors listed on the patent.

[13] This measure is defined at the year-assignee level, restricting the sample to year-assignees with at least two inventors. Results hold with higher thresholds or defining the measure at the assignee-city-year level to capture a more granular notion of workplace.

the allocation of inventors to projects within organizations.

Taken together, the match between inventors and technologies appears to be primarily driven by inventors sorting into technologies, rather than into organizations. This finding is in line with evidence on the importance of inventors, not only of firms, in driving the innovation process (Bhaskarabhatla et al., 2021). The results also persist for inventors in academic institutions, suggesting the match cannot be explained solely by managers allocating inventors to projects.

4. The Diffusion of Polarized Technologies

In this section, we show that the political party of inventors shapes the *diffusion* of polarized technologies. We measure diffusion through patent citations, which trace knowledge flows by linking patents to the technologies upon which they are built (Jaffe et al., 1993, 2000).

In Figure 4, we report the results of estimating Equation (1) on dependent variables taking value one if inventor i ever cited technology j, and zero otherwise. Compared to Republicans, Democrats are 13% more likely to ever cite green technologies, 19% more likely to ever cite female-health technologies, and 27% less likely to ever cite weapons. The results are similar when we exclude citations from patents in the same technology j.

The findings also hold when the dependent variable is the overall number of citations by inventor i to technology j, or the share of citations to technology j over the total number of citations.[14]

What drives the match between inventors and their propensity to cite polarized technologies? This is likely to be driven, at least in part, by a higher propensity of inventors to cite others with the same party affiliation. Indeed, we find that inventors are more likely to cite those with the same party affiliation, in line with the literature on party affiliation as a driver of segregation in social interactions (e.g., Gentzkow and Shapiro, 2011), and on the importance of networks for the diffusion of innovation (e.g., Jaffe et al., 1993, 2000, Singh, 2005, Subramani and Saksena, 2024).[15]

5. Discussion

We have shown that inventors patent technologies aligned with the views of their political party, and that this pattern is mirrored in the citation of these technologies in follow-on innovation. Differential economic returns or hiring by organizations do not explain the results.

[14] More details in Appendix Tables A.9 and A.10.

[15] These results are reported in Appendix Table A.11.

Additionally, a similar match persists for inventors patenting in universities, a group with plausibly more freedom to select the direction of their innovation. These findings suggest that inventor-level decisions, beyond product and labor market demand, play an important role in generating the match with polarized technologies.

Why do inventors select different technologies depending on their party affiliation? At least three mechanisms could be at play. First, inventors may have different information or beliefs about the returns to working on a given technology. This is consistent with evidence on a polarization of beliefs by political party (e.g., Alesina et al., 2020). Second, inventors may derive utility (or disutility) from working on a specific technology. This is in line with evidence that non-pecuniary characteristics are important drivers of occupational choice (e.g., Stern, 2004, Cassar and Meier, 2018). Utility may derive from inventors producing innovation aligned with their own views, which are similar to the views of their political party. Alternatively, inventors may wish to align with the views of their party due to social image concerns (Bénabou and Tirole, 2006). Third, inventors may have been exposed to different technologies when growing up. This is in line with evidence that the childhood environment has a lasting effect on the direction of innovation (Bell et al., 2018). At the same time, party affiliation is also likely to be transmitted across generations (e.g., Brown et al., 2023). The choice of technology, as well as that of party affiliation, may therefore reflect that of their parents or childhood environment (possibly independently one from the other).

Our results add to a growing literature documenting that inventors' demographic characteristics, such as gender, age, and geographic location, shape the direction of innovation. We add to this evidence by showing that another dimension of identity, namely the party affiliation of inventors, also shapes the content and diffusion of their technologies. While our evidence does not speak directly to the consequences of political polarization in the production and diffusion of innovation, below we discuss potential implications for economic growth.

Party-based sorting into technologies may reduce interaction among inventors with different party affiliations. Together with the lower diffusion across parties, this may result in fewer novel innovations, consistent with evidence that diversity of backgrounds fosters the creation of new ideas (Posch et al., 2024). Additionally, less collaboration may harm productivity, consistent with evidence that teams with both Republican and Democrat employees achieve higher performance (Evans et al., 2024).[16] As a consequence, the political divide in the content and diffusion of innovation could result in lower growth. Our results suggest, albeit descriptively, that this may be larger, the larger the set of polarized technologies, and

[16]Polarization may also harm growth through a misallocation of talent. As we are comparing close technologies, the effect is likely to be small unless talents are technology-specific, e.g., different for female-health innovations than for other health innovations.

the larger the divide in views over a given issue. Ultimately, the costs of political polarization for innovation and growth remain an open question and an important avenue for future research.

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Tables

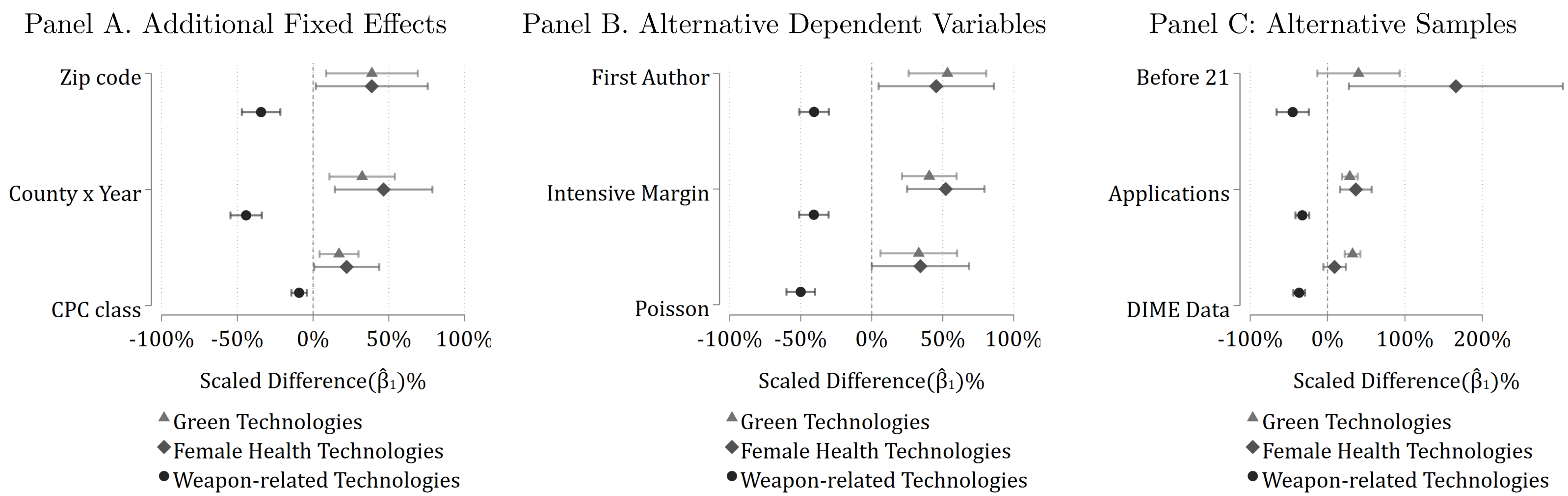
Table 1: Party Affiliation and Polarized Technologies

	Green Technologies			Female Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat ($\hat{\beta}_1$)	0.0024***	0.0036***	0.0034***	0.0037***	0.0023***	0.0019***	-0.0099***	-0.0067***	-0.0067***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0014)	(0.0010)	(0.0010)
Other ($\hat{\beta}_2$)	0.0016*	0.0019**	0.0019**	0.0020**	0.0012	0.0014*	-0.0057***	-0.0038***	-0.0040***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0009)	(0.0009)
Female ($\hat{\beta}_3$)			0.0012			0.0069***			-0.0027***
			(0.0010)			(0.0011)			(0.0007)
$\hat{\beta}_2 - \hat{\beta}_1$	-0.0008	-0.0016	-0.0015	-0.0017	-0.0010	-0.0005	0.0041	0.0028	0.0028
P-value ($\hat{\beta}_2 - \hat{\beta}_1$)	[0.3527]	[0.0560]	[0.0867]	[0.0170]	[0.1394]	[0.5056]	[0.0000]	[0.0007]	[0.0006]
N. of Inventors	95,595	95,595	95,302	95,595	95,595	95,302	95,595	95,595	95,302
% of Dem.	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78
$\mathbb{E}(LHS)$ for Rep.	0.011	0.011	0.011	0.005	0.005	0.005	0.017	0.017	0.017
Scaled Difference %	21.61	32.49	31.48	68.12	41.63	34.72	-57.74	-39.05	-39.40
Patent Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓	×	✓	✓
Birth Year FE	×	×	✓	×	×	✓	×	×	✓

Notes. The unit of observation is an inventor. The sample includes USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter register data. The outcome variable is a dummy equal to one if an inventor was ever granted a patent in technology j, and zero otherwise. Technologies j are defined as: green (columns 1-3), female-health (columns 4-6), and weapon-related (columns 7-9). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, and county fixed effects. Columns 2, 3, 5, 6, 8, and 9 include technology-section fixed effects. Columns 3, 6, and 9 also include a female dummy and inventor birth-year fixed effects. "Democrat" is a dummy equal to one if the inventor is a registered Democrat, equal to zero otherwise. "Other" is a dummy equal to one if an inventor is registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and zero otherwise. The omitted party dummy is equal to one if the inventor is a registered Republican, and zero otherwise. "Female" is a dummy equal to one if the inventor is female, equal to zero otherwise. $\hat{\beta}_2 - \hat{\beta}_1$ shows the difference between the coefficient of "Other" and that of "Democrat." The square brackets report the p-value of the t-test for this difference. "Scaled Difference" is defined as $\hat{\beta}_1$ divided by the mean of the dependent variable in the sample of Republican inventors. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Figures

Figure 1: Party Affiliation and Polarized Technologies: Robustness Checks

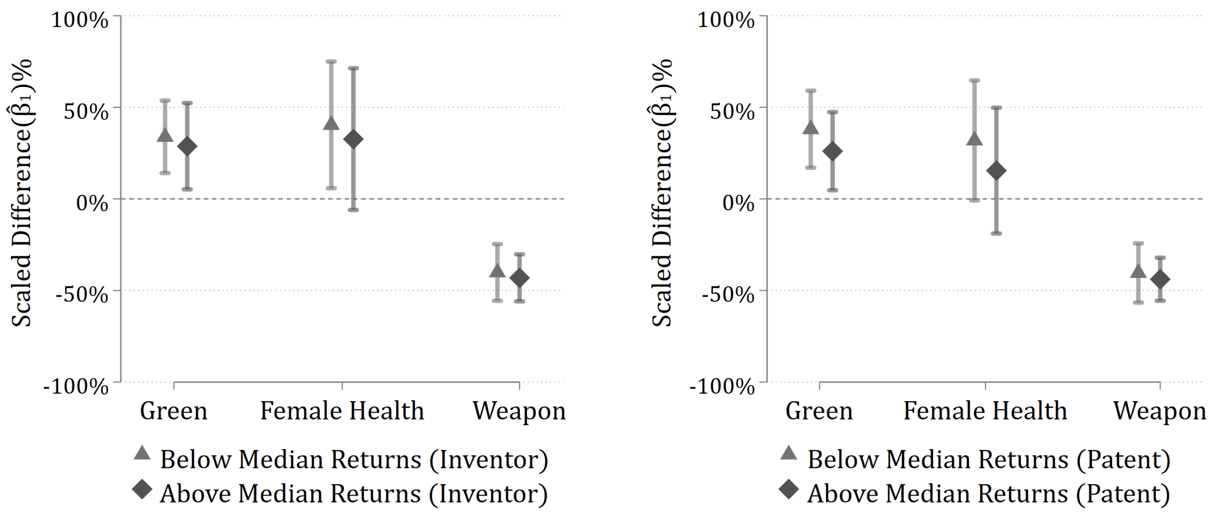


Notes. All panels report scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated with Equation (1), for j equal to green, female-health, or weapon-related technologies. The unit of observation is an inventor. In Panel A and B, the sample includes USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. Panel A reports estimates adding the following fixed effects to Equation (1): 1. zip code (top rows, N=94,806); 2. county×year (middle rows, N=66,714); 3. CPC class (bottom rows, N=95,302). In Panel B, y is: 1. probability of ever patenting j as first inventor (top rows, N=95,295); 2. number of patents in j over total number of patents granted to the inventor over the period (middle rows, N=95,302); 3. total number of patents in j granted to the inventor over the period, estimated through a Poisson model (bottom rows, N=12,476). Panel C shows estimates from Equation (1) on alternative samples: 1. inventors who registered their current affiliation at age 21 or younger (top rows, N=9,042); 2. inventors who filed a patent application between 2001 and 2023, with y equal to the probability of ever filing an application in j (middle rows, N=110,045); 3. inventors who made a political contribution since 2001 (bottom rows, N=152,395). This sample includes all U.S. states, and party affiliation is defined as detailed the main text (section 3.3). As these data do not contain information on year of birth, we do not include these fixed effects. Scaled differences are defined as $\hat{\beta}_1$ divided by the mean of the outcome variable for Republicans. All plots report 90 percent confidence intervals. The associated regression estimates are reported in Appendix Table A.5.

Figure 2: The Role of Returns

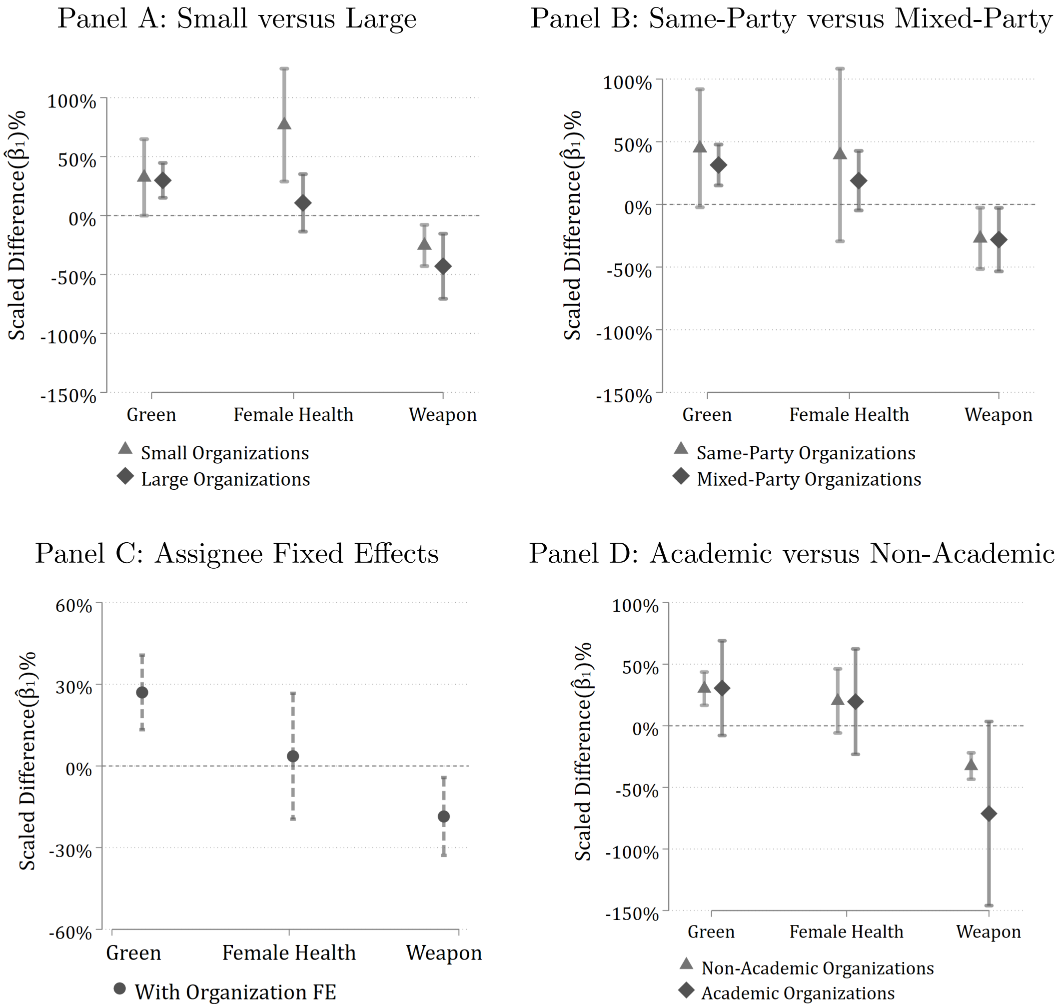
Panel A. Low- versus High-Citation Inventors

Panel B. Low- versus High-Citation Patents



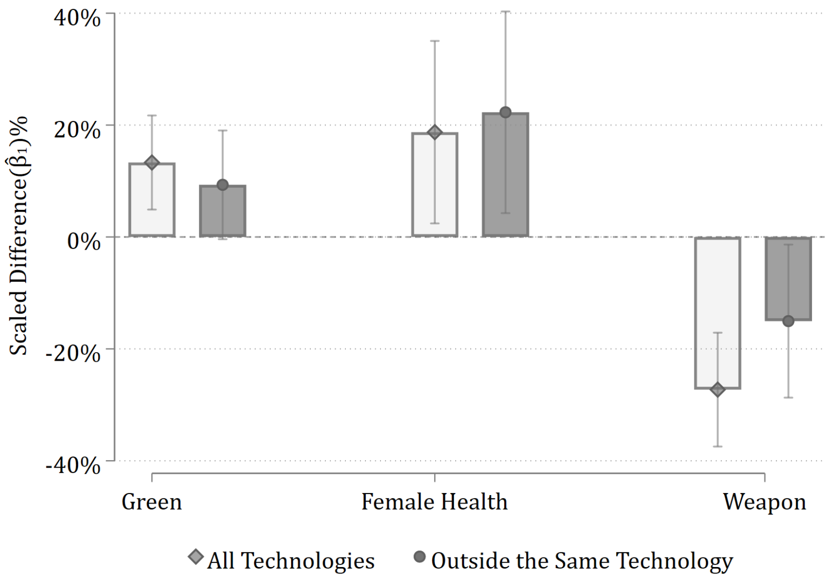
Notes. Each plot reports scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated using Equation (1). We adjust forward citation counts for truncation, following Hall et al. (2001), and we weight forward citations by the number of inventors listed on the patent. In Panel A, we start from the patent-inventor sample, which includes all USPTO inventors who were granted a patent between 2001 and 2021 merged with NY, NJ, FL, and PA voter registration data, and compute the inventor-level average of the adjusted forward citation count, following Akcigit et al. (2016). We split observations based on the median value of the inventor-level average adjusted citation count and estimate Equation (1) on each inventor-level subsample ($N_{below} = 44,330, N_{above} = 27,782$). In Panel B, we start from the patent-inventor sample, which includes all USPTO inventors who were granted a patent between 2001 and 2021 merged with NY, NJ, FL, and PA voter registration data, and compute the patent-level average of the adjusted forward citation count. We split observations based on the median value of patent-level average adjusted forward citations and estimate Equation (1) on each inventor-level subsample ($N_{below} = 49,045, N_{above} = 44,059$). In Panels A and B, the first pair of bars reports $\hat{\beta}_1$ where j is a green technology; the second pair of bars, for j equal to a female-health technology; the third pair of bars, for j equal to a weapon-related technology. In all panels, "Scaled Difference" is defined as the estimated coefficient of Democrat ($\hat{\beta}_1$) divided by the mean of the outcome variable for Republicans. All plots report 90 percent confidence intervals. The associated regression estimates are reported in Appendix Table A.6.

Figure 3: The Role of Organizations



Notes. Panels A, B, and D report scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$) estimated with Equation (1) on different inventor-level subsamples. In Panel A, we start from the patent-inventor-assignee sample, which includes all USPTO inventors granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter data, and split it into assignee-years with 3 or fewer inventors ("Small Organizations", N = 32,564), and those with 4 or more inventors ("Large Organizations", N = 52,960). In Panel B, we start from the patent-inventor-assignee sample, which includes all USPTO inventors granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter data, and we split it into assignee-year combinations with both Democrat and Republican inventors ("Mixed-Party Organizations", N = 54,715) and those with only Democrat or only Republican inventors ("Same-Party Organizations", N = 21,361). We remove observations with fewer than two inventors per assignee-year. In Panel C, we add assignee fixed effects to Equation (1), using the sample of inventors-assignees, which includes all USPTO inventors granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter data (N = 92,688, with 69,584 unique inventors). In Panel D, we start from the patent-inventor-assignee sample, including all USPTO inventors granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter data, and split it based on whether the assignee is a university ("Academic Organizations", N = 8,618) or not ("Non-Academic Organizations", N = 72,313). In all panels, "Scaled Difference" is defined as $\hat{\beta}_1$ divided by the mean of the outcome variable for Republicans. All plots report 90 percent confidence intervals. The associated regression estimates are reported in Appendix Table A.7.

Figure 4: The Diffusion of Polarized Technologies



Notes. Each plot reports scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated using Equation (1). The unit of observation is one inventor. The sample includes USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. Each bar reports the results of estimating Equation (1) on a dependent variable taking value one if an inventor has ever cited a patent in technology j, and zero otherwise. For the first pair of bars, j is a green technology. The second pair of bars reports results for j equal to a female-health technology, and the third for j equal to a weapon-related technology. In each pair of bars, the first the reports results estimated on the full sample (after excluding self-citations, N = 45,917). The second bar reports results excluding observations where the cited patent belongs to the same technology j as the citing patent (N = 45,886, 45,893, and 45,784 for green, female health, and weapon-related, respectively). "Scaled Difference" is defined as $\hat{\beta}_1$ divided by the mean of the dependent variable in the sample of Republican inventors. All plots report 90 percent confidence intervals. The associated regression estimates are reported in Appendix Table A.8.

Polarized Technologies

Online Appendix

Gaia Dossi **Marta Morando**

A. Supplementary Results

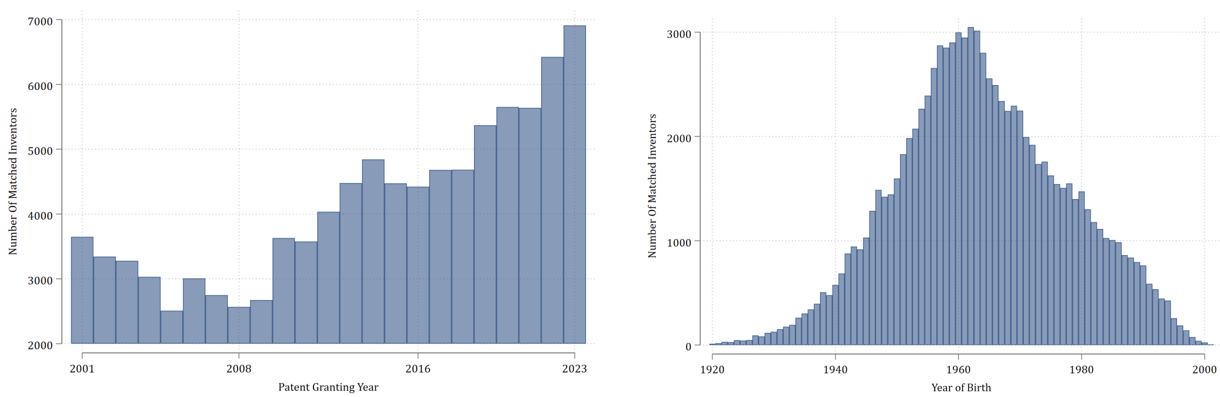
A.1. Descriptive Statistics

Table A.1: Descriptive Statistics

	Democrat		Republican		Democrat-Republican	
	Mean	Standard Deviation	Mean	Standard Deviation	Standardized Difference	P-value Difference Test
	(1)	(2)	(3)	(4)	(5)	(6)
Female Dummy	0.183	0.386	0.088	0.283	0.277	0.000
Birth Year	1965	14.600	1962	13.120	0.215	0.000
Median Family Income (USD)	120,000	50,750	110,000	40,080	0.216	0.000
Section A	0.351	0.477	0.304	0.460	0.101	0.000
Section B	0.233	0.423	0.311	0.463	-0.174	0.000
Section C	0.235	0.424	0.155	0.361	0.203	0.000
Section D	0.015	0.120	0.016	0.124	-0.009	0.218
Section E	0.038	0.191	0.076	0.265	-0.164	0.000
Section F	0.104	0.306	0.173	0.378	-0.198	0.000
Section G	0.485	0.500	0.385	0.487	0.201	0.000
Section H	0.305	0.460	0.279	0.449	0.056	0.000
Section Y	0.235	0.424	0.263	0.440	-0.066	0.000

Notes. This table shows descriptive statistics (mean and standard deviation) of inventors affiliated with the Democratic party (Columns 1 & 2) and the Republican party (Columns 3 & 4). Column 5 shows the standardized difference between Democrat and Republican inventors in the full sample of NY, NJ, PA, and FL inventors. Column 6 reports the p-value for the test for differences in means, assuming unequal variances. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. Sections are defined as: human necessities (A), performing operations and transporting (B), chemistry and metallurgy (C), textile and paper (D), fixed construction (E), mechanical engineering, lighting, heating, weapons, blasting engines or pumps (F), physics (G), electricity (H), new technological developments (Y).

Figure A.1: Distribution of Inventors by Patent Granting Year and Year of Birth



Notes. These figures show the distribution of the number of inventors by patent grant year (LHS) and by year of birth of inventors (RHS). The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data.

A.2. Additional Robustness Checks

A.2.1. Sample Restrictions

Table A.2: Party Affiliation and Polarized Technologies, Sample of Male and Female Inventors

	Green Technologies			Female-Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Male Sample									
Democrat $\hat{\beta}_1$	0.0027***	0.0037***	0.0036***	0.0026***	0.0015**	0.0015**	-0.0101***	-0.0070***	-0.0072***
	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0007)	(0.0007)	(0.0014)	(0.0011)	(0.0011)
N. of Inventors	82,547	82,547	82,547	82,547	82,547	82,547	82,547	82,547	82,547
% of Dem.	33.77	33.77	33.77	33.77	33.77	33.77	33.77	33.77	33.77
$\mathbb{E}(LHS)$ for Rep.	0.011	0.011	0.011	0.005	0.005	0.005	0.018	0.018	0.018
Scaled Difference %	23.75	32.31	31.69	54.77	31.89	32.25	-55.38	-38.45	-39.77
Panel B: Female Sample									
Democrat $\hat{\beta}_1$	0.0018	0.0015	0.0013	0.0053**	0.0048*	0.0047*	-0.0038**	-0.0032**	-0.0033**
	(0.0018)	(0.0017)	(0.0017)	(0.0025)	(0.0025)	(0.0025)	(0.0015)	(0.0014)	(0.0014)
N. of Inventors	12,738	12,738	12,736	12,738	12,738	12,736	12,738	12,738	12,736
% of Dem.	48.81	48.81	48.8	48.81	48.81	48.8	48.81	48.81	48.8
$\mathbb{E}(LHS)$ for Rep.	0.006	0.006	0.006	0.013	0.013	0.013	0.006	0.006	0.006
Scaled Difference (%)	31.25	26.30	22.16	40.09	36.29	35.87	-62.21	-52.21	-54.07

Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. Panel A restricts the sample to male inventors, while Panel B restricts it to female inventors. The outcome variable is a dummy equal to one if an inventor was ever granted a patent in technology j, and zero otherwise. Technologies j are defined as: green (columns 1-3), female health (columns 4-6), and weapon-related (columns 7-9). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, county fixed effects, and a dummy "Other" equal to one for inventors registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and equal to zero otherwise. Columns 2, 3, 5, 6, 8 and 9 include section fixed effects. Columns 3, 6, and 9 control for inventor birth-year fixed effects. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is equal to one if the inventor is a registered Republican, and zero otherwise. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

A.2.2. Different Outcome Variables

Table A.3 replicates Table 1 with dependent variables the probability of ever patenting a technology j where the technology j is defined based on the classification developed by the Cooperative Patent Classification (CPC) system, instead of a dictionary-approach.

– A technology j is classified as "Green" if it belongs to the CPC class Y02. The class Y02 is defined as "Technologies or Applications For Mitigation or Adaptation against Climate Change."

– Given that there is no class or subclass devoted to female health, a technology j is classified as "Female health" if it belongs to one of the following CPC groups: A41D13/0017 (Professional, industrial or sporting protective garments, e.g. surgeons' gowns or garments protecting against blows or punches, specially adapted for women), A61B2017/00805 (Treatment of female stress urinary incontinence), A61B5/0091 (For mammography), A61B5/4294 A61B2010/0074 (Vaginal secretions), A61B5/4288 (Mammary secretions), A61B5/4306 (For evaluating the female reproductive systems, e.g. gynaecological evaluations), A61B5/4312 (Breast evaluation or disorder diagnosis), A61B5/4318 (Evaluation of the lower reproductive system for women), A61B5/4325 (Evaluation of uterine cavities, e.g. uterus, fallopian tubes, ovaries), A61B5/4331 (of the cervix), A61B5/4337 A61N2005/0611 (of the vagina), A61B5/6875 (of uterus), A61B5/035 (Intra-uterine probes therefor), A61B5/033 (Uterine pressure), A61B6/502 A61B8/0825 G06T2207/30068 (for diagnosis of breast, i.e. mammography), A61B8/406 (using means for diagnosing suspended breasts), A61B10/0041 (detection of breast cancer), A61B2017/4233 (Operations on Fallopian tubes, e.g. sterilization), A61B2017/4225 (Cervix uteri), A61B2017/4216 (Operations on uterus, e.g. endometrium), A61B17/42 (Gynaecological or obstetrical instruments or methods), A61B17/4241 (Instruments for manoeuvring or retracting the uterus), A61F6/06 (Contraceptive device for use by female), A61F6/065 (Condom-like devices worn by females), A61F6/08 (Pessaries, i.e. devices worn in the vagina to support the uterus, remedy a malposition or prevent conception), A61F6/14 A61F6/142 A61F6/144 A61F6/146 A61F6/148 A61F6/16 (Intra-uterine type), A61F6/12 A61F6/18 (Inserters or removers), A61F6/22 (Implantable in tubes), A61F6/225 (Trancervical), A61F5/455 (For collecting urine or discharge from female member), A61F5/4553 (Placed in the vagina, e.g. for catamenial use), A61F13/202 A61F13/2085 A61F13/2088 A61F13/2091 A61F13/2094 A61F13/2097 (Catamenial tampons), A61F13/2045 (Cup-shaped tampons), A61F13/34 (Means for withdrawing tampons e.g. withdrawal strings),
A61F2013/4729 (Combining catamenial pad and tampon), A61F15/003 (Dispenser for catamenial tampons), A61F2/12 (Mammary prostheses and implants), A61F13/472 (Sanitary towels for female use), A61F2007/0021 A61F2007/005 (Heating or cooling appliances for medical or therapeutic treatment of the human body: female breast, genitals), A61F13/145 (Bandages, dressings or absorbent pads; First-aid kits, specially adapted for female body), G01N33/57415 A61K2239/49 A61K2039/812 (Breast cancer), G01N33/57411 (Cervix cancer), A61B1/303 (Instruments for performing medical examinations: for the vagina, i.e. vaginoscopes),
A61B2018/00559 A61M2210/14 (Female reproductive organs), A61H19/34 (For clitoral stimulation), A61K9/0036 (Devices retained in the vagina or cervix for a prolonged period, e.g. intravaginal rings, medicated tampons, medicated diaphragms), A61K9/0039 (Devices re-

tained in the uterus for a prolonged period, e.g. intrauterine devices for contraception); A61K47/6855 A61K51/1051 (The tumour determinant being from breast cancer cell); A61M2210/1007 (Breast, mammary); A61M2210/1092 (Female anatomical part of the body); A61N1/0524 (Vaginal electrodes); A61P15/02 (Feminine contraceptives); A61P15/12 (For climateric disorders); A61P5/30 (Oestrogen); G01N33/57449 (Cancer of ovaries); G01N33/57442 (Cancer of uterus or endometrius); G01N33/57411 (Cancer of cervix); G01N33/57415 (Cancer of breast); G01N2800/361 (Menstrual abnormalities or abnormal uterine bleeding, e.g. dysmenorrhea); G01N2800/362 (Menopause); G01N2800/364 (Endometriosis); A61K31/566 (Related to estrone); A61K31/57 (Related to pregnane or progesterone); A61K31/567 (Related to mestranol, norethandrolone); C12N5/0682 C12N2502/243 (Cells of the female genital tract); A61K31/565 (Related to estrane, estradiol); A61H2205/082 (Breast devices); A61B10/0291 (Instrument for biopsy of uterus); A61G2200/12 (Type of patients: women); C07K16/3015 (From tumor cells: breast); G06C3/00 (Related to menstruation table); A61B5/4343, A61B5/435 A61B5/4356 A61B5/4368 (Pregnancy and labour mounting); A61F2/005 (Filters or appliances: with pressure applied to urethra by an element placed in the vagina); A61F2013/15016 (Pads for bras); A61F5/4556 (Portable urination aids); A61F13/141 (Milk breast pads); A61B10/0012 (Ovulation-period determination); A61B5/4288 (Mammary secretion); C12M21/06 (For in vitro fertilization); A61F5/03 (Teat or breast support); A61M1/06 A61M1/815(Milk pumps); A61J13/00 (Breast nipple shield); A61K35/54 (Ovaries, Ova, Ovules, Embryos, Foetal cells, Germ cells); A61P15/04 (For inducing labour or abortion); G01N2800/36 (Gynecology or obstetrics).

– A technology j is categorized as "Weapon-related" if it belongs to CPC class F41 ("Weapons") or F42 ("Ammunition; Blasting").

Table A.3: Party Affiliation and Polarized Technologies, Different Outcome Variables

	Green Technologies			Female-Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0046*	0.0070***	0.0061***	0.0025***	0.0012*	0.0012*	-0.0136***	-0.0088***	-0.0088***
	(0.0026)	(0.0018)	(0.0017)	(0.0007)	(0.0007)	(0.0007)	(0.0017)	(0.0013)	(0.0013)
N. of Inventors	95,587	95,587	95,293	95,587	95,587	95,293	95,587	95,587	95,293
% of Dem.	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78
$\mathbb{E}(LHS)$ for Rep.	0.114	0.114	0.114	0.007	0.007	0.007	0.026	0.026	0.026
Scaled Difference (%)	4.01	6.12	5.35	36.72	17.20	17.64	-52.20	-33.98	-33.99

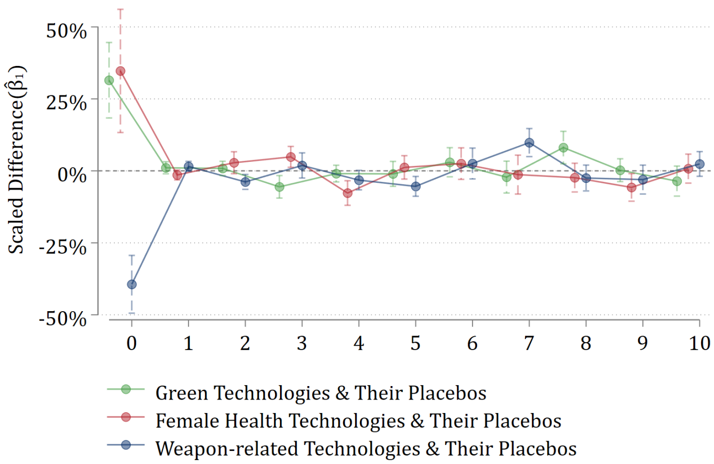
Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. The outcome variable is a dummy equal to one if an inventor was ever granted a patent in technology j, and zero otherwise. Technologies j are defined as described in section A.2.2. Specifically, green technologies are defined as patents in CPC class Y02 (columns 1-3), female-health technologies are defined as patents in various CPC groups belonging to classes A41, A61, C07, C12, G01, and G06 (columns 4-6), and weapon-related technologies are defined as patents in CPC classes F41 and F42 (columns 7-9). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, county fixed effects, and a dummy "Other" equal to one for inventors registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and equal to zero otherwise. Columns 2, 3, 5, 6, 8 and 9 include section fixed effects. Columns 3, 6, and 9 control for inventor birth-year fixed effects and a female dummy. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is equal to one if the inventor is a registered Republican, and zero otherwise. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

A.2.3. Placebo Technologies

We define a set of "placebo" technologies following the methodology of Bell et al. (2018). We take all inventors producing polarized technologies and focus on all other technologies they patent. Then, we rank these technologies by frequency of overlap and divide them into deciles. Afterwards, we estimate a version of Equation (1) where the dependent variable is a dummy equal to one if the inventor has ever patented that technology, equal to zero otherwise.

The results of this analysis are shown in Figure A.2. The first three dots report the results of this estimation for polarized technologies, while the subsequent dots for placebo technologies. The green line connects scaled differences for green technologies (distance 0) and their respective placebos, binned in deciles (distance 1-10). The red line connects scaled differences for female-health technologies (distance 0) and their respective counterfactuals, binned into deciles (distance 1-10). The blue line connects scaled differences for weapon-related technologies and their respective placebos, binned into deciles (distance 1-10). Across all technologies, the point estimate is at least four times larger for the polarized technology compared to the associated placebos, and always statistically significantly higher.

Figure A.2: Comparison With Placebo Technologies



Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. The figure reports scaled differences and the 90% confidence interval for the estimation of Equation (1) for green, female, weapon technologies and the associated placebo technologies. Scaled differences are defined as $\hat{\beta}_1$ divided by the mean of the outcome variable for Republican inventors. The green line connects scaled differences for green technologies (distance 0) and their associated placebos, binned in deciles (distance 1-10). The red line connects scaled differences for female-health technologies (distance 0) and their associated placebos, binned into deciles (distance 1-10). The blue line connects scaled differences for weapon-related technologies and their associated placebos, binned into deciles (distance 1-10). We define a set of "placebo" technologies following the methodology of Bell et al. (2018). We consider all inventors patenting polarized technologies and focus on all other non-polarized technologies they patent. Placebo technologies are ranked from most to least overlap with the associated polarized technology, and are then divided into deciles. The first decile (distance 1) groups the ten placebo technologies that are closest to polarized technologies, the second decile (distance 2) the ten next closest placebo technologies, and similarly for the remaining deciles.

A.2.4. Patent-level Analysis

We estimate a specification at the patent level:

$$y_{p,t,c,s,a} = \beta_1 \text{Democrat}_p + \beta_2 \text{Other}_p + \beta_3 \text{Female}_p + \gamma_t + \delta_c + \zeta_s + \mu_a + \epsilon_{p,t,c,s,a} \tag{A.2}$$

where p is a patent, c is the county of residence of the first-listed inventor, t is the grant year, s is the technology section, and a is the average birth year across inventors listed on the patent, rounded to the nearest integer. The outcome variable is an indicator equal to one if the patent is classified as technology j, and zero otherwise. "Democrat," "Other," and "Female" are defined, differently in each specification, based on the team of inventors listed on the patent. Standard errors are clustered by the county of residence of the first-listed inventor.

In Table A.4, we report the results of estimating Equation (A.2). In columns 1-3, we restrict the sample to single-inventor patents. In the remaining columns, we restrict the sample to patents granted to teams (i.e., at least two inventors). In columns 4-6, party affiliation is defined as the share of Democrats in the team. In columns 7-9, we define a team as "Democrat" if all members are registered Democrats, and similarly for "Other" and "Republican," and we construct a dummy for mixed-affiliation teams.

Table A.4: Party Affiliation and Polarized Technologies, Patent-Level

	Solo-Authored			Teams			Homogeneous		
	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0031**	0.0012	-0.0074***	0.0056***	0.0017	-0.0038***	0.0051***	0.0013*	-0.0029***
	(0.0016)	(0.0009)	(0.0019)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0008)	(0.0011)
N. of Patents	53,189	53,189	53,189	122,026	122,026	122,026	122,026	122,026	122,026
% of Dem.	31.26	31.26	31.26	37.11	37.11	37.11	23.29	23.29	23.29
$\mathbb{E}(LHS)$ for Rep.	0.005	0.003	0.019	0.006	0.005	0.004	0.004	0.002	0.007
Scaled Difference (%)	60.44	42.44	-40.03	88.23	37.89	-88.85	134.73	53.40	-40.54

Notes. This table shows the results of estimating Equation (A.2) on the sample of patents granted between 2001 and 2023 to at least one inventor that is matched to voter registration data in FL, NJ, NY, or PA. In columns 1-3, we restrict the sample to patents with a single author. A patent is defined as "Democrat" based on the party affiliation of its unique inventor. These specifications control for a dummy "Other" taking value one for patents whose inventor is registered as an unaffiliated voter or with a party that is neither the Democratic nor the Republican party, and zero otherwise. In columns 4-6, we restrict the sample to patents with at least two inventors matched to voter registration data. "Democrat" is defined based on the share of Democrats among all inventors listed on the patent ("team"). These specifications control for the share of "Other" inventors in the team. In columns 7-9, we restrict the sample to patents with at least two inventors. A patent is defined as "Democrat" if *all* inventors listed in a team are registered with the Democratic party. These specifications control for a dummy variable taking value one if all members of the team are classified as "Other," and equal to zero otherwise, and for a dummy taking value one if the team includes at least one Democrat and one Republican, at least one Democrat and one inventor classified as "Other," or at least one Republican and one inventor classified as "Other," and equal to zero otherwise. The outcome variable is a dummy equal to one if an inventor was ever granted a patent in technology j, and zero otherwise. Technologies j are defined as: green (columns 1, 4, and 7), female health (columns 2, 5, and 8), and weapon-related (columns 3, 6, and 9). All specifications also include: i.) patent grant year dummies; ii.) county fixed effects, for the county of residence of the first listed inventor in a patent; iii.) inventors birth-year fixed effect, for the average birth year in a team; iv.) the share of female inventors in a team; v.) technology-section fixed effects. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for "Republican" patents (columns 1-3), for the full sample (columns 4-6), and for homogeneous "Republicans" teams (columns 7-9). Standard errors clustered by county of the first-listed inventor are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

A.3. Main Robustness Checks

Table A.5: Party Affiliation and Polarized Technologies, Robustness Checks

	Zip Code FE			County × Year			CPC Class FE		
	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0088**	0.0048*	-0.0119***	0.0021**	0.0016**	-0.0070***	0.0019**	0.0012*	-0.0016***
	(0.0042)	(0.0028)	(0.0027)	(0.0008)	(0.0007)	(0.0010)	(0.0009)	(0.0007)	(0.0005)
N. of Inventors	94,806	94,806	94,806	66,714	66,714	66,714	95,302	95,302	95,302
% of Dem.	35.82	35.82	35.82	36.44	36.44	36.44	35.78	35.78	35.78
$\mathbb{E}(LHS)$ for Rep.	0.023	0.012	0.035	0.006	0.004	0.016	0.011	0.005	0.017
Scaled Difference (%)	38.82	38.71	-34.31	32.38	46.53	-44.20	17.12	22.19	-9.21

	First Author			Intensive Margin			Poisson		
	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0011***	0.0007*	-0.0030***	0.0020***	0.0015***	-0.0056***	0.2861**	0.2948*	-0.6935***
	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0009)	(0.1232)	(0.1552)	(0.1224)
N. of Inventors	95,295	95,295	95,295	95,302	95,302	95,302	22,432	84,649	12,476
% of Dem.	35.78	35.78	35.78	35.78	35.78	35.78	34.46	37.15	27.49
$\mathbb{E}(LHS)$ for Rep.	0.002	0.001	0.007	0.005	0.003	0.014	0.093	0.015	0.213
Scaled Difference (%)	53.31	45.41	-40.60	40.52	52.15	-40.76	33.12	34.28	-50.02

	Before 21			Applications			DIME Data		
	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related	Green	Female Health	Weapon-related
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0030	0.0046**	-0.0093***	0.0038***	0.0024***	-0.0037***	0.0041***	0.0008	-0.0061***
	(0.0024)	(0.0023)	(0.0026)	(0.0008)	(0.0008)	(0.0006)	(0.0008)	(0.0007)	(0.0008)
N. of Inventors	9,042	9,042	9,042	110,045	110,045	110,045	152,395	152,395	152,395
% of Dem.	35.37	35.37	35.37	37.81	37.81	37.81	54.26	54.26	54.26
$\mathbb{E}(LHS)$ for Rep.	0.007	0.003	0.021	0.013	0.007	0.011	0.013	0.008	0.017
Scaled Difference (%)	40.02	165.93	-45.05	28.77	36.60	-32.57	32.36	9.10	-36.68

Notes. The unit of observation is an inventor. The top three panels report scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated using regression Equation (1) with j equal, in turn, to green, female-health, and weapon-related technologies. In the top and middle panel, the sample includes all USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. The first panel from the top shows the estimates augmenting Equation (1) with the following fixed effects: 1. zip code (columns 1-3); 2. county×year (columns 4-6); 3. CPC class (columns 7-9). The analysis includes a total of 129 CPC classes. The second panel shows estimates from Equation (1) with three alternative specifications: 1. the probability of ever patenting technology j is defined only for the first author of the patent (columns 1-3); 2. the outcome variable is the number of patents in technology j divided by the total number of patents granted to the inventor over the period (columns 4-6); 3. the outcome variable corresponds to the total number of patents in technology j granted to the inventor over the period, estimated through Poisson pseudo-likelihood regression (columns 7-9). The third panel shows the estimates from Equation (1) with three alternative samples: 1. the subsample of inventors who registered their current affiliation when they were 21 years old or younger (columns 1-3); 2. the sample of inventors who filed a patent application between 2001 and 2023 (columns 4-6); 3. the sample of inventors who made a contribution to a political campaign since 2000, derived from the Database on Ideology, Money in Politics, and Elections (DIME) (columns 7-9). In the patent application sample, the outcome is defined as the probability of ever filing a patent application in technology j. The DIME sample spans all U.S. states. We define inventors as "Democrat" if they donated more to the Democratic party than to the Republican one, and "Republican" inventors symmetrically. In all other cases, inventors are classified as "Other. The DIME data do not have information on the year of birth, thus, the estimates in columns 7-9 of the third panel do not control for birth-year fixed effects. In all panels, the scaled difference is the estimated coefficient $\hat{\beta}_1$ divided by the mean of the outcome variable for Republicans. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

A.4. The Role of Returns

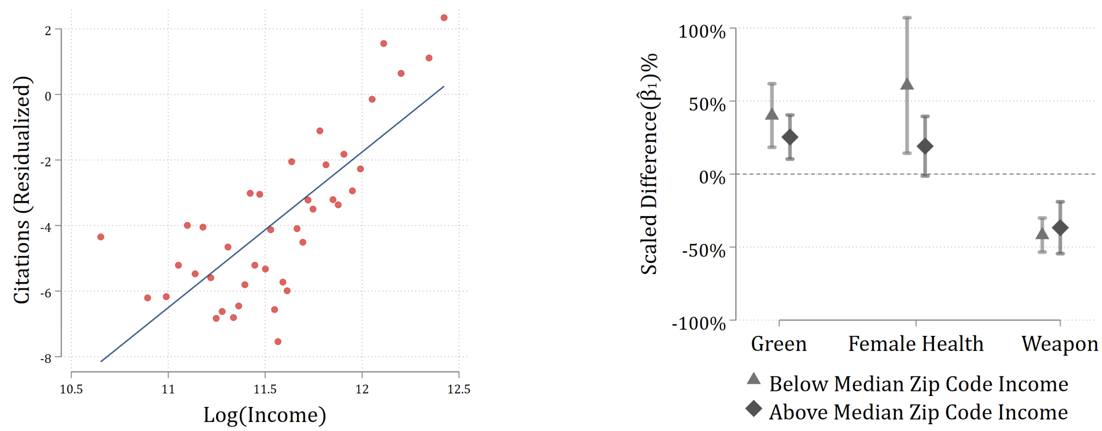
Table A.6: Party Affiliation and Polarized Technologies, Split by Median Citations

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) Below Median Citations	(2) Above Median Citations	(3) Below Median Citations	(4) Above Median Citations	(5) Below Median Citations	(6) Above Median Citations
Panel A: Inventor						
Democrat $\hat{\beta}_1$	0.0030***	0.0039**	0.0017*	0.0021	-0.0065***	-0.0090***
	(0.0011)	(0.0019)	(0.0009)	(0.0015)	(0.0015)	(0.0016)
N. of Inventors	44,311	27,801	44,311	27,801	44,311	27,801
% of Dem.	33.88	36.16	33.88	36.16	33.88	36.16
$\mathbb{E}(LHS)$ for Rep.	0.009	0.013	0.004	0.006	0.016	0.021
Scaled Difference %	33.63	29.18	40.35	32.80	-40.21	-43.02
Panel B: Patent						
Democrat $\hat{\beta}_1$	0.0031***	0.0029**	0.0015	0.0008	-0.0053***	-0.0091***
	(0.0010)	(0.0014)	(0.0009)	(0.0010)	(0.0013)	(0.0015)
N. of Inventors	49,045	44,059	49,045	44,059	49,045	44,059
% of Dem.	34.31	35.80	34.31	35.80	34.31	35.80
$\mathbb{E}(LHS)$ for Rep.	0.008	0.011	0.005	0.005	0.013	0.021
Scaled Difference (%)	38.05	26.05	31.92	15.44	-40.43	-43.86

Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. In Panel A, we split the sample by the median of the average citation count for inventors, while Panel B splits the sample by the median of the average citation count for patents. The outcome variable is a dummy equal to one if an inventor was ever granted a patent in technology j, and zero otherwise. Technologies j are defined as: green (columns 1-2), female-health (columns 3-4), and weapon-related (columns 5-6). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, as well as county, inventor birth year, technology-section fixed effects, a female dummy, and a dummy "Other" equal to one if an inventor is registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and equal to zero otherwise. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is equal to one if the inventor is a registered Republican, and zero otherwise. We adjust forward citation counts for truncation, following Hall et al. (2001). Our measure of adjusted forward citations is weighted by the number of inventors listed on the patent. In Panel A, we start from the patent-inventor sample and compute the inventor-level average of the adjusted forward citation count, following Akcigit et al. (2016). We split observations based on the median value of the inventor-level average adjusted citation count and estimate Equation (1) on each inventor-level subsample. In Panel B, we start from the patent-inventor sample and compute the patent-level average of the adjusted forward citation count. We split observations based on the median value of the patent-level average adjusted forward citations and estimate Equation (1) on each inventor-level subsample. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Figure A.3: The Role of Returns: Zip Code Income

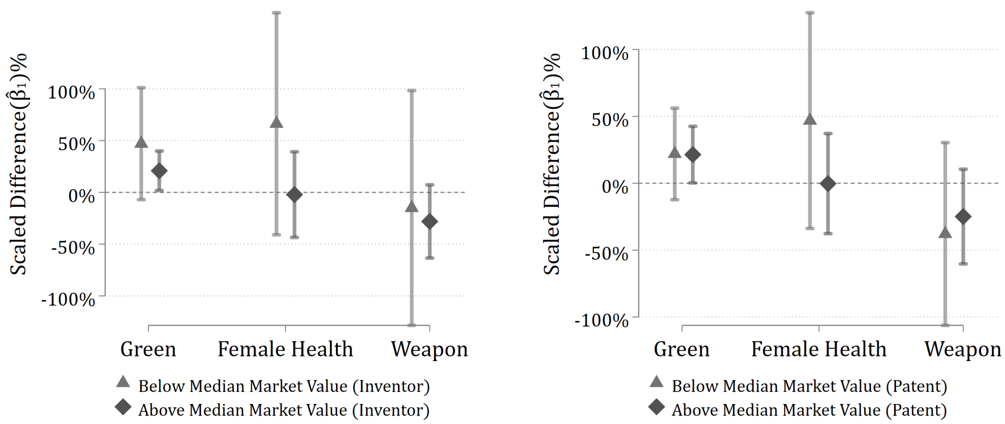
Panel A: Average Zip Code Income and Citations   Panel B. Inventor Median Zip Code Income



Notes. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. Panel A shows a binned scatter plot with 40 equally sized bins and the line of best fit showing the relationship between citations and median household income in zip code of residence (N=72,332). The x-axis displays the logarithm of the median zip code household income, computed as an average at the inventor level. The y-axis displays the average adjusted inventor-level citations, calculated as the total adjusted forward citations divided by the number of patents produced by each inventor over the period 2001-2023 (Akcigit et al., 2016). Forward citation counts are adjusted for truncation (Hall et al., 2001), residualizing by year and weighting by the number of inventors listed on the patent. Panel B reports scaled differences for the coefficient of "Democrat," $\hat{\beta}_1$, estimated using regression Equation (1) and 90 percent confidence intervals. We split observations based on the median household income of the zip code of residence of inventors, which corresponds to \$104,521 (N_{below} = 47,700, N_{above} = 47,393). The first pair of bars reports $\hat{\beta}_1$ where j is a green technology; the second pair corresponds to a female-health technology; the third to a weapon-related technology. Scaled differences are computed by dividing the estimated coefficient by the mean of the outcome variable for Republicans.

Figure A.4 replicates the Section 3.4 exercise using the alternative return measure from Kogan et al. (2017). We split the sample based on the median value of the average market value (`xi_real`), either computed at the patent or inventor level. This measure captures the economic value of innovation based on stock market reactions to patent grants. Since not all patents can be linked to stock market reactions, this measure is available for approximately half of the patent-inventor sample, which explains why estimates are noisy.

Figure A.4: The Role of Returns: Low- versus High-Stock Market Returns



Notes. Each plot reports the scaled differences for the coefficient "Democrat" ($\hat{\beta}_1$). We start from the patent-inventor sample, which includes all USPTO inventors who were granted a patent between 2001 and 2021 merged with NY, NJ, FL, and PA voter registration data, and compute the inventor-level and patent-level average of patents' stock market value, weighted by the number of inventors and residualized by year fixed effects. We split observations based on the median value of these measures and estimate Equation (1) in each subsample The first pair of bars reports $\hat{\beta}_1$ where j is a green technology; the second corresponds to a female-health technology; the third to a weapon-related technology. "Scaled Difference" is defined as the estimated coefficient of Democrat ($\hat{\beta}_1$) divided by the mean of the outcome variable for Republicans. All plots report 90 percent confidence intervals.

A.5. The Role of Organizations

Table A.7: Party Affiliation and Polarized Technologies, by Assignee Characteristics

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) Same-Party Organizations	(2) Mixed-Party Organizations	(3) Same-Party Organizations	(4) Mixed-Party Organizations	(5) Same-Party Organizations	(6) Mixed-Party Organizations
Democrat $\hat{\beta}_1$	0.0031	0.0036***	0.0016	0.0012	-0.0034*	-0.0017*
	(0.0020)	(0.0011)	(0.0017)	(0.0009)	(0.0018)	(0.0009)
N. of Inventors	21,361	54,715	21,361	54,715	21,361	54,715
% of Dem.	33.78	39.35	33.78	39.35	33.78	39.35
$\mathbb{E}(LHS)$ for Rep.	0.007	0.012	0.004	0.006	0.012	0.006
Scaled Difference %	44.81	31.47	39.44	18.97	-27.09	-28.10
	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) Academic Organizations	(2) Non-Academic Organizations	(3) Academic Organizations	(4) Non-Academic Organizations	(5) Academic Organizations	(6) Non-Academic Organizations
Democrat $\hat{\beta}_1$	0.0050	0.0031***	0.0046	0.0010	-0.0020	-0.0036***
	(0.0038)	(0.0009)	(0.0061)	(0.0008)	(0.0013)	(0.0007)
N. of Inventors	8,618	72,313	8,618	72,313	8,618	72,313
% of Dem.	52.98	35.55	52.98	35.55	52.98	35.55
$\mathbb{E}(LHS)$ for Rep.	0.016	0.010	0.024	0.005	0.003	0.011
Scaled Difference %	30.56	30.13	19.59	20.18	-71.23	-32.67
	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) Small Organizations	(2) Large Organizations	(3) Small Organizations	(4) Large Organizations	(5) Small Organizations	(6) Large Organizations
Democrat $\hat{\beta}_1$	0.0025	0.0036***	0.0035***	0.0006	-0.0039**	-0.0026**
	(0.0015)	(0.0011)	(0.0013)	(0.0009)	(0.0016)	(0.0010)
N. of Inventors	32,564	52,960	32,564	52,960	32,564	52,960
% of Dem.	34.16	38.97	34.16	38.97	34.16	38.97
$\mathbb{E}(LHS)$ for Rep.	0.008	0.012	0.005	0.006	0.015	0.006
Scaled Difference %	32.35	29.83	76.71	10.75	-25.38	-43.01
	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) Without Organization FE	(2) With Organization FE	(3) Without Organization FE	(4) With Organization FE	(5) Without Organization FE	(6) With Organization FE
Democrat $\hat{\beta}_1$	0.0040***	0.0025***	0.0011	0.0002	-0.0024***	-0.0014**
	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0006)	(0.0007)
N. of Inventors	69,584	69,584	69,584	69,584	69,584	69,584
% of Dem.	38.28	38.28	38.28	38.28	38.28	38.28
$\mathbb{E}(LHS)$ for Rep.	0.009	0.009	0.005	0.005	0.007	0.007
Scaled Difference (%)	42.88	27.01	21.86	3.57	-31.64	-18.55

Notes. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. In the top three panels, the unit of observation is an inventor, while in the bottom panel, it is an inventor-assignee. The outcome variable is a dummy equal to one if an inventor was ever granted a patent in technology j, and zero otherwise. Technologies j are defined as: green (columns 1-2), female health (columns 3-4), and weapon-related (columns 5-6). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, as well as county, inventor birth year, technology-section fixed effects, a female dummy, and a dummy "Other" equal to one if inventor i is registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and equal to zero otherwise. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is equal to one if the inventor is a registered Republican, and zero otherwise. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

A.6. The Diffusion of Polarized Technologies

Table A.8: Party Affiliation and the Diffusion of Polarized Technologies

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1)	(2)	(3)	(4)	(5)	(6)
	All Technologies	Outside the Same Technology	All Technologies	Outside the Same Technology	All Technologies	Outside the Same Technology
Democrat $\hat{\beta}_1$	0.0050***	0.0031	0.0041*	0.0045**	-0.0081***	-0.0028*
	(0.0019)	(0.0020)	(0.0022)	(0.0022)	(0.0018)	(0.0016)
N. of Inventors	45,917	45,886	45,917	45,893	45,917	45,784
% of Dem.	36.51	36.51	36.51	36.51	36.51	36.59
$\mathbb{E}(LHS)$ for Rep.	0.038	0.034	0.022	0.020	0.030	0.019
Scaled Difference (%)	13.31	9.32	18.74	22.29	-27.28	-15.03

Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. The outcome variable is a dummy equal to one if an inventor has ever cited a patent in technology j, and zero otherwise. Columns 1, 3, and 5 report results estimated on the full sample (after excluding self-citations). Columns 2, 4, and 6 report results excluding observations where the cited patent belongs to the same technology j as the citing patent. Technology j is defined as: green (columns 1-2), female health (columns 3-4), and weapon-related (columns 5-6). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, as well as county, inventor birth year, technology-section fixed effects, a female dummy, and a dummy "Other" equal to one for inventors registered as unaffiliated voters or with a party that is not the Democratic or Republican party, and equal to zero otherwise. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is a variable equal to one if the inventor is a registered Republican, and zero otherwise. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table A.9: Party Affiliation and the Diffusion of Innovation, Poisson Count Model

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1)	(2)	(3)	(4)	(5)	(6)
	All Technologies	Outside the Same Technology	All Technologies	Outside the Same Technology	All Technologies	Outside the Same Technology
Democrat	0.1720*	0.1794*	0.4070*	0.4229**	-0.5819***	-0.6366***
	(0.1039)	(0.1081)	(0.2155)	(0.2151)	(0.1380)	(0.1454)
N. of Inventors	44,501	44,389	43,477	43,453	44,017	43,550
% of Dem.	36.96	36.98	37.26	37.26	36.87	37.09
$\mathbb{E}(LHS)$ for Rep.	0.108	0.106	0.077	0.075	0.117	0.099
Scaled Difference ($e^{\hat{\beta}_1} - 1$) %	18.77	19.65	50.23	52.64	-44.12	-47.09

Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. The table shows the estimated coefficients for the Poisson pseudo-maximum likelihood regression where the outcome variable is the sum of citations by inventor i to technology j. Columns 1, 3, and 5 report results estimated on the full sample (after excluding self-citations). Columns 2, 4, and 6 report results excluding observations where the cited patent belongs to the same technology j as the citing patent. Technology j is defined as: green (columns 1-2), female health (columns 3-4), and weapon-related (columns 5-6). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, as well as county, inventor birth year, technology-section fixed effects, a female dummy, and a dummy "Other" equal to one if inventor i is registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and equal to zero otherwise. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is equal to one if the inventor is a registered Republican, and zero otherwise. Scaled differences are computed as the percentage of the exponential of the coefficient (incidence-rate ratios), $e^{\hat{\beta}_1}$, minus one. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table A.10: Party Affiliation and the Diffusion of Polarized Technologies, Intensive Margin

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1)	(2)	(3)	(4)	(5)	(6)
	All Technologies	Outside the Same Technology	All Technologies	Outside the Same Technology	All Technologies	Outside the Same Technology
Democrat $\hat{\beta}_1$	0.0015**	0.0006	0.0009	0.0010**	-0.0060***	-0.0017***
	(0.0006)	(0.0004)	(0.0006)	(0.0005)	(0.0009)	(0.0005)
N. of Inventors	45,917	45,886	45,917	45,893	45,917	45,784
% of Dem.	36.51	36.51	36.51	36.51	36.51	36.59
$\mathbb{E}(LHS)$ for Rep.	0.007	0.005	0.004	0.003	0.014	0.005
Scaled Difference (%)	20.57	10.33	22.80	33.56	-43.55	-34.68

Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. The outcome variable is the number of citations by inventor i to technology j divided by the total number of citations by inventor i over the period. Columns 1, 3, and 5 report results estimated on the full sample (after excluding self-citations). Columns 2, 4, and 6 report results excluding observations where the cited patent belongs to the same technology j as the citing patent. Technology j is defined as: green (columns 1-2), female health (columns 3-4), and weapon-related (columns 5-6). All specifications include year dummies, each taking value one if an inventor was granted a patent in that year, and zero otherwise, as well as county, inventor birth year, technology-section fixed effects, a female dummy, and a dummy "Other" equal to one for inventors registered as unaffiliated voters or with a party that is not the Democratic or Republican party, and equal to zero otherwise. "Democrat" is a dummy equal to one if an inventor is a registered Democrat, and zero otherwise. The omitted party dummy is a variable equal to one if the inventor is a registered Republican, and zero otherwise. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table A.11: The Diffusion of Polarized Technologies by Party Affiliation

	Cited: Democrat			Cited: Other			Cited: Republican		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.1341***	0.1198***	0.1176***	0.0088	0.0019	-0.0008	-0.1475***	-0.1410***	-0.1381***
	(0.0074)	(0.0071)	(0.0073)	(0.0073)	(0.0075)	(0.0072)	(0.0090)	(0.0089)	(0.0088)
Other $\hat{\beta}_2$	0.0347***	0.0244***	0.0209***	0.1194***	0.1144***	0.1105***	-0.1196***	-0.1147***	-0.1130***
	(0.0063)	(0.0061)	(0.0062)	(0.0075)	(0.0076)	(0.0073)	(0.0095)	(0.0091)	(0.0090)
N. of Inventors	28,775	28,775	28,658	28,775	28,775	28,658	28,775	28,775	28,658
% of Dem.	36.98	36.98	37.01	36.98	36.98	37.01	36.98	36.98	37.01
$\mathbb{E}(LHS)$ for Rep.	0.634	0.634	0.634	0.603	0.603	0.603	0.782	0.782	0.782
Scaled Difference (%)	21.17	18.91	18.55	1.45	0.32	-0.14	-18.86	-18.03	-17.66

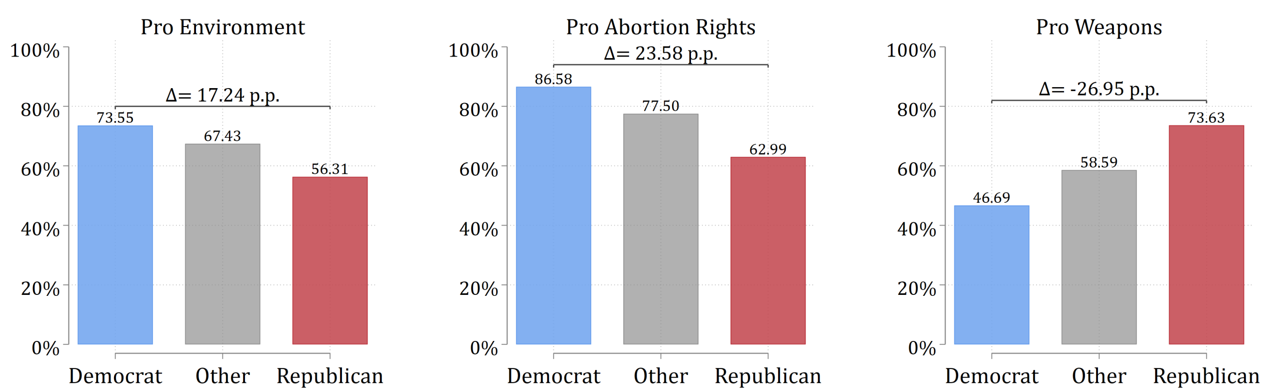
Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. In columns 1 to 3, the outcome variable is a dummy equal to one if inventor i has ever cited a patent by a Democrat inventor, and equal to zero otherwise. In columns 4 to 6, the outcome variable is a dummy equal to one if inventor i has ever cited a patent by an unaffiliated inventor or one registered with a third party, and equal to zero otherwise. In columns 7 to 9, the outcome variable is a dummy equal to one if inventor i has ever cited a patent by a Republican inventor, and equal to zero otherwise. All specifications include year dummies, each taking value one if the citing inventor was granted a patent in that year, and zero otherwise, and county fixed effects. Columns 2, 3, 5, 6, 8 and 9 include technology-section fixed effects. Columns 3, 6, and 9 control for birth-year fixed effects and a female dummy. "Democrat" is a dummy equal to one if the inventor is a registered Democrat, equal to zero otherwise. "Other" is a dummy equal to one if an inventor is registered as an unaffiliated voter or with a party that is not the Democratic or Republican party, and zero otherwise. The omitted party dummy is a variable equal to one if the inventor is a registered Republican, and zero otherwise. "Scaled Difference" is defined as the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

B. Survey Analysis

In this section, we analyze survey data from the Cumulative Cooperative Election Study (CCES) (Kuriwaki, 2024). The CCES aggregates and harmonizes all the yearly waves of the Cooperative Election Study (CES), a survey on a range of questions related to political behavior and preferences, from 2006 to 2021. Figure A.5 reports the percentage of respondents that support the environment, abortion rights, and the use of weapons, by the party of registration. We classify parties as described in the main text. "Democrat" refers to individuals registered with the Democratic party, "Republican" refers to individuals registered with the Republican party, and "Other" to individuals registered as unaffiliated voters or with a party that is not the Democratic or Republican party. The figure shows a gap of around 20 percentage points between registered Democrats and Republicans, even after residualizing by demographic characteristics. The views of individuals registered with "Other" parties (which include the unaffiliated), are approximately in the middle between those of registered Democrats and those of registered Republicans.

Figure A.6 replicates the analysis using a continuous measure of partisan identity. It shows the relationship between partisan identity and views on all CCES topics, including the environment, abortion rights, and gun control.[17] This allows us to compare the strength of the relationship for the environment, abortion rights, and gun control, with other topics central to public debate. The environment, abortion rights, and gun control stand out as especially polarized. Even after controlling for multiple individual characteristics and fixed effects, moving from an individual who is "strongly Democrat" to someone who is "strongly Republican" is associated with about a 30 percentage point change in agreement. In particular, strongly Democrat respondents are more likely to support gun control, environmental regulation, and abortion rights.[18] Based on the absolute value of the slope of the line of best fit, Republican and Democrat respondents also differ in their support for affirmative action, immigration, and gay marriage. In our analysis, we focus on the environment, abortion rights, and gun control as these are the topics that we are clearly able to map to the specific content of technologies, among those that are highly polarized in the political debate.

Figure A.5: Support by Issue and Party Affiliation, CCES



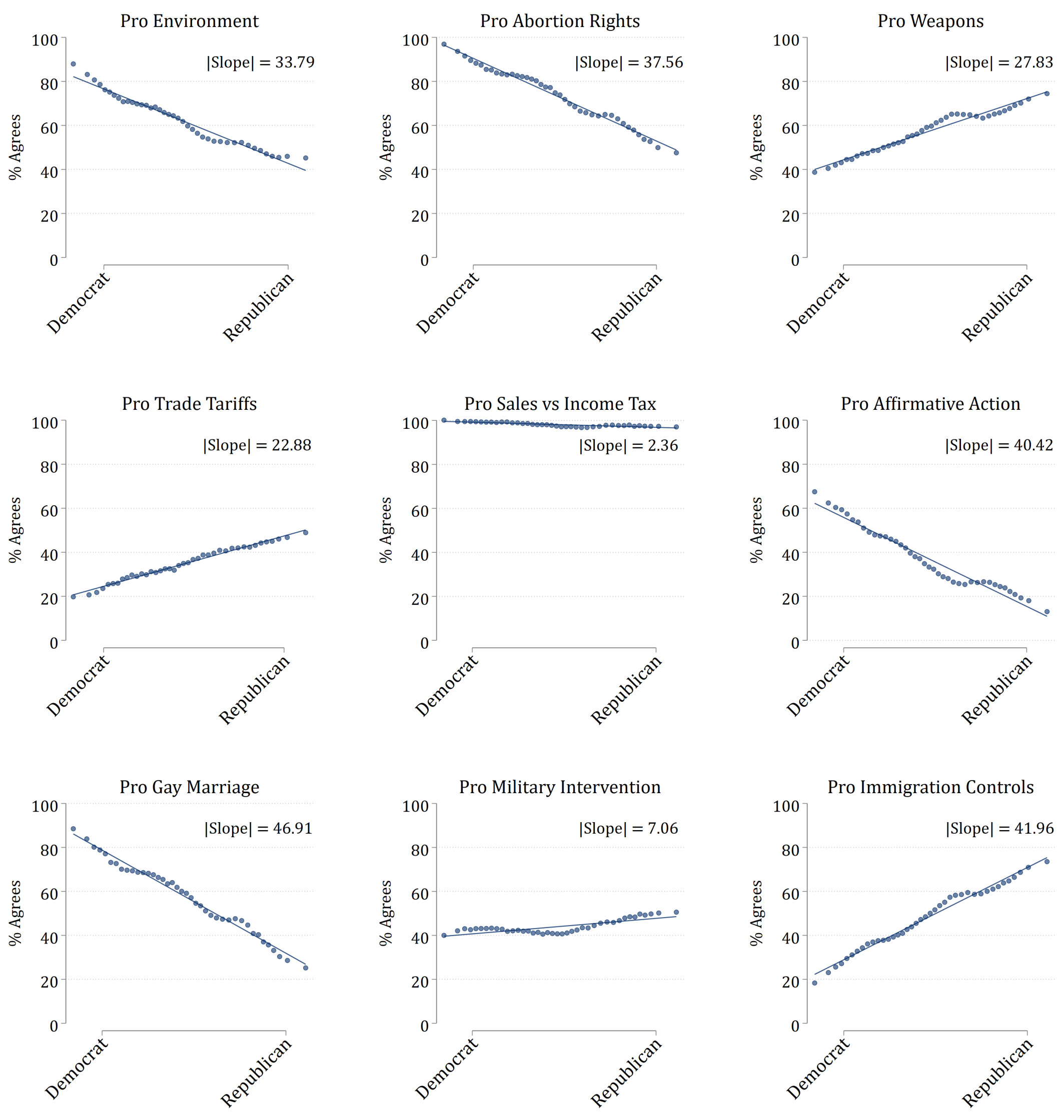
Notes. The figure reports the percentage of people who support the environment, abortion rights, and the use of weapons by party of registration, using CCES data. We restrict the sample to US citizens and we exclude individuals whose partisan identity (variable `pid7`) corresponds to "Not Sure" or "Don't know." This sample includes 495,777 respondents. The variable on the y-axis corresponds to the percentage of respondents who support a given topic, residualized by a female dummy, the age of respondents and fixed effects for county, year, employment status, race, education, and family income. These variables are constructed by harmonizing a set of CCES questions related to each topic into three discrete values (0, 0.5, 1) and rescaling them to be in the range [0, 100]. We define "Pro Environment" based on the following questions: `enviro_airwateracts`, `enviro_carbon`, `enviro_mpg_raise`, `enviro_renewable`, and `enviro_scale`. We define "Pro Abortion Rights" based on the following questions: `abortion_scale`, `abortion_conditional`, `abortion_always`, and `abortion_prohibition`. We define "Pro Weapons" based on the following questions: `guns_assaultban`, `guns_bgchecks`, `guns_names`, `guns_permits`, `guns_scale`. On the x-axis, we plot the party affiliation of respondents, which we define based on the variable `vv_party_gen`. "Democrat" refers

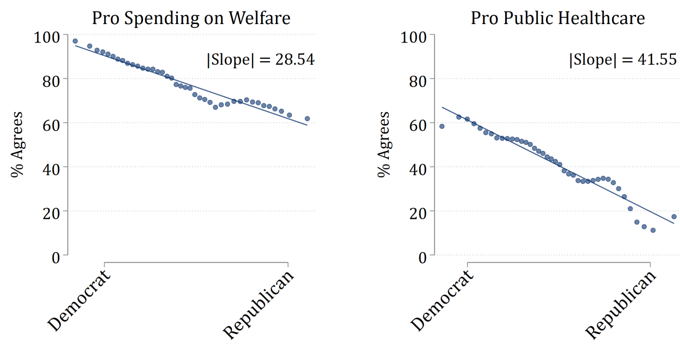
[17] The CCES specifically asks questions relevant to the public debate.

[18] Unreported results (available from the authors) show similar patterns using the General Social Survey (GSS) data and restricting the sample to respondents with characteristics similar to inventors.

to individuals registered with the Democratic party, "Republican" refers to individuals registered with the Republican party, and "Other" to individuals registered as unaffiliated voters or with a party that is not the Democratic or Republican party. Δ indicates the percentage point difference in support for each topic between registered Democrats and Republicans.

Figure A.6: Comparing Partisan Gradients in Support for Fundamental Issues, CCES





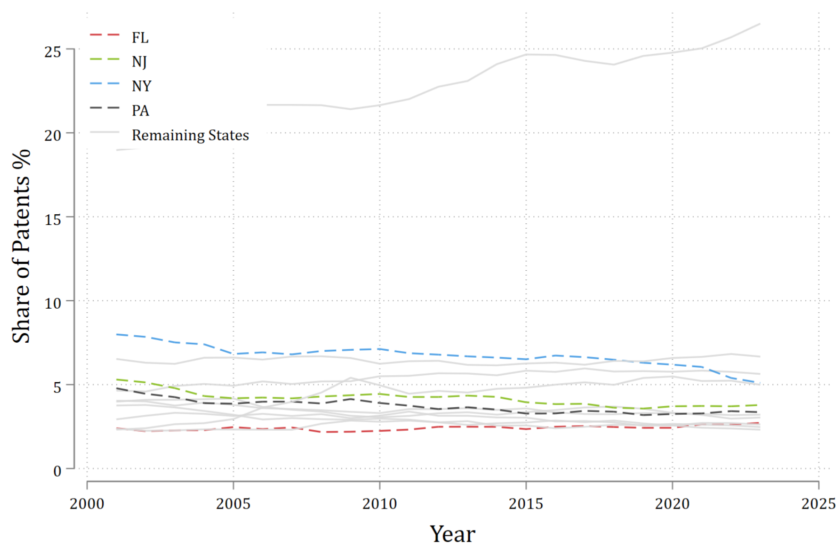
Notes. The figure reports binned scatter plots with 40 equally sized bins and the line of best fit showing the relationship between partisan identity and support for different issues from the Cooperative Congressional Election Study (CCES). We restrict the sample to US citizens and we drop individuals whose partisan identity (variable `pid7`) corresponds to "Not Sure" or "Don't know." This sample includes 495,777 respondents. On the x-axis, we plot the variable expressing partisan identity, `pid7`, rescaled to range between 0 and 1, where 0 represents individuals who identify as "Strongly Democrat," and 1 represents those who identify as "Strongly Republican." The "Democrat" label corresponds to those who identify as "Strongly Democrat," and the "Republican" label corresponds to those who identify as "Strongly Republican." The variable on the y-axis corresponds to the percentage of respondents who agree with supporting a given topic. These variables are constructed by harmonizing a set of CCES questions related to each topic into three discrete values (0, 0.5, 1) and rescaling them to be in the range [0, 100]. Following the modules provided by the CCES, we group questions into eleven broad categories. The only difference compared to the number of CCES modules consists in splitting the category "Other" into "Pro Gay Marriage", "Pro Affirmative Action" and "Pro Sales vs Income Tax." We define each topic through the following questions: 1. "Pro Environment" using `enviro_airwateracts`, `enviro_carbon`, `enviro_mpg_raise`, `enviro_renewable`, and `enviro_scale`; 2. "Pro Abortion Rights" using `abortion_scale`, `abortion_conditional`, `abortion_always`, and `abortion_prohibition`; 3. "Pro Weapons" using `guns_assaultban`, `guns_bgchecks`, `guns_names`, `guns_permits`, `guns_scale`; 4. "Pro Trade Tariffs" using `trade_canmex_include`, `trade_canmex_except`, and `trade_china`; 5. "Pro Sales vs Income Tax" using `incometax_vs_salestax`; 6. "Pro Affirmative Action" using `affirmativeaction`; 7. "Pro Gay Marriage" using `gaymarriage_legalize`, `gaymarriage_ban`, and `gaymarriage_scale`; 8. "Pro Military Intervention" using `military_democracy`, `military_genocide`, `military_helpun`, `military_oil`, `military_protectallies`, and `military_terroristcamp`; 9. "Pro Immigration Controls" using `immig_legalize`, `immig_border`, `immig_deport`, `immig_employer`, `immig_police`, `immig_reduce`, `immig_report`, `immig_services`, and `immig_wall`; 10. "Pro Spending on Welfare" using `spending_welfare`, `spending_police`, `spending_infrastructure`, `spending_healthcare`, and `spending_education`; 11. "Pro Public Healthcare" using `healthcare_aca`, `healthcare_acamandate`, and `healthcare_medicare`. Each binned scatter plot controls for a female dummy, age of the respondent, and fixed effects for county, year, employment status, race, education, and family income.

C. Data Appendix

C.1. Contribution of New York, New Jersey, Pennsylvania, and Florida to Total Innovation in the United States

Between 2001 and 2023, New York, New Jersey, Pennsylvania, and Florida contributed to more than 17% of total U.S. innovation, placing them among the top quartile of U.S. states by total number of patents. The yearly share of patents granted to (at least one) inventors residing in these states has also remained remarkably stable over time, as depicted in Figure A.7.

Figure A.7: Yearly Share of Patents by State



Notes. The figure plots the evolution of the yearly share of patents (by state of residence of inventors) for the U.S. states belonging to the top quartile in terms of total innovation in the period 2001-2023. Patent counts are weighted by the total number of inventors. The top quartile for total innovation during the period 2001-2023 includes the following states: CA, NY, TX, MA, WA, NJ, PA, IL, MI, MN, OH, NC, and FL. The dashed blue line indicates the yearly share of patents produced by inventors residing in NY; the dashed green line indicates the yearly share of patents produced by inventors residing in NJ; the dashed black line indicates the yearly share of patents produced by inventors residing in PA; the dashed red line indicates the yearly share of patents produced by inventors residing in FL. The other grey lines indicate the yearly share of patents produced by inventors residing in the remaining states.

C.2. List of States with Open and Closed Primaries

The U.S. states with closed primaries are: Connecticut, Delaware, District of Columbia, Florida, Kentucky, Maryland, Nevada, New Jersey, New Mexico, New York, Oregon, Pennsylvania. The states with open primaries are: Alabama, Arkansas, Colorado, Georgia, Illinois, Indiana, Iowa, Kansas, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, New Hampshire, North Carolina, Ohio, Rhode Island, South Carolina, Tennessee, Texas, Vermont, Virginia, West Virginia, Wisconsin, Wyoming. The remaining states have mixed systems. Open states are those with open primaries for presidential, congressional and state elections. Similarly for closed states. This classification is derived from `https://openprimaries.org/rules-in-your-state/` and the National Conference of State Legislatures.

C.3. Details on Inventor-Voter Sample Construction

C.3.1. Pre-Match Cleaning

To merge the two datasets, we begin by cleanining and standardizing names. First of all, we extracted suffixes (e.g., "sr.", "jr.", "junior", "II", "I" etc.) from names in both datasets and stored them in a separate variable. Additionally, we removed nicknames–denoted by parentheses or quotes–in the USPTO data. One major difference in how names are formatted between the two datasets is that the patent data report names split into first and last name, while the voter data separate names into first, middle, and last. Following Bell et al. (2018), we split inventors' first names whenever there is a single space, and we consider the first string as the first name, while the second string as the initial of the middle name or the middle name itself. Some inventors' names are composed of more than 2 words. In those cases, we store these variables separately and we consider only the first middle name for the merge.

The final patent dataset includes around 7.5 million inventor-patent pairs for the whole U.S. between 2001 and 2023. To further reduce the possibility of false positives when merging the two datasets, we truncated voter data according to age, by dropping those born after 2002 and before 1920. Jones (2010) find that there are no great achievers before the age of 19 and that only 7% of the sample is 26 or fewer years old. Kaltenberg et al. (2023) constructed a new patent dataset, by scraping information on the year of birth of inventors. They further restrict their dataset to inventors that are at least 15 years old and at most 89. We also disregard all the voters with missing first name, last name, or city of residence. We drop those with the length of the last name or city of residence equal to one character or if the lengths of the first name and middle name are both equal to one character. We replace voters' gender with the most common value if it is missing. In the very few instances where voters have duplicate records, if one voter is, *at least once*, registered as Democrat (Republican), and the other times she is registered under Independent, Other, or Blank, we consider her as Democrat (Republican).[19] We drop those voters that are registered as both Democrat and Republican (around 1% of the sample).

[19] In the remaining cases, we replace the party affiliation with the most frequent value.

C.3.2. Matching Algorithm

We adopt a conservative matching algorithm that matches exact strings on first names, last names, and city of residence.[20] This procedure minimizes the presence of false positives. Additionally, we only keep matches with the same initial letter of the middle name or when the middle name is missing from at least one of the two datasets.

Whenever one inventor is matched to multiple voters, we disregard the following matches: I. whenever age is implausible, i.e. older than 89 or younger than 22 either in the first or last patenting year, following Kaltenberg et al. (2023); II. whenever, among the duplicates, some do not have coherent middle initials (e.g., one missing and another not missing), but one of the matches has exactly the same middle initial; III. whenever the same inventor is matched to voters with different party affiliations. Of the remaining duplicates, we keep matches randomly. Whenever one voter is matched to multiple inventors, we first keep matches with the same middle initials. Again, we keep matches randomly for the remaining duplicates. All the results are unchanged if we keep only exact matches and disregard duplicates altogether.

We match more than 304,229 patents over a total of 573,324, corresponding to a match rate of almost 53%. This corresponds to more than 8% of total U.S. innovation over the period 2001-2023. Our final dataset includes 95,600 inventors.

C.3.3. Match Validation

We validate our matching procedure in three ways. First, we compare the descriptive characteristics of our inventors to those documented in the literature. Second, we qualitatively show that the differences between matched inventors and the full sample of registered voters go in the expected direction. Third, more formally, we perform equivalence tests to compare matched and unmatched inventors.

First, we compare the descriptive statistics of the voter-inventor sample with those found in the literature. First, 13% of all inventors are women in our final sample, which is similar to the figure of 11% found in (Akcigit and Goldschlag, 2023), and 12% found in the USPTO data using an imputed gender measure. In our sample, the average age at the granting year is 50, spanning years from 2001 to 2023. This is in line with Jones (2009), Akcigit and Goldschlag (2023), who show that inventors are getting older over time. Using the replication data from Jones (2009), based on a subset of more than 50,000 inventors, the average age at the granting year is 49 for the period 1975-1999. In the Florida subsample, Black inventors represent 4% of the sample and most inventors are white, in line with the findings in Akcigit and Goldschlag (2023).

Relative to the full sample of registered voters in New York, New Jersey, Florida and Pennsylvania, the matched sample of inventors displays characteristics in line with prior evidence. Inventors live in richer zip code areas (median family income of around 114,000 USD compared to around 83,000 USD for the full population)[21], they are prevalently white (79% compared to 60% in FL in

[20] Following the procedures adopted by Bell et al. (2018), Teso et al. (2023) and Fos et al. (2022).

[21] The latter figure is obtained using zip code-level data in 2022 from the Missouri Census Data Center.

2017) or Asian (5% compared to 2% in FL in 2017)[22], they are mostly men (87% of inventors are men, while in the voter registration data gender is balanced).

To show more rigorously that our matched voter-inventor sample is not likely to be biased, we perform equivalence tests in Table A.12.[23] Similarly to Teso et al. (2023), we test the null hypothesis that the difference between matched and unmatched inventors is economically large and consider "economically large" differences those that exceed 10% of a standard deviation. The p-values for equivalence tests are presented in the last column of Table A.12. We consider a total of 22 variables related to inventors' characteristics, place of residence, and patenting activity. Out of all characteristics that we test, only two have meaningful differences between the matched and unmatched samples.

Importantly, unmatched and matched inventors have similar lengths and number of consonants in their names. Matched and unmatched inventors are also similar in terms of gender, income, population of their city of residence, and share of Democrats living in their counties. Matched inventors tend to live in counties with on average more Republicans than unmatched inventors (32% compared to 31%).

In terms of patenting activity, we reject the null of economic differences between matched and unmatched inventors. They patent in similar technological sections, on average.[24] Similarly, matched and unmatched inventors are on average producing technologies of similar impact measured by forward citations. Matched inventors are on average granted a patent in 2014, while unmatched in 2013, which is in line with the fact that the voter registration data are recent snapshots.

C.4. Campaign Contribution Data

As a robustness check and validation exercise, we use data on the universe of campaign contributions obtained from Stanford's Database on Ideology, Money in Politics, and Elections (DIME) database (Bonica, 2019), which includes all contributions from individuals and organizations between 1979 and 2016. Adam Bonica kindly shared with us the rest of the data up to 2018. For consistency with the voter data, we restrict the sample to contributions starting from the 2000 election cycle. The DIME data contain information on the contributors' names, city of residence, employers, occupations, the amount donated, the recipient committee, and, importantly, the political affiliation of the committee. Following Fos et al. (2022), we use the cumulative donation amount to a party to infer the party affiliation. An individual is classified as a Democrat if total donations to the Democratic party exceed those to the Republican party throughout his or her donation history, and vice versa. We exclude individuals who donated to both parties. All remaining contributors are

[22] Only 7.00% of inventors have Hispanic origins, while in 2017 they make up almost 16% of the total Florida registered voters; also Black inventors are 4% of the matched sample, while in 2017 in FL they are almost 14%.

[23] We follow the literature and conduct equivalence tests rather than difference tests, as they are more suitable when working with large samples. In fact, the latter may lead to over-rejecting the null of no difference (e.g., Teso et al., 2023).

[24] A patent can belong to multiple sections and an inventor can patent multiple patents, thus we considered for each inventor the share of patents in each section.

Table A.12: Difference in observables between matched and unmatched inventors

	Matched		Unmatched		Matched-Unmatched	
	Mean (1)	Standard Deviation (2)	Mean (3)	Standard Deviation (4)	Standardized Difference (5)	P-value Equivalence Test (6)
Gender	0.134	0.341	0.151	0.358	-0.047	0.000
Num Consonants First Name	3.682	1.141	3.609	1.254	0.060	0.000
Num Consonants Middle Name	0.826	1.284	0.726	1.282	0.078	0.000
Num Consonants Last Name	4.138	1.400	4.032	1.575	0.070	0.000
Length First Name	5.842	1.516	5.820	1.754	0.013	0.000
Length Middle Name	1.201	1.976	1.078	1.998	0.062	0.000
Length Last Name	6.489	1.970	6.429	2.334	0.027	0.000
City-level Log(Income)	12.680	1.397	12.580	1.364	0.073	0.000
City-level Log(Population)	11.030	1.819	10.990	1.711	0.023	0.000
County-level Democrats (%)	0.412	0.111	0.416	0.104	-0.042	0.000
County-level Republicans (%)	0.322	0.111	0.307	0.107	0.141	1.000
A Section (mean)	0.285	0.435	0.291	0.443	-0.012	0.000
B Section (mean)	0.197	0.368	0.172	0.358	0.068	0.000
C Section (mean)	0.162	0.349	0.192	0.383	-0.083	0.000
D Section (mean)	0.010	0.087	0.010	0.091	-0.001	0.000
E Section (mean)	0.043	0.191	0.034	0.174	0.047	0.000
F Section (mean)	0.100	0.281	0.081	0.260	0.072	0.000
G Section (mean)	0.366	0.452	0.358	0.459	0.018	0.000
H Section (mean)	0.235	0.395	0.260	0.420	-0.061	0.000
Y Section (mean)	0.151	0.316	0.151	0.329	0.001	0.000
Granting Year (mean)	2014	6.358	2013	6.822	0.149	1.000
Patent Citations	14.960	39.230	18.490	50.520	-0.075	0.000

Notes. This table shows descriptive statistics (mean and standard deviation) of inventors matched to voter records (Columns 1–2) and unmatched to voter records (columns 3–4). Column 5 shows the scaled difference between matched and unmatched in the full sample of NY, NJ, PA and FL inventors. Column 6 reports the largest p-value for the equivalence test of means using a two one-sided t-tests approach. The null hypothesis is that the difference is larger than 10% of a standard deviation, or smaller than -10% of a standard deviation. The sample includes all inventors resident in NY, NJ, PA and FL between 2001 and 2023.

classified as "Other," consistent with the party classification from voter data. In the main analysis, we use voter registration data rather than campaign contribution data for two reasons. First, the measure of political affiliation is more direct in the voter data, while with DIME it is constructed indirectly by summing up the contributions. Political contributions can be influenced by various factors beyond political preferences, such as individuals' attempts to exert political influence. Thus, as suggested by Fos et al. (2022), voter registration data provide a more reliable indicator of party affiliation than political contributions. Additionally, individuals donate to committees that cannot be linked to any party or give an equal amount of dollars to different parties, potentially adding noise to this measure. Second, the matched contributor-inventor sample is likely a non-random sample of the population of U.S. inventors. For example, inventors who donate could be those with stronger political preferences. Thus, the external validity of the results is more limited when using this sample, compared to the matched voter-inventor sample. We use a similar matching procedure to the one described above for the voter-inventor sample, with two differences. First, we screen out "wrong" matches using the occupation of the donors. We manually select a list of occupations that are likely unrelated to innovation, e.g., bankers, nurses, educators. Second, as we do not have information on donors' age, we cannot restrict the sample to inventors aged between 22 and 89 as we do with the voter data. Conditional on having the residence in FL, NJ, NY, or PA, there are 53% Democrat and 24% Republican inventors in the matched DIME dataset, while 36% and 35% in the matched voter dataset, respectively. This is in line with Fos et al. (2022), who argue that Republican executives are often "hidden" compared to Democrat executives as they make campaign contributions that are not directly linked to the Republican party.

C.5. Outcome Variable Construction: Dictionary Approach

This section outlines the methodology to define outcome variables with the dictionary approach.

C.5.1. Green Technologies

To classify patents as "green" technologies, we proceed in eight steps.

1. To minimize false positives, we restrict the set of patents to those belonging to CPC class Y02 ("Technologies or Applications for Mitigations or Adaptations against Climate Change").

2. We define a list of adjacent words which, if present in the patent abstract, classify it as a green technology: "adaptive capacity," "air cleaning," "alternative energ," "anti-pollution," "automobile pollution," "biodiversity," "biofuels," "carbon capture," "carbon dioxide control," "carbon emissions," "carbon footprint," "circular economy," "climate change," "climate warming," "climatic condition," "clean energ," "co2 control," "conversion of co2," "conversion of carbon dioxide," "carbon dioxide removal," "electric efficien," "emission control system," "emissions system," "engine emissions," "environmental enhancement," "environmental pollution," "evaporative emissions," "ghg emissions," "global warming," "green energ," "green pellets," "greenhouse gas," "hydrogen engine," "hydropower," "non-fossil fuel," "non fossil fuel," "oil pollution," "polluting emissions," "pollution control," "reducing carbon dioxide," "reducing co2," "reduction of carbon dioxide," "reduction of co2," "smart grid," "smart-grid," "solar panel," "solar thermal," "wind energ," "wind farm," "wind park," "wind plant," "wind power."

3. We similarly define a list of non-adjacent words that, if both present in the patent abstract, classify the patent as a green technology:

   - "carbon dioxide" jointly with one of the following: "particulate emission," "coal," "capture," "absorption," "automobile," "oil," "environment," "gas," "energy," "air," "vehicle," "water," "traffic," "power," "fuel,"
   - "ch4" jointly with one of the following: "sorbent," "reduction," "reduce," "decrease," "remov," "recycl," "captur," "purif,"

- “co2” jointly with one of the following: “particulate emission,” “coal,” “capture,” “absorption,” “oil,” “automobile,” “environment,” “gas,” “fuel,” “power,” “energy,” “air,” “vehicle,” “traffic,” “water,”
- “emissions” jointly with one of the following: “sorbent,” “reduction,” “reduce,” “decrease,” “sorbing,” “remov,” “captur,” “purif,” “control,”
- “geothermal” jointly with one of the following: “energ,” “heat,”
- “methane” with “sorbent,” “reduction,” “reduce,” “decrease,” “sorbing,” “remov,” “recycl,” “captur,” “purif,” “absorb,”
- “n2o” jointly with one of the following: “sorbent,” “reduction,” “reduce,” “decrease,” “sorbing,” “remov,” “captur,” “absorb,”
- “nitrous oxide” jointly with one of the following: “sorbent,” “reduction,” “reduce,” “decrease,” “remov,” “captur,” “purif,” “absorb,”
- “ozone” jointly with one of the following: “layer,” ”shield,”
- “photovoltaic” jointly with one of the following: “energ,” “environ,”
- “pollution” jointly with one of the following: ”gas” ”energy” ”air” ”water” ”traffic” ”vehicle” ”power” ”fuel” ”particulate emission”
- “recyclable” jointly with one of the following: “material”
- “renewable” jointly with one of the following: ”energ” ”power”
- “sf6” jointly with one of the following: “reduce,” “decrease,” “sorbing,” “remov,”
- “solar” jointly with one of the following: “energ”, ”power”
- “sulfur hexafluoride” jointly with one of the following: “reduction,” “reduce,” “decrease,” “sorbing,” “remov,” “recycl,” “absorb,”
- “sustainable” jointly the following: “energ”
- “wind turbine” jointly with one of the following: “energ,” “environ.”

4. In order to remove false positives, we recode the dummy “green technology” equal to zero for patents whose abstracts contain one of the following adjacent words: “audio tape,” “dialysis,” “drugs,” “light pollution,” “networking environment,” “newspaper,” “telemetry.”

5. Similarly, we recode the dummy “green” technology equal to zero for patents whose abstracts contains one of the following non-adjacent words:

   - “emission” jointly with one of the following: “radio,” “communication,” “evaporative,” “cooking,” “light,” “optical,” “orthopedic,” “acoustic,” “sound,” “video,” “radiat,” “emi,” “emc,” “infrared,” “spectral,” “dust,” “electromagnetic,” “housing,” “telephone,” “signals,” “vapor,” “fluorescent,” “light,” “tomography,” “urea,” “tobacco.”
   - “pollut” jointly with one of the following: “noise” or “sound.”

6. We recode as green equal to zero a patent that is classified as a "brown" technology. We define as "brown" patents whose abstracts contain one of the following adjacent words: "combustion engine," "combustion-engine," "fuel compound," "fracing," "fracking," "gasoline," "hydraulic fracturing," "hydrocarbon well," "hydrofracturing," "hydrofracking," "internal combustion," "internal-combustion," "oil drilling," "oil sand," "oil shale," "oil-sand," "oil-shale," "petrol ," "petroleum drilling," "shale oil," "well logging," "well oil."

7. We recode as "brown" patent whose abstract contains one of these non-adjacent terms: "drill" together with "oil" or "petroleum."

8. Finally, we recode "brown" patents as equal to zero if they include one of the following terms: "emission," "recycling."

C.5.2. Female-Health Technologies

To classify patents as "female health" technologies, we proceed in four steps.

1. To minimize false positives, we restrict the set of patents to those belonging to CPC classes: A41 ("Wearing Apparel"), A61 ("Medical or Veterinary Science; Hygiene"), C07 ("Organic Chemistry"), C12 ("Biochemistry; Beer; Spirits; Wine; Vinegar; Microbiology; Enzymology; Mutation or Genetic Engineering"), G01 ("Measuring, Testing"), and G06 ("Computing, Calculating, or Counting").

2. We select a list of terms related to female reproductive health starting from Koning et al. (2019) (Appendix B, p.p. 35-36). If at least one of the following adjacent words is present in the patent abstract, we classify the patent as a "female health" technology: "abortion," "aborticide," "abortus," "adenomyosis," "amniocentesis," "amenorrhe," "anovulation," "antiestrogen," "areola," "artificial insemination," "bartholin," "birth control," "birth defects," "blasting," "blastocyst," "blastosphere," "blastula," "boomerangs," "brassiere," "breast cancer," "breast cyst," "breast pump," "breast tumor," "breastfe," "breastpu," "brenner tumor," "c section," "caesarean," "casesarian," "cervices," "cervix," "cesarean," "child bearing," "childbearing," "chorioamnionitis," "clitoral," "clitori," "colposcopy," "colpitis," "colpotomy," "contraceptive pill," "culdoscopy," "cystocele," "dysmenorrhea," "ectopic," "eclampsia," "eclamptic," "endometrial," "endometri," "endocele," "estrogen," "estradiol," "estrus," "extrauterine," "fallopian," "female circumcision," "female condom," "female fertility," "female genital," "female patient," "females," "fertility in women," "fetal," "fetalis," "feticide," "fetoscopy," "fetus," "fgm," "fimbria," "foetus," "gestagen," "g spot," "graanfian follicles," "grafenberg spot," "granulosa," "grfenberg spot," "gravidarum," "green infrastructure," "gynatresia," "gynecolog," "hematocolpos," "hematometra," "hellp syndrome," "high solar reflectance," "hormonal imbalance," "hot flash," "hot flush," "hydrocolpos," "hyperemesis," "hymen," "hymenal," "hysterectom," "hysterotomy," "hysteroscop," "in vitro fertilisation," "in vitro fertilization," "infibulation," "intraepithelial," "intrauterine," "iud," "labia," "labium," "lactation," "lactating," "leakage reduction," "leukorrhea," "lumpectomy," "luteal," "luteoma,"

"mammaplasty," "mammary," "mammectomy," "mastitis," "mastectom," "mastectomy," "mammalian cancer," "menopaus," "menorrhagia," "menses," "menstrua," "metrorrhagia," "miscarriage," "mons pubis," "montes pubis," "multiovulate," "myometrium," "nonoxynol," "oocyte," "oogonium," "oophoritis," "oosphere," "oestrus," "oestrone," "oestrogen," "oligohydramnios," "oviducal," "oviduct," "ovarian," "ovariectomy," "ovaries," "ovary," "ovulat," "ovum," "papanicolaou," "pap smear," "pap test," "parovarian cyst," "pcos," "pelvic inflammatory disease," "pessaries," "pessary," "placentae," "postabortion," "postmenopausal," "postpartum," "postpregnancy," "pre term birth," "preeclampsia," "preeclamptic," "premenopausal," "preterm birth," "preterm delivery," "prenatal," "preovulatory," "progesterone," "progestin," "progestog," "pseudovar," "puerperal," "pyelectasis," "pyometra," "rectovaginal,"
"salpingectomy," "salpingitis," "salpingosto," "skene glands," "smallarm," "solar cooling," "solar energy," "solar heat," "solar power," "solar thermal," "solar-power," "spermicide," "stillbirth," "symphysiotomy," "thecoma," "thermal insulation," "tolerance to drought," "tolerance to heat," "tolerance to salinity," "trachelectomy," "transgenic plants," "trophoblastic," "turner syndrome," "uterine fibroids," "uterine," "uterus," "vagina," "vagini," "vacuum absorption," "vacuum curettage," "vacuum glazing," "vacuum insulation," "vasa previa," "vesicovaginal," "vestibular bulb," "vulva," "vulvectomy," "vulviform," "vulvodynia," "vulvovagi," "water filtration," "wet nurse," "womb."

3. We remove false positives related to male health. We select a list of adjacent words which, if present in the patent abstract, recodes the dummy "female-health technology" as zero: "alport syndrome," "androgenetic alopecia," "aspermia," "asthenozoospermia," "azoospermi," "bald," "baldness," "balanitis," "balanoposthitis," "bph," "bulbourethral glands," "cavernos," "castration," "circumcis," "corpus cavernosum," "cowper glands," "cremaster muscle," "cryptorchid," "deferens," "dht," "ejaculation," "ejaculator," "erection," "erectile," "epididym," "finasteride," "flutamide," "foreskin," "fournier gangrene," "glans penis," "gonadal dysgenesis," "gonadoblastoma," "haemophilia," "hematocele," 'hematospermia," "hemospermia," "hydrocele," "hypospadia," "impotence," "impotent," "infecund," "inseminat," "interseminal," "isd," "klinefelter syndrome," "male fertility," "male patient," "micropenis," "microphallus," "oligospermia," "orchiectomy," "orchiopexy," "orchitis," "paraphimotic," "paraphimoses," "paraphimosis," "paternal," "penes," "penial," "penile," "penis," "periurethral," "peyronie," "phimoses," "phimosis," "phimotic," "priapism," "priapismic," "prepuce," "preseminal," "prostate," "prostatectomy," "prostatic," "prostatitis," "psa," "psma," "puboprostatic," "retropubic," "scrota," "scrotum," "semen," "seminal," "seminoma," "sertoli," "sildenafil," "sperm," "spermatogenesis," "spermatozoa," "testes," "testicles," "testicular," "testis," "testosterone," "teratozoospermia," "transrectal," "transrectal ultrasound," "transurethral," "turp," "urethra," "varicoceles," "vasculogenic impotenc," "vasectomy," "vasovasostomy," "vasa deferentia," "y chromosome."

4. We remove false positives linked to animal health. Specifically, we recode the dummy "female

health" as zero if one of the following adjacent words is present in the patent abstract: "animals," "bird," "cow," "cows," "gilt", "gilts," "mammals," "pig," "pigs," "poultry," "pregnant leach," "pregnant liquor," "sow," "sows."

C.5.3. Weapon-related Technologies

To classify patents as weapon-related technologies, we proceed in five steps.

1. To minimize false positives, we restrict patents to belong to CPC classes F41 ("Weapons"), and F42 ("Ammunition; Blasting").

2. We define a list of adjacent words which, if present in the patent abstract, we classify the patent as a "weapon-related" technology: "armaments," "armor," "armour," "artillery," "blasting," "boomerangs," "bomblet," "bullet," "bullets," "cannons," "carbine," "coilgun," "detonator," "firearm," "fuze," "fuzes," "grenade," "ground mine," "gun," "gunfire," "guns," "handgun," "howitzer," "land mine," "magazine loader," "mine neutraliz," "mine clearing," "military," "missile," "modular target system," "munition," "naval mine," "ordnance," "percussion cap," "personal defense," "pistol," "projectile," "railgun," "revolver," "rifle," "rifles," "shooting," "shooting target," "silencer," "slingshot," "smallarm," "submarine mine." "torpedo," "weapon."

3. We define a list of non-adjacent words which, if both present in the patent abstract, classify the patent as a "weapon-related" technology:

   - "ballistic" jointly with one of the following words: "protector," "barrier," "shield," "attack," "resist," "bunker,"
   - "bomb" jointly with one of the following words: "rack," "aircraft," "target," "blast," "deactivator," "detonator," "aerial," "fir," "pilot," "arming," "plane,"
   - "detonati" jointly with one of the following words: "fire," "explosiv,"
   - "explosive" jointly with one of the following words: "combat," "blast," "firing," "armament," "launch,"
   - "mine" jointly with one of the following words: "target," "firing," "launch," "exploding," "explosiv," "detection,"
   - "mortar" jointly with one of the following words: "bomb," "cartridge," "fir,"
   - "submarine" jointly with one of the following words: "launch" "explosiv"
   - "submersive" jointly with one of the following words: "launch" "explosiv"

4. We define a list of adjacent words such that, if present, the dummy variable "weapon-related" technologies is recoded as zero. This is to avoid false positives, as these terms are related to toys or other utensils: "acoustic signature," "adhesive gun," "air dehumidifier,"

"air pollutant," "air traffic control," "applicator gun," "applying gun," "armor heat," "armor tape," "armor wire," "armored sponge," "articulating arm," "arc gun spray," "armored sponge," "bait forming gun," "ballistic modifier," "ballistic parachute," "ballistic separator," "baloon gun," "band armor," "basketball," "beverage," "blast gun," "blaster gun," "blasting media," "blasting particles," "blind fastener," "blood flow," "blow gun," "bb gun," "body piercing," "boomerangs," "cake," "calking gun," "cassette magazine," "caulk gun," "cement gun," "chemical ionization," "chipping gun," "chromatography," "cleaning gun," "coating gun," "coke," "color," "corpus cavernosum," "crimping gun," "cutting gun," "delivery gun," "detonator gun," "diode gun," "dispensing gun," "dispensing head," "dispensing nozzle," "dispensing pipe," "driver gun," "drain gun," "drill gun," "drink," "ear piercing," "electron gun," "electron," "electrode gun," "electrostatic gun," "electrons," "energy gun," "fan gun," "fastener gun," "fastening gun," "fishing pole," "fishing rod," "flood gun," "flocking gun," "fluid injection gun," "foam gun," "form of a gun," "food," "gaming console," "gene," "genetic," "glue gun," "golf," "grease gun," "gun drill," "gun like configuration," "gun puffing," "gun roving," "gun shaped," "gun type," "heated gun," "heat gun," "heating gun," "hockey," "howitzer," "impact gun," "industrial waste," "injection gun," "injector gun," "injuries," "insemination gun," "interlock armor," "ion gun," "irrigation," "joining gun," "lacrosse," "laser gun," "marker gun," "massage gun," "media blasting," "meat," "microplasma," "modular target system," "motorist," "mud gun," "munition," "nail gun," "nailing gun," "nano crystal," "newsfeed," "nozzled gun," "nuts," "oil and gas," "oil gun," "paint ball gun," "paint gun," "paternal," "patient," "perforation gun," "perforator gun," "personal defense," "pets," "peening gun," "photo shooting," "pistol like configuration," "pistol shaped," "playing card," "plasma gun," "plasma spray," "pole gun," "pneumatic conveyance," "pole gun," "precision plasma," "prepuce," "propellant gun," "puboprostatic," "radar gun," "railgun," "rivet gun," "sandy production," "scanner gun," "screenplay," "sealant gun," "servo gun," "shooting video," "shotgun microphone," "shotgun stick," "silencer," "siphon gun," "slingshot," "slot armor," "snow gun," "snow making gun," "snowmaking," "soldering gun," "soldering pencil," "spiderweb maker gun," "spinal spacer," "spool gun," "spray gun," "spraying gun," "sprinkler gun," "sports," "sport," "staple gun," "stapling gun," "steam gun," "stud gun," "surgical," "surface cleaning," "sputter gun," "sputtering gun," "t shirt," "tablet gun," "tagging gun," "tape gun," "texture gun," "thermal gun," "torque gun," "toy," "transrectal ultrasound," "treatment gun," "tube gun," "turp," "vaccine," "vent topper," "vertical bullet," "video game," "video shooting," "video take," "voice network," "washer gun," "water gun," "weld gun," "well logging," "well oil," "winding gun," "welding gun."

5. We similarly define a list of non-adjacent words such that, if present, the dummy variable "weapon-related" technology is recoded as zero.

   – "armor" jointly with the word "cable,"

   – "gun" jointly with the word "pneumatic."